ECONOMIC POLICY

SVERIGES RIKSBANK

77th Economic Policy Panel Meeting

20-21 April 2023

Casualties of border changes: Evidence from nighttime lights and plant exit

Kristian Behrens, Maria Kuznetsova

CEPR CESifo SciencesPo.

Casualties of border changes: Evidence from nighttime lights and plant exit*

Kristian Behrens† Maria Kuznetsova‡

March 9, 2023

Abstract

We investigate the economic effects of the Russia-Ukraine conflict—following the 2014 annexation of Crimea—on Russian border regions. While southern regions gained market access to Crimea, northern regions lost market access to Ukraine because of tighter border controls and the closing of many border crossings. Using nighttime lights satellite data and geo-referenced manufacturing plant-level data, we show that regions with deteriorating market access saw less growth in lights—translating into about 3.4%–4% lower growth in GDP—and more plant exit—about 1.5 percentage points—after 2014. Exploiting variations in closed local border crossings in the northern regions, we find these effects to be localized and likely driven by less cross-border labor flows.

Keywords: border changes; nighttime lights; manufacturing plant exit; cross-border labor flows; conflict between Russia and Ukraine.

JEL classification: F51; F15; R11; R12.

*We thank the editor Mathias Thoenig, two anonymous reviewers, as well as Julien Martin, Florian Mayneris, and Marlon Seror for helpful discussions and suggestions. Behrens gratefully acknowledges financial support from the SSHRC Insight Grants program ('Cities in motion', grant #435-2016-1246; and 'Neighborhood change and businesses', grant #435-2021-1017). Kuznetsova gratefully acknowledges financial support from the HSE University Basic Research Program.

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

‡Center for Market Studies and Spatial Economics, 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. Using nighttime lights satellite data and geo-referenced manufacturing plant-level data, we find that regions with deteriorating market access saw less growth in lights—translating into about 3.4%–4% lower growth in GDP—and more plant exit—about 1.5 percentage points—after 2014. The regional economic effects of changes in market access are thus sizeable and unequally distributed.

Understanding the *causes and consequences* of territorial conflict and border changes is important. It is well understood by now that territorial conflict is more endemic and likely to escalate when: (i) there are contested boundaries, i.e., borders do not play their institutional role of creating a predictable environment (e.g., Hensel, 2000; Simmons, 2005); (ii) previously integrated territories have become independent or have been split, creating borders where there were none before (e.g., Resnick, 2012; Michalopoulos and Papaioannou, 2016; Cederman et al., 2022); and (iii) there are strong cross-border ethnic ties and a long shared history (e.g., Resnick, 2012). Conflict is also more likely between contiguous neighbors since political events closer to home are perceived as more threatening and because military force can be projected more easily close to home (Hensel, 2000). We explain in Section 2—when reviewing the geopolitical context—that the Russia-Ukraine conflict seems driven by all of these usual factors. Our paper, therefore, has not much to add to the literature on the causes of territorial conflict.

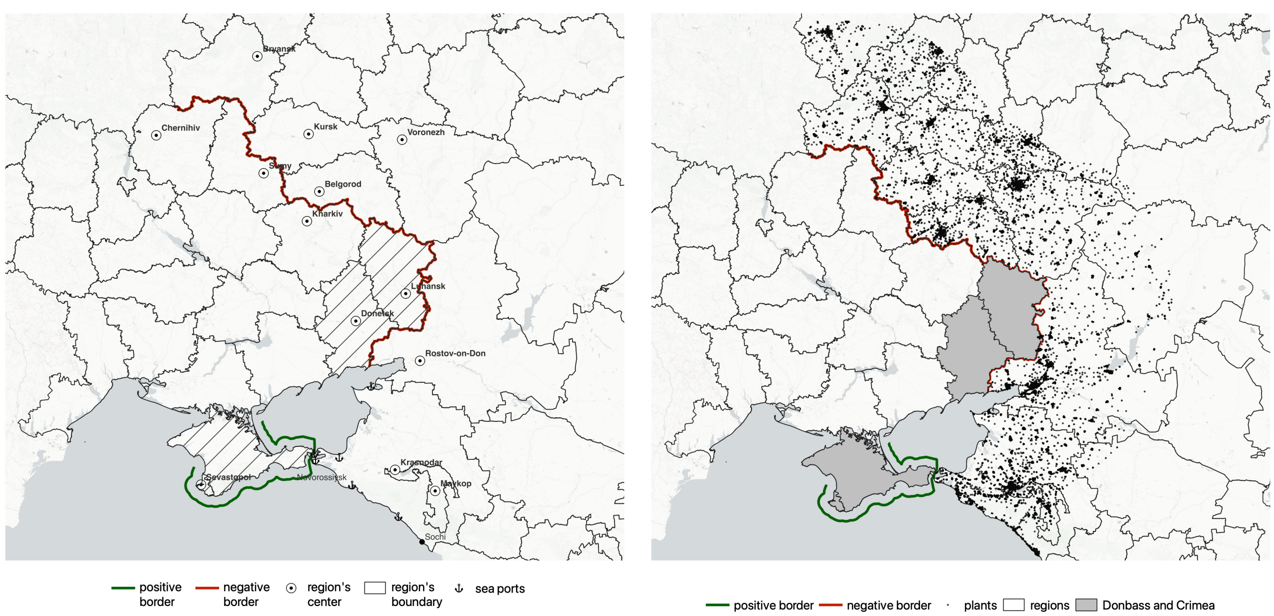
Instead, we contribute to the growing literature on the *economic consequences of conflict*. We are particularly interested in the effects of changes in regional market access—driven by conflict—on economic outcomes, irrespective of direct conflict-related destruction. To this end, we look at the Russian border regions—which were not a direct scene of conflict—to assess the effects of changes in market access on economic outcomes. Panel (a) of Figure 1 shows our study region along the Russia-Ukraine border.[1]

[1] The conflict largely unfolded in the Donbass and in Crimea. Zhukov (2016) and Kochnev (2019) document

One difficulty in identifying the causal effects of changes in market access is that the 2014 annexation triggered a sharp international response: wide-ranging trade sanctions were imposed on Russia—which responded with its own import restrictions—and the ruble fell substantially. To tackle this problem, we exploit north-south differences across regions. While international sanctions arguably affected regions in similar ways, market access to Ukraine deteriorated in the north—where closed border crossings and tighter border controls limited the movement of goods and people—and improved in the south—where the border with Crimea disappeared.

Figure 1: Our study area and the distribution of plants along the Ukrainian border.

(a) The study area (b) Distribution of plants



Notes: The figure depicts our study area. Panel (a) shows the major cities along the border on both sides and highlights merchant sea ports. Panel (b) depicts the distribution of manufacturing plants in Russia from the Ruslana and Interfax SPARK databases within 300 kilometers from the border with Ukraine. We plot the distribution of all plants active at some point between 2006 and 2018. Both panels show the border segments. The 'positive border segment' (in green)—where market access improved—is in the south close to Crimea; whereas the 'negative border segment' (in red)—where market access deteriorated—is in the north.

Our paper relates to a large literature on the effects of changes in economic integration. One strand of that literature investigates the aggregate effects of conflict on trade between

the conflict-related costs on the Ukrainian side for the Donetsk and Luhansk regions in the Donbass. For more results on the economic effects of conflict on the geography of economic activity and firm-level outcomes in conflict regions, see, e.g., Abadie and Gardeazabal (2003); Guidolin and La Ferrara (2007); Camacho and Rodriguez (2013); Collier and Duponchel (2013); Berman and Couttenier (2015); Harari and Ferrara (2018).

countries. As expected, conflict reduces trade and generates substantial economic costs.[2] Another strand of that literature focuses 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). That literature shows that border regions that experience a negative shock to market access see less population and wage growth than unaffected regions.

More recently, and closer to our contribution, several studies have leveraged spatially and economically more disaggregated data—namely nighttime lights satellite data and firm-level data—to study the effects of market access on regional outcomes.[3] That literature finds that: (i) the spatial effects of changes in market access on border regions are *highly localized*, usually at less than 50 kilometers; (ii) the effects *differ substantially* across locations, depending crucially on their initial 'exposure' to the other regions' economic activity (e.g., Yang et al., 2022; Vermeulen, 2022) ; and (iii) these highly localized effects may be driven by *economic activity that is very sensitive to distance frictions*, e.g., small-scale local cross-border trade (e.g., Eberhard-Ruiz and Moradi, 2019).

Using satellite and geo-referenced plant-level data, we confirm that the effects of changes in market access on Russian border regions are localized and differ substantially across regions, depending on the regions' pre-conflict exposure to Ukraine. Our results are robust and hold for a broad range of exposure measures: border regions in Russia more exposed to negative changes in market access—namely the regions in the north—saw less growth

[2]Simmons (2005, p.842) finds that *"border disputes have led to serious economic opportunity costs, even in cases where trade partners have never exchanged an explicit military threat."* The presence of a territorial dispute between country pairs is associated with a 28% decline in the value of their bilateral trade in the short run. This finding runs counter the idea that trade integration increases the opportunity cost of conflict between neighbors, which should reduce conflict. Martin et al. (2008) show that increasing multilateral trade openness may explain why trade is not as strongly associated with less conflict as one would expect: less trade with neighbors in an increasingly globalized world reduces the opportunity cost of conflict with neighbors.

[3]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 (e.g., Elvidge et al. 1997; Chen and Nordhaus 2011; Henderson et al. 2012; Michalopoulos and Papaioannou 2012; Pinkovskiy and Sala-i Martin 2016; Bruederle and Hodler 2018). We show in Appendix B.1 (see Figures B1–B3) that the harmonized nighttime lights satellite data we use correlate well with regional per capita GDP, as well as with municipal employment, wages, and the number of manufacturing plants. Closely related to our study, Lee (2018) uses nighttime lights data to investigate the unequal regional effects of sanctions in North Korea; and Brülhart et al. (2022), use nighttime lights data to document how international borders generally reduce economic activity.

in lights and more plant exit than less exposed border regions—namely the regions in the south.

To shed additional light on the economic mechanisms that may drive the results, we look at a more granular geography and examine changes *within* the four northern Russian regions bordering Ukraine (Voronezh, Bryansk, Kursk, and Belgorod; see panel (a) of Figure 1). We leverage a new data set on the closings of local border crossings that affect the movement of people but not the movement of commercial goods (since commercial trade was never allowed across these border crossings). We find that locations that experienced a larger increase in their distance to the closest open border crossing saw less growth in nighttime lights and marginally more plant exit (though this latter effect is mostly insignificant). Our finding suggest, as in Eberhard-Ruiz and Moradi (2019), that *distance-sensitive local economic links*—such as local cross-border labor movements or small-scale cross-border trade—may partly explain the localized nature and different magnitude of the effects.

The remainder of the paper is organized as follows. Section 2 summarizes the geopolitical context. Section 3 explains our data, the construction of our key variables, and provides some preliminary descriptive evidence. Section 4 shows our estimation results for the economic effects along the north-south dimension of the border. We provide a detailed discussion on possible confounding factors in Section 5. Section 6 zooms onto the northern border regions and shows that the closing of border crossings had localized effects. Last, Section 7 concludes. We relegate data discussions, technical details, and additional estimation results to an extensive set of (online) appendices.

2 Geopolitical context and setting

Russia and Ukraine—separated since 1991—always maintained a high level of cultural and economic integration. This was especially true in the (south)eastern part, where cross-border industrial and ethnic ties were strong. Although a new border de facto appeared in 1991, following the collapse of the Soviet Union, that border remained largely symbolic and was not enshrined in a formal treaty. Starting in the early 2000s—in the wake of the Orange Revolution and the arrival of a more pro-western president—Ukraine progressively sought to distance itself from the former Soviet bloc by turning increasingly to the West. The ensuing tensions—one of the debated questions was already the status of the Crimean peninsula—led to the ratification of a formal border treaty by the parliaments of both countries in April 2004.[4]

Yet, even following the treaty, the degree of economic integration between border regions in the two countries remained strong. This can be seen using nighttime lights data. Figure 2 depicts non-parametric gradient estimates of average 1992–2013 lights intensities as a function of distance to the border.[5] Up to about 30 kilometers the gradient increases; it then has a large plateau on both sides of the border and starts to decrease again beyond 100 kilometers. The average nighttime lights intensity 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 that in the 100–200 kilometers distance band. This is different from the findings by Brülhart et al. (2022), who document that from 1995 to 2013 nighttime lights in the world were on average 37% *dimmer* at a land border between countries than 200 kilometers away from that border. This suggests that the Russia-Ukraine border was an 'atypically highly integrated border', with substantial population and economic activity located close-by in the strongly integrated border regions.

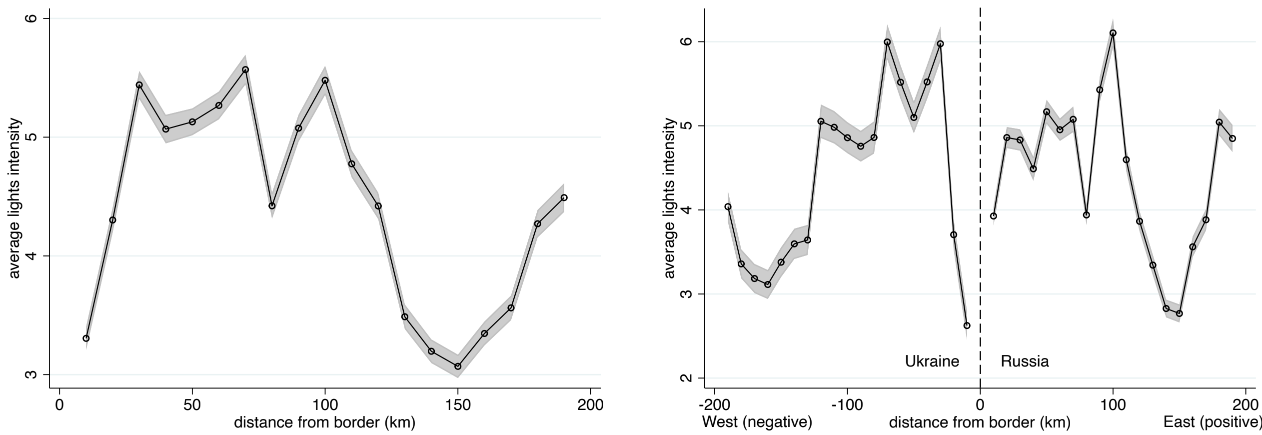
Despite the high level of integration, relations between Russia and Ukraine started to deteriorated after 2004 as delicate questions such as stronger border demarcations, a European orientation, NATO membership, the role of Sevastopol as a base for the Black Sea

[4]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.

[5]Following Brülhart et al. (2022) and, more generally, a large literature on gradient estimates in spatial economics, we depict non-parametric estimates of the distance gradient using distance-bin dummies.

Figure 2: Non-parametric nighttime lights distance gradients.

(a) Both countries jointly. (b) Both countries separately.



Notes: Non-parametric estimates of nighttime lights distance gradients using distance-bin dummies between 0 and 200 kilometers for 10 kilometers bins. The 95% confidence bands are shaded in gray. Nighttime lights are measured for 1×1 kilometer cells, excluding water-masked cells. Panel (a) depicts the distance gradient for both countries jointly, while panel (b) depicts it for each country separately.

fleet, and gas transit through Ukraine made it on the agenda. Russia increasingly feared its 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 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 approved by Ukraine in September 2013. This prompted strong reactions from Moscow, which called into question the recognition of the bilateral border treaty.[6] 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 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—

[6]Sergei Glazyev, adviser to President Vladimir Putin at that time, "suggested that if Ukraine signed the agreement, Russia would consider the bilateral treaty that delineates the countries' borders to be void." (The Guardian, September 22, 2013).

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, collectively known as Donbass—carried out their own local referenda. As a result, two republics were self-proclaimed on April 8 and April 27, 2014, respectively. An armed conflict with Ukrainian forces in the Donbass followed these declarations of independence.

