Agent-Based Modeling of Economic Migration: Laying the Groundwork for Skill-Based Migration

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Abstract

This paper investigates skilled migration by examining the interaction between micro-level drivers of migration and the macro-level influences, specifically economic agglomeration centers. We develop and analyze two agent-based models (ABM) to study how the influence of wage gradients and agent attributes, guided by Hein de Haas's aspirations-capabilities framework, shape migration patterns. This paper lays the groundwork for future research on skill-based migration. The simulations generate emergent spatial patterns in employment and wage distribution, suggesting that the order of the of model execution affects the prominence of these patterns.

Introduction

Global migration has profoundly shaped human history for thousands of years. From the initial dispersal of Homo sapiens out of Africa into Europe and Asia to the present day, where approximately 281 million individuals, representing one out of every thirty people globally, reside outside their birth countries [1], migration has been an enduring phenomenon in our history.

Skilled migration, a subset of global migration, is driven by factors such as the need to secure resources, the aspiration for better economic and social opportunities, the imperative to flee inhospitable environments, and the innate curiosity to explore. Migration has shaped the demographic, cultural, and economic landscapes of the world, weaving a rich cross-cultural tapestry. This movement raises important questions about risk, integration, identity, and economic impact in both sending and receiving countries.

Migration is a complex issue but often misinterpreted due to a scarcity and asymmetry of data, the lack of a comprehensive theoretical framework, and insufficient scholarly work. According to the World Migration Report 2022, only 45 governments provide reliable migration data, highlighting the challenges in understanding global migration patterns [1]. In a recent study, researchers overcame this challenge by using Facebook data from 3 billion active users from January 2019 through December 2022 to measure global migration [2].

Addressing labor shortages requires policymakers in affected countries and regions to carefully analyze international migration patterns and estimates of migration flows. In an interconnected and globalized world, skilled migration has become a significant force shaping a competitive labor market by filling critical workforce gaps and diversifying talent pools. Skilled individuals, equipped with tertiary education, specialized knowledge, and in-demand technical expertise, are increasingly seeking opportunities beyond their national borders [3]. Firms, local economies, and institutions play a crucial role in facilitating the flow of talent across borders, often attracted by the cost savings and competitive advantages offered by larger, more diverse global talent pools.

Skilled migration represents a critical yet often neglected dimension in existing labor market analysis. Traditional migration theories are limited in providing a comprehensive explanatory framework. Push-pull model guided by neoclassical economics [6] assume rational actors and costless, unrestricted relocation. Assuming rational actors in migration theory is overly simplistic by basing motivation to migrate on utility maximization. Traditional migration theory also assumes that an individual's migration preferences remain constant and do not change over their lifetime.

This paper aims to address these limitations and provide a more nuanced approach to representing heterogenous migrants' attributes guided by Hein de Haas's aspirations-capabilities framework [4]. Since migration does not occur in a vacuum, agglomeration economies are used in this paper as an example of a macro structure influencing migration decision-making. The agglomeration economies model is based on Schweitzer's unemployed agents as Active Brownian Particles agents searching for employment [9]. This approach provides a more holistic and nuanced understanding of micro-level and macro-level drivers for skilled migration.

The Aspirations-Capabilities Framework (ACF) in Migration Studies

Social scientists have sought to understand the motivations behind an individual's decision to relocate for work. The Thomas Schelling's 1971 model explored an individual's simple preference to live amongst similar neighbors demonstrated how micro-level preferences can lead to macro-level segregation. The model simplifies real-world complexities by assuming relocation is costless and unrestricted. Beyond an individual's simple preferences, people's worldviews and migration preferences do not remain static and evolve over time.

Everett Lee's [6] push-pull model, introduced in 1966, suggests that an individual's willingness to migrate is influenced by both push factors (e.g. economic hardship, political instability, or violence) that compel them to leave their place of origin and pull factors (e.g. better opportunities, improved lifestyle, and greater personal freedoms) that attract them to a new destination. Lee's model recognizes the role of demographic factors such as age, gender, race, and social class, it does not fully account for human agency. The push-pull model depicts migrants as passive actors responding to external structural forces, without fully accounting for their participation in the decision-making process.

The limitations of traditional migration theories in explaining skilled migration have highlighted the need for more nuanced theoretical frameworks. Hein de Haas [4] defines human mobility as people's capability to choose where to live, including the option to stay rather than a passive response to static push and pull factors. De Haas's aspirations-capabilities framework (ACF) synthesizes Isaiah Berlin's 1969 concepts of positive and negative liberty [7] and Amartya Sen's 1999 capabilities framework [8]. De Haas proposes that migration is shaped by the interaction between individual decision making and the influence of macro-level structures or institutions.

ACF theorizes that migration aspirations are dynamic and evolve as individuals' life circumstances change, aligning with broader life goals. These desires are shaped by factors like exposure to different cultures, openness in their temperament, and how individuals inform themselves of the state of the world and global affairs. Skilled migrants, which are often highly educated, are equipped with in-demand skills and more informed about the world around them. De Haas identifies two main categories of migration aspirations [4]:

- **Instrumental aspirations**: Migration is viewed as a means to achieve goals, such as better job prospects or fleeing persecution – similar to the rational utility-maximizing model.
- **Intrinsic aspirations**: Migration is desired for its own sake, motivated by exploration, personal growth, or adventure.

Capabilities, influenced by Sen's capability approach, refer to the personal freedoms and resources that enable individuals to realize their potential. This is based on the degree to which an individual has full agency, encompassing the freedom to choose where to relocate to but also the freedom to remain. A critical component of capability is access to resources, such as credit, to support the financial burden and risks associated with the journey and settling at the destination. In ACF [4], there are different categories of personal liberties [7]:

- **Positive liberty ("Freedom To")**: An individual is empowered to act and has access to resources for migration:
    - **Economic:** Ability to finance the migration costs.

    - **Social:** Support from networks, including family, friends, and professional contacts.
    - **Culture**: Knowledge, education, language proficiency
    - **Physical**: Health and ability to undertake the journey
- **Negative liberty ("Freedom From")**: An individual does not face restrictions or barriers that prevent them from migrating. These include examples such as restrictive immigration policies, lack of humanitarian rights, oppression or conflict at the origin or destination.

The synergy between the ACF and agent-based modeling (ABM) is significant. ACF provides the theoretical foundation for understanding an individual's propensity to migrate and ABM offers a computational framework to model heterogeneous micro-level drivers in the decision-making process. By defining simple rules for individual agent behavior based on de Haas's migration theoretical principles, an ABM can be a robust tool for discovering emergent migration patterns.

Agglomeration Economies as a Macro Structure

Skilled migrants evaluate the opportunities and lifestyles in potential destinations and factor them into their decision. While individuals possess agency in their decision to migrate, their decisions are shaped by their perceptions of available opportunities. Agglomeration economic centers are one example of a structural force that attracts skilled migrants.

Concentrated areas of firms, known as economic hubs, create cooperative environments that increase productivity, lower costs through shared resources, and facilitate knowledge spillovers. These hubs, offering lucrative career prospects, attract companies competing talent in the global labor market by providing appealing incentives. Although these areas may suffer from high living costs and overcrowding, their strong economies of agglomeration and potential for innovation continue to draw migrants.

Active Brownian Particles (ACP) to simulate Agglomeration Economies

In his 1998 paper, Frank Schweitzer utilized Active Brownian Particles (ACP) to simulate migration and economic agglomeration [9]. Using mathematics and simulation, Schweitzer created a minimalist model of unemployed agents seeking jobs based on local wage conditions. Cooperative dynamics were integrated through a production function affecting hiring and firing rates, thereby driving local economic activity.

