Hazard Function Guided Agent-Based Models: A Case Study of Return Migration from Poland to Ukraine

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Abstract

The Russian invasion of Ukraine in February 2022 has led to the largest forced migration crisis in Europe since World War II, with millions displaced both internally and internationally. Among the displaced, approximately 4.2 million individuals have returned, highlighting the significance of return migration as a critical phase in the migration continuum. Existing studies on return migration are limited in scope, relying on survey-based approaches that suffer from demographic bias, lack of validation against ground truth, and inability to account for uncertainty. We propose a novel computational framework for modeling the return of conflict-induced migrants, using agent-based models (ABMs) and their surrogates. These models are grounded in hazard functions and account for sociopolitical contexts. Our proposed ABMs outperform baseline methods in estimating return migration from Poland to Ukraine by at least 42% and by as much as 57% in terms of normalized root mean squared error (NRMSE). Further, to illustrate the utility of such models for policymakers, we conduct two case studies that estimate the duration of displacement and characterize the demographic breakdown among the returnees.

1 Introduction

The Russian invasion of Ukraine that began on February 24, 2022, has caused, among other things, the largest forced migration in Europe since the end of World War II [UNHCR, 2023]. As of August 2024, around 3.7M people have been reported to be internally displaced in various parts of Ukraine [IOM, 2024]. Around 6.8M people have been displaced as refugees, among which around 6.2M have taken shelter in various European countries [UNHCR, 2024]. According to the 2025 Humanitarian Needs and Response Plan, 12.7M people are estimated to be in need of multidimensional humanitarian assistance. One such dimension considers potential migrants who have already returned or who are seeking to return to Ukraine once the situation deescalates. The return migration to Ukraine began as early as April 2022. With the out-migration from Ukraine seemingly halted, return migration is the most prominent dimension that needs addressing at present.

Reports suggest that around 4.2M people have returned to Ukraine as of October 2024 [IOM, 2024]. Even though return migration is identified to be among the highest of priorities among the multi-dimensional top-down management issues surrounding international migration [Cassarino, 2008], there is a paucity of systematic literature surrounding return migration [Adhikari and Hansen, 2014; Şahin-Mencütek, 2024; Zetter, 2021; Toth-Bos *et al.*, 2019]. In fact, available studies attempting to tackle return migration in the context of the conflict in Ukraine have relied on survey-based approaches [van Tubergen *et al.*, 2024; Maidanik, 2024; Studien, 2024]. While potentially useful in identifying key factors driving return migration, three limitations raise concerns regarding the applicability of these survey-based approaches in the long run. *First,* these surveys are conducted with a subsample of the population, which can make these studies demographically **biased**. *Second,* models fitted from these survey responses are not validated against any ground truth observations, making their **validity** questionable. *Third*, models developed from these studies are not probabilistic, making them unable to account for the **uncertainty** associated with return migration, which is inherent in spatiotemporal human mobility [Zhou *et al.*, 2021]. Thus, a computational tool that can overcome these limitations is imperative.

Contributions: To address the above limitations, we assembled a **multidisciplinary team** consisting of *computer scientists* and *political scientists*. By integrating AI-driven modeling and political science insights, our work makes the following contributions to address one dimension of the pressing societal challenge of forced displacement.

- *First*, Using the concept of hazard functions we propose three agent-based models (ABMs) to study return migration from a conflict-induced country by considering relevant contexts (e.g., social and political), with each ABM adding more contextual layers than the previous. We also propose surrogates to these ABMs that generate aggregated summary reports with lower computational expense. *To the best of our knowledge*, this is the first work that computationally models conflict-induced return migration without relying on survey-based approaches.

- *Second,* we evaluate our models against baselines and show their superiority in modeling the first wave of return migration from Poland to Ukraine, which lasted roughly until the end of July 2022. We also perform additional experiments to quantify the uncertainties in the model.
- *Third,* we conduct two case studies that underscore the utility of these models in generating policy-relevant information. The first case study involves finding the mean length of displacement. Validated against ground truth estimates from subsidiary reports, this study shows the accuracy of the emergent behavior of the ABM. The second case study, which analyzes the demographic patterns of returnees using the fast surrogate models, shows the efficacy of our model in ensuring fair resource allocation based on requirements.

