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Kristian Behrens and Maria Kuznetsova

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Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
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JEL Classification: F51, F15, R11, R12

Keywords: border changes, crossborder movements, nighttime lights, manufacturing plant exit, conflict between Russia and Ukraine

Kristian Behrens - behrens.kristian@uqam.ca
University of Quebec at Montréal and CEPR

Maria Kuznetsova - mariya.kuznetsova@hse.ru
HSE University

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Kristian Behrens† Maria Kuznetsova‡

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†Department of Economics, Université du Québec à Montréal (ESG-UQAM), Canada; and CEPR, UK. E-mail: behrens.kristian@uqam.ca

‡HSE University, Russian Federation. E-mail: mariya.kuznetsova@hse.ru

1 Introduction

We exploit the Russia-Ukraine conflict—following the annexation of Crimea in 2014—as a natural experiment to provide evidence for the economic effects of changes in market access on the performance of border regions. Contrary to previous literature that has analyzed the effects of the creation or the removal of borders at different points in time, we focus on *heterogeneous changes* that occur simultaneously along a single international border.[1] Whereas regions in the south of Russia saw an increase in their market access as the border with Crimea de facto disappeared, regions in the north saw a decrease in their market access as the Ukrainian government shut down border crossings and restricted the movements of goods and of people.

We find that Russian border regions relatively more exposed to Ukraine had worse economic outcomes—as measured by growth in nighttime lights and manufacturing plant exit—after 2014 than less exposed regions. In particular, regions relatively more exposed to the north as compared to the south fared worse. Using a variety of exposure measures based on market potential and distance, the growth in nighttime lights post 2014 was about 40% lower for the most exposed areas compared to the least exposed areas; whereas the exit probability of plants post 2014 increased by about 34% more for the most exposed plants compared to the least exposed plants. These figures suggest the economic costs of border frictions are sizeable and geographically localized.

To measure the economic effects of border changes on border regions, we first leverage nighttime lights satellite data. These data have become fairly standard in economic research and have been widely and successfully used in settings such as ours where sub-national quality data are not available.[2] While nighttime lights are reasonable proxies for aggregate

[1]See, e.g., Redding and Sturm (2008) and Ahlfeldt et al. (2015) for an analysis of the economic effects of German division and reunification and of the Berlin wall; and Brülhart et al. (2012) and Brülhart et al. (2018) for an analysis of the economic effects of the fall of the Iron Curtain.

[2]See, among others, Elvidge et al. (1997); Chen and Nordhaus (2011); Henderson et al. (2012); Michalopoulos and Papaioannou (2012); Pinkovskiy and Sala-i Martin (2016); and Bruederle and Hodler (2018). We show in Online Appendix B.1 that the harmonized DMSP nighttime lights satellite data we use correlate well with regional GDP, as well as with municipal employment (manufacturing and services), wages (manufacturing and services), and the number of manufacturing plants. See Figures B.1–B.3.

economic activity, their precise relationship to the underlying economic variables is usually less clear. We thus leverage an alternative dataset containing a large number of manufacturing plants in Russia, which we precisely georeference, to understand whether plants in more negatively exposed regions had worse economic outcomes, i.e., exited more. The results from both datasets are surprisingly consistent: regions more exposed to adverse border changes saw less growth in lights and more plant exit than less adversly affected border regions.

Having substantiated significant changes along the north-south axis of the Russia-Ukraine border, we look at a more granular geography and provide evidence for highly localized changes *within the north.* To do so, we assemble a new dataset with detailed information on all border crossings between Russia and Ukraine and exploit the closing of a subset of them. Historically, the regions on both sides of the border—especially to the north in the Belgorod region and close to the Donbass—were a highly integrated industrial center and labor market.[3] Daily cross-border movements were numerous so that simplified procedures for crossing the border for the local populations were in place: residents of border regions could cross the border at numerous local border crossings in the region they are residents of, and they could stay on the territory of the neighboring state for personal or work-related reasons. The commercial import or export of merchandise at these local border points was prohibited, i.e., trade did not flow through these points. Starting March 2015, the Ukrainian government shut down all local border crossings and only kept open the international border crossings. This generated substantial variation in the distances local populations had to travel in order to cross the border, but did not materially change the geography of borders for goods trade. These changes in the geography of border crossings should thus mainly affect the movements of people which—being less mobile than goods—should lead to quite localized effects.

We exploit these changes and show they affect local economic outcomes: areas where

[3]Zayats et al. (2017) provide an informal discussion and case study for the potential importance of cross-border labor flows. They explain how the conflict has lead to a significant decrease in the trans-border intensity of worker movements and the exchange in the institutional, infrastructural, human, and economic domains more generally.

the distance to the nearest open border crossing increased more following the conflict saw less growth in nighttime lights. Since large cities are close to international border crossings that remained open after 2015, they suffered less compared to more rural areas where access to the neighboring country deteriorated substantially. In terms of plant exit, we do not find strong effects of changes in distance on this outcome. Yet, we find a robust effect of more exit in the large cities, although the interactions with the changes in distance are imprecisely measured because there was little change in distance to the nearest border crossings in the large cities.

Our paper is mainly related to two strands of literature. First, it is related to the literature on the economic effects of borders on the location and size of economic activity (e.g., Hanson, 1996; Redding and Sturm, 2008; Brülhart et al., 2012; Ahlfeldt et al., 2015; Brülhart et al., 2018). We complement that literature by providing evidence showing that there are highly heterogeneous and quite localized effects that can be linked to changes in the local geography of border crossings. Our paper is also closely related to recent work by Lee (2018) who uses nighttime lights to investigate the unequal regional effects of sanctions in North Korea. It is further closely related to Brülhart et al. (2019) who document how international borders generally reduce economic activity. Both of these papers solely use nighttime lights whereas we also leverage geo-referenced plant-level data to better understand effects at the firm level.

Second, it is related to the literature on the economic effects of conflict on the geography of economic activity and firm-level outcomes (e.g., Guidolin and La Ferrara, 2007; Camacho and Rodriguez, 2013; Collier and Duponchel, 2013; Berman and Couttenier, 2015; Harari and Ferrara, 2018). It is clear that economic activity is strongly and directly disrupted by armed conflict through combat-related destructions.[4] We instead focus on how conflict affects economic activity indirectly through changes in borders and economic channels and not through direct destruction of physical and human capital.

[4]While Zhukov (2016) and Kochnev (2019) have documented the costs on the Ukrainian side for the Donbass—Donetsk and Luhansk regions—to our knowledge the local economic costs of the conflict on the Russian side have not been documented yet.

The remainder of the paper is organized as follows. Section 2 summarizes the context and provides some descriptive evidence for our key results. Section 3 explains our data and key variables. Section 4 shows our estimation results for the economic effects along the north-south dimension of the border. Section 5 zooms onto the northern border regions and shows that the closing of border crossings had localized effects on the exposed areas. Last, Section 6 concludes. We relegate data details to the Data Appendix and numerous technical details to a supplemental Online Appendix.

2 Context and first descriptives

Russia and Ukraine—separated since 1991 following the collapse of the Soviet Union—maintained a high level of cultural and economic integration. Yet, Ukraine progressively sought to distance itself from the former Soviet bloc, especially in terms of its foreign policy. After independence in 1991, one of the debated questions was the status of the Crimean peninsula, and relations between Russia and Ukraine deteriorated during 2005–2010.[5] Following the Orange Revolution and the arrival of a more pro-western president, the delicate questions of stronger border demarcations, a European orientation, NATO membership, the role of Sevastopol as a base for the Black Sea fleet, and gas transit through Ukraine were put on the agenda.[6] Russia increasingly feared the weaker ties with Ukraine. During 2010–2013, the relationship stabilized as agreements concerning the Black Sea naval bases and preferential gas supply were reached. Ukraine also signed the CIS Free Trade

[5] The Crimean peninsula was transferred under the Soviet leader Nikita Khrushchev to Ukraine by a decree of the RSFSR Council of Ministers on February 5, 1954, in what is believed to be a move to strengthen the Russian influence in Ukraine. Some on the Russian side argued that the transfer was unconstitutional or illegal to begin with, although it had been carried out within the legal framework in place at the time of the transfer (as Mark Kramer notes, "both the RSFSR and the UkrSSR had given their consent via their republic parliaments." For details and historic documents, see `https://www.wilsoncenter.org/publication/why-did-russia-give-away-crimea-sixty-years-ago?`). After Ukrainian independence in 1991, Crimea was granted the status of autonomous republic. Its major city, Sevastopol, also enjoyed a special status. Crimea has always played a special role for Russia due to its strategic location on the Black Sea. It hosts most of the Russian Black Sea fleet and allows to control access to the Sea of Azov via the Strait of Kerch.

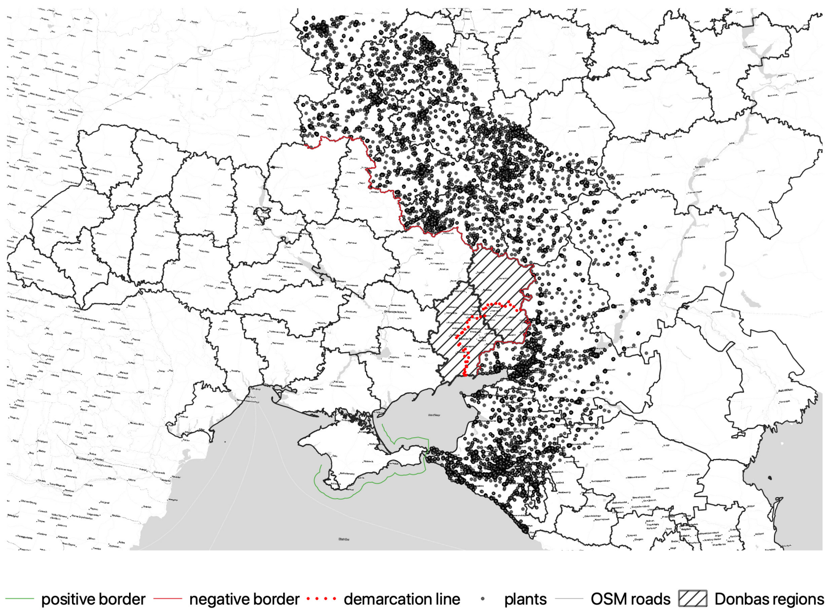
[6] In 2006 and 2009, two major gas conflicts led to termination of gas supplies to Ukraine and subsequent Ukrainian reluctance to resume the transit of Russian gas through its territory. Russia has since developed new routes to decrease its dependence on Ukraine as a transit country.

Agreement that brought it back more closely into the Russian orbit. Yet, the question of a tighter integration with the European Union (EU) remained. In early 2012, the EU and Ukraine initialized the EU Association agreement, which was finally approved by Ukraine in September 2013. However, the Ukrainian government subsequently decided to suspend the signing of the Association Agreement in favor of closer ties to Russia and the Eurasian Economic Union. This sparked a wave of civil unrest (the 'Euromaidan') which led to the ousting of the incumbent president.

In late February 2014, following the unrest, pro-Russian demonstrations were held in the Crimean city of Sevastopol. A few days later, during the referendum of March 16, 2014, a majority of respondents expressed their desire for Crimea—populated by a majority of ethnic Russians—to join Russia. Although Ukraine and the international community at large condemned the referendum, Crimea de facto joined Russia via the accession agreement signed in Moscow on March 18, 2014 and two new federal subjects—the Republic of Crimea and the federal city of Sevastopol—were created. In the wake of the annexation, two eastern regions of Ukraine—Donetsk and Luhansk—carried out their own local referenda. As a result, two self-proclaimed republics were declared on April 8 and April 27, 2014, respectively. An armed conflict with Ukrainian forces followed these declarations of independence. The conflict in the region known as Donbass is still ongoing and the question on the status of the territories not settled.

The Russia-Ukraine conflict—following the protests of 2013 and the annexation of Crimea in March 2014—provides a good laboratory to investigate the economic consequences of changes in international borders for two major reasons. First, since Russia and Ukraine are historically highly integrated countries—with substantial cross-border movements of goods and of people—any change in the border is likely to have important economic effects. We can reveal the degree of economic integration between the Russian and Ukrainian border regions using nighttime lights data. Brülhart et al. (2019) show that between 1995–2013 nighttime lights in the world were on average 37% *dimmer* at a land border between countries than 200 kilometers away from that border. That picture is very different in our context: the average nighttime lights intensity between 1992–2013 in the 0–100 kilometers distance band from the border is 25.15% *brighter* on the Russian side and 18.47% brighter on the Ukrainian side as compared to the 100–200 kilometers distance band. Hence, substantial economic activity is located along the strongly integrated border regions. This can also be seen by looking at the distribution of manufacturing plants along the border, as shown in Figure 1.

Figure 1: Distribution of plants along the Ukrainian border.



Notes: Distribution of manufacturing plants from the Ruslana and Interfax SPARK databases in Russia within 300km from the border with Ukraine. We plot the distribution of all plants active at some point between 2006 and 2018. The positive border segment (in green) in the south is the sea border with Crimea. The negative border segment (in red) in the north is the land border. The Donbass is also highlighted on the map. The conflict demarcation line in the Donbass is gathered from OpenStreetMap.

Changes in NTL intensities following the 2014 conflict reveal the important effect of the conflict on economic activity and point towards a strong decrease in revealed border integration: after 2014, the 0–100km 'lights premium' drops to 9.85% on the Russian side and to 9.86% and the Ukrainian side.[7] In other words, regions closer to the border suffered

[7]Kolosov et al. (2016, p.395) is a rare study of the intensity of cross-border interactions between Russia and other post-Soviet countries between 2010–2014. They document that the border with Ukraine is one of the most permeable and widely used before the conflict starts: "On the border of *Ukraine* a high intensity of citizen movement was replaced in 2014 by a sharp drop along with a concomitant increase in barrier function. Under the influence of the crisis in bilateral relations, the number of border crossings via road and rail *checkpoints* decreases almost twofold. As well, the largest reduction in flow occurred in Belgorod and

more in the wake of the conflict than regions further away, at least as measured by nighttime lights.

Second, while the foregoing evidence shows that the border regions suffered from the conflict, the averages we report mask substantial heterogeneity. Following the annexation of Crimea the border between Russia and Ukraine de facto disappeared in the south, whereas it was subject to substantially tighter restrictions in the north.[8] We can thus investigate finely how differential changes in market access affect economic activity in the same period. We conjecture that the regions close to the southern sea border with Ukraine—which were exposed to *positive border changes*—benefit from increased market access and less frictions in the movement of goods and people and should thus experience positive economic effects; whereas the regions close to the northern land border with Ukraine—which were more exposed to *negative border changes*—suffer from worse market access and more frictions in the movement of goods and people and should thus incurr negative economic consequences.

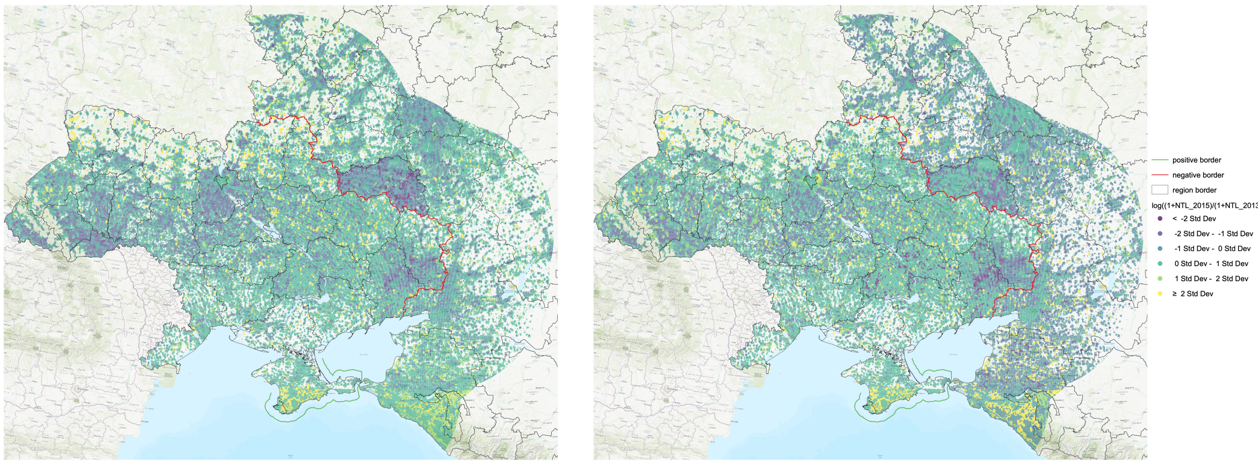
Figure 2 shows changes in (log) nighttime lights along the border. We depict changes between 2013–2015, i.e., one year before and one year after the start of the conflict in 2014. Panel (a) shows the distribution of changes using the raw NTL series, whereas panel (b) shows the changes where we weight the NTL series using regional GDP (see Appendix A for details). A cursory look at Figure 2 already reveals the heterogeneous changes along the border. In particular, lights seem to grow brighter in the south (near the positive border segment in green) and dimmer in the north (near the negative border segment in red). Growth appears especially poor in the Belgorod region, which is only 70 kilometers away from Kharkiv, the closest large city in Ukraine. On the Ukrainian side, the Donbass significantly lost lights (see. e.g., Kochnev, 2019), whereas Crimea significantly gained in

Kursk oblasts, including via the busiest road *checkpoints* of Troebortnoe–Bachevsk (by 60%) and Hoptovka–Nekhoteevka (by 30%). Meanwhile, at many checkpoints in Rostov oblast, the number of border crossings in 2014 increased, primarily due to refugees.” The increase in border crossings in the Donbass region illustrates that the border was no longer tightly controlled by Ukrainian government forces in the region bordering the conflict area.

[8] The case of the border along the Donbass region is unclear, since this border was no longer fully under the control of the Ukrainian government and hence movements across that border were hard to control.

Figure 2: Distribution of log changes in nighttime lights, 2013–2015.

(a) Raw data (b) GDP weighted



Notes: Changes in the log of nighttime lights between 2013 and 2015, using the harmonized DMSP–VIIRS series from Li et al. (2020). We plot changes in terms of standard deviations from the mean change in each country for each 1×1 kilometer grid cell. We add 1 to the NTL measure to keep the zeros and restrict ourselves to a 300km distance band. Darker colors show below-average growth in nighttime lights, i.e., a relative decrease in economic activity; whereas lighter colors show above-average growth in nighttime lights, i.e., a relative increase in economic activity. We suppress all water-masked cells and 'empty' cells that never show any light emissions. The 2013–2014 changes look similar. A detailed description of the NTL satellite data is provided in Appendix A.1.

lights. The main activity close to Donbass in Russia is concentrated in the Rostov-on-Don area, which does not display a clear positive or negative pattern in NTL changes. One potential explanation is that, although the area is close to the region of armed conflict in the Donbass, it is also close to the southern part that gained better market access to the Crimean peninsula. Another explanation is that the Rostov-on-Don region served as a gateway for firms in the separatist controlled areas of the Donbass to maintain economic ties and to ship goods to export markets.[9]

To explore more formally how NTL intensity varies with border changes, we use an event-study approach. More precisely, we estimate the following model:

$$y_{i,t} = \alpha_i + \delta_t + \sum_{\substack{\tau=-m \\ \tau\neq 0}}^{p} \left(\gamma_\tau D_\tau \ln \exp_i\right) + \varepsilon_{i,t}, \qquad (1)$$

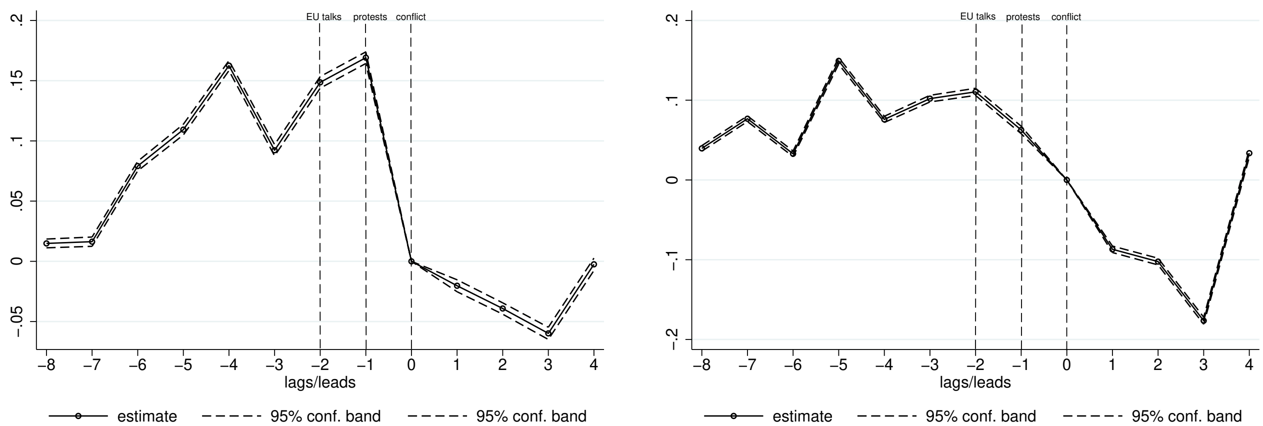
where $y_{i,t}$ is (log of 1 plus) the GDP-weighted NTL of cell i in year t; $\ln \exp_i$ is a time-

[9]Kochnev (2019) provides a detailed account of the banking and trade sanctions that were imposed on the firms in the separatist controlled regions and cites evidence on how these sanctions were evaded.

invariant pre-conflict measure of cell i's exposure to the border; and α_i and δ_t are cell- and year fixed effects. We fix 2014 as the start of the conflict and include $m = 8$ pre-treatment leads and $p = 4$ post-treatment lags. The dummy D_τ equals 1 for the corresponding lead or lag, and 0 otherwise.

