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# ABSTRACT

## The True Cost of War*

Measuring the economic impact of a war is a daunting task. Common indicators like casualties, infrastructure damages, and gross domestic product effects provide useful benchmarks, but they fail to capture the complex welfare effects of wars. This paper proposes a new method to estimate the welfare impact of conflicts and remedy common data constraints in conflict-affected environments. The method first estimates how agents regard spatial welfare differentials by voting with their feet, using pre-conflict data. Then, it infers a lower-bound estimate for the conflict-driven welfare shock from partially observed post-conflict migration patterns. A case study of the conflict in Eastern Ukraine between 2014 and 2019 shows a large lower-bound welfare loss for Donetsk residents equivalent to between 7.3 and 24.8 percent of life-time income depending on agents' time preferences.

**JEL Classification:** D74, J61, I131

**Keywords:** conflict, revealed-preferences, internally displaced people

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# 1 Introduction

Wars have complex economic and social consequences. Conflict-driven deaths, physical destruction, and economic disorganization levy unambiguously heavy tolls on societies. However, accounting for the whole burden of wars on human well-being is challenging. On the one hand, it is generally difficult to measure how the intangible fallout of wars, including institutional degradation, erosion of social trust, and eruption of psycho-social trauma, can affect economies over time. On the other, even otherwise measurable factors, including common economic indicators like prices, employment, and trade, may not be recorded accurately in times of conflict, rendering a systematic assessment difficult. With these challenges, economic impact assessments of wars often reflect only a subset of the broad and persistent misery engendered by large-scale human violence.

To better account for the complex welfare impacts of wars, this paper proposes an alternative approach that relies on a general and flexible migration model, where economic agents choose between regions with different characteristics. The model is estimated using gross bilateral migration patterns before the onset of the conflict. This helps first to establish how economic agents regard spatial welfare differentials by voting with their feet. Next, the estimated model is used to infer the magnitude of the conflict-driven welfare shocks from partially-observed migration patterns after the onset of the conflict. Thus, an increase in migration outflows, together with the estimated responsiveness of agents to welfare differentials across regions, yield a measure of how economic agents perceive the conflict-driven welfare shock.

This approach has several desirable properties. First, it relies on the revealed preferences of economic agents to account for what matters in assessing the welfare impact of wars. A preference-based welfare concept better captures the intangible consequences of wars (e.g., cultural effects or trauma from physical and sexual violence) as it covers both pecuniary and non-pecuniary factors affecting individual well-being. Second, because the analyst abstains from specifying the composition of welfare–thus, effectively delegating the model selection problem largely to economic agents themselves, data constraints are significantly relaxed in our approach. Collecting and publishing reliable data is especially difficult during a war. As purportedly coined by the US Senator Hiram Warren Johnson in 1918, “the first casualty when war comes is truth”. While many socioeconomic indicators suffer from this problem during war, our approach relies on migration away from conflict, which is typically well-recorded by humanitarian organizations for coordinating assistance. Importantly, our method only requires data from a subset of potential migration destinations, not all of them. It is possible to omit some destinations, international or local, to overcome data collection issues or other empirical problems. Overall, the ability to ease a pervasive model-selection problem and circumvent potentially prohibitive data constraints help to achieve a more complete inference about the welfare impact of wars.

To show these points formally, we first set up a general discrete choice framework with random utility, where agents choose among a finite number of locations. This decision is guided by (i) location-specific fixed utility common to all agents in a given location, (ii) an individual-specific utility for each location, and (iii) bilateral mobility costs associated with migration. For generality, the framework remains agnostic about the components of location-specific fixed utility, which can include wages, local amenities and, potentially, expected future utility, among others. We do not impose any strong assumptions on whether the people are myopic or forward-looking, how much they discount the future outcomes, or how they form their expectations about the future after conflict. Then, we derive a sufficient statistic equation and mark the lower-bound estimates for the welfare impact of a war.

To estimate the main parameters of the model, we consider a case study: the conflict in Eastern Ukraine (i.e., the Donbas Region, covering Donetsk and Luhansk oblasts) between 2014 and 2019[1]. Specifically, we estimate the inter-region migration elasticity parameter using flows among Ukrainian regions prior to the conflict in 2014. This estimate is then used to back out the welfare impact of the war in Donbas as revealed by the flows of about 1.4 million internally displaced people (IDPs) after 2014. Our data includes yearly regional statistics and bilateral gross migration flows from the State Statistic Services (UkrStat) for 2008-2012 and IDP numbers from the Ukrainian Ministry of Social Policy for 2014-2019.

Our empirical analysis yields a migration elasticity parameter between 0.46 and 0.68 depending on the agents' risk aversion and time preferences. Using these estimates and an inversion equation, we then map moving probabilities onto welfare, and compute the welfare shocks implied by the post-conflict migration outflows from Eastern Ukraine. Finally, following the literature, we compute the equivalent income losses implied by these welfare shocks. Specifically, we answer the following question: what would be the rate of income loss that makes an average individual equally worse off as the conflict? Our estimates for Donetsk oblast show a 7.3 to 24.8 percent equivalent life-time income loss, depending on time preferences, vis-a-vis the average pre-conflict income when agents are risk neutral. This range is equivalent to 27.7 to 38.1 percent income-loss for a duration of 10 years. The magnitude of welfare loss is similar for the Luhansk oblast. These estimates are driven by the (ex ante) perceived welfare shocks by economic agents, which trigger migration decisions, and they should be interpreted as the lower bounds of the welfare impact. When conflicts affect welfare in non-conflict areas significantly or boost mortality significantly,[2] thereby distorting migration numbers, the actual impact can be larger. We also discuss possible caveats to our analysis and provide several robustness tests, including inter alia the possibility of transit migration from recorded destinations (a potential threat to the identification assumption) and the presence of unobserved heterogeneity at the source (a possible bias in welfare calculations if some groups are less likely to migrate). Our results hold for a wide array of robustness tests.

To our knowledge, this paper is the first to estimate the economic impact of war by using preference-based approaches inferred from migration patterns. There is a large and growing body of research focusing on the economic and social impact of wars.[3] This includes a strand that uses synthetic control methods to estimate the GDP impact of war, starting with Abadie and Gardeazabal, 2003.[4] There is also a diverse body of research that uses

[1]Note that the data used in this paper covers a period before the war in 2022, which was not foreseen at the time of the analysis.

[2]Onder et al., 2019 discuss the conditions for analyzing the income equivalent of the mortality driven decreases in statistical life spans, with an application to the Syrian conflict.

[3]For an excellent review of the economic causes and consequences of wars, see Blattman and Miguel, 2010, and for a comprehensive review of recent advances in understanding the long term implications of exposure to war on human behavior, with an emphasis on cooperative social behavior, see Bauer et al., 2016.

[4]For an overview of this approach, including the conditions shaping its feasibility, see Abadie, 2021.

various methods of inference to measure conflict-driven impact on health and experienced well-being (Clark et al., 2020 and Bendavid et al., 2021), on macroeconomic indicators like GDP, investments, and fiscal flows (Edwards, 2014, and Auray and Eyquem, 2019), and on international trade flows (Glick and Taylor, 2010). Among the latter group, Korovkin and Makarin, 2019 estimate the impact of the conflict in Eastern Ukraine on Ukrainian firms' trade with the Russian Federation between 2013 and 2016 by exploiting the spatial variation of pre-conflict Russian-speaking population as a proxy in a difference-in-difference setting. Unlike our approach, however, these studies limit attention to a subset of welfare components – often pecuniary ones only. In the international trade literature, Artuç et al., 2010 estimate the welfare generated by mobility using labor flows, and Arkolakis et al., 2012 calculate income gains from trade using trade flows. Two other recent examples of similar approaches are Caliendo et al., 2019 and Kleinman et al., 2023. These studies also use inversion equations either to directly back-out welfare or to solve the optimization problem of agents. Different from them, our method is implemented using partially observed outflow data, instead of stayer data, which may be unobserved or unreliable in conflict environments.

This paper proceeds as follows. Section 2 lays out a general and stylized discrete-choice framework for the welfare impact analysis. Section 3 introduces the Eastern Ukraine case study. Section 4 presents the estimates for migration elasticities, welfare implications, and the equivalent income shock from the conflict. Section 5 discusses the key findings and caveats. The last section concludes.

# 2 Model

Consider an economy with $K$ locations. In this economy, agents can choose new locations in every period based on their preferences. For an agent $i$ located in location $k$, the total utility associated with moving to location $l$ at time $t$ can be expressed as $U_t^l - C_t^{kl} + z_t^{i,l}$, where $U_t^l$ is a location-specific utility for all agents in $l$, $C_t^{kl}$ is the cost of moving, which is equal to zero for stayers, and $z_t^{i,l}$ is a random utility associated with location $l$ specific to agent $i$. Agents are homogeneous except for the random utility shock. Individuals choose the utility maximizing location $l^*$ such that

$$l^* = \arg\max_l \left( U_t^l - C_t^{kl} + z_t^{i,l} \right).$$

We assume that location-specific utility, $U_t^k$, is represented with the function $U_t^k = U^k(.)$, which is strictly monotonic, continuous, and at least twice differentiable in its arguments, where $U^k : \mathbb{R}^n \to \mathbb{R}$. We are agnostic about the arguments of $U^k(.)$, which can include wages, a scalar measure of local amenities, and, possibly, expected future utility. After a shock, like a conflict, agents can establish expectations about the future or they might be myopic. That is, they can make decisions using only the outcomes of a given period in a static environment or consider a stream of future outcomes and their present discounted values in a dynamic environment. Therefore, we do not impose a dynamic or static structure on the location-specific utility or any strong assumptions about the risk perception of agents–they can be risk-neutral or risk-averse. We consider alternative specifications for $U^k(.)$ in the estimation section.