2 Related Work

Return Migration: An early work [Biondo *et al.*, 2012] that employed a computational approach to model return migration in the context of voluntary migration, assumed that each migrant has two associated social networks, one at home and another abroad. Using a single-agent perspective, they calculated utility at home and abroad as functions of the networks and decaying expectation, and when the utility abroad becomes less than the utility at home, they assumed that the migrant would return. Since the work was done in the context of voluntary migration and used a single-agent perspective, it is not directly applicable to our case. A more recent work [Alrababah *et al.*, 2023] attempted to model return intentions of Syrian refugees based on survey responses of around 3000 refugees living in Lebanon. They identified safety at home and network effects to be the key factors behind return migration and commented that the effect of host countries do not play a significant role during short-term migration. A recent work [van Tubergen *et al.*, 2024] studied return migration in the context of the Ukraine war by collecting survey responses from 18,000 Ukrainian refugees. They attempted to model return migration considering three perspectives: (a) contextual (e.g., economic, social attachment), (b) source country (e.g., security) and (c) cross country (e.g., language). Although done in the context of conflict-induced forced migration, these two studies are based on surveys, which are often time consuming. Furthermore, both works have acknowledged the respondent group to be demographically biased, which may fail to paint a general picture.

Hazard Function: Although hazard functions have been used extensively in areas such as biometrics and industrial engineering to examine life-expectancy and product failures [Lee and Horvitz, 2017; Rizzuto *et al.*, 2017; Saikia and Barman, 2017], researchers have also applied them in other contexts. For example, Liu et al. [2017] applied hazard function to study influence of one user over another in social networks. Auld et al. [2011] developed a competing hazard model based on the Weibull hazard function and used it to simulate the daily activities of individuals. Azzarri et al. [2009] developed a duration model based on the log-logistic hazard to understand the factors behind migration and return of Albanian migrants, based on surveys. However, the method was developed in the context of voluntary migration

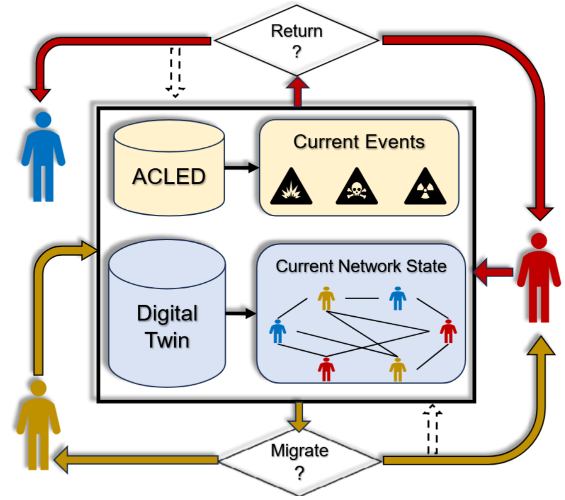


Figure 1: Architecture of a conceptual ABM to capture one cycle of migration of an agent. (From bottom left) a susceptible agent (brown) from a conflict-induced region decides to migrate based on conflict context and network influence and becomes a migrated agent (red). Afterward, when the conflict situation improves and their peer start to return, they may also return (blue). Our proposed model primarily focuses on the decision pathway (solid arrow) marked in red. The dashed arrows indicate operation that updates the state of the agents and the network.

and the temporal resolution was yearly, making it infeasible to study short-term conflict-induced migration. Finally, hazard functions have also been used in conjunction with ABMs in various domains. For example, Wu et al. [2020] used ABM simulation to infer the hazard of transmission and that of recovery. Billari et al. [2007] uses an ABM and a hazard function to study the influence of an agent's age and social pressure on the likelihood of the agent getting married. These examples illustrate applicability of ABMs in conjunction with hazard functions to model various social issues.

3 Methodology

3.1 Overview

The concepts of hazard and survival functions lie at the core of our modeling. While existing literature attempts to quantify return intention by considering different combinations of factors based on survey responses, we start with the basic assumption that every migrant wants to return eventually. As we point out in this section, this latent intention can be accommodated in the simplest of our modeling approaches to the very complex ones. First, we discuss these models under the hood of the ABM framework, with the assumption that the time of migration of each agent is known, along with other properties. Subsequently, we discuss learnable surrogates of the ABMs which can be leveraged to generate important results with less computational expense.

3.2 Hazard and Survival Functions

Hazard and survival functions were conceptualized and further developed by Cox [1959; 1972]. We briefly review these concepts to make our paper self-contained. Additional information can be found in several textbooks (e.g., [Cox and Oakes, 1984; Kleinbaum and Klein, 2012; Miller, 1981]).

Hazard and survival functions are defined for a random variable T with an underlying probability distribution function (PDF) $p(T = t)$ and a cumulative distribution function (CDF) $F(T \leq t)$ that gives the probability that an event has occurred by time t. The **survival function** $S(t)$ is defined as the complement of the CDF. Thus, $S(t) = 1 - F(t) = \int_t^\infty p(x)dx$, which gives the probability that the event of interest has not occurred by time t.

The **hazard function** $h(t)$ is often defined in conjunction with the survival function. Considering the event of interest as a failure, $h(t)$ is interpreted as the *instantaneous rate of failure* given that the failure has not occurred by time t. Mathematically, $h(t)$ is defined by $h(t) = \frac{p(t)}{S(t)} = -\frac{\partial}{\partial t} \log S(t)$. It follows that $S(t) = \exp\left(-\int_0^t h(u)du\right)$.

