EXPLORING URBAN SHRINKAGE VIA COMPUTATIONAL APPROACHES: A CASE STUDY OF THE CITY OF DETROIT

by

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Dedication

"All models are wrong, but some are useful."

– George E. P. Box

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Abstract

EXPLORING URBAN SHRINKAGE VIA COMPUTATIONAL APPROACHES: A CASE STUDY OF DETROIT

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While the world's total urban population continues to grow, not all cities are witnessing such growth, some are actually shrinking. This shrinkage causes several problems to emerge including population loss, economic depression, vacant properties and the contraction of housing markets. Such problems challenge efforts to make cities sustainable. While there is a growing body of work on study shrinking cities, few explore such a phenomenon through computational approaches. To further explore on this phenomenon, this work mainly focuses on three main questions: RQ1:How does urban shrinkage emerge at the macro-level through the simulation of housing trades at the individual level? RQ2: How can patterns of shrinkage be measured through a simulation? RQ3: To what extent can urban shrinkage be revealed by the analysis of newspaper articles?

This work uses Detroit Tri-County Area as a study area to explore these three research questions. Two agent-based models (ABM) are built to simulate the housing trades within the Detroit Tri-County Area and the two models' results capture the city of Detroit's shrinkage from the aspect of decreasing numbers of households at the macro-level, which can be considered as the population loss. In addition, a pattern with a collapsing downtown housing market can be measured by visualizing the simulation results. By utilizing natural

language processing (i.e., topic modeling) on a large number of newspapers related to Detroit, insights related to Detroit's shrinkage can be linked to the side effects of the economy recession on Detroit's automobile industry, local employment status, and housing market. The two agent-based models built in this work significantly add to the nascent field of inquiry by specifically capturing how the buying and selling of houses can lead to urban shrinkage from the bottom-up, which contributes to the computational social science (CSS) field of social simulation modeling. The topic modeling extends the field of text-contents analysis by identifying the insights related to urban shrinkage phenomenon from a large number of newspapers, which adds to the field of social information extraction under the CSS domain.

Part I

Background

Chapter 1: Introduction

1.1 Motivation

While the world's urban population continues to grow, this growth is not equal [1]. Some cities are actually shrinking, and the list of shrinking cities expands every year and currently includes Leipzig in Germany, Urumqi in China, along with Detroit in the United States [2–4]. The definition of urban shrinkage commonly refers to a metropolitan area that experiences significant population loss in a very short period of time. The causes of urban shrinkage have been the source of much debate but can be broadly attributed to a combination of factors relating to deindustrialization, suburbanization (i.e., urban sprawl), and demographic withdrawal (see: [5–7]). It has also been noted that urban shrinkage poses a significant challenge to urban sustainability from urban planning, development and management point of view due to declining populations and changes in land use [8].

The challenges brought by shrinking cities, especially in and around the city's traditional downtown core area, result in many problems, such as population loss, economic depression (due to loss in tax revenue), a growth in vacant properties, and the contraction of the land and housing markets. From a more general perspective, cities that focus too much on one branch of economic growth can not be regarded as sustainable. Such cities are more vulnerable if the specific industry declines [9] (as was the case for Detroit, its reliance on the manufacturing industry). Hence, a particular industry's decline will cause people to lose their jobs and unemployment rates to rise. Residents in such cities may therefore leave their current location in order to find employment opportunities in other areas. The employment mobility results in a large number of properties in shrinking cities to be left vacant, when the population in a city declines. Significant amounts of vacant land and abandoned properties across an entire urban area are one of the key characteristics of a shrinking city [10]. Not only do these vacant (abandoned) properties potentially result in higher rates of crime [11], but they also impact the local economy and contract the local housing market [12]. For example, local governments collect less property tax revenue due to vacant properties. Therefore, they have less money to allocate to public safety and infrastructure, potentially accelerating the population decline. In other words, the economic decline may worsen, and the vacant properties may lead to an oversupply of stock within local housing markets. Therefore, it is rational to expect house prices to decrease and if the population continues to decline, the local housing market may contract or collapse completely [13].

Numerous factors, including regional housing market trades, job suburbanization, deindustrialization, economic downturns, increasing unemployment rates, racial conflict and population loss account for the causes of shrinking cities and the consequent contraction of the housing market at the macro-level. With respect to population loss, this leads to a decrease in demand for existing houses, which will lead to the depression of the housing market [13]. Turning to the deindustrialization process, this will accelerate the contraction of the housing market as employees in specific industries (e.g., manufacturing) become unemployed and seek employment elsewhere, which results in more houses in residential areas becoming vacant [14]. From the perspective of racial conflict, this may lead to the housing market continuously contracting because people may be forced to leave the city by unfair discrimination [15, 16]. Lastly, the fourth process associated with urban shrinkage, that of suburbanization, sees residents choosing new locations based on their own preferences and financial backgrounds rather than choosing to live in declining and potentially unsafe communities, which also causes the local housing market to contract [17]. For example, in Detroit, the continued suburbanization of jobs and racial conflicts has driven people from Detroit's downtown areas. More generally speaking, deindustrialization and the loss of manufacturing, construction, and retail has accounted for 60 percent of job losses in the 100 largest United States metro areas over the last few decades [18]. People working in such sectors become unemployed and seek employment elsewhere [14].

As discussed, a shrinking city's collapse can be explained at the macro-level, there are few efforts to explore such a phenomenon at the individual-level. At the same time, the computational social science research framework provides the potential to explore urban shrinkage at the individual level. For example, agent-based modeling can be utilized to explore urban shrinkage at individual-level. Hence, the first motivation of this work is to explore a shrinking city's housing market from the micro-level via computational approaches. One of the motivations of this work is to explore the housing market in a shrinking city from the micro-level interactions, specifically based on individual preferences and trading interactions. Therefore, agent-based modeling is selected as a tool to simulate and analyze a shrinking city's housing market. Considering simulation is one of the approaches in the computational toolkit. Hence the other motivation is utilizing a computational approach other than simulation to explore urban shrinkage. With respect to the gowning body of text content analysis works utilizing Natural language processing (NLP), insights of various topics have been disclosed by analyzing both social media data (e.g., drug cartel [19] and newspapers (e.g., drone attacks [20]). Therefore, another motivation of this work is to reveal insights related to urban shrinkage utilizing NLP approaches on newspaper articles.

1.2 Research Questions

Based on these two motivations, **this work focuses on the following three research questions**: RQ1:How does urban shrinkage emerge at the macro-level through the simulation of housing trades at the individual level? RQ2: How can patterns of shrinkage be measured through a simulation? RQ3: To what extent can urban shrinkage be revealed by the analysis of newspaper articles?

1.3 Contributions to Computational Social Science

With respect to the computational social science (CSS) research domain, it refers to the interdisciplinary investigation of social phenomena from multi-scales with the development and application of computational methods [21, 22]. Various research fields are under the

CSS domain, including social information extraction, social networks, social complexity, social simulation modeling, etc. [21]. In this work, two techniques are selected from the CSS toolbox: computational modeling and analysis techniques. With respect to the computational modeling techniques, agent-based modeling, initialized by real census data, is utilized to simulate a shrinking city's housing market, which adds to the field of inquiry by capturing the urban shrinkage from the bottom-up. The implementation of agent-based modeling contributes to the CSS field of social simulation modeling. Turning to the analysis techniques, this work uses NLP, which is an advanced computational technique to further reveal the insights related to urban shrinkage from newspaper articles. Utilizing NLP to conduct newspaper articles content analysis has the potentials to contribute to the field of social information extraction within the CSS domain.

1.4 Organization of the Dissertation

This work can be divided into three major parts: 1) Background, 2) Methodology and 3) Results. The Background part firstly introduces the motivation and goals of this work in Chapter 1. Chapter 2 introduces the study area by providing provides several basic empirical data analyses related to the study area. Lastly, Chapter 3 provides a literature review with respect to static and dynamic computational modeling techniques being utilized in the urban study, especially in the study of urban shrinkage. Within the Methodology part, Chapter 4 outlines all models utilized in this work along with detailed discussions in Chapter 5, 6 and 7. Turning to the Results part, Chapter 8 and 9 illustrate all models' results. Chapter 10 concludes this works by summarizing the findings and contributions of this work, along with identifying the potential for future study.

Chapter 2: Study Area

Based on the motivations and research questions, this work conducts a case study on a representative shrinking area to further explore urban shrinkage. Among the shrinkage cities in North America, Detroit is one of the most famous shrinking cities [7]. However, when people refer to Detroit, they always refer to Detroit Metropolitan Area or Detroit Metropolitan Statistical Area, which contains six counties: Wayne, Oakland, Macomb, Livingston, St. Clair, and Lapeer Conty. This work selected the three most populous counties (i.e., Wayne County, Oakland County and Macomb County) inside the Metropolitan Area (shown Figure 2.1), which is called the Detroit Tri-County Area and measured 5,095 km^2. Specifically, a representative shrinking city, Detroit (discussed in Section 2.1), is located in Wayne County, while Oakland County is a prosperous nationwide area (discussed in Section 2.2). The rationale for choosing this study area is that the Detroit Tri-County Area comprises both of a shrinking and a prosperous area. This distinction between shrinkage and prosperous areas not only provides macro-level heterogeneities related to various socioeconomic factors, but also has the potential to enrich the heterogeneities at the micro-level when utilizing computational approaches (e.g., agent-based model). With respect to providing more information related to the study area, Section 2.1 summarizes the factors that lead to Detroit's shrinkage, while Section 2.2 distinguishes the city of Detroit and its surrounding area (i.e., area other than the city of Detroit) by demonstrating empirical analysis on various socioeconomic factors.

2.1 A Shrinking Detroit

The city of Detroit is the largest city in Michigan, located in the Great Lakes area of the United States, which has also been given the moniker the "Rust Belt region." There are

Figure 2.1: Study Area.

many stories that discuss the greatness of this city during the 1950s – when the automobile manufacturing sector rapidly expanded and its population reached its peak [23]. However, today's stories often describe how the city of Detroit has declined and shrunk in different ways over the last 60 years. Specifically, how a growing city can rapidly become a declining one, if it is focused on only one branch of economic production (e.g., in the case of Detroit, this was the automobile). One of the most significant phenomena that this city has witnessed is population loss, a decrease of over 60% in the last 60 years and 25% in the ten years up to the 2010 census [24].

