THE UNIVERSITY OF
SYDNEY

CSYS5010 Final Report

Study on the Influences of the Australian Housing Market

Group 3

Zechen Zhu (540323234);

Huiming Zhang (490110593);

Yucheng Fu (540471476)

June 6, 2025

Contents

1 Aims and Design

1.1 Hypothesis and Aims

Over the past two decades, Australian house prices have risen sharply and cyclically, driven by a combination of factors such as interest rates, population growth and market speculation.

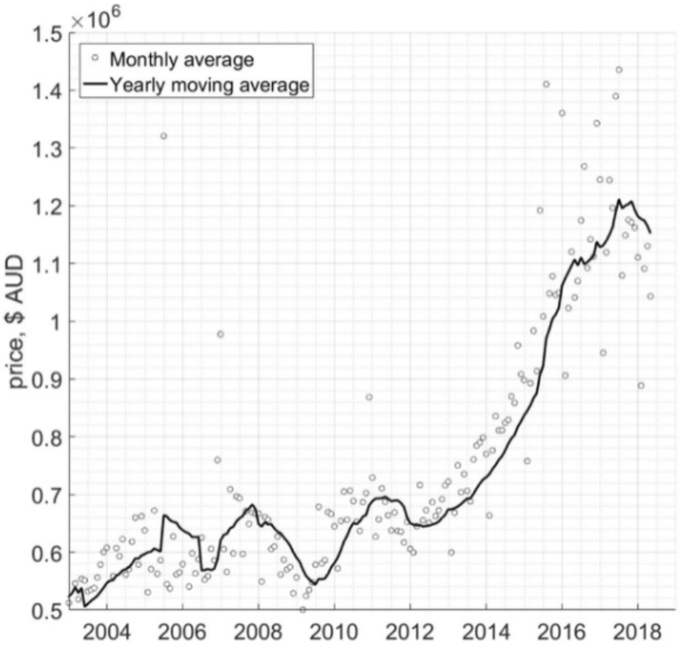

Figure 1: *Greater Sydney Historical House Price (Glavatskiy et al., 2021).*

Here is our hypothesis:

The fluctuations in Australia's housing market can be reasonably simulated through the coupled relationships among spatial factors, amounts of population and houses, developers' behavioral expectations, and government policies.

This project aims to develop an agent-based housing market model to uncover the micro mechanisms behind property price volatility in Australia, with a focus on the interplay between spatial values, policy regulation, and demographic heterogeneity. Different from traditional economic models, we use the Agent-Based Modelling (ABM) method to simulate the local decision-making of heterogeneous agents (households, developers) in the spatial environment, so as to observe the dynamic evolution of housing prices, homeownership, and wealth inequality in the overall market.

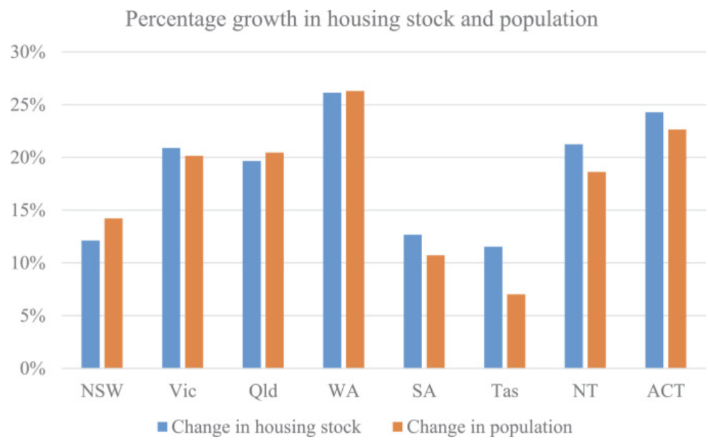

Figure 2: *Percentage growth in the stock of housing (all dwellings) and population between 2005 and 06 and 2015–16(Ma, Liu, Edwards, & Sing, 2021).*

1.2 Model Fundamentals and Extensions

This project is based on the classic Sugarscape model (Epstein & Axtell, 1996). The original model is used to explain the phenomenon of wealth differentiation(Carstensen, 2015; Gilbert et al., 2009), and its core mechanism is that agents move and survive in space according to the distribution of "sugar".