3.3 Problem Formulation

Let A be the set of agents and X be the set of conflict-induced regions. Each agent $a \in A$ has the following attributes. First, their migration time T_a^M, the time at which agent a migrates to a different country. For agents a who never migrate, we set $T_a^m = \infty$. Second, their origin $x_a \in X$. Additionally, let $G_A(A, E_A)$ be the network formed by the agent set A where E_A corresponds to the agent pair who may exert peer influence over one another. Let $\mathcal{N}_a$ be the set of agents who are the neighbors of agent a induced by the edges E_A. We assume that the edge set E_A does not change over time.

Let $h_a(t > T_a^m)$ denote the hazard rate of an agent at time t that represents instantaneous rate of the agent failing to stay migrated (i.e., returning to x_a). While recurring movements are possible, we assume that agents only leave their countries of migration when their goal is return migration. Applying the formula for $S(t)$ in the discrete-time scenario, the probability $S_a(t+1)$ that the agent will stay migrated at time $t+1$ given that it has remained a migrant up to time t, can be written as $S_a(t+1) = \exp\left(-\sum_{t'=0}^{t} h_a(t')\right)$. By doing a Bernoulli sampling based on $S_a(t)$ (where Bern(p) indicates that the Bernoulli trial leads to success with probability p), we can estimate return state of an agent at time t. Formally, let $r_a(t)$ denote the state whether an agent has returned by time t or not. Then, $r_a(t) \sim \text{Bern}(S_a(t))$ tells us the return state of agent a at time t (if the agent has not already returned). Thus, modeling the hazard function $h_a(t)$ will allow us to control the return dynamics in various ways. Subsequent sections describe how we employ various strategies to progressively refine the hazard function by employing various societal factors that play a key role in conflict-induced migration scenarios. Across all the models $h_a(t \leq T_a^m) = 0$, which constrains agents from returning before migration. Thus, from here on, $h_a(t)$ corresponds to $h_a(t > T_a^m)$.

3.4 ABM of Return Migration

Model 1: Basic Hazard (BASE)

Motivation: In the context of forced migration, it is well established that the general intention of displaced individuals is to eventually return to their place of origin [Zetter, 2021]. Therefore, the decision to return can be effectively seen as a time-to-event problem, where the "event" is the act of returning. The hazard function is often used for survival analysis in discrete-time simulation [Suresh *et al.*, 2022]. Thus, it is a natural choice for modeling return migration dynamics.

Formulation: Various forms of hazard functions are used in the literature. A comprehensive list of these various forms, along with their mathematical properties and corresponding survival functions has been described in [Van Wijk and Simonsson, 2022]. Our initial model uses the simplest of these forms where we consider the hazard rate to be constant for all agents at all times. Thus, the ABM is characterized by:

$$h_a(t) = h \tag{1}$$

It indicates that at any time $t > T_a^m$, agent a has a constant value h of baseline hazard rate that controls their likelihood of returning if they have not already returned by that time. It can be shown that, if the hazard rate is constant, the underlying probability distribution for the time to return can be expressed as a geometric distribution [Chakraborty and Gupta, 2015]. Thus, $P(r_a(t) = 1) = h \times (1-h)^{t-T_a^m}, \forall a, \forall t$.

Agent Dynamics: Thus, the *Basic Hazard Guided ABM* works as follows. Initializing the baseline hazard rate h, at every time step t, all the agents a with $T_a^m < t$ and $r_a(t-1) = 0$ calculate $S_a(t)$ (probability of not returning) based on the baseline hazard h. Then, $r_a(t)$ is sampled from $S_a(t)$.

A more nuanced analysis can be conducted by classifying the agents into groups and assigning each group a separate hazard rate. While we explore this in a case study, our goal is to provide the foundation for adding more layers of complexity starting from the simplest of assumptions. Therefore, while acknowledging the possibility of agent class-based hazard rates, we refrain from doing so in our initial evaluations.

Model 2: Conflict Context Influenced Hazard ($C^{\mathcal{L}}$)

Motivation: Having established the basic ABM for modeling return migration, we next consider what other contexts to incorporate in calculating the hazard rate and how to incorporate them. Several survey reports conducted on Ukrainian migrants to identify key factors behind their intention to return can help us in this regard. One report published by IOM [Sohst *et al.*, 2024] indicates that *improved security situation in origin community/Ukraine* is the primary motive behind Ukrainian refugees' return in the short term. In another, safety was marked as the primary factor for return by more than 45% of the participants [Sologoub, 2024].