In the last 60 years, various social activities related to social justice have taken place in the U.S., aiming to mitigate unfair racial discrimination. Especially the African American people suffered unjust racial segregation across the land of America, including Detroit. One noticeable event caused by racial discrimination is the race riots of 1967, which can be considered another factor that worsened the population loss situation, because the majority of residents left the city fearing violence (i.e., white flight) [25–27]. However, the white flight was not only driven by the racial tension on the streets. It was also driven by racial discrimination off the streets. For example, African American people had low access to newly-built suburbanized house mortgages and they usually faced unfair insurance policies [16, 28]. With the combination of the federal suburbanization process and racial discrimination, the population of Detroit kept dropping after 1967. Deindustrialization swept through the city of Detroit and its surrounding regions [29], which started after World War II with several factories moving to suburban areas [28]. In the 1950s, deindustrialization did not lead to instant population decline because there were still job opportunities in the city of Detroit before the city faced the foreign competition brought by globalization [12, 23, 28]. However, in the 1970s, Detroit's automobile manufacturing industry started to deindustrialize and collapse with the impacts of foreign competition and the auto industry integration [14]. As a result of deindustrialization, employment opportunities became limited in Detroit and some previous auto industry employees left the city, which contributed to the population loss. As a result of population loss, large numbers of vacant properties and vacant land are now dispersed to almost every corner of the city. There were approximately 60,000 vacant parcels of land and about 78,000 vacant structures, of which 38,000 were considered dangerous in 2014 [23]. This population decline also resulted in the housing market shrinking from both the demand and supply sides [30]. In addition, the city of Detroit declared bankruptcy on July 18, 2013 [4]. Therefore, the city of Detroit is an excellent example of a shrinking city caused by population loss, racial conflicts, deindustrialization, and housing market contraction, eventually leading to the city becoming bankrupt in 2013.

2.2 Prosperous Suburban

Section 2.1 introduces the city of Detroit as a great example of a shrinking city. However, the surrounding suburban area of Detroit can be considered prosperous or outstanding, even from a national perspective. For example, its neighborhood county (i.e., Oakland County) is the 21st richest county in the United States [31]. Hence, a set of empirical analyses are conducted to distinguish the city of Detroit and its neighborhood area within this Section. This work's study area mainly focuses on Detroit Tri-County Area as shown by Figure 2.1, which measures 5,095 km^2 and contains Wayne County, Oakland County and Macomb County. As discussed in Section 2.1, the shrinkage of Detroit is the consequence of population loss, racial conflicts, deindustrialization and housing market contraction, so variables related to population change, household income status and house value are collected from the 2019 Census dataset (i.e., latest data can be found) to display the spatial heterogeneity among the Tri-County Area [32]. Table 2.1 shows the description of each variables. Census tract level data are collected based on these variables and the data are prepossessed by using Python and visualized in QGIS.

With respect to the population changes, data related to the Detroit Tri-County Area and the city of Detroit each census year were collected and analyzed [31]. Table 2.2 shows the changes in population from 1930 to 2020. The population of both the Tri-County Area and the city was growing from the 1930s to the 1950s. However, the city's population has

Table 2.1: Census Data Variables for the Empirical Analysis.

Variable	Description
`ME_FIN_20`	Median household income within each Census Tract
`MD_V_20`	Median house value within each Census Tract
`BP_PER_20`	The percentage of population below poverty line within each Census Tract

Table 2.2: Population Changes in Tri-county Area between 1930 to 2010.

Year	Tri-county Area	City of Detroit	Percentage of City's Population as of Tri-county Area's Population
1930	2,177,343	1,568,662	72%
1940	2,377,329	1,623,452	68%
1950	3,016,197	1,849,568	61%
1960	3,762,360	1,670,144	44%
1970	4,199,931	1,514,063	36%
1980	4,043,633	1,203,339	30%
1990	3,912,679	1,027,974	26%
2000	4,043,467	951,270	24%
2010	3,863,924	713,777	18%
2020	3,949,173	672,351	17%

declined since the 1960s and continues to decline till today. In contrast, the Tri-County Area's population peaked in the 1970s and remained at approximately 4 million till today. Even with minor fluctuations from the 1980s to the 2020s. Turning to the city's population to Tri-County Area's population, this percentage shows the declining trend from an initial 72 % in the 1930s to today's 17 %.

Two related variables are selected from the census dataset to reveal the heterogeneities of income status: 1) percentage of population below the poverty line and 2) median income status in 2019. Data related to these two variables are linked to the census track boundary to show the spatial heterogeneities among the study area. Figure 2.2 (A) illustrates the status of the percentage of the population below the poverty line. The spatial heterogeneities can be easily identified as the color become darker, closer to the city of Detroit. Figure 2.2 (B)

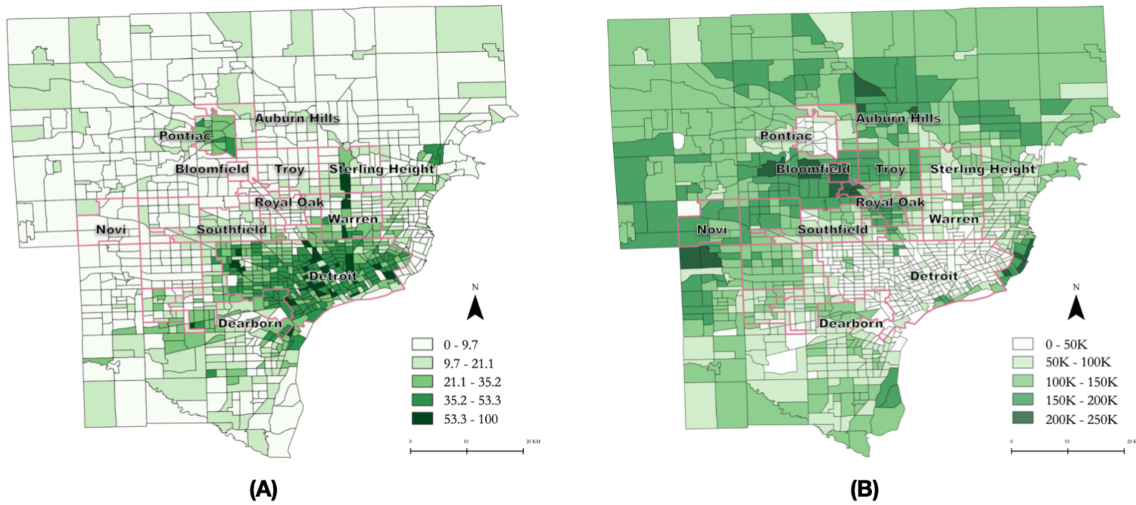

Figure 2.2: 2019 Income Status in Detroit Tri-County Area: (A) Percentage of Population that Below Poverty Line; (B) Median Household Income.

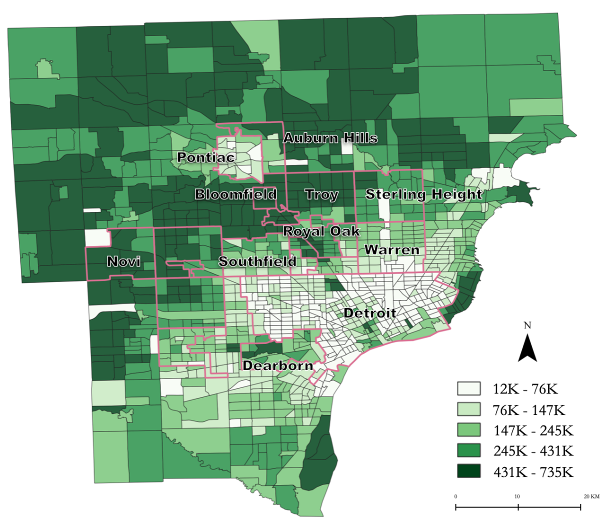

Figure 2.3: 2019 Median House Value Status.

shows that a large number of lower income tracts can be measured within the boundary of the city, while most of the higher income tracts are located in the cities on the North side of Detroit, like Troy, Novi and Bloomfield. Similar spatial heterogeneities are measured for the variable of the median house value as shown in Figure 2.2. A large number of tracts with median house value can be identified outside the city of Detroit. While within the city, despite a few tracts in downtown and suburban area showing high median house value, the major tracts within the city are showing a status of the lower house value.

2.3 Summary

As discussed in Section 2.2, selected variables (e.g., population change, income and poverty status and median house value status) have been analyzed and visualized by demonstrating the spatial heterogeneities among the whole study area. Through the analysis, a shrinking inner city (i.e., the city of Detroit) and a prosperous suburban (i.e., the rest of the study area) can be identified. The difference between the inner city and suburban in the Detroit Tri-County Area provides a unique story of the study area, which also offers more heterogeneities when utilizing computational approaches, such as agent-based modeling. Therefore, Detroit Tri-County Area, which comprises a declining downtown core area and a prosperous suburban area, is an excellent example to explore the urban shrinkage for this work.

Chapter 3: Literature Review

The phenomenon of urban shrinkage has already drawn a lot of attention globally. In the academic area, urban shrinkage is explored through several aspects. Hence, previous efforts are discussed in this section and Figure 3.1 shows the structure of this section. Previous literature can be divided into two main aspects: 1)Static Approaches; 2)Dynamic Computational Approaches. Static Approaches contains works related to both qualitative and quantitative methods; furthermore, statistical and computational works are discussed under quantitative methods. Also, efforts related to cellular automata and agent-based modeling are identified as dynamic computational approaches.

3.1 Static Approaches

3.1.1 Qualitative

With respect to the qualitative works, theoretical mechanism analysis has been discussed through numerous case studies focusing on shrinking cities worldwide [9, 14, 23, 33, 34]. To summarize, both internal and external factors lead to the urban shrinkage. As for the internal factors, a city or metropolitan has its own evolution cycle to grow and decline, including total of four stages: 1) urbanization; 2) suburbanization; 3) de-urbanization; 4) re-urbanization [35,36]. Urbanization refers to the development and the population growth in the traditional center area of a city. The suburbanization process occurs when the population growth and development shrift from the city center to its suburban area (i.e., urban sprawl). Suburbanization may start with an undeveloped center area. De-urbanization takes place with population loss in the traditional center area. Re-urbanization refers to the traditional center area that attracts people back to the center area [37]. Within this evolution cycle, external factors (e.g., globalization, policy change) may accelerate and impact on each stage

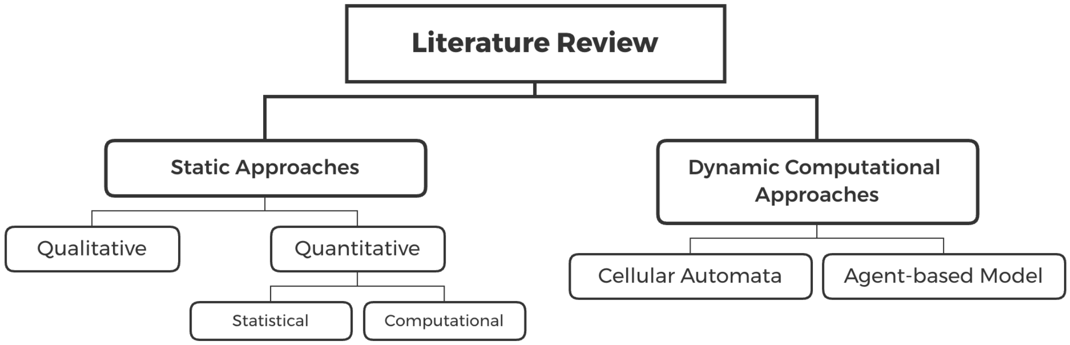

Figure 3.1: Literature Review Structure.

of a city's evolution cycle positively (i.e., growth) or negatively (i.e. shrinkage) [14, 33]. For example, in Detroit, globalization leads to further deindustrialization and population loss, while in Northeastern China, the shrinkage is brought by policy changes.