While the agents share a common location-specific utility component, $U_t^k$, their total utility can vary due to individual-specific random shocks and origin-destination-specific moving costs. To calculate the expected utility, an agent in location $k$ must consider values from each potential decision from their optimization problem. Formally, the welfare, $W_t^k$, is defined as:

$$W_t^k \equiv E_z \max_l \left( U_t^l - C_t^{kl} + z_t^{i,l} \right),$$

where the expectation is taken over the random shocks before their realization. Following the literature, we assume that $z_t^{i,l}$ is drawn from a mean zero Gumbel distribution[5] with scale parameter $1/\theta$, we get a closed form solution for the expected total utility: $W_t^k = \frac{1}{\theta} \log \left[ \sum_l \exp \left( U_t^l - C^{kl} \right)^{\theta} \right]$, where $l \in \{1, 2, ..., K\}$. The expected total utility, $W_t^k$, also gives a measure of welfare in this framework. The distributional assumption ensures tractability of the optimization problem similar to a multinomial-logit model, and the expression for the moving probability from $k$ to $l$ becomes:

$$m_t^{kl} = \left( \frac{\exp \left( U_t^l - C_t^{kl} \right)}{\exp \left( W_t^k \right)} \right)^{\theta}, \tag{1}$$

where $0 < m_t^{kl} < 1$.

This equation will help us to map migration flows onto welfare under certain conditions even when such flows are only partially observed. We will refer to $\theta$ as the migration elasticity parameter, since it determines the mobility of agents in response to value differentials[6].

**Introducing conflict:** With the onset of the conflict, location-specific utilities change and some agents respond to this shock by relocating. Imagine that conflict occurs in some of the regions with varying intensities. Let us denote variables at an arbitrary reference time before the conflict as $m_0^{kl}$, $U_0^k$, $W_0^k$ and $C_0^{kl}$. We use $\Delta$ operator to denote change after the conflict such that $\Delta x_t = x_t - x_0$ for any variable $x_t$.

Thus, the flow equation (1) can be expressed as

$$\Delta \log m_t^{kl} = \theta \Delta U_t^l - \theta \Delta C_t^{kl} - \theta \Delta W_t^k. \tag{2}$$

After rearranging the terms, we get an expression for the expected welfare in $k$ as

$$\Delta W_t^k = \left( \Delta U_t^l - \Delta C_t^{kl} \right) - \frac{1}{\theta} \left( \Delta \log m_t^{kl} \right).$$

This expression implies that it is possible to back out expected welfare in $k$ using only (i) fixed utility in $l$ net of moving costs $\left( \Delta U_t^l - \Delta C_t^{kl} \right)$, (ii) change in log flows from $k$ to

[5]Note that the Gumbel distribution allows, without loss of generality, the derivation of a tractable analytical solution. It is also possible use a formulation with Frechet distribution, which is a special case of our model as we will explain in Section 4.2.

[6]Specifically, it is equal to $\theta = \left[ \partial (m_t^{kl}/m_t^{kl'}) / \partial (U_t^l - U_t^{l'}) \right] / \left[ m_t^{kl}/m_t^{kl'} \right]$ which can be interpreted as the migration semi-elasticity. More commonly, it is equal to migration elasticity when the utility function has a logarithmic form, or isomorphically when Frechet distribution is used, which is a specific case of our model.

any destination $l$, i.e. $\left(\Delta \log m_t^{kl}\right)$, and (iii) parameter $\theta$. We would not need any other information related to other destinations. Note that this result directly follows from the properties of the discrete choice optimization problem given the distributional assumptions, as the expected maximized total utility associated with choices, conditional on choosing them, are equalized. While it is empirically desirable to use as many destinations as possible, it is feasible and practical to omit some destinations when such flows are unobserved.[7] Hence, summing this expression over a subset of destinations, $\Phi$, after multiplying with arbitrary weights, $\phi_l$, yields a general expression for the welfare:

$$\Delta W_t^k = \sum_{l \in \Phi} \phi_l \left(\Delta U_t^l - \Delta C_t^{kl}\right) + \frac{1}{\theta} \sum_{l \in \Phi} \phi_l \left(-\Delta \log m_t^{kl}\right), \tag{3}$$

where $\phi_l \geq 0$ and $\sum_{l \in \Phi} \phi_l = 1$.

Equation (3) comprises two economically intuitive terms on the right hand side: The first term, $\sum_{l \in \Phi} \phi_l \left(\Delta U_t^l - \Delta C_t^{kl}\right)$, accounts for the average loss in regions in $\Phi$ (net of the changes in moving costs and weighted by $\phi_l$), and the second term, $\frac{1}{\theta} \sum_{l \in \Phi} \phi_l \left(-\Delta \log m_t^{kl}\right)$, accounts for the additional loss specific to location $k$. These two terms, together, represent the total change in fixed welfare associated with $k$. To map the observed changes in migration patterns onto changes in welfare, we need to restrict the first term (the change in utility net of moving costs) by assuming that it is non-positive, i.e., there exists a subset $\Phi$ of destinations and weights $\phi_l \geq 0$ for $l \in \Phi$ such that war does not increase the average weighted utility in $\Phi$ net of moving cost, thus $\sum_{l \in \Phi} \phi_l \Delta \left[U_t^l - C_t^{kl}\right] \leq 0$, where $k$ is a conflict location. Intuitively, this *"war does not increase net utility in all destinations"* assumption does not pose a strong restriction. After the war, all non-conflict destinations may become more attractive relatively as the conflict locations become less attractive in comparison. But, not all destinations should become more attractive in absolute terms compared to pre-war. In practice, we just need to use a non-empty but also non-exhaustive subset of destinations for which this assumption holds to utilize this equation to estimate a lower-bound for the impact of war.

We can now analyze the upper bounds of changes in welfare, i.e. the lower bound of a negative impact, by using information on post-conflict migration. The following proposition establishes this formally.

**Proposition 1** *The upper bound of change in welfare in conflict location $k$ (i.e., the lower bound of the welfare impact) can be expressed as*

$$\Delta W_t^k \leq \frac{1}{\theta} \sum_{l \in \Phi} \phi_l \left(-\Delta \log m_t^{kl}\right),$$

*if the condition $\sum_{l \in \Phi} \phi_l \Delta \left[U_t^l - C_t^{kl}\right] \leq 0$ holds, where $\phi_l \geq 0$ are weights for destinations such that $\sum_{l \in \Phi} \phi_l = 1$.*

Intuitively, this proposition suggests that the upper bound of expected welfare change can be calculated by using only the changes in flows of agents from conflict locations to a

[7] This convenient feature of our method gives an advantage over backing out utility using gravity regressions, such as Artuç and McLaren, 2015, when flows to some destinations are not observed.

subset of destinations, $m_t^{kl}$, and the migration elasticity parameter $\theta$. When expressed in logs, the upper bound of a utility change in a conflict location is proportional to the change in the probability of staying minus the probability of leaving. To characterize this, we do not need the flow data between non-conflict locations or inflows to conflict locations, which may not be captured in the absence of a humanitarian situation. However the number of internally displaced people, i.e. flows out of conflict regions, is often well documented by the international organizations to program assistance.

Note that the calculated welfare change in Proposition 1 is an upper bound rather than a precise point estimate because it is missing the term $\sum_{l\in\Phi} \phi_l \left(\Delta U_t^l - \Delta C_t^{kl}\right)$ from equation (3), which accounts for the average utility loss in all regions weighted by $\phi_l$, net of the changes in moving costs. As long as this term is non-positive, Proposition 1 will hold. Proof of the proposition and proofs of all other equations used in the model are available in Appendix A2. It is possible to extend the proposition to changes in location-specific utility $U_t^k$, which is provided in Appendix A3.

# 3 Case Study: The Conflict in Eastern Ukraine

In this section, we take our model to data, considering the conflict in Eastern Ukraine between 2014 and 2019. A few characteristics of this conflict make such an application feasible. First, migration patterns among Ukrainian regions were documented in detail before the conflict. Second, the conflict was regionally contained for the period covered in this analysis and the war in 2022 (3 years after the last data in our analysis) was not foreseen. Third, with a relatively low-intensity conflict, demographic mobility remained feasible throughout the period of analysis, with many people crossing the contact line routinely for daily needs. With these characteristics, we can implement the procedure developed in the previous section.

## 3.1 Background

Ukraine's Eastern regions have historically been home to the country's industrial core, including coal mining, metallurgy, and chemical industries. Before World War I, these regions produced more than three quarters of the pig iron and coal output of the Russian Empire. Under the Soviet industrialization programs, Donbas became the most heavily settled region of Ukraine, attracting people from elsewhere in Ukraine and from other parts of the union.[8]

After the collapse of the Soviet Union, however, the region's industrial infrastructure saw very limited modernization. To offset the eroding competitiveness, the industry was increasingly granted subsidies in key inputs like electricity, gas, and coal. Nonetheless, with dissipating favorable external conditions after the Global Financial Crisis in 2008, which include a slowing demand for steel and increasing modern production capacity in previous export markets of Ukraine, and as the subsidy component of energy inputs shrank after disputes with Russia, the challenges faced by the region's aging economy grew. By 2013, Donetsk and Luhansk still had relatively larger populations and economies than other regions. However, they were losing people to other parts of the country (net out-migration),

[8]For a detailed analysis of the social and economic conditions in Donbas before and after the onset of the conflict in 2014, see World Bank, 2021.

partially because of social challenges (i.e., high crime rates, alcoholism, and drug abuse) and environmental problems (pollution from mining and industry).

The onset of the conflict in 2014 changed the economic and demographic characteristics of these regions dramatically. Before the onset of the war in 2022, about 38 percent of the combined territories of Donetsk and Luhansk oblasts were outside the Ukrainian government's control (less than 4 percent of total Ukrainian land), which was demarcated by a 457 kilometer line of contact. This division imposed additional obstacles to economic activity, especially the provision and transportation of industry inputs and outputs like coal and steel. Despite the hostilities, however, migration was not prohibited. Ukrainians routinely crossed the contact line for family visits, shopping, and using ATMs for withdrawing pensions. Overall, there were about 1.4 million IDPs registered by the country's Ministry of Social Policy between 2014 and 2019, close to half of whom remained displaced within the territories of Donetsk and Luhansk oblasts, and the other moved elsewhere within Ukraine.