These cooperative effects are modeled using a Cobb-Douglass production function, where a firm's hiring and firing rates influence the emergence of economic centers over time [9]. In equation (1), the production function presented by Y is expressed as a function of $l(r,t)$, the local density of employed agents at location r and time t. Labor is assumed to be the sole input, with a uniform common β across the region. When $\beta > 1$, the model reflects increasing returns to scale; otherwise, it reflects decreasing returns to scale.

$$Y\{l(r,t)\} = \frac{h}{A_c + A_u\{l(r,t)\}} \cdot i \cdot l^{\beta(r,t)} \qquad (1)$$

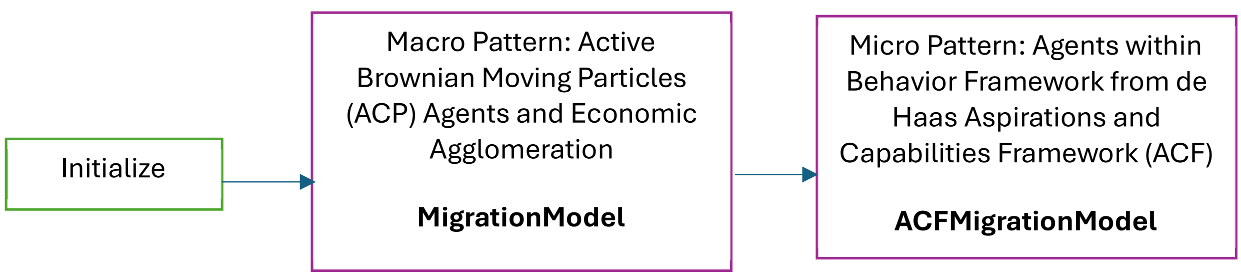
The A_u represents summarized firm output e.g. Kapital and is assumed to be constant. The A_C term is the non-linear cooperative effects from interactions among the agents. In a Cobb-Douglas production function where only labor is considered, the revenue function is derived from the production function, and the marginal revenue is the derivative of that revenue function with respect to the labor input. Thus, as derived by Schweitzer [9], the wage of potential agent as a function of local density of employed agents at location r at time t with given input parameters $\bar{A}, a_1, a_2$ is in equation (2):

$$\omega\{l(r,t)\} = \frac{A}{2}\left[1 + \exp(a_1 l + a_2 l^2)\right] \beta l^{\beta-1} + \frac{A}{2}\left[1 + \exp(a_1 l + a_2 l^2)\right] (a_1 + 2a_2 l) l^{\beta} \quad (2)$$

Unemployed agents move towards regions with high wages and greater densities of employed agents, potentially leading to agglomeration. With this understanding of de Haas's aspirations-capabilities framework and Schweitzer's Active Brownian Particles (ABP) model of economic agglomeration, we now turn to the agent-based models in this paper.

Model Introduction and Overview

The paper presents two agent-based models of migration that combine the macro-level with the micro-level perspectives. At a high level, the simulation architecture consists of two ABMs: Active Brownian Particles ABM and Aspirations-Capabilities Framework ABM.



As shown in the diagram, the ACP ABM, called the MigrationModel, is executed first. This results in an economic landscape that identifies agglomeration economies emerging solely based on agent behaviors e.g. seeking jobs, firms hiring and firing rates, and the mechanisms of wage determination. The output of the MigrationModel serves as the initial input to the starting locations for ACFMigrationModel, which features agents attributed with aspirations and capabilities that influence their decision to migrate to high wages and greater densities of employed agents.

MigrationModel

The MigrationModel is initialized with agents in an economic landscape, as represented by wages. Each cell contains a single ACP agent. There are no pre-existing spatial variations or wage hotspots; every location starts with a wage of zero. Initially, fifty percent of agents are employed, and the rest are unemployed. These ACP agents become the sole determinants of the nascent wage landscape. This direct causal link from initial agent configuration to the first iteration of the wage map is designed to show the self-organization of economic patterns. It ensures that any emergent spatial structures in wages are not biased or pre-conditioned by arbitrary initial wage settings, allowing for a clearer study of how such patterns arise from agent interactions and system dynamics. Consequently, any wage patterns or agglomerations that develop during the simulation can be attributed to the model's endogenous dynamics: agent job-seeking behaviors, interaction rules, and the mechanisms of wage determination.

MigrationModel uses these steps for calculating and updating the wage field. First, a variable, luv, is calculated to represent the local labor density, for each cell. Luv takes the total number of employed agents within the Moore neighborhood (including the center cell) and divides by the size of that neighborhood. It is assumed that neighborhood size is greater than 0.

$$luv = \frac{total\ employed\ in\ neighborhood}{neighborhood\ size} \tag{3}$$

If luv is equal to 0 because there are no agents employed in the neighborhood, then a minimum wage is assigned to the cell. If luv is greater than 0, Schweitzer's wage equation (2) is used to calculate wage and assigned to the cell [9]. At each discrete time step of the MigrationModel, the wage field is updated, and a randomly selected agent moves. The values in the wage field are dynamic, re-calculated at each step based on the evolving spatial distribution and employment status of the agents.

Active Brownian Particles (ABP) Agents

Active Brownian Particles agents are characterized by their current location and employment status e.g. either employed or unemployed. At initialization, all agents are randomly placed on the grid. Fifty percent of the agents are employed, and the remaining are unemployed. Employed agents remain in their location while unemployed agents move in each simulation step. Migration and employment dynamics are driven by the wage function. Unemployed agents, with access only to local wage information, move toward regions with higher wages and to greater concentrations employed agents.

The model is given an initial hiring and firing rate, but these rates are updated during the simulation by the minimum wage parameter. Firms hire agents when their marginal revenue is greater than the minimum wage and it is profitable. When the marginal revenue falls below the potential wage, hiring is not profitable, which can lead to firms firing workers. Besides being fired, employed agents may voluntarily quit their employment if they are drawn to potentially higher wages in other locations.

MigrationModel Model Parameters

The MigrationModel parameters can be adjusted to examine specific scenarios:

- **Number of agents**: Determines the initial spatial density of agents in the landscape.
- **Economic landscape size**: Defines landscape dimensions, the initial spatial density of the agents and available space for movement.
- $\boldsymbol{\beta}$: A constant input parameter used in Cobb-Douglas production function $l^{\beta}(r,t)$, based on local employment density.
- **A**: A constant input parameter representing base productivity when cooperative effects are negligible and utilized when calculating local wage field.

- **Hiring rate** and **Firing rate:** Global firm's hiring and firing rate and given initially but update dynamically based on the marginal revenue and minimum wage.
- **Minimum wage**: A global constant input parameter.

MigrationModel Steps using ABP Agents

The model's main function in the step() method represents the agents' movements during a single simulation time step.

1. Agents are ordered in a random sequence using mesa library agents [10].
2. Only unemployed agents move:
    a. Views their neighbors in a Moore neighborhood.
    b. Calls the update wage and compares the wage in their current cell to the wage of neighboring cells.
    c. The wage gradient drives the unemployed agent towards a cell with higher wages.
    d. They attempt to move to this location and if it is already occupied, they try moving to a random unoccupied neighboring cell.
    e. Potentially changing their employment status.
3. Update wage field method calculates new wage for each location based on the locations of the employed agents on the grid.
    a. Calculates local labor density (luv) by identifying Moore neighborhood, counting the number of employed agents and dividing by the number of total cells.
    b. Calculates wage for a cell based on luv and input parameters A, a_1, a_2 using equation (1). If luv > 0, then the cell's wage is set to term1 + term2 otherwise, it is set to minimum wage.

$$
\begin{aligned}
term1 &= (A\,/\,2) * (1 + e^{(a1 * luv + a2 * (luv^2))}) * 0.5 * (luv ** (-0.5)) \\
term2 &= (A\,/\,2) * e^{(a1 * luv + a2 * (luv^2))}) * (a1 + 2 * a2 * luv) * (luv ** 0.5)
\end{aligned}
\tag{4}
$$

4. Data Collection: record employment statistics

ACFMigrationModel (Aspirations-Capabilities Framework)

The ACFMigrationModel inherits from MigrationModel and shares the methods for calculating wage gradient and model parameters. However, it introduces a new agent type: ACF agents and accepts the initial locations from the output of the MigrationModel.