Formulation: We incorporate conflict context for modeling return migration dynamics into the ABM as follows. Let, $Z_a \subseteq X$ denote the regions observed by agent a. Let $c(z,t)$ denote the conflict context[1] of region z at time t. We use this conflict context to modify the baseline hazard rate as follows.

$$h_a(t) = h \times \left(1 - \frac{1}{K} \sum_{z \in Z_a} \sum_{t'=0}^{W} c(z, t - t' - \mathcal{L})\right) \tag{2}$$

Here, $\mathcal{L}$ is a lag parameter that controls the time of the latest conflict context. Since migration decisions involve planning

[1] Conflict context is a scalar quantity to measure the intensity of conflict in a region at a particular time. More details are in Section 4.

and travel time [Wycoff *et al.*, 2024], choosing such parameter is important for temporal mapping of a migrant from intending to return to being recorded as a returnee at the border. The window parameter W is used to reduce the effect of noise present in the data recording conflict context [Mehrab *et al.*, 2022]. Finally, K is a normalizing constant so that the right-side term of the multiplication is bounded between 0 and 1. In the evaluation section, we describe how these are configured. From Equation (2), we can see that when the conflict context is high, the baseline hazard will be scaled down, indicating that the likelihood of return will decrease and vice-versa.

Agent Dynamics: Thus, the *Conflict Context Influenced Hazard Guided ABM* works as follows. At every discrete-time step t, all the agents a with $T_a^m < t$ and $r_a(t-1) = 0$ look at the conflict contexts of each region $z \in Z_a$ from time $t - \mathcal{L} - W$ to $t - \mathcal{L}$ and incorporate it to scale the baseline hazard h following Equation (2). This scaled hazard is used to calculate the return probability of each agent.

Researchers have used other forms of hazard functions (e.g., Weibull) to include additional covariates [Auld *et al.*, 2011]. However, these covariates are added in the exponent term while the baseline hazard rate is kept as separate. Since conflict context is significant to return dynamics, we choose this functional form to let it affect the baseline hazard. Moreover, the other forms of hazard functions have additional parameters. Since this study aims at developing the simplest possible model with a minimal set of parameters, we refrain from using functional forms that introduce additional parameters and complexities.

Model 3: Conflict and Peer influenced Hazard ($C^{\mathcal{L}}$P)

Motivation: According to many social and behavioral theories (e.g., theory of planned behavior [Ajzen, 1991], herd behavior [Banerjee, 1992]), peer influence is a key factor behind driving one's decisions. It has also been established that both conflict events and peer influence are important in driving migration decision-making [Mehrab *et al.*, 2024b]. Following this, in our final model, we incorporate peer influence along with conflict context. We do so using the threshold model, a well-known model used for capturing peer influence [Valente, 1996; Granovetter, 1978]. Traditionally threshold model is used in the context of peer influence by having agents go through state transition when the number of neighbors with a particular state exceeds some threshold [Hancock *et al.*, 2022; Qiu and others, 2022]. Since we are modeling the return state with hazard function, we use the threshold model instead to have the agents transition using different hazard functions.

Formulation: Let, $q_a(t) = \sum_{a' \in \mathcal{N}_a} r_{a'}(t)$ be the number of neighbors of a who have returned by time t. We express $h_a(t)$ in the form of a piecewise hazard function as follows.

$$h_a(t) = \begin{cases} h_\ell \cdot \left(1 - \sum\limits_{z \in Z_a} \sum\limits_{t'=0}^{W} \frac{c(z, t-t'-\mathcal{L})}{K}\right) & \text{if } \frac{q_a(t)}{|\mathcal{N}_a|} \geq \tau_a \\ h_s \cdot \left(1 - \sum\limits_{z \in Z_a} \sum\limits_{t'=0}^{W} \frac{c(z, t-t'-\mathcal{L})}{K}\right) & \text{otherwise.} \end{cases} \tag{3}$$

Here, τ_a ($0 \leq \tau_a \leq 1$) is the fractional active threshold parameter required to influence agent a. Since considering different thresholds across agents is difficult, we consider a simpler model where each agent has the same fractional active threshold parameter (i.e., $\forall a \in A, \tau_a = \tau$). While we do not impose any constraint here, ideally one can expect h_ℓ to be larger than h_s, since when more people are returning it should drive a neighboring agent more likely to return.

Agent Dynamics: Thus, the *Conflict Context and Peer Influenced Hazard Guided ABM* works as follows. At every time step t, all the agents a with $T_a^m < t$ and $r_a(t-1) = 0$ look at the fraction of their neighbors who have migrated and returned. If the fraction is larger (smaller) than τ, they choose a baseline hazard of h_ℓ (h_s). Then, they look at the conflict contexts of each region $z \in Z_a$ from time $t - \mathcal{L} - W$ to $t - \mathcal{L}$ and incorporate it to scale the baseline hazard and subsequently calculate the return probability using it.