3.1.2 Quantitative

Shifting the focus to quantitative works, data always plays an important role in such research. Different types of data have been utilized to explore urban shrinkage from different perspectives. With respect to census data, such data has been applied to reveal urban inequalities and to measure trajectories of neighborhood changes in a shrinking city [13, 38]. While in China, census data is also used as evidence to guide policymakers and urban planners to adjust the planning paradigm from urban growth to urban shrinkage [39]. Other than census data, remote sensing data has also been utilized as the data source to explore various topics within the urban shrinkage research field. For example, urban vacant land can be identified using high-resolution remote sensing images [40]. In addition, remote sensing data (e.g., nighttime imagery) is applied to identify shrinking cities in China and Kazakhstan [41, 42]. Furthermore, with the combination of census data and remote sensing data (i.e., Landset imagery), a shrinking city's residential area decline is modeled through capturing the vacancy issue [10].

Although various types of data are utilized in quantitative studies to study urban shrinkage, few studies use text-data (e.g., newspaper, social media) to reveal the insights related to urban shrinkage. With the growing body of research utilizing social media text data to study various topics, social media text-data measure the emergence of communities holding different opinions on vaccination discussion and healthy diet [43, 44]. Also, the geo-tagged social medial text-data allows us to understand the awareness of drug cartels in Mexico and the United State [19]. For the role of social media text-data in urban studies, the social media text-data has been applied to understand the human movement during a natural disaster in urban area [45–47]. Moreover, social media text-data has the potential to explore abstract aspects of urban life that are linked to places and offer an alternative approach to the study of cities, which can be considered as the volunteered geographic information at the micro level [48].

Newspapers, a more traditional text-data source with a longer history than social media text-data, are also applied in various studies. In addition, newspapers are one of the traditional sources for social scientists to extract information by utilizing content analysis techniques [21]. For example, newspaper contents analysis have been utilized in the field of public health (e.g., Japan vaccination crisis [49], Canadian seasonal flu vaccine [50]), social activities (e.g., feminism activities [51]) and urban studies (e.g., French urban violence [52], Detroit's urban development issues [53], house price inflation of the UK [54]). Therefore, this work selects newspaper articles as the text data source to conduct the content analysis to further explore urban shrinkage.

With respect to the content analysis, it's possible to conduct such analysis with NLP, which is an emerging advanced computational approach that enables a machine (i.e., a computer) to understand human written words or statements through algorithms [55]. Various types of NLP works have been done, including information retrieval, information extraction, text categorization, summarization, sentiment analysis, machine translation, etc. [56]. Under the branch of information extraction, topic modeling, an unsupervised machine learning technique that aims to extract related word groups and similar expressions from a collection of text documents, provides the potential to explore urban shrinkage by analyzing the newspaper contents [57]. Among the methods within topic modeling, Latent Dirichlet Allocation (LDA) is one of the most applied and conventional methods exploring various studies including public opinion on pandemic (e.g., [58]), social movement studies (e.g., [59]), climate change (e.g., [60]), bioinformatics (e.g., [61]) and etc. [57, 62]. Other than LDA, Latent semantic analysis, Non-Negative Matrix Factorization, and Probabilistic Latent semantic analysis are conventional methods within the topic modeling [56]. However, the limitation of these methods is that they fail to capture the semantic relationships among words within a certain article or sentence, which leads to resulting topics representing the text-data inaccurately [63]. While an emerging language model, BERT can capture the semantic relationships among words and sentences, which shows the accuracy in representing documents and offers the potential to find the topics related to urban shrinkage from text-data (i.e., newspaper articles) [64, 65]. Thus, this work selects BERT from various NLP topic modeling techniques and conducts analyses on a large number of newspaper articles to reveal the coverage related to urban shrinkage over time.

3.2 Dynamic Computational Modeling Approaches

Dynamic computational approaches fall within either the cellular automata or agent-based modeling methodologies [66]. This section discusses the rationale for exploring urban shrinkage via dynamic computational approaches (unlike more static aggregate ones such as spatial interaction models). Moreover, the reasons why utilize an agent-based modeling approach are discussed by introducing works related to the topics of land markets (which as noted above are one of the main consequences of urban shrinkage). However, before discussing this, our rationale for choosing computational approaches is that they allow us to test what-if scenarios and experiments in the safe environment of a computer. By taking advantage of this environment, several existing classic computational models have simulated Detroit's urban growth instead of shrinkage. Tobler [67] simulated the urban growth from the population growth perspective. The NBER Urban Simulation Model simulated Detroit's urban structure changes through the impact of employment distribution, change in transportation methods, increasing incomes and population growth [68]. Turning to the efforts related to dynamic computational modeling methodologies, a wide-range of topics have been used to explore under the umbrella of urban dynamics (see for example: [69, 70]). Two computational modeling methodologies: Cellular Automata and Agent-based Modeling are two main methods that have been widely utilized within the urban dynamics studies, which will be discussed in Section 3.2.1 and 3.2.2.

3.2.1 Cellular Automata

One of the most widely explored areas with such models is that of land use change and urban sprawl is one of the most explored directions, especially with the use of Cellular Automata [71]. For example, the SLEUTH [72] model, which has successfully simulated land use transitions relating to the urban sprawl around the world (e.g., San Francisco, Washington, D.C.-Baltimore area, and "Chongqing, China, etc.) [73, 74]. Recently, cellular Automata models equipped with more advanced machine learning methods (e.g., Neural network and Random Forest) have been utilized to simulate urban expansion in China with enhanced accuracy over more traditional Cellular Automata models [75, 76]. A closely related but slightly different approach to explore land use change through the perspective of the urban sprawl is that of agent-based modeling. The major difference between agent-based modeling and Cellular Automata is that in agent-based models, one represents heterogeneous agents and each agent can have their own rule set which is generally not the case for Cellular Automata models where transition rules tend to be homogeneous [77–80]. By utilizing agent-based modeling, have explore a variety of issues ranging from urban growth [81], land use/ cover change[82], creative cities [83], to that of urban migration [84]. Focusing more on residential dynamics, agent-based models have been used to explore residential choices and gentrification [85–87]. However, as noted by Schwarz et al. [88] there is a gap in simulating urban shrinkage through agent-based modeling approaches.

3.2.2 Agent-based Modeling

Readers might be wondering why one might want to utilize agent-based modeling for urban shrinkage. One reason is that the ability of agent-based models to capture the hierarchical structure of systems from the bottom up. In the sense, they focus on how individual interactions of entities (e.g., individuals buying and selling houses) at the micro-level allow us to capture more emergent phenomena at the macro-level (e.g., land markets). As such agent-based models can provide insights into the target phenomenon or system of interest, especially for complex systems that involve human-environmental interactions [89, 90]. In such systems, humans can impact the environment by their actions. In an oppsite direction, the environment can impact the humans (e.g., [89]). Housing and land markets are excellent examples of human-environmental systems as the main components in such markets at the micro-level are buyers and sellers[91]. They make their own decisions to trade or interact with each other and are impacted by the environment (e.g., economic and physical conditions) which can lead to a variety of housing market dynamics emerging over time at the macro-level.

Secondly, agent-based modeling, unlike other modeling techniques, allows us to represent individuals as autonomous heterogenous entities. Each agent has different attributes (e.g., income) and makes decisions based on what they know about other agents as well as the environment in which they are located [77, 92]. With respect to housing and land markets, this is an important consideration as all actors in the system (e.g., the buyers and seller) have different socioeconomic backgrounds, housing preferences, along with the different bid and ask-price strategies[91, 93]. Therefore through the implementation of an agent-based model these heterogeneous characteristics and unique behaviors can be represented and simulated.

With respect to modeling markets, Gode and Sunder [94] were one of the first to demonstrate how agent-based models could be utilized to capture supply and demand. In their abstract model, traders were selected at random to buy and sell goods. Through these interactions, the model results have demonstrated how supply and demand curves observed in "real" world situations could emerge through simulation. Turning to the simulation of land and housing markets by using agent-based modeling approaches, Axtell et al. [95] identified the potential to utilize agent-based modeling to understand economics and financial markets, especially the housing market. Indeed, there are substantial works related to agent-based models simulating land and housing markets. Filatova et al. [96] demonstrated how heterogeneous agents with different ask and bid pricing behaviors could generate a land market in a stylized abstract environment. At the same time, the model captured urban growth, which was validated against Alonso's [97] theory of land rent within a monocentric city. Other researchers have also explored land markets emerging from the bottom up and how they impact land use within cities (e.g., [87, 93]). For example, Torrens and Nara [87] simulated the demand and supply sides of a land market to explore urban gentrification in an area of Salt Lake City in Utah. However, while agent-based modeling of residential housing choices and land markets has started to show its potential as a valuable methodology to explore urban issues from the bottom up, no studies have explored land markets and urban shrinkage. Studies utilizing agent-based modeling to explore the urban shrinkage to date have mainly focused on land-use and residential dynamics (e.g., [98]) and not housing market dynamics.

3.3 Summary

Through the discussion in Section 3.1, newspaper text-data is one of the traditional sources for text-content analysis to extract social information, which can be utilized as the data source to explore urban shrinkage in this work. To conduct text-content analysis on newspapers, BERT is selected from topic modeling methods to gain insights related to Detroit's shrinkage over time. With respect to the discussion in Section 3.2, capturing housing markets is essential for understanding urban shrinkage, as the contraction of housing markets is caused by population loss under the urban shrinking situation [12]. Hence, a model of urban shrinkage should capture not only residential dynamics but trades (or lack of) within the housing market. Therefore, two agent-based models stylized on different spatially explicit data will be presented in this work to simulate the urban shrinkage in the Detroit Tri-county area in order to explore how micro-level housing trades impact on macro-level shrinkage by capturing trades between sellers and buyers within different dynamic sub-housing markets.

Part II

Methodology

Chapter 4: Methodology

As discussed in Chapter 3, agent-based models and topic modeling will be utilized to answer the research questions in this work. This chapter broadly introduces the modeling techniques to be utilized in this work. Section 4.1 provides a brief description and simulation goals of two agent-based models and how to use the simulation technique to answer the RQ1 and RQ2. While Section 4.2 introduces the overall design and workflow of the utilization of topic modeling, which attempts to answer the RQ3.

4.1 Agent-Based Modeling

As noted in Section 3.2, this work aims to explore urban shrinkage by simulating housing transactions and the aggregate market conditions relating to urban shrinkage. Therefore, models built in this work focus on housing trades or transactions within various housing markets rather than the economy as a whole (however, variables within the model capture employment). Hence, two agent-based models are built to capture urban shrinkage by simulating a housing market stylized on the Detroit Tri-county. The first model aims to test the initial idea of exploring urban shrinkage through simulation approaches. To avoid the circumstances of computationally intensive and time-consuming, a relatively small area is used to stylize the model, as shown in Figure 4.1 (A). The temporal resolution of this model is one year and the model simulates the housing trades from the year 2010 to 2015.