ACF Agents

The ACF Agents inherit all attributes and methods from ABP agents but in addition, include attributes from the aspirations-capabilities framework. These agents, equipped with local knowledge, have a location, have employment status, and only move to an unoccupied cell. Unemployed ACF agents move toward higher wages and greater densities of employed agents. Noise is added when their selected cell is not available by allowing agents to randomly select a nearby unoccupied cell.

The additional attributes of ACF Agents are:

- **Skill**: A randomly assigned value between 1-5 representing agent's skill level from low to high.
- **Wage expectation:** A randomly assigned value between 15-25.
- **Decision value:** A randomly assigned value used in agent's decision-making to migrate and randomly assigned between 0.1 – 0.5 at initialization.
- **Aspiration factor:** Default value of 0.2, showing the influence of expected wage.
- **Capabilities factor:** Default value of 0.3, representing the influence of skill on decision-making.
- **Decision threshold**: A constant input parameter that whether an ACF agent moves based on their decision value.

Model Steps

The ACF MigrationModel places agents to the final positions of ABP agents in the economic landscape of wages inherited from the MigrationModel ABM. The ACF agent utilizes the same movement mechanics as the ABP agent. They also factor in their decision value using their given aspiration and capability factors. If their decision value is greater than the decision threshold, this will determine if the ACF agent moves. The ACF agents' decision-making process combines local wage information from the agglomeration economies environment with agent-specific attributes such as wage expectations, aspiration, capability, and skill.

In each step, the ACF Agents:

1. Inherited from ABP Agents, only move is unemployed
2. Change their employment status between employed and unemployed in each simulation time-step.
3. Update their wage expectations based on the following:
    a. ACF agents evaluate whether to stay or potentially move based on the decision value calculated as follows:

       decision value = (aspiration factor * wage differential) + (capability factor * skill) (4)

    b. Wage differential is the difference between wages at their current location and in neighboring locations.
    c. Agents are imbued with their skill, aspiration factor, and capability factor that does not change throughout the simulation.
    d. If the decision value exceeds the agent's decision threshold, they move.

Results

To analyze the dynamics of the proposed agent-based models, three experiments were conducted. The first experiment examines the MigrationModel and ABP agents by itself, without the influence of the ACFMigration Model. The second experiment focuses on the ACF Migration Model and ACF agents by itself. Finally, the third experiment integrates both models, using the final wage field and agent positions from the MigrationModel as inputs for the ACFMigrationModel. This sequential execution of the two ABMs design allows us to isolate and then combine the effects of macro-level agglomeration and micro-level agent behavior to study migration. Discussion of results from a sample run of each experiment follows.

Experiment 1

In the first experiment, using the Migration Model with 320 Active Brownian Particles (ABP) agents occupying 80% of an economic landscape grid comprised of twenty rows and twenty columns, the model steps through the simulation in 1,000 time-steps. The cell in the economic landscape is initialized with wage starting at zero and minimum wage as 0.1.

The simulation results, as shown in the histogram, indicate a strong shift towards employment among the ABP agents over time. Although the model began with an equal number of employed and unemployed agents, the final distribution shows a considerably larger population of employed agents. An explanation for this is the initial hiring and firing rates set in the model creating this bias.

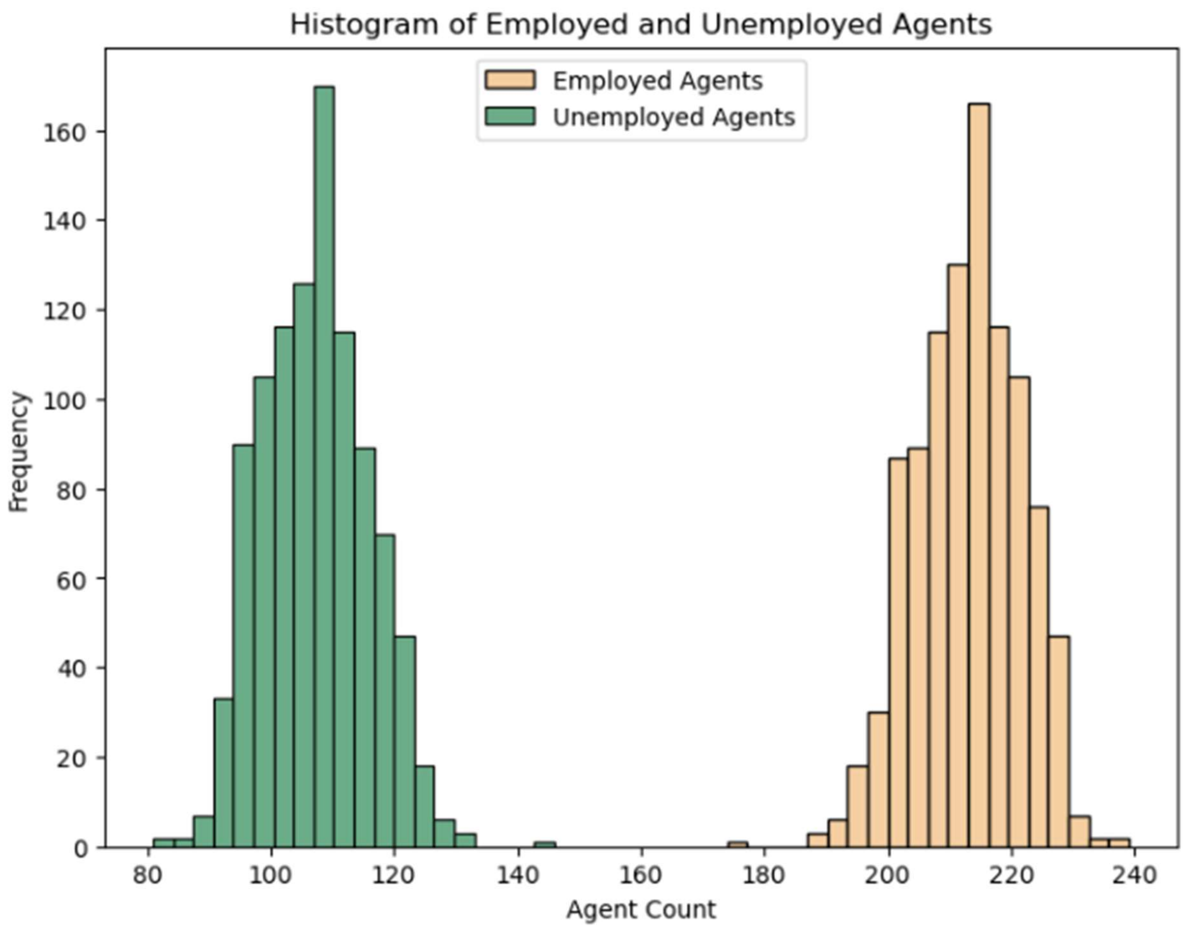


Figure 1 Histogram of Employed and Unemployed Agents (Experiment 1)

This suggests that the dynamics of the migration model, over the course of the simulation, lead to a net increase in employment among the agents.

A heatmap of the wage gradients in this simulation shows one dominant hub in the north east quadrant, represented by a single yellow cell, surrounded by less densely clustered regions shown in shades of green.