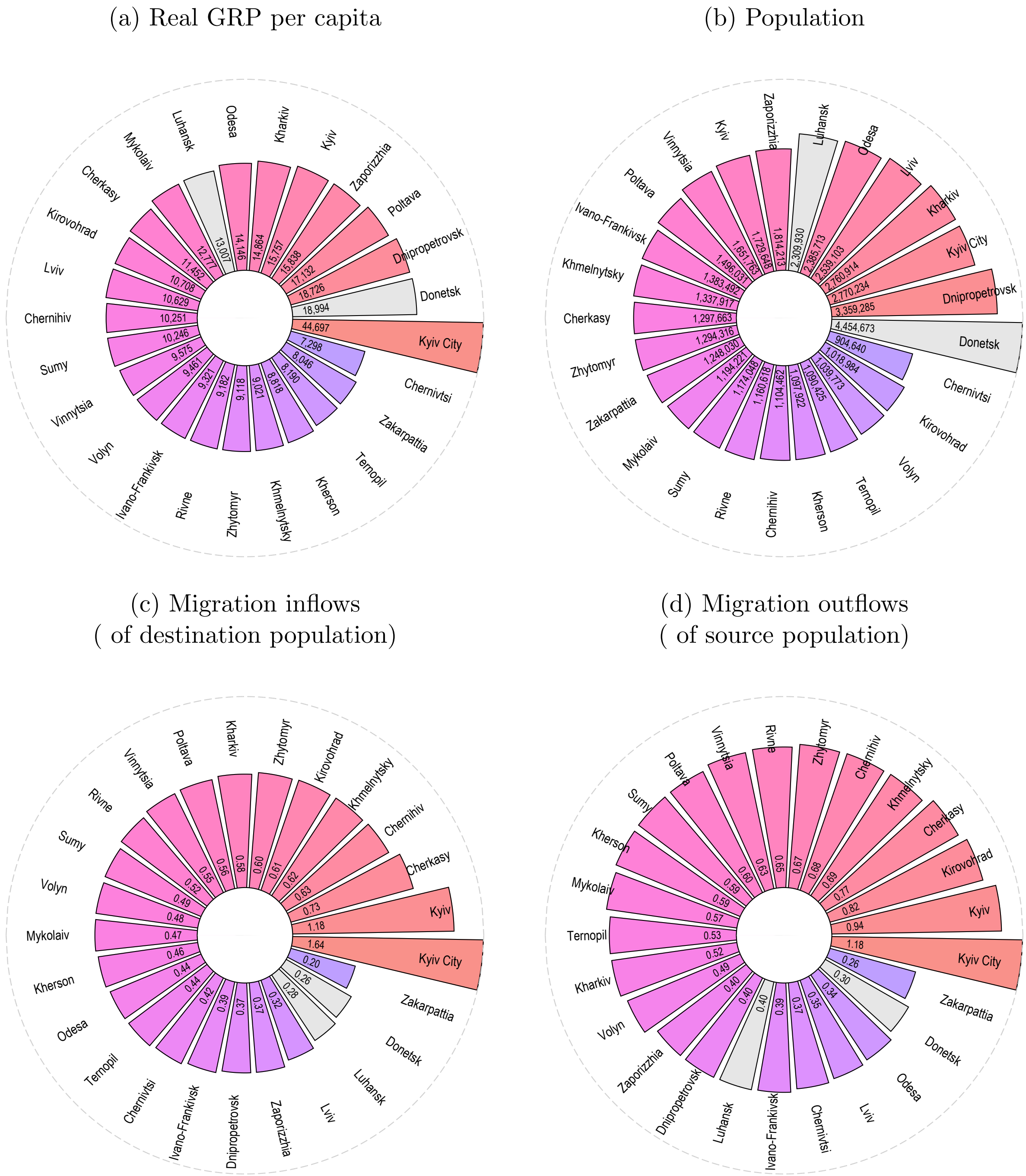
## 3.2 Data

Our analysis considers all 25 administrative regions (oblasts) in Ukraine, including Kyiv city as a special region. For the purposes of this paper, the pre-conflict period (2008-2012) is defined as the 5-year period before the Maidan protests in 2013, and the post-conflict period is between 2014 and 2019 (the last year of our data). All regional statistics for the pre-conflict period, including population and average per capita income numbers, are based on the official information gathered by the State Statistics Services of Ukraine (UkrStat). Our data also includes gross bilateral migration flows between oblasts for the same period, which were reported in UkrStat's demographic yearbooks. Information on these flows reflects the official registrations of residence recorded by the State Migration Service of Ukraine.

Descriptive statistics show that Donetsk and Luhansk regions were among the most populous oblasts in Ukraine before the onset of the conflict in 2014 (Figure 1b). With 4.5 million and 2.3 million residents, they were ranked 1st and 7th among all regions, respectively. They also had relatively high real gross regional product per capita (2nd and 9th, respectively). Compared to other regions, however, migration flows into Donbas were relatively small. Incoming migrants constituted only 0.26 percent of local population in Donetsk, and 0.28 percent in Luhansk, putting them among the least attractive regions (24th and 25th among all) for migrant arrivals (Figure 1c). Among the most important sources of migrants were neighboring regions. Donetsk, for example received 22.8 percent of all its inflows from Kharkiv, 20.7 percent from Luhansk, and 12.3 percent from Dnipropetrovsk.

Migration outflows from Donbas were also small. While the nation-wide interregional migration outflow rate stood at 0.56 percent of population annually, it was only 0.3 and 0.4 percent in Donetsk and Luhansk— the 2nd and the 7th lowest rates among all regions, respectively. Before the conflict, migrants leaving Donbas largely concentrated in neighboring regions and in Kyiv city. For example, of all migrants from Donetsk and Luhansk oblasts, on average, 31 percent went to Kharkiv every year, and 18 percent to Kyiv city (Figure 2). More distant or economically less attractive regions received fewer migrants from Donbas.

Figure 1: Regional statistics before conflict, 2008-12 annual averages




(a) Real GRP per capita

(b) Population

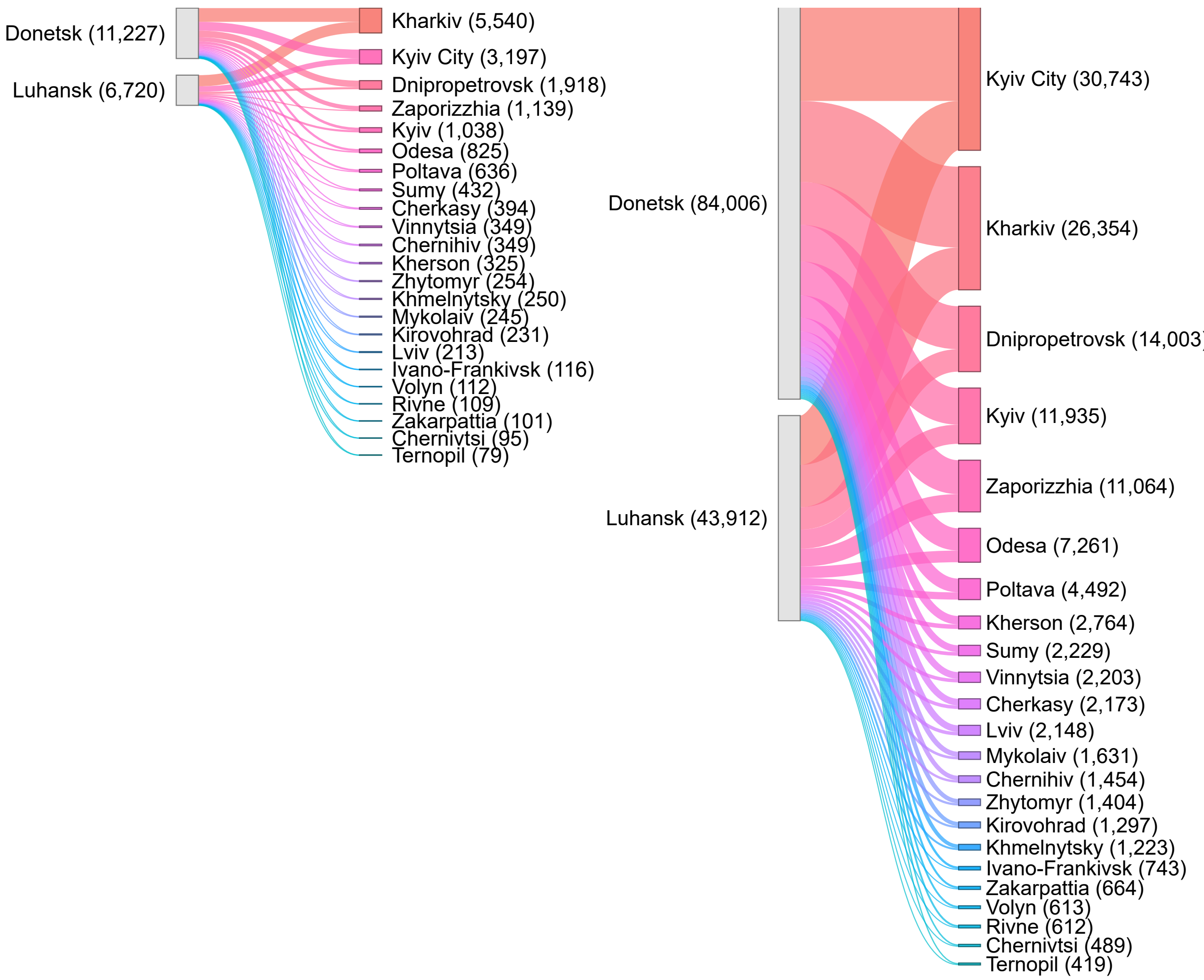
(c) Migration inflows
( of destination population)

(d) Migration outflows
( of source population)

*Notes:* Figures show annual averages by oblast for the pre–conflict period, 2008-2012, sorted in ascending order. Donetsk and Luhansk oblasts are represented in shades of gray, while other oblasts are shown by a range of colors transitioning from purple (lowest) to red (highest).

Figure 2: Migration outflows and forced displacement from Donbas, annual averages

(a) Pre-conflict migration outflows (2008-12) (b) IDP outflows after the conflict (2014-19)




*Notes:* Panel 2a shows gross migration outflows from Donetsk and Luhansk oblasts by destination (annual averages, 2008-2012). Panel 2b shows official IDP numbers (annualized, 2014-2019).