Our objective is to better understand and measure the potential economic costs of the conflict following the annexation of Crimea for the border regions in Russia. This conflict provides a good laboratory to study the economic consequences of changes in international borders for two reasons. First, as discussed and shown above, Russia and Ukraine were highly integrated—especially in the border regions. Hence, any changes in borders there are likely to have important economic effects. A first look at the changes in lights intensities before and after 2014 (see Figure A1 in Appendix A.1) reveals the potential effect of the conflict on economic activity and suggests a decrease in border integration: between 2014–2018, the 0-100 kilometers 'lights premium' drops to 9.85% on the Russian side and to 9.86% on the Ukrainian side. In other words, regions closer to the border suffered more in the wake of the conflict than regions further away, at least as revealed by nighttime lights.[7]

Second, while border regions seemed to suffer from the conflict, the averages we report above 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 from the Ukrainian authorities 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

[7]Figure A1 in Appendix A.1 depicts changes in (log) nighttime lights for 1×1 kilometer cells along the border between 2013–2015, i.e., one year before and one year after the start of the conflict in 2014. We see heterogeneous changes along the border. In particular, lights appear to grow brighter in the south—close to Crimea—and dimmer in the north and the Donbass.

[8]What happened to the border along the Donbass region is less clear, since it was no longer fully under the control of the Ukrainian government and hence movements across that border were hard to monitor.

Crimea—which are exposed to *positive border changes* following the annexation—benefit from increased market access and less frictions to the movement of goods and people; whereas the regions close to the northern land border with Ukraine—which were more exposed to *negative border changes* due to tighter controls—suffered from decreased market access and more frictions to the movement of goods and people. Thus, if market access matters, economic outcomes should improve in the south and deteriorate in the north.

3 Data, variables, and first descriptives

Data. We begin by providing information on our main data sources and the construction of our proxies for economic outcomes. Our key dependent variables are based on cell-level nighttime lights, combined with regional GDP data, and plant-level exit information.

In an ideal world, we would directly measure GDP at the cell level and use it as our dependent variable. However, these data obviously do not exist. Hence, we use nighttime lights to spatially disaggregate regional GDP and apportion it to cells using lights intensity as weights. We rely on publicly available satellite data based on DMSP and VIIRS and use mainly the yearly series of Harmonized NTL (henceforth, HNTL) developed by Li et al. (2020). We will make explicit the remaining cases where we rely on other satellite data such as the quarterly VIIRS series. The HNTL data span the period 1992–2018 and provide a consistent time-series at a spatial resolution of 1×1 kilometer cells. We extract all cells for the European part of Russia (3,886,810 cells) and for Ukraine (811,399 cells).[9] In what follows, we refer to the European part of Russia as Russia for short. More details on our nighttime lights data are given in Appendix A.1.

We combine the HNTL data with regional GDP data from Goskomstat for Russia and from Ukrstat for Ukraine. Formally we construct a lights-weighted measure of GDP for

[9]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.

cell i in region r, denoted $i(r)$, in year t as follows:

$$\omega_{i(r),t} = \text{GDP}_{r,t} \frac{\text{NTL}_{i,t}}{\sum_{k \in r} \text{NTL}_{k,t}}, \tag{1}$$

where $\text{NTL}_{i,t}$ denotes cell i's raw NTL luminosity. Equation (1) simply apportions regional GDP to each cell in the region based on its share in regional luminosity. While this procedure obviously has limitations, we think it at least partly allows us to control for large differences across regions (due to, e.g., regional specialization in high vs. low value-added activity or more urban vs. more rural regions). This seems especially important for regions with large cities where the DMSP lights are often top coded and where we may thus underestimate the GDP as measured by lights compared to less-lit regions.

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 Unified State Register of Legal Entities—as well as their de facto address and main national industry classification (OKVED). We create a variable taking value 1 if plant p exits in year t and value 0 otherwise. We drop all plant-year observations for the years the plant did not exist (i.e., all years prior to entry) or already left (i.e., all years past exit).[10] We define exit based on the status updates from the Unified State Register of Legal Entities. Close to 90% of what we call 'exit' is administratively related to: (i) no more banking and fiscal activity of the plant, meaning it has de facto ceased commercial operations; or (ii) a formal liquidation or bankruptcy procedure involving the plant.

We further have information on the plant's age and whether it belongs to a multi-unit firm or not.[11] We keep all plants in the European part of Russia and drop the small share of

[10]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 Unified State Register of Legal Entities, including day and month, we can further disaggregate the data to the quarterly level, which we use in Section 6.

[11]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

those we cannot geocode precisely or for which we cannot reconstruct industry codes. After basic data cleaning, we are left with 672,158 geo-referenced plants that are representative of Russian manufacturing. Panel (b) of Figure 1 illustrates the distribution of plants along the border. Additional details on the data are relegated to Appendix A.2.

Variables. To explore more formally how economic outcomes in Russia changed along the border after 2014, we will regress our outcomes on variables capturing either pre-conflict exposure to economic activity in Ukraine or exposure to changes in the ease with which economic activity can operate across the border. These can be captured in a variety of ways. Our measures can be broadly divided into *absolute* exposure measures and *relative* exposure measures. The former do not pay attention to the position of cells or plants with respect to the northern and southern parts of the border, whereas the latter do. In what follows, we construct and use the following six measures.

As a first absolute measure, we create a dummy variable that takes value 1 for all plants or cells less than 150 kilometres from the border, and 0 otherwise.[12]

As a second absolute measure we compute, for each cell i and plant p, a market potential that captures their exposure to economic activity in Ukraine and in Russia. To alleviate notation, we provide expressions for cells only, those for plants being identical when replacing i with p. Our preferred measure combines information on NTL luminosity and regional GDP for Ukrainian and Russian regions. We define for each cell i in Russia its exposure to economic activity in Ukraine as follows:

$$\mathrm{GMP}_{i,t}^{\mathrm{UKR}} = \sum_{r \in \mathcal{R}_{\mathrm{UKR}}} \sum_{j \in r} \omega_{j(r),t} \mathrm{e}^{-\alpha d_{i,j}}, \tag{2}$$

where $\mathcal{R}_{\mathrm{UKR}}$ denote the set of regions in Ukraine; and $\omega_{j(r),t}$ is given by (1). Expression (2) is a (negative exponential) distance-weighted measure of cell i's exposure to GDP in Ukraine. Replacing i with p, we can construct the same measure for each plant p. Observe

even then there are too many missing observations.

[12] Our results are largely robust to using alternative distance bands between 50 and 200 kilometers.

that the counterpart based on raw lights instead of GDP is given by

$$\text{LMP}_{i,t}^{\text{UKR}} = \sum_{r \in \mathcal{R}_{\text{UKR}}} \sum_{j \in r} \text{NTL}_{j,t} \mathrm{e}^{-\alpha d_{i,j}}. \tag{3}$$

We can compute (2) and (3) by summing across cells in Russia (instead of Ukraine), which provides then a measure of the cell's or plant's exposure to economic activity in Russia. We will use the latter as a control in many of our subsequent regressions.[13]

Observe that (2) and (3) are time varying. We considered exploiting them in a dynamic panel specification but decided not to do so. The main reason is that exposure to GDP or NTL provide 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 pre-conflict average exposure (2009–2013) to NTL as follows (results using three year averages are very similar):

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

The measures (4) capture whether cell i (or plant p) was heavily exposed to GDP or NTL—our proxies 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.

The foregoing two measures capture exposure to Ukraine but do not treat the border in the north and the border in the south differently. We thus also construct four relative measures that capture how cells or plants are differentially exposed to the northern and southern parts of the border.

[13] Expressions (2) and (3) are not theory-based and require a value for α. We choose $\alpha = 0.01$ (we also checked our results for $\alpha = 0.05$) in our preferred specification and consider only cells in Russia or in Ukraine that are less than 500 kilometers from the border. These choices are made to reduce the computational burder in constructing these measures. We have more than 1 million cells in Russia at 500 kilometers from the border, and more than 800 thousand cells in Ukraine. Constructing the market potential measure for the cells thus requires computing almost one billion distances and smoothing them. Eberhard-Ruiz and Moradi (2019, p.263) use $\sigma = 0.042$ as their distance decay for Africa, which lies within our parameter range. They also state that their results are unchanged to doubling or halving the value of their decay parameter.

As a first relative measure, we construct the ratio of the great circle (GC) distance from the positive border segment in the south to the negative border segment in the north:

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

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 due to tighter border restrictions). We expect that more exposed cells i suffered more than less exposed cells after 2014.

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 as a second relative measure the network distance on the main road system from each plant p to the border:[14]

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

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 crossings of the negative border segment to be exposed negatively to changes in market access and thus to exit more; while plants located closer to the sea-ports of the positive border segment should be positively affected and exit less.

As a third and fourth relative measure, we directly leverage latitude information which by definition captures north-south differences. More precisely, we use as a third relative

[14]We did not compute the network distance for cells. There are many cells (some of them lit) that do not fall near any road and for which it is thus hard to compute a meaningful shortest path on the road network.

measure the sample mean-centered latitude:

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

Finally, we construct a discretized version of our latitude measure, where we subdivide the continuous measure into three 'latitude bands'—North, Donbass, and South—as a fourth relative exposure measure.

To summarize, we conjecture that observations more exposed to economic activity in Ukraine pre-conflict and observations that experienced a relative decrease in market access due to the conflict have worse outcomes—less cell-level NTL growth and more plant-level 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.

First descriptives. To provide intuition for how economic outcomes changed along the border in 2014, we begin with an event study. More precisely, we estimate the following two models

$$y_{i,t} = \alpha_i + \delta_t + \sum_{\tau \neq 2014} (\gamma_\tau D_\tau \ln \exp_i) + \varepsilon_{i,t}, \tag{8}$$

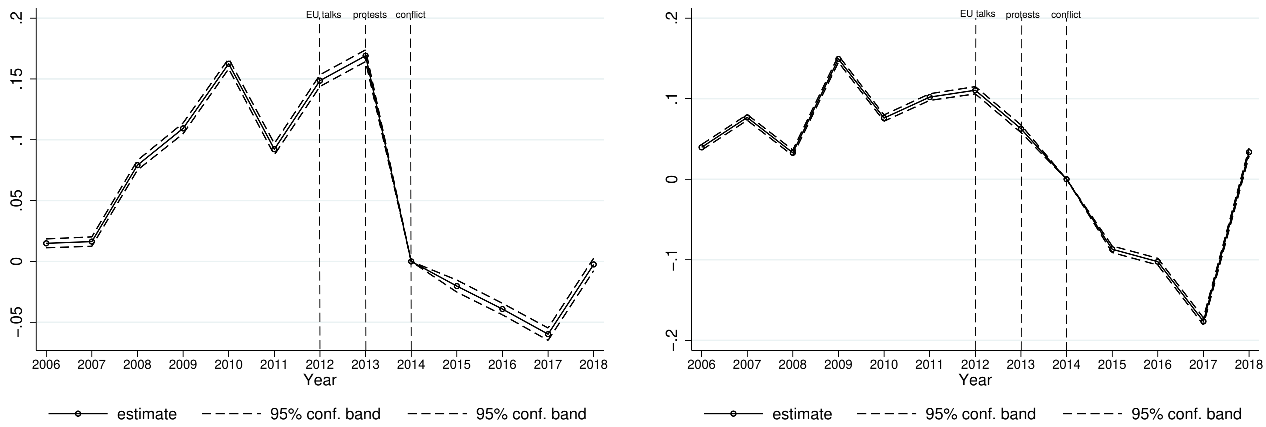
$$y_{p,t} = \alpha_p + \delta_t + \sum_{\tau \neq 2014} (\gamma_\tau D_\tau \ln \exp_p) + \mathbf{X}_{p,t}\beta + \varepsilon_{p,t}, \tag{9}$$

where $y_{i,t}$ is the log of (1 plus) the GDP of cell i in year $t = 2006, \ldots, 2018$; $y_{p,t}$ is a dummy variable taking value 1 if plant p exits in year t and 0 otherwise; $\ln \exp_i$ and $\ln \exp_p$ are our pre-conflict measures of exposure; $\mathbf{X}_{p,t}$ are plant-level controls; α_i and α_p are cell- and plant fixed effects; and δ_t are year fixed effects. We take 2014 as the start of the conflict and include the eight years before the annexation (2006-2013) and the four years following it (2015-2018). The dummy D_τ equals 1 for year τ, and 0 otherwise.

Figure 3 shows estimates of (8). Panel (a) plots results for all cells in Russia up to 200 kilometers from the border and measures a cell's exposure to the border by GDP market

Figure 3: Event study plots for changes in nighttime lights.

(a) Cells' GDP and market potential (b) Cells' GDP and relative distance



Notes: The dependent variable is GDP of cell i in year t as constructed from (1). Panel (a) depicts the coefficients obtained from (8), where exposure is measured by the log of market potential in Ukraine for cells up to 200 kilometers in Russia. Panel (b) depicts the coefficients obtained from (8), 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 200 kilometers in Russia.

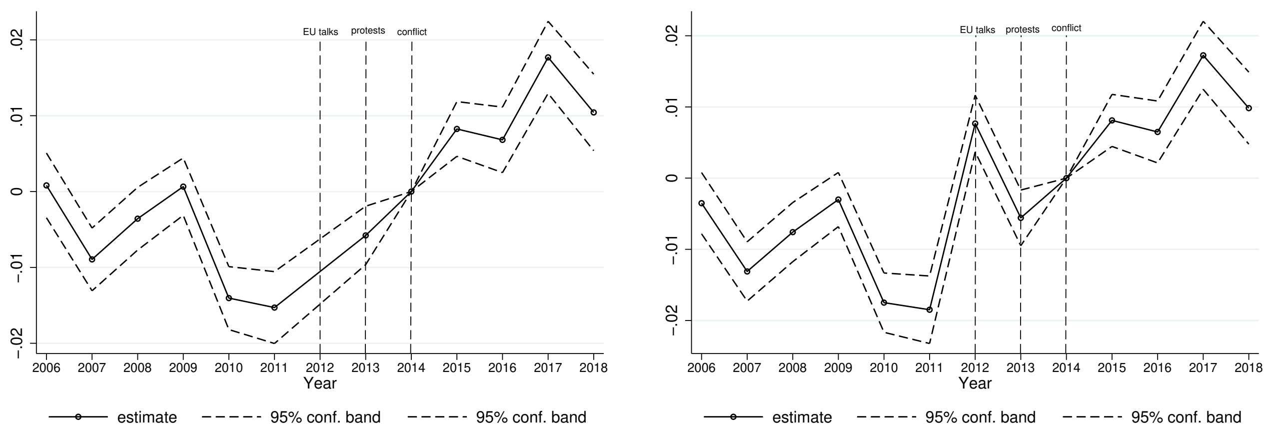
potential (4) in Ukraine. As shown, cell-level GDP in Russia was positive and increasing before 2013–2014, i.e., cells relatively more exposed to Ukrainian market potential grew more pre-conflict. This pattern gets reversed around 2013 in the wake of the violent Euro Maidan protests in Kiev and the ensuing armed conflict that erupted in the Donbass: cells relatively more exposed pre-conflict grew relatively less post-conflict. Panel (b) replicates our analysis using relative GC distance (5) as a cell's exposure measure. As shown, changes in cell-level GDP in Russia were relatively stable before 2014 and, if anything, the coefficients were positive and increasing. In words, cells relatively far from the south (i.e., relatively close to the north) grew more. This pattern gets again reversed around 2013: 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.[15]

[15]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

Figure 4: Event study plots 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 p exits in year t and 0 otherwise. Panel (a) depicts the coefficients obtained from (9), 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 plants up to 200 kilometers in Russia. Panel (a) excludes the year 2012 since, as explained in the text and in Online Appendix E, 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.