The second model simulates the whole Detroit Tri-County area, measuring 5,095 km^2 as shown in Figure 4.1(B). Compared to the first model, the second model is more advanced by enhancing four perspectives: 1) enlarging the simulation area to the whole study area; 2) introducing another type of agent, especially a bank type agent; 3) enhancing the trade functions by incorporating agents' preferences when it comes to buying a house; 4) adding

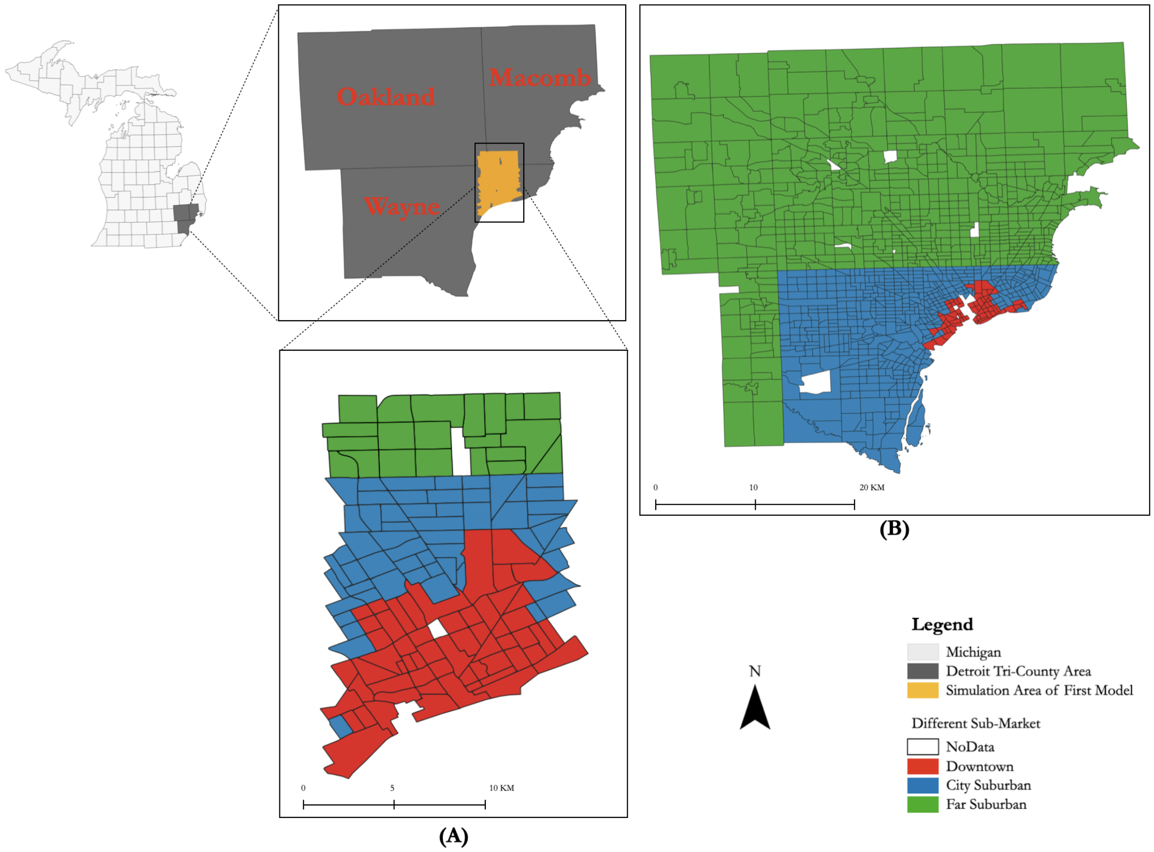

Figure 4.1: Simulation Area For Both Models, (A) First ABM Simulation Area; (B) Second Model Simulation Area.

additional household dynamics, such as employment status change. This model's temporal resolution is the same as the first model (e.g., one year). However, in the second model, 20 years is chosen as this will cover the years 1990, 2000 and 2010, in which census data is available for both verification and validation. The design details for both models are provided by utilizing the Overview, Design concepts and Details (ODD) protocol by Grimm et al. [99], which are discussed in Chapter 5 and 6.

4.2 Topic Modeling

As discussed in Section 1.1 and 3.2, this work also aims to reveal the discussions related to urban shrinkage through a computational approach other than simulation. Therefore one of the NLP approaches (i.e., topic modeling) is selected to be utilized in this work. In addition, a new type of text data (i.e., news articles) is chosen as the data source for the topic modeling to explore urban shrinkage. Thus, utilizing topic modeling aims to detect the discussions related to urban shrinkage over the years by using news article text data. Chapter 7 provides the step-by-step details of the topic model approaches utilized in this work.

Chapter 5: Initial Agent-based Model

5.1 Overview

This Chapter provide details of the initial model utilizing the Overview, Design concepts and Details (ODD) Protocol for a model exploring urban shrinkage by simulating a stylized housing market based on Detroit, Michigan [99]. Section 5.2 discuses model design concepts and Section 5.3 provides implementation details of the model. The model itself was created utilizing NetLogo 6.1 [100]. The model graphical user interface is displayed in Figure 5.1. The model itself and detailed ODD document are available at: `https://github.com/njiang8/Urban_Shrinkage_ABM_Housing_Market`.

5.1.1 State Variables and Scales

This model focuses on housing trades or transactions within various housing markets rather than the economy as a whole (however, variables within the model capture employment, as will be discussed next). Hence, trades between buyers and sellers within these different sub-housing markets are simulated by this model. The whole Detroit Tri-County area can be divided into three sub-housing markets, including downtown, city suburban and far suburban housing markets by referencing the spatial data as depicted in Figure 4.1 (A). Both the downtown area and suburban areas are within Wayne county. The difference is that the downtown area is defined by Detroit opportunity zone data [101]. While the suburban area excludes the downtown area. The rest of the study area we call far suburban, which is not part of Wayne County and is comprised of Oakland and Macomb counties and its distance to the downtown area is much further. In order to model, simulate and experiment with the housing market, we chose NetLogo, as it has capabilities to handle the spatial data needed to build the model and allows for rapid prototyping. However, there are constraints to the

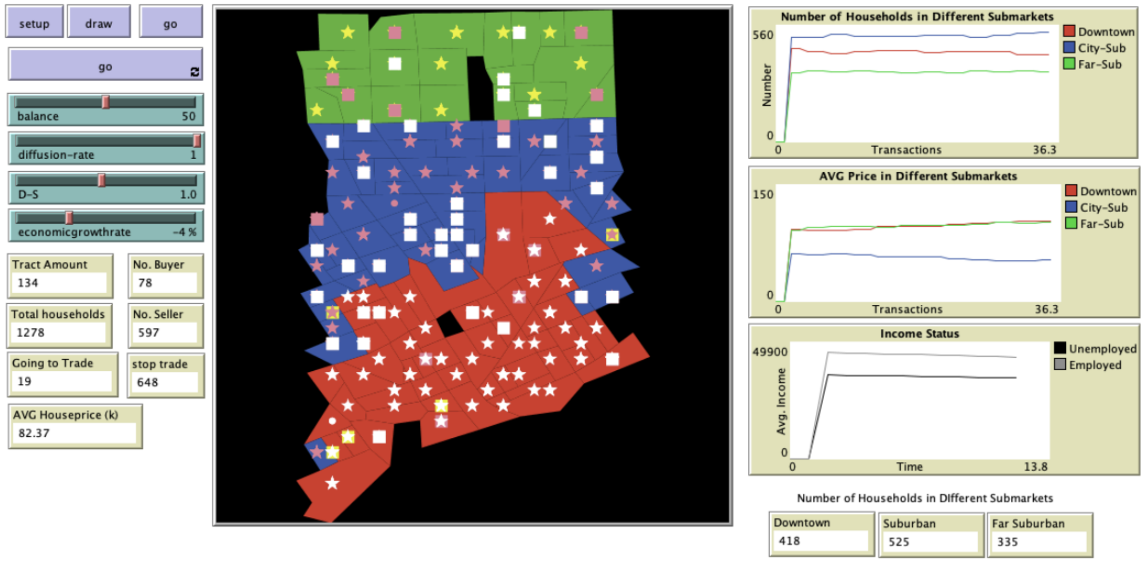

Figure 5.1: Initial Model graphical user interface, including input parameters, monitors and charts recording key model properties and the study area itself.

platform specifically relating to scalability (both in terms of agents and spatial resolution. Hence, instead of modeling the whole study area, only a certain area was selected to build the model, which covers all three sub-markets, also shown by Figure 5.1. The UML diagram displays the sequence of all function events in this model in Figure 5.2, which demonstrates the model flow and dynamics.

The main agent in this model are households who live in the Detroit Tri-County area. For the purpose of simplification, in this model, one agent is used to represent 100 households. Each agent comprises various attributes that result in a heterogeneous population. Except for the attribute HPOLY, the rest of the agents' attributes were selected for the inclusion within the model based on relevant literature summarized by Table 5.1. Agents are heterogeneous and vary in their characteristics (e.g. ID, neighborhood type) and finical backgrounds (e.g. income). Furthermore, agents can be categorized into two types: buyer and seller households, and they are all goal-oriented. Buyers have one goal, which is to find an affordable house by proposing a bid-price to sellers. On the other hand, a seller's goal is to post an asking price and maximize the profits from the trades (this will be further

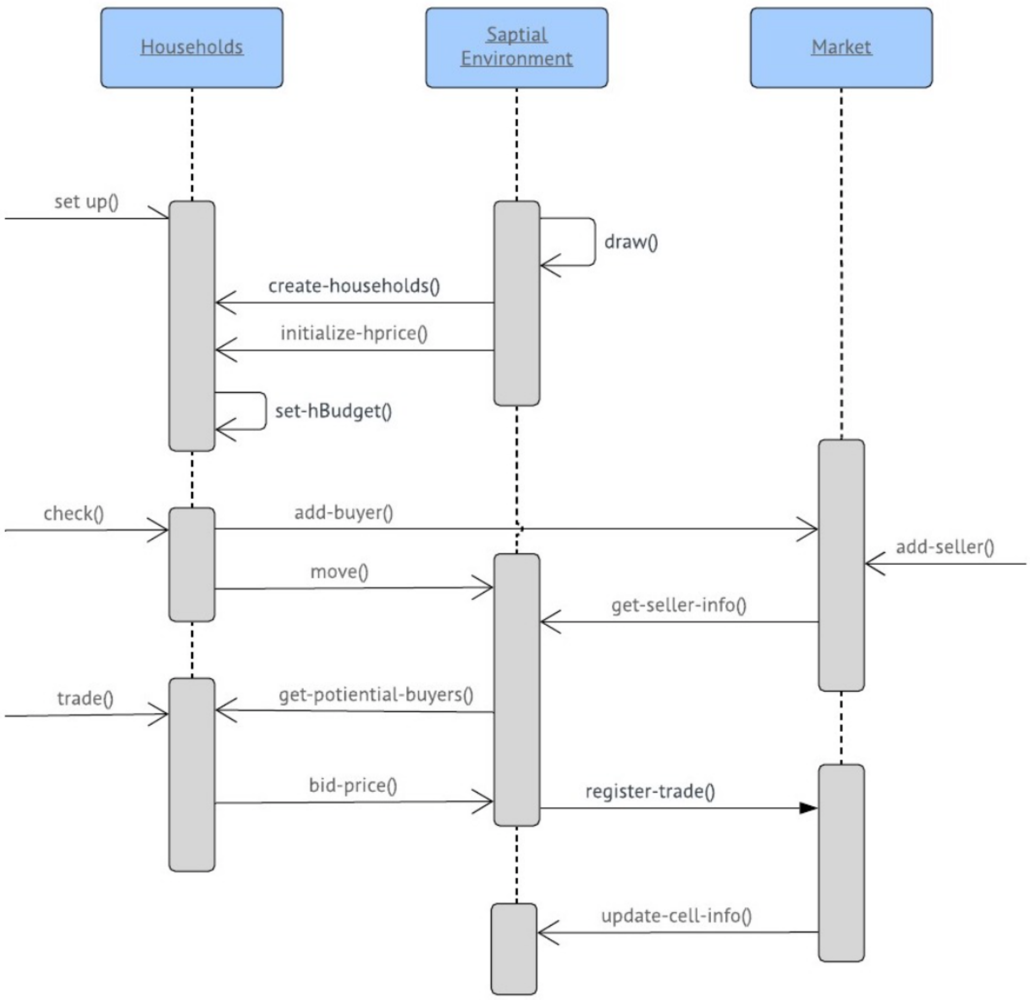

Figure 5.2: UML Sequence Diagrams of the Initial Model.