Figure 3: Event study plots with lags and leads for nighttime lights.

(a) GDP-NTL and market potential (b) GDP-NTL and relative distance



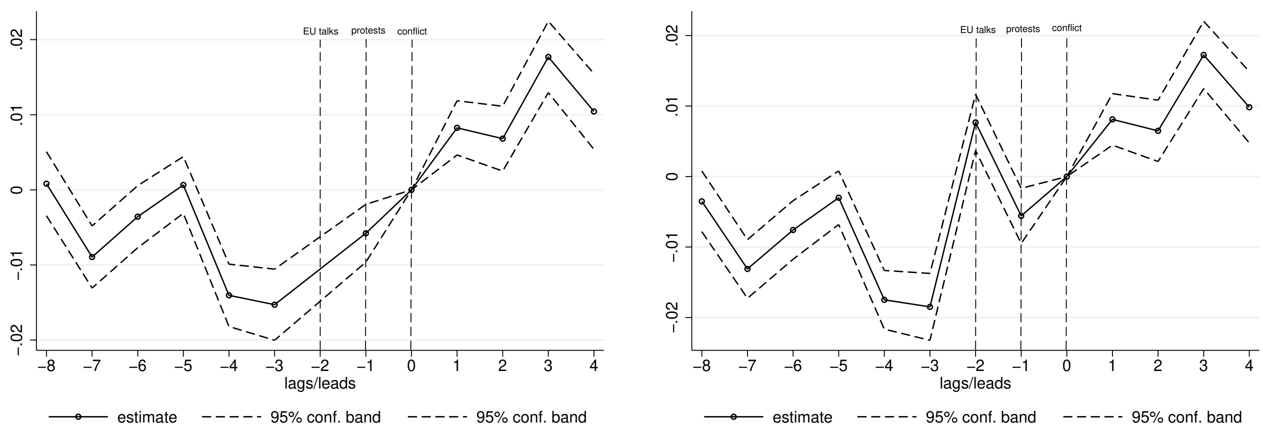
Notes: The dependent variable is the GDP-weighted NTL intensity of cell i in year t. Panel (a) depicts the coefficients obtained from (1), where exposure is measured by the log of market potential in Ukraine for cells up to 200km in Russia. Panel (b) depicts the coefficients obtained from (1), where exposure is measured by the log of great circle distance to the southern border relative to the GC distance to the northern border for cells up to 200km in Russia.

Figure 3 shows the estimates of (1) for changes in GDP-weighted NTL. Panel (a) plots results for all cells up to 200km from the border and measures a cell's exposure to the border by market potential in Ukraine. Formally, market potential is constructed by aggregating up GDP-weighted cell-level NTL intensity in Ukraine and deflating it by a decreasing function of distance to the cells in Russia (we explain in detail in Section 3 our variables, see (2)). We take the average market potential over the pre-conflict period 2011–2013 as our measure of a cell's exposure. Panel (a) shows that changes in cells' GDP-weighted NTL were positive and increasing before 2013–2014. In words, cells relatively more exposed to Ukrainian market potential grew more pre-conflict. This pattern gets reversed around 2013 in the wake of the violent Euro Maidan protests in Kiev and the ensuing armed conflict that erupted in the Donbass: cells more exposed pre-conflict grew less post-conflict. Panel (b) replicates our analysis using the ratio of the distance from the border in the south to the distance from the border in the north as a cell's exposure measure (see (5) in Section 3). As shown, changes in cells' NTL were relatively stable before 2014 and, if anything, the coefficients were positive and increasing. In words, lights in cells relatively far from the south and close to the north grew more. This pattern gets again reversed around 2013 in the wake of the EU accession agreement and the Euro Maidan protests: nightlights started to fall in the north relative to the south.

Taken together, panels (a) and (b) show that cells in Russia relatively more exposed to pre-conflict market potential in Ukraine or relatively closer to the negative border segment in the north compared to the positive border segment in the south saw relatively less growth (or more decline) in their lights starting around 2013.[10]

Figure 4: Event study plots with lags and leads for plant exit.

(a) Plant exit (excl. 2012) (b) Plant exit (incl. 2012)



Notes: The dependent variable is a dummy that takes value 1 if plant i exits in year t and 0 otherwise. Panel (a) depicts the coefficients obtained from (1), where exposure is measured by the log of great circle distance to the southern border relative to the GC distance to the northern border for cells up to 200km in Russia. We exclude the year 2012 since, as explained in the text and in Online Appendix C, the exit rates show an abnormal pattern in that year. We further control for the minimum distance to the border to isolate the effect of relative position. Panel (b) shows the same figure but includes the abnormal patterns for the year 2012.

Changes in nighttime lights are one way to measure changes in overall economic activity. To gain further insights, we replicate the event study analysis using another measure

[10] The HNTL series combines the DMSP and VIIRS satellite series, using 2013 for purposes of intercalibration. One may thus be worried that the fall in lights is an artifice of a change in series. We do not believe this is a problem because the coefficients we report capture the *differential effect* of exposure to market potential or distance to the border. Any change in the series that is not neutralized by the intercalibration procedure would affect all cells irrespective of their exposure to Ukraine. See Li et al. (2020) for more details on the quality of the series' intercalibration.

of changes in economic activity, namely plant-level exit. We re-estimate model (1) using as the dependent variable $y_{i,t}$ an indicator that takes value 1 if plant i exits in year t, and 0 otherwise. We again take 2014 as our base year and the summation includes $m = 8$ pre-treatment leads and $p = 4$ post-treatment lags. The remaining variables are identical, safe that we add plant i's age as an additional time-varying control as a rough proxy for the plant's 'productivity'.

Panel (a) of Figure 4 plots the results for all plants up to 200km from the border, using the distance to the positive border in the south relative to the negative border in the north as our exposure measure. The figure shows that the coefficients are negative or zero before 2014, whereas they start to increase after 2011 and become positive after 2014.[11] In other words, plants relatively more exposed to the northern border that became less easy to cross tended to exit more after 2014 compared to plants less exposed to that border and more exposed to the southern border that disappeared.

To summarize, Figures 3 and 4 provide descriptive evidence that economic activity in the Russian border regions with Ukraine—as measured by either lights or manufacturing plant exit—was improving for more exposed cells and plants before 2012 but started to deteriorate around that date. Put differently, we see a change in trends starting around 2012 when Ukraine and the EU initiated the Association Agreement, which correlates with a substantial decrease in the growth in nightlights and trade, and a substantial increase in plant exit, especially in the wake of the 2013 violent Euro Maidan protests in Kiev and the 2014 conflict following the annexation of Crimea.

[11] Panel (a) excludes 2012, which has an abnormally large exit rate. This pattern has been documented before. Iwasaki et al. (2016, p.169) attribute it to *"to the world economic crisis, whose impact arrived with some time-lag."* While this may be one explanation, we document in Online Appendix C that a mixture of changes in legal enforcement and in the tax environment in 2011–2012 are more likely drivers of this observed spike. Note there is some correlation of the increased exit in 2012 with our measure of exposure. As argued in Online Appendix C, this is mostly due to abnormally large exit in the Rostov-on-Don region, located close to the Donbass. While we have no good explanation of why that may be the case—since exit was generally higher in 2012 everywhere—we do not think that this poses a serious problem for our subsequent estimates.

3 Data and variables construction

We now provide information on our main datasources and the way we construct our exposure measures. For the sake of conciseness, we relegate details to the data appendix.

As explained in Section 2, our key dependent variables are cell-level nighttime lights and plant-level exit information. We rely on publicly available nighttime lights satellite data based on DMSP and VIIRS. We use mainly the yearly series of Harmonized NTL (henceforth, HNTL) developed by Li et al. (2020), and we will make explicit the remaining cases where we rely on other satellite data such as the VIIRS series. The HNTL data span the period 1992–2018 and provide a consistent time-series at a spatial resolution of 1×1 km cells. We extract all cells for the European part of Russia (3,886,810 cells) and for Ukraine (811,399 cells).[12] In what follows, we refer to the European part of Russia as Russia for short. More details on the nightlights data are relegated to Appendix A.1.

Turning to our plant-level data, we collect information on manufacturing plants in Russia from Bureau van Djik's Ruslana and Interfax's SPARK databases. More precisely, we collect all manufacturing plants that were active at some point between 2006 and 2018. Our data provide detailed information on active plants and those that enter or exit. For most plants, we know the exact date of entry and exit—as recorded in the Federal State Register—as well as their de facto address and main national industry classification (OKVED). We create a variable taking value 1 if the plant exits in year t and value 0 otherwise. We drop all plant-year observations for years the plant did not exist (i.e., all years prior to entry) or already left (i.e., all years past exit).[13] We further know the plant's age and whether it belongs to a multi-unit firm or not.[14] We keep all plants in the European part of Russia and drop the small share of those we cannot geocode precisely or for which

[12]The European part of Russia is bounded to the east by the Ural. See Figure 1 in Aleksandrova et al. (2020) for a map. Cell counts exclude water-masked cells and cells that report zeros in all years.

[13]We keep the few plants that enter and exit in the same year. Dropping them does not change our results. Since plants report the precise date of exit from the Federal State Register, including day and month, we can further disaggregate the data to the quarterly level, which we use as a robustness check.

[14]The remaining variables in the dataset—size and various legal and financial indicators—are too sparse and non-representative to be used. Only listed firms are generally required to provide that information, and even then there are too many missing observations.

we cannot reconstruct OKVED 2007 industry codes. After basic data cleaning, we are left with 672,158 geo-referenced plants that are representative of Russian manufacturing. Figure 1 illustrates the distribution of plants along the border. Additional details on the data are relegated to Appendix A.2.

Cells' NTL intensities and manufacturing plants' exit dummies are our key dependent variables. Turning to the explanatory variables, we measure cells' or plants' exposure to changes in the border between Russia and Ukraine in a variety of ways. Our measures can be broadly divided into *absolute* exposure measures and *relative* exposure measures. The former do not pay special attention to the position of cells or plants with respect to the positive and negative border segments, whereas the latter do.

Absolute measure 1: Distance band. We create a dummy variable that takes value 1 for all plants or cells less than 150 kilometres from the border, and 0 otherwise.[15]

Absolute measure 2: Market potential. For each plant and cell, we construct measures of market potential that capture the cell's or plant's exposure to economic activity in Ukraine. Our preferred measure combines information on NTL luminosity and regional GDP for Russian and Ukrainian regions. Formally, the GDP-weighted market potential for cell or plant i in year t is defined as follows:

$$\mathrm{GMP}^c_{i,t} = \sum_r \sum_{j \in r} \omega^c_{j(r),t} \mathrm{e}^{-\alpha d_{i,j(r)}}, \quad \text{where} \quad \omega^c_{j(r),t} = \mathrm{GDP}_{r,t} \frac{\mathrm{NTL}^c_{j(r),t}}{\sum_{k \in r} \mathrm{NTL}^c_{k,t}} \tag{2}$$

where $c = \{\text{Russia}, \text{Ukraine}\}$, and r denotes the region. Expression (2) is a (negative exponential) distance-weighted measure of i's exposure to the NTL intensity emanating from all cells j in country c, weighted by regional GDP. We also construct an unweighted measure as follows:

$$\mathrm{LMP}^c_{i,t} = \sum_{j \in c} \mathrm{NTL}^c_{j,t} \mathrm{e}^{-\alpha d_{i,j}}. \tag{3}$$

[15]We discuss results for other distance bands in the Appendix A.3.

Observe that these measures are not theory-based and require a value for α. We choose $\alpha = 0.01$ in our preferred specification and consider only cells in Russia or in Ukraine that are less than 500km from the border. Our results are not sensitive to the former choice. The latter is made to reduce the computational burder in constructing these measures.[16]

Measures (2) and (3) vary with time. We could thus consider exploiting them in a dynamic panel specification. We decided not to do so. The main reason is that exposure to (GDP-weighted) NTL provides too little meaningful year-on-year variation since these measures are smoothed across hundreds of thousands of cells. We instead construct a measure of pre-treatment exposure based on the market potentials using the five-year average 2009–2013 exposure to NTL as follows:[17]

$$\ln(\exp_i^{\mathrm{NTL}}) = \ln\left(\frac{1}{5}\sum_{t=2009}^{2013} \mathrm{LMP}_{i,t}^{c}\right), \quad \ln(\exp_i^{\mathrm{GDP}}) = \ln\left(\frac{1}{5}\sum_{t=2009}^{2013} \mathrm{GMP}_{i,t}^{c}\right). \tag{4}$$

Measures (4) capture whether the cell or plant was heavily exposed to (GDP-weighted) NTL—our proxy for economic activity—in Ukraine or Russia before the beginning of the conflict in 2014. We expect that plants or cells more exposed to Ukrainian market potential in the pre-treatment period suffered more than less exposed plants or cells post treatment. We will use the exposure of cells and plants in Russia to Russian market potential as a control in our regressions.

Relative measure 1: Great circle distance. We construct as measure of relative exposure the ratio of the great circle (GC) distance from the positive border segment in the south to the negative border segment in the north (see Figure 1 for the former, in green, and the

[16] We have more than 1 million cells in Russia at 500km from the border, and more than 800K cells in Ukraine. Constructing the market potential measure for the cells thus requires computing almost one billion distances and smoothing them. This procedure needs to be repeated for each value of α (we did it for $\alpha = 0.01$ and $\alpha = 0.05$).

[17] Results using three year averages over 2011–2013 are very similar.

latter, in red). Formally:

$$\ln(\exp_i^{\text{GC}}) = \ln\left(\frac{\min_{j\in\mathcal{V}_P} d_{i,j}^{\text{GC}}}{\min_{k\in\mathcal{V}_N} d_{i,k}^{\text{GC}}}\right), \tag{5}$$

where $\mathcal{V}_P$ and $\mathcal{V}_N$ are the sets of vertices for the positive and negative border segments, respectively. Expression (5) is the ratio of the minimum distance to the border positively affected by the annexation of Crimea (i.e., the southern part of the border that experienced an increases in market access) and the minimum distance to the border negatively affected by the annexation of Crimea (i.e., the northern part of the border that experienced a decrease in market access via tighter border restrictions). We expect that more exposed plants or cells suffered more than less exposed plants or cells after 2014.

Relative measure 2: Network distance. Since crow-fly distance may not be a good approximation of travel distance, and since borders can only be crossed at specific points, we compute the network distance on the main road system from each plant i to the border:[18]

$$\ln(\exp_i^{\text{ND}}) = \ln\left(\frac{\min_{j\in\mathcal{B}_P} d_{i,j}^{\text{ND}}}{\min_{k\in\mathcal{B}_N} d_{i,k}^{\text{ND}}}\right), \tag{6}$$

where $\mathcal{B}_P$ and $\mathcal{B}_N$ are the sets of border crossing points for the positive and negative border segments, respectively (see Appendix A.3 for additional details). We expect plants located closer to the crossing points along the negative border segment to be exposed negatively to market access changes and thus to exit more; while we expect plants located closer to the sea-ports of the positive border segment to be positively exposed to the market access changes and thus to exit less.

Relative measure 3: Latitude. Cells and plants in the northern part of the border regions may have been more exposed to the hardening border with Ukraine, while those in the southern part were more exposed to the softening border with Crimea. Thus, we use

[18] We did not compute the network distance for each cell to the border. There are many cells that do not fall near any road and for which it is thus hard to compute a meaningful shortest path on the road network.

latitude as an additional proxy for exposure:

$$\ln(\exp_i^{\text{LAT}}) = \ln\left(\text{lat}_i\right). \tag{7}$$

We center (7) on the mean latitude in our sample.

Relative measure 4: Latitude bands. We finally also construct a discretized version of our latitude measure, where we subdivide the continuous measure into three 'latitude bands': the North, the Donbass, and the South.

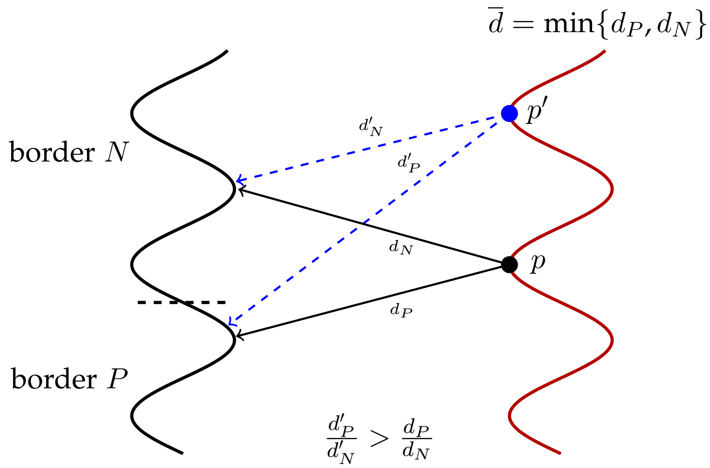
To summarize, we consider six alternative ways to measure a cell's or plant's exposure to economic activity in Ukraine: (i) two absolute exposure measures—distance bands and market potential—that do not pay special attention to the North-South dimension of the border; and (ii) four relative exposure measures—relative great circle and network distances, latitude, and latitude bands—where we pay special attention to the position of cells or plants with respect to the positive and negative border segments. We conjecture that more exposed observations, both in absolute and in relative terms, have worse outcomes—less NTL growth or higher chance of exit—in the post-treatment period. By construction, our exposure measures (4)–(7) are time-invariant so that we cannot disentangle them from cell or plant fixed effects. However, we can estimate their differential effect in the post treatment period, and this is the effect that we are interested in.

4 Empirical analysis

We now present a difference-in-differences (DiD) analysis. Ideally, we would observe treated and untreated cells or plants and estimate a standard DiD specification. However, there is no clear control group in our setting since all cells and plants were treated to some extent. We thus work within a framework where *observations differ by treatment intensity*. We use our exposure measures from Section 3 to measure that intensity.

As explained before, we conjecture that the treatment was stronger for plants and cells closer to the border, especially those closer to the negative border segment in the north relative to the positive border segment in the south. This suggests we may use plants far from any border segment as controls. However, this is problematic for two reasons. First, we have only access to a limited set of variables for each plant or cell, therefore making it hard to find suitable controls using a matching procedure. Second, it is hard to argue that plants far from the border would have followed the same trend as plants close to the Ukrainian border had the events of 2014 not occurred. We thus use a different strategy and exploit geographic variation we think allows for meaningful comparisons. Figure 5 illustrates the variation that we use in our data.

Figure 5: Relative distance along border-distance isocurves.