Like in other conflict situations, Ukraine faced major data constraints after the onset of the conflict. Most importantly, a complete record of the gross bilateral migration flows among Ukrainian regions is not available in the post-conflict period. Instead, we use information on the IDPs from Donbas as an indicator of the conflict-driven out-migration. By October 2019, the total number of officially registered IDPs were reported at 1,412,589 (21 percent of the combined population of Donetsk and Luhansk oblasts before the conflict). While 55 percent of all IDPs were registered in Donbas, the rest was registered elsewhere in Ukraine. This outflow exhibited a pattern similar to the pre-conflict migration outflows, occurring at a much larger scale (Figure 2–reporting annualized values). For IDPs fleeing the conflict in Donbas, Kyiv city (153,715), Kharkiv oblast (131,769), and Dnipropetrovsk oblast (70,012) were among the top destinations. However, other oblasts received IDPs from Donbas too.[9]

[9] Crimea is excluded from the analysis as Ukrainian sources ceased reporting data for it after 2014.

# 4 Quantification

Our theoretical results in Section 2 do not rely on the specific components of the utility function or any model parameters apart from the migration elasticity parameter $\theta$, which needs to be quantified. However, to estimate the migration elasticity parameter, we need to define the components of agents' utility functions and time preferences. This specification will then allow us to assess the size of the conflict-driven welfare loss in pecuniary terms.

## 4.1 Characterizing the utility function

In this subsection, we consider a structure for the utility function to estimate the migration elasticity parameter and map changes in welfare onto changes in income. To keep the analysis as general as possible, we adopt a flexible formulation for the location-specific utility $U_t^k$ to allow for different risk aversion and time discounting parameters.

Consider the following form for the location-specific utility:

$$U_t^k = \upsilon\left(w_t^k\right) + \eta^k + \beta E_t E_z \max_l \left(U_{t+1}^l - C_{t+1}^{kl} + z_{t+1}^{i,l}\right),$$

where the income component of the utility is $\upsilon\left(w_t^k\right) = \frac{\left(w_t^k\right)^{1-\sigma} - 1}{1-\sigma}$ and $w_t^k$ represents wages. The parameter $\eta^k$ is a location-specific, non-pecuniary, and non-random utility-shifter. The intertemporal discount factor is $\beta$, and the risk aversion parameter is $\sigma$. Therefore, the agents decide based on $w_t^k$, $\eta_t^k$ and the expected next period utility subject to the discount factor $\beta$.

This specification provides ample generality and covers common labor mobility models with homogeneous agents in the literature. For example, setting $\beta = 0$ makes the agents myopic and the model static. If we also set $\sigma = 1$, the flow equation becomes isomorphic to the characterization of trade flows by Eaton and Kortum, 2002, subject to a log-transformation. When we set $\beta > 0$ and assume risk-neutral agents, i.e. $\sigma = 0$, the model becomes isomorphic to Artuç et al., 2010, with a minor modification by adding the utility shifter $\eta^k$. It is important to note that this framework is agnostic about how workers form their expectations about the future, i.e. the structure of expectation operator $E_t$, and the components of the utility shifter $\eta^k$. We next turn to estimating the migration elasticity parameter using this specification.

## 4.2 Estimation

To estimate the migration elasticities in pre-conflict Ukraine, we follow the estimation strategy suggested by Artuç and McLaren, 2015. Equation (1) gives the number of people moving from region $k$ to region $l$. Multiplying this expression with the number of people located in $k$ in the previous period, we get

$$\log\left(m_t^{kl} L_{t-1}^k\right) = \theta U_t^l - \theta C_t^{kl} + \left(\log L_{t-1}^k - \theta W_t^k\right), \tag{4}$$

where $L_{t-1}^k$ is the number of people located in $k$ at $t-1$. This yields an equation that can be interpreted as a Poisson Pseudo Maximum Likelihood (PPML) regression equation:

$$y_t^{kl} = \exp\left[a_t^l + b_t^k + c_t \log \delta^{kl}\right] + \varepsilon_{1t}^{kl}, \tag{5}$$

where $y_t^{kl}$ is the number of people moving from $k$ to $l$, $\delta^{kl}$ is the distance between $k$ and $l$, $a_t^l$ is the destination fixed effect, $b_t^k$ is the origin fixed effect, $c_t$ is the time varying moving cost coefficient, and $\varepsilon_{1t}^{kl}$ is a sampling error. In this specification, each coefficient has a structural interpretation where $a_t^l = \theta U_t^l$, $b_t^k = -\theta W_t^k + \log L_{t-1}^k$ and $c_t \log \delta^{kl} = -\theta C_t^{kl}$.

Next, we estimate the migration elasticity parameter $\theta$ using the following regression equation:

$$\alpha_t^k = \theta \upsilon\left(w_t^k\right) + \gamma^k + \varepsilon_{2t}^k, \tag{6}$$

where $\alpha_t^k$ is constructed from first stage estimates such that $\alpha_t^k = a_t^k - \beta\left(-b_{t+1}^k + \log L_t^k\right)$. We consider various values for the time discount factor $\beta$ and the risk aversion parameter $\sigma$ of the function $\upsilon\left(w_t^k\right) = \frac{\left(w_t^k\right)^{1-\sigma}-1}{1-\sigma}$. The coefficient $\theta$, which is the inverse of the Gumbel scale parameter for the random utility shock $z_t^k$, can be interpreted as the migration elasticity. The coefficient $\gamma^k$ is a fixed effect and it can be interpreted as the location specific utility shifter mentioned in the model $\gamma^k = \theta\eta^k$. Finally, $\varepsilon_{2t}^k$ is the error term.

We use two period lagged wages as instruments in (6) following Artuç et al., 2010 and Artuç and McLaren, 2015. Table 1 shows the estimates for the migration elasticity parameter ($\theta$) under different time discount factors ($\beta$) and degrees of risk aversion ($\sigma$). Other things being equal, more patience (larger $\beta$) and a lower risk aversion (smaller $\sigma$) both increase the estimated migration elasticity. To see this, note that where a higher risk aversion is not the culprit behind the observed migration patterns, a higher migration elasticity should be. While $\theta$ is estimated at 0.458 with myopic ($\beta = 0$) and relatively risk averse ($\sigma = 1$) agents, it is estimated at 0.682 with relatively patient ($\beta = 0.97$) and risk neutral ($\sigma = 0$) agents. In one of the preferred specifications, where agents are risk averse and forward looking with $\beta = 0.90$, the implied income elasticity of emigration is 0.601, which means a 10 percent increase in income reduces emigration probability by 6.01 percent. Overall, this number which implies a Gumbel scale parameter equal to about 1.67, and our other estimates, are comparable with the previous estimates in the literature.

We next turn to estimating the welfare impact of the conflict. As discussed in the earlier proposition, an upper bound of the welfare changes due to the conflict, i.e., a lower bound of the welfare impact, can be backed out by using the estimated migration elasticities and the post-conflict migration outflow. We observe the flows from two conflict locations to 23 non-conflict locations between 2014 and 2019. For this exercise, we include all non-conflict locations as destinations and include only conflict locations as origins. We set weights proportional to initial flows, i.e. $\phi_l \propto m_0^{kl}$. Table 2 shows the results for Donetsk and Luhansk oblasts separately, using the common estimated migration elasticity parameter and oblast-specific IDP outflows. Note that factors that lead to a higher migration elasticity reduce the welfare impact as agents become more sensitive to shocks in a certain location and evade them by migrating elsewhere. Both a higher degree of risk aversion (greater $\sigma$) and a more forward-looking time discounting (larger $\beta$) increase the estimated migration elasticity (Table 1) and, therefore, reduce the estimated welfare impact as shown in Table 2.

Table 1: Estimates for migration elasticity parameter ($\theta$)

| | $\beta = 0.97$ | $\beta = 0.90$ | $\beta = 0$ |
|---|---|---|---|
| $\sigma = 0$ | 0.682 | 0.667 | 0.479 |
| | (0.053) | (0.063) | (0.197) |
| $\sigma = 1$ | 0.612 | 0.601 | 0.458 |
| | (0.027) | (0.035) | (0.162) |

*Notes:* IV regression results based on equation (6). Standard errors in parentheses. $\sigma$ denotes the degree of relative risk aversion in a CRRA utility, and $\beta$ is the time discount factor.

Table 2: The estimated welfare impact of the conflict by region

| | $\sigma = 0$ | | $\sigma = 1$ | |
|---|---|---|---|---|
| | Donetsk | Luhansk | Donetsk | Luhansk |
| $\beta = 0.97$ | -2.91 | -2.60 | -3.24 | -2.90 |
| | (0.15) | (0.29) | (0.16) | (0.32) |
| $\beta = 0.90$ | -2.97 | -2.66 | -3.30 | -2.95 |
| | (0.15) | (0.29) | (0.16) | (0.33) |
| $\beta = 0$ | -4.14 | -3.70 | -4.33 | -3.88 |
| | (0.21) | (0.41) | (0.22) | (0.43) |

*Notes:* $\sigma$ denotes the degree of relative risk aversion in a CRRA utility, and $\beta$ is the time discount factor. Standard errors, in parentheses, are calculated using bootstrapped samples of destinations included in $\Phi$ repeated 5000 times.

These estimates provide a lower bound for the adverse impact of the conflict. To see this, remember that the term $\sum_l \phi_{l\in\Phi}\left(\Delta U_t^l - \Delta C_t^{kl}\right)$ in equation (3) is unobserved and missing from the expression provided in Proposition 1, but expected to be negative. Intuitively, this term defines the average impact of the conflict on location-specific utility in non-conflict regions within $\Phi$, net of the changes in moving costs. Thus, unless non-conflict regions included in $\Phi$ benefit from the conflict in average terms, the adverse impact of the conflict should be at least as large as our estimates.

Next, we will convert the welfare loss calculated in Table 2 to its equivalent monetary loss, which helps to interpret the welfare loss estimates in more conventional terms.

## 4.3 Equivalent income shock for the welfare loss

We have so far discussed the welfare shock emanating from the conflict as inferred from migration numbers. This revealed-preference based approach has several desirable properties. One of these is the feasibility of the analysis under severe data constraints commonly observed in post-conflict environments. Another one is its ability to extend the impact assessment of conflict by going beyond the shocks to income (like GDP effects) and including non-monetary dimensions of well-being as embodied in individual preferences and manifested in migration data.

It is possible to consider the changes in the non-monetary aspects of well-being in monetary terms. A large literature on equivalent income as a preference-based index of well-being has characterized the axiomatic underpinnings of this conversion.[10] Consider a conflict-driven hypothetical income loss suffered by the agents in the conflict region $k$ just before the onset of the conflict. The loss prevails for $T$ periods regardless of the location choice after the onset of the conflict, and could be explained by various factors like trauma and transition costs, among others. What would be the rate of income loss that makes the agents equally worse off as the conflict? To compute this, we need to specify the duration of the loss, $T$, risk aversion parameter, $\sigma$, and discount factor $\beta$.