We next estimate model (9) for plant exit in Russia, adding plant p's age as a rough control for its productivity. Panel (a) of Figure 4 shows the results for all plants up to 200 kilometers from the border, using relative GC distance (5) 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.[16] In other words, plants relatively more exposed to the northern border tended to exit more after 2014 compared to plants less exposed to that border and more exposed to the southern border.

To summarize, Figures 3 and 4 provide suggestive evidence that economic activity in

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.

[16]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 E 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 E, 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. In Section 5.5, we present evidence from the Central Bank's 'Business Climate Indicator' that suggests exit is not primarily driven by firms' expectations about the worsening relations between Russia and Ukraine.

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.

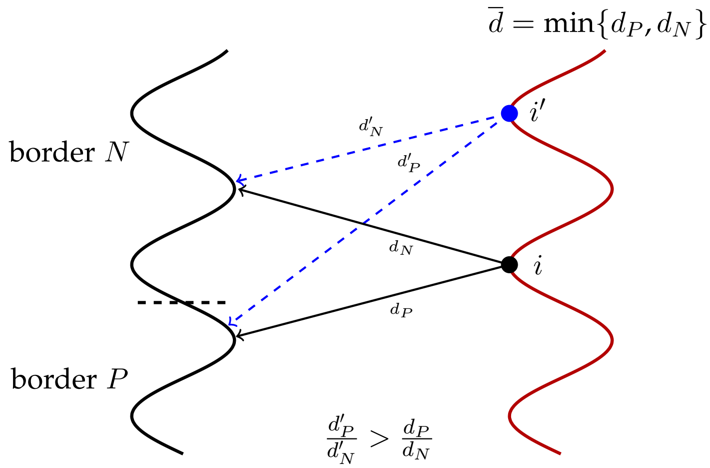
4 Empirical analysis

We now turn to our 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 or cells 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 or cells far from the border would have followed the same trend than plants or cells close to the 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 uses cells to illustrate the variation that we use in our data. As shown, our empirical strategy compares less exposed cells i (that received a 'smaller dose' of treatment) with more exposed cells i' (that received a 'larger dose' of treatment). Exposure depends both on the overall distance to the border, and the relative position along the border. Cells

Figure 5: Relative distance along border-distance isocurves.



i and i' in Figure 5 are located on the same border-distance isocurve $\overline{d} = \min\{d_P, d_N\}$, but cell i' is more strongly exposed to the negative border N, whereas cell i is more strongly exposed to the positive border P (i.e., $d'_P/d'_N > d_P/d_N$). We thus anticipate worse outcomes for cell i' compared to outcomes for cell i, conditional on being on the same distance iso-curve. Hence, in our empirical specification, we estimate the 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 GDP regressions

We first regress our proxy for economic activity of cell i in year t on absolute and relative exposure to Ukraine as follows:

$$\ln(y_{i,t}+1) = \beta_0 + \gamma_1(\text{post}_{2014} \times \ln \text{minDist}_i) + \gamma_2(\text{post}_{2014} \times \ln \exp_i) + \alpha_i + \delta_t + \varepsilon_{i,t}, \quad (10)$$

where $y_{i,t}$ is GDP of cell i in year t, as constructed in (1).[17] Furthermore, $\ln \text{minDist}_i$ is the minimum GC distance of cell i from the border (without distinguishing the positive from the negative 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 relatively more exposed to the negative border on economic performance after 2014.

Table 1: Changes in cell-level GDP 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 (10). 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 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 apportioned GDP (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. To reveal the different effects of treatment intensity along the border, we 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

[17] Since we include cell fixed effects, the coefficients on $\ln \text{minDist}_i$, post_{2014}, and $\ln \exp_i$ are not identified. We add 1 to the dependent variable to deal with cells having zero lights (and thus by construction zero GDP). Intensive-margin estimates, using non-zero cells only, yield similar but somewhat smaller results.

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 A1 and our expectations on the effects of changes in market access in the two zones.

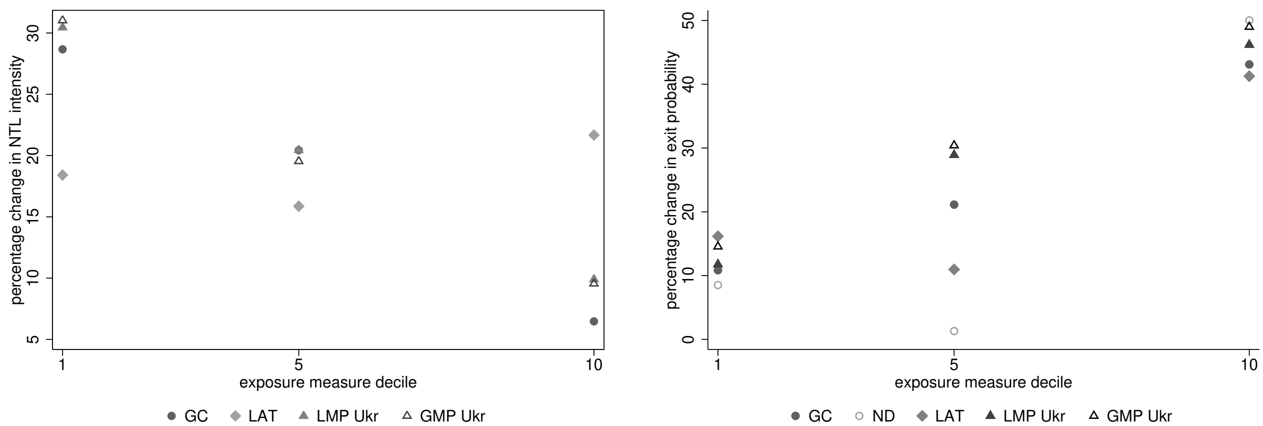
Columns (3) and (4) show results using the market potentials constructed from the raw NTL data and using cell-level GDP. The negative coefficients reveal that, as expected, cells more exposed to economic activity in Ukraine pre conflict lost after 2014 compared to initially less exposed cells. Columns (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 less exposed cells. Furthermore, this effect varies with treatment intensity 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, differential changes along the border induce differential changes in economic activity, as measured by nighttime lights.

How large are the post 2014 effects of changes in nighttime lights on GDP? Panel (a) of Figure 6 illustrates the magnitude of the economic effects of the different exposure measures on cell-level GDP using the predicted changes in the dependent variable at the 1st, 5th, and 10th deciles, respectively. On average, cell-level GDP increased by about 30% in the post 2014 period at the 1st decile, whereas it increased on average by about 10% at the 10th decile. In other words, cell-level GDP increased by about 20% less for the most exposed cells compared to the least exposed cells in the post treatment period. Recall that our measure of 'cell-level GDP' is simply the regions' GDP apportioned to the cell based on its

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

(a) Nighttime lights (b) Plant exit



Notes: Scatter plots of the average change in cell-level GDP 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. The estimates in panel (a) exclude cells that were unlit before 2014 and became lit after 2014. The qualitative results including the extensive margins are similar, but the changes are larger because of unlit cells' large percentage changes.

luminosity. Hence, in the end, our cell-level measure is still based mainly on luminosity. To translate it into a GDP equivalent, we need estimates of the elasticity of GDP with respect to nighttime lights. In Appendix B.1, we follow Henderson et al. (2012) and Hodler and Raschky (2014) and estimate the elasticity of regional per capita GPD to regional average nighttime lights to be around 0.2 in Russia; the long difference estimates between 1996-1997 and 2017-2018 are 0.17. Thus, a 20% difference in nighttime lights changes for the most exposed cells corresponds approximately to a 3.4% to 4% difference in GDP changes, a sizeable effect.[18]

[18]Henderson et al. (2012) report 0.33 and 0.31 for their elasticities, and Hodler and Raschky (2014) find 0.23 and 0.39, respectively. Using their larger values implies that a 20% difference in cell-level GDP changes for the most exposed cells maps into a 6.6% and 6.2%, or a 4.6% and 7.8% difference in GDP changes. Using nighttime lights satellite data for Africa, Eberhard-Ruiz and Moradi (2019) estimate the economic gains for border cities following a regional trade agreement to be about 5% of GDP, close to the figures we report.

4.2 Plant exit regressions

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

$$\begin{aligned} y_{p(s),t} \quad = \quad & \beta_0 + \beta_1 \text{post}_{2014} + \beta_2 \ln \text{minDist}_p + \beta_3 \ln \exp_p + \mathbf{X}_{p,t}\beta_4 \\ & + \gamma_1(\text{post}_{2014} \times \ln \text{minDist}_p) + \gamma_2(\text{post}_{2014} \times \ln \exp_p) + \alpha_{p(s),t} + \varepsilon_{p,t}, \end{aligned} \tag{11}$$

where $y_{p(s),t}$ takes value 1 if plant $p(s)$ in industry s exits in year t, and value 0 otherwise; $\ln \exp_p$ is one of our exposure measures from Section 3; and $\mathbf{X}_{p,t}$ are (time-varying) plant-level controls. In (11), $\alpha_{p(s),t}$ are either industry-year or plant fixed effects. When using plant fixed effects, we 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 as in (4) in Section 3. We view the latter two variables as aggregate controls for economic conditions in the regions surrounding each plant. We estimate (11) 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 confirm that there is a differential effect along the border on exit after 2014 depending on initial exposure. While plants were more likely to exit in the south before 2014, they are less likely to do so after 2014. Table 3 shows that 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 (based on either raw lights or lights-weighted GDP). Columns (5)–(8) reveal that relative

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 p 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 lights-weighted GDP (4)). Standard errors are clustered at the plant level.

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 p 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 apportioned GDP (4). Standard errors are clustered at the plant level.

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 columns (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.[19]

How large is the post 2014 effect on the exit probability of plants? We first compute the raw exit rate over the 2006–2013 period, which is 7.02%. As is well known (e.g., Iwasaki et al. 2016), yearly exit rates are much lower in Russia than in more developed countries

[19]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.

and this clearly shows in our data. The raw exit probabilities over the 2014–2018 period, is 7.63%, i.e., an increase of 0.61 percentage points or 8.7%. Table A.1 in Appendix A.4 reports the predicted exit rates pre- and post-2014 by exposure deciles (1st, 5th, and 10th deciles, respectively) and shows that they vary systematically with pre-conflict exposure to Ukraine. The increase at the first decile (least exposed) is about 0.5 to 1 percentage points, whereas that at the 10th decile (most exposed) is about 2 to 2.5 percentage points. Given the baseline exit probabilities, these are sizeable numbers which show that the 2014 conflict had effects of quite different magnitude depending on the plants' initial exposure to Ukraine. Panel (b) of Figure 6 graphically illustrates the magnitude of the economic effect of the different exposure measures on plant exit using our predicted exit probabilities. As for nighttime lights, there is a sizeable effect: about 11% in the post 2014 period at the 1st decile, and about 45% at the 10th decile.

4.3 Robustness checks

We run a large number of robustness checks, which we briefly summarize here. Most tables and additional details are relegated to Online Appendix C.

First, instead of using the relative distance to the borders—conditional on overall minimum distance to the border—we estimate specification (11) using separate minimum great circle and network distances to the positive and the negative border segments, respectively. Table 4 shows that the two measures have separately the expected effect and are individually significant in most of our estimations.

Second, we re-estimate Table 1 using raw NTL as the dependent variable instead of lights apportioned cell-level GDP. Table C.3 shows the results. They are qualitatively similar, although some coefficients are smaller in magnitude.

Third, we re-estimate Tables 1 and C.3 including all cells up to 500 kilometers from the border and using distance bands of 50 kilometers or 100 kilometers instead of 150 kilometers. Our results are again robust to those choices.

Fourth, we run our regressions using 2012—when the EU Accession Agreement was

Table 4: Changes in cell-level GDP and plant exit by distance to the positive and negative borders.

	Cell-level GDP and GC			Plant exit and GC			Plant exit and ND		
	(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: $\ln(1 + \text{cell} - \text{level GDP})$ in columns (1)–(3); and a dummy that equals 1 if a plant exits in year t and 0 otherwise in columns (4)–(9). 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.

initiated—as an alternative treatment date to check whether the effects started to materialize earlier than 2014. Tables C.4 and C.5 in Online Appendix C 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.

Fifth, we make use of more granular exit information and create exit indicators based on year-quarter information. We also use quarterly information from the VIIRS NTL data to compute our measure of exposure to market potential in Ukraine. Tables C.6 and C.7 in Online Appendix C show that our estimates are qualitatively as those for the annual exit regressions in Tables 2 and 3, yet the magnitudes of the coefficients decrease.

Sixth, we verified that none of our results change if we use heteroscedasticity robust standard errors instead of clustered ones.

Last, we run regressions where we include only the 90% of plants that 'truly exit', i.e., we exclude plants that exit because of accession and mergers. Tables C.8–C.9 in Online Appendix C shows that our coefficients of interest are unaffected by these changes.

5 The role of market access

We now provide additional evidence which suggests that differential changes in market access drive differential changes in economic outcomes for the Russian regions bordering Ukraine. We first explain why access to the Crimean market seems important for the southern Russian regions. We then provide additional analyses to rule out potential confounders that might drive our results through channels different from market access. We relegate detailed estimation results to Online Appendix D to save space. We then leverage, in a final Section 6, new data we assembled to show that the closing of border crossings explains some of the local variation we see in the northern regions (Bryansk, Kursk, Belgorod, and Voronezh). This suggests that market access matters for economic outcomes in those regions also via the cross-border movement of people, and that its effects can be highly localized.

5.1 The importance of the Crimean market

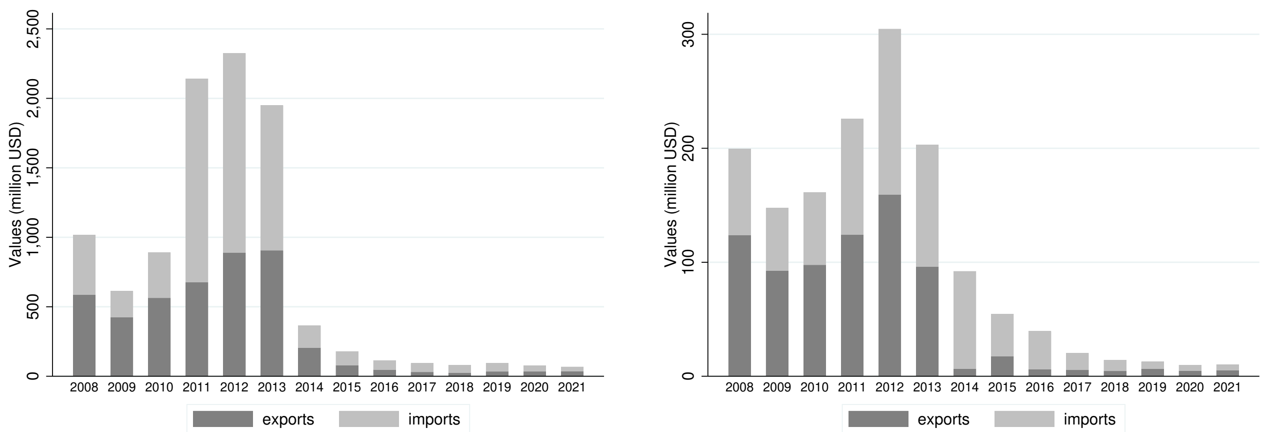
Crimea's average population, including Sevastopol, for the three years before the annexation in 2014 was 2,296,290, and its GDP was about 6.5 billion USD in nominal prices. The population grew to 2,304,074 on average between 2015–2018, while GDP reached 8.9 billion USD in nominal prices by 2018. Hence, Crimea had a per capita GDP of about 3,863 USD in 2018. By comparison, the close southern Russian region to Crimea on the mainland—Krasnodar Krai—had an average population of 5,310,593 pre-conflict, and 5,484,914 post-conflict, with average GDP about 48.5 billion USD, which dropped to about 40 billion USD in 2018. Hence, the Krasnodar region had a per capita GDP of 7,293 USD in 2018.