Our empirical strategy compares less exposed plants (that received a 'smaller dose' of treatment) with more exposed plants (that received a 'larger dose' of treatment). Exposure depends both on the overall distance to the border, and the relative position along the border. Points p and p' in Figure 5 are located on the same border-distance isocurve $\overline{d} = \min\{d_P, d_N\}$, but point p' is more strongly exposed to the negative border N, whereas point p is more strong strongly exposed to the positive border P (i.e., $d'_P/d'_N > d_P/d_N$). We expect worse outcomes for the cell or plant in p' compared to outcomes for the cell or plant in p, conditional on being on the same distance iso-curve. Hence, in our empirical specification, we estimate the treatment effect of the exposure measure conditional on distance from the border. We limit ourselves to a buffer of 300 kilometers from the border, which provides a large enough sample (580,945 cells and 80,287 plants) and restricts the geographic variation to an area we think allows for meaningful comparisons.

4.1 Cell-level NTL regressions

We first regress nighttime lights for cell i in year t on absolute and relative exposure to Ukraine as follows:

$$
\begin{aligned}
\ln(y_{i,t}+1) &= \beta_0 + \beta_1 \text{post}_{2014} + \beta_2 \ln \text{minDist}_\text{i} + \beta_3 \ln \exp_i \\
&\quad + \gamma_1(\text{post}_{2014} \times \ln \text{minDist}_i) + \gamma_2(\text{post}_{2014} \times \ln \exp_i) + \alpha_i + \delta_t + \varepsilon_{i,t}, \qquad (8)
\end{aligned}
$$

where $y_{i,t}$ is the GDP-weighted NTL measure for cell i in year t. In (8), $\ln \text{minDist}_i$ is the minimum distance of cell i from the border; post_{2014} is a dummy variable taking value 1 starting in 2014; and α_i and δ_t are cell- and year fixed effects, respectively. Last, $\varepsilon_{i,t}$ is the error term. Our coefficient of interest is γ_2, which captures the differential effect of being more exposed to the negative border on economic performance after 2014.

Table 1: Changes in GDP-HNTL by distance band and exposure, before and after 2014.

	(1) distance band	(2) distance band	(3) LMP Ukr	(4) GMP Ukr	(5) GC	(6) LAT	(7) LAT bands
post2014	0.951^a	0.952^a	1.668^a	1.290^a	1.764^a	0.519^a	0.878^a
	(0.002)	(0.002)	(0.033)	(0.030)	(0.012)	(0.006)	(0.007)
post2014 × band	-0.124^a						
	(0.002)						
post2014 × band(positive)		0.430^a					
		(0.007)					
post2014 × band(negative)		-0.172^a					
		(0.002)					
post2014 × ln minDist			0.015^a	0.032^a	-0.119^a	0.079^a	0.046^a
			(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
post2014 × Lat(Donbas)							-0.345^a
							(0.004)
post2014 × Lat(North)							-0.245^a
							(0.003)
post2014 × exposure			-0.081^a	-0.058^a	-0.211^a	-0.031^a	
			(0.002)	(0.002)	(0.002)	(0.000)	
Observations (cell-year)	8,133,230	8,133,230	8,133,230	8,133,230	8,133,230	8,133,230	8,133,230
R-squared	0.675	0.677	0.676	0.676	0.678	0.676	0.677

Notes: OLS estimation of (8). All regressions include cell- and year fixed effects. Standard errors are clustered at the cell level. band is a dummy variable taking value 1 if the cell is less than150 kilometers from the border, and 0 otherwise. band(positive) is a dummy with value 1 if the cell is both less than 150 kilometers from the positive border and is closer to the positive border than to the negative border. band(negative) is constructed in the same way, but for the negative border. We include all cells up to 300km from the border. exp is our exposure measure as indicated in the column header (GC = great circle distance (5); LAT = centered latitude, (7); LMP Ukr and GMP Ukr = market potential based on either raw NTL or GDP-weighted NTL, (4)).

Table 1 summarizes our results. Starting with column (1), we see that cells within 150 kilometers from the border grew less after 2014 than cells within 150–300 kilometers. Hence, lights dimmed on average close to the border in the post-treatment period, consistent with the descriptive evidence from Section 2. The distance-band dummy likely masks substantial heterogeneity in the treatment effect along the north-south axis, as we already pointed out. We thus split our distance-band dummy from column (1) into two parts, one for being close to the negative border segment in the north, and one for being close to the positive border segment in the south. Column (2) shows that the average effect in column (1) is indeed highly heterogeneous: splitting it into a positive and a negative part reveals that cells close to the border in the north lost in luminosity, whereas cells close to the border in the south gained in luminosity, in line with Figure 2.

Columns (3) and (4) show results using the market potentials constructed from the raw NTL and the GDP-weighted NTL. The negative coefficients reveal that, as expected, cells more exposed to economic activity in Ukraine pre conflict lost post 2014 compared to initially less exposed cells. Columns (5)–(7) show results using our different relative exposure measures. Column (5) shows that cells more exposed to the negative border than to the positive border—as measured by the relative GC distance—grew less post 2014. Columns (6) and (7) show that this result continues to hold if we measure relative exposure by the cell's latitute, either continuously or using latitude bands. Column (6) shows that both the area close to the Donbass and the north saw less growth in lights post 2014 than the south, with a stronger negative effect in the Donbass latitude band.

Overall, our DiD estimates show that cells more exposed to Ukraine pre-conflict saw a dimming in their lights compared to cells less exposed. Furthermore, this effect is heterogeneous along the border, as cells located closer to the negative border segment relative to the positive border segment experienced a dimming in their lights compared to cells located closer to the positive border segment relative to the negative border segment. In other words, heterogeneous changes along the border induce heterogeneous changes in economic activity as measured by nighttime lights.

How large are the post 2014 effects on changes in nighttime lights? Panel (a) of Figure 6 illustrates the magnitude of the economic effect of the different exposure measures on NTL intensity using the predicted changes in NTL at the 1st, 5th, and 10th deciles, respectively. On average, NTL intensity increased by about 55% in the post 2014 period at the 1st decile, whereas it increased on average by about 15% at the 10th decile. In other words, NTL growth in the post treatment period was about 40% lower for the most exposed cells compared to the least exposed cells. Online appendix Figure B.1 estimates that the elasticity of regional GPD to regional nighttime lights between 2008–2013 was 0.865 in Russia. Thus, a 40% difference in NTL growth for the most exposed cells corresponds approximately to a 34.6% difference in GDP growth, a sizable effect.

4.2 Plant-level exit

We next run regressions using as dependent variable plant-level exit information. More precisely, we estimate the following model:

$$\begin{aligned} y_{i(s),t} \quad = \quad & \beta_0 + \beta_1 \text{post}_{2014} + \beta_2 \ln \text{minDist}_i + \beta_3 \ln \text{exp}_i \\ & + \gamma_1 (\text{post}_{2014} \times \ln \text{minDist}_i) + \gamma_2 (\text{post}_{2014} \times \ln \text{exp}_i) + \mathbf{X}_{i,t} \gamma + \alpha_{i(s),t} + \varepsilon_{i,t}, \end{aligned} \tag{9}$$

where $y_{i(s),t} = \text{exit}_{i(s),t}$ takes value 1 if plant $i(s)$ in industry s exits in year t, and value 0 otherwise. In (9), $\alpha_{i(s),t}$ are either industry-year or plant fixed effects, and $\mathbf{X}_{i,t}$ are (time-varying) plant-level controls. Our key coefficient of interest is again γ_2.

We estimate (9) using different combinations of fixed effects and controls. More precisely, when using plant fixed effects we also include year fixed effects and control for plant age, the only time-varying plant-level characteristic in our dataset. When using industry-year fixed effects, we control for: (i) whether the plant belongs to a multi-unit firm; (ii) the average population of the municipality the plant is located in; (iii) a dummy taking value 1 if the plant is located in a big city and 0 otherwise; and (iv) the plant's average exposure to market potential in Russia constructed from either raw NTL or GDP-weighted

NTL as described in Section 3. We include the latter variable as an aggregate control for economic conditions in the regions surrounding each plant and take its pre-conflict average over 2009–2013. We estimate (9) using a linear probability model, but probit regressions yield very similar results.

Tables 2 and 3 show our results using industry-year and plant fixed effects, respectively. Columns (1) and (2) in Table 2 show that there is again a heterogeneous effect of the border on exit post 2014 along the north-south dimension. While plants were more likely to exit in the south pre 2014, they are less likely to do so post 2014. As Table 3 shows, these results are less clear-cut when controlling for unobserved plant-level characteristics. Indeed, plants tended to exit a bit less close to the border post 2014, though there is still a differential in favor of the south compared to the north.

Columns (3)–(4) in Tables 2 and 3 show that plants more exposed to Ukrainian market potential pre-conflict tended to exit more post conflict for both market potential measures. Columns (5)–(8) reveal that relative exposure is positively associated with the probability of plant exit. Put differently, plants more exposed to the negative border are more likely to exit post 2014 than less exposed plants. This finding holds for all our relative exposure measures and is thus robust. The only a priori unexpect result is the either negative or zero interaction term between post 2014 and the Donbass latitude band in column (8) of both tables. This result suggests that plants in the Donbass latitude band were not more likely to exit post 2014, which may reflect the ambiguous border changes in the conflict region of the Donbass. While the Ukrainian government remained in control of the border in the north and made it less permeable—and completely lost control of the border in the south—the border in the contested region was controlled by no one perfectly. Kochnev (2019) cites evidence suggesting that firms in the separatist controlled areas of the Donbass, following the trade restrictions with the rest of Ukraine and the disruption of access to banking, partly shipped goods to outside markets using intermediate firms located in the area bordering the Donbass in Russia. Furthermore, there was a substantial influx of refugees into that regions. In a nutshell, whether this affected firms in the region positively or negatively is unclear, but our estimates do not reveal more exit post 2014.

Table 2: Plants' exit probability before and after 2014, industry-year fixed effects.

	(1) distance band	(2) distance band	(3) LMP Ukr	(4) GMP Ukr	(5) GC	(6) ND	(7) LAT	(8) LAT bands
band	0.001							
	(0.001)							
post2014 x band	-0.002^c							
	(0.001)							
band(positive)		0.005^b						
		(0.002)						
band(negative)		0.000						
		(0.001)						
post2014 x band(positive)		-0.017^a						
		(0.003)						
post2014 x band(negative)		-0.001						
		(0.001)						
ln minDist			-0.006^a	-0.006^a	0.001	-0.001^c	-0.000	0.003^a
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
post2014 x ln minDist			0.015^a	0.012^a	0.004^a	0.002^b	-0.000	-0.003^a
			(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Lat(Donbas)								0.012^a
								(0.001)
Lat(North)								0.003^b
								(0.002)
post2014 x Lat(Donbas)								-0.014^a
								(0.002)
post2014 x Lat(North)								0.009^a
								(0.002)
exposure			-0.005^a	-0.005^a	0.001	-0.001^a	0.000	
			(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	
post2014 x exposure			0.013^a	0.011^a	0.005^a	0.003^a	0.001^a	
			(0.002)	(0.002)	(0.001)	(0.000)	(0.000)	
Plant controls	✓	✓	✓	✓	✓	✓	✓	✓
Geographic controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	532,440	532,440	532,440	532,440	532,440	532,440	532,440	532,440
R-squared	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.047

Notes: The dependent variable is a dummy with value 1 if plant i exits in year t, and 0 otherwise. All regressions include industry–year fixed effects. $band$ is a dummy variable with value one if the plant is less than 150 kilometers from the border, whereas $band(positive)$ is a dummy with value 1 if the plant is less than 150 kilometers from the positive border, and it is closer to the positive border than to the negative border. $band(negative)$ is constructed in the same way, but for the negative border. $\ln$ minDist is the minimum great circle distance from the border. We include all plants up to 300 kilometers from the border. exp is our exposure measure as indicated in the column header (GC = great circle distance (5); ND = network distance (6); LAT = centered latitude, (7); LMP Ukr and GMP Ukr = market potential based on either raw NTL or GDP-weighted NTL, (4)). Standard errors are clustered at the plant level.

How large is the post 2014 effect on the exit probabilities of plants? Panel (b) of Figure 6 illustrates the magnitude of the economic effect of the different exposure measures on plant exit using the predicted exit probabilities at the 1st, 5th, and 10th deciles, respectively. On average, the exit probability increased by about 11% in the post 2014 period at the 1st decile, whereas it increased on average by about 45% at the 10th decile. In other words, the exit probability post treatment increased by about 34% more for the most exposed plants compared to the least exposed plants. As for nighttime lights, this is a sizeable effect.

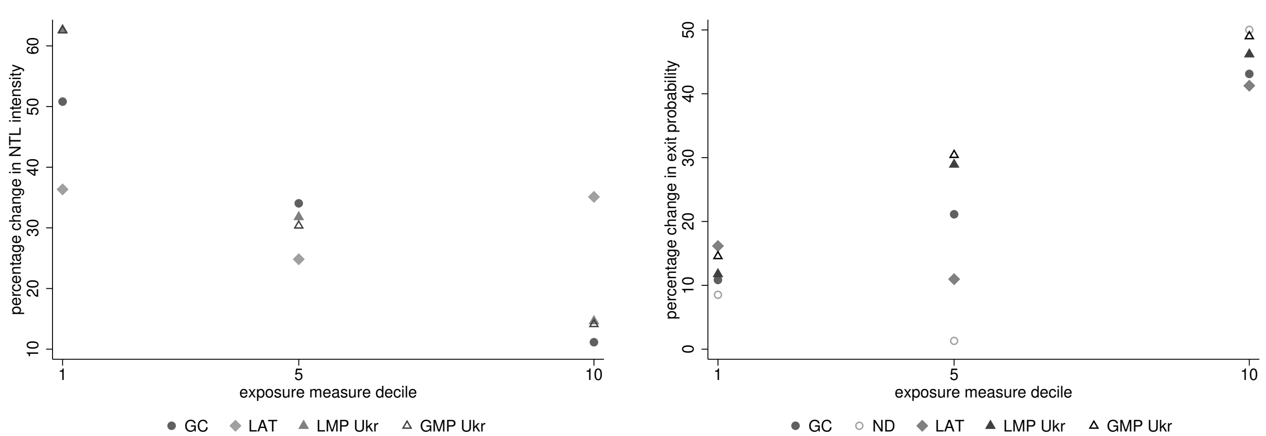
Table 3: Plants' exit probability, within-plant variation, before and after 2014.

	(1) distance band	(2) distance band	(3) LMP Ukr	(4) GMP Ukr	(5) GC	(6) ND	(7) LAT	(8) LAT bands
post2014	0.294[a]	0.294[a]	0.064[b]	0.160[a]	0.210[a]	0.260[a]	0.280[a]	0.264[a]
	(0.003)	(0.003)	(0.031)	(0.029)	(0.008)	(0.006)	(0.006)	(0.007)
post2014 x band		-0.008[a]						
		(0.002)						
post2014 x band(positive)		-0.030[a]						
		(0.004)						
post2014 x band(negative)		-0.005[a]						
		(0.002)						
post2014 x ln minDist			0.018[a]	0.011[a]	0.014[a]	0.006[a]	0.002[b]	0.003[b]
			(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
post2014 x Lat(Donbas)								0.003
								(0.003)
post2014 x Lat(North)								0.026[a]
								(0.002)
post2014 x exposure			0.013[a]	0.008[a]	0.012[a]	0.005[a]	0.003[a]	
			(0.002)	(0.002)	(0.001)	(0.001)	(0.000)	
Plant controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	528,147	528,147	528,147	528,147	528,147	528,147	528,147	528,147
R-squared	0.222	0.222	0.222	0.222	0.222	0.222	0.222	0.222

Notes: The dependent variable is a dummy with value 1 if plant i exits in year t, and 0 otherwise. All regressions include plant fixed effects. $band$ is a dummy variable with value one if the plant is less than 150 kilometers from the border, whereas $band(positive)$ is a dummy with value 1 if the plant is less than 150 kilometers from the positive border, and it is closer to the positive border than to the negative border. $band(negative)$ is constructed in the same way, but for the negative border. $\ln$ minDist is the minimum great circle distance from the border. We include all plants up to 300 kilometers from the border. exp is our exposure measure as indicated in the column header (GC = great circle distance (5); ND = network distance (6); LAT = centered latitude, (7); LMP Ukr and GMP Ukr = market potential based on either raw NTL or GDP-weighted NTL, (4)). Standard errors are clustered at the plant level.

Figure 6: Predicted post-treatment changes by exposure decile.

(a) Nighttime lights (b) Exit probability



Notes: Scatter plots of the average change in NTL or in the exit probability in each decile post 2014 compared to pre 2014. Each decile reports the distribution of the increase for our continuous exposure measures. 'Exposure measure decile' 5, e.g., depicts the distribution of the average change in NTL or in the exit probability for cells or plants with exposure between the 40th and 50th percentiles for each of the continuous exposure measures in columns (3)–(6) of Table 1 and (3)–(7) of Table 3.

4.3 Robustness checks

We run a large number of robustness checks which we succintly summarize here. Details and additional tables are mostly relegated to Online Appendix G.

Table 4: Changes in GDP-HNTL and plant exit by positive and negative distance to the border.

	GDP-HNTL (GC dist.)			Plant exit (GC dist.)			Plant exit (ND dist.)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
post2014	1.858^a	0.481^a	0.686^a	0.188^a	0.276^a	0.183^a	0.255^a	0.287^a	0.267^a
	(0.015)	(0.006)	(0.019)	(0.010)	(0.006)	(0.012)	(0.007)	(0.006)	(0.007)
post2014 × ln min dist	0.093^a	-0.825^a	-0.757^a	0.001	0.033^a	-0.002	0.001	0.023^a	0.013^a
	(0.001)	(0.008)	(0.011)	(0.001)	(0.004)	(0.005)	(0.001)	(0.003)	(0.003)
post2014 × ln dist pos	-0.225^a		-0.034^a	0.016^a		0.017^a	0.006^a		0.004^a
	(0.002)		(0.003)	(0.001)		(0.002)	(0.001)		(0.001)
post2014 × ln dist neg		0.903^a	0.838^a		-0.030^a	0.003		-0.020^a	-0.012^a
		(0.008)	(0.010)		(0.003)	(0.005)		(0.002)	(0.003)
Cell or plant fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	8,133,230	8,133,230	8,133,230	528,147	528,147	528,147	528,147	528,147	528,147
R-squared	0.677	0.679	0.679	0.222	0.222	0.222	0.222	0.222	0.222

Notes: The dependent variables are: $\ln(1 + \text{GDP-HNTL})$ in columns (1)–(3); and a dummy that equals one if a plant exits in year t and zero otherwise in columns (4)–(9). Our results are qualitatively the same if we use HNTL as the dependent variable. The sample includes all cells or plants within 300 kilometers from the border. Standard errors are clustered at the cell or plant level. The positive and negative distances to the border are measured by either the great circle (GC) distance in columns (4)–(6) or network (ND) distance in columns (7)–(9). Columns (4)–(9) include ln age of the plant as a time-varying control.

First, instead of using the relative distance to the borders—conditional on overall distance to the border—we estimate specification (9) using separate GC and ND distance measures for the positive and for the negative border segments. Starting with cells and nighttime lights, columns (1)–(3) of Table 4 show significant effects for both distance to the positive and the negative border segments: if a cell is located further away from the positive border, it grew less in lights; whereas if it is located further away from the negative border, it grew more in lights. Repeating the exercise at the plant level—as shown in columns (4)–(6) for the great circle distance and in columns (7)–(9) for the network distance—reveals that the effect of distance to the positive border is more stable and dominates, i.e., plants located further from the positive border tend to exit more in the post-treatment period. The result for distance to the negative border is mostly insignificant for the great-circle distance measure, and significantly negative for the network distance measure. Section 5 analyzes in more detail the heterogeneous changes that took place along the northern border by exploiting the closing of a subset of the border crossings. This heterogeneity in changes along the northern border segment may explain the insignificant average result for the negative border in our exit regressions in Table 4 and why the effect is mainly loaded on the distance to the positive border.