Table 5.1: Initial Model Agent attributes.

Attribute	Description	Reference
ID	Unique ID for households	[96]
HNT	Household neighborhood type that indicated which sub-housing market is household located	[101]
HPOLY	Polygon ID indicated which polygon is household on	Author estimation
HINCOME	Income of the household	[102], [87]
HBUDGET	Budget for annual housing cost and purchasing new house	[96]
BUYER?	Boolean value, if true, buyer household	[96]
SELLER?	Boolean value, if true, seller household	[96]
BIDPRICE	Only associate with buyer households	[96]
ASKPRICE	Only associate with seller households	[96]
EMPLOYED?	Boolean value, if true, household has job, else, no jobs	[102]
TRADE?	Boolean value, if true, indicates household will trade	[96]

discussed in Section 5.4).

The other component of this model is the environment, which contains three different elements: 1) Geospatial; 2) Artificial housing market comprising three different sub-markets: Downtown, Suburban and Far Suburban; 3) Economic environment. The geo-spatial environment provides the geographic boundary of the whole simulation area and the boundaries of the three sub-housing markets. Also, the geo-spatial environment provides a physical environment for all agents moving around. However, the artificial housing market is a hidden environment that can capture the trades between buyer households and seller households. As for the economic environment, this is a hidden environment that reflects the economic status of the Detroit area. The temporal scale in this model is one year that is reflected by the one tick in the NetLogo. Every year, households make decisions to become buyers and trade with sellers.

5.1.2 Process Overview and Scheduling

As discussed above, household agents are the main components in the model and the key attribute of the household is their incomes (i.e., HINCOME), which provides the heterogeneity within the world and is updated as the simulation processes, which is described in Section 5.4.1. There are several models that have used income to control residential decision making (e.g. [97, 102]). Accordingly, in this model, each household will make decisions based on their income (i.e., HINCOME) status, which is either stay or leave the current location. During each time step of the simulation, households will check if they can still afford their current living location based on their annual budgets (i.e., HBUDGET) calculated from their income. Also this income attribute informs the house trading process. The affordability check will be explained in detail in Section 5.4.1. Once the buyer households decide to enter the housing market, and before the buyer start interacting with sellers, they can choose to enter one of the three sub-marketss by comparing their annual budget (i.e. HBUDGET) with each sub-markets's average house price (which will be discussed further in Section 5.2.2 and 5.4.1). When the buyers enter certain sub-markets, they are able to choose sellers within the sub-markets and bid-prices with them. The households' decision-making process is displayed in Figure 5.3.

5.2 Design Concepts

5.2.1 Observing

In order to capture the housing market's dynamic, we measure various variables hierarchically. At the macro-level, the overall average house price as well as the total number of buyers and sellers within the study area is recorded at each time step of the simulation. On the meso-level, each sub-market will capture the average prices and household amounts throughout the simulation to reflect the differences among the three sub-markets.

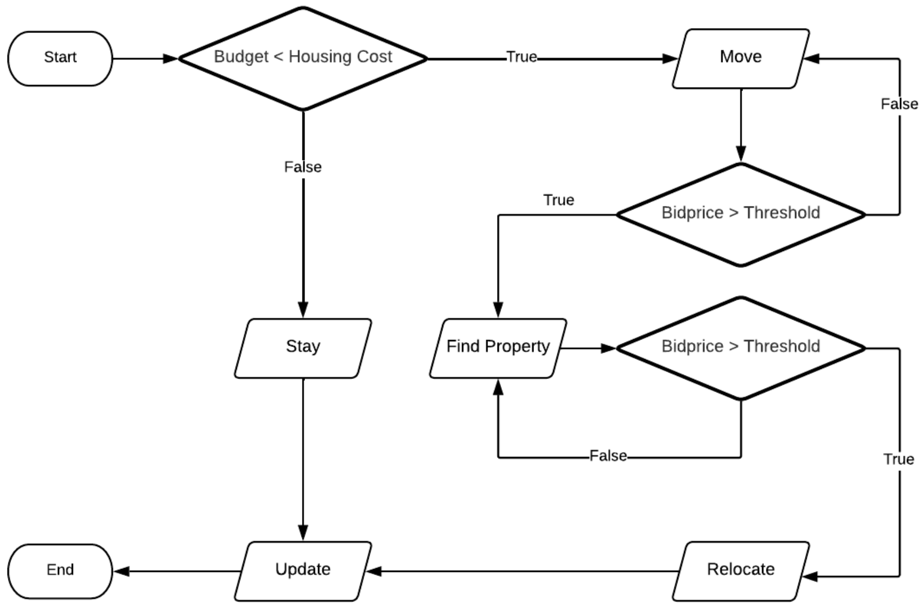

Figure 5.3: Household Decision-Making Process for Stay or Leave Current Location.

5.2.2 Sensing

Housing trades are the main interaction in our model. All household agents know which sub-markets they are located in and the house prices they currently live in. As discussed in Section 5.4.1, they set budgets based on their incomes. Households who become buyers will use their budgets to set the bidprices (i.e., BIDPRICE). Sellers will set the ask-prices (i.e., ASKPRICE) based on current house prices. Before buyers make trades with sellers, they will know the average ask-price of a certain area of the sub-market, which are interactions with environments, as well as indicate buyers' finance capabilities to trade in this area. Once the buyer finds a seller to trade with, they agree upon the price, and then the trade will happen. Further discussions related to the negotiation process are provided in Section 5.4.1.

5.3 Details

5.3.1 Initialization

The initialization of the model is based on socioeconomic and geospatial data of the study area. The data (e.g., income, employment status, house prices) comes from the American Community Survey [103], for each census tract in the study area. This data is used to initialize the number of agents within the simulation. Due to computational constraints, we only represent 1% (i.e., 1278) of the total number of households within the study area. As the socioeconomic data is aggregated, we only have average house prices along with upper and lower quartiles within each census tract. Therefore in order to assign house prices, we use this distribution (referred to Balance in the model code). Specifically, the total amount of agents is divided by the balance, and an equal number of agents are then assigned a house price by adding a random number within the upper quartile range to the average. In contrast, the other half is assigned a house price by a random number between the lower quantile and the average. For example, if we had two agents, the average house price was 50; the upper and the lower quartiles were 75 and 25. In this case, one agent would be given a value of 50 plus a random number between 50 and 75, the other agent would be given 50 minus a random number between 25 and 50. We do this to ensure we get a range of house prices within a census tract.

Another input parameter is the diffusion rate, which controls the probability of an agent moving out of a sub-market (the default setting is 1, that is, household agents can move out of their current sub-market if they desire to). This diffusion rate was inspired by Patel et al. [102] who used the same concept to explore residential movement but also is akin to what we observe with urban growth, whereby residents in inner cities move to more suburban locations. There are also two other user settable input parameters; one is the economic growth rate (which is discussed in Section 5.4.2) and the demand and supply (D-S parameter), which controls the ratio of buyers and sellers. Table 5.2 provides an overview of the model input parameters along with their default values.

Table 5.2: Initialization parameters default values.

Parameters	Default Value	Description	Reference
Diffusion Rate(DR)	1	Control the household movement to another neighborhood	[102]
Balance	50	Control the initialization house price of households	Author estimation
D-S	1.0	Control the demand and supply scenario	Author estimation

Table 5.3: Census Variables for Model Initialization.

Variable	Description	Usage
H_I_K	The number households fall in various income ranges (i.e., 10k to 15K)	Initialize the agents and their incomes
H_V_K	The percentage of households falls to various house value ranges (i.e., 50k to 100K)	Initialize the agent house price
H_EM_R	Employment status of each census tract	Add employment status for each agent

5.3.2 Inputs

Data plays an important role in model parameterization, initialization, verification and validation. This work applies two categories of vector data: spatial and socioeconomic data. Spatial data include 1) Detroit city boundary (shown in Figure 4.1); 2) Tri-county area boundary including Wayne County, Oakland County and Macomb County; 3) All census tract boundaries for the Tri-County area. The census tract boundaries can be associated with socioeconomic data, which can be considered as the linkage between the spatial data and socioeconomic data, which is acquired from American Community Survey (ACS) 2010 [32], as shown by Table 5.3.

5.4 Sub Models

5.4.1 Housing Market

There are total of four stages for the simulation process: 1) check current affordability; 2) generate sellers based on demand and supply (D-S) which is defined in Table 5.2; 3) Search; 4) Trade and move.

First, households will check their affordability on their current living sites by comparing their annual budget (i.e., HBUDGET) and the minimum housing cost (which we describe below). To check this, all households will set their budgets, which represent 34% of their income (i.e., HINCOME) and can be used on annual house fees, including property tax, annual maintenance and etc. [104]. The minimum housing cost includes property tax, the house's maintenance fee and mortgage payment. To calculate the minimum housing cost, three percentage numbers are referenced, including 1.52% of the house price for the property tax, 1.3% of the house price for the annual maintenance fee and 4.54% of the house price for mortgage payment [105–107]. Hence, we set 7.38% of the house price as the minimum cost, which indicates the lowest annual cost for a house. Suppose one household's minimum housing cost exceeds the annual budget (i.e., HBUDGET), which indicates this household cannot afford the current house. In that case, they will enter the housing market and become a buyer (i.e., BUYER?).

Secondly, sellers (i.e., SELLER?) will be generated based on the demand and supply status to the other side of the housing trade. The demand and supply status is controlled by the parameter D-S that users can set. If D-S is set to 1, it indicates equal demand and supply (i.e., the same number of sellers and buyers in the model). If D-S is less than 1, demand exceeds supply, and fewer sellers will be generated. If D-S is greater than 1, supply exceeds demand, and more sellers will be generated.

Thirdly, the parameter diffusion rate (D) is introduced to this model to control the households' movements (akin to searching) to different sub-markets. This is a similar concept that Patel et al. [102] used to control agents' choice to leave or stay in slum areas. Users can also set the parameter D value: 0 indicates that buyer households can only move within the same sub-market that they are living now; 1 indicates buyer households can move among different sub-markets.