To gauge the importance of the Crimean market for the south, we can leverage trade statistics. Panels (a) and (b) of Figure 7 show how Crimea's foreign trade changed significantly between 2010 and 2017. Both imports and exports with the rest-of-the-world literally disappeared after the annexation, meaning that Crimea—including Sevastopol—now trades almost exclusively with the Russian Federation (which is classified as 'domestic trade').[20] Overall, panels (a) and (b) suggest that the Crimean market has become important for Russia as both an export destination and an import source. Given the well-established role of gravity in shaping trade patterns, the Crimean market should be more important

[20] See also Komissarova et al. (2018) for a discussion and figures on Crimean trade before and after 2014.

Figure 7: Total exports and imports for the Republic of Crimea and the city of Sevastopol.

(a) Republic of Crimea (b) Sevastopol



Notes: Total value of exports from and imports to Crimea. Panel (a) depicts trade figures for the Republic of Crimea. Panel (b) depicts trade figures for the city of Sevastopol. The trade data sources are UkrStat (`ukrstat.gov.ua`) before 2014, and CrimeaStat (`crimea.gks.ru`) from 2014 onwards.

for nearby Russian regions such as Krasnodar Krai, especially after the completion of the bridge over the strait of Kerch in 2018 which provides a land route to access Crimea. Since, as documented above, Crimean has about 40% of the population of Krasnodar and about 31% of its GDP per capita, we think the potential increase in market size for the Krasnodar region is sizeable.

Is it the market potential of Crimea that directly matters, or the possibility to indirectly access other markets via Crimea? First, we believe it is immaterial whether the better market access stems directly from the Crimean market or whether it stems from the markets that the Crimean market allows to access indirectly. Second—and more importantly—we think there is no reason this should be the case. We have seen that foreign trade of Crimea has almost vanished. Furthermore, the port of Novorossiysk (Krasnodar region) on the Russian mainland has direct access to the Black Sea and is one of the largest merchandise ports in Russia (see panel (a) of Figure 1). Although much attention has been given to the ports of Crimea in the discussion of their strategic role for Russia, that strategic role is essentially military: the Black Sea fleet was historically stationed in Crimea, and the naval bases were much more important to Russia than the commercial ports in that region.

5.2 Sanctions after 2014

A first potential confounder for changes in market access to Ukraine may be the imposition of mutual sanctions between an alliance of Western countries and Russia in the aftermath of the Crimean annexation in 2014. It is a priori unclear whether these sanctions—which targeted specific industries and groups of countries on the Western and on the Russian sides—may have differential north-south effects that could confound our difference-in-differences estimates. Although the sanctions targeted specific product groups, they might have had a disproportionate impact on regions with a large share of firms in the sanctioned industries, and those may be close to the border in the north.[21]

To deal with this concern, we construct an exposure measure to sanctions at the municipal district level (see Appendix A.3 for details). We then re-estimate our baseline models for cells and plants in Tables 1–3 including our constructed measure of exposure to sanctions interacted with the post-2014 dummy to see how cells and plants in municipalities more exposed to trade sanctions in the pre-treatment period behaved differentially after the conflict. In all regressions, the baseline exposure effects are of similar magnitude and significance, i.e., accounting for the sanctions does not change our original estimates (see Tables D.12-D.14 in Online Appendix D). The effect of the exposure to sanctions post-2014 is positive for cells, i.e., cells grew more in the post-2014 period in municipalities initially more exposed to sanctions. For plant exit, the inclusion of the sanctions control shows no significant effect on plant exit with industry-year fixed effects (see Table D.13), and weakly negative effects in regressions with plant fixed effects (see Table D.14). Our coefficient of interest, i.e., post-2014$\times$exposure, remains largely unchanged. Overall, we find a weak regional effect of the sanctions, and it does not affect our estimates regarding the importance of market access to Ukraine for the Russian border regions.

[21] For a full list of sanctioned/embargoed goods, as well the as countries supporting them, see Bělín and Hanousek (2021) and Crozet and Hinz (2020). Note that there were mutual sanctions: Western countries sanctioned the export of specific goods to Russia, and Russia retaliated by restricting the imports of other (mainly agricultural) goods from Western countries.

5.3 The 2014 Winter Olympic Games in Sochi

The 2014 Winter Olympic Games in Sochi are a second potential confounder. Sochi is a city on the Black Sea in the Krasnodar region, about 300 kilometers away from the southern Russian-Ukrainian sea border (see panel (a) of Figure 1). It hosted the 2014 Winter Olympic Games, the second-most expensive Olympics ever (Müller, 2014). One may a priori be concerned that both the geographic orientation (favoring the south) and the timing (just before the annexation) overlap with the two key dimensions we exploit to identify the causal effect of market access in our DiD framework. Clearly, the Olympics could explain the differential performance of the southern regions—especially since they had an explicit 'regional development' dimension (see, e.g., Müller 2014)—so that better economic outcomes would have occurred irrespective of the annexation of Crimea. Public investments in regional development, and the economic activity generated before and during the Olympics, may confound the positive impact of better market access in the south.

We have carefully investigated this problem and show below that our results do not seem driven by the Olympics. First, Figures 3 and 4 show that the differential growth prior to 2014 was in favor of the north, which got reversed after 2014. Thus, if there is a 'Sochi effect' prior to 2014, removing it would imply that the change in trend we see after 2014 is even more pronounced. Second, for a 'Sochi effect' to bias our estimates in the wrong direction, we would need that the growth post 2014 due to the Winter Olympics be much stronger than the growth pre 2014, which runs counter the empirical (and anecdotal) evidence discussed in Müller (2014) and Firgo (2021).[22] The post-2014 effect—if there is one at all—seems to have been weak and short lived.

To check that it is not public spending on the Winter Olympics that drives our results (or support to firms in view of the Olympics), we run various regressions where we include controls for the distance to Sochi. We compute the shortest (great circle) distance to Sochi

[22] Firgo (2021) documents that Olympic Winter Games generally have no specific positive long-run effect on host regions, but in the eight years between attribution and hosting there is a positive growth effect for regions in terms of GDP per capita. For the 2014 winter Olympics, this effect appears to have been sizeable. As explained, this would only reinforce the change in trend we see.

from all cells and plants in our sample. In our preferred specification, we estimate a model where we control for cell or plant distances from Sochi within 0-50 kilometers, 50-100 kilometers, and 100-150 kilometers distance bands (see Tables D.15–D.18 in Online Appendix D for cell luminosity and plant exit, respectively). All our main results survive this new specification although—as expected—the magnitude of some coefficients decreases.[23] We also experimented with a continuous distance measure for all cells from Sochi, but in that case we obtain a variable that is too collinear with our exposure measure and that is very likely to soak up the variation due to exposure to Ukraine.[24]

The results in Tables D.15–D.16 in Online Appendix D show that after 2014, cells close to Sochi grew faster than cells located further away, but the main results for our exposure measures remain quantitively and qualitatively unchanged: even conditional on distance from Sochi, cells more exposed to Ukraine in the south grew more than less exposed cells. We repeat this exercise with plant exit in Tables D.17-D.18. We see more exit for plants up to 100 kilometers from Sochi than their more distant counterparts. Again, the inclusion of additional Sochi controls does not alter the results for our exposure measures, and now even when including the 150 kilometers distance band to Sochi all coefficients are qualitatively the same: plants more exposed to Ukraine pre-2014 tended to exit more post-2014, conditional on their distance from Sochi.[25] We thus believe it is fair to say that Sochi does not explain our main results.

[23]The only qualitative change is that the post-2014 coefficients on market potential flip when the 100–150 kilometers distance bands are included (but they remain all unchanged in sign for the other exposure measures). We verified that the market potential exposure coefficients flip when we include the interaction of post-2014 and the log of the minimum distance to the border jointly with the Sochi 100–150 kilometers distance band. This suggests that, in that region, the two spatial variables are quite collinear.

[24]We also think it makes little sense to assume that there is a 'Sochi effect' that stretches along the whole border with Ukraine (if there is a 'Sochi effect' at all, which some of the literature we consulted casts doubts on). We are thus more confident in our results using the distance bins from Sochi up to 150 kilometers.

[25]The results on plant exit seem more robust to the combination of the 100–150 kilometers distance band to Sochi and the interaction between the post-2014 dummy and the log of the minimum distance to the border. We are not able to explain exactly why that is so, but the NTL data is more regular and gridded than the plant-level data, which suggests that the spatial structure of the data might generate collinearities in cells along various distance isocurves.

5.4 Public investments and subsidies

A third potential set of confounders may be subsidies to private or state-run businesses, which target more the south than the north. There might be politically motivated investments to support private firms, but we do not have much evidence for this. We know about a free economic zone that has been established in the territories of the Republic of Crimea and the city of Sevastopol by the Federal Law of November 29, 2014.[26] This free economic zone seems, however, both relatively small and is not on the Russian mainland and thus does not show up in our data used for estimation.

Another politically motivated support is related to import substitution policy, investments into which amount to more than 3 trillion rubles from 2015 to 2021, with direct government funding totalling more than 500 billion rubles according to the Federation Council Committee on Economic Policy. Import substitution programs aim to reduce dependencies on imports especially in the agricultural, machinery, and IT sectors. The former might have had a disproportionate impact on the southern regions—Krasnodar and Rostov—which traditionally have substantial agricultural production. The trade embargoes on food products, introduced in 2014 as retaliation to Western sanctions, may have boosted the growth of the agro-industrial complex. Yet, Shagaida and Uzun (2016) rather attribute the growth in the agricultural sector post-2014 to the devaluation of the ruble, which created favorable conditions for more domestic production. We have seen when discussing sanctions in Section 5.2 that there was some more growth in lights after 2014 in municipalities more exposed to sanctions, yet weak effects on manufacturing plant exit. This may be due to the positive effect of import sanctions on the agro-industrial production. However, the link between agriculture and lights is usually weak, and we have shown before that our baseline estimates do not change much when controlling for sanctions. Also, our estimates for manufacturing plant exit seem not directly related to changes in the agricultural sector.

Turning to public investments, substantial investments were made in Crimea, especially

[26]`https://www.economy.gov.ru/material/file/d4cae5f3397494aafc525c3720e8eb0b/report_2020.pdf` (accessed on February 7, 2023).

to connect its energy- and transportation grids to those in Russia. First, there is the 'Power bridge' to Crimea, which are cables, overhead power lines, and substations built to connect the Crimean energy system to the energy system of the Russian Federation. Its construction started in June 2014, and was completed in 2016, for a total cost of about 800 million dollars. Second, the bridge to Crimea over the strait of Kerch was built, which provides road and rail access to Crimea. Its construction started in 2016 and was completed in 2018 for a total cost of about 4 billion dollars.[27] These two large public investment projects to link Crimea to the Russian power- and transportation grid may partly explain the growth in lights and the higher survival of plants in the southern Russian regions if they benefitted from the extra economic activity generated by these constructions. We do not view this as problematic for our estimates since the activity generated by these projects is directly linked to the new access to the Crimean market. In other words, we would not have seen this beneficial effect in the south had the annexation not occurred and access to serve the Crimean market become more important.

Last, we also considered whether military presence could explain differential growth in lights in favor of the south. It is hard to answer this question, but we are inclined to think 'probably not'. Around 2014 there was no discussion anywhere of any massive military ramp up close to the Ukrainian border, especially in the south, that could have affected lights (contrary to the ramp up before the full-scale invasion in 2022, where western intelligence agencies and media extensively documented and analyzed the increased military presence along the border).

5.5 Expectations about future conflict

A last potential confounder, similar to one in Redding and Sturm (2008), are people's expectations in 2014 about a future deterioration of the relationship with Ukraine. Although this is a possibility, it is a priori hard to see why this would affect more expectations in

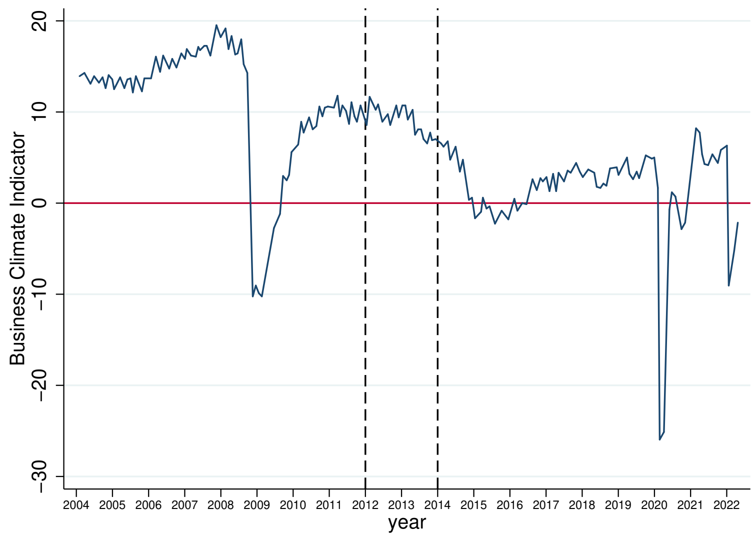
[27] Since the opening of the bridge for exploitation in 2018, it has been crossed by more than 21 million automobiles, more than 3 million trucks, and 233 thousand buses. The recorded number of crossings per day in both directions in 2020 was 37,374 vehicles. This reinforces our idea that Crimea has become an important market and destination for firms and people in the southern border regions.

the north than in the south. It is also hard to measure, but we can capture it partly and indirectly using public opinion polls.

The state-owned polling institution Russian Public Opinion Research Center (WCIOM) and the non-governmental polling organization Levada Center (which has since been classified as a foreign agent) both reveal a similar picture of public opinion among Russians about their expectation concerning the future development of the conflict between Russia and Ukraine. On November 5, 2014, WCIOM published results stating that *"twice as many respondents say that the situation in Ukraine remains unchanged today as in August of this year (50% and 23%, respectively). At the same time, the proportion of respondents who believe that the situation is worsening significantly decreased (from 72% to 38%)."* Levada conducted a survey on August 22-25, 2014, which shows that *"Russians however believed that it was unlikely that the tensions between Russia and Ukraine would escalate into a major war. Close to six out of ten respondents (59%) did not believe, in 2014, that there is a war between the two countries."* To summarize, it does not seem that there was a general feeling that escalation of the situation was imminent and unavoidable. Unfortunately, we do not have more detailed opinion surveys on the border regions' populations, so that these results should be taken with a grain of salt. People close to the border may have perceived things differently than in Moscow, St. Petersburg, or the far-away regions in the east.

A final piece of suggestive evidence comes from a measure of firms' expectations about the development of the economy using the Business Climate Indicator (BCI). This indicator is computed on a monthly basis by the Central Bank of Russia based on a large representative survey of about 14 thousand non-financial firms. The questions and answers provide a good view of firms' perceived operating conditions, taking into account a large range of internal and external factors. The BCI reflects factual and expected changes in production and demand, where expectations are the firms' assessments on the dynamics over the next three months. A one month lead of this indicator shows a fairly high correlation with GDP and provides thus a good forecast of expected future changes in the economy. Figure 8 shows monthly changes in the BCI from 2004 to 2022. We clearly see three sharp drops: in

Figure 8: Business Climate Indicator in Russia.



Notes: Business Climate Indicator (BCI), seasonally adjusted monthly data points. The BCI is computed as a geometric mean of Current BCI and Expected BCI. Current (expected) BCI is a geometric mean of the balance of responses on (expected) changes in production and demand. The balance of responses is the difference between the share of those who answered 'more' and the share of those who answered 'less', as a percentage of the sum of the shares of answers. The figure is adapted from: `https://econs.online/articles/ekonomika/ekonomicheskaya-aktivnost-indikator-banka-rossii/` (Source: Central Bank of Russia).

the midst of financial crisis of 2008; at the onset of the COVID-19 pandemic in 2020; and at the beginning of the 'special military operation' in Ukraine in 2022. Observe that the expectations about the business climate were rather stable around 2012 and start to decrease in late 2013 following the Euro Maidan. However, we do not see any sharp drop near the level of the financial crisis, COVID, or the invasion of 2022.