The model retains the "visual" and "metabolic" mechanisms in Sugarscape to simulate the information perception range and affordability of a family or developer, respectively. Through the "sugar" mechanism, the model depicts the process of families withdrawing from the market due to financial pressure and developers making construction decisions due to market signals and policy factors.

In order to get closer to the background of Australia's housing policy, we added a number of controllable variables to the model, such as the initial number of developers and houses, the probability of loan rejection, the yearly loan payment ratio and the vacancy threshold. These parameters are controlled by sliders on the NetLogo platform, allowing researchers to flexibly set different policy and economic conditions to simulate a variety of market scenarios, such as credit tightening, development restrictions, and increasing population density.

1.3 Research implications

Compared with traditional economic models, ABM has the ability of spatial expression, behavioral heterogeneity simulation and excellent dynamic tracking function, which is especially suitable for studying the housing price fault in the urban fringe, the trend of housing concentration and the marginalization of low-income groups. At the same time, this model also has good scalability, and in the future, it can further add elements such as the rental market, population migration mechanism, and transportation and commuting costs to build a more complete housing market ecosystem. In summary, the model not only has theoretical value for academic research, but also provides a concrete and controllable analytical tool for policymakers.

2 Implementation and developement process

2.1 Based Model and Minimal Model

We used the Sugarscape as the based model. On the grid, each patch's sugar capacity is first loaded from a "sugar-map" txt file. Then agents are placed at random patches, and each agent is distributed with a random amount of sugar to represent wealth, a vision radius, a metabolism rate, and a maximum lifespan. At every tick, each agent moves to the richest unoccupied patch within its vision, collects all the sugar there, and then consumes sugar according to its metabolism. If an agent runs out of sugar or exceeds its maximum lifespan, it dies and is replaced by a new agent randomly generated on a patch without any agent. Meanwhile, each patch increases 1 unit of sugar at the end of each tick, up to its original capacity.

2.2 Basic Housing-Market construction

We try to use `setup-patches` to initialize the land and build on the minimal model by extending the agents into three breeds: families, houses, and developers. We also replace "sugar" which previous represented wealth with the more abstract concept called "value". The higher the sugar on a patch, the more valuable the land, and the higher the housing prices there.

The `setup-houses` sets houses to be blue and uses the shape "house", and distributes different prices based on each patch's value. Patches with the highest sugar correspond to the city center, while lower-sugar patches represent the suburbs.

Families and developers still follow the minimal model's initial "setup" and "go" rules, moving to the richest unoccupied patch. By default they develop themselves toward high-value areas. In `setup-families`, families are drawn as red circles and set with random wealth and income. The information of wealth bases on the investigation of wealth inequality in Australia. Additionally, each family's annual income I is then drawn from a normal distribution

$$I_i \sim \mathcal{N}(\mu_I, \sigma_I^2) \quad \text{with } \mu_I = 90\,000,\ \sigma_I = 15\,000,\ I_i > 0,$$

reflecting Australian household income statistics.

In `setup-developers`, developers are set as green triangles. Compared with the families, developers are configured similarly, but with a broader vision. Figure 3 shows the initialization setup of the model.

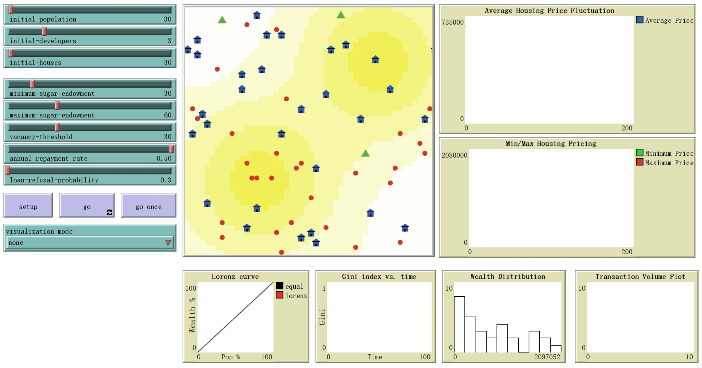

Figure 3: *Initialization setup of the model.*

2.3 Sell, Purchase and Vacancy Mechanisms

To simulate a mortgage-driven market, families may purchase vacant houses either outright (if $W_i \geq P_h$) or via a fixed-term loan. Loan eligibility is governed by a loan-refusal probability α; approved loans use the standard annuity formula

$$A = L\frac{r(1+r)^N}{(1+r)^N - 1}$$

to compute the annual repayment schedule, where $L = (1-\alpha)P_h$, r is the annual interest rate, and N is the loan term in years. Each tick families first repay any outstanding mortgage, then collect income, then execute house-search via `turtle-move`: they either buy the cheapest visible vacant house, or relocate to the patch with highest land value. When selling, families list owned houses at a 3 % markup; successful transactions transfer wealth and increment a `housing-transactions` counter. Unpurchased houses accrue vacancy-ticks; if these exceed a vacancy-threshold T, the house is removed.