It can be seen that we have progressively added layers to our model to incorporate contexts of different dimensions, making the models progressively more powerful in capturing return migration dynamics. However, as this has two additional parameters (a different baseline hazard and the threshold), it will be computationally more expensive to calibrate.

3.5 Surrogate Models of Return Migration

In this section, we propose some surrogates to the ABMs operating in the aggregated population space rather than the individual agent space. While we lose some granularity by doing so, we significantly reduce the computational cost.

The problem formulation for return migration in the aggregated population space is as follows. Let $M = \langle m(1), m(2), ..., m(T) \rangle$ be the temporal estimates of migrants, where $m(t)$ is the number of migrants at time t. We define R to be the $T \times T$ return matrix, where $r_{i,j}$ is defined as the number of returnees at time i among those who migrated at time j. Thus, by definition, when $i \leq j$, $r_{i,j} = 0$. Our goal is to find the values $r_{i,j}, \forall i, j : i > j$. We will refer to these as the **non-trivial** entries of the R matrix. In the remainder of this subsection, we describe three surrogates corresponding to the three proposed ABMs; each description shows how the non-trial values of R are computed.

Surrogate to the BASE model

Let h be the constant hazard rate defined as the parameter of BASE. Let $Q_{i,j}$ denote the number of remaining migrants at the time i from time j who survive (i.e., do not return), calculated by $Q_{i,j} = m(j) - \sum_{k<i} r_{k,j}$. Thus, the surrogate to BASE computes the non-trivial entries $r_{i,j}$ as follows.

- $r_{i,j} = Q_{i,j}\left(1 - e^{-h(i-j)}\right)$ if $i > j$

Surrogate to the $C^{\mathcal{L}}$ Model

Similar to how the problem space in the aggregated population space, the surrogate also assumes conflict context at a global level. Let h_c^t be the conflict-influenced hazard expressed as $h_c^t = h \times (1 - \frac{1}{K} \sum_{x \in X} \sum_{t'=0}^{W} c(x, t - t' - \mathcal{L}))$, where $W, K, \mathcal{L}$ have similar meanings as described for $C^{\mathbf{L}}$. Thus, the non-trivial entries $r_{i,j}$ can be calculated as follows.

- $r_{i,j} = Q_{i,j}\left(1 - e^{-h_c^i(i-j)}\right)$ if $i > j$

Surrogate to the $C^{\mathcal{L}}$P model
Since $C^{\mathcal{L}}$P considers peer influence at the local neighborhood level of agents, an exact formulation of this peer influence is difficult for the surrogate working at aggregated population space. We approximate the peer influence as follows. Let, $\tilde{r}(t) = \sum_{t'=1}^{t} \sum_{j=1}^{t'} r_{i,j}$ be the total number of people who have returned by time t. Let h_{cp}^{t} be the conflict and peer influenced hazard expressed as follows.

$$h_{cp}^{t} = \begin{cases} h_\ell \times \left(1 - \sum\limits_{x\in X} \sum\limits_{t'=0}^{W} \frac{c(x,t-t'-\mathcal{L})}{K}\right) & \text{if } \frac{\tilde{r}(t)}{N} \geq \tilde{\tau} \\ h_s \times \left(1 - \sum\limits_{x\in X} \sum\limits_{t'=0}^{W} \frac{c(x,t-t'-\mathcal{L})}{K}\right) & \text{otherwise} \end{cases}$$

where N is the total number of agents. This essentially is a peer influence considered at the overall population level instead of the local neighborhood level. Using this, this surrogate calculates non-trivial $r_{i,j}$ as follows.

- $r_{i,j} = Q_{i,j}\,(1 - e^{-h_{cp}^{i}(i-j)})$ if $i > j$

Here, the exponent term contains the conflict and peer-influenced hazard term h_{cp}^{i} which is defined above. It can be seen that while these surrogate models can generate aggregated level outputs, they cannot generate detailed individual agent level behavior. However, since the outputs of surrogate models can be generated with great computational efficiency, if they are similar to the results of ABM, they can be used as components of beneficial software tools for policymakers.

3.6 Model Calibration

In order to find a parameter configuration (e.g., hazard rate, threshold parameter) that best fits the model, we define a *loss function* that combines the capability of the model to capture the scale and trend of the observed return estimate and apply a black-box optimization technique, namely *Bayesian optimization*, to optimize this loss function. Bayesian optimization is applied when the parameter space has a small dimension (typically < 20), the objective function is computationally extensive and its gradient is non-trivial to evaluate ([Frazier, 2018]).