Second, we re-estimate Table 1 using raw NTL as the dependent variable instead of GDP-weighted NTL. Table G.1 shows the results. They are qualitatively similar to the GDP-weighted results, although some coefficients are smaller in magnitude. This suggests that weighting by GDP provides a better measure of economic activity than using raw NTL, which is reassuring.

Third, we re-estimate Tables 1 and G.1 including all cells up to 500 kilometers from the border. The results are again robust. We further checked using both the raw NTL and the GDP-weighted NTL at 300 and 500 kilometers the robustness of our results to the choice of the distance band. Using distance bands of 50 kilometers or 100 kilometers instead of 150 kilometers yields qualitatively similar results, although the standard errors increase with smaller bands due to shrinking sample sizes. The exposure coefficients do not change qualitatively, i.e., cells relatively more exposed to the negative border segment or to market potential from Ukraine saw less growth in lights post 2014.[19]

Last, as discussed in Section 2, the relations between Russia and Ukraine started to deteriorate from 2012 onwards after the EU Accession Agreement was initiated. We thus use 2012 as an alternative treatment date to check whether the effects started to materialize earlier than 2014. We re-estimate Tables 1 and G.1 taking 2012–2018 as our post-treatment period. The results in Tables G.2 and G.3 in Online Appendix G closely mirror those of our baseline case, but are smaller in magnitude. Hence, the bulk of the decrease in nighttime lights occurred after 2014 in the wake of the annexation of Crimea and the armed conflict in the Donbass that followed.

Turning to plant-level exit, we make use of more granular exit information and create exit indicators based on year-quarter information. We combine these with the quarterly

[19]Concerning the distance bands, the estimates in columns (1)–(2) of Tables 2 and 3 are sensitive to the choice of the distance band threshold. For instance, with industry-year fixed effects, plants up to 50km from the border are more likely to exit than more distant plants and the effect is of the same magnitude and sign for the plants located closer to the negative border conditional on being further away from the positive border. But once we condition on productivity differences across plants using plant fixed effects, both effects become insignificant.

information from the VIIRS NTL data to compute a measure of exposure to market potential in Ukraine using the monthly VIIRS series averaged over quarters (see Appendix A.1 for additional details). We set 2014-Q2 as the beginning of the treatment period. Since the VIIRS data start in 2012-Q2, we measure exposure to NTL in Ukraine as the average over the pre-treatment period 2012-Q2 to 2014-Q1.[20] Tables G.4 and G.5 in Online Appendix G show the results. As can be seen, the estimates point in the same direction as the annual exit regressions in Tables 2 and 3, yet the magnitudes of the coefficients are smaller.

Last, none of our results change if we use heteroscedasticity robust standard errors instead of clustered ones. We do not report these results to save space but they are available upon request. Overall, we find robust evidence that economic activity—as measured by nighttime lights and plant exit—suffered more in areas more strongly exposed to the negative border changes in the north relative to the positive border changes in the south.

5 The local effects of closed border crossings

We have shown until now that there is substantial heterogeneity in the effects of border changes when comparing the north to the south. While changes in the south were mostly positive—increased market access due to the annexation of Crimea—changes in the north were mostly negative. We now exploit more granular information on the closing of specific border crossings in the north to analyze the heterogeneity in the spatial changes and to better capture their local effects.

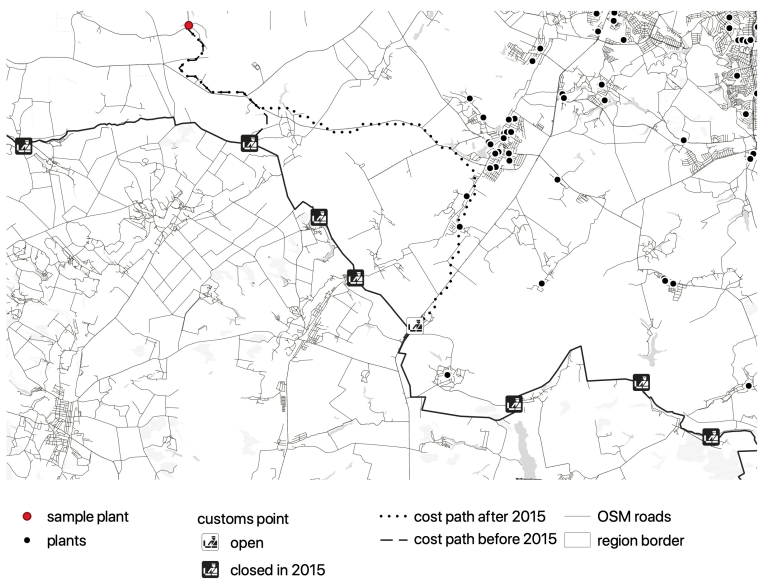
5.1 Context

In 1995, Russia and Ukraine signed an inter-governmental agreement about co-operation of border regions. In 2001, this agreement was upgraded to the program of interregional and trans-border co-operation. The aim of the latter was to faciliate cross border commuting. Recall that the region was a highly integrated industrial center and labor market before

[20] Since we do not have quarterly regional GDP figures we do not report results for weighted NTLs.

the collapse of the Soviet Union, a pattern that still persists. Daily cross-border movements were numerous so that simplified procedures for crossing the border for the local populations were of great importance. According to the agreement, residents of border regions could cross the border at *local border crossings* in the region they were residents of. They could stay on the territory of the neighboring state only within the region into which they entered through the local border crossing, be it for private or for work reasons. The commercial import or export of merchandise at these local border points was prohibited, i.e., trade did not occur through these points but had to flow through *international border crossings* only. The latter were equiped with facilities to take care of customs declarations and other formalities associated with trade.

Figure 7: Example of changes in local border crossings and distance travelled.



Notes: Illustration of changes in least-cost paths before and after the closure of local border crossings in 2015. Authors' computations using the OSM road network and 500×500 meters grid cells.

We provide a detailed descriptions of the international and local border crossings and our data sources in Online Appendix E. To understand the following analysis, it is enough to explain that there were a large number of different types of border crossings between Russia and Ukraine: (i) international border crossings equiped for commercial use and not reserved for local populations; (ii) equiped local border crossings reserved for local populations that could be crossed by motorized non-commercial vehicles for work and personal purposes; and (iii) informal local border crossings reserved for local populations that could be crossed without any formalities using non-motorized vehicles for work and personal purposes. In the wake of the conflict and starting in March 2015, the Ukrainian government shut down all local border crossings and only kept the international border crossings in service. This generated substantial variation in the distances local populations had to travel in order to cross the border. Consequently, workers in some areas had to travel much longer distances and plants in some areas saw substantial changes in their access to labor. We use this variation to investigate whether: (i) NTL intensity in cells that experienced a substantial increase to the nearest border crossing grew less; and if (ii) plants in zones that experienced a large increase in distance to the nearest border crossings saw their exit probability change significantly compared to other plants.

Figure 7 illustrates the changes in distance to the closest open border crossing in the wake of the conflict. As shown, the need to travel farther to the closest open international border crossings could substantially increase the road distance. In what follows, we restrict the analysis to the northern part of the border as the border tightening was more stringent and enforced there (recall that the border was no longer under the control of the Ukrainian government in the regions bordering the Donbass and in Crimea). More precisely, we focus on the four regions in Russia bordering Ukraine at a latitude above the Donbass (Belgorod, Kursk, Bryansk, and Voronezh regions; see Figure C.1 for a map).

5.2 Empirical analysis

To investigate the effects of changes in distance to the nearest open border crossing after the beginning of the conflict, we estimate the following model:

$$\begin{aligned} y_{i,t} \;=\;& \beta_0 + \beta_1(\text{post}_{2015\text{-Q1}} \times \text{bigCity}) + \beta_2(\text{post}_{2015\text{-Q1}} \times \Delta\text{crossingsDist}_{i,t}) \\ & + \gamma_1(\text{post}_{2015\text{-Q1}} \times \Delta\text{crossingsDist}_{i,t} \times \text{bigCity}) + \alpha_i + \delta_t + \varepsilon_{i,t}, \qquad (10) \end{aligned}$$

where $y_{i,t}$ is either $\ln(1 + \text{NTL}_{i,t})$ for the case of nighttime lights or an exit dummy for the case of plants. $\text{post}_{2015\text{-Q1}}$ is a dummy variable taking value 1 starting in the first quarter of 2015 and zero otherwise. In (10), $\Delta\text{crossingsDist}_{i,t}$ is the log change in the shortest distance to the nearest border crossing post-2015-Q1 compared to the shortest distance to the nearest border crossing before 2015-Q1. We measure $\Delta\text{crossingsDist}_{i,t}$ using either great circle distance or road network distance. We also use a weighted version of these measures to account for the fact that some border crossings are more important than others.[21] More precisely, we associate with each border crossing a weight based on the NTL value of the cells of the crossing's main settlements (see Appendix A.3 for details); and α_i are cell- or plant fixed effects, and δ_t are year fixed effects, respectively.

We estimate (10) for the set of (international and local) equipped border crossings in the four northern regions, both up to 50 kilometers and 100 kilometers distance. We restrict ourselves to these shorter distances because we think that the main effects of the closing of the local border crossings are through the movement of people, which affects cross-border labor supply and reduces expenditure due to less cross-border shopping. There are two reasons that lead us to believe so. First, as explained above, the local border crossings cannot be used for commercial merchandise trade. Thus, their closing should not affect trade in goods.[22] Second, we provide evidence in Appendix F that shows both imports and exports had an effect on plant exit, but that there was no specific spatial pattern. Put differently, the trade shock affects firms at large but does not explain why some areas have performed more poorly than others. To focus on local changes, our preferred specification is for 50 kilometers since we think that cross-border movements—both for commuting or shopping—no longer matter much beyond that distance.

In what follows, we pay special attention to the distinction between big cities and rural regions. Indeed, the major international crossings are better connected to the large cities, which may hence be affected differently. In particular, large cities generally saw much less

[21] Unfortunately, we could not obtain any information on cross-border flows.

[22] We do not consider that the diversion of people towards the international points may create congestion there and thus increase trade costs for goods via longer delays.

changes in their distance to the nearest open border crossing as the international crossing points remained open.

Table 5: Changes in distance to border crossings and NTL, equipped- and all points, 50km buffer.

	(1)	(2)	(3)	(4)
	Equipped points		All points	
	GC	GCW	GC	GCW
post2015-Q1	0.080^a	0.077^a	0.082^a	0.076^a
	(0.000)	(0.000)	(0.000)	(0.000)
post2015-Q1 × ΔcrossingDistance	-0.020^a	-0.080^a	-0.019^a	-0.085^a
	(0.000)	(0.002)	(0.000)	(0.003)
post2015-Q1 × bigCity	0.364^a	0.356^a	0.393^a	0.380^a
	(0.014)	(0.013)	(0.024)	(0.017)
post2015-Q1 × ΔcrossingDistance × bigCity	-2.978^a		-1.466^b	-5.381^b
	(0.606)		(0.580)	(2.171)
Cell fixed effects	✓	✓	✓	✓
Year-quarter fixed effects	✓	✓	✓	✓
Observations	8,216,500	8,216,500	8,216,500	8,216,500
R-squared	0.875	0.875	0.875	0.875

Notes: The dependent variable is $\ln(1 + \text{NTL}^{\text{VIIRS}})$, where $\text{NTL}^{\text{VIIRS}}$ is the luminosity of a 500×500 meters cell within a 50 kilometers buffer from the northern part of the border, i.e. Belgorod, Kursk, Bryansk and Voronezh regions. Columns (1)–(2) provide results for the equipped points. Columns (3)–(4) provide results for all points. Change in distance is measured by the great circle distance to the nearest border crossing. Standard errors are clustered at the cell level. The way we measure the distance change is indicated in the column header (GC = great circle distance (5); GCW = great circle distance weighted by border point settlements' NTL (A.4)). The triple coefficient in column (2) is not identifiable, because non-zero changes in distance (A.1) have systematically zero weight (A.3) associated with the closest point and vice versa (see Appendix A.3 for details).

Table 5 shows results for the relation between changes in distance to the border and nighttime lights. Since the treatment starts in March 2015, we use the more recent quarterly VIIRS nighttime lights data rather than the yearly HNTL and a finer spatial resolution of 500×500 meters grid cells near the border. Our results show that lights grew more strongly in large cities after 2015-Q1, but conditional on that less so in areas that experienced a substantial increase in distance from the nearest open border crossing. In other words, lights in the large cities that had better access to international border crossings that were not closed in the wake of the conflict grew more than lights in other places. Conditional on that, places where cross-border movements of people became more costly—as the distance to the nearest open border crossing increased—saw on average slower growth in lights. The major part of the economic cost of the border changes, as measured by nighttime lights, fell on rural areas that saw their distance to the closest open border crossings increase substantially.

Table 6 replicates Table 5 using the exit dummy as the outcome variable. Columns (1)–(8) show that plants in big cities—essentially Belgorod at less than 50 kilometers and

Table 6: Changes in distance to border crossings and exit, equipped- and all points, 50km buffer.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Equipped points				All points			
	GC	ND	GCW	NDW	GC	ND	GCW	NDW
post2015-Q1	0.045[a]	0.044[a]	0.045[a]	0.044[a]	0.044[a]	0.044[a]	0.044[a]	0.044[a]
	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)
post2015-Q1 x ΔcrossingDistance	-0.006	-0.001	-0.029[c]	-0.021	-0.003	0.000	-0.026	-0.018
	(0.006)	(0.007)	(0.016)	(0.039)	(0.006)	(0.006)	(0.030)	(0.040)
post2015-Q1 x bigCity	0.006[a]	0.008[a]	0.007[a]	0.007[a]	0.008[a]	0.008[a]	0.007[a]	0.007[a]
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
post2015-Q1 x ΔcrossingDistance x bigCity	0.146	3.304[a]			-0.059	-0.018	-0.242	-0.056
	(0.158)	(0.138)			(0.099)	(0.102)	(0.490)	(0.395)
Plant controls	✓	✓	✓	✓	✓	✓	✓	✓
Plant FE	✓	✓	✓	✓	✓	✓	✓	✓
Year-quarter FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	126,593	126,593	126,593	126,593	126,593	126,593	126,593	126,593
R-squared	0.061	0.061	0.061	0.061	0.061	0.061	0.061	0.061

Notes: The dependent variable is the plant exit dummy. The sample includes all plants that were active in 2015 within a 50 kilometers buffer from the northern part of the border (Belgorod, Kursk, Bryansk and Voronezh regions). The 50 kilometers buffer includes only Belgorod as a big city. Columns (1)–(4) provide results for equipped points. Columns (5)–(8) provide results for all points. Standard errors are clustered at the plant level. The way we measure distance is indicated in the column header (GC = great circle distance (5); ND = network distance (6); GCW = great circle distance weighted by border point settlements' NTL, (A.4); NDW = network distance weighted by border point settlements' NTL (A.4)). Standard errors are clustered at the plant level. The triple coefficients in columns (3)–(4) are not identifiable, because non-zero changes in distance (A.1) have systematically zero weight (A.3) associated with the closest point and vice versa (see Appendix A.3 for details).

Belgorod and Kursk at 100 kilometers—saw more exit post 2015 compared to plants in more rural areas or smaller cities. Controlling for big cities, there are basically no effects of the increase in distance on plant exit: although almost all point estimates are negative, only one is weakly significant. Table E.1 in Online Appendix E shows that the absence of significant distance effects conditional on the big city dummy are probably driven by the fact that there is only little change in accessibility to the border for plants in large cities, whereas the bulk of the variation stems from plants in rural areas. While this pattern in the data also affects the estimates in Table 5, the much larger sample size—especially for the rural areas—explains the much more precise estimates there. Overall, the triple difference specification seems too demanding given our dataset, though it still suggests that plants in more competitive environments such as big cities tended to exit more than plants located outside in less tough markets (see Table G.6).

To summarize, we find evidence that nighttime lights grew less in areas that experience an increase in their distance to the nearest open border crossing compared to areas that did not experience such an increase. The effects are particularly strong in the big cities. Concerning plant exit, we only find more exit post 2015 in large cities but there are no strong spatial patterns.

5.3 Robustness checks

We examine the sensitivity of our nighttime lights estimates to changes in the distance threshold and the set of local border crossings. Table G.7 in Appendix G shows the nighttime lights results with a 100 kilometers buffer instead of the 50 kilometers buffer in Table 5. The results are very similar irrespective of the distance threshold. We also replicate the results of Table 6 using a 100 kilometers distance threshold from the border. Table G.6 in Online Appendix G shows the results. The coefficients are almost identical, suggesting a higher probability of exit post 2015-Q1 in larger cities compared to more rural areas. The negative estimates for the interaction term between post 2015 and the distance are slightly larger and more precisely estimated, suggesting that, if anything, exit was slightly lower in rural areas where the distance to the nearest open crossing increased.

6 Conclusion

Using the Russia-Ukraine conflict—following the annexation of Crimea in 2014—we provide evidence that changes in borders affect the economic outcomes of border regions substantially and sometimes quite locally. Exploiting the heterogeneity of the border changes between the south of Russia—which gained better market access to Crimea—and the north of Russia—which lost market access because of border closings and tighter controls—we show that improved access led to relatively more growth in nighttime lights and relatively less exit of manufacturing plants. The economic effects are sizable: lights grew by about 40% more in the least negatively exposed regions compared to the most negatively exposed regions; whereas the exit probability of manufacturing plants increased by about 34% more.

Using new data on all international and local border crossings between Russia and Ukraine, we find that changes in the geography of open border crossings correlate with economic outcomes in the border regions. Given that these border changes did not affect the flow of goods but the flow of people, we view this as suggestive evidence that cross-border movements of people are important to understand the economic outcomes of border regions. This seems especially true at a very localized level where the cross border movements of goods no longer matter substantially.

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Appendix material

This set of appendices is structured as follows. In Appendix A.1, we provide a brief description of our nighttime lights data. In Appendix A.2, we explain our plant-level data. Last, Appendix A.3 provides details on the other variables and measures used in the study.

Supplemental details on our data and technical details are relegated to an extensive separate set of online appendices.

Appendix A Data

Appendix A.1 Nighttime lights.

We rely on publicly available nighttime lights satellite data based on the DMSP Operational Linescan System (DMSP, for short) and Suomi NPP VIIRS (VIIRS, for short). DMSP and VIIRS were developed for different purposes and thus measure lights differently. Whereas the former has a relative coarse measure between 0 (no lights) and 63 (most intensive lights, top-coded), the latter measures lights more continuously, captures low-lit areas better, and is not top-coded. DMSP was discontinued in late 2013 and gradually replaced by VIIRS starting 2012. The former offers a spatial resolution of 1×1 kilometers grid cells, whereas the latter provides a resolution of 500×500 meters.

To our knowledge, Li et al. (2020) are the first to harmonized the DMSP and VIIRS series globally. The harmonized NTL series (HNTL, for short) comprises temporally calibrated

DMSP nighttime lights (1992–2013) and DMSP-like nighttime lights from VIIRS (2014–2018) using 2013 to assess the relationship between DMSP and VIIRS. The HNTL series of Li et al. (2020) spans 1992–2018 at a spatial resolution of 1×1 kilometers cells. The lights intensity is measured by a digital number (DN) value ranging between 0–63. We focus on the period 2005–2018 in our analysis.

The VIIRS data cover a more recent period and go back a little before 2014. We utilize quarterly VIIRS nighttime lights from 2012-Q2 to 2018-Q4 in several ways during our study. First, we compute market potential measures as in (3) for quarterly regressions and use it in robustness checks (see Tables G.4 and G.5 in the Online Appendix G). Second, we use it to estimate changes in NTL intensity in response to changes in distance to the nearest border crossing in Section 5 (see Table 5). There, we also use the VIIRS data to compute the intensity of lights at night for the settlements associated with cross-border movements (see Online Appendix A.3). Last, we use it to provide robustness checks—especially for plant exit using quarterly data—in Online Appendix G. A more detailed description of our nighttime lights data, its preparation and post-processing, are relegated to Online Appendix B.1.

Appendix A.2 Plant-level data.