We cannot rule out that part of the changes along the border between 2014 and 2018 were due to expectations about future conflict, but the evidence from opinion polls and the BCI suggest that this is unlikely to be the whole story.

6 More evidence on market access: The local effects of closed border crossings

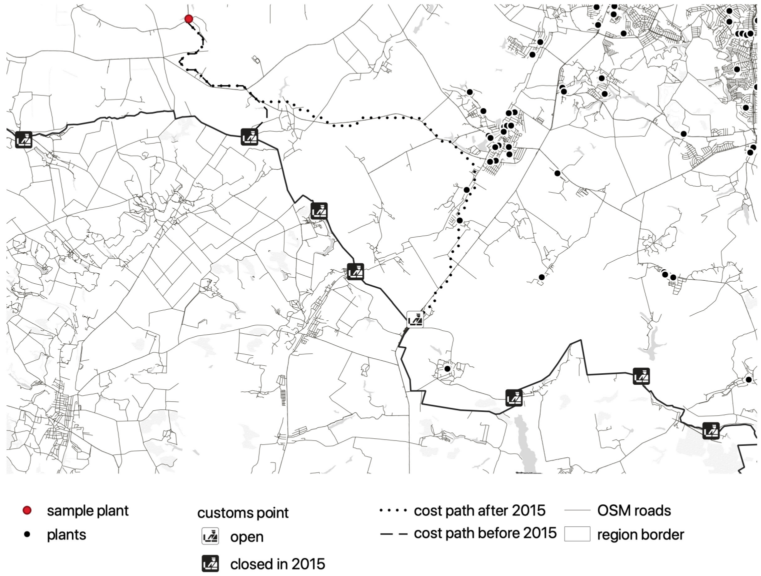
Having ruled out a number of possible confounders, we now present some additional evidence for the role of market access. To this end, we leverage a novel dataset we constructed on local border crossings and exploit changes in them over time. Our analysis is restricted to the northern border regions 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 1).

6.1 Context and importance of cross-border interactions

In 1995, Russia and Ukraine signed an inter-governmental agreement about co-operation of border regions to facilitate cross border commuting. 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. We provide a detailed description of the local and international border crossings and our data sources in Online Appendix G.

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 potential access to labor. We exploit this variation to investigate whether: (i) nighttime lights 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 open border crossings saw their exit probability change significantly compared to other plants. Figure 9 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

Figure 9: 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.

substantially increase the road distance.

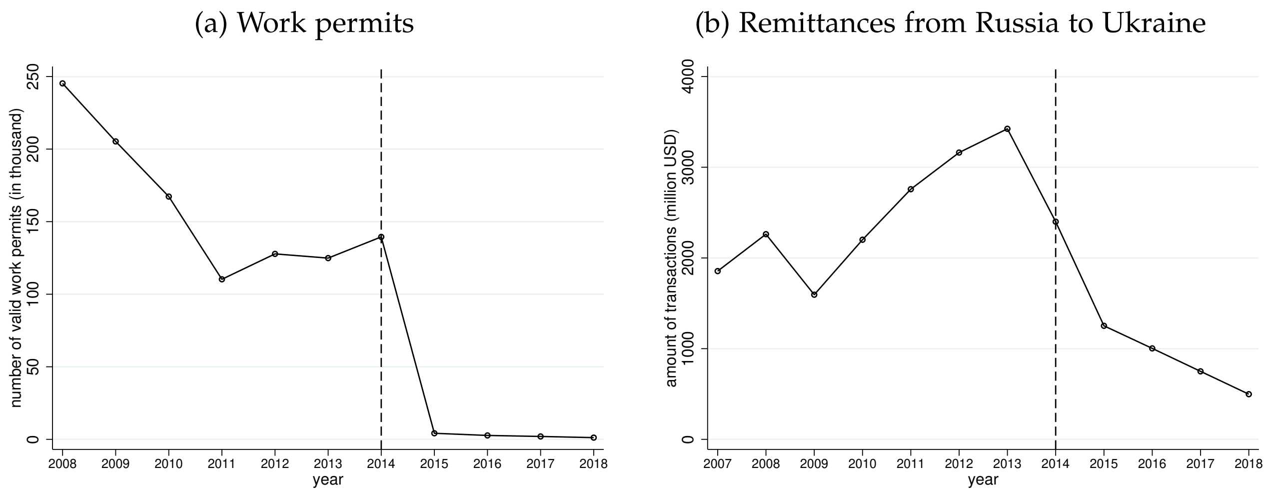
We now provide several pieces of evidence on the intensity of cross-border interactions between Russia and Ukraine.[28] We first document the importance of the Ukrainian workforce in Russia prior to 2014, and show that it dropped substantially after the annexation. Panel (a) of Figure 10 shows statistics on the number of Ukrainians with a valid work permit in Russia.[29] The number declines very strongly after 2014. Of course, since these are

[28]Direct evidence on cross-border movements is rare and most of it is anecdotal. Kolosov et al. (2016, p.395) is one 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 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."* Zayats et al. (2017) provide an informal discussion and case study for the potential importance of crossborder 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.

[29]Although getting a work permit is the most common way for employment, these figures underestimate the exact number of Ukrainians working in Russia. First, as there is a visa-free regime in force between the two countries, citizens of Ukraine who have a temporary residence permit or a residence permit do not need a work permit. Second, starting from 2010 foreign workers from visa-free countries can buy a license

national statistics—no detailed regional statistics are available—they include Ukrainians working in Moscow or in far-away places like the Siberian oil fields. However, gravity for trade-, migration-, and commuting flows suggest that more Ukrainians should work closer to Ukraine and that the decrease should be stronger in the border regions.

Figure 10: Number of Ukrainians with valid work permits and amount of remittances.



Notes: Panel (a) depicts number of Ukrainians with a valid work permit in Russia. Panel (b) depicts the total amount of money remitted to Ukraine.

A second—more indirect—way to trace changes in cross-border labor flows are trans-border payments. We can approximate the importance of Ukrainian workers in Russian firms by using the total amount of remittances sent from residents and non-residents to Ukraine. According to Russian legislation, foreign workers (whether they are residents or non-residents) cannot receive their salary in cash and must open a bank account labeled in rubles. Workers who temporarily work in Russia or workers who cross the border but live in Ukraine thus must remit their earnings back to Ukraine via the banking system.[30] We

to work at companies that have been officially allocated quotas to hire foreign nationals (see Vakulenko and Leuhin 2015 for a description of the channels of legal employment of migrants in Russia). The demand for work licenses increased manifold against the backdrop of the new law on the duration of stay for visa-free migrants in January 2014. Experts emphasize the serious impact of the Ukrainian crisis on migrant workers from Ukraine as most of them have families left in Ukraine but are afraid to go home for fear that they will not be able to return to work (see `https://russiancouncil.ru/analytics-and-comments/analytics/perspektivy-migratsii-naseleniya-iz-ukrainy-v-rossiyu-v-svet/`). Nevertheless, the number of people from Ukraine who had a work license also dropped from about 256 thousand in 2014 to about 43 thousand in 2020. Last, according to the Federal Migration Service, there are 1.6 million Ukrainians, who came to Russia to earn money. These are mostly residents of the eastern regions of Ukraine..

[30]Ukraine is among the largest recipients of money transfers from Russia. Ukraine is also among the main senders of money transfers to Russia, with a large share of money transferred to residents.

thus think that changes in remittances capture quite accurately changes in the importance of the Ukrainian workforce in Russia.

Panel (b) of Figure 10 depicts the cross-border money transfers made by foreigners (with or without resident status in Russia) in favor of residents and non-residents in Ukraine, with and without opening a bank account.[31] These transfers are explicitly called 'remittances' by the Central Bank of Russia. The figure shows a large drop in cross-border payments from Russia to Ukraine starting in 2014. Note that the drop before 2017 cannot be readily attributed to the mutual ban on foreign payment systems in Russia and Ukraine, which took effect only later in 2017. Thus, the drop before 2017 largely reflects the weakening economic ties and lower remittances from Russia to Ukraine as much less Ukrainians had valid permits to work in Russia (see panel (a) of Figure 10).

Figure 10 suggests that the number of Ukrainians working in Russia and remitting money to Ukraine dropped very strongly after the annexation of Crimea in 2014. Although these are national statistics and include Ukrainians not working in the border regions—e.g., those in Moscow or the far-eastern oil fields—we think they also include many Ukrainians who previously worked in the Russian border regions and transferred their salary back to Ukraine via the banking system.

6.2 Empirical analysis

We now provide evidence for the effects of the closing of local border crossings on cell-level nighttime lights and plant exit. Since the border crossings were closed starting in March 2015, we exploit quarterly VIIRS nighttimes lights data from 2012 onwards.[32] To this end,

[31]This includes credit organizations, banks, money transfer systems, and the Russian Post. Money transfer systems do not require to open a bank account but are included in the data.

[32]Quarterly nighttime lights series are constructed from VIIRS nighttime lights, which are not top-coded and better capture activity in low-lit areas. This is especially important for our study region along the northern border with Ukraine, where we have cross-border settlements in low-lit areas as well as large cities (e.g., Belgorod) located close to the border. The data are also available at a finer spatial resolution of 500×500 meters grid cells. We also use quarterly exit information for plants in that case. We must depart from our preferred choice of lights apportioned cell-level GDP as our dependent variable since we do not have quarterly GDP. We thus use the raw nighttime lights .

we estimate the following model:

$$\begin{aligned} y_{i,t} \;=\;& \beta_0 + \beta_1(\text{post}_{\text{2015-Q1}} \times \text{bigCity}_i) + \beta_2(\text{post}_{\text{2015-Q1}} \times \Delta\text{crossingsDist}_{i,t}) \\ & + \gamma_1(\text{post}_{\text{2015-Q1}} \times \Delta\text{crossingsDist}_{i,t} \times \text{bigCity}_i) + \alpha_i + \delta_t + \varepsilon_{i,t}, \end{aligned} \tag{12}$$

where $y_{i,t}$ is the log of (1 plus) the nighttime lights intensity of cell i; or an exit dummy for plant p (we display (12) for cells only, but we estimate it also for plants in what follows). In (12), $\text{post}_{\text{2015-Q1}}$ is a dummy variable taking value 1 starting in the first quarter of 2015 and zero otherwise; α_i are cell (or plant) fixed effects; and δ_t are year fixed effects, respectively. $\Delta\text{crossingsDist}_{i,t}$ is the log change in the shortest distance to the nearest border crossing post-2015-Q1 compared to the shortest distance to the nearest crossing before 2015-Q1. We measure the latter using either great circle distance for plants and cells, or road network distance for plants. We also use a weighted version of these measures to account for the fact that some border crossings are more important than others.[33]

We estimate (12) for the set of (international and local) equipped border crossings in the four northern regions. We restrict ourselves to a shorter distance of either 50 or 100 kilometers to focus on the effects going through the movement of people—which affects cross-border labor supply and cross-border shopping. As explained before, the local border crossings cannot be used for commercial merchandise trade. Thus, their closing does not change the geography of trade in goods.[34] We also 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 change in their distance to the nearest open border crossing as the international crossing points all remained open.

Table 5 shows results for the relation between changes in distance to the nearest open

[33]Unfortunately, direct information on cross-border flows seems to be non-existent. We construct a border crossing weight based on the NTL value of the cells of the crossing's main associated settlements (see Appendix A.3 for details on that procedure).

[34]We provide evidence in Online Appendix H 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.

Table 5: Changes in NTL and distance to border crossings.

	(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 $\ln(1+\mathrm{NTL}^{\mathrm{VIIRS}})$, where $\mathrm{NTL}^{\mathrm{VIIRS}}$ 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 border points, while columns (3)–(4) provide results for all border points. Change in distance is measured by the great circle distance to the nearest open 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 see (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).

border crossing and nighttime lights. We see 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; and 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 Belgorod and Kursk at 100 kilometers—saw more exit post 2015-Q1 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 G.1 in Online Appendix G 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,

Table 6: Changes in distance to border crossings and plant exit.

	(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).

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 very demanding on our data. We provide a number of additional robustness checks for our results in Online Appendix C.

To summarize, we find some evidence that nighttime lights grew less in areas that experienced a larger increase in their distance to the nearest open border crossing compared to areas that did not experience a large increase. These effects are highly localized at less than 50 kilometers from the border and vary substantially across locations. Concerning plant exit, we only find more exit post 2015 in large cities but there are no strong spatial patterns. Overall, the empirical evidence for plant exit is not very strong, but we need to keep in mind that there is a systematic relation between the magnitude of the change in distance and city size since the international border crossings close to the larger cities remained open. This makes identification more complicated, especially for plants which are strongly concentrated in the large cities, and may explain why the results are mostly driven by big cities. Even if the exercise is very demanding on our data, it still suggests there are effects that may percolate through local cross-border labor movements.

7 Conclusion

Using the Russia-Ukraine conflict following the annexation of Crimea in 2014 as a natural experiment, we provide evidence that changes in borders—and the associated changes in market access—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 to Ukraine because of closed border crossings and tighter controls—we show that regions more exposed to increased border frictions saw less growth in lights and more plant exit after 2014: compared to the least exposed regions, the most exposed ones saw a 3.4%–4% smaller change in GDP and a 1.5 percentage points higher plant exit rate.

Our results contribute to a recent literature that leverages spatially and economically disaggregated data to understand the regional effects of economic integration and conflict. We confirm the robustness of several key insights from that literature. First, the spatial effects of changes in market access are highly localized. Second, the effects vary substantially across places and firms, depending crucially on their initial 'exposure' to economic partners. Finally, these highly localized effects may be partly driven by economic activity that is very sensitive to distance frictions. While Eberhard-Ruiz and Moradi (2019) find this to be small-scale local cross-border trade in Africa, our findings for Russia and Ukraine suggest it may also be due to cross-border labor movements.

More work is required to better understand the economic consequences of conflict and the channels through which it affects border regions. This seems especially important in a world where territorial conflict among neighbors unfortunately remains endemic.

References

Abadie, Alberto and Javier Gardeazabal, "The economic costs of conflict: A case study of the Basque Country," *American Economic Review*, 2003, *93* (1), 113–132.

Ahlfeldt, Gabriel M, Stephen J Redding, Daniel M Sturm, and Nikolaus Wolf, "The economics of density: Evidence from the Berlin Wall," *Econometrica*, 2015, *83* (6), 2127–2189.

Aleksandrova, Ekaterina, Kristian Behrens, and Maria Kuznetsova, "Manufacturing (co) agglomeration in a transition country: Evidence from Russia," *Journal of Regional Science*, 2020, *60* (1), 88–128.

Bělín, Matěj and Jan Hanousek, "Which sanctions matter? Analysis of the EU/Russian sanctions of 2014," *Journal of Comparative Economics*, 2021, *49* (1), 244–257.

Berman, Nicolas and Mathieu Couttenier, "External shocks, internal shots: the geography of civil conflicts," *Review of Economics and Statistics*, 2015, *97* (4), 758–776.

Bloom, Nick, Stephen Bond, and John Van Reenen, "Uncertainty and investment dynamics," *The Review of Economic Studies*, 2007, *74* (2), 391–415.

Bruederle, Anna and Roland Hodler, "Nighttime lights as a proxy for human development at the local level," *PloS One*, 2018, *13* (9), e0202231.

Brülhart, Marius, Céline Carrère, and Federico Trionfetti, "How wages and employment adjust to trade liberalization: Quasi-experimental evidence from Austria," *Journal of International Economics*, 2012, *86* (1), 68–81.

_ , Olivier Cadot, and Alexander Himbert, "Let There Be Light: Trade and the Development of Border Regions," 2022. Journal of International Economics (revise and resubmit).

Brülhart, Marius, Céline Carrère, and Frédéric Robert-Nicoud, "Trade and towns: Heterogeneous adjustment to a border shock," *Journal of Urban Economics*, 2018, *105*, 162–175.