2.4 Developer Rebuilding and Dynamics

Developers, with a larger `vision-dev`, go to the most attractive vacant regions. Whenever `dead-count` of the removed houses is positive, each tick one developer invokes `replenish-vacant-houses` to sprout a new house on a nearby patch: if neighboring houses exist, the new value equals the local average; otherwise it is drawn by `create-house-on-patch` connected with `psugar`. The prices of vacant houses decay 2% per tick until they reach \$10,000, and developers thus ensure a dynamic equilibrium between demolition and construction.

2.5 Visualization and Statistical Analysis

We use NetLogo's built-in plotting to record five key outputs each tick: housing price fluctuation (mean `house-value` over time), min/max housing price (minimum and maximum `house-value` over time), wealth distribution (family `wealth` histogram), transaction volume (count of completed purchases), and inequality metrics (Lorenz curve and Gini index via `update-lorenz-and-gini`). In addition, we export time-series data each tick and employ Python scripts to generate enhanced visualizations.

3 Analysis of Results

Based on the data collected from running the NetLogo model, this study analyzes the following four scenarios that are closely related to real-life situations.

3.1 Regional Effects on Population and Housing Distribution

In most cities in reality, employment opportunities, educational resources, and medical facilities are often unevenly distributed, and residents will naturally move closer to these resource-intensive areas. This study simulates this population migration and aggregation process, and intuitively shows the impact of geographical location on housing demand. The simulation results show that housing prices in "hot spots" where resources are concentrated have risen significantly due to strong demand, as shown in *Figure 4*.

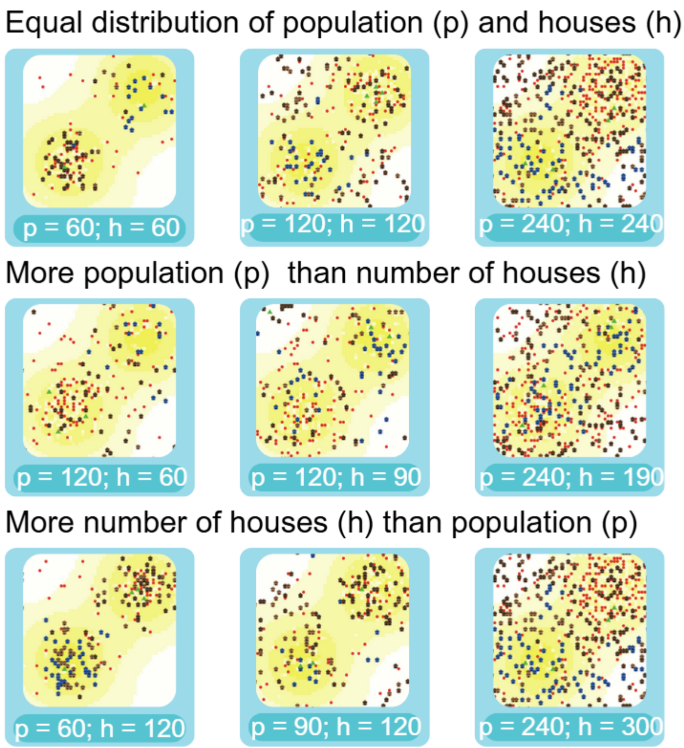

Figure 4: *Simulation results of population and house migration based on geographical location and resource distribution.*

This trend is particularly evident when the total population and the number of houses are small, and the distribution of housing prices is more easily driven by geographical factors. Especially when the population is less than the number of houses, the resource aggregation effect is more quickly manifested, and the spatial differentiation of housing prices is more prominent.