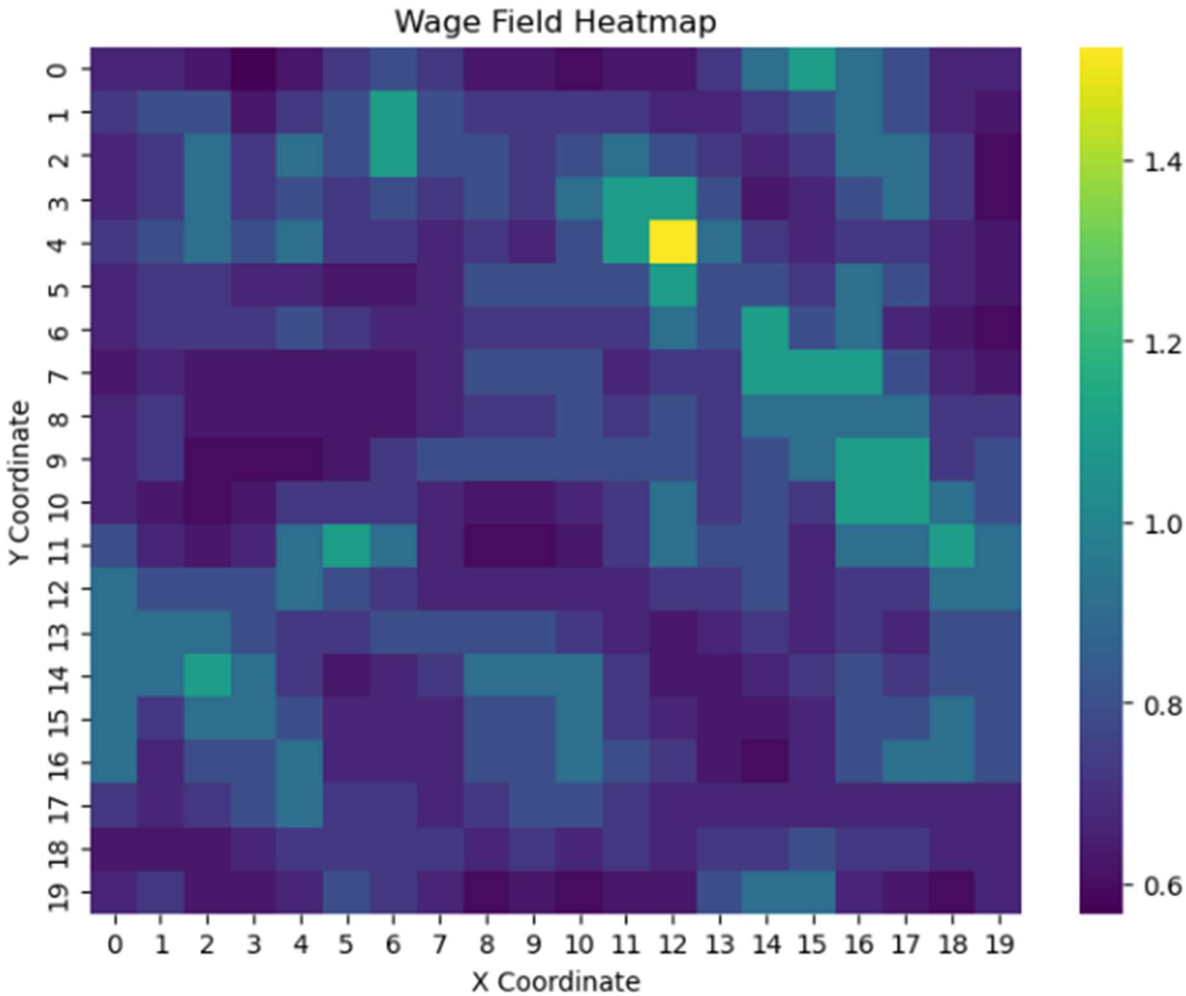


Figure 2 Heatmap of Wage Differentials (Experiment 1)

The following 3D Scatter plot illustrates the spatial distribution of employed agents in the economic landscape across the X and Y axes. Visually, there are no strong patterns of clustering; instead, there are localized regions with higher concentration of employed agents.

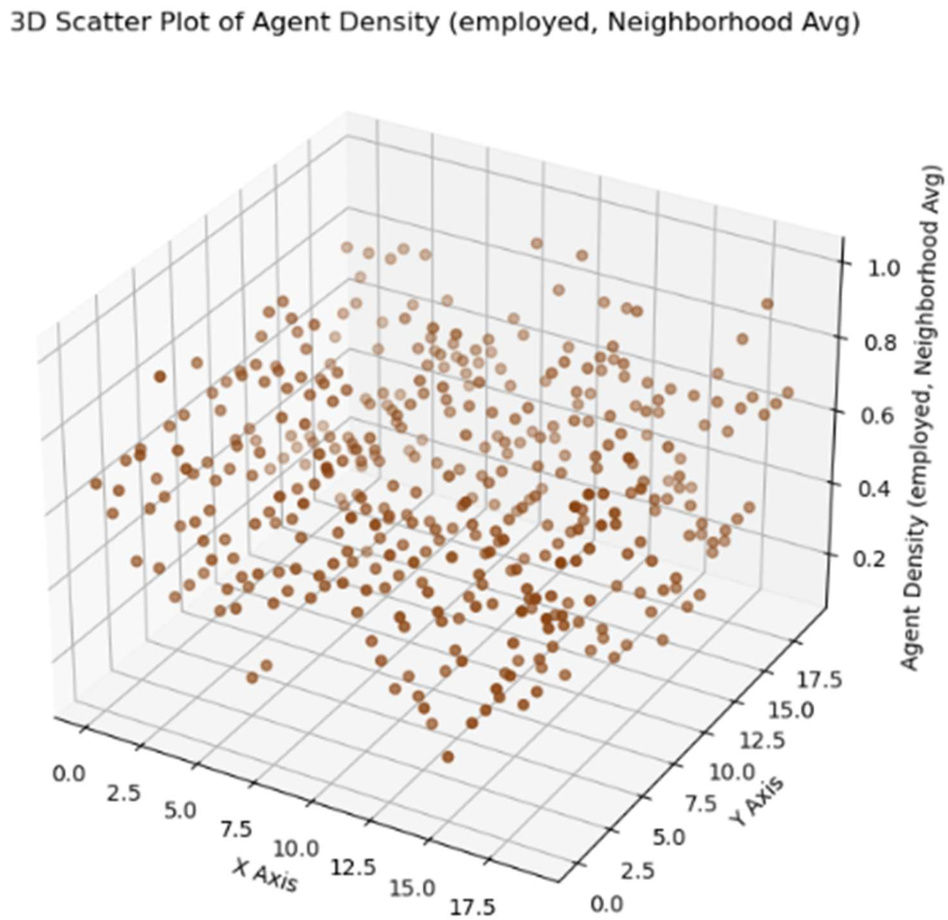


Figure 3 3D Scatterplot of Employed Agents Density (Experiment 1)

The 2D contour map of employed agents clearly shows multiple hotspots based on spatial distribution of employed agents. The areas where contour lines are tightly packed appear as peaks or localized regions of high concentration across the grid of twenty rows and columns. An example of the denser concentration (~ 0.88) of employed agents is highlighted in red in the figure below.