Let $R_\theta = \langle r_\theta(1), r_\theta(2), ..., r_\theta(T)\rangle$ be daily return estimates provided by our models (ABM or surrogate) parameterized by θ. Let, $\tilde{R} = \langle \tilde{r}(1), \tilde{r}(2), ..., \tilde{r}(T)\rangle$ be the observed number of returnees which we want to calibrate our model. We define the following loss function.

$$L(\theta) = \lambda_e \text{RMSE}(R_\theta, \tilde{R}) + \lambda_c(1 - \text{PCC}(R_\theta, \tilde{R})) \quad (4)$$

The first term calculates the root mean squared error (RMSE) between the model estimate and the ground truth estimate whereas the second term calculates the Pearson correlation coefficient (PCC) between the model estimate and the observed estimate. Here, λ_e and λ_c are weight coefficient hyperparameters. Our proposed loss can help the model avoid getting stuck in local minima in terms of just the traditional RMSE loss. We present a justification for this claim and perform experiments to validate our claim in the online supplementary material [Mehrab *et al.*, 2025]

Baseline	NACRPS		NRMSE		PCC	
L^{21}	N/A		0.223		0.569	
L^{30}	N/A		0.213		0.617	
L^{40}	N/A		0.211		0.628	
L^{45}	N/A		0.207		0.647	
	NACRPS		**NRMSE**		**PCC**	
Ours	ABM	S-ABM	ABM	S-ABM	ABM	S-ABM
BASE	0.067	0.062	0.12	0.131	0.95	0.92
C^{21}	0.059	0.060	0.112	0.135	0.93	0.91
C^{21}P	0.057	0.062	0.106	0.126	0.93	0.91
C^{30}P	0.051	0.083	0.089	0.102	0.95	0.93
C^{35}P	0.052	0.051	0.094	0.128	0.96	0.94
C^{40}P	0.056	0.054	0.107	0.169	0.95	0.89

Table 1: Evaluation of return estimation of proposed ABMs and their corresponding surrogates (denoted as S-ABM). The metrics are reported by comparing the median estimate of the ABM (or surrogate) with the ground truth. Each instance of ABM takes around 10 minutes and the surrogate takes around 3 seconds to run.

4 Evaluation

The following subsection provides an overview of the configurations of our experiments and the subsequent subsections describe the results and case studies. All evaluation and studies involve the case of the return migrants from Poland to Ukraine during the early period of the Russian invasion of Ukraine. While we cannot comprehensively evaluate the generalizability of the model due to inadequacy of ground truth pertaining to diverse scenario, we emphasize that our model can be applied in other conflict scenarios as well.

4.1 Experimental Setup

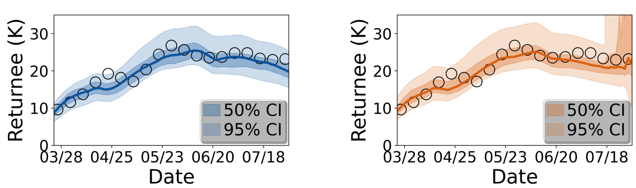
Datasets: We parse the conflict events of Ukraine during the Feb-Aug 2022 period from ACLED [2010]. For the agent data, we use the synthetic household data described in [Mortveit *et al.*, 2020]. We collect the synthetic households of Ukraine and the associated synthetic individuals. These households represent the agents in our model. Finally, we obtain the border-crossing data from Polish border guards [Portal, 2022] and use the number of Ukrainians crossing a Poland-Ukraine border between February 24, 2022 and August 01, 2022 as the ground truth.

Building Block Models: Since our problem formulation requires knowing the migration time of the agents to estimate their return time (Figure 1), we first apply the ABM-TPB model [Mehrab *et al.*, 2024a] to assign each migrant a refugee or internally displaced (IDP) status. Then, we apply the method proposed in [Pandey *et al.*, 2023] to place each refugee in one of the six neighboring countries of Ukraine and apply our methodology on the refugees placed in Poland. To account for the uncertainties associated with these models, we run 100 realizations of ABM-TPB model to create a Digital Library (DL) of simulations (see supplementary material [Mehrab *et al.*, 2025] for details) by using Latin Hypercube Sampling (LHC) over the parameter spaces for ABM-TPB. From the DL, we select the 30 best performing simulations. Then, we run our models for return migration over each of these simulations 30 times.

Hyperparameters: We create the agent network G_A using Kleinberg's Small World Model (KSW) [2000] using the methods and parameters described in [Mehrab *et al.*, 2024b]. The same network is also used for the ABM-TPB model. Across all the $C^{\mathcal{L}}$ and $C^{\mathcal{L}}$P models, we use a constant window parameter $W = 7$ days and the lag parameter $\mathcal{L} \in \{21, 30, 35, 40\}$ days. To reduce the number of possible covariate combinations, we also set $Z_a = X, \forall a \in A$ for our ABM models. Future research can explore how limiting the scope of observation to different radii of neighboring regions can change the outcome of the model and how this can be done across agents of various demographic groups. Finally, we use daily total fatalities from ACLED as the conflict context to our ABMs and their surrogates and K is chosen to be the maximum value among all conflict contexts.