Our plant-level data come from two main providers: Interfax's SPARK and Bureau van Dijk's Ruslana. We identify individual plants using national identifiers—Russian National Nomenclature of Businesses and Organizations (OKPO) and Tax Identification Number (INN). We geo-reference plants using the Yandex Maps API service to map the de facto address—where a plant operates—to geographic coordinates. Each plant reports a date of entry, a date of exit, and its primary activity according to the Russian Classification of Economic activities (OKVED). The classification changed in 2014. For some plants registered after 2014, we only know their OKVED2014 code. We thus create a concordance between OKVED2007 and OKVED2014. Additional details on plant-level data and their treatment are provided in Online Appendix B.2.

Appendix A.3 Other variables and measures.

Distance measures. We measure—for each NTL cell and plant—its distance to the positive border segment in the south and the negative border segment in the north. We compute the great circle (GC) distance to the closest border vertex using either the plant's coordinates or the NTL cell's centroid. For each plant, we also use OpenStreetMap's road network layers to compute the shortest path using the network distance (ND) to the nearest border customs points. For plants in the south, access to Crimea is via the sea of Azov or the Black sea.[23] We construct the shortest path to the ports providing access to Crimea and take this as the network distance to the positive border segment. Additional details are relegated to Online Appendix D.

Geographic variables. We first construct various distance band dummies, either for the border in general or for the positive and the negative border segments separately.[24] Second, we use settlement polygons and points from OpenStreetMap to construct a 'big city' dummy that takes value 1 if the observation is located in a city with at least 300,000 inhabitants. Third, we create a categorized variable indicating whether the plant or the NTL cell lies to the south (lat $<$ 47.14), in the same latitude (47.14 $<$ lat $<$ 49.89), or north (lat $>$ 49.89) of the Donbass. Last, we collect data on the precise locations of all international border crossings between Russia and Ukraine; and we construct data for all local border crossings that exist to simplify local cross-border movements between bordering regions in Russia and Ukraine. We provide details in Online Appendix E.

Other variables. We obtain yearly data on municipal populations in Russia between 2012–2018 from Goskomstat's Database of Municipal Districts. Because those series fluctuate too much to be reliable in their time dimension, we use their averages. We further obtain GDP for each region from Goskomstat for Russia and from Ukrstat for Ukraine. Regional

[23] We disregard the recent bridge across the strait of Kerch that was only opened to traffic in May 2018.

[24] We select 150km as our preferred specification because it captures most of the big cities along the border. In robustness checks, we also use 50km and 100km. The 100km band cuts through many cities, whereas the 50km band has a substantially smaller sample size with much less economic activity.

GDP for Russia is provided for the years 2004–2019 in current prices. Since Crimea and Sevastopol became subjects of the Russian Federation in 2014, we construct GDP series for these regions pre-2014 using official statistics from Ukrstat in current U.S. dollars. We use the average exchange rate between U.S. dollars and Russian rubles pre-2014 from the IMF to compute GDP values for Crimea and Sevastopol.

Changes in the distance to the nearest open border crossing. We measure changes in distance to the nearest border crossing point as follows:

$$\Delta \text{crossingDistance}_i^{\text{D}} = \ln \left(\frac{\min_{j \in \mathcal{B}_{post-2015}} d_{i,j}^{\text{D}}}{\min_{j \in \mathcal{B}_{pre-2015}} d_{i,k}^{\text{D}}} \right), \tag{A.1}$$

where $d_{i,j}^{D}$ is distance measured as great-circle or network distances $D \in \{GC, ND\}$ between plant i and border crossing point j. The set $\mathcal{B}$ is defined as either all border crossing points or the set of equipped border crossing points only.

We do not observe cross-border movements directly so that we need to construct a proxy (weight) for the intensity with which a border crossing is used. We measure that intensity for crossing j before the conflict using a gravity-like equation as follows:

$$\text{pointAttract}_j = \frac{\text{avgNTL}_{k(j)} \times \text{avgNTL}_{m(j)}}{\text{dist}^2_{\text{k(j),m(j)}}}, \tag{A.2}$$

where $\text{avgNTL}_{m(j)}$ and $\text{avgNTL}_{k(j)}$ are the average of the sum of nighttime lights over the years 2013–2014 for the pair of settlements $k(j)$ and $m(j)$ in Russia and Ukraine, associated with crossing point j; and $dist_{k,m}$ is GC distance between the centroids of the settlement pair. The average radiance is computed from VIIRS 500×500 meters cells. We normalize our measure of point attractiveness as follows:

$$\text{pointAttractMinMax}_j = \frac{\text{pointAttract}_\text{j} - \min(\text{pointAttract})}{\max(\text{pointAttract}) - \min(\text{pointAttract})} \in [0, 1]. \tag{A.3}$$

Finally, we derive the weighted changes in distance to the nearest open border crossing as follows:

$$\Delta\text{crossingDistanceWeighted}_i^D = \Delta\text{crossingDistance}_i^D \times \text{pointAttractMinMax}_j, \quad (A.4)$$

where $\Delta crossingDistance_i$ can be measured using either great circle or network distance.

Supplemental Online Appendix

This set of appendices complements the main text and the Data Appendix with technical details. Appendix B contains information on nighttime lights and plant-level data. Appendix C elaborates on the abnormally large plant exit rates in 2012. Appendix D provides detailed information on the construction of our network distance measures. Appendix E explains the construction of our border crossings dataset and provides information on the cross-border movements between Russia and Ukraine. Appendix F provides additional results on nighttime lights and plant exit using trade data. Last, Appendix G contains additional tables and results.

Appendix B Additional information on our data

Appendix B.1 Nighttime lights data.

DMSP and VIIRS. There are two generations of nighttime lights imagery: the Defense Meteorological Satellite Program Operational Linescan System (DMSP, 1992–2013); and the Suomi National Polar-orbiting Partnership Visible Infrared Imaging Radiometer Suite (VIIRS, 2012–today) and its predecessor. Although both detect light emissions at night stemming from human activity, the two sources are not directly comparable. The latter is able to capture lights in low-lit areas and does not suffer from saturation problems in urban cores, as it has enhanced spatial and radiometric resolution. Each pixel of VIIRS data stores radiance values at about 500-by-500 meters cells. VIIRS records radiance values of lights at night in nano watts per square centimeter per steradian (nW/cm^2/sr); whereas DMSP composites provide an average digital number (DN) for about 1-by-1 km cells, with values ranging from 0 to 63.[25] Two major shortcomings of DMSP data are top-coding of urban cores and light-blooming effects falsely illuminating dimmed places.

Nighttime lights satellite imagery has been shown to be a promising data source to

[25]All reported spatial resolution metrics are evaluated at the equator.

approximate economic development across the globe, especially when official statistics are poorly measured or unavailable at a finer geographic resolution (see Donaldson and Storeygard 2016 and Michalopoulos and Papaioannou 2017 for reviews). Although the longer temporal horizon of DMSP makes those data more suited to economic analysis, VIIRS is gradually gaining in popularity as it seems to be superior at predicting subnational GDP distributions (Gibson and Boe-Gibson 2021; Gibson et al. 2021).

Harmonized nighttime lights. Continuous detection of change in economic activity requires spatially and temporally uninterrupted and comparable series of nighttime lights. To this end, Li et al. (2020) have *harmonized* nighttime lights series spanning the period 1992–2018. First, they inter-calibrated the stable DMSP series spanning 1992–2013 (else it is hard to make temporal comparison as satellites lack on-board calibration). The stable version of lights is cloud-free and excludes sunlit data, glare, moonlit data, aurora, and fires. Next, they utilize monthly cloud-free VIIRS Day Night Band composites excluding sunlit, moonlit, fires, aurora and temporal lights, to construct annual series from 2012–2018. The year 2013 is used to quantify relations between DMSP and VIIRS. Finally, DMSP-like series constructed from VIIRS data from 2014–2018 are integrated with the DMSP series from 1992—2013 with a spatial resolution of 1-by-1 km cells, and DNs ranging from 0 to 63. The resulting series have been shown to be spatially and temporally more reliability for the regions with luminance greater than 20 DN.[26]

Quarterly VIIRS. For our robustness checks, we construct *quarterly* nighttime lights series from the VIIRS cloud-free monthly composites (version 1) provided by the Earth Observation Group.[27] This version of the VIIRS composites contain aurora, fires, boats, and other temporal lights, and it is filtered to exclude lightning, lunar illumination, cloud-cover, and

[26]The harmonized nighttime lights series can be downloaded from: `https://figshare.com/articles/dataset/Harmonization_of_DMSP_and_VIIRS_nighttime_light_data_from_1992-2018_at_the_global_scale/9828827/2` in GeoTIFF format.

[27]The VIIRS monthly composites can be downloaded from: `https://eogdata.mines.edu/products/vnl/`. Large-scale processing is done with the Google Earth Engine service.

stray light.[28] We extracted monthly average radiance values and the number of cloud free observations from April 2012 to December 2018 for the grid cells up-to 500 km from the border for Russia and Ukraine. To be consistent with the harmonized nighttime lights series, we resampled the original 500-by-500 meters cells into 1-by-1 km cells.[29] We computed quarterly average radiance values weighted by the number of cloud free observations for each cell.

Post-processing of nighttime lights. Due to solar illumination toward the poles—mainly in the summertime—the quality of average radiance values is low and should undergo straylight correction (Elvidge et al., 2017). At the time of writing this article, straylight correction is available starting January 2014. Therefore, we utilize the straylight corrected VIIRS series whenever possible and drop the second quarters in 2012–2013 as they contain zero or abnomraly small values of radiance in what a temporal trend would suggest. Finally, we drop the top and bottom 0.5% of observations that represent radiance outliers, and we get rid of all cells that are unlit during the whole study period.

We further process the harmonized nighttime lights series and quarterly VIIRS series to mask water bodies. Pixels that fall into water surfaces were excluded by applying the water masks provided by the European Commission Global Surface Water.[30] We resampled 30-by-30 meter cells of water occurrence to 1-by-1 km cells and mask all cells with more than 50% of water surface.

We decided to keep gas flares unmasked for several reasons. First, according to the Earth Observation Group's gas flaring maps, derived from the VIIRS series, the number of sites in Russia with gas flares are negligible within 300 km distance from the border, with a majority of sites being located closer to Crimea.[31] Second, keeping gas flares in our analysis

[28]Non-filtered sources of lights are not a concern for our study area. Besides, the measures of market potential, where quarterly VIIRS series are utilized, are smoothed across space.

[29]For the mechanisms' section on movement of people, we employ quarterly VIIRS nighttime lights at the original 500-by-500 meter cells resolution. The processing steps to construct the series are the same as for the quarterly VIIRS discussed above. We use finest available resolution to better capture local economic activity along the border for Ukraine and Russia.

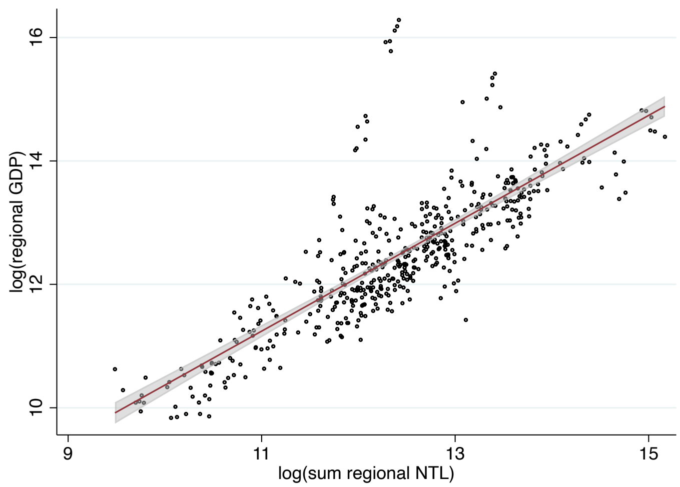
[30]Source for the water surface: `https://global-surface-water.appspot.com/download`

[31]See `https://viirs.skytruth.org/apps/heatmap/flarevolume.html` for the map of gas flaring sites.

is desirable since they are directly related to extractive economic activity that is important for the cross-border economies of Russia and Ukraine.The appearance of new gas flaring sites and the disappearance of existing ones are indicators of change in economic activity.

Nighttime lights and regional GDP. Nighttime lights and regional GDP are strongly correlated in our data. Figure B.1 shows the linear log-log relationship between nighttime lights—aggregated at the regional level—and regional GDP. A simple OLS regression yields an estimated elasticity of 0.865 (standard error 0.028) with adjusted R^2 of 0.665.

Figure B.1: Pooled OLS estimates of regional NTL and GDP (HNTL, 2008–2013, all of Russia).



Notes: Scatterplot (all years and regions pooled), with year fixed effects, linear estimation and confidence band. The slope is 0.865 (standard error 0.028) and the adjusted R^2 is 0.665.

Nighttime lights and municipal employment (wages). We estimate the cross-sectional relation between municipal employment (wages) and nighttime lights.[32] We restrict our sample to municipalities up to 300km from the border. We first compute the sum of harmonized nighttime lights (HNTL) per municipality per year. We then average the computed nighttime lights across the years 2011–2013. We apply the same averaging procedure for

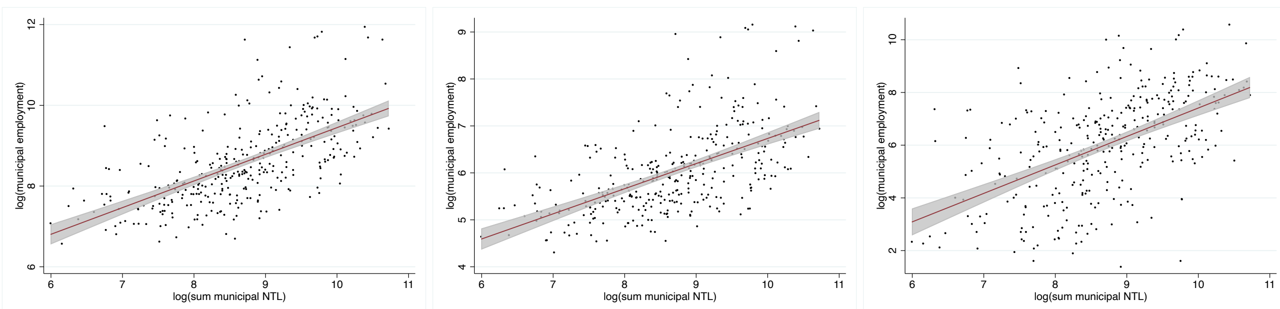
[32]Employment and wages are from Goskomstat's Municipal Database collected by the INID project (`https://data-in.ru/data-catalog/datasets/115/`). Wage is the average monthly wage, computed by dividing the monthly total payroll by the average number of employees and multiplied by the number of months in the reporting period.

municipal employment and wages. We trim the top and bottom 1% extreme values from both series and then regress the log of municipal employment or wages on the log of the sum of municipal nighttime lights. We provide separate estimates for total employment and wages for all sectors, for services only, and for manufacturing only.[33]

Figure B.2: OLS cross-section estimates of municipal NTL and employment or wage levels (HNTL, 2010–2013, 300km buffer).

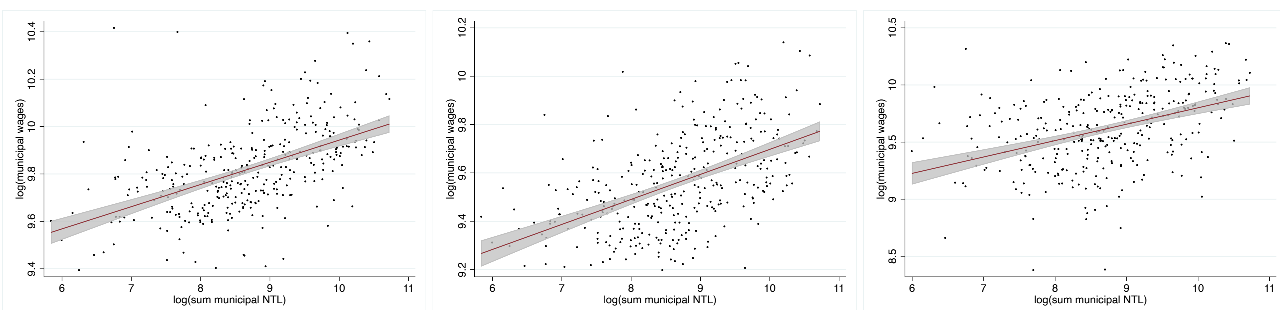
(1) Relation between municipal NTL and employment levels

(a) Total (b) Services (c) Manufacturing



(2) Relation between municipal NTL and wage levels

(a) Total (b) Services (c) Manufacturing



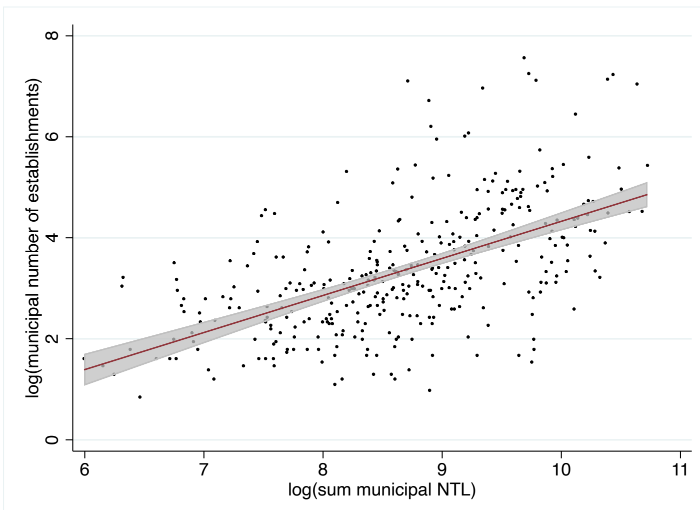
Notes: Scatterplots for all municipalities up to 300km, averaged across 2011–2013. We show linear estimations with their confidence bands. We trim the bottom and top 1% of the variables. Total employment (panels (a)) refers to the average number of employees across all industries. Services (panels (b)) refers to the average number of employees in sectors G–K and M–O in OKVED2007; G–N and P–S in OKVED2014. Manufacturing (panels (c)) refers to sector D in OKVED2007 and C in OKVED2014. In panel (1a) the slope is 0.66 (standard error 0.044) and the adjusted R^2 is 0.39. In panel (1b) the slope is 0.535 (standard error 0.04) and the adjusted R^2 is 0.337. In panel (1c) the slope is 1.08 (standard error 0.09) and the adjusted R^2 is 0.297. In panel (2a) the slope is 0.094 (standard error 0.009) and the adjusted R^2 is 0.273. In panel (2b) the slope is 0.103 (standard error 0.009) and the adjusted R^2 is 0.267. In panel (2c) the slope is 1.144 (standard error 0.018) and the adjusted R^2 is 0.171.

The results for employment and wages are presented in panels (1) and (2) of Figure B.2. As can be seen, the log of nighttime lights alone explains 40% of the variation in log

[33]Services refer to sectors G–K and M–O in OKVED2007; G–N and P–S in OKVED2014. Manufacturing refers to sector D in OKVED2007 and C in OKVED2014.

employment and 27% of the variation in log wages, respectively. The estimated elasticities range from 0.53 to 1.08 for employment and from 0.1 to 1.14 for wages. Mellander et al. (2015) provide estimates at the finest available level for Sweden, namely 250-by-250 meter grid cells in urban areas and 1000-by-1000 meters grid cells in rural areas, using OLS DMSP in single cross section. They find employment and wages elasticities to nighttime lights of 0.42 and 0.176 respectively. In another study, Gibson and Boe-Gibson (2021) estimate nighttime lights elasticities of GDP for the service sector and the private goods sector to be 1.097 and 0.960 respectively, using VIIRS version 2 series for single cross-section estimates and US county-level data.

Figure B.3: Municipal NTL and number of manufacturing establishments (HNTL, 2010–2013, 300km buffer).



Notes: Scatterplot for all municipalities up to 300km, averaged across 2011–2013. We show linear estimations with their confidence bands. We trim the bottom and top 1% of the variables. The slope is 0.734 (standard error 0.055) and the adjusted R^2 is 0.326.