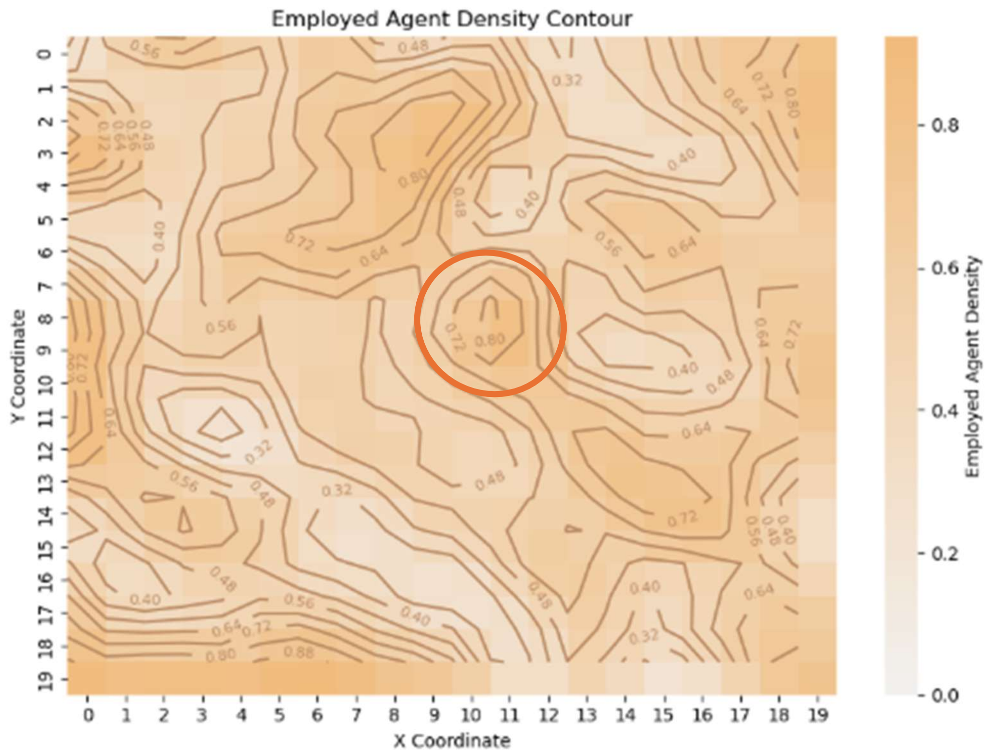


Figure 4 2D Contour Map of Employed Agents (Experiment 1)

Experiment 2

In the second experiment, using the ACFMigrationModel instantiated with 320 ACF agents on the same economic landscape with the same dimension as the MigrationModel, the model steps through the simulation in 1,000 time-steps. The cell in the economic landscape is initialized with wage starting at zero and minimum wage as 0.1.

The results from this experiment bear a strong resemblance to Experiment 1 based on the output visualizations. The histogram indicates a strong shift towards employment among the ACF agents after the simulation steps.

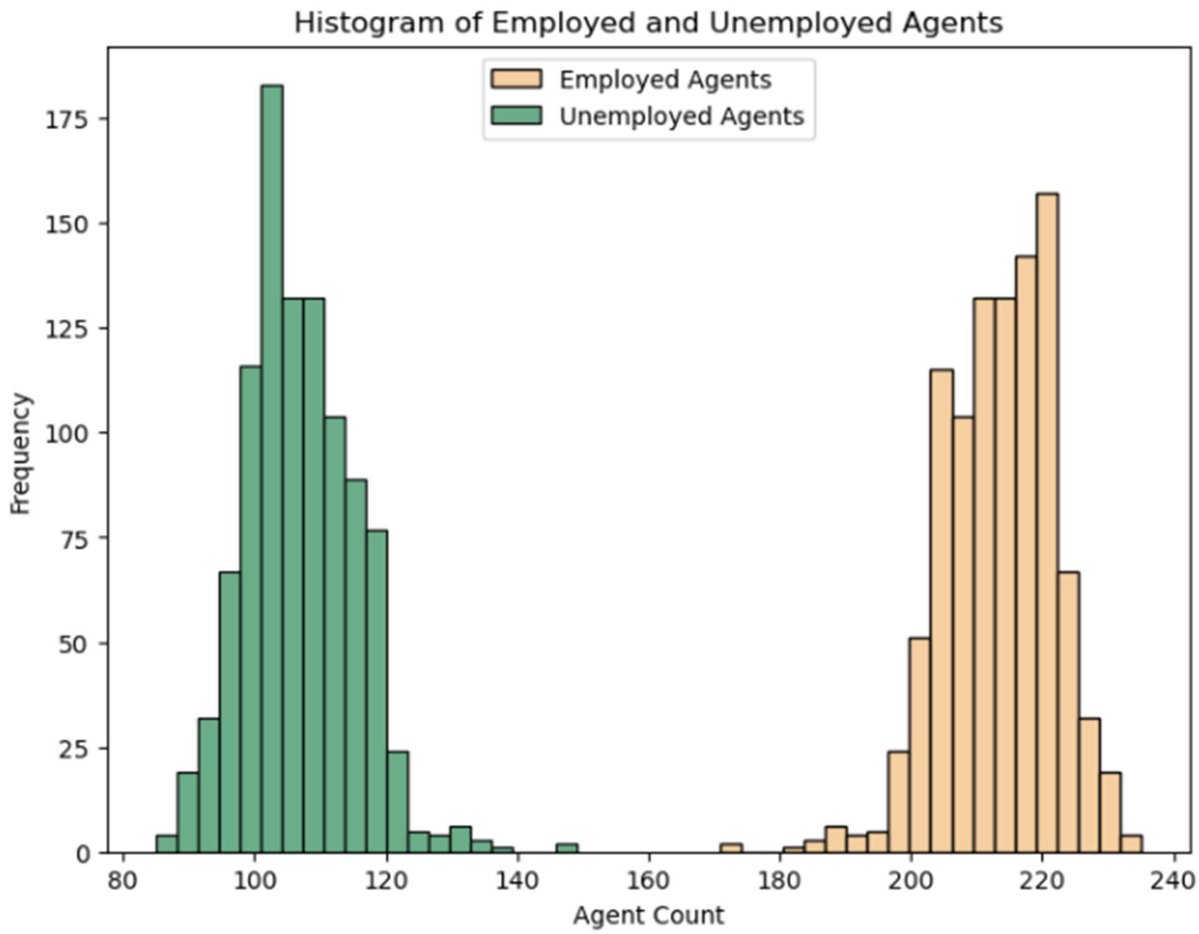


Figure 5 Histogram of Employed and Unemployed Agents (Experiment 2)

Instead of a single dominant hub in the wage gradient from experiment 1, there are multiple dominant hubs (yellow) in the southeast quadrant and due east, and multiple, smaller-scale agglomeration economies (shades of green). Independent of the dominant hubs are smaller spatially dense areas appearing in this experiment.