3.2 Impact of Population-to-Housing Ratio on the Gini Index

In cities with growing populations, the balance between population size and housing supply directly affects the operation mechanism of the housing market and the distribution pattern of social wealth. When the number of houses cannot effectively cover population demand, housing competition will intensify, affecting housing price changes and possibly widening social inequality. To explore this relationship, the ratio of total population to number of houses is systematically adjusted to observe the changes in the Gini coefficient under different policies, as shown in *Figure 5*.

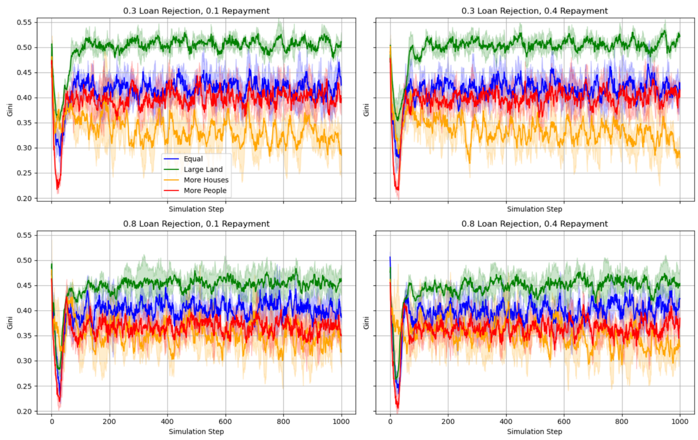

Figure 5: *Gini coefficient trend chart under different housing ratios and government policy combinations.*

The simulation results reveal a seemingly counterintuitive but realistic phenomenon:

- Regardless of any different policies, when the population and number of houses are very large, even if the houses are "enough" overall, the wealth distribution is more uneven, as shown by a significant increase in the Gini coefficient. This shows that in a large-scale system, even if the total amount of resources is sufficient, factors such as location priority and differences in migration speed may still lead to the concentration of resources in a few individuals, thereby exacerbating social inequality.
- In contrast, when the number of houses is greater than the population and the overall number is low, the model shows a more balanced wealth distri-

bution pattern and a lower Gini coefficient. This is because in a small-scale system, resource competition is relatively mild, and individuals are more likely to obtain housing and survival resources, thereby improving overall fairness.

In addition, in a high population scenario, despite the sufficient number of houses, market competition still drives house prices up rapidly. This finding reminds us that when formulating housing policies, simply increasing housing supply may not be able to effectively alleviate inequality.

3.3 Loan Rejection and Repayment Policies in Housing Market Dynamics

On the other hand, as an important regulator of the housing market, the government's credit policies, such as loan issuance standards and repayment rules, have a profound impact on housing prices and social equity. This study constructed a housing market simulation under government intervention based on the Sugarscape model, focusing on the impact of two key policy variables, loan rejection rate and annual repayment ratio, on housing prices and income distribution.

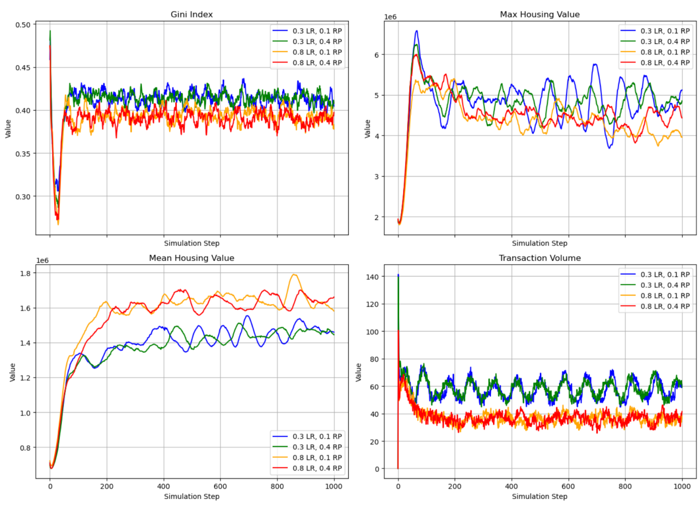

Figure 6: *Changes in market indicators under different government loan policy settings.*

The simulation results show that although increasing the loan rejection rate, that is, tightening loan policies, has suppressed the ability of some residents to buy houses, it has slowed down the widening of income gaps to a certain extent and reduced the overall level of income inequality, as can be seen from the decline in the Gini coefficient in *Figure 6*. This may be because relatively wealthy people are also subject to loan restrictions, which has suppressed their further accumulation of housing assets.