Metrics: We first evaluate Normalized Root Mean Squared Error (NRMSE), to measure accuracy of the model estimation. The second metric is Normalized Average Continuous Ranked Probability Score (NACRPS), used to quantify how well the model can account for uncertainty in its estimation. Finally, we also evaluate the Pearson Correlation Coefficient (PCC) to quantify how well the model can capture the trend in the observed data. These metrics are described in detail in the online supplementary material [Mehrab *et al.*, 2025].

Baseline: As baselines for our models, we create some vanilla linear regression models L^D, $D \in \{20, 30, 40, 45\}$. Here, D represents the number of days of historical conflict contexts each model uses as features. For these models, we consider both the number of events and the fatalities of events as conflict context. Note that these models are not probabilistic in nature; so, they cannot account for uncertainties.



(a) C^{30}P (b) Surrogate of C^{30}P

Figure 2: Best Performing ABM and Surrogates for estimating return migrants from Poland to Ukraine. Circles represent ground truth data. Visualizations corresponding to other models of Table 1 can be found in the online Supplement. 50% (95%) CI corresponds to the 50% (95%) confidence interval of the model estimate.

4.2 Experimental Validation

Table 1 summarizes the performance of our proposed models against the baseline methods. We describe our main findings in the next two subsections. For a more comprehensive set of experiment results, see the online supplementary material [Mehrab *et al.*, 2025].

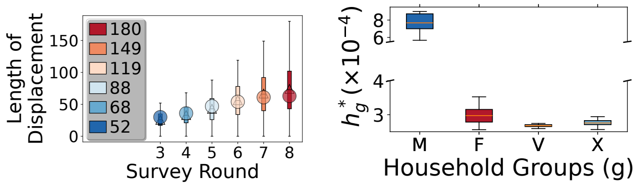
Error and Correlation: The best ABM (C^{30}P) has a median NRMSE of 0.089, an improvement of around 57% compared to the best-performing regressor (L^{45}, with an NRMSE of 0.207). Even the simplest ABM (BASE) has a 42% improvement in NRMSE compared to L^{45}. The surrogates also outperform the baseline methods. The best-performing surrogate (surrogate of C^{30}P) has a median NRMSE of 0.102, a 51% improvement over L^{45}. Further, our proposed models capture the trend of the return migration better than baseline methods, with PCC constantly being higher than 0.9. These results underscore the capability of the proposed hazard-based models to capture the scale and trend of the return migration accurately. Notably, $C^{\mathcal{L}}$P models always seem to perform better than BASE or $C^{\mathcal{L}}$, thus bringing out the importance of considering different layers of sociopolitical contexts in capturing return dynamics. We elaborate on this through an ablation study (see Supplementary material [Mehrab *et al.*, 2025]).

Surrogate vs ABM: The proposed surrogate models are able to produce estimates comparable to their ABM counterparts. We take the C^{30}P as an example, which has the best performance in terms of NRMSE. Its surrogate has an NRMSE of 0.102, which is worse only by 14.6% compared to the NRMSE of its ABM counterpart. However, the surrogate model takes around three seconds to generate the return estimate whereas the ABM takes close to 10 minutes for one instance to execute. Such a significant improvement in computation time may compensate for the penalty in accuracy. However, it must be noted that the more sub-optimal the ABM gets, the performance of its surrogate gets progressively worse. For example, the performance drop in NRSME of the surrogate for C^{35}P is almost 36.1% (0.128 vs 0.094) and for C^{40}P is around 57%. This behavior also underscores the importance of choosing a good lag parameter. Effect of the lag parameter is further discussed in the online Supplementary material [Mehrab *et al.*, 2025].

4.3 Uncertainty Quantification

It is important to quantify the uncertainty associated with a probabilistic model designed for generating return migration estimates. To do so, we analyze the NACRPS of the models tabulated in Table 1. *First,* we notice that adding layers of complexity to BASE decreases NACRPS, suggesting improvement of both point forecasts and probabilistic forecasts. *Second,* the $C^{\mathcal{L}}$P ABMs with lower NRMSE have low NACRPS as well; thus, these models not only have reasonable point prediction accuracy, but the uncertainty associated with probabilistic return estimation is also accounted for more effectively. *Third*, adding layers of complexity to the surrogate models do not necessarily improve NACRPS. As example, when conflict context is introduced with the BASE, the NACRPS slightly improves with a decline in NRMSE. But, when peer influence is added, the NACRPS declines as NRMSE improves. Thus, there is a tradeoff between accuracy and uncertainty across these surrogate models. If we compare the C^{30}P surrogate with its ABM counterpart in Figure 2, we realize that the poor NACRPS of the surrogate is due to high uncertainty interval (shaded region) at the later period (Figure 2b), which does not happen for the ABM (Figure 2a). In the ABM, since peer influence comes from the local neighborhood of each agent, the threshold is unlikely to be met by all agents at once. For the surrogates, peer influence is calculated by looking at the entire population. Thus, the transition occurs for everybody simultaneously. Across multiple simulations, uncertainty propagated by this sharp transition is observed intensely, leading to higher NACRPS values.