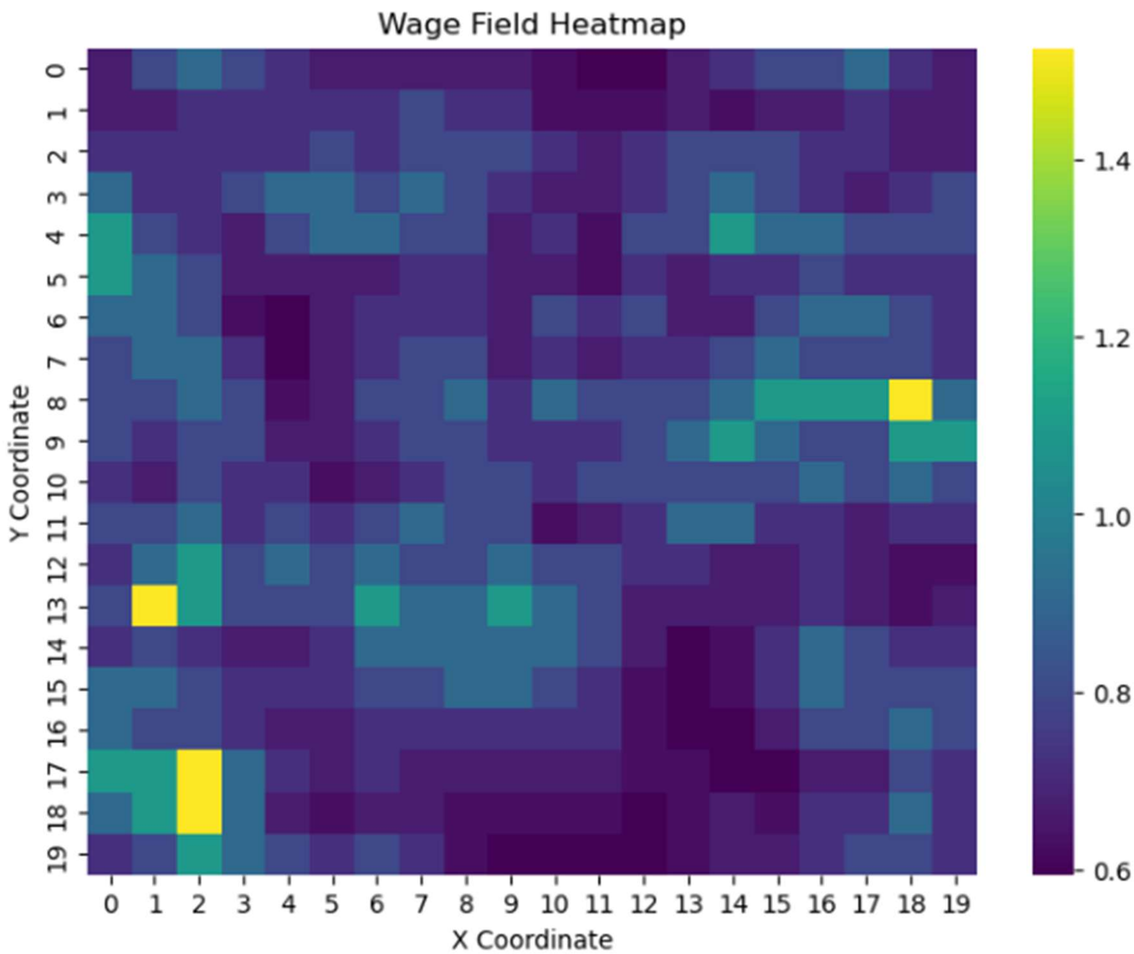


Figure 6 Heatmap of Wage Differentials (Experiment 2)

The 3D scatter plot showing employed ACF Agents has weak localized clustered regions. The results are not surprising as ACF agent inherited attributes and movement from the ABP agent. The aspiration factor was set to 0.2 and the capabilities factor was set to 0.3 in this experiment run and may not have affected the decision value threshold. Additional parameter tuning is required.

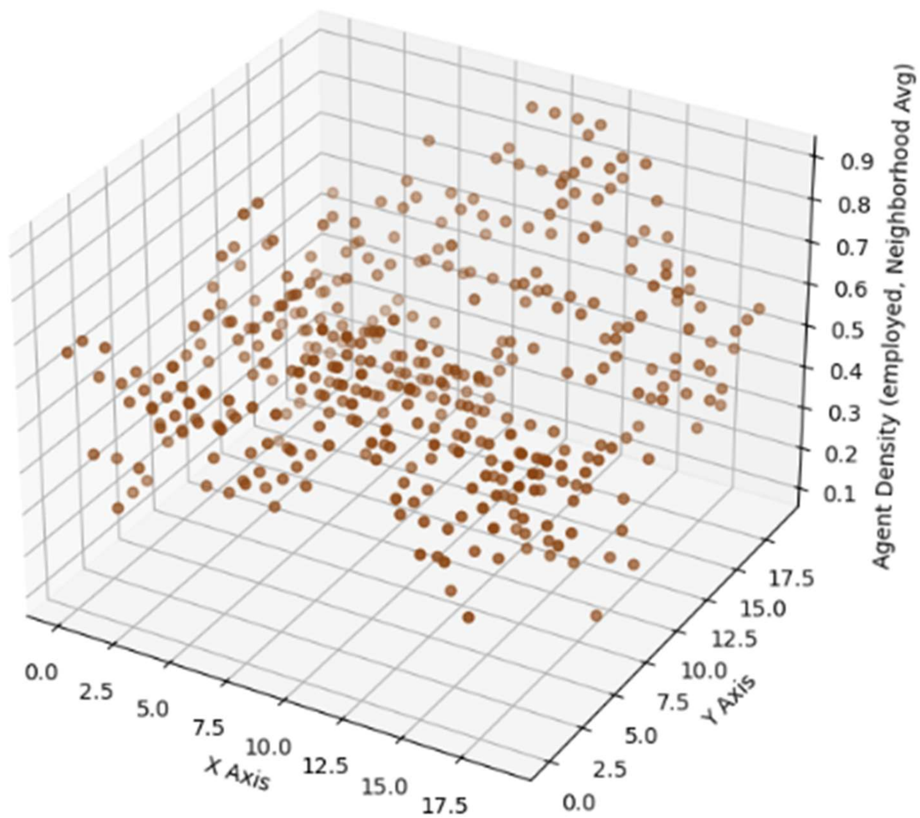


Figure 7 3D Scatterplot of Employed Agents Density (Experiment 2)

Experiment 2's 2D contour map reveals dispersion of higher concentrations of employed agents, one of which, reaching a density of approximately 0.80, is highlighted in red. This denser employed region appears larger and wider compared to experiment 1, leading to a compression of unemployed agent areas.

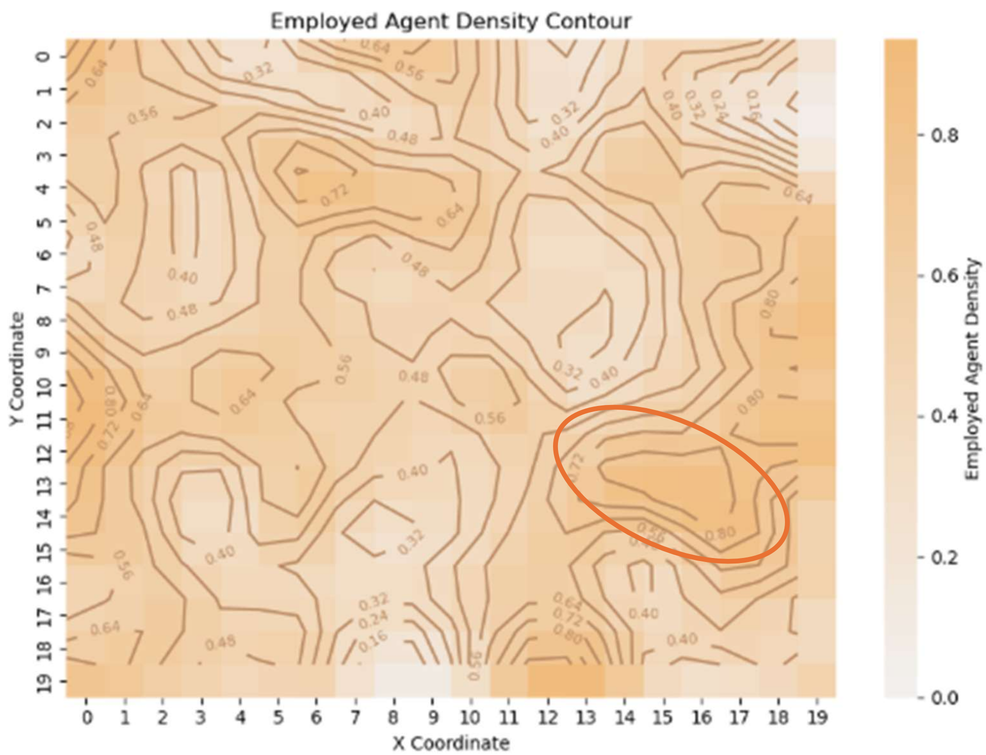


Figure 8 2D Contour Map of Employed Agents (Experiment 2)

Experiment 3

In the third experiment, the simulation runs with MigrationModel with cells in the economic landscape are initialized with wage starting at zero and minimum wage as 0.1. and the creation of 320 ABP agents. After the simulation is completed, the output is saved from the ABM. A new instance of the ACFMigrationModel creates 320 ACF agents and uses the economic landscape of wages inherited and places ACF agents on the final locations of agents from the run of the prior ABM. The ACFMigrationModel is executed 1,000 time-steps. Discussion of an example run follows.