Figure B.3 shows the log-log relation between the number of manufacturing establishments per municipality and municipal nighttime lights. We again observe a strong cross-sectional correlation between lights and our measure of economic activity. The correlation being of course not perfect, using plants directly instead of lights allows us to capture a broader range of effects than using lights alone.

Appendix B.2 Plant-level data.

Geocoding. Business intelligence providers such as Ruslana and SPARK keep track of the address where plants operate. The Ruslana database stores information on address updates by selecting a random sample of plants each year and by checking if their contact details are up-to-date. All plants in our sample have updates for their address at least once since 2006. The SPARK database marks the address field as 'place of business'.

The precise location of each plant is obtained through the geocoding of their *de facto* address using the Yandex Maps API service.[34] Most of our plants are geocoded at the finest available precision, i.e., rooftop. Additionally, SPARK Interfax already uses the Yandex Maps to provide the precise location of each plant. We cross-checked the accuracy of our locations in our sample using their data.

About 5% of the plants' locations in our sample have postal office centroids as geographical coordinates since we were unable to obtain precise coordinates for these plants. The precise location of each postal office centroid is gathered from the Russian Postal Office Service that covers all postal offices in Russia.[35].

Industry concordance. A substantial revision of the Russian classifier of economic activity (OKVED, for short) took place in 2014. For instance, the publishing sector was moved from manufacturing to services.[36] In our sample, we have plants that report their primary economic activity in the 2007 classification, using both 2007 and 2014 versions of OKVED codes, or the 2014 versions only. We harmonize the 2014 and 2007 codes to allow for a consistent analysis. To do so, we first compute the frequency of occurrences for OKVED2007–OKVED2014 pairs in the total number of OKVED2014 occurrences in our sample. We

[34] See `https://yandex.com/dev/maps/` for details. The Yandex Maps geocoding service provides better addresses for small settlements in Russia than Google Maps.

[35] See `https://www.pochta.ru/offices` for details. The standards for the location of postal offices in Russia requires one postal office to serve 15,000 people in cities with more than 500,000 people, or one postal office to serve 6,000 people cities with less than 100,000 inhabitants. Our study area is densely populated compared with the eastern regions in Russia and, therefore, postal code centroids capture plants' locations fairly precisely.

[36] Manufacturing sectors at the two-digit level in OKVED 2014 range from 10 to 33, whereas in its predecessor OKVED 2007 they range from 15 to 37.

then take the pair of OKVEDs with the maximum frequency and extract a corresponding OKVED2007 code to create a concordance between OKVED2007 and OKVED2014.

Coverage. Our manufacturing plant data provide a very exhaustive coverage of the universe of Russian manufacturing plants. Table B.1 below provides detailed yearly information on our sample, including entry and exit information, whereas Table B.2 shows a snapshot of our sample and compares it with the official information from the Federal State Register (FSR) for the 18 regions that intersect our buffer of 300 kilometers from the border with Ukraine. Table B.2 shows that our plant coverage is nearly exhaustive, especially in the border regions.

Table B.1: Distribution of plants by years and their status.

	100km			200km			300km			RUE		
	Active	Exit	Enter	Active	Exit	Enter	Active	Exit	Enter	Active	Exit	Enter
2006	12,622	763	1,427	26,662	1,545	2,792	35,258	2,153	3,686	297,916	25,893	30,039
2007	13,286	933	1,418	27,909	2,166	2,754	36,791	2,968	3,605	302,062	33,380	31,190
2008	13,771	879	1,188	28,497	2,240	2,416	37,428	2,948	3,216	299,872	23,236	27,992
2009	14,080	578	980	28,673	1,176	1,905	37,696	1,599	2,547	304,628	12,355	22,963
2010	14,482	1,099	996	29,402	2,194	2,051	38,644	2,850	2,770	315,236	25,018	24,949
2011	14,379	1,237	1,048	29,259	2,564	2,177	38,564	3,721	2,902	315,167	34,375	25,218
2012	14,190	1,719	1,032	28,872	2,988	2,152	37,745	3,897	2,823	306,010	29,020	24,514
2013	13,503	964	1,067	28,036	1,910	2,262	36,671	2,480	2,934	301,504	29,238	29,103
2014	13,606	791	1,304	28,388	1,661	2,732	37,125	2,281	3,615	301,369	25,610	32,220
2015	14,119	671	1,203	29,459	1,693	2,446	38,459	2,152	3,262	307,979	17,895	24,520
2016	14,651	1,484	1,144	30,212	2,728	2,571	39,569	3,683	3,472	314,604	41,201	25,686
2017	14,311	1,310	1,160	30,055	3,031	2,329	39,358	3,743	3,155	299,089	33,349	23,624
2018	14,161	1,461	922	29,353	3,291	1,867	38,770	4,144	2,503	289,364	38,460	19,274

Notes: Active refers to the total number of plants in our Ruslana-SPARK database before year t and liquidated in or after year t. Exit refers to the total number of plants that entered before year t and liquidated at year t. Entry refers to the total number of plants that registered in year t. RUE refers to the Russian European part. Source: authors' own computations.

In 2012, the FSR reports 55,805 registered manufacturing plants in the 18 border regions (column (2)), and we have 54,436 in our sample (column (3)). The coverage is therefore exceptionally high at 97.6%. Furthermore, column (4) shows that the differences between our sample and the FSR are small in all regions and that there is no systematic bias in the reporting of plants in our Ruslana-SPARK dataset.

Trade concordance. Because the period we cover starts in 2005 and ends in 2020, we download WITS trade data in two harmonised systems at the four-digit level: HS02 and HS07. First, we use correlation and conversion tables to find the concordance between

Table B.2: Comparing the Federal State Register with the Ruslana-SPARK dataset.

Region name	OKTMO	2005	(1) 2011 FSR	(2) 2012 FSR	(3) 2012 R-S	(4) Δ (2)-(3)	(5) 2013 FSR	(6) 2018 FSR
Belgorod region	14 000 000	2489	3272	3257	3148	-109	3344	3001
Bryansk region	15 000 000	2141	2173	2141	2089	-52	2176	1 671
Voronezh region	20 000 000	6361	4745	4689	4637	-52	4818	3 717
Kaluga region	29 000 000	3725	3195	3138	3094	-44	3223	2 856
Kursk region	38 000 000	2137	1865	1884	1880	-4	1862	1 506
Lipetsk region	42 000 000	2283	1868	1823	1742	-81	1863	1 788
Orlov region	54 000 000	1634	1603	1596	1517	-79	1616	1 271
Smolensk region	66 000 000	2414	2470	2441	2349	-92	2497	2 162
Tambov region	68 000 000	1282	1390	1412	1366	-46	1449	1 212
Republic of Adygheya	79 000 000	915	758	764	720	-44	774	678
Republic of Kalmykya	85 000 000	997	464	428	462	34	326	137
Krasnodar region	3 000 000	15494	10349	10497	10789	292	10514	9 104
Astrahan region	12 000 000	1897	1383	1375	1339	-36	1423	1 051
Volgograd region	18 000 000	4819	4002	3943	3507	-436	4039	2 948
Rostov region	60 000 000	12069	8103	7649	7315	-334	7671	6 668
Republic of Karachay-Cherkessia	91 000 000	1296	562	563	561	-2	586	528
Stavropol region	7 000 000	5649	3910	3911	3829	-82	3909	3 028
Saratov region	63 000 000	4994	4379	4294	4092	-202	4396	3 388
Total border regions		72,596	56,491	55,805	54,436	-1,369	56,486	46,714
Total Russia (all regions)		478,413	403,942	404,959	368,332		401,872	309,846

Notes: FSR = Federal State Register (Source: before 2016—Digest of regions of Russian Federation, after 2016—EMISS). R-S = Ruslana-SPARK Interfax. The numbers account for manufacturing sector only.

these two harmonised systems. Additionally we drop the unspecified destinations 'world' and 'unspecified' from exports and imports. Next, we map the Harmonized Commodity System to the Commodity Nomenclature for Foreign Economic Activities (TNVED) used by the Eurasian Economic Union, which has a concordance with the Russian Classification of Products by Economic Activities (OKPD). This, in turn, is matched to OKVED industry codes at the four-digit level.

Several comments are inorder. First, TNVED provides a concordance with the HS12 codes. Therefore, we need to map the HS02 WITS data to the HS12 classification. Second, we need to align trade data to the OKVED2007 classification. Therefore, as an additional step, we construct a cross-walk from OKPD2014 to OKPD2007. The latter matches OKVED2007 at the first four digits. Finally, following the above steps, we build a concordance between HS02 and OKVED2007. The resulting cross-walk has a large number of many-to-many relations. In cases where one HS02 code has many OKVED2007 codes we have no choice but to apportion equally export and import values across these codes. We also have HS02 products with no corresponding HS12 code. Fortunately, these products are not among the most extensively traded between Russia and Ukraine. We provide a list in the footnote.[37]

Appendix C Spike in the exit rates in 2012

In this appendix we provide additional details about the unusual exit patterns of firms in 2012. More precisely, we discuss the spike in exit rates in 2011–2012 and rule out several problems that could affect our data.

First, we analyzed the Ruslana-SPARK data in detail to rule out the possibility of measurement error in exit dates. To this end, we collected the exit dates for all plants within a 300km buffer from the border that were liquidated in 2012 from the Uniform State Register of Legal Entities. Out of 3,904 plants that exited from our sample in 2012, we could collect records for 3,876 of them, among which 99% indeed report 2012 as their exit year. We also checked whether high exit rates in 2012 are specific to any sector, area, or quarter of the year. None of those drive the results.

Second, we compared our figures for the total number of plants by region and industry, and the number of exits, with aggregate numbers from the Federal Statistics Service (Rosstat). Statistics on active/entering/leaving legal entities across all sectors for the regions within a 300km buffer from the border indicate an increase in exit rates in 2012 among

[37]Natural sponges of animal origin; Vegetable materials of a kind used primarily as stuffing or as padding, whether or not put up as a layer with or without supporting material; Vegetable materials of a kind used primarily in brooms or in brushes, whether or not in hanks or bundles; Fulminates, cyanates and thiocyanates; Phosphides, whether or not chemically defined, excluding ferrophosphorus; Articles of leather, or of composition leather, of a kind used in machinery or mechanical appliances or for other technical uses; Floor coverings on a base of paper or of paperboard, whether or not cut to size; Sisal and other textile fibres of the genus Agave, raw or processed but not spun; tow and waste of these fibres (including yarn waste and garnetted stock); Felt hats and other felt headgear, made from the hat bodies, hoods or plateaux of heading No 6501, whether or not lined or trimmed; Glazed ceramic flags and paving, hearth or wall tiles; glazed ceramic mosaic cubes and the like, whether or not on a backing; Glass inners for vacuum flasks or for other vacuum vessels; Cloth (including endless bands), grill and netting, of copper wire; expanded metal, of copper; Copper springs; Cooking or heating apparatus of a kind used for domestic purposes, non-electric, and parts thereof, of copper; Lead bars, rods, profiles and wire; Lead tubes, pipes and tube or pipe fittings; Zinc tubes, pipes and tube or pipe fittings; Tin plates, sheets and strip, of a thickness exceeding 0,2 mm; Tin foil (whether or not printed or backed with paper, paperboard, plastics or similar backing materials), of a thickness (excluding any backing) not exceeding 0,2 mm; tin powders and flakes; Tin tubes, pipes and tube or pipe fittings; Typewriters other than printers of heading 8471; word-processing machines; Parts and accessories; Keyboard pipe organs; harmoniums and similar keyboard instruments with free metal reeds; Mouth organs; Wheeled toys designed to be ridden by children; dolls' carriages; Dolls representing only human beings.

the northern region of Kaluga, the regions bordering Donbas—Voronezh and Rostov—and the Kalmykya region bordering Rostov to the east. The same regions experienced also higher entry rates in 2012. Generally, most of the regions along the border with Ukraine experienced high exit rates in 2011 and 2012.

Table C.1: Firm entry and exit in the 18 border regions, 2011–2013.

				2011			2012			2013	
Region name		OKTMO	active	created	liquidated	active	created	liquidated	active	created	liquidated
Belgorod region	north/donbass	14 000 000	33 369	3 942	2 841	34 244	4 079	3 201	35 344	3 958	2 858
Bryansk region	north	15 000 000	21 223	2 466	2 513	21 003	2 340	2 560	21 536	1 921	1 388
Voronezh region	north/donbass	20 000 000	52 149	6 859	5 763	52 291	7 244	7 102	54 872	5 904	3 323
Kaluga region	north	29 000 000	25 053	2 764	3 083	25 083	3 524	3 494	25 712	2 295	1 666
Kursk region	north	38 000 000	21 919	2 447	2 723	22 061	2 322	2 180	22 492	2 113	1 682
Lipetsk region	north	42 000 000	22 138	2 744	3 085	22 366	2 827	2 599	23 243	2 218	1 341
Orlov region	north	54 000 000	14 825	1 437	1 685	15 192	1 457	1 090	15 685	1 404	911
Smolensk region	north	66 000 000	22 799	3 021	3 041	23 041	2 424	2 182	24 230	2 181	992
Tambov region	north	68 000 000	17 115	1 893	2 688	16 909	1 512	1 718	17 209	1 535	1 235
Republic of Adygheya	south	79 000 000	6 399	639	660	6 476	647	570	6 606	692	562
Republic of Kalmykya	donbass	85 000 000	6 244	945	1 628	5 327	1 873	2 790	3 772	2 686	4 241
Krasnodar region	south	3 000 000	123 664	15 236	14 199	127 211	13 672	10 125	130 405	16 403	13 209
Astrahan' region	donbass	12 000 000	16 742	2 262	2 557	16 916	1 635	1 461	17 509	1 435	842
Volgograd region	donbass	18 000 000	51 970	9 066	10 856	52 475	5 734	5 229	54 152	5 340	3 663
Rostov region	donbass	60 000 000	91 804	9 307	7 463	87 757	12 949	16 996	90 166	10 211	7 802
Rep. of Karachay-Cherkessia	south	91 000 000	6 065	893	869	6 174	599	490	6 377	553	350
Stavropol region	south	7 000 000	43 324	4 092	4 079	44 019	3 936	3 241	45 127	3 442	2 334
Saratov region	north/donbass	63 000 000	48 674	6 803	10 736	48 204	5 632	6 102	49 674	5 045	3 575

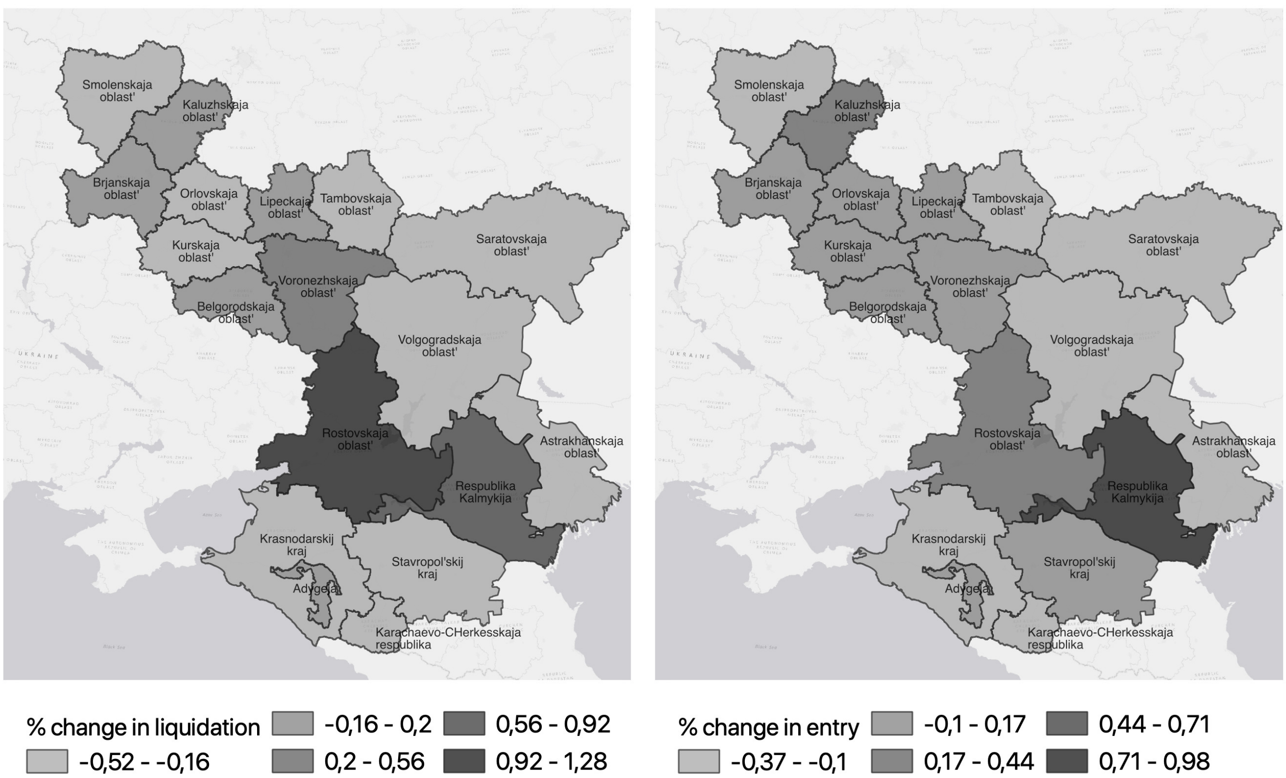
Notes: Data from the Federal State Register (https://фси.рф/Main/StatisticalInformation). The numbers account for all registered legal entities irrespective of their sector of activity.

Table C.1 and Figure C.1 below show that exit spiked in 2012 in the Rostov region, increasing by almost 130% between 2011 and 2012. At the same time, entry also increased substantially, but by far less (only about 40%). In general there was thus much more turn over and, especially, more exit. Observe that this is unlikely to be linked to any 'anticipation effects' that firms may have had in that region regarding the future conflict. Indeed, it has been shown that exit and entry tend to be lower in periods of high uncertainty because the option value of 'business as usual' increases, thus "making firms more cautious when investing or divesting" (Bloom et al., 2007). To summarize, it is hard to understand why the Rostov region in particular was so strongly affected and experienced a spike in exit and an increase in entry.

We know that there was generally a substantial increase in plant exit in Russia in 2011-2012. What may be the possible reasons? There are not many papers exploring the exit dynamics of firms in Russia in general, and for the period we analyze in particular. The closest to our analysis is the study by Iwasaki et al. (2016). They study national and regional factors explaining the creation and destruction of firms in Russia between 2008 and 2014. They document the increase in exit rates in 2011 and more volatility afterwards, and attribute this to a lagged effect of the financial crisis. While this may be true, we think that there are two other important explanations.

Figure C.1: Regional percentage changes in liquidations and entries.

(a) Liquidations (b) Entries



Notes: The figure depicts the regions in Russia located within a 300km buffer from the border with Ukraine. Each regions' color-graduation reflects % changes in liquidations and entries from 2011 to 2012, all legal entities. Darker colors refer to more liquidations/entries, whereas lighter colors refer to less liquidations/entries, respectively.

First, important legislative changes were enacted by the Federal Tax Service during that period. In January 2011, a sharp increase in the rate of enterprises' insurance contributions to social security took effect, with rates increasing from 26% to 34%. Given that enterprises were not yet able to reach their pre-crisis levels of production, the additional fiscal burden may have driven many firms out of business. The new contributions were especially damaging to sectors with a high share of wages in total costs, i.e., manufacturing, which are also among those that suffered the most from the 2008 financial crisis. Second, in December 2011, a new article in the Criminal Code was introduced which imposed strict penalties for the registration of legal entities through fictitious persons. This severe action was a response to the high number of shell companies in the Russian economy. Anticipating the new severe criminal penalties starting in 2012, many fictitious companies were shut down, which could also explain the uptick in recorded exit rates (and the uptick in entry rates, as owners may re-register their business in compliance with the new legislation).

Table B.1 above shows the distribution of the number of manufacturing plants by year and their status—active, entering, or exiting—for distance bands up to 300km and for the European part of Russia. Overall, we observe higher exit figures in 2012 for all manufacturing plants up to 300km and an increase in entry in the years that follow. This suggests there was some reorganization of businesses in response to legislative changes.