However, an increase in the loan rejection rate will also lead to an increase in average housing prices. As the number of buyers who can pass the approval decreases, the market supply pressure is relatively reduced, while the competition among buyers who still have the financial ability to buy houses has intensified, pushing up the price of tradable properties.In contrast, the policy variable of adjusting the annual repayment ratio has a relatively limited impact on housing prices. Regardless of whether the annual repayment ratio is high or low, its effect on market activity and price fluctuations is not significant, indicating that home buyers are more concerned about "whether they can get a loan" rather than "how to repay the loan".

3.4 Impact of Developer Quantity on Housing Price Dynamics

In addition, as one of the leading providers of housing supply, the number and behavior patterns of real estate developers are often considered to have a significant impact on housing prices. To verify this hypothesis, this study introduces the "developer" agent role based on the Sugarscape model to simulate the housing launch behavior of different numbers of developers in the market and examine its impact on housing price fluctuations and the overall market level. The results are shown in *Figure 7.*

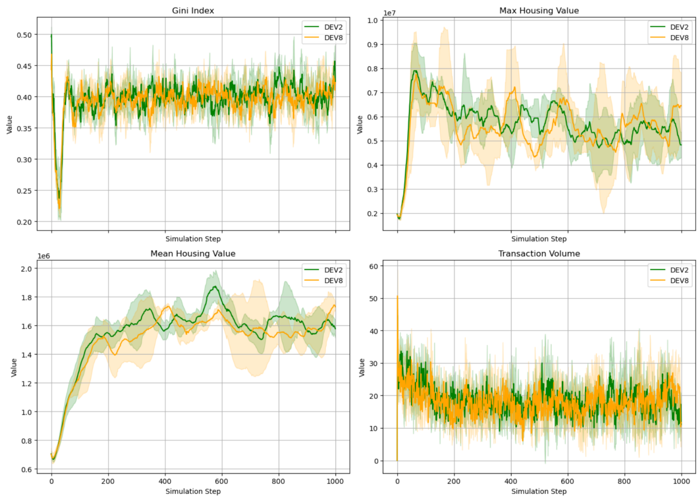

Figure 7: *Changes in market indicators under different numbers of developers.*

The simulation results show that with the increase in the number of developers, housing price volatility increases significantly. Because more developers bring more frequent housing listing rhythms and price adjustment strategies, which exacerbates market instability. More local price highs and lows appear in the market, showing greater fluctuations. However, from the overall trend, the impact of the number of developers on average housing prices is relatively limited. Even if the number of developers increases significantly, the long-term central change in housing prices is not obvious, indicating that the number of supply-side participants is not the main factor determining housing price levels, but is more driven by variables such as resource distribution, population structure and government policies.

This result suggests that the increase in the number of developers in the market may bring short-term price uncertainty, but it is difficult to fundamentally change housing price levels or solve housing affordability issues by increasing the number of developers.

4 Critical Assessment

4.1 Relationship of model findings to existing literature

By simulating the interaction of heterogeneous agents such as households and developers in the spatial environment, this model reveals the behavioral mechanisms of housing price rise, wealth differentiation and urban structure evolution. The results show that the number of population and houses, spatial value distribution, credit availability and agent differentiation are the key factors influencing the dynamics of the housing market. This is in line with the classic framework of DiPasquale & Wheaton (1992) on the interaction between land and use value, and is also highly consistent with the ABM idea proposed by Carstensen (2015) that "price fluctuations can emerge from micro rules"(Gilbert, Hawksworth, & Sweeney, 2009).

In addition, the model shows how credit policy and developer behavior can jointly shape the regional development path, which further complements the shortcomings of the traditional model in policy evaluation. Through spatial evolution and indicator visualization, we not only verify the theoretical predictions, but also present them concretely, which provides new simulation support for the literature.

4.2 Model Verification: Current Strategies and Future Directions

At present, we have conducted preliminary verification of the model through three methods: the first is the model reproducibility test, which shows that the results are stable under the same initial conditions; the second is the extreme scenario test, where the model output is still in line with expectations when extreme but reasonable parameters are input; the third is the known pattern reproduction, where the model successfully simulates real-life phenomena such as crowd gathering.