Formally, let $\psi_t^k < 0$ be the income loss in period $t$ in location $k$, with the new income given as $w_t^k + \psi_t^k$. We set the hypothetical income loss such that $\upsilon(w_t^k + \psi_t^k) - \upsilon(w_t^k) = \upsilon(w_t^l + \psi_t^l) - \upsilon(w_t^l)$ for every $k$ and $l$, therefore the mobility decisions of agents are unaffected. For simplicity, we also abstract from any time variation by fixing the changes in instantaneous utility over periods, $\upsilon(w_t^k + \psi_t^k) - \upsilon(w_t^k) = \upsilon(w_{t+1}^k + \psi_{t+1}^k) - \upsilon(w_{t+1}^k)$.

With these two simplifications, the problem is to identify the specific loss that continues for $T$ periods for an agent with wage $w_0^k$ and changes their expected present discounted value, i.e.welfare, by $\Delta W_t^k$ units. The welfare loss can be expressed as

$$\Delta W_t^k = \sum_{t=0}^{T-1} \beta^t \left( \upsilon \left( w_0^k + \psi_0^k \right) - \upsilon \left( w_0^k \right) \right).$$

which, with rearrangement, yields

$$\psi_0^k = \upsilon^{-1} \left( \frac{1-\beta}{1-\beta^T} \Delta W_t^k + \upsilon \left( w_0^k \right) \right) - w_0^k, \tag{7}$$

where the percent change in income is $100 \times (\psi_0^k / w_0^k)$ for the initial period in location $k$. Note that the percent change in income is calculated relative to the income at $t = 0$.

In the absence of a prior regarding the duration of the income shock for Eastern Ukraine, we consider alternatives values, $T \in \{1, 10, \infty\}$. Table 3 shows the income equivalent of the welfare shocks presented earlier in Table 2. The conflict driven welfare shock in Donetsk corresponds to a 7.28 percent income loss in every period vis-a-vis the average pre-conflict income when the loss is permanent ($T = \infty$) and agents are risk neutral ($\sigma = 0$) and very patient ($\beta = 0.97$). With less persistent shocks (smaller $T$), the same group of agents, suffer 27.72 percent income loss for 10 years. A higher future discounting (lower $\beta$) increases the income equivalent of the welfare shock. For instance, for $T = 10$ and $\sigma = 1$, the equivalent income shock is 39.74 percent in Donetsk when $\beta = 0.90$ – about a third greater than the case with $\beta = 0.97$.

[10] Starting with the seminal work of Usher, 1973, the equivalent income approach has gained increasing popularity in comparing well-being across countries and years. For a more detailed discussion on this, see Becker et al., 2005, Adler and Fleurbaey, 2016, and Onder et al., 2019.

Table 3: Income equivalent of the welfare loss, percent

| | | $T = 1$ | | $T = 10$ | | $T = \infty$ | |
|---|---|---|---|---|---|---|---|
| | | Donetsk | Luhansk | Donetsk | Luhansk | Donetsk | Luhansk |
| $\sigma = 0$ | $\beta = 0.97$ | -242.61 | -245.41 | -27.72 | -28.04 | -7.28 | -7.36 |
| | | (11.93) | (27.07) | (1.36) | (3.09) | (0.36) | (0.81) |
| | $\beta = 0.90$ | -247.92 | -250.79 | -38.06 | -38.50 | -24.79 | -25.08 |
| | | (12.20) | (27.66) | (1.87) | (4.25) | (1.22) | (2.77) |
| | $\beta = 0$ | -345.22 | -349.21 | - | - | - | - |
| | | (16.98) | (38.52) | - | - | - | - |
| $\sigma = 1$ | $\beta = 0.97$ | -96.08 | -94.48 | -30.93 | -28.18 | -9.26 | -8.32 |
| | | (0.62) | (1.69) | (1.25) | (2.60) | (0.43) | (0.88) |
| | $\beta = 0.90$ | -96.31 | -94.77 | -39.74 | -36.43 | -28.10 | -25.55 |
| | | (0.59) | (1.63) | (1.49) | (3.14) | (1.16) | (2.40) |
| | $\beta = 0$ | -98.69 | -97.93 | - | - | - | - |
| | | (0.28) | (0.86) | - | - | - | - |

*Notes:* Values in percent of the welfare in the base-year (pre-conflict) welfare. $\sigma$ is the degree of relative risk aversion in a CRRA utility, $\beta$ is the time discount factor, and $T$ denotes the number of years with income losses. Standard errors, in parentheses, are calculated using bootstrapped samples of destinations included in $\Phi$ repeated 5000 times.

# 5 Discussion

The economic impact estimates provided in this paper differ from more conventional metrics like GDP effects in several dimensions. Besides including non-pecuniary aspects of welfare, they also reflect the agents' expectations about the future in a rational expectations framework (while this assumes that agents do not make systematic errors, they are not required to have perfect foresight). These differences, combined with the missing GDP impact estimates for the conflict between 2014 and 2019, make it difficult to benchmark our estimates.[11]

An important feature of the analysis in this paper is its ability to infer lower bound estimates of the economic impact from migration flows into only a subset of destinations. For example, when flows abroad can not be measured accurately (as in the case of the war in Eastern Ukraine), flows within the country can provide sufficient information to conduct the assessment. This feature follows from the equalization of expected maximized utility associated with choices, conditional on choosing them, regardless of whether displacement to other destinations is welfare-enhancing ex post or not. This property also allows the exclusion of some regions when moving costs might decline significantly due to humanitarian concerns (e.g., border openings for refugee outflows), potentially threatening our "war does

[11] Regional GDP numbers produced by the Ukrainian Statistics Office (UkrStat) excluded the non-government controlled areas (NGCAs) in Donetsk and Luhansk oblasts starting from 2014. World Bank, 2021 uses nightlight emission levels as crude proxies for economic activity in the Donbas region. Estimates show a 7.2 percent reduction in Luhansk GCA, 42.9 percent reduction in Luhansk NGCA, 20.2 reduction in Donetsk GCA, and 28.1 percent reduction in Donetsk NGCA. These are, of course, only indicative.

not increase net utility in all destinations" assumption. Although having such destinations in the sample set, $\Phi$, does not break this assumption as long as they do not tilt the sign of the average across all regions, they can be excluded from the analysis to remove any doubts.

A potential concern in this case could be that some IDPs who register in non-conflict areas may be using these locations as stops en route to living abroad (i.e., transit migration), possibly decreasing the effectiveness of exclusion of foreign regions. To alleviate such concerns, we reproduce our estimations by (i) excluding Ukrainian regions on the country's western border (which could provide a natural gateway into Europe), in addition to (ii), excluding regions with airports serving more than 100,000 passengers annually plus regions in the western border, (iii) focusing only on the neighbors of Luhansk and Donetsk oblasts, (iv) focusing on the 10 largest regions in Ukraine, and (v) focusing on the 10 smallest regions. The results (Appendix A4) are similar to our original estimates both qualitatively and quantitatively. Robustness tests suggest that a sharp decline in the utility in Donbas was the main factor causing a sudden but balanced increase in mobility to non-conflict regions within Ukraine, rather than destination specific positive shocks or an unbalanced decline in moving costs.

Another potential concern could be that population movements may not be voluntary, that is, civilians may be forced to move (or stay), during an active conflict. However, the presence of such coercion does not invalidate discrete choice logic in our framework. To see this, suppose people are forced to stay (such as a risk of imprisonment or violence for movers). For potential migrants, this condition is analogous to an extreme increase in moving costs $C_t^{kl}$, and it further reduces the net utility $\left(U_t^l - C_t^{kl}\right)$ for all destinations $l \neq k$. Therefore, while the actual welfare impact may be significantly higher, the lower-bound welfare impact estimate revealed by the observed migration patterns is not violated, by the condition $\sum_{l \in \Phi} \phi_l \Delta \left[U_t^l - C_t^{kl}\right] \leq 0$ in Proposition (1). Next, consider forced displacement (such as a risk of imprisonment or violence for stayers). Again, this is analogous to a large decline in utility, $U_t^k$, for the current location, which reduces both the welfare $W_t^k$ and the out-migration probability $\log m_t^{kl}$. However, the subsequent hike in the welfare impact estimates is not arbitrary. On the contrary, it reflects the actual welfare loss driven by the coercion itself, which comes with the war.

Generalizing this last point, we can consider a broader set of issues regarding the exact nature of the shock. It may be tempting to think that, in our framework, revealed preferences do not only reflect the distaste for war, but also for other factors like a future political regime change. This point is essentially about what is conflict driven and what is not – a daunting problem. For example, humanitarian aid is almost always present in conflict environments, yet it is not strictly driven by conflicts. To bypass this problem, the case at hand (conflict, inclusive of endogenous responses) can appropriately be compared with the counterfactual (no-conflict), including all present and future changes that come with the conflict as expected by the rational agents.

Finally, like in other conflict affected environments, our data is not rich enough to explicitly consider ex ante heterogeneity in migrant profiles. While we are unable to assess if there has been a shift in the migrant profiles before and after the conflict, we observe a strong similarity in the composition of migration destinations between the two periods (Figure 2). This is consistent with the idea that a pervasive shock to utility in Donbas is the primary driver of the post-conflict mobility, and it suggests no major discontinuity in the decision making processes regarding mobility. Nevertheless, to further explore how heterogeneity in unobserved migrant characteristics might affect our analysis, in Appendix A1, we compare the welfare impact estimates based on our methodology in the absence of heterogeneity with the "true" welfare impact (the weighted average of the impact for two hypothetically different types) by using a wide range of pre-conflict migration ratios, post-conflict migration ratios, and population shares between the two types. Results show that the true average impacts under heterogeneity and the estimated impacts without heterogeneity are considerably close under reasonable ranges along these dimensions. However, since our method relies on migration patterns, the welfare of groups that are extremely unlikely to migrate within Ukraine before or after the conflict, and thus do not appear in our data, are not accounted for.