Camacho, Adriana and Catherine Rodriguez, "Firm exit and armed conflict in Colombia," *Journal of Conflict Resolution*, 2013, *57* (1), 89–116.

Cederman, Lars-Erik, Seraina Rüegger, and Guy Schvitz, "Redemption through Rebellion: Border Change, Lost Unity, and Nationalist Conflict," *American Journal of Political Science*, 2022, *66* (1), 24–42.

Chen, Xi and William D Nordhaus, "Using luminosity data as a proxy for economic statistics," *Proceedings of the National Academy of Sciences*, 2011, *108* (21), 8589–8594.

Collier, Paul and Marguerite Duponchel, "The economic legacy of civil war: firm-level evidence from Sierra Leone," *Journal of Conflict Resolution*, 2013, *57* (1), 65–88.

Crozet, Matthieu and Julian Hinz, "Friendly fire: The trade impact of the Russia sanctions and counter-sanctions," *Economic Policy*, 2020, *35* (101), 97–146.

Donaldson, Dave and Adam Storeygard, "The view from above: Applications of satellite data in economics," *Journal of Economic Perspectives*, 2016, *30* (4), 171–98.

Eberhard-Ruiz, Andreas and Alexander Moradi, "Regional market integration in East Africa: Local but no regional effects?," *Journal of Development Economics*, 2019, (140), 255–268.

Elvidge, Christopher D, Kimberley E Baugh, Eric A Kihn, Herbert W Kroehl, Ethan R Davis, and Chris W Davis, "Relation between satellite observed visible-near infrared emissions, population, economic activity and electric power consumption," *International Journal of Remote Sensing*, 1997, *18* (6), 1373–1379.

_, Kimberly Baugh, Mikhail Zhizhin, Feng Chi Hsu, and Tilottama Ghosh, "VIIRS night-time lights," *International Journal of Remote Sensing*, 2017, *38* (21), 5860–5879.

Firgo, Matthias, "The causal economic effects of Olympic Games on host regions," *Regional Science and Urban Economics*, 2021, *88*, 103673.

Gibson, John and Geua Boe-Gibson, "Nighttime lights and county-level economic activity in the United States: 2001 to 2019," *Remote Sensing*, 2021, *13* (14), 2741.

— , **Susan Olivia, Geua Boe-Gibson, and Chao Li**, "Which night lights data should we use in economics, and where?," *Journal of Development Economics*, 2021, *149*, 102602.

Guidolin, Massimo and Eliana La Ferrara, "Diamonds are forever, wars are not: Is conflict bad for private firms?," *American Economic Review*, 2007, *97* (5), 1978–1993.

Hanson, Gordon H, "Economic integration, intraindustry trade, and frontier regions," *European Economic Review*, 1996, *40* (3-5), 941–949.

Harari, Mariaflavia and Eliana La Ferrara, "Conflict, climate, and cells: a disaggregated analysis," *Review of Economics and Statistics*, 2018, *100* (4), 594–608.

Henderson, J Vernon, Adam Storeygard, and David N Weil, "Measuring economic growth from outer space," *American Economic Review*, 2012, *102* (2), 994–1028.

Hensel, Paul R., "Territory: Theory and evidence on geography and conflict," in John A. Vasquez, ed., *What Do We Know about War?*, Boulder, CO: Rowman and Littlefield, 2000.

Hodler, Roland and Paul A Raschky, "Regional favoritism," *The Quarterly Journal of Economics*, 2014, *129* (2), 995–1033.

Iwasaki, Ichiro, Mathilde Maurel, and Bogdan Meunier, "Firm entry and exit during a crisis period: Evidence from Russian regions," *Russian Journal of Economics*, 2016, *2* (2), 162–191.

Kochnev, Artem, "Dying Light: War and Trade of the Separatist-Controlled Areas of Ukraine," *The Vienna Institute for International Economic Studies Working Papers Series*, 2019, – (161), 1–40.

Kolosov, VA, MV Zotova, and AB Sebentsov, "The barrier function of Russia's borders," *Regional Research of Russia*, 2016, *6* (4), 387–397.

Komissarova, I.P., E.A. Mayorova, and O.S. Karashchuk, "Trade of the Republic of Crimea: trends, issues and development prospects," *Russian Journal of Enterpreneurship*, 2018, *19* (3), 775–788.

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

Li, Xuecao, Yuyu Zhou, Min Zhao, and Xia Zhao, "A harmonized global nighttime light dataset 1992–2018," *Scientific Data*, 2020, *7* (1), 1–9.

Martin, Philippe, Thierry Mayer, and Mathias Thoenig, "Make trade not war?," *The Review of Economic Studies*, 2008, *75* (3), 865–900.

Mellander, Charlotta, José Lobo, Kevin Stolarick, and Zara Matheson, "Night-time light data: A good proxy measure for economic activity?," *PloS one*, 2015, *10* (10), e0139779.

Michalopoulos, Stelios and Elias Papaioannou, *National institutions and African development: Evidence from partitioned ethnicities*, National Bureau of Economic Research Cambridge, MA, 2012.

_ **and** _ , "The Long-Run Effects of the Scramble for Africa," *American Economic Review*, 2016, *106* (7), 1802–1848.

_ **and** _ , "Spatial patterns of development: A meso approach," Technical Report, National Bureau of Economic Research 2017.

Müller, Martin, "After Sochi 2014: costs and impacts of Russia's Olympic Games," *Eurasian Geography and Economics*, 2014, *55* (6), 628–655.

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

Redding, Stephen J and Daniel M Sturm, "The costs of remoteness: Evidence from German division and reunification," *American Economic Review*, 2008, *98* (5), 1766–97.

Resnick, Uri, "Explaining post-independence conflict," *Dynamics of Asymmetric Conflict*, 2012, *5* (1), 31—-54.

Shagaida, Natalya and Vasily Uzun, "Import substitution in agriculture," *Russian Economic Development*, 2016, *23* (3), 63–67.

Simmons, Beth A., "Rules over Real Estate: Trade, Territorial Conflict, and International Borders as Institution," *Journal of Conflict Resolution*, 2005, *49* (6), 823—848.

Vakulenko, Elena and Roman Leuhin, "Study of demand for foreign migrant labor in Russian regions according to quota applications submitted," *Applied Econometrics*, 2015, (1 (37)), 67–86.

Vermeulen, Wessel N., "Stuck outside the single market: Evidence from firms in central and eastern Europe," *Journal of Comparative Economics*, 2022, (50), 415—434.

Yang, Benjian, Mark D Partridge, and Anping Chen, "Do border effects alter regional development: evidence from a quasi-natural experiment in China," *Journal of Economic Geography*, 2022, *22* (1), 103–127.

Zayats, DV, MV Zotova, NL Turov, and MI Klyuchnikov, "Impact of crisis in Russia–Ukraine relations on cross-border interactions in Belgorod oblast," *Regional Research of Russia*, 2017, *7* (4), 384–394.

Zhukov, Yuri M., "Trading hard hats for combat helmets: The economics of rebellion in eastern Ukraine," *Journal of Comparative Economics*, 2016, *44* (1), 1–15.

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.

Datasets. 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 kilometer 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 kilometer cells. The lights intensity is measured by a digital number (DN) value ranging from 0 to 63. We focus on the period 2005–2018 in our analysis.

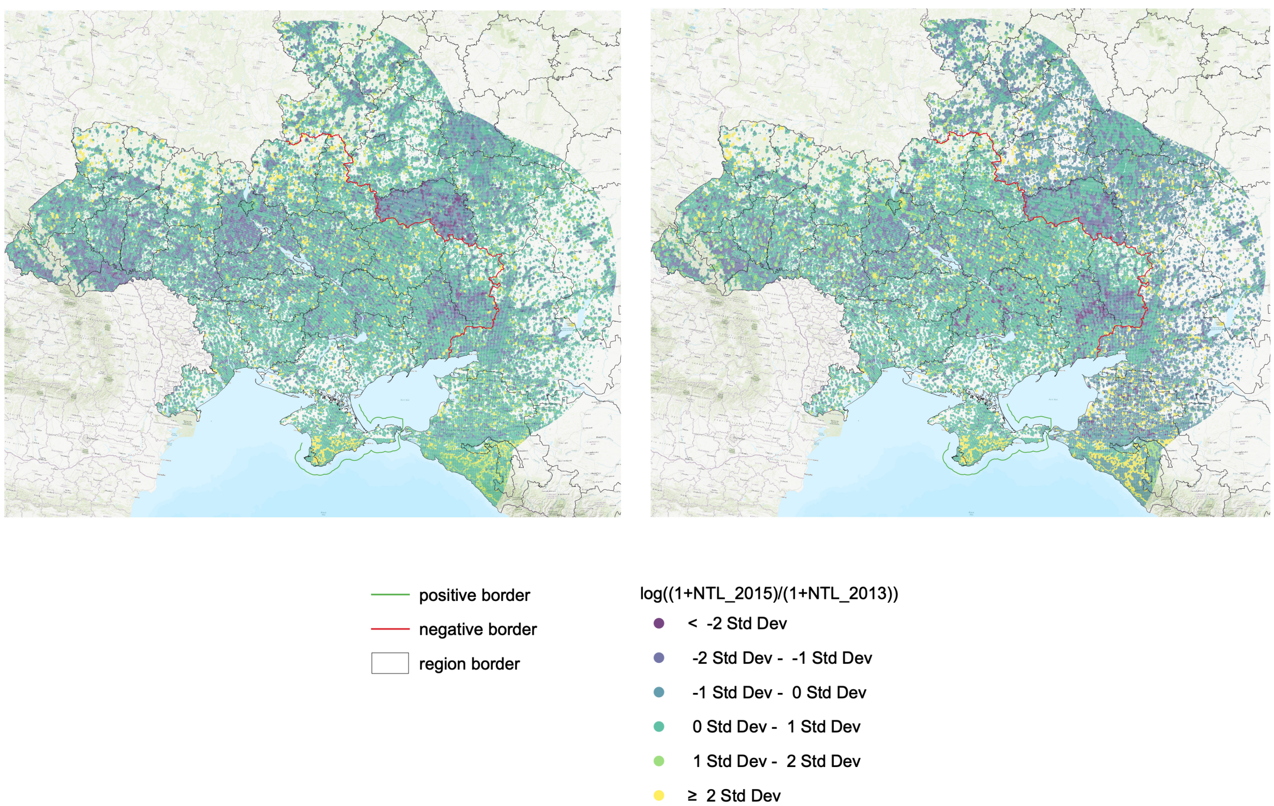
The VIIRS data cover a more recent period and go back a little before 2014. We utilize quarterly VIIRS nighttime lights from 2012-Q2 to 2018-Q4 in several ways during our study. First, we compute market potential measures as in (3) for quarterly regressions and use it in robustness checks (see Tables C.6 and C.7 in the Online Appendix C). Second, we use it to estimate changes in NTL intensity in response to changes in distance to the nearest border crossing in Section 6 (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 Appendix A.3). Last, we use it to provide robustness checks—especially for plant exit using quarterly data—in Online Appendix C. A more detailed description of our nighttime lights data, its preparation and post-processing, are relegated to Online Appendix B.1.

Changes in lights along the border. Figure A1 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. Panel (a) shows the distribution of changes using the raw NTL series, whereas panel (b) shows the changes in GDP which we apportioned using nighttime lights (see equation (1) in Section 3).

Figure A1: Distribution of log changes in nighttime lights, 2013–2015.

(a) Raw data

(b) GDP apportioned using lights.



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 300 kilometers 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 lights emissions. The 2013–2014 changes look similar. A detailed description of the NTL satellite data is provided in Appendix A.1.

Figure A1 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 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.[35]

Appendix A.2 Plant-level data.

Data sources. 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.

Plant exit. We construct the exit reason for all plants within 300 kilometers distance from the border using the Ruslana and SPARK Interfax databases. We have tried to make these statuses as comparable as possible across the two datasets.[36] There are many reasons

[35]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.

[36]Unfortunately, this is not perfect for several reasons: (1) Ruslana and SPARK have semantically similar statuses from the Unified State Register of Legal Entities, but in some cases using a different wording or formulation; (2) in the latest updates we extracted in 2021 we have detailed statuses in Russian, whereas they were in English in our previous extracts; and (3) SPARK provides their own aggregate classification that we

for plant exit. The top-5 reasons that are provided in our datasets (which draw from administrative records of the Unified State Registry of Legal Entities) are the following:

- Removed from the State Register of Legal Persons under p.2 sec.21.1 of FL from 08.08.2001 #129-NL, i.e., did not submit reporting documents required by the legislation of the Russian Federation on taxes and fees in the last 12 months, and did not carry out operations on at least one bank account; recognized as having effectively ceased its activities (27.80% of cases).
- Exclusion from the Unified State Register of Legal Entities of an Inactive Legal Entity (24.90% of cases).
- Liquidated (22.66% of cases).
- Termination of a legal entity in connection with its liquidation on the basis of an arbitration court ruling on the completion of bankruptcy proceedings (7.27% of cases).
- Exclusion from the Unified State Register of Legal Entities due to the presence of information about a legal entity in the Unified State Register of Legal Entities about which a record of unreliability has been made (6.66% of cases).

The first two reasons (about 50% of the cases) relate to firms that have simply ceased any activity—no banking or fiscal operations are carried out anymore. There has, however, not been a formal bankruptcy or liquidation procedure for these firms. These include mostly small firms that disappear and go out of business. The next two reasons (about 30% of the cases) relate to formal bankruptcy or liquidation procedures involving the courts. These are usually larger firms where many stakeholders try to secure claims during a formal liquidation of the firm. The last reason corresponds to firms which do not maintain an administrative record in compliance with tax requirements, i.e., the information about either the location or the owner are not 'trustworthy'. Such firms must update their information within six months or else they are considered liquidated and removed from the State

partly used in our previous analysis and which we had to unfold again.

Register. Thus, close to 90% of what we consider 'plant exit' is administratively related to: (i) no more activity; or (ii) a formal liquidation or bankruptcy procedure. Note that exit may also occur through accession—whereby a new party acquires a majority stake in the company—or mergers. These two categories are also present in our data, but they account for a small part of the cases of exit. More precisely, we have the following two categories:

- Ceased operations by accession (3.57% of cases)
- Ceased operations by merger (0.86% of cases)

Thus, we think that our measure of 'exit' captures 'true exit' in most cases.

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.[37] We construct the shortest path to the sea ports providing access to Crimea as the network distance to the positive border. Additional details are in Online Appendix F.

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.[38] 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

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

[38]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.

> 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 G.

Measure of exposure to sanctions. First, we compute the total value of exports to Russia from countries imposing sanctions in the sanctioned and embargoed products. The former are extraction equipment and double-use products, whereas the latter are mainly food products. Next, we construct a crosswalk from the HS product classification to OKVED2007 industry codes (see the intermediate steps in Online Appendix B.2 for details). This allows us to construct a raw measure of the share of plants in industries under sanctions in the total number of plants in each municipal district, which we average over three years before the conflict. Next, we compute per plant trade values in each sanctioned industry and municipality. Last, we sum these values and weight them by the share of sanctioned plants in the municipality. Since our data do not allow us to do anything more detailed, we assume that plants in non-sanctioned industries had zero trade in sanctioned goods.

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 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:

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

where $d_{p,j}^{D}$ is distance measured as great-circle or network distances $D \in \{GC, ND\}$ between plant p 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:

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

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 $\text{dist}_{k,m}$ is the 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:

$$\Delta\text{crossingDistanceWeighted}_p^{D} = \Delta\text{crossingDistance}_p^{D} \times \text{pointAttractMinMax}_j, \tag{A.4}$$

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

Appendix A.4 Additional results.

Table A.1 shows the conditional exit probabilities before and after 2014 by exposure decile.