Appendix D Network distance

We compute the shortest distance on the road network for a plant to the closest border crossing point in several steps.

First, we obtain Open Street Map road layers for Russia and Ukraine.[38] We keep only major cargo-passenger roads with highway keys: primary, secondary, tertiary, motorway and trunk.[39]

Second, we reproject the road layer to EPSG:28407 Pulkovo 1942 Gauss-Kruger zone 7 which is used in Russia onshore and leads to the least distortions in the study area. We clip the road layer with our 300km buffer from the border for both countries. Then, we construct a vector grid of 1-by-1 km cells for the study area.[40] For each cell we compute the number of lines from the road layer that intersect the cell and convert it to a binary

[38] OSM layers can be downloaded from: `https://download.geofabrik.de/`.

[39] When looking at the movement of people, we use all roads from the OSM layers as local cross-border movement can take place at rural places. In the latter case we compute network distance only for the plants that are located in the four Northern regions bordering Ukraine: Bryansk, Kursk, Belgorod and Voronezh.

[40] When looking at the movement of people, we construct a 500-by-500 meters vector grid.

variable with value 1 if there is at least one road that crosses the cell, and zero otherwise. We further convert the vector grid to the raster layer and use road count dummies as a value associated with each pixel.

Third, we use the R package *gdistance* to compute a transition matrix from the raster. The package represents the raster as a graph with each node being a cell centroid, such that each cell is connected to its 8 neighbours. Transition values among nodes are defined as the minimum value between adjacent nodes. It restricts movement on the graph only through the nodes that are connected by a road. If a road connecting a plant and a border crossing point cannot be found, we compute the shortest great-circle distance from this plant to the nearest plant and sum its network distance with the great-circle distance.

Last, we use plants as points of origin and the set of all border crossings as destination points to compute the shortest distance on the constructed road network.

Appendix E Border crossings

The Government of the Russian Federation approved the concept of cross-border co-operation in 2001 (#196-p). Its purpose is to increase the welfare of populations close to the border, strengthen good relationships between neighbors, and provide stable development of bordering regions of Russia and neighbor countries. In 2003, Russia joined the European Outline Convention on Trans frontier co-operation between Territorial Communities or Authorities (Madrid Convention). In December 2011, Kaliningrad oblast and major centers in the north of Poland formed a new zone for local border traffic, the regulation contributing to the promotion of the strategic partnership between the European Union and the Russian Federation.[41] Among the prioritized directions of cross-border co-operation are: frontier trade, investment projects, production and technical co-operation, transport and communication co-operation, environmental protection, law enforcement, migration and local labor markets, as well as scientific and humanitarian co-operation.

[41] Regulation (EU) No 1342/2011 of the European Parliament and of the Council of 13 December 2011 amending Regulation (EC) No 1931/2006 as regards the inclusion of the Kaliningrad oblast and certain Polish administrative districts in the eligible border area.

Russia–Ukraine agreements. In the early 1990s, Russia and Ukraine signed a number of agreements on cross-border cooperation. The basic agreement that determines the rules—and the list of points for border crossing by persons, vehicles, and cargo between Russia and Ukraine—is the *Agreement between the Government of Russian Federation and the Government of Ukraine on checkpoints on the state border between the Russian Federation and Ukraine from February 8, 1995*. The agreement was amended in 2006 and 2011. The second agreement, *Agreement between the Government of the Russian Federation and the Cabinet of Ministers of Ukraine on the procedure of crossing the Russian–Ukrainian state border by residents of the border regions of the Russian Federation and Ukraine from April 21, 2006*, was developed to preserve economic, cultural, and other traditional ties between the populations of the border regions of the Russian Federation and Ukraine.[42]

The latter agreement on local cross-border movement defines eligibility criteria to cross the border. First, it defines the list of border regions on the Russian and Ukrainian sides of which residents can cross the border through the list of local border crossings. In 2006 only residents of bordering municipal districts were eligible for simplified procedures of border crossings. In 2012, the policy was extended to include all bordering regions. By 2014 there were six Russian regions bordering Ukraine: Belgorod, Bryansk, Voronezh, Krasnodar, Kursk and Rostov. On the Ukrainian side there were six regions: Crimea, Donetsk, Luhansk, Sumsk, Kharkov and Chernigov. Second, residents eligible to cross the border at local border crossings must be citizens of the Russian Federation or Ukraine and permanently reside in the border regions. Residents of border regions can cross the border at local border points of the region of which they are residents, and stay in the territory of a neighboring state only within the region into which they entered through the local crossing point. Third, local border crossings are defined as places at the border, which are equipped by the competent authorities of the states and through which the residents of

[42]Its aim was to realize the implementation of provisions from prior agreements: the Agreement between the Russian Federation and Ukraine on cooperation and interaction on border issues of 3 August 1994, the Agreement between the Government of the Russian Federation and Government of Ukraine on cooperation in border regions of the Russian Federations and Ukraine of 27 January 1995, and the Agreement between the Government of the Russian Federation and the Government of Ukraine on checkpoints on the state border between the Russian Federation and Ukraine of 8 February 1995.

border regions cross the border under the terms of this agreement. Fourth, residents of border regions can cross the border on foot, on bicycles, motorcycles, horse-drawn carts and cars, boats belonging to them, as well as by road and ferry public transport of interstate communication within the border regions. Last, residents of border regions can move goods that are not intended for production or other commercial activities across the border at local border crossing points, in an amount not exceeding the standards for the import (export) of goods without payment of customs duties and taxes provided by the legislation of the two countries.

Border crossings. A *point* where the border can be crossed is defined in the agreements as a *pair of settlements* that link the two countries via a road.[43] We manually collected the geographic coordinates of border crossing points by means of Yandex Maps. For the international or intergovernmental border crossing points, location descriptions can be found on the web-site of the Ministry of Transport. For the local border crossing points, the only information available is the name of the settlement on both sides of the border. We use this information and Yandex Maps route service to find the point where the border crosses a road linking pairs of settlements.

To avoid cumbersome labelling of border crossing points that serve different purposes, e.g., international, intergovernmental, contractual bilateral, and local, we will refer to the first three as international and to the last one as local. The core difference is that the latter can only be used by residents of bordering regions, and that no merchandise for the purposes of production or commerce may be carried through, as discussed previously.

According to the agreements, there were 48 international and 138 local border crossing points in service in the six bordering regions before the conflict. The breakdown of the number of international and local border crossing points (in parentheses) in the bordering regions is as follows: Belgorod 13(74); Bryansk 6(9); Kursk 4(13); Voronezh 2(4); Rostov 14(38); and Krasnodar, 9.[44]

[43]For the purposes of our research, we use information on automobile border crossings and sea ports leaving railway crossings aside.

[44]In Krasnodar, all border crossing points are sea ports. If a local point has the same pair of settlements

We further identify the subsample of local points that are *equipped*, i.e., that comply with the requirements for the construction and equipment of local border crossings developed by the competent authorities of the two countries. This is required because the agreement on local border movement provides only the list of potential border crossing points but remains silent about the terms of the arrangement. Since there is no official database of equipped local points, we refine the list with the external sources, such as official websites of local administration, informal forums discussing local border crossing or news in the media about opening/planning of new local points from the agreement. We restrict ourselves to the four northern regions as they are the ones where we see border crossing being closed in 2015, a point we further discuss in detail below.

Border closure policy. In the wake of the armed conflict, the Government of Ukraine began unilaterally to close border crossing points. First, on February 18, 2015, 23 border crossing points were closed, 4 international and 19 local.[45] Next, in March 2015, Ukraine demanded international passports to cross the border for Russian citizens. This automatically lead to closure of all local border crossing points for Russians. Russia did not introduce reciprocal restrictions on border crossing for Ukrainians. Although there are no official statistics on cross-border movements via local points that we have access to, it seems that the flow of people from Ukraine to Russia decreased but more so for the flow of people from Russia to Ukraine.[46]

The restrictions on cross-border movements had larger effect for people who extensively used local points to cross the border with Ukraine. This creates an exogenous change in commuting distance for Russian residents of border regions. We focus on the four northern regions to exploit variation in distance to the nearest border crossing after 2015. We exclude the Rostov region as it borders the area of armed conflict, which is not under the control

as an international point, we treat it as a duplicate and assume that the less stringent international rules for crossing the border apply.

[45] The order of Cabinet of Ministers of Ukraine #106-p.

[46] Trans-border payments from Russia to Ukraine dropped after 2014. Historically, there is s disproportionally larger flow of labor migrants from Ukraine to Russia than from Russia to Ukraine. This tendency holds since the early nineties.

of Ukrainian Government, and the Krasnodar region, as it borders Crimea which became a subject of the Russian Federation in 2014.

For the four northern regions, affected by changes in distance to border crossing points, the number of all local points and equipped local points (in parentheses) is as follows: Bryansk 9(2); Kursk 13(13); Belgorod 74(6); and Voronezh 4(4). We employ both sets of points in our analysis.

NTL weights for border crossings. Since we do not observe statistics on the volume of cross-border movements before and after the conflict, we use the intensity of nighttime lights as a proxy for the importance of each border crossing point. We proceed in several steps. First, for each settlement associated with the border crossing point on the Russian and the Ukrainian sides, we compute the sum of 500-by-500 meters cell luminosity from the annual VIIRS dataset.[47]

Next, we compute the average intensity of nighttime lights for each settlement for the years 2013–2014. We also compute the geodetic distance between centroids of settlement pairs. With this at hand, we build weights for each border crossing point using a gravity-like relation: the weight is the product of the average pre-conflict light intensity of a settlement pair divided by the squared distance between them.

Finally, we normalize these weights to fall into the interval $[0, 1]$ and use them either as analytical weights or as multipliers for changes in distance to the border crossing points in our regressions. We only report the latter results, but the former are qualitatively identical and available upon request.

Distribution of changes in distances. Up to 50 kilometers from the border and using the great circle distance, the distance to the nearest open border crossing has changed for 41% and 77% of the plants when using equipped points or all points, respectively. Conditional on non-zero change and for all border crossings (equiped or not), the distance change

[47] Settlement polygons are gathered from the OpenStreetMap database. If a settlement is defined as a point instead of a polygon, we put a buffer around it with a radius equal to the average distance between border crossing settlement's vertices in Russia and Ukraine, respectively.

varies from close to 0 to about 40 kilometers, with a mean of 10 kilometers and a standard deviation of 6.5. If measured by network distance, the shares of plants with non-zero change are 17% and 34%, respectively. Conditional on non-zero change and for all border crossings (equiped or not), it varies from close to 0 to 56 kilometers, with a mean of 15 kilometers and a standard deviation of 5. For the equipped points only, the distributions are similar. Hence, on average, the distance to the nearest open border crossing increased by up to 10–15 kilometers, a significant increase in commuting distance for residents who travel on a daily basis between the states.

Table E.1: Means, standard deviations, and CVs for ΔcrossingDistance for plants.

	Mean				Standard deviation				Coefficient of variation			
	100km		50km		100km		50km		100km		50km	
	bigCity dummy		bigCity dummy		bigCity dummy		bigCity dummy		bigCity dummy		bigCity dummy	
	0	1	0	1	0	1	0	1	0	1	0	1
GC all points	0.165	0.021	0.193	0.017	0.199	0.012	0.269	0.013	1.21	0.55	1.39	0.79
GC equiped points	0.125	0.014	0.139	0.005	0.182	0.013	0.250	0.008	1.45	0.93	1.81	1.80
ND all points	0.116	0.003	0.142	0.004	0.184	0.010	0.254	0.013	1.59	3.95	1.79	2.98
ND equiped points	0.093	0.000	0.101	0.000	0.160	0.000	0.220	0.000	1.73	79.90	2.18	62.57

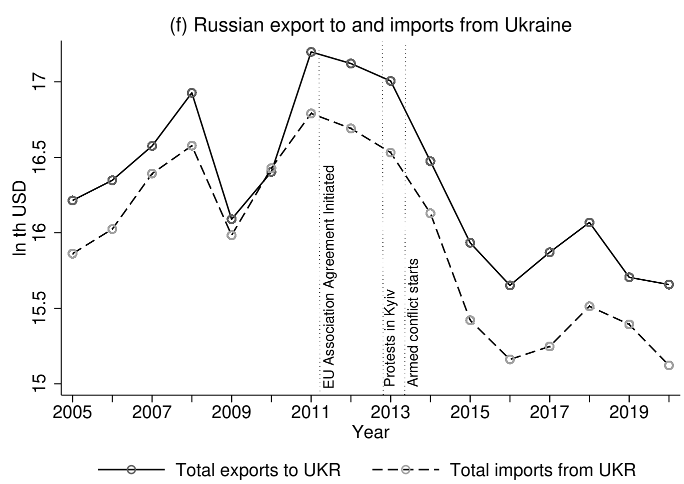
Notes: Mean, variance, and coefficient of variation for the change in the distance to the nearest open border crossing post 2015. We show results separately for the different distance measures (great circle, GC; and network distance, ND), the type of border points (equipped vs all), and according to whether or not the plant is in a big city.

Table E.1 shows the coefficient of variation for the log changes in distance to the nearest open border crossing using either great-circle distance or network distance, separately for plants in big cities and the rest of the plants. For the great circle distance there is less dispersion in distance changes in big cities than in less urbanized areas as larger cities kept access to functioning international border crossings. For the network distance the pattern is the opposite, there is more dispersion in distance to the border crossings in big cities. The explanation is that there are more zero changes in distance for plants in large cities as measured by the road network as the dense road networks in the cities are well connected to the international border crossings.

Appendix F The role of trade exposure

Trade relations between Russia and Ukraine were historically very important yet became increasingly strained in the wake of Ukraine's growing westward orientation. They substantially deteriorated starting 2012–2013 following mutual trade bans and sanctions, and trade plummeted after the conflict in 2014. While Ukraine was the tenth most important Russian export market in 2013 with 15.2 billion USD of exports, and the fourth largest importer in 2013 with 15.8 billions USD of imports, these figures fell to sixteenth for exports with 6.6 billions USD and to twelfth for imports with 4.8 billion USD in 2019.[48] Figure F.1 shows the evolution of imports from and exports to Ukraine. Trade increased before 2011–2012 in the wake of the 2007–2008 trade collapse, but started to decrease markedly from 2012 onwards. The largest drop occurred between 2013 and 2015 in the wake of the protests and the ensuing conflict. Observe that the overall pattern closely correlates with the ones documented in Figures 3 and 4 for changes in NTL and for plant exit.

Figure F.1: Changes in imports and exports between Russia and Ukraine.



Notes: Russian imports from and exports to Ukraine, millions of current USD. See Appendix A.3 for information on the data.

Contrary to nighttime lights, trade data provide variation that differs by plants across industries. We thus make use of these data to investigate the effect of trade on plant exit. We proceed in two steps. First, we retrieve industry-year estimates for exit using fixed effects, controlling for plant-level observables and exposure to the border changes. Second, we regress the estimated industry-year fixed effects from the first step on industry-level

[48] All figures from the UN Comtrade Statistics available at `https://comtrade.un.org/`

measures of trade intensity with Ukraine.[49] Formally, in the first step we estimate:

$$y_{i(s),t} = \beta_0 + \beta_1 \ln \text{minDist}_i + \beta_2 \ln \exp_i + \mathbf{X}_{i,t}\gamma + \alpha_{s,t} + \varepsilon_{i,t}, \tag{F.1}$$

where $y_{i(s),t} = \text{exit}_{i(s),t}$ takes value 1 if plant $i(s)$ in industry s exits in year t, and 0 otherwise. In the second step, we then estimate:

$$\begin{aligned} \widehat{\alpha}_{s,t} &= \beta_0 + \beta_1 \text{post}_{2014} + \beta_2 \text{tradeShareVA}_s \\ &\quad + \gamma_1 (\text{post}_{2014} \times \text{tradeShareVA}_s) + \delta_t + \varepsilon_{s,t}, \end{aligned} \tag{F.2}$$

where $\widehat{\alpha}_{s,t}$ are the estimated industry-year fixed effects from (F.1); tradeShareVA$_s$ is our measure of industry-level trade exposure; and δ_t are year fixed effects.[50] We construct tradeShareVA$_s$, as the export (or import) share of the 3-digit industry s in the value added of its 2-digit industry. In line with our other exposure measures, we take the average for 2011–2013, i.e., preceeding the conflict in 2014. Our coefficient of interest in (F.2) is γ_1. A positive estimate means that industries more exposed to trade with Ukraine before 2014 saw more exit in the wake of the conflict.

Table F.1: Regression of industry-year fixed effects on average trade exposure.

	(1) LMP Ukr	(2) LMP Ukr	(3) GMP Ukr	(4) GMP Ukr	(5) GC	(6) GC	(7) ND	(8) ND	(9) LAT	(10) LAT	(11) LAT bands	(12) LAT bands
post2014	0.024^{a}	0.023^{a}	0.024^{a}	0.023^{a}	0.024^{a}	0.023^{a}	0.024^{a}	0.023^{a}	0.024^{a}	0.023^{a}	0.024^{a}	0.023^{a}
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
tradeShareVA(export)	-0.044		-0.044		-0.043		-0.044		-0.043		-0.043	
	(0.054)		(0.054)		(0.055)		(0.055)		(0.055)		(0.055)	
post2014 x tradeShareVA(export)	0.063^{c}		0.063^{c}		0.062^{c}		0.063^{c}		0.062^{c}		0.062^{c}	
	(0.036)		(0.036)		(0.036)		(0.036)		(0.036)		(0.036)	
tradeShareVA(import)		-0.185^{b}		-0.185^{b}		-0.186^{b}		-0.185^{b}		-0.187^{b}		-0.187^{b}
		(0.076)		(0.076)		(0.075)		(0.076)		(0.075)		(0.075)
post2014 x tradeShareVA(import)		0.136^{b}		0.136^{b}		0.135^{b}		0.136^{b}		0.135^{c}		0.134^{c}
		(0.068)		(0.068)		(0.068)		(0.068)		(0.068)		(0.068)
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1,224	1,224	1,224	1,224	1,224	1,224	1,224	1,224	1,224	1,224	1,224	1,224
R-squared	0.143	0.149	0.143	0.149	0.143	0.149	0.143	0.149	0.143	0.149	0.143	0.149

Notes: Results for the second step (F.2). Imports and exports are computed at the 3-digit industry level relative to the 2-digit industry-level value added and we use their average between 2011–2013 as our measure of trade exposure. We include all plants up to 300 kilometers from the border. The exposure measure included in the first step is indicated in the column header (GC = great circle distance (5); ND = network distance (6); LAT = centered latitude, (7); LMP Ukr and GMP Ukr = market potential based on either raw NTL or GDP-weighted NTL, (4)). Standard errors are clustered at the industry level.

[49] We could do the regression in a single step. However, since our trade measures vary only at the industry-year level, we cannot include industry-year fixed effects in that case, thus running the risk of not controlling for confounding factors in the first step. We thus prefer to use a two-step procedure.

[50] We explain in Appendix A.3 how we map the HS4 product classification of the WITS database to the OKVED 2007 3-digit level data for our plants.

Table F.1 shows the results of the second step (F.2). The interaction terms between the post-2014 dummy and the average pre-treatment trade exposure are significantly positive for both imports and exports. Hence, plants in industries trading more heavily with Ukraine before the conflict saw more exit in the wake of the conflict than plants in industries that traded less. This result holds regardless of how we measure exposure in the first step, the estimates being virtually identical. Observe that the effects are larger and more precisely estimated for imports than for exports, which is probably linked to the trade patterns between the two countries.[51]

Table F.1 exploits industry-level variation but no spatial variation. Yet, the spatial distribution of more or less exposed industries varies substantially across space, especially between large cities—which are likely more exposed to trade—and more rural areas. In what follows, we more finely exploit that variation. More precisely, we investigate whether plants located in big cities and/or municipalities more exposed to trade are more strongly affected than plants in rural areas and/or municipalities less exposed to trade. We consider that cities with population above 300,000 are big. Trade figures at the municipal level are not available, but we can construct a shift-share type proxy for municipal exposure to trade with Ukraine using local industry shares and industry-level trade measures as follows:

$$\text{municipal\_exp}_m = \sum_{s(m)} \left[\frac{\#\text{plants}_{s(m)}}{\sum_{t(m)} \#\text{plants}_{t(m)}} \times \text{tradeShareVA}_s \right], \tag{F.3}$$

where the first term is the average 2011–2013 share of plants in industry s in municipal district m; and tradeShareVA_s is defined as before for either imports or exports.[52]

[51] Russia exports mainly oil, gas, and other mineral products to Ukraine, whereas it imports a substantial amount of metallurgical products, machinery, and equipment (Zhukov, 2016). In our data, the top-three industries in which plants are most likely to exit post 2014 are 'Manufacturing of other non-metallic mineral products', 'Manufacturing of fabricated metal products', and 'Manufacturing of machinery and equipment'. They are also among the most exposed to trade with Ukraine pre 2014 both in terms of exports and imports.