Like the previous experiments, the histogram indicates a strong shift towards employment among the agents after the simulation steps. This could be an indication of a strong bias of employment in the models or lack of deterrents. The initial hiring and firing values need to be fine-tuned.

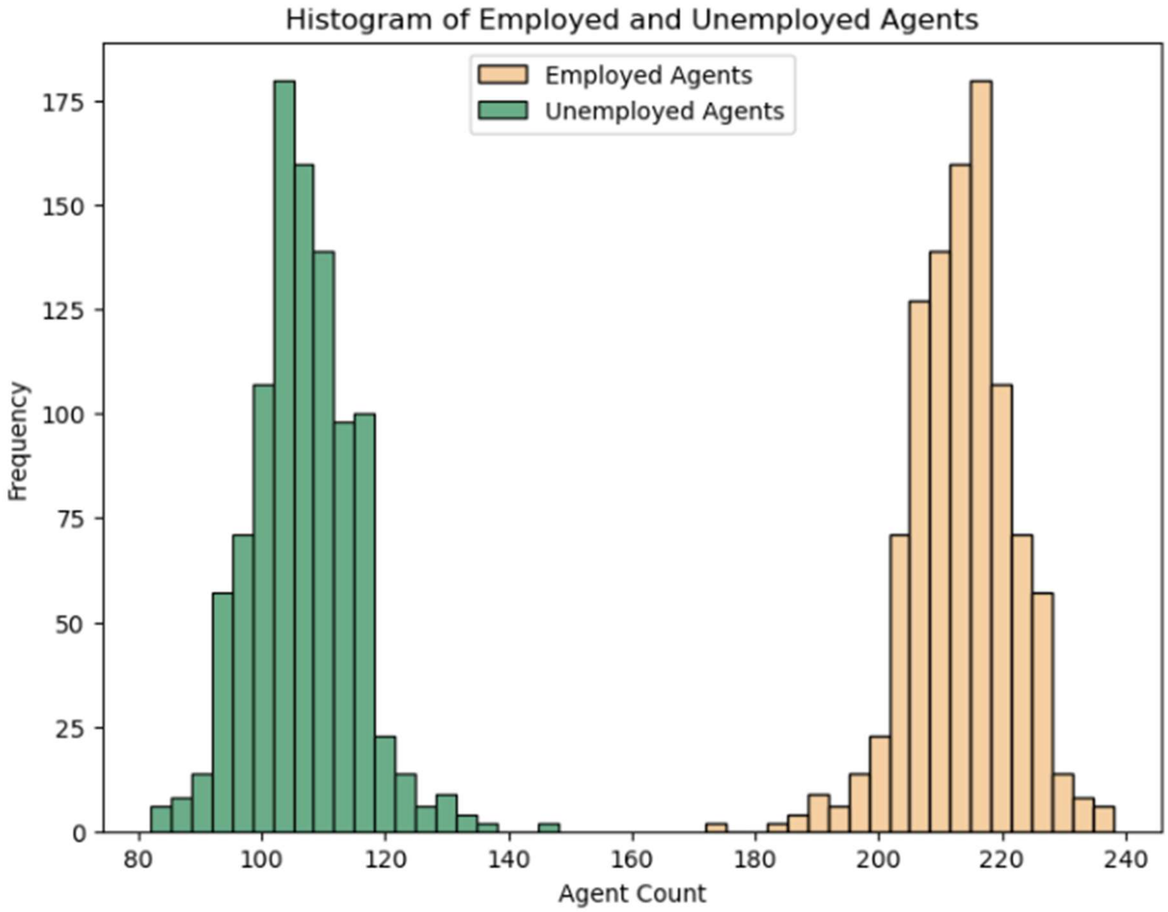


Figure 9 Employed to Unemployed Agents Ratios Over Time (Experiment 3)

The 3D scatter plot of side-by-side comparison of employed and unemployed agents does not show strong cluster pattern but instead, localized regions of higher densities of employed and employed agents.

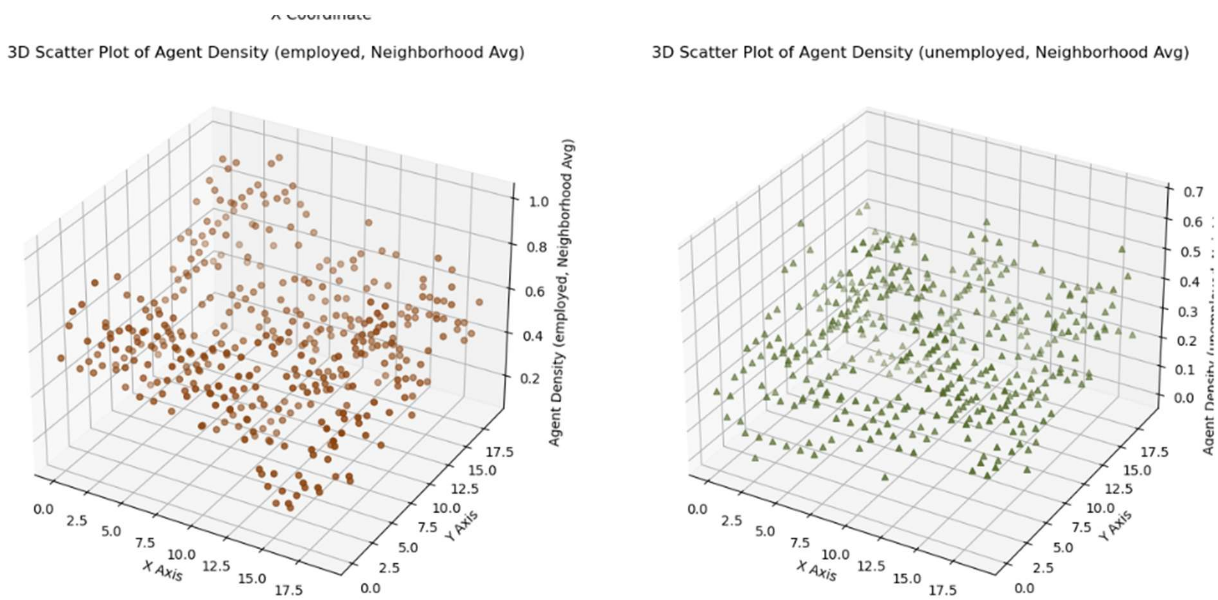


Figure 10 3D Scatterplot of Employed Agents Density (Experiment 3)

Clearer visually than the scatter plots, the wage field heatmap from experiment 3 shows three dominant economic hubs displayed as yellow cells, surrounded by multiple, smaller scale agglomeration economies in shades of by green. Independent of the dominant hubs are smaller spatially dense areas as found in prior experiment 2.