In the future, we will further comprehensively test the accuracy and applicability of the model through comparison with actual housing prices and geographic data, prediction of future housing price trends, cross-validation, and expert evaluation.

4.3 The advantages and applicability of the model

Agent behavior is heterogeneous and local. There are differences between households and developers in terms of wealth level, scope of vision, rules of behavior, etc., and make decisions based on local information, which is closer to the logic of real market operation. The dynamic feedback mechanism of our model is clear. This model simulates the causal relationship between loan thresholds and home-purchasing behavior, revealing the impact of credit policies on home price allocation.

After introducing "Developer" agents into the model, the effects of various numbers of developers on market stability were successfully simulated. Based on the Sugarscape framework, the actual trend of "different housing prices due to different regions" has been successfully replicated, and the impact of resource accumulation on housing price structures is revealed through population movement simulations. This model sets family agents with different levels of wealth, preferences, and risk tolerance, exhibit significantly differentiated behaviors in different policy and market conditions, forming a true pattern of wealth differentiation and inequality. All of the above methods are suitable for our research on the objectives.

4.4 The limitations of the model

Although this model has strong ability to simulate spatial heterogeneity and behavioral feedback mechanisms, it still has some limitations. First, the behavior rules in the model are simplified, which may not fully reflect the real-world decision-making process, and are sensitive to the initial parameters, which can easily lead to fluctuations in the results (Schelling, 1971).

Secondly, the current simulations have not been systematically verified, and the rationality mainly depends on the intuitive judgment of the trend. In the future, quantitative calibration can be carried out by introducing house prices, income distributions, transaction records and geographic data published by the Australian Bureau of Statistics (ABS).

In addition, the model does not include key real-world factors such as population migration, rental market dynamics, and urban boundary constraints, which may reduce its predictive power and policy applicability. As Ma et al. (2021) point out, there is a complex dynamic correlation between house price fluctuations and residential construction activity and urban spatial development patterns, a process that is better reflected in the extended model framework.

This study was set at 1000 ticks on a time scale to simulate market evolution. However, this scale cannot directly correspond to the 1,000 years in reality, and is therefore not suitable for evaluating long-term housing price trends, and has only relative temporal evolutionary significance. In addition, the data based on the model analysis is to plot and interpret the same indicator after repeating three times. Although the stability is improved to a certain extent, the lower number of repetitions may mask the key fluctuation information and affect the capture and judgment of extreme or atypical situations.

4.5 Future improvement directions and expansion scenarios

In order to improve the realistic explanatory power and prediction ability of the model, the following extensions can be introduced in the future: adding the rental market and landlord behavior to distinguish first-time buyers from multi-suite investors; Introduce commuting costs and transportation networks to improve the realism of urban spatial structure; Combined with GIS data assignment patch attributes, the docking with real geography is realized. In addition, the model framework can be transferred to other fields, such as simulating the process of urban expansion, analyzing the equity of public facilities distribution, and the impact of population migration on infrastructure layout.

Total words: 2999 in-text

References

[1] Carstensen, F. (2015). Agent-based modeling of housing markets: Explaining housing price bubbles and crashes. *Journal of Artificial Societies and Social Simulation*, 18(1), 6. https://doi.org/10.18564/jasss.2660

[2] Dawid, H., Harting, P., & Neugart, M. (2021). Agent-based macroeconomic modeling and policy analysis: The Eurace model. *Journal of Economic Behavior & Organization*, 189, 588–620. https://doi.org/10.1016/j.jebo.2021.07.027

[3] DiPasquale, D., & Wheaton, W. C. (1992). The markets for real estate assets and space: A conceptual framework. *Real Estate Economics*, 20(2), 181–198. https://doi.org/10.1111/1540-6229.00579

[4] Epstein, J. M., & Axtell, R. (1996). *Growing artificial societies: Social science from the bottom up*. MIT Press.

[5] Gilbert, N., Hawksworth, J. C., & Sweeney, P. (2009). An agent-based model of the housing market: Analysis and policy exploration. In A. Heppenstall, A. Crooks, L. See, & M. Batty (Eds.), *Agent-based models of geographical systems* (pp. 431–446). Springer. https://doi.org/10.1007/978-90-481-8927-4_22

[6] Schelling, T. C. (1971). Dynamic models of segregation. *Journal of Mathematical Sociology*, 1(2), 143–186. https://doi.org/10.1080/0022250X.1971.9989794