# 6 Conclusion

This paper proposes an alternative approach to assessing the welfare impact of wars. First, it shows that such welfare impact can be inferred from changes in migration outflows from the conflict-struck area by using a discrete-choice framework. Next, it applies this framework to the conflict in Eastern Ukraine between 2014 and 2019–long before the war in 2022.

Empirical estimates yield migration elasticity parameters ranging between 0.458 and 0.682 depending on agents' risk aversion and time preferences. Using these estimates, and the post-conflict migration patterns, the paper then estimates the implied welfare shocks and their income equivalent. Accordingly, the pre-conflict residents of Donetsk oblast are estimated to suffer at least 7.3 to 24.8 percent equivalent life-time income loss when agents are risk neutral. This income loss range is equivalent to 27.72 to 38.06 percent income-loss for a duration of 10 years. The estimates for the Luhansk oblast are of similar magnitude.

The approach developed in this paper helps to avoid a pervasive model-selection problem, i.e., characterizing accurately the structure of individual welfare, including both pecuniary and non-pecuniary aspects. It also helps to circumvent potentially prohibitive data constraints, enabling a more complete inference about the welfare impact of wars. However, it is important to note that both the welfare impact estimates and the corresponding income equivalents discussed in this paper present lower bound estimates. The actual impact can be significantly greater.

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# The True Cost of War: Appendix

**Erhan Artuc, Nicolas Gomez-Parra & Harun Onder**

## A1 The Impact of Heterogeneity

As we do not have access to any demographic information of the pre-conflict migrants, we cannot study the impact of conflict on different groups. We also cannot calculate if the underlying unobserved heterogeneity causes some bias in our estimates. Similar to other papers in the literature, our measure calculated by inverting average mobility can potentially be different from the weighted average of welfare impact on unobserved groups. To assess potential problems with using inversion equation without considering underlying heterogeneity, we conduct robustness tests using simulated heterogeneity. Our tests can also be informative for other similar approaches in the literature used to either to calculate welfare or solve the dynamic optimization problem, such as Caliendo et al., 2019, Artuç et al., 2010 and Kleinman et al., 2023.

Suppose there are two types of agents in the population, Type A and Type B, who cannot be differentiated in the data. One of these types faces systematically lower moving costs than the other, thus, is more likely to migrate before the conflict. That is, $R_0 \equiv m^{kl}_{A,0}/m^{kl}_{B,0}$ for every $l \neq k$, where $R_0 > 0$, and $m^{kl}_{A,0}$ and $m^{kl}_{B,0}$ are the probabilities of Type A and B agents moving from location $k$ to $l$ before the onset of conflict. Such a wedge in moving costs and probabilities can be driven by differences based on gender, age, political views, or any other relevant factor.

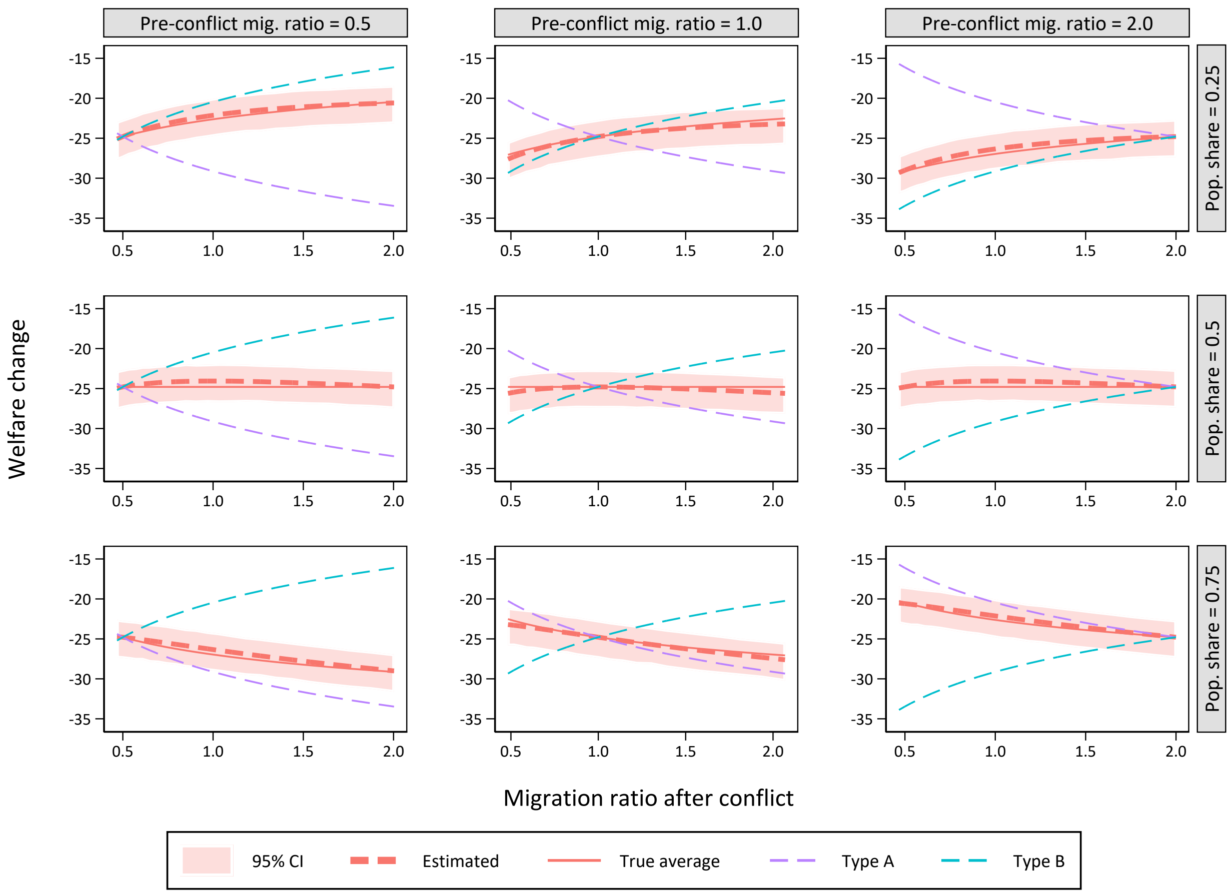
Further assume that the welfare change after the conflict is not equal for Type A and Type B individuals, as the equivalent income shock, $\psi^k_0$, varies across types. As a result, post-conflict mobility patterns, defined as $R_t \equiv m^{kl}_{A,t}/m^{kl}_{B,t}$, diverge from the pre-conflict patterns significantly, i.e., both $R_t \leq R_0$ and $R_t \geq R_0$ are possible. Using this simple illustrative structure which can capture a large variety of heterogeneity, we can explore how existence of unobserved types can potentially impact our estimates.

Figure A1 compares the "estimated" welfare impact based on our methodology in the absence of heterogeneity with the "true average" welfare impact (the weighted average of the impact for two different types) by using a wide range of pre-conflict migration ratios, post-conflict migration ratios, and population shares between the two type. The figure was generated with migration elasticity parameter associated with $\beta = 0.90$, welfare measure for $T = 10$ and using Donetsk migration data. In each graph, the vertical axis shows the welfare change (in percent of the initial value) and the horizontal axis shows the migration ratio after the conflict, $R_t$. Welfare impacts for Type A and Type B agents are shown by purple and blue dashed lines, respectively, and the true averages are shown by the red solid line. Our estimates are shown by the red dashed line, with the associated 95 percent confidence interval shown by the shaded red area. This exercise is repeated using different assumptions. The columns in the matrix of figures feature different initial migration ratios, $R_0 = \{0.5, 1.0, 2.0\}$, while the rows of the matrix show different population shares of Type A agents, that is, $Population_A/Population_{Total} = \{0.25, 0.5, 0.75\}$.

While the indicator ranges are chosen to cover a large number of potential cases, they also encompass several interesting cases imperfectly observed in the Ukrainian data. For example, while males constituted 47.3 percent of the working age population in Donbas before the conflict, they were only 40.6 percent among the working age IDPs who moved from Donbas to the rest of Ukraine after the conflict (World Bank, 2021), rendering them 24 percent less likely to move compared to females. In the absence of before-conflict migration observations, figures in the middle row provide the closest set up. Similarly, while pensioners constituted 24.2 percent of the workforce in Donbas, they were only 21.7 percent of the workforce among IDPs from Donbas residing elsewhere in Ukraine, implying a 13 percent lower probability to move compared to others in the workforce. We cannot distinguish between different political affiliations on the basis of their migration patterns. However, a non-negligible magnitude of refugee flows to Russia after 2014 implies that the war has not been welfare improving, even for those who may seem to be less likely to oppose it.

Overall, the true average impacts under heterogeneity and the estimated impacts without heterogeneity are considerably close under reasonable ranges of heterogeneity as shown in the Figure A1. In supplementary exercises (available upon request), we observe some extreme cases where the true average breaches the confidence interval. This includes a case with nearly symmetrical groups (pre-conflict migration ratio = 1, population shares = 0.5), where one group is more than about 3.2 times more likely to be displaced after the conflict. Another case is when a minority group, which was relatively more inclined to migrate before the conflict (pre-conflict migration ratio = 1, population share of A = 0.75), becomes relatively less mobile after the conflict, leading to a breach at a post-conflict migration ratio equal to about 4.7.

Figure A1: Welfare change estimates with two types of agents




*Notes:* Figure shows the welfare change for Type A and Type B agents (purple and blue dashed lines, respectively), the true average welfare change (solid red line), and the welfare change estimated using our method (dashed red line) when types are unobserved. Columns vary with initial Type A relative to Type B migration ratios $R_0$={0.5, 1.0, 2.0} and rows vary with the initial population weight of Type A agents $Population_A/Population_{Total} = \{0.25, 0.5, 0.75\}$.

## A2 Proofs

Assume that $z_t^{i,l}$ is distributed Gumbel with location $-\gamma/\theta$, and scale $1/\theta$, where $\gamma$ is the Euler's constant. The value of location and scale parameters imply that the mean is zero. Define the following variables for convenience: $\iota \equiv \exp(-\gamma/\theta)$, $x_{kl} \equiv \exp\left(U_t^l - C_t^{kl}\right)$, $\Phi_k \equiv \left(\sum (x_{kl})^\theta\right)^{\frac{1}{\theta}}$, $\zeta_l \equiv \exp z_t^{i,l}$. Then $\zeta_l$ is distributed Frechet with location 0, scale $\iota$ and shape $\theta$. Thus pdf and cdf of $\zeta_l$ are $f(\zeta_l) = \theta(\zeta_l/\iota)^{-1-\theta} \exp\left(-(\zeta_l/\iota)^{-\theta}\right)$ and $F(\zeta_l) = \exp\left(-(\zeta_l/\iota)^{-\theta}\right)$ respectively. Additionally define $B_{kl} \equiv (x_{kl})^\theta/(\Phi_k)^\theta$.