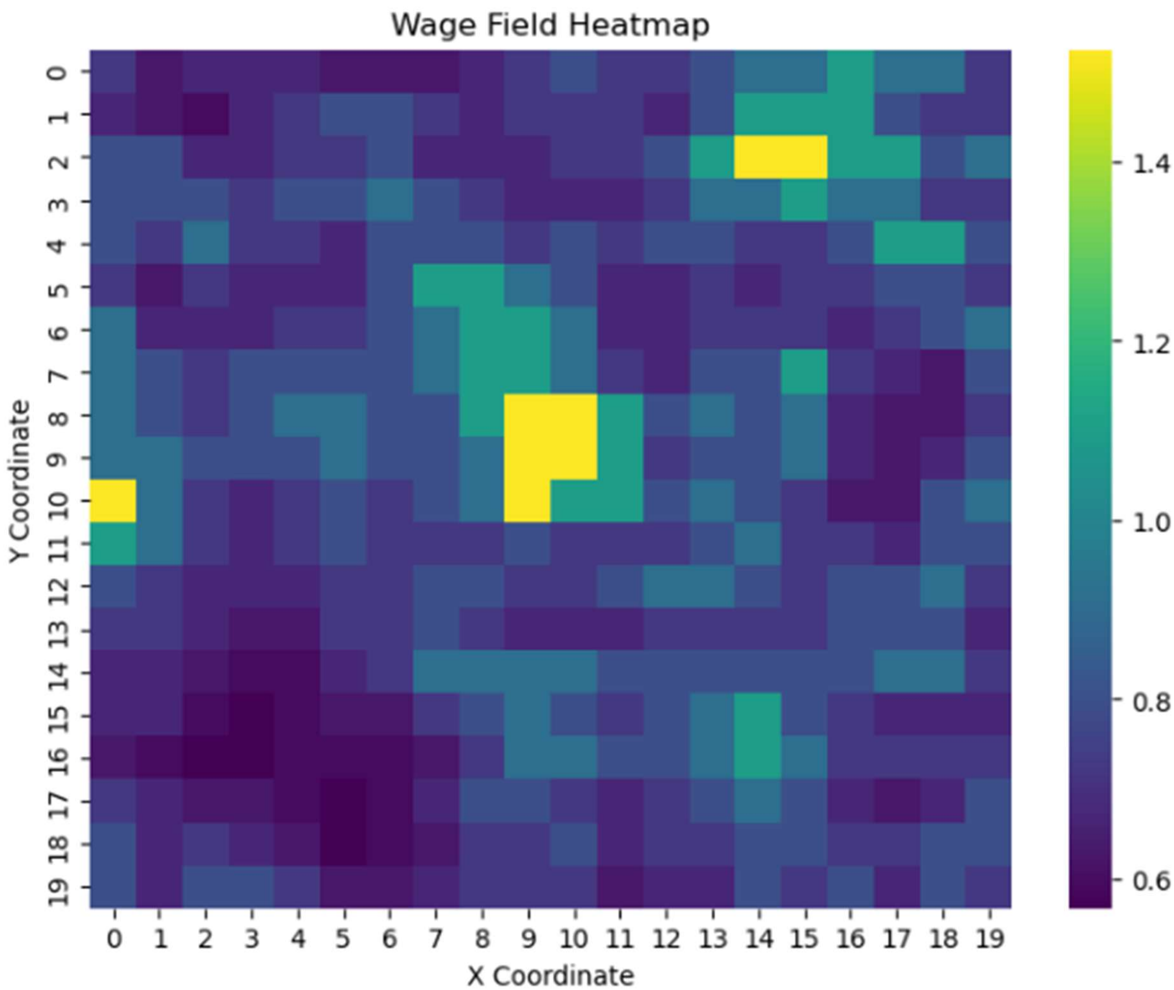


Figure 11 Wage Field Heatmap (Experiment 3)

Experiment 3's 2D contour map reveals multiple, more pronounced hot spots of employed agents based on their spatial distribution. An example region with a higher density of employed agents from previous experiments has been enlarged, while lower density areas have been further compressed.

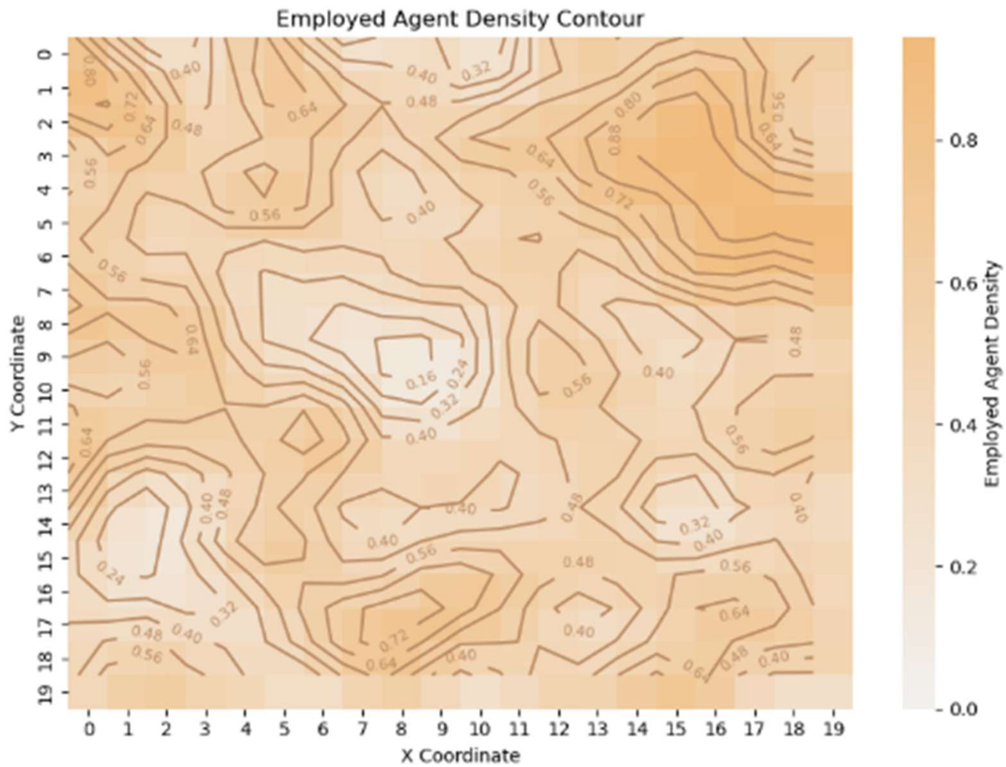


Figure 12 2D Contour Map of Employed Agents Locations (Experiment 3)

Across the three experiments and using only visual inspections, both ABMs consistently show a result of higher proportion of employed agents to unemployed agents. This could suggest that the models require parameter tuning so that they do not inject a bias towards employment in the models. In contrast, the spatial patterns of these employed agents differ between experiments. In experiment 1, utilizing the basic ABP model, it exhibits a more centralized wage structure and localized concentrations of employed agents which could be drawn towards the dominant wage hub. Experiment 2, incorporating the ACF framework, displays a more decentralized wage landscape with multiple smaller agglomeration economies which could indicate the agentic influence of using aspirations and capabilities factors. The overall employment ratio mirrors experiment 1 but the spatial clustering of employed agents appears less pronounced. This again could be caused by the initial parameter settings of the ACF model. Finally, experiment 3, which sequentially runs the ABP and ACF models combined, yields a similar overall greater result of employed agents than unemployed but visually, the patterns of employed agents are more pronounced. With ACFMigrationModel inheriting locations of ABP agents and the wage field, they exert a significant influence on the subsequent spatial organization of employment under the ACF framework. Experiment 3's design of executing MigrationModel first and then the ACFMigrationModel, may have influenced the resulting spatial patterns present. These experiments did not explore the influence of skill on migration. This important factor will be incorporated into subsequent investigations.

Conclusion

This paper presented two agent-based models, MigrationModel and ACFMigrationModel, to simulate skilled migration by integrating micro-level individual decision-making with with macro-level economic structures. The MigrationModel uses Active Brownian Particles to simulate the formation of economic centers based on wage dynamics, and the second model incorporates the de Haas's aspirations and capabilities framework to model individual migration choices within these economic landscapes.

Visual inspection of the simulation results from three experiments highlights the need for parameter tuning to confirm the models are not introducing unintended artifacts. Initial insights from the ABMs show emergent spatial patterns of employment and wage distribution, highlighting the role of wage gradients and individual attributes in shaping migration flows.

The order in which the ABMs are executed appears to greatly influence the prominence of these spatial patterns, but additional work is required to confirm this effect. Overall, this work lays the groundwork for future work on skill-based migration and its broader implications for labor markets and economic geography.

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