As for the key interaction within the model, the trade (and subsequent moving) process comprises two stages: 1) Find sellers; 2) Bid prices. For the first stage of trade, buyers will find certain sub-market to enter and find sellers inside the sub-market to bid prices on the houses. For buyers, the main goal is to find affordable houses, so they will check if they can afford houses after the movement to new sub-markets. To determine whether they can afford houses or not, buyers have knowledge related to the average house prices of the markets they just moved to, which is calculated by the ask-prices (i.e., ASKPRICE) of all sellers within the same polygon (i.e., HPOLY). The buyers will set the bid-price (i.e., BIDPRICE), which is 2.5 times of their gross income [108]. If their bid-price is greater than the average house price of a certain sub-market, they will enter that sub-market and search for affordable houses. If not, they will continually move (i.e., search) until they find affordable sub-markets where they can purchase a house. After buyers' movements, the sellers will set the ask-price based on the house price and find a buyer to complete the trade. Sellers have goal of maximizing the profits from the trade so that they will choose the buyer with the best bid-price. After the trade is completed, the trade will be registered by the housing market.

5.4.2 Economic Environment

The economic environment is the invisible hand in this model, which impacts the income (i.e., HINCOME)of each household and the house prices [102]. As shown in equation 5.1, the incomes dynamics are based on the economic growth and employment status of the agents. I_{t+1} is the income at time $t+1$, I_t is the income at time t and G is the economic growth. The α represents the employment status. If one household has a job, α will be the ln of G's absolute value; if not, it will be -0.1.

$$I_{t+1} = I_t * (1 + \alpha) \tag{5.1}$$

During the simulation, the house prices will also have dynamic changes affected by the economic growth (G) rate. However, the G will impact the price based on different sub-markets. The house price is updated by Equation 5.2, where H_{t+1} represents house price at time $t + 1$ after updating, H_t reflects the original house price at time t, G is the economic growth.

$$H_{t+1} = \begin{cases} H_t * (1 - 0.5 * G) & Downtown \\ H_t * (1 * 2 * G) & CitySuburban \\ H_t * (1 - 0.25 * G) & FarSuburban \end{cases} \tag{5.2}$$

5.5 Model Outputs

In Section 1.1, the contraction of the housing market and population loss are the consequences of urban shrinkage, which is the goal to explore with this model (as discussed in Sections 3.2 and 5.1). In order to explore this, a range of outputs are generated by the model. To test if the macro-level urban shrinkage can be captured through the micro-level housing trade interactions with respect to the household changes in every sub-market. Hence, a decline in households within the downtown area is expected as one key output of the first model. More outputs are captured by the model discussed in Chapter 6, which uses the first model as a foundation.

Chapter 6: Extended Model: Agent-based Model

6.1 Overview

Moving forward from the initial model (discussed in Chapter 5), this chapter provides details of the extended model with the ODD protocol for exploring urban shrinkage by simulating a generalized housing market based on the whole Detroit Tri-County Area, Michigan [99]. In Section 6.1 provides a brief overview of the study area and the agents in the model. Section 6.2 discuses model design concepts and Section 6.3 provides implementation details of the model. NetLogo 6.1 was utilized to create the model [100]. The model itself and detailed ODD document [99] are available at: `github.com/njiang8/UrbanShinkageDMV`, while the graphical interface is shown in Figure 6.1. This chapter provides the coed and data of the model to allow readers not only to replicate the results presented in this paper but also to extend the model based on various research areas and purposes.

6.1.1 State Variables and Scales

As noted in Section 4.1, this model aims to explore urban shrinkage by simulating housing transactions and the aggregate market conditions relating to urban shrinkage. Therefore this model focuses on housing trades or transactions within various housing markets rather than the economy as a whole. However, variables within the model that capture employment will be discussed in Section 6.4.2. Hence, trades between buyers and sellers within different sub-housing markets are simulated by this model. The whole Detroit Tri-County area can be divided into three sub-housing markets, which comprise of: 1)downtown, 2) city suburban, and 3) far suburban housing markets by utilizing spatial data for an area of 5,095 km^2 as shown in Figure 4.1 (B). Both the downtown area and suburban areas are within Wayne County. The difference is that the downtown area is defined by Detroit opportunity zone

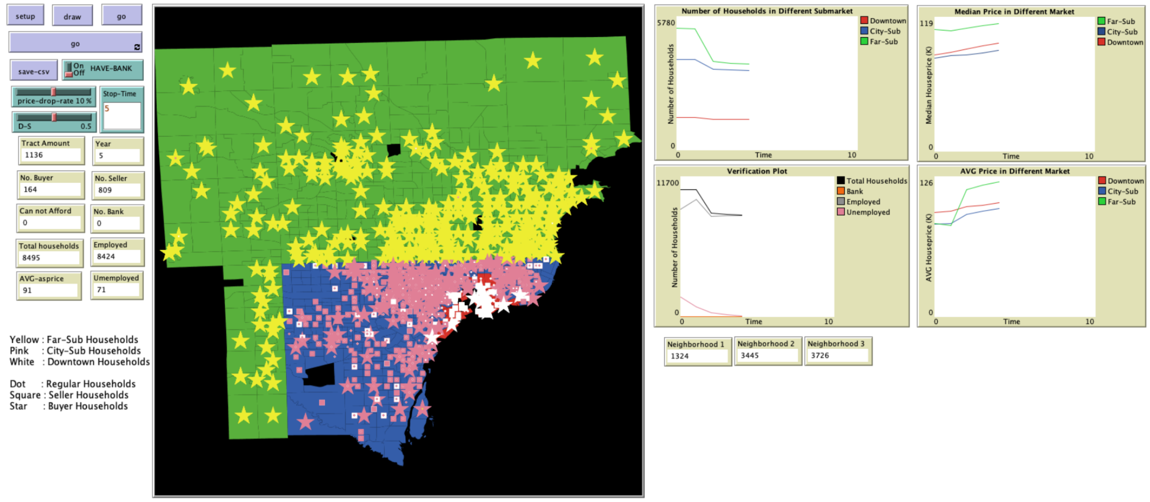

Figure 6.1: Model graphical user interface.

data [101], while the city suburban areas exclude the downtown area. The rest of the study area, which is called far suburban comprising part of Wayne County that is not defined as downtown or city suburban along with Oakland and Macomb Counties, where the distance to the downtown area is much greater. In order to model, simulate and experiment with the housing market, NetLogo is selected as the simulation tool, as it has capabilities to handle the spatial data needed to build the model and allows for rapid prototyping. The sequence of all the events in this model is displayed by the unified modeling language (UML) diagram in Figure 6.2, which demonstrates the model flow and dynamics.

There are two types of agents in this model, households and banks. The main agent is households who live in the Detroit Tri-County area. In the model, one agent is used to represent 100 households for simplification. Agents comprise various attributes that result in a heterogeneous population. Except for the attribute HPOLY, the rest of the agents' attributes were selected for inclusion within the model based on relevant literature, which is summarized in Table 6.1. Agents are heterogeneous and vary in their characteristics (e.g., ID, neighborhood type (i.e., HNT)) and financial backgrounds (i.e., HINCOME). Furthermore,

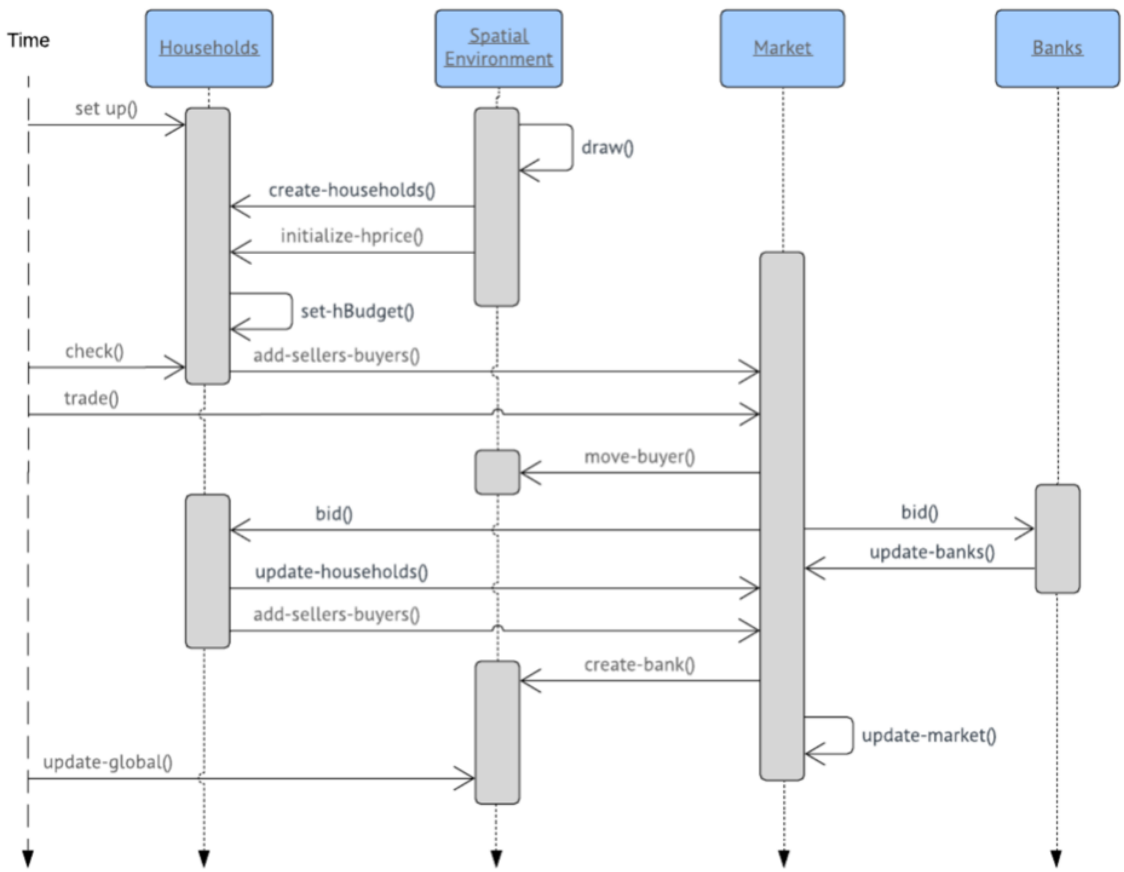

Figure 6.2: UML Sequence Diagrams of the Extended Model

Table 6.1: Agent attributes.

Attribute	Description	Agent Type	Reference
ID	Unique ID for households	Household	[96]
HNT	Household neighborhood type that indicated which sub-housing market is household located	Household	[101]
HPOLY	Polygon ID indicated which polygon is household on	Household & Bank	Author estimation
HINCOME	Income of the household	Household	[102], [87]
HBUDGET	Budget for annual housing cost and purchasing new hou	Household	[96]
ROLE	0: Regular household; 1: Buyer; 2: Seller; 3: Bank	Household	[96]
BIDPRICE	Only associate with buyer households	Household	[96]
ASKPRICE	Only associate with seller households	Household & Bank	[96]
EMPLOYED?	Boolean value, if true, household has job, else, no jobs	Household	[102]
TRADE?	Boolean value, if true, indicates household will trade	Household & Bank	[96]
YEAR	Years that the household entered the market	Household	[102]

household agents can be categorized into two types: buyers and sellers, and they are all goal-oriented. All buyers have one goal: finding an affordable house by proposing a bid-price to sellers. If buyers cannot find affordable properties in four consecutive years, they will be removed from the system. On the other hand, sellers aim to post an ask-price and maximize their profits from the trades (this will be further discussed in Section 6.4.1). Sellers who fail to sell their houses are forced to leave the system. At that time, the bank agent takes over the unsold houses and attempts to sell these houses. Further details about the role of banks are provided in Section 6.3.1. As for the attributes of the bank agents, only three attributes are inherited from sellers, which are summarized in Table 6.1.