Table A.1: Conditional exit probabilities by exposure measure and decile.

exit probability		exposure		
$\hat{y}_{\text{pre}-2014}$	$\hat{y}_{\text{post}-2014}$	decile	measure	% change
0.0617	0.0685	1	GC	10.889
0.0651	0.0789	5	GC	21.147
0.0553	0.0791	10	GC	43.042
0.0622	0.0675	1	ND	8.563
0.0747	0.0754	5	ND	0.947
0.0538	0.0811	10	ND	50.680
0.0602	0.0699	1	LAT	16.208
0.0621	0.0691	5	LAT	11.417
0.0562	0.0793	10	LAT	41.212
0.0628	0.0702	1	LMP Ukr	11.778
0.0616	0.0796	5	LMP Ukr	29.151
0.0512	0.0748	10	LMP Ukr	46.110
0.0627	0.0718	1	GMP Ukr	14.608
0.0615	0.0803	5	GMP Ukr	30.468
0.0505	0.0752	10	GMP Ukr	48.922

Notes: Mean predicted exit probabilities, based on (11), for the 1st, 5th, and 10th decile of the exposure measures. We report results using plant fixed effects.

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 provides details on and tables for the robustness checks we report in the main text. Appendix D provides additional results on the role of market potential. Appendix E elaborates on the abnormally large plant exit rates in 2012. Appendix F provides detailed information on the construction of our network distance measures. Appendix G explains the construction of our border crossings dataset and provides information on the cross-border movements between Russia and Ukraine. Last, Appendix H provides additional results on nighttime lights and plant exit using trade data.

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.[1] Two major shortcomings of DMSP data are top-coding of urban cores and light-blooming effects falsely illuminating dimmed places.

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

Nighttime lights satellite imagery has been shown to be a promising data source to 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.[2]

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.[3] 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

[2]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.

[3]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.[4] 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.[5] 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.[6] 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.[7] Second, keeping gas flares in our analysis

[4]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.

[5]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.

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

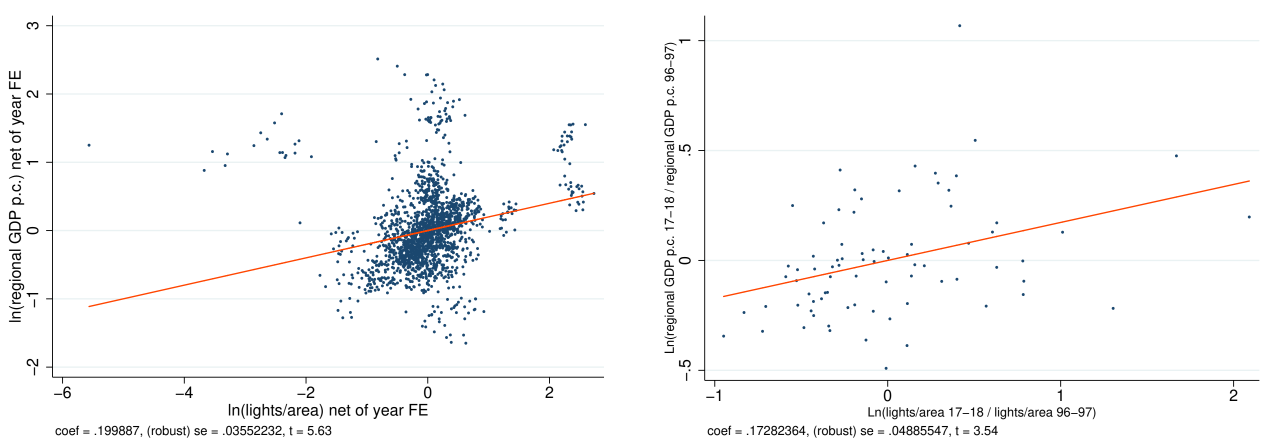
[7]See `https://viirs.skytruth.org/apps/heatmap/flarevolume.html` for the map of gas flaring sites.

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. We provide estimates of the nighttime lights elasticity of GDP for Russian regions. Panel (a) of Figure B1 shows the log-log relationship between nighttime lights—averaged at the regional level—and regional GDP per capita. A simple OLS regression yields an estimated elasticity of 0.2 (standard error 0.035). Panel (b) plots the relation between long differences (2017-2018 vs 1996-1997) in log average nighttime lights and log regional GDP per capita. The estimated elasticity is 0.17 (standard error 0.049). Our estimates are close, but a bit smaller, than cross-country estimates reported in Henderson et al. (2012) and Hodler and Raschky (2014). The former find 0.307 for changes in log GDP per capita and log of average lights, and 0.327 for long differences; whereas the latter find 0.386 for regressions using a cross-section of subnational regions, and 0.227 for long differences.

Figure B1: OLS estimates of regional NTL and GDP per capita (HNTL, 1996–2018, all of Russia).

(a) Pooled (b) Long Differences



Notes: Relation between log of regional GDP per capita and log of average nighttime light intensity as in Hodler and Raschky (2014). Panel (a) shows the log-log best linear fit (all years and regions pooled), net of year fixed effects. Panel (b) depicts the long difference in the log of average nighttime lights and the log of regional GDP per capita. Lights intensity is a weighted average of the cells in a region, with weights being the share of a grid cell's size in the region's area (see Henderson et al. (2012) for details). As in Henderson et al. (2012), we exclude cells in the polar circle above 66 degrees of latitude. In the long-run estimates, observations are averaged for the last two years 2017-2018 and for the first two years 1996-1997.

Nighttime lights and municipal employment (wages). We estimate the cross-sectional relation between municipal employment (wages) and nighttime lights.[8] We restrict our sample to municipalities up to 300km from the border. We first compute the average 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 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 average of municipal nighttime lights. We provide separate estimates for total employment and wages for all sectors, for services only, and for manufacturing only.[9]

The results for employment and wages are presented in panels (1) and (2) of Figure B2. As can be seen, the log of nighttime lights explains 38% of the variation in log employment and 32% of the variation in log wages, respectively. The estimated elasticities range from 0.58 to 1.31 for employment and from 0.1 to 0.18 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 B3 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.

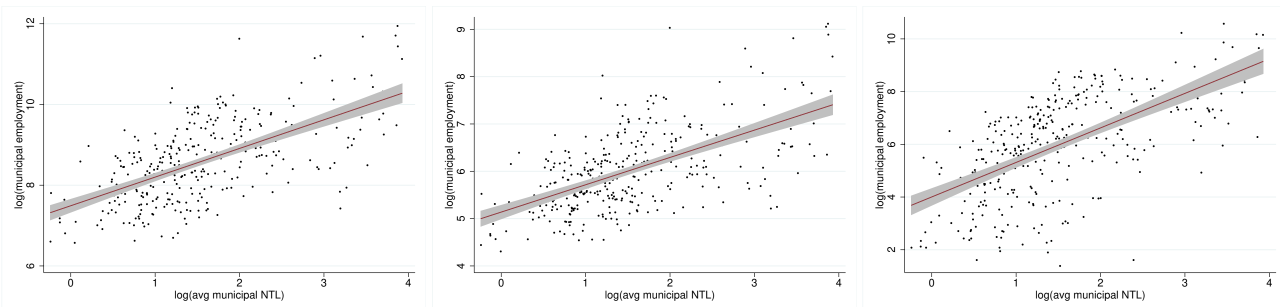
[8] Employment and wages are from Goskomstat's Municipal Database collected by the INID project (`https://data-in.ru/data-catalog/datasets/115/`). Wage is the average monthly wage, computed by dividing the monthly total payroll by the average number of employees and multiplied by the number of months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

[9] 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.

Figure B2: OLS cross-section estimates of municipal NTL and employment or wage levels (HNTL, 2010–2013, 300km buffer).

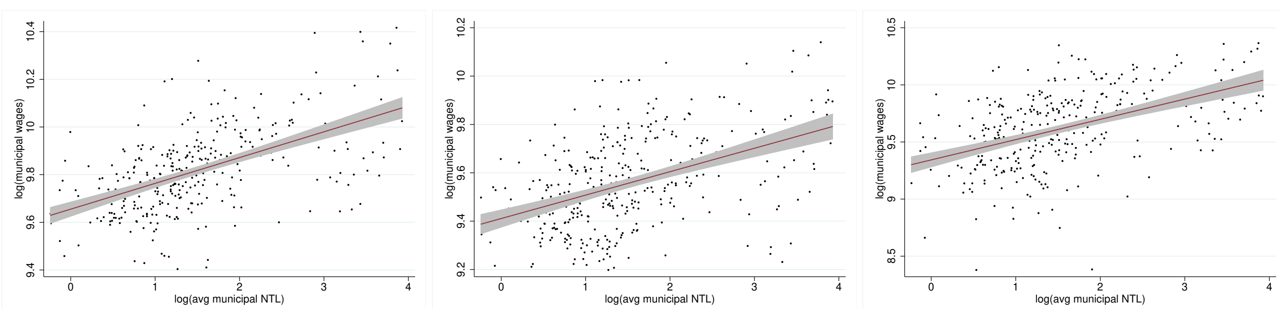
(1) Relation between municipal NTL and employment levels

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



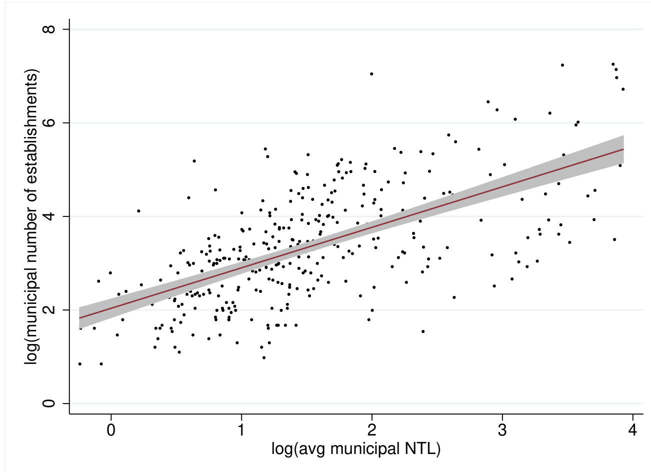
(2) Relation between municipal NTL and wage levels

(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. HNTL nighttime lights are averaged at the municipal level. 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 0.71 (standard error 0.05) and the adjusted R^2 is 0.4. In panel (1b) the slope is 0.58 (standard error 0.05) and the adjusted R^2 is 0.36. In panel (1c) the slope is 1.31 (standard error 0.08) and the adjusted R^2 is 0.38. In panel (2a) the slope is 0.11 (standard error 0.01) and the adjusted R^2 is 0.32. In panel (2b) the slope is 0.1 (standard error 0.01) and the adjusted R^2 is 0.2. In panel (2c) the slope is 0.18 (standard error 0.016) and the adjusted R^2 is 0.24.

Figure B3: Municipal NTL and number of manufacturing establishments (HNTL, 2010–2013, 300 kilometers 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 0.86 (standard error 0.06) and the adjusted R^2 is 0.41.

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.[10] 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

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

Service that covers all postal offices in Russia.[11].

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.[12] 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 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.

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.

[11]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.

[12]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.

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.

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.

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 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.[13]

[13]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;

Appendix C Robustness checks

We run a large number of robustness checks which we succinctly summarize here.

Robustness checks from Section 4.3. First, instead of using the relative distance to the borders—conditional on overall distance to the border—we estimate specification (11) 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.

Second, we re-estimate Table 1 using raw nighttime lights as the dependent variable instead of cell-level GDP. Table C.3 shows the results. They are qualitatively similar to those using cell-level GDP, although some coefficients are smaller in magnitude. This suggests the cell-level GDP provides a better measure of economic activity than raw NTL, i.e., weighting by regional GDP matters.

Third, we re-estimate Tables 1 and C.3 including all cells up to 500 kilometers from the border. The results are again robust. We further checked using both the raw NTL and cell-level GDP 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

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.

Table C.3: 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 using cell-level GDP (4)).

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.[14]

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 C.3 taking 2012–2018 as our post-treatment period. The results in Tables C.4 and C.5 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.

Concerning 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 information from the VIIRS NTL data to compute a measure of exposure to market poten-

[14]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.

Table C.4: 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 $\ln(\text{HNTL}_i + 1)$. 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 cell-level GDP (4)).

Table C.5: Changes in cell-level GDP 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 $\ln(\text{GDP} - \text{HNTL}_i + 1)$. All regressions include cell and year fixed effects. Standard errors are clustered at the cell level. band is a dummy with value one if 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.

tial 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.[15] Tables C.6 and C.7 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.

Table C.6: 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 p 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.

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

Table C.7: 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 p 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 for plants.

Table C.8: Plant exit, before and after 2014, industry-year fixed effects. Top exit statuses.

	(1) distance band	(2) distance band	(3) LMP Ukr	(4) GMP Ukr	(5) GC	(6) ND	(7) LAT	(8) LAT bands
band	-0.000							
	(0.001)							
post2014 x band	-0.002^{c}							
	(0.001)							
band(positive)		0.007^{a}						
		(0.002)						
band(negative)		-0.001						
		(0.001)						
post2014 x band(positive)		-0.017^{a}						
		(0.003)						
post2014 x band(negative)		-0.000						
		(0.001)						
ln min dist border			-0.006^{a}	-0.006^{a}	0.001	-0.001	0.000	0.003^{a}
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
post2014 x ln min dist border			0.014^{a}	0.011^{a}	0.005^{a}	0.002^{a}	0.000	-0.003^{a}
			(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Lat(Donbas)								0.012^{a}
								(0.002)
Lat(North)								0.004^{b}
								(0.002)
post2014 x Lat(Donbas)								-0.016^{a}
								(0.002)
post2014 x Lat(North)								0.010^{a}
								(0.002)
exposure			-0.006^{a}	-0.005^{a}	0.001	-0.001^{a}	0.000^{b}	
			(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	
post2014 x exposure			0.013^{a}	0.010^{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	502,780	502,780	502,780	502,780	502,780	502,780	502,780	502,780
R-squared	0.050	0.051	0.051	0.051	0.051	0.051	0.051	0.051

Notes: The dependent variable is a dummy with value 1 if plant p 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 lights-weighted GDP, (4)). Standard errors are clustered at the plant level.

Table C.9: Plant exit, within-plant variation, before and after 2014. Top exit statuses.

	(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]	0.087[a]	0.190[a]	0.203[a]	0.255[a]	0.278[a]	0.266[a]
	(0.003)	(0.003)	(0.029)	(0.027)	(0.008)	(0.006)	(0.006)	(0.007)
post2014 x band	-0.009[a]							
	(0.002)							
post2014 x band(positive)		-0.028[a]						
		(0.004)						
post2014 x band(negative)		-0.007[a]						
		(0.002)						
post2014 x ln min dist border			0.016[a]	0.010[a]	0.015[a]	0.007[a]	0.003[a]	0.002[c]
			(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
post2014 x Lat(Donbas)								-0.001
								(0.003)
post2014 x Lat(North)								0.029[a]
								(0.002)
post2014 x exposure			0.012[a]	0.006[a]	0.013[a]	0.006[a]	0.003[a]	
			(0.002)	(0.002)	(0.001)	(0.000)	(0.000)	
Plant controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	498,814	498,814	498,814	498,814	498,814	498,814	498,814	498,814
R-squared	0.223	0.223	0.223	0.223	0.223	0.223	0.223	0.223

Notes: The dependent variable is a dummy with value 1 if plant p 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 lights-weighted GDP, (4)). Standard errors are clustered at the plant level.