**Lemma A1** Subject to optimality, the probability of moving from $k$ to $l$ is equal to

$$m_t^{kl} = \frac{(x_{kl})^{\theta}}{(\Phi_k)^{\theta}}.$$

**Proof.** Optimality requires that $\zeta_l x_{kl} \geq \zeta_j x_{kj}$ for every $j \neq l$. This means $\zeta_j \leq \zeta_l x_{kl}/x_j$. For a given $\zeta_l$, the probability of this outcome is $\prod_{l \neq j} F(\frac{x_{kl}}{x_{kj}}\zeta_l)$. The unconditional probability is

$$\begin{aligned}
m_t^{kl} &= \int_0^{\infty} f(\zeta_l) \prod_{j \neq l} F(\frac{x_{kl}}{x_{kj}}\zeta_l) d\zeta_l, \\
&= \int_0^{\infty} \frac{\theta}{\iota}\left(\frac{\zeta_l}{\iota}\right)^{-1-\theta} \exp\left(-\left(\frac{\zeta_l}{\iota}\right)^{-\theta}\right) \prod_{j \neq l} \exp\left(-\left(\frac{x_{kl}}{x_{kj}}\left(\frac{\zeta_l}{\iota}\right)\right)^{-\theta}\right) d\zeta_l, \\
&= \int_0^{\infty} \frac{\theta}{\iota}\left(\frac{\zeta_l}{\iota}\right)^{-1-\theta} \prod_{j=1}^{K} \exp\left(-\left(\frac{x_{kl}}{x_{kj}}\frac{\zeta_l}{\iota}\right)^{-\theta}\right) d\zeta_l, \\
&= \int_0^{\infty} \frac{\theta}{\iota}\left(\frac{\zeta_l}{\iota}\right)^{-1-\theta} \exp\left(-\left(\frac{x_{kl}}{\Phi_k}\frac{\zeta_l}{\iota}\right)^{-\theta}\right) d\zeta_l, \\
&= \int_0^{\infty} \frac{\theta}{\iota}\left(\frac{\zeta_l}{\iota}\right)^{-1-\theta} \exp\left(-(B_{kl})^{-1}\left(\frac{\zeta_l}{\iota}\right)^{-\theta}\right) d\zeta_l,
\end{aligned}$$

define $u = \exp\left(-(B_{kl})^{-1}\left(\frac{\zeta_l}{\iota}\right)^{-\theta}\right)$ then

$$\begin{aligned}
m_t^{kl} &= \int_0^1 B_{kl}\, du, \\
&= B_{kl}.
\end{aligned}$$

■

**Lemma A2** The expected value of the iid random shock for a given destination conditional on the destination being the optimal choice, $E\left(z_t^{i,l} | \zeta_l x_{kl} \geq \zeta_j x_{kj}; \forall j \neq l\right)$, is equal to $-\frac{1}{\theta}\log m_t^{kl}$.

**Proof.** Based on the previous proof of Lemma A1, we can write

$$m_t^{kl} E\left(z_t^{i,l} | \zeta_l x_{kl} \geq \zeta_j x_{kj}; \forall j \neq l\right) = \int_0^{\infty} \log(\zeta_l)\left(\frac{\theta}{\iota}\right)\left(\frac{\zeta_l}{\iota}\right)^{-1-\theta} \exp\left(-(B_{kl})^{-1}\left(\frac{\zeta_l}{\iota}\right)^{-\theta}\right) d\zeta_l,$$

$$= \int_{-\infty}^{\infty} z_t^{i,l} \left( \frac{\theta}{\exp(-\frac{\gamma}{\theta})} \right) \exp\left( z_t^{i,l} + \frac{\gamma}{\theta} \right)^{-1-\theta} \exp\left( -(B_{kl})^{-1} \exp\left( z_t^{i,l} + \frac{\gamma}{\theta} \right)^{-\theta} \right) \exp(z_t^{i,l}) dz_t^{i,l},$$

$$= \int_{-\infty}^{\infty} \theta z_t^{i,l} \exp\left( -\theta z_t^{i,l} - \gamma - (B_{kl})^{-1} \exp\left( -\theta z_t^{i,l} - \gamma \right) \right) dz_t^{i,l},$$

Define $\kappa \equiv \log(B^{-1})/\theta$,

$$m_t^{kl} E\left( z_t^{i,l} | \zeta_l x_{kl} \geq \zeta_j x_{kj}; \forall j \neq l \right) = \exp(-\theta\kappa) \left[ \int_{-\infty}^{\infty} \theta z_t^{i,l} \exp\left( -\theta z_t^{i,l} + \theta\kappa - \gamma - \exp\left( -\theta z_t^{i,l} + \theta\kappa - \gamma \right) \right) dz_t^{i,l} \right],$$

Note that the expression in brackets is expected value of a random Gumbel variable with scale $1/\theta$ and location $\kappa - \gamma/\theta$, and therefore it is equal to $\kappa$. Note that $\kappa = -\frac{1}{\theta} \log m_t^{kl}$ and $\exp(-\theta\kappa) = m_t^{kl}$. Thus

$$\begin{aligned} m_t^{kl} E\left( z_t^{i,l} | \zeta_l x_{kl} \geq \zeta_j x_{kj}; \forall j \neq l \right) &= \exp(-\theta\kappa) \left[ \kappa \right], \\ &= m_t^{kl} \left[ -\frac{1}{\theta} \log m_t^{kl} \right], \end{aligned}$$

Finally

$$E\left( z_t^{i,l} | \zeta_l x_{kl} \geq \zeta_j x_{kj}; \forall j \neq l \right) = -\frac{1}{\theta} \log m_t^{kl}.$$

■

**Lemma A3** The expected welfare can be expressed as function of net utility at a given destination, flows to that destination and the migration elasticity parameter such that

$$W_t^k = \frac{1}{\theta} \log \left[ \sum_l \exp\left( U_t^l - C^{kl} \right)^{\theta} \right].$$

**Proof.**
From Lemma A2, we can write

$$\begin{aligned} W_t^k &= \sum_l m_t^{kl} \left( U_t^l - C_t^{kl} + E\left( z_t^{i,l} | \zeta_l x_{kl} \geq \zeta_j x_{kj}; \forall j \neq l \right) \right), \\ &= \sum_l m_t^{kl} \left( U_t^l - C_t^{kl} - \frac{1}{\theta} \log m_t^{kl} \right), \end{aligned}$$

then from Lemma A1, we can inset the expression for $m_t^{kl}$, thus

$$\begin{aligned} W_t^k &= \sum_l m_t^{kl} \left( \log x_{kl} - \frac{1}{\theta} \log \left[ \left( \frac{\log x_{kl}}{\Phi_k} \right)^{\theta} \right] \right), \\ &= \sum_l m_t^{kl} \left( \log x_{kl} - \log x_{kl} + \log \Phi_k \right), \\ &= \sum_l m_t^{kl} \left( \log \Phi_k \right), \\ &= \log \Phi_k \sum_l m_t^{kl}, \\ &= \log \Phi_k, \end{aligned}$$

Therefore $W_t^k = \frac{1}{\theta} \log \left[ \sum_l \exp \left( U_t^l - C^{kl} \right)^{\theta} \right]$.
■

**Lemma A4** The moving probability is equal to

$$m^{kl} = \left( \exp(U_t^l - C_t^{kl}) / \exp(W_t^k) \right)^{\theta},$$

where the denominator is equal to the exponential of the expected welfare.

**Proof.** From Lemma A1 we can write that $m_t^{kl} = \frac{(x_{kl})^{\theta}}{(\Phi_k)^{\theta}}$. Then using Lemma A3, we can modify it as $m_t^{kl} = \frac{(x_{kl})^{\theta}}{(\exp W_t^k)^{\theta}}$ ■

**Proof of proposition 1**

**Proof.** The proof of Proposition 1 directly follows from Lemma A4, which gives the moving probability equation 1 in the main text.

The flow equation implies that

$$\Delta W_t^k = \Delta U_t^l - \Delta C_t^{kl} - \frac{1}{\theta} \Delta \log m_t^{kl},$$

then we can add this expression for destinations in $\Phi$

$$\Delta W_t^k = \sum_{l \in \Phi} \phi_l \left( \Delta U_t^l - \Delta C_t^{kl} \right) + \sum_{l \in \Phi} \phi_l \left( -\frac{1}{\theta} \Delta \log m_t^{kl} \right),$$

Since $\sum_{l \in \Phi} \phi_l \left( \Delta U_t^l - \Delta C_t^{kl} \right) \leq 0$, we can establish an inequality:

$$\Delta W_t^k \leq \sum_{l \in \Phi} \phi_l \left( -\frac{1}{\theta} \Delta \log m_t^{kl} \right).$$

■

## A3 Extending Proposition 1 to location-specific utility

**Proposition A1** The upper bound of change in location-specific fixed utility in conflict location $k$ (i.e., the lower bound of the impact) can be expressed as

$$\Delta U_t^k \leq \frac{1}{\theta} \sum_{l \in \Phi} \phi_l \left( \Delta \log m_t^{kk} - \Delta \log m_t^{kl} \right),$$

if the condition $\sum_{l \in \Phi} \phi_l \Delta \left[ U_t^l - C_t^{kl} \right] \leq 0$ holds, where $\phi_l \geq 0$ are weights for destinations such that $\sum_{l \in \Phi} \phi_l = 1$.