5 Case Studies



(a) Length of migration before return reported in IOM surveys at different rounds (Circles) vs model median estimate (Triangles) with 50% CI (Rectangle). Days elapsed since war is indicated in the legend.

(b) Demographic pattern of return. Each boxplot corresponds to the calibrated hazard rate over 20 surrogate instances. The groups are categorized based on household composition, discussed in Table 2.

Figure 3: Two case Studies conducted using our proposed models

5.1 Return Time Estimation

For our first case study, we aim to understand an aspect of utmost importance to policymakers. The question we want to address is the following. *What is the expected length of displacement before someone conducts return migration?* An answer to this question helps policymakers to decide whether the migrants require long-term integration programs or short-term emergency responses [World Bank, 2025]. It can also help policymakers plan for advocating a ceasefire on various frontlines, given migrants displaced from vicinities return after a certain period [Associated Press, 2024].

To answer this question, we calculate the length of stay across agents at different periods of the Ukraine war using the output from the C^{30}P ABM. Figure 3a shows distribution of the length of displacement, along with the reported mean length of displacement provided in the IOM general survey reports [IOM, 2022]. We can see that the reported mean length agrees well with the model estimates. Moreover, the increase in the length of displacement before return with the progression of the war is correctly estimated by our model. This signifies that our proposed hazard-guided ABM is appropriate for time-to-return modeling as this emergent behavior matches qualitative observation and captures overall return migration dynamics.

5.2 Demographic Pattern of Returnees

Our second case study aims to estimate the demographic composition of returning migrants. Since ground truth containing demographic details is not available regarding return migrants, such estimates can help policymakers in tailoring targeted reintegration initiatives [Battistella, 2018] or allocating social/medical services based on the psychological needs of specific demographic groups [Migration Observatory, 2011]. Here, the question we want to address is: *What is the likelihood of return for migrants from different demographic groups?* Fitting hazard rate parameters across various demographic groups can answer this question.

Group	Household Description	Migrant ratio (%)
M	Adult males only	1.47±0.41
F	Adult females only	6.07±0.23
V	Elderly (and/or) children	71.64±0.34
X	Adult males and females	20.81±0.16

Table 2: Group categorization based on demographic attributes. These groups were chosen upon careful discussion with the Political scientists in our team. Right column shows the distribution of each group as a migrant from ABM-TPB simulation.

Therefore, we modify the surrogate of BASE as follows. We first categorize each household into one of the four groups outlined in Table 2. Then, we initialize $h_g, \forall g \in \{M, F, V, X\}$ and the surrogate model produces return estimates for the groups individually. The aggregation of return estimates of all groups is calibrated to match the total return estimates Once calibrated, the hazard rates of individual groups in Figure 3b reveal interesting emergent properties.

First, we notice that the adult male-only households have a high hazard rate compared to other groups. This indicates their high propensity to return to Ukraine, which can be attributed to the mandate requiring adult males to participate in the war. *Second*, we observe that households with vulnerable groups (i.e., elderly, children) are the least likely to return. This implies that the threat of security is greatest among families with children and elderly. *Third,* we observe that female-only households have hazard rates similar to the vulnerable groups compared to the male-only households, again indicating their greater concern for security compared to adult males. Consequently, females without partners are slightly more likely to return than females with male partners, which corroborates with prior findings [Sologoub, 2024], indicating the possibility of having a partner alongside to be more motivating to settle in a new place. *Finally,* there is less variance in hazard rate across the V group, compared to the other groups. Since the largest portion of migrants is comprised of this group, a slight variation from the calibrated hazard rate may cause a large deviation from the ground truth. Overall, the ability to produce demographically detailed estimates underscores the usefulness of the model in building decision-support tools for policymakers.

6 Concluding Remarks

We developed novel agent-based models (ABMs) for return migration, experimentally evaluated these models and conducted case studies using these models to demonstrate their usefulness in generating policy-relevant information. Our models can be seamlessly incorporated to work with prior computational models that generate outflow of Ukrainian migrants and subsequently place them in one of the neighboring countries. Therefore, our work provides the path to develop the first end-to-end ABM of forced migration that is jointly able to capture these heterogeneous migration dynamics. Future work can explore the return dynamics of internally displaced people and consequently, address the dynamics of recurring migration.

Ethical Statement

The work reported in this paper proposes agent-based models for studying several aspects of returning migrants during conflicts. Such models are useful in developing software tools that will be beneficial to policymakers. The paper presents simulation-based evaluations of the models using a synthetic dataset discussed in one of the cited references and other public domain datasets.

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