The other component of this model is the environment, which contains two different elements: 1) Geo-spatial; 2) Artificial housing market comprising three different sub-markets: downtown, city suburban and far suburban. The geo-spatial environment provides a geographic boundary of the whole simulation area and the boundaries of the three sub-markets. Also, the geo-spatial environment provides a physical environment for all agents to move around and the places where the households are located in. This environment also contains the artificial housing market which captures the housing trades between buyers and sellers. The temporal scale in this model is one year which is reflected by one time step in the NetLogo model. Every year, households make decisions to become buyers and trade with sellers or banks. Our rationale for choosing a year is that it is unlikely for households to move more than once a year, and many other residential models use a 1 year time step (e.g., [81, 85, 98, 109, 110]).

6.1.2 Process Overview and Scheduling

As discussed in Section 6.1, household and bank agents are the main entities in the model. The key attribute of the households is their income (i.e., HINCOME) level, which provides heterogeneity within the world and is updated as the simulation progresses (see Section 6.4.2). There are several models that have used income to control residential decision making (e.g., [96, 97, 102]). Accordingly, in this model, each household makes their decisions based on their income status, that is, to either stay or leave their current locations, as shown by Figure 6.3. During each time step of the simulation, households will check if they can still afford their current living location based on their annual budget (i.e.,HBUDGET), which is calculated from their income. In addition, this income attribute also informs housing trades (i.e., what they can afford to buy). This affordability check will be explained in detail in Section 6.4.2. Once the buyer household decides to enter the housing market, they search for sellers (which include banks) to interact with based on their annual budget (i.e., HBUDGET). Similar to the real world, where buyers are restricted to what they can afford, buyers within the model choose sellers within the filtered list and offer a bid (i.e., a bid-price)

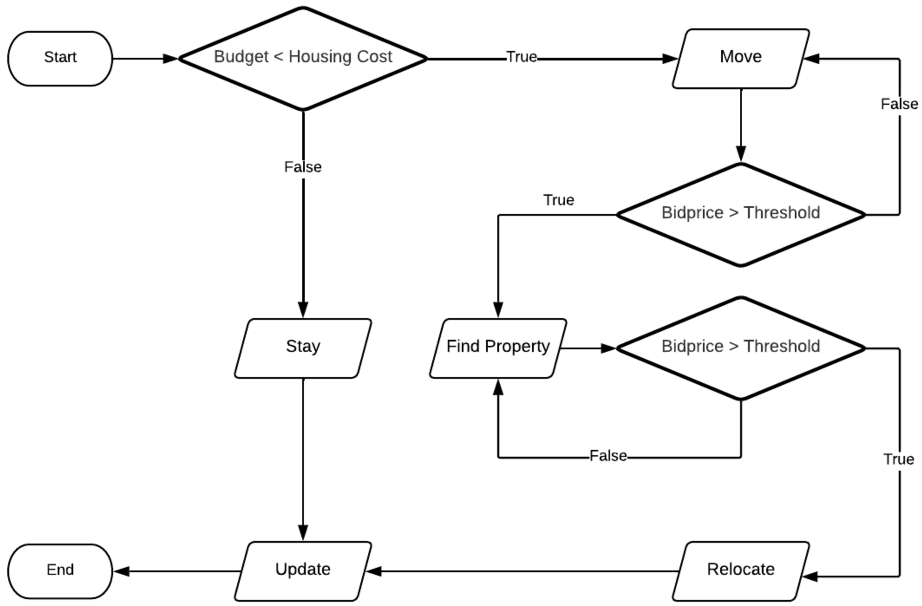

Figure 6.3: Household Decision-Making Process for Stay or Leave Current Location.

to either sellers or banks, which are discussed further in Section 6.2.1 and Section 6.4.1.

6.2 Design Concepts

6.2.1 Observing

In order to capture the housing market dynamics, this model measures various variables hierarchically, of which the details will be discussed in Section 6.5. At the macro-level, average and median house prices are recorded at each time step of the simulation, along with the total number of buyers and sellers within the study area. At the micro-level, each sub-market captures the average and median house prices and the number of households through the entire simulation to reflect the differences among the three sub-markets in order to see if any shrinkage is occurring.

6.2.2 Sensing

All household and bank agents know which sub-markets they are located in and the price of the house they currently live in. As discussed in Section 6.4.1, they set budgets based on their own incomes and the budgets can be updated along with changes in income at each time step of the simulation. Housing trades are the main interaction in our model. Households who become buyers will use their budget to set the bid-prices (i.e., BIDPRICE). For buyers who fail to trade with sellers in one time step, the bid-price (i.e., BIDPRICE) will increase in the next time step. Each seller will set their ask-price (i.e., ASKPRICE) based on the current house price. The ask-prices (i.e., ASKPRICE) will decrease in next time step, if the seller fails to sell their current house. Banks have similar behaviors to that of sellers. The only difference is that bank decreases their ask-price at a greater rate. The rationale for this is that due to banks may want to sell the house within short time frame [111]. Details related to bid-price and ask-price dynamics are discussed in Section 6.4.2. Within the housing market, buyers make trades with sellers and they will know every seller's ask-price, which allows buyers to choose a specific seller based on their financial capabilities. The trade will happen once the buyer finds a seller to trade with and agree upon the price. Further discussions related to the negotiation process are provided in Section 6.4.1.

6.3 Details

6.3.1 Initialization

The initialization of the model is based on socioeconomic and geospatial data of the study area. The socioeconomic data (e.g., income, employment status, house prices) comes from Decennial Census[103] for each census tract in the study area. Before applying this data to initialize the number of household agents within our simulation, the data was preprocessed using Python to allow for efficient input into the NetLogo platform. Due to the computational constraints of NetLogo, simulations that entail a large number of agents are computationally intensive and time-consuming. To mitigate this, this model therefore only represents 1% (i.e., 10602) of the total number of households within the study area. Details related to different scales (10% and 1%) experiments are discussed in Section 8.3.3.

The model initializes the household agents tract by tract. There are a total of three stages during the initialization process: 1) Create households; 2) Assign employment status; 3) Assign house price. The households are initialized by using the income background from the census dataset. For instance, if 500 households fall into the $10,000 to $15,000 income range for a certain tract, five household agents will be generated with their incomes assigned to this range. As for the income, if the household agent is generated within the $10,000 to $15,000 income range, the income of this household will be ten plus a random integer between 5. After the generation of the households, several socioeconomic attributes are introduced to the household agents, such as employment status and house prices, which provides the household agents with more heterogeneous attributes. The employment status is extracted directly from the census dataset to assign each household agent an employment status. For instance, if 20% of the households are employed in a particular tract, the model will assign 20% of households in this tract as employed, and the rest of them will be unemployed. The procedure of assigning the house price for each household is similar to assigning employment status. The percentage of households falling into various house value ranges is used to assign the house value. For instance, if 20% of households' house values fall into $50,000 to $100,000, those households' house values will be 50 plus a random integer within 50.

In addition, three input parameters are used to initialize the model. The first is the demand and supply condition (D-S parameter) which controls the ratio of buyers and sellers. The model generates sellers based on the number of buyers. For instance, when set to default (i.e., 0.5), the total number of buyers and sellers initialized is equal which indicates equal demand and supply. For instances, 0.1 would reflect demand exceeds supply (i.e., more buyers than sellers). While 0.9 would be the opposite (Section 8.3 shows the results of changing this parameter). The second input parameter, HAVE-BANK? allows the model to add a bank agent. When set to its default (i.e., True), the bank agent is added to the model (more details about the bank agent are given in Section 6.4.2). The last input parameter

Table 6.2: Initialization parameters default values.

Parameters	Default Value	Description	Reference
D-S	0.5	Demand and supply, can be controlled by the user; the default value indicates equal demand and supply	Author estimation
HAVE-BANK?	True	Allow banks agent to be added to the model; default value indicates banks will be added	Author estimation
Price-Drop-Rate	5%	Ask-prices decrease rate, can be controlled by the user; the default indicates 5% decrease of ask-price, if the house is not sold.	[86]

is Price-Drop-Rate, inspired by what we see in the real world. In a sense, that is when a house has been on the market for several months, the seller often drops the price. A notable model that does something similar is that of O'Sullivan [86], which decreased the percentage of each seller's ask-price in the next time step if the property remained unsold. Table 6.2 provides an overview of the model input parameters along with their default values.

6.3.2 Inputs

Data plays a vital role in model parameterization as discussed in Section 6.3.1 with respect to the initialization of the simulation. Furthermore, data plays a role in validation which is discussed in Section 8.3. This work uses two categories of vector data: spatial and socioeconomic data. Spatial data include: 1) Detroit city boundary (shown in Figure 4.1 (B)); 2) Tri-County area boundary including Wayne County, Oakland County, and Macomb County; 3) All census tract boundaries for the Tri-County area. The census tract boundaries can be associated with socioeconomic data acquired from the census dataset [103], as shown by Table 6.3.

Table 6.3: Census Variables for Model Initialization.

Variable	Description	Usage
H_I_K	The number households fall in various income ranges (i.e., 10k to 15K)	Initialize the agents and their incomes
H_V_K	The percentage of households falls to various house value ranges (i.e., 50k to 100K)	Initialize the agent house price
H_EM_R	Employment status of each census tract	Add employment status for each agent

6.4 Sub Models

6.4.1 Housing Market

There are a total of three stages for the simulation process: 1) affordability check of household; 2) generation of sellers and buyers; 3) Trade and move-in. First, households will check the affordability of their current house by comparing their annual budget (i.e., HBUDGET) and the minimum housing cost (described below). To check this, all households will set their budgets, which represents 34% of their income (i.e., HINCOME) and can be used on annual house fees, including property tax, annual maintenance, mortgage payments, etc. [104]. To calculate the minimum housing cost, three percentage numbers are referenced including 1.52% of the house price for the property tax, 1.3% of the house price for the annual maintenance fee, and 4.54% of the house price for mortgage payment [105–107]. Hence, set 7.38 % of the house price as the minimum housing cost, which indicates the lowest annual cost for a house. If one household's minimum housing cost exceeds the annual budget (i.e., HBUDGET), which indicates the household cannot afford their current house, they will enter the housing market. Secondly, the buyers and sellers are generated based on demand and supply (D-S) which was discussed in 6.3.1.