**Proof.** From Lemma A4, which gives equation (2) in the main text, we can write

$$\Delta U_t^l = \Delta W_t^k + \frac{1}{\theta} \Delta \log m_t^{kl} + \Delta C_t^{kl},$$

and

$$\Delta U_t^k = \Delta W_t^k + \frac{1}{\theta} \Delta \log m_t^{kk},$$

then subtracting $U^l$ from $U^k$ we find

$$\Delta U_t^k - \Delta U_t^l = \frac{1}{\theta} \left( \Delta \log m_t^{kk} - \Delta \log m_t^{kl} \right) - \Delta C_t^{kl},$$

after adding the expression above across locations with weights $\phi_l \geq 0$ we find

$$\Delta U_t^k = \frac{1}{\theta} \sum_{l \in \Phi} \phi_l \left( \Delta \log m_t^{kk} - \Delta \log m_t^{kl} \right) + \sum_{l} \phi_l \left( \Delta U_t^l - \Delta C_t^{kl} \right),$$

Note that $\sum_{l \in \Phi} \phi_l \left( \Delta U_t^l - \Delta C_t^{kl} \right) \leq 0$ by construction. Thus

$$\Delta U_t^k \leq \frac{1}{\theta} \sum_{l \in \Phi} \phi_l \left( \Delta \log m_t^{kk} - \Delta \log m_t^{kl} \right).$$

■

## A4 Additional Tables for Robustness

Table A1: Income equivalent of the welfare loss, percent - excluding the regions on the western border

| | | $T=1$ | | $T=10$ | | $T=\infty$ | |
|---|---|---|---|---|---|---|---|
| | | Donetsk | Luhansk | Donetsk | Luhansk | Donetsk | Luhansk |
| $\sigma=0$ | $\beta=0.97$ | -241.18 | -242.57 | -27.56 | -27.71 | -7.24 | -7.28 |
| | | (13.15) | (29.94) | (1.50) | (3.42) | (0.39) | (0.90) |
| | $\beta=0.90$ | -246.46 | -247.89 | -37.84 | -38.06 | -24.65 | -24.79 |
| | | (13.43) | (30.59) | (2.06) | (4.70) | (1.34) | (3.06) |
| | $\beta=0$ | -343.18 | -345.17 | - | - | - | - |
| | | (18.71) | (42.60) | - | - | - | - |
| $\sigma=1$ | $\beta=0.97$ | -96.00 | -94.29 | -30.78 | -27.90 | -9.21 | -8.23 |
| | | (0.69) | (1.90) | (1.38) | (2.88) | (0.48) | (0.97) |
| | $\beta=0.90$ | -96.23 | -94.59 | -39.56 | -36.10 | -27.96 | -25.30 |
| | | (0.66) | (1.83) | (1.65) | (3.47) | (1.28) | (2.66) |
| | $\beta=0$ | -98.65 | -97.83 | - | - | - | - |
| | | (0.31) | (0.97) | - | - | - | - |

*Notes:* Values in percent of the welfare in the base-year (pre-conflict) welfare. $\sigma$ is the degree of relative risk aversion in a CRRA utility, $\beta$ is the time discount factor, and $T$ denotes the number of years with income losses. Standard errors, in parentheses, are calculated using bootstrapped samples of destinations included in $\Phi$ repeated 5000 times.

Table A2: Income equivalent of the welfare loss, percent - excluding the regions on the western border and those with airports serving more than 100,000 passengers annually

| | | $T=1$ | | $T=10$ | | $T=\infty$ | |
|---|---|---|---|---|---|---|---|
| | | Donetsk | Luhansk | Donetsk | Luhansk | Donetsk | Luhansk |
| $\sigma=0$ | $\beta=0.97$ | -217.98 | -226.36 | -24.90 | -25.86 | -6.54 | -6.79 |
| | | (6.29) | (13.77) | (0.72) | (1.57) | (0.19) | (0.41) |
| | $\beta=0.90$ | -222.76 | -231.32 | -34.20 | -35.52 | -22.28 | -23.13 |
| | | (6.43) | (14.07) | (0.99) | (2.16) | (0.64) | (1.41) |
| | $\beta=0$ | -310.17 | -322.09 | - | - | - | - |
| | | (8.96) | (19.59) | - | - | - | - |
| $\sigma=1$ | $\beta=0.97$ | -94.55 | -93.09 | -28.28 | -26.31 | -8.36 | -7.70 |
| | | (0.46) | (1.17) | (0.69) | (1.37) | (0.23) | (0.45) |
| | $\beta=0.90$ | -94.84 | -93.42 | -36.56 | -34.16 | -25.65 | -23.83 |
| | | (0.44) | (1.13) | (0.83) | (1.68) | (0.64) | (1.26) |
| | $\beta=0$ | -97.96 | -97.20 | - | - | - | - |
| | | (0.23) | (0.65) | - | - | - | - |

*Notes:* Values in percent of the welfare in the base-year (pre-conflict) welfare. $\sigma$ is the degree of relative risk aversion in a CRRA utility, $\beta$ is the time discount factor, and $T$ denotes the number of years with income losses. Standard errors, in parentheses, are calculated using bootstrapped samples of destinations included in $\Phi$ repeated 5000 times.

Table A3: Income equivalent of the welfare loss, percent - using only the neighbors of Donetsk and Luhansk Oblasts

| | | $T = 1$ | | $T = 10$ | | $T = \infty$ | |
|---|---|---|---|---|---|---|---|
| | | Donetsk | Luhansk | Donetsk | Luhansk | Donetsk | Luhansk |
| $\sigma = 0$ | $\beta = 0.97$ | -223.79 | -215.78 | -25.57 | -24.65 | -6.71 | -6.47 |
| | | (9.52) | (70.09) | (1.09) | (8.01) | (0.29) | (2.10) |
| | $\beta = 0.90$ | -228.69 | -220.51 | -35.11 | -33.86 | -22.87 | -22.05 |
| | | (9.73) | (71.63) | (1.49) | (11.00) | (0.97) | (7.16) |
| | $\beta = 0$ | -318.44 | -307.04 | - | - | - | - |
| | | (13.55) | (99.74) | - | - | - | - |
| $\sigma = 1$ | $\beta = 0.97$ | -94.96 | -92.17 | -28.92 | -25.25 | -8.57 | -7.36 |
| | | (0.59) | (3.59) | (1.02) | (6.48) | (0.35) | (2.25) |
| | $\beta = 0.90$ | -95.23 | -92.53 | -37.32 | -32.86 | -26.24 | -22.85 |
| | | (0.56) | (3.46) | (1.23) | (7.73) | (0.95) | (6.02) |
| | $\beta = 0$ | -98.16 | -96.69 | - | - | - | - |
| | | (0.28) | (1.80) | - | - | - | - |

*Notes:* Values in percent of the welfare in the base-year (pre-conflict) welfare. $\sigma$ is the degree of relative risk aversion in a CRRA utility, $\beta$ is the time discount factor, and $T$ denotes the number of years with income losses. Standard errors, in parentheses, are calculated using bootstrapped samples of destinations included in $\Phi$ repeated 5000 times.

Table A4: Income equivalent of the welfare loss, percent - using only the largest 10 oblasts

| | | $T = 1$ | | $T = 10$ | | $T = \infty$ | |
|---|---|---|---|---|---|---|---|
| | | Donetsk | Luhansk | Donetsk | Luhansk | Donetsk | Luhansk |
| $\sigma = 0$ | $\beta = 0.97$ | -247.78 | -249.08 | -28.31 | -28.46 | -7.43 | -7.47 |
| | | (15.23) | (35.76) | (1.74) | (4.09) | (0.46) | (1.07) |
| | $\beta = 0.90$ | -253.21 | -254.54 | -38.88 | -39.08 | -25.32 | -25.45 |
| | | (15.56) | (36.54) | (2.39) | (5.61) | (1.56) | (3.65) |
| | $\beta = 0$ | -352.58 | -354.43 | - | - | - | - |
| | | (21.67) | (50.88) | - | - | - | - |
| $\sigma = 1$ | $\beta = 0.97$ | -96.34 | -94.72 | -31.47 | -28.54 | -9.45 | -8.44 |
| | | (0.72) | (2.03) | (1.58) | (3.39) | (0.55) | (1.15) |
| | $\beta = 0.90$ | -96.56 | -95.00 | -40.39 | -36.86 | -28.60 | -25.88 |
| | | (0.69) | (1.96) | (1.88) | (4.07) | (1.47) | (3.14) |
| | $\beta = 0$ | -98.80 | -98.04 | - | - | - | - |
| | | (0.31) | (1.01) | - | - | - | - |

*Notes:* Values in percent of the welfare in the base-year (pre-conflict) welfare. $\sigma$ is the degree of relative risk aversion in a CRRA utility, $\beta$ is the time discount factor, and $T$ denotes the number of years with income losses. Standard errors, in parentheses, are calculated using bootstrapped samples of destinations included in $\Phi$ repeated 5000 times.

Table A5: Income equivalent of the welfare loss, percent - using only the smallest 10 oblasts

| | | $T = 1$ | | $T = 10$ | | $T = \infty$ | |
|---|---|---|---|---|---|---|---|
| | | Donetsk | Luhansk | Donetsk | Luhansk | Donetsk | Luhansk |
| $\sigma = 0$ | $\beta = 0.97$ | -218.36 | -231.67 | -24.95 | -26.47 | -6.55 | -6.95 |
| | | (7.43) | (19.26) | (0.85) | (2.20) | (0.22) | (0.58) |
| | $\beta = 0.90$ | -223.14 | -236.75 | -34.26 | -36.35 | -22.31 | -23.67 |
| | | (7.60) | (19.68) | (1.17) | (3.02) | (0.76) | (1.97) |
| | $\beta = 0$ | -310.71 | -329.65 | - | - | - | - |
| | | (10.58) | (27.41) | - | - | - | - |
| $\sigma = 1$ | $\beta = 0.97$ | -94.58 | -93.51 | -28.33 | -26.84 | -8.37 | -7.88 |
| | | (0.53) | (1.48) | (0.81) | (1.90) | (0.27) | (0.63) |
| | $\beta = 0.90$ | -94.86 | -93.83 | -36.61 | -34.80 | -25.69 | -24.31 |
| | | (0.52) | (1.44) | (0.98) | (2.31) | (0.75) | (1.75) |
| | $\beta = 0$ | -97.98 | -97.42 | - | - | - | - |
| | | (0.27) | (0.80) | - | - | - | - |

*Notes:* Values in percent of the welfare in the base-year (pre-conflict) welfare. $\sigma$ is the degree of relative risk aversion in a CRRA utility, $\beta$ is the time discount factor, and $T$ denotes the number of years with income losses. Standard errors, in parentheses, are calculated using bootstrapped samples of destinations included in $\Phi$ repeated 5000 times.