[52] We compute the average share of plants in industry s as the sum of plants in industry s in 2011, 2012, and 2013, divided by the total sum of plants in 2011, 2012, and 2013.

Table F.2: Municipal exposure to trade with Ukraine and NTL growth.

	(1) exports	(2) imports	(3) exports	(4) imports
post2014 x ln minDist	0.124[a]	0.120[a]	0.075[a]	0.066[a]
	(0.019)	(0.019)	(0.020)	(0.020)
post2014 x ln municipal_exp	0.054[b]	0.077[a]	0.124[a]	0.178[a]
	(0.021)	(0.026)	(0.026)	(0.032)
post2014 x bigCity	0.085	0.248[c]	0.114	0.175
	(0.110)	(0.141)	(0.130)	(0.141)
post2014 x ln municipal_exp x bigCity	-0.275[a]	-0.269[a]	-0.262[a]	-0.297[a]
	(0.073)	(0.065)	(0.072)	(0.068)
Cell fixed effects	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓
Observations	8,104,796	8,104,796	8,104,796	8,104,796
R-squared	0.696	0.697	0.679	0.679

Notes: The dependent variable is $\ln(1 + \text{HNTL})$ in columns (1)–(2) and $\ln(1 + \text{GDP} - \text{HNTL})$ in columns (3)–(4). Municipal exposure is measured as in (F.3). Standard errors are clustered at the municipal district level.

We estimate the following model:

$$\begin{aligned} \ln y_{i,t} &= \beta_0 + \beta_1 \text{post}_{2014} + \beta_2 \ln \text{minDist}_i + \beta_3 \text{municipal\_exp}_i + \gamma_1 (\text{post}_{2014} \times \ln \text{minDist}_i) \\ &+ \gamma_2 (\text{post}_{2014} \times \text{bigCity}_i) + \gamma_3 (\text{post}_{2014} \times \text{municipal\_exp}_i) \\ &+ \gamma_4 (\text{post}_{2014} \times \text{bigCity}_i \times \text{municipal\_exp}_i) + \alpha_i + \delta_t + \varepsilon_{i,t}, \end{aligned} \tag{F.4}$$

where $y_{i,t}$ is either the raw or the GDP-weighted NTL of cell i in year t. Table F.2 shows our estimates of (F.4) using municipal exposure (F.3) as our exposure mesure. We include the triple interaction between post 2014, municipal exposure, and the big city dummy to see whether there is a systematic differences between urban and rural places. As shown, lights grew faster in municipalities further away from the border. They also grew less in more exposed municipalities in large cities compared to more exposed rural municipalities. This suggests that either our exposure measure overstates the exposure of rural places—since they host firms that do in fact not trade a lot—or that exposure is truly much larger in big cities where plants suffered more as a consequence.

Table F.3 shows our estimates of (9) where the dependent variable is plant-level exit. We again include the triple interaction between post 2014, municipal exposure, and the big city dummy to see whether there is a systematic differences between urban and rural places. As can be seen, we do not find any substantial effects of municipal exposure on

Table F.3: Municipal exposure to trade with Ukraine and plant exit.

	(1) exports	(2) imports	(3) exports	(4) imports
ln minDist	-0.000	0.000		
	(0.002)	(0.002)		
post2014 x ln minDist	-0.001	-0.001	0.001	0.001
	(0.004)	(0.004)	(0.004)	(0.003)
ln municipal exp	-0.005^{b}	-0.006^{b}		
	(0.002)	(0.002)		
post2014 x ln municipal exp	0.001	0.003	-0.004^{c}	-0.003
	(0.003)	(0.003)	(0.002)	(0.002)
post2014 x big city dummy	0.012	0.010	0.030^{a}	0.026^{a}
	(0.011)	(0.010)	(0.010)	(0.010)
big city dummy x ln municipal exp	-0.000	0.002		
	(0.004)	(0.004)		
post2014 x ln municipal exp x big city dummy	0.001	-0.002	0.003	0.001
	(0.007)	(0.006)	(0.011)	(0.010)
Plant controls	✓	✓	✓	✓
Geographic controls	✓	✓		
Observations	532,433	532,433	528,140	528,140
R-squared	0.046	0.047	0.222	0.222

Notes: The dependent variable is a dummy taking value 1 if plant i exits in year t, and 0 otherwise. Municipal exposure is measured as in (F.3). Columns (1)–(2) condition on industry-year fixed effects. Columns (3)–(4) condition on plant and year fixed effects. Standard errors are clustered at the municipal district level.

plant exit. The only significant coefficient is that for big cities after 2014: in the wake of the conflict, exit was stronger in big cities. As argued above, this suggests that big cities were more exposed given the measure we use, probably because they host more plants involved in international trade. Overall, we find little evidence that manufacturing plants in more exposed municipalities tended to exit more in the wake of the 2014 conflict.

The results in Tables F.1 and F.3 hold if we replace exports or imports with total trade (exports plus imports). The resulting coefficients are significantly positive, i.e., plant exit increased in more trade-exposed industries.

Appendix G Additional tables and results

Table G.1: Changes in HNTL by distance band and exposure, before and after 2014.

	(1) distance band	(2) distance band	(3) LMP Ukr	(4) GMP Ukr	(5) GC	(6) LAT	(7) LAT bands
post2014	0.479[a]	0.478[a]	2.124[a]	1.616[a]	0.783[a]	-0.227[a]	0.088[a]
	(0.002)	(0.002)	(0.026)	(0.024)	(0.009)	(0.005)	(0.006)
post2014 × band	-0.223[a]						
	(0.002)						
post2014 × band(positive)		0.303[a]					
		(0.005)					
post2014 × band(negative)		-0.264[a]					
		(0.002)					
post2014 × ln minDist			-0.001	0.019[a]	-0.034[a]	0.127[a]	0.101[a]
			(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
post2014 × Lat(Donbas)							-0.271[a]
							(0.003)
post2014 × Lat(North)							-0.246[a]
							(0.003)
post2014 × exposure			-0.167[a]	-0.141[a]	-0.171[a]	-0.026[a]	
			(0.002)	(0.002)	(0.001)	(0.000)	
Observations (cell-year)	8,133,230	8,133,230	8,133,230	8,133,230	8,133,230	8,133,230	8,133,230
R-squared	0.695	0.696	0.696	0.696	0.698	0.696	0.697

Notes: The dependent variable is $\ln(\text{HNTL}_i + 1)$. All regressions include cell and year fixed effects. Standard errors are clustered at the cell level. band is a dummy with value one if the cell is less than 150 kilometers from the border; whereas band(positive) is a dummy with value one if the cell is less than 150 kilometers from the positive border, and is closer to the positive border than to the negative border. band(negative) is constructed in the same way, but for the negative border. minDist is the minimum great circle distance from the border. We include all cells up to 300 kilometers from the border. exp is our exposure measure as indicated in the column header (GC = great circle distance (5); LAT = centered latitude, (7); LMP Ukr and GMP Ukr = market potential based on either raw NTL or GDP-weighted NTL, (4)).

Table G.2: Changes in HNTL by distance band and exposure, before and after 2012.

	(1) distance band	(2) distance band	(3) LMP Ukr	(4) GMP Ukr	(5) GC	(6) LAT	(7) LAT bands
post2012	0.433[a]	0.433[a]	1.747[a]	1.452[a]	0.545[a]	0.026[a]	0.194[a]
	(0.002)	(0.002)	(0.020)	(0.019)	(0.008)	(0.004)	(0.004)
post2012 × band	-0.128[a]						
	(0.002)						
post2012 × band(positive)		0.174[a]					
		(0.004)					
post2012 × band(negative)		-0.153[a]					
		(0.002)					
post2012 × ln minDist			-0.019[a]	-0.009[a]	-0.009[a]	0.073[a]	0.058[a]
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
post2012 × Lat(Donbas)							-0.170[a]
							(0.002)
post2012 × Lat(North)							-0.114[a]
							(0.002)
post2012 × exposure			-0.122[a]	-0.110[a]	-0.089[a]	-0.006[a]	
			(0.001)	(0.001)	(0.001)	(0.000)	
Observations (cell-year)	8,133,230	8,133,230	8,133,230	8,133,230	8,133,230	8,133,230	8,133,230
R-squared	0.693	0.694	0.694	0.694	0.694	0.694	0.694

Notes: The dependent variable is $\ln(\text{HNTL}_\text{i} + 1)$. All regressions include cell and year fixed effects. Standard errors are clustered at the cell level. band is a dummy with value one if cell is less than 150 kilometers from the border, whereas band(positive) is a dummy with value one if the cell is less than 150 kilometers from the positive border, and is closer to the positive border than to the negative border. band(negative) is constructed in the same way, but for the negative border. We include all cells up to 300 kilometers from the border. exp is our exposure measure as indicated in the column header (GC = great circle distance (5); LAT = centered latitude, (7); LMP Ukr and GMP Ukr = market potential based on either raw NTL or GDP-weighted NTL, (4)).

Table G.3: Changes in GDP-HNTL by distance band and exposure, before and after 2012.

	(1) distance band	(2) distance band	(3) LMP Ukr	(4) GMP Ukr	(5) GC	(6) LAT	(7) LAT bands
post2012	0.908^{a}	0.910^{a}	1.236^{a}	1.008^{a}	1.604^{a}	0.744^{a}	0.986^{a}
	(0.002)	(0.002)	(0.026)	(0.024)	(0.010)	(0.005)	(0.006)
post2012 × band	-0.034^{a}						
	(0.002)						
post2012 × band(positive)		0.320^{a}					
		(0.006)					
post2012 × band(negative)		-0.068^{a}					
		(0.002)					
post2012 × ln min dist border			0.004^{b}	0.015^{a}	-0.105^{a}	0.031^{a}	0.008^{a}
			(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
post2012 × Lat(Donbas)							-0.251^{a}
							(0.003)
post2012 × Lat(North)							-0.152^{a}
							(0.003)
post2012 × exposure			-0.034^{a}	-0.020^{a}	-0.146^{a}	-0.017^{a}	
			(0.002)	(0.002)	(0.001)	(0.000)	
Observations (cell-year)	8,133,230	8,133,230	8,133,230	8,133,230	8,133,230	8,133,230	8,133,230
R-squared	0.675	0.675	0.675	0.675	0.676	0.675	0.676

Notes: The dependent variable is $\ln(\mathrm{GDP} - \mathrm{HNTL}_i + 1)$. All regressions include cell and year fixed effects. Standard errors are clustered at the cell level. band is a dummy with value one if cell is less than 150 kilometers from the border, whereas band(positive) is a dummy with value one if the cell is less than 150 kilometers from the positive border, and is closer to the positive border than to the negative border. band(negative) is constructed in the same way, but for the negative border. We include all cells up to 300 kilometers from the border.

Table G.4: Quarterly exit regressions with industry fixed effects, before and after 2014.

	(1) distance band	(2) distance band	(3) LMP Ukr	(4) GC	(5) ND	(6) LAT	(7) LAT bands
post2014	0.032^{a}	0.032^{a}	-0.039^{a}	0.022^{a}	0.027^{a}	0.029^{a}	0.034^{a}
	(0.001)	(0.001)	(0.007)	(0.002)	(0.002)	(0.002)	(0.002)
band	0.001^{a}						
	(0.000)						
post2014 × band	-0.001^{a}						
	(0.000)						
band(positive)		0.003^{a}					
		(0.001)					
band(negative)		0.001^{a}					
		(0.000)					
post2014 × band(positive)		-0.004^{a}					
		(0.001)					
post2014 × band(negative)		-0.001^{b}					
		(0.000)					
ln minDist			-0.003^{a}	-0.001^{a}	-0.002^{a}	-0.000^{c}	-0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
post2014 × ln minDist			0.005^{a}	0.002^{a}	0.001^{a}	0.001^{b}	-0.001^{c}
			(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Lat(Donbas)							0.003^{a}
							(0.000)
Lat(North)							0.001^{b}
							(0.000)
post2014 × Lat(Donbas)							-0.005^{a}
							(0.001)
post2014 × Lat(North)							0.002^{a}
							(0.000)
exposure			-0.002^{a}	-0.000	-0.001^{a}	0.001^{a}	
			(0.000)	(0.000)	(0.000)	(0.000)	
post2014 × exposure			0.005^{a}	0.001^{a}	0.001^{a}	0.000^{a}	
			(0.000)	(0.000)	(0.000)	(0.000)	
Plant controls	✓	✓	✓	✓	✓	✓	✓
Geographic controls	✓	✓	✓	✓	✓	✓	✓
Observations	1,968,299	1,968,299	1,968,299	1,968,299	1,968,299	1,968,299	1,968,299
R-squared	0.008	0.008	0.008	0.008	0.008	0.008	0.008

Notes: The dependent variable is a dummy with value 1 if plant i exits in quarter and year t, and 0 otherwise. All regressions include industry and quarter–year fixed effects. $band$ is a dummy variable with value one if the plant is less than 150 kilometers from the border, whereas $band(positive)$ is a dummy with value 1 if the plant is less than 150 kilometers from the positive border, and it is closer to the positive border than to the negative border. $band(negative)$ is constructed in the same way, but for the negative border. ln minDist is the minimum great circle distance from the border. We include all plants up to 300 kilometers from the border. exp is our exposure measure as indicated in the column header (GC = great circle distance (5); ND = network distance (6); LAT = centered latitude, (7); LMP Ukr = market potential based on raw NTL, (4)). Standard errors are clustered at the plant level.

Table G.5: Quarterly exit regressions with plant fixed effects, before and after 2014.

	(1) distance band	(2) distance band	(3) LMP Ukr	(4) GC	(5) ND	(6) LAT	(7) LAT bands
post2014	0.092^a	0.092^a	0.002	0.068^a	0.082^a	0.088^a	0.083^a
	(0.001)	(0.001)	(0.010)	(0.003)	(0.002)	(0.002)	(0.002)
post2014 × band	-0.002^a						
	(0.001)						
post2014 × band(positive)		-0.008^a					
		(0.001)					
post2014 × band(negative)		-0.002^a					
		(0.001)					
post2014 × ln minDist			0.007^a	0.004^a	0.002^a	0.001^b	0.001^b
			(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
post2014 × Lat(Donbas)							0.001
							(0.001)
post2014 × Lat(North)							0.008^a
							(0.001)
post2014 × exposure			0.006^a	0.003^a	0.002^a	0.001^a	
			(0.001)	(0.000)	(0.000)	(0.000)	
Plant controls	✓	✓	✓	✓	✓	✓	✓
Observations	1,967,577	1,967,577	1,967,577	1,967,577	1,967,577	1,967,577	1,967,577
R-squared	0.071	0.071	0.071	0.071	0.071	0.071	0.071

Notes: The dependent variable is a dummy with value 1 if plant i exits in year and quarter t, and 0 otherwise. All regressions include plant and quarter–year fixed effects. $band$ is a dummy variable with value one if the plant is less than 150 kilometers from the border, whereas $band(positive)$ is a dummy with value 1 if the plant is less than 150 kilometers from the positive border, and it is closer to the positive border than to the negative border. $band(negative)$ is constructed in the same way, but for the negative border. ln minDist is the minimum great circle distance from the border. We include all plants up to 300 kilometers from the border. exp is our exposure measure as indicated in the column header (GC = great circle distance (5); ND = network distance (6); LAT = centered latitude, (7); LMP Ukr = market potential based on raw NTL, (4)). Standard errors are clustered at the plant level.

Table G.6: Changes in distance to border crossings and plant exit, 100 kilometers buffer.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Equipped points				All points			
	GC	ND	GCW	NDW	GC	ND	GCW	NDW
post2015-Q1	0.049^a	0.048^a	0.049^a	0.048^a	0.049^a	0.048^a	0.048^a	0.048^a
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
post2015-Q1 x ΔcrossingDistance	-0.009	-0.005	-0.040^b	-0.044	-0.007	-0.005	-0.046	-0.060
	(0.006)	(0.007)	(0.016)	(0.039)	(0.005)	(0.006)	(0.029)	(0.039)
post2015-Q1 x bigCity	0.001	0.007^a	0.003	0.007^a	0.003	0.007^a	0.006^a	0.007^a
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
post2015-Q1 x ΔcrossingDistance x bigCity	0.372^a	3.003^a	2.017^a		0.168^c	-0.112	0.534	-0.393
	(0.081)	(0.112)	(0.435)		(0.090)	(0.101)	(0.488)	(0.389)
Plant controls	✓	✓	✓	✓	✓	✓	✓	✓
Plant FE	✓	✓	✓	✓	✓	✓	✓	✓
Year-quarter FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	237,658	237,658	237,658	237,658	237,658	237,658	237,658	237,658
R-squared	0.059	0.059	0.060	0.059	0.059	0.059	0.059	0.059

Notes: The dependent variable is the plant exit dummy. The sample includes all plants that were active in 2015 within 100 kilometers buffer from the Northern part of the border, i.e., Belgorod, Kursk, Bryansk and Voronezh regions. The 100 kilometers buffer includes Belgorod and Kursk as a big cities. Columns (1)–(4) provide results for equipped points. Columns (5)–(8) provide results for all points. Standard errors are clustered at the plant level. The way we measure distance is indicated in the column header (GC = great circle distance (5); ND = network distance (6); GCW = great circle distance weighted by border point settlements' NTL, (ADD); NDW = network distance weighted by border point settlements' NTL (ADD)). Standard errors are clustered at the plant level.

Table G.7: Changes in distance to border crossings and NTL, 100 kilometers buffer.

	(1)	(2)	(3)	(4)
	Equipped points		All points	
	GC	GCW	GC	GCW
post2015-Q1	0.077[a]	0.074[a]	0.078[a]	0.073[a]
	(0.000)	(0.000)	(0.000)	(0.000)
post2015-Q1 × ΔcrossingDistance	-0.024[a]	-0.084[a]	-0.022[a]	-0.098[a]
	(0.000)	(0.002)	(0.000)	(0.003)
post2015-Q1 × Big City Dummy	0.366[a]	0.359[a]	0.322[a]	0.282[a]
	(0.014)	(0.012)	(0.020)	(0.010)
post2015-Q1 × ΔcrossingDistance × Big City Dummy	-5.264[a]	-44.595[a]	-1.791[a]	-2.283
	(0.480)	(3.772)	(0.599)	(2.102)
Cell fixed effects	✓	✓	✓	✓
Year-quarter fixed effects	✓	✓	✓	✓
Observations	15,580,675	15,580,675	15,580,675	15,580,675
R-squared	0.878	0.878	0.878	0.878

Notes: The dependent variable is $\ln(1+\text{NTL}^{\text{VIIRS}})$, where $\text{NTL}^{\text{VIIRS}}$ is the luminosity of a 500×500 meters cell within a 50 kilometers buffer from the northern part of the border, i.e. Belgorod, Kursk, Bryansk and Voronezh regions. Columns (1)–(2) provide results for the equipped points. Columns (3)–(4) provide results for all points. Change in distance is measured by great circle distance to the nearest border crossing. Standard errors are clustered at the cell level.The way we measure distance is indicated in the column header (GC = great circle distance (5); ND = network distance (6); GCW = great circle distance weighted by border point settlements' NTL, (ADD); NDW = network distance weighted by border point settlements' NTL (ADD)).