As for the key interaction within the model, the trade process (and subsequent moving in) comprises two stages: 1) buyers find sellers and 2) negotiation on the price. For the first stage of the trade, buyers will search for sellers (i.e., moving around the physical environment). While buyers can enter every sub-market, buyers may not enter the downtown sub-market first due to perceived issues with neighborhood security, which may negatively impact buyer's households' decisions when purchasing a new home [17]. Hence, it's rational to assume that properties in the downtown sub-market are less preferred compared to city suburban and far suburban. As such, a buyer may enter the far suburban sub-market first and then search for sellers (i.e., homes for sale) because of the perceived notions of overall safety conditions and a better quality of life in the far suburban areas [17]. If a buyer is not able to find a seller in far suburban sub-market, the buyer will enter the suburban sub-market and continue to search for sellers. Rather than exclude buyers from the downtown sub-market, a buyer may only enter the downtown sub-market if they cannot find any sellers in both far suburban and city suburban sub-markets. To determine whether the buyer can afford a house or not, buyers have knowledge related to all of the sellers' ask-prices, which is analogous to what we see when using a real estate website to search for a new home. The buyers will set the bid-price (i.e., BIDPRICE), which is 2.5 times their gross income [108]. When a buyer searches for a new location, they keep checking the ask-prices (i.e., ASKPRICE) of the sellers located in that area. Buyers will then sort out a list of sellers based on their initial bid-prices (i.e., BIDPRICE) when they move to a new area. For example, sellers with ask-prices less than 1.1 times that of a certain buyer's bid-price and greater than that buyer's bid-price may be sorted into the list. If there is only one seller in a specific area, the buyer will only bid on one house in one time step. However, if there are more sellers in a specific area, the buyer's bid-price may be reviewed by all those sellers located in the same area, which can be considered as multiple bids in the same area in one time step (hence buyers can make multiple offers in one time step). After this stage, the sellers attempt to complete a trade. The sellers' goal is to maximize their profit from the trade so that they will choose the buyer with the best bid-price. After the trade is completed, the trade will be recorded.

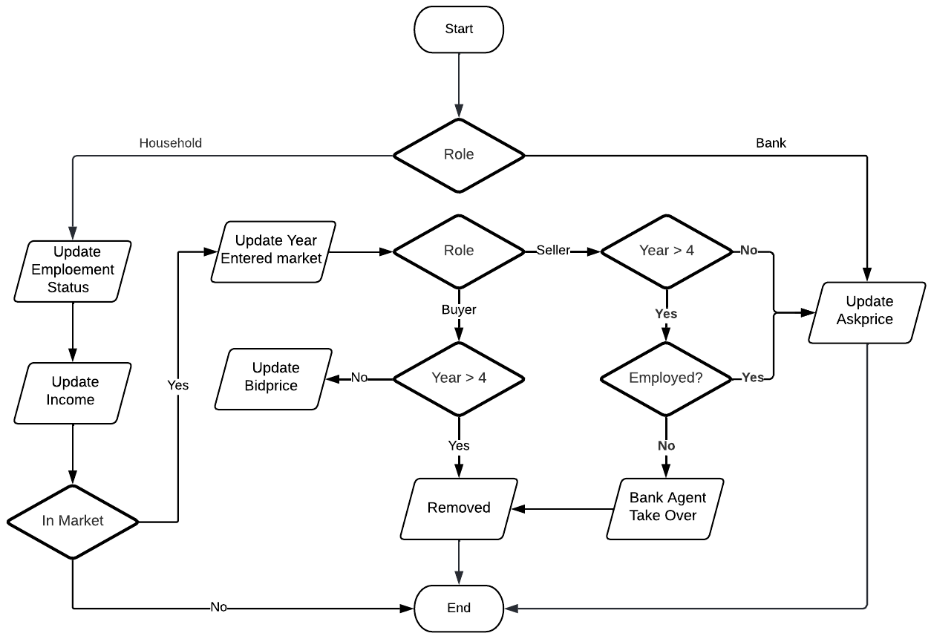

Figure 6.4: Household Dynamics.

6.4.2 Households and Banks Dynamics

Several dynamics are introduced to the household and bank agents to imitate real-world circumstances. The process is shown in Figure 6.4. For all households, employment status (EMPLOYED?) may change each time step, which is inspired by Patel et al.[102]. For example, employed households have a certain probability of losing their job; similarly, unemployed households may have a probability of finding a job. As shown by Equation 6.1, the income dynamics are based employment status of the agents. I_{t+1} is the income at time $t+1$, I_t is the income at time t and α represents the employment status. If one household has a job, α will be the ln 0.5; if not, it will be -0.1. The employment status, therefore, impacts the households' income (HINCOME), which has a direct influence on their annual housing budget.

$$I_{t+1} = I_t * (1 + \alpha) \tag{6.1}$$

Population dynamics are reflected both by the sellers and buyers. As for sellers, if employed, but are unable to sell their houses over four consecutive years (i.e., time steps) they may stay and keep trying to sell the house until a buyer is found. While, for sellers who are unemployed, if they cannot sell the house for four consecutive years, they will be removed from the system (akin to foreclosure). At that time, the bank agent may take over their houses and keep trying to sell them. From the buyer's side, if they are unable to find a house to purchase in four consecutive years, they will be removed from the system. This dynamic indicates that those buyers who cannot afford a house in any of the sub-markets based on their finical status may move out from our study area to somewhere else. Also, the dynamics of bid and ask prices are added to the model. From the seller's side, the ask-price (ASKPRICE) may decrease when the house is not sold [86]. For example, in the model, if a seller or a bank fails to sell a house, the ask-price will decrease based on the Price-Drop-Rate in the next time step which is shown in Equation 6.2. ASK_{t+1} is the ask-price at time $t+1$, ASK_t is the ask-price at time t and PDR represents Price-Drop-Rate. The Banks agent's ask-price drop rate is doubled compared to that of a seller household. This reflects the banks wishing to clear their inventory and recoup money owed as quickly as possible.

$$ASK_{t+1} = \begin{cases} ASK_t * (1 - PDR) & Sellers \\ ASK_t * (1 - 2 * PDR) & Banks \end{cases} \tag{6.2}$$

As for the buyers, the bid-prices (i.e., BIDPRICE) are impacted by their income (i.e., HINCOME). Other than that, buyers who fail to find a seller or bank to trade with may increase their bid-price based on their budget (i.e., HBUDGET) as shown in Equation 6.3. BID_{t+1} is the bid-price at time $t+1$, BID_t is the bid-price at time t and β is the random number generated based on how much percentage can buyers bid-price exceed their initial offer. In our model, 0.1 is used, which indicates a buyer's bid-price may not exceed %110 of the initial bid-price. This β concept is based loosely on land market models (e.g., [93, 96]) where buyers have a willingness to pay up to a certain percentage point over their initial

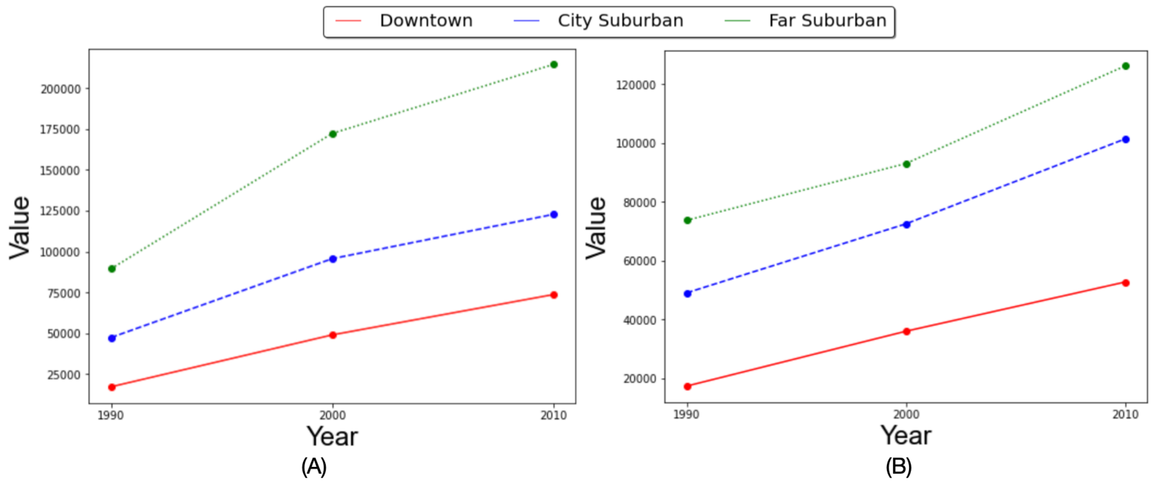

Figure 6.5: 1990, 2000 and 2010 Census Data on Median House Prices, (**A**) Median House Price, (**B**) Median House Price without Inflation

bid-price.

$$BID_{t+1} = BID_t * (1 + \beta) \tag{6.3}$$

6.4.3 Economic Environment

The economic environment is the invisible hand in the model and considers house prices' inflation, which imitates economic inflation. Although the trend of the economy in Detroit has been downwards, for example, there are few extreme cases where homes have been sold for $1 [112]. According to 1990, 2000, and 2010 census data, the overall house prices show an upward trend as seen in Figure 6.5(A). The Median house prices are all increasing. One reason for this relates to general inflation. However, when disregarding the impact of inflation by using the United States inflation calculator [113], the house prices still keep increasing over time, as shown in Figure 6.5(B). Hence, in the model, house prices will increase during the simulation based on annual inflation rates taken from [113].

6.5 Model Outputs

In Section 1.1, the contraction of the housing market and population loss are the consequences of urban shrinkage, which is what is explored with this model (as discussed in Sections 3.2 and 4.1). As a result, this model specifically focused on the changes in the number of households and the changes in house prices within different sub-markets to explain the urban shrinkage. As discussed in Section 6.5, these selected outputs are the result of the housing trades in the model. To capture the changes in house prices, median and average house prices of each sub-market are used to reflect the price dynamics. At the same time, median and average house prices for each census tract are also recorded by the model to show the spatial disparity of the house prices.

Chapter 7: Topic Modeling

7.1 Overview

As discussed in Section 1.1 and 4.2, the purpose of this chapter's model is to investigate the discussions related to urban shrinkage over the years by utilizing topic modeling in a new source of text data (i.e., news articles). This section provides details of topic modeling and Figure 7.1 shows the workflow of the topic modeling along with the tasks under each step. Specifically, the first step is to collect news articles from LexisNexis as discussed in Section 7.2. Secondly, data preprocessing is conducted for the collected data, which is discussed in Section 7.3). The third step comprises the yearly statistics and the investigation of topics by using the preprocessed data, which are discussed in Section 7.4. Step 4 (i.e., Section 7.5) illustrates the interpretation of the resulting topics based on the characteristics of urban shrinkage.

7.2 Step 1: Data Collection

Newspaper text data used in this work was collected via LexisNexis using a keyword search. The keywords "Detroit", "shrink", and "decline" were used for the search of the news articles. These keywords were selected based on the characteristics of the study area and the urban shrinkage as discussed in Section 1.1 and 2. Specifically, "Detroit" represents the study area of this work. The term "shrink" not only includes words sharing the same root (i.e., shrinking and shrinkage) but also stands for this work's topic: urban shrinkage. As for "decline", it can find different characteristics of urban shrinkage (e.g., population decline and decline of the economy). However, LexisNexis has limited resources for newspaper articles earlier than 