We also run a set of robustness checks for exit regressions, where we include only the exit categories that we believe represent 'true exit'. Tables C.8–C.9 summarize our results and show that our coefficients of interest are unaffected by dropping the 10% of firms for which the exit status may be related to reasons that do not really correspond to exit in the sense of 'no more operations' or 'liquidation or bankruptcy' (e.g., exit through accession or mergers). To further strengthen our confidence that we capture 'true exit', we provide correlation of exit with employment changes. We do not have very detailed employment figures, but we can show that plant exit at the level of municipal districts (municipalities) is negatively correlated with total manufacturing employment changes in municipal districts. The correlation between the change between $t-1$ and t of the log of one plus total manufacturing employment and the change between $t-1$ and t of the log of one plus the number of exiting plants is about -0.05 (significant at the 1% level). A simple log-log regression of the exit on the change of log total manufacturing employment, including year dummies, yields an estimate of -0.03 (Huber-White robust standard error of 0.0128, and R-squared of 0.02, significant at the 5% level). Thus, there is a negative and significant (albeit relatively weak) correlation between manufacturing plant exit and changes in aggregate manufacturing employment at the municipality level in our data. This effect does not change if we control for the entry of new plants as the latter variable is insignificant in our regressions.

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.

Robustness checks from Section 6.2. We examine the sensitivity of our nighttime lights estimates to changes in the distance threshold and the set of local border crossings.

Table C.10: 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, ((A.4)); NDW = network distance weighted by border point settlements' NTL ((A.4))).

Table C.10 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 C.11 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.

Table C.11: 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, ((A.4)); NDW = network distance weighted by border point settlements' NTL ((A.4))). Standard errors are clustered at the plant level.

Appendix D Results for the role of market accss

This appendix contains additional results for Section 5. In particular, we provide regression results for the effects of sanctions and the 2014 Winter Olympic Games in Sochi.

Table D.12: Changes in cell-level GDP before and after 2014 (exposure to sanctions).

	(1) distance band	(2) distance band	(3) LMP Ukr	(4) GMP Ukr	(5) GC	(6) LAT	(7) LAT bands
post2014	0.832^a	0.847^a	1.636^a	1.270^a	1.701^a	0.462^a	0.814^a
	(0.004)	(0.004)	(0.033)	(0.030)	(0.013)	(0.006)	(0.007)
post2014 x band	-0.120^a						
	(0.002)						
post2014 x band(positive)		0.424^a					
		(0.007)					
post2014 x band(negative)		-0.167^a					
		(0.002)					
post2014 x ln min dist border			0.008^a	0.024^a	-0.118^a	0.076^a	0.044^a
			(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
post2014 x Lat(Donbas)							-0.338^a
							(0.004)
post2014 x Lat(North)							-0.237^a
							(0.003)
post2014 x exposure			-0.085^a	-0.064^a	-0.208^a	-0.029^a	
			(0.002)	(0.002)	(0.002)	(0.000)	
post2014 x ln mun exposure to sanctions	0.008^a	0.007^a	0.008^a	0.008^a	0.004^a	0.005^a	0.005^a
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(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	0.677	0.677

Notes: OLS estimation of (10). 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 cell-level GDP (4)). All specifications include log of three-year average of municipal exposure to sanctions before 2014.

Table D.13: Plant exit before and after 2014, industry-year fixed effects (exposure to sanctions).

	(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 min dist border			-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 min dist border			0.015[a]	0.012[a]	0.005[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[c]	-0.001[a]	0.000	
			(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	
post2014 x exposure			0.014[a]	0.011[a]	0.005[a]	0.003[a]	0.001[a]	
			(0.002)	(0.002)	(0.001)	(0.000)	(0.000)	
ln mun exposure to sanctions	-0.000	-0.000	-0.000[c]	-0.000[c]	-0.000	-0.000	-0.000[c]	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
post2014 x ln mun exposure to sanctions	0.000	0.000	0.000	0.000	-0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(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 p 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 cell-level GDP (4)). Standard errors are clustered at the plant level. All specifications include log of three-year average of municipal exposure to sanctions before 2014.

Table D.14: Plant exit, within-plant variation, before and after 2014 (exposure to sanctions).

	(1) distance band	(2) distance band	(3) LMP Ukr	(4) GMP Ukr	(5) GC	(6) ND	(7) LAT	(8) LAT bands
post2014	0.306^a	0.304^a	0.077^b	0.175^a	0.226^a	0.272^a	0.297^a	0.279^a
	(0.008)	(0.008)	(0.032)	(0.030)	(0.011)	(0.010)	(0.010)	(0.011)
post2014 x band	-0.008^a							
	(0.002)							
post2014 x band(positive)		-0.029^a						
		(0.004)						
post2014 x band(negative)		-0.005^a						
		(0.002)						
post2014 x ln min dist border			0.017^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)	
post2014 x ln mun exposure to sanctions	-0.001	-0.001	-0.001	-0.001	-0.001^b	-0.001	-0.001^b	-0.001^b
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
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 p 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. $\ln \text{minDist}$ 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 lights-weighted GDP, (4)). Standard errors are clustered at the plant level. All specifications include log of three-year average of municipal exposure to sanctions before 2014.

Table D.15: Changes in cell-level GDP, before and after 2014 (exposure to Sochi, 100km).

	(1) distance band	(2) distance band	(3) LMP Ukr	(4) GMP Ukr	(5) GC	(6) LAT	(7) LAT bands
post2014	0.917^a	0.918^a	1.032^a	0.800^a	1.632^a	0.567^a	0.848^a
	(0.002)	(0.002)	(0.033)	(0.030)	(0.012)	(0.006)	(0.007)
post2014 x band	-0.090^a						
	(0.002)						
post2014 x band(positive)		0.460^a					
		(0.007)					
post2014 x band(negative)		-0.138^a					
		(0.002)					
post2014 x ln min dist border			0.038^a	0.049^a	-0.103^a	0.066^a	0.039^a
			(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
post2014 x Lat(Donbas)							-0.285^a
							(0.004)
post2014 x Lat(North)							-0.182^a
							(0.003)
post2014 x exposure			-0.032^a	-0.017^a	-0.182^a	-0.020^a	
			(0.002)	(0.002)	(0.002)	(0.000)	
post2014 x Sochi 0-50km	0.753^a	0.752^a	0.707^a	0.725^a	0.559^a	0.610^a	0.600^a
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
post2014 x Sochi 50-100km	0.998^a	0.997^a	0.967^a	0.981^a	0.798^a	0.869^a	0.848^a
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
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	0.677	0.679	0.677	0.677	0.679	0.678	0.678

Notes: The dependent variable is $\ln(\text{GDP} - \text{HNTL}_i + 1)$. All regressions include cell and year fixed effects. Standard errors are clustered at the cell level. band is a dummy with value one if 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. Sochi 0-50km distance band equals to one if the cell is less than 50 kilometers from Sochi city center, and zero otherwise. Other Sochi distance bands are constructed similarly.

Table D.16: Changes in cell-level GDP, before and after 2014 (exposure to Sochi, 150km).

	(1) distance band	(2) distance band	(3) LMP Ukr	(4) GMP Ukr	(5) GC	(6) LAT	(7) LAT bands
post2014	0.867[a]	0.869[a]	0.543[a]	0.522[a]	1.370[a]	0.634[a]	0.778[a]
	(0.002)	(0.002)	(0.033)	(0.030)	(0.012)	(0.006)	(0.007)
post2014 x band	-0.040[a]						
	(0.002)						
post2014 x band(positive)		0.497[a]					
		(0.007)					
post2014 x band(negative)		-0.089[a]					
		(0.002)					
post2014 x ln min dist border			0.049[a]	0.051[a]	-0.069[a]	0.046[a]	0.031[a]
			(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
post2014 x Lat(Donbas)							-0.181[a]
							(0.004)
post2014 x Lat(North)							-0.073[a]
							(0.003)
post2014 x exposure			0.007[a]	0.009[a]	-0.128[a]	-0.003[a]	
			(0.002)	(0.002)	(0.002)	(0.000)	
post2014 x Sochi 0-50km	0.803[a]	0.801[a]	0.789[a]	0.790[a]	0.648[a]	0.759[a]	0.716[a]
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
post2014 x Sochi 50-100km	1.047[a]	1.046[a]	1.036[a]	1.036[a]	0.888[a]	1.009[a]	0.964[a]
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
post2014 x Sochi 100-150km	1.141[a]	1.133[a]	1.133[a]	1.132[a]	0.975[a]	1.110[a]	1.061[a]
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
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	0.681	0.682	0.681	0.681	0.682	0.681	0.681

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. Sochi 0-50km distance band equals to one if the cell is less than 50 kilometers from Sochi city center, and zero otherwise. Other Sochi distance bands are constructed similarly.

Table D.17: Plant exit, before and after 2014, industry-year fixed effects (exposure to Sochi).

	(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	-0.003^{b}							
	(0.001)							
band(positive)		0.005^{b}						
		(0.002)						
band(negative)		0.000						
		(0.001)						
post2014 x band(positive)		-0.018^{a}						
		(0.003)						
post2014 x band(negative)		-0.001						
		(0.002)						
ln min dist border			-0.007^{a}	-0.006^{a}	0.001	-0.001	-0.000	0.003^{a}
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
post2014 x ln min dist border			0.017^{a}	0.014^{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^{c}
								(0.002)
post2014 x Lat(Donbas)								-0.015^{a}
								(0.002)
post2014 x Lat(North)								0.008^{a}
								(0.002)
exposure			-0.006^{a}	-0.006^{a}	0.001	-0.001^{a}	0.000	
			(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	
post2014 x exposure			0.016^{a}	0.013^{a}	0.004^{a}	0.004^{a}	0.001^{a}	
			(0.002)	(0.002)	(0.001)	(0.000)	(0.000)	
Sochi 0-50km	-0.001	-0.001	-0.007^{b}	-0.006^{c}	-0.003	-0.008^{b}	-0.002	-0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Sochi 50-100km	0.001	0.001	-0.003	-0.002	-0.000	-0.004	-0.000	0.001
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Sochi 100-150km	0.003	0.003	0.001	0.002	0.002	0.001	0.003	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
post2014 x Sochi 0-50km	0.012^{b}	0.012^{b}	0.030^{a}	0.025^{a}	0.016^{a}	0.031^{a}	0.020^{a}	0.018^{a}
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
post2014 x Sochi 50-100km	-0.015^{c}	-0.015^{c}	-0.005	-0.008	-0.010	-0.002	-0.008	-0.009
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
post2014 x Sochi 100-150km	-0.026^{a}	-0.026^{a}	-0.019^{a}	-0.022^{a}	-0.021^{a}	-0.019^{a}	-0.019^{a}	-0.020^{a}
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
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	0.047	0.046	0.046	0.046	0.046	0.047

Notes: The dependent variable is a dummy with value 1 if plant p 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 cell-level GDP (4)). Standard errors are clustered at the plant level. Sochi 0-50km distance band equals to one if the cell is less than 50 kilometers from Sochi city center, and zero otherwise. Other Sochi distance bands are constructed similarly.

Table D.18: Plant exit, within-plant variation, before and after 2014 (exposure to Sochi).

	(1) distance band	(2) distance band	(3) LMP Ukr	(4) GMP Ukr	(5) GC	(6) ND	(7) LAT	(8) LAT bands
post2014	0.296^a	0.296^a	0.059^c	0.163^a	0.210^a	0.258^a	0.279^a	0.264^a
	(0.003)	(0.003)	(0.032)	(0.030)	(0.008)	(0.007)	(0.006)	(0.008)
post2014 x band	-0.011^a							
	(0.002)							
post2014 x band(positive)		-0.032^a						
		(0.004)						
post2014 x band(negative)		-0.007^a						
		(0.002)						
post2014 x ln min dist border			0.018^a	0.012^a	0.014^a	0.007^a	0.003^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			0.014^a	0.007^a	0.011^a	0.006^a	0.003^a	
			(0.002)	(0.002)	(0.001)	(0.001)	(0.000)	
post2014 x Sochi 0-50km	-0.000	-0.000	0.016^b	0.008	0.010	0.031^a	0.019^a	0.016^b
	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
post2014 x Sochi 50-100km	-0.030^a	-0.029^a	-0.020^b	-0.024^a	-0.017^c	-0.009	-0.012	-0.013
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
post2014 x Sochi 100-150km	-0.037^a	-0.037^a	-0.031^a	-0.034^a	-0.027^a	-0.027^a	-0.020^a	-0.020^a
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
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 p 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 lights-weighted GDP, (4)). Standard errors are clustered at the plant level. Sochi 0-50km distance band equals to one if the cell is less than 50 kilometers from Sochi city center, and zero otherwise. Other Sochi distance bands are constructed similarly.

Appendix E 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 the northern region of Kaluga, the regions bordering Donbass—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 E.1 and Figure E1 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). Furthermore, Figure 8 shows that there was very little change in firms' evaluation of the business climate in 2011–2012 that could

Table E.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.

have explained why there would be suddenly massive exit. 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.

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 Decem-

Figure E1: 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.

ber 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 F 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.[16] We keep only major cargo-passenger roads with highway keys: primary, secondary, tertiary, motorway and trunk.[17]

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.[18] For each cell we compute the number of lines from the road layer that intersect the cell and convert it to a binary variable with value 1 if there is at least one road that crosses the cell, and zero otherwise.

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

[17] 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.

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

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 G 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.[19] 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.

[19] 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.[20]

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

[20] 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.[21] 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.[22]

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

[22]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.[23] 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.[24]

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.

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

[24]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.[25]

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

[25] 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 G.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

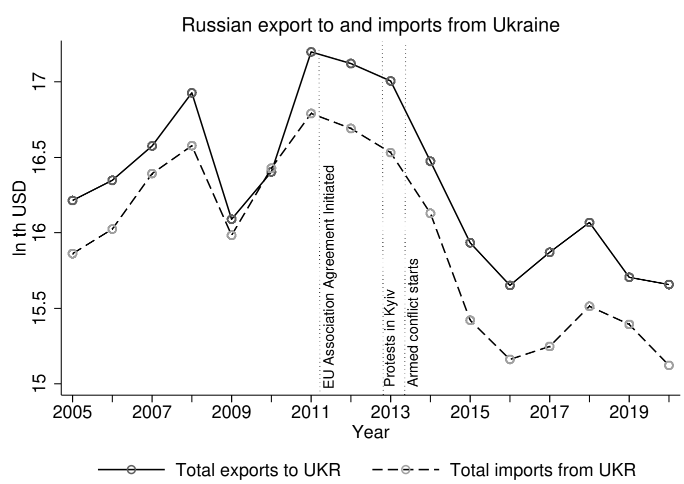
Notes: Mean, variance, and coefficient of variation for the change in the distance to the nearest open border crossing post 2015. We show results separately for the different distance measures (great circle, GC; and network distance, ND), the type of border points (equipped vs all), and according to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

Table G.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 H 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.[26] Figure H1 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 H1: 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

[26]All figures from the UN Comtrade Statistics available at `https://comtrade.un.org/`. The fall in trade between Ukraine and Russia is also linked to increasing import substitution policies that started before the annexation (e.g., Ukrainian locomotive production fell by 47% in 2013 in the wake of the tensions around the EU accession agreement; see Zhukov 2016).

measures of trade intensity with Ukraine.[27] Formally, in the first step we estimate:

$$y_{p(s),t} = \beta_0 + \beta_1 \ln \text{minDist}_p + \beta_2 \ln \exp_p + \mathbf{X}_{p,t}\gamma + \alpha_{s,t} + \varepsilon_{p,t}, \tag{H.1}$$

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

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

where $\widehat{\alpha}_{s,t}$ are the estimated industry-year fixed effects from (H.1); tradeShareVA$_s$ is our measure of industry-level trade exposure; and δ_t are year fixed effects.[28] 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 (H.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 H.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 (H.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 lights-weighted GDP, (4)). Standard errors are clustered at the industry level.

[27] 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.

[28] 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 H.1 shows the results of the second step (H.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.[29]

Table H.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:

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

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.[30]

[29]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.

[30]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 H.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 (H.3). Standard errors are clustered at the municipal district level.

We estimate the following model:

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

where $y_{i,t}$ is either the raw or the lights-weighted GDP of cell i in year t. Table H.2 shows our estimates of (H.4) using municipal exposure (H.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 H.3 shows our estimates of (11) 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 H.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 p exits in year t, and 0 otherwise. Municipal exposure is measured as in (H.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 H.1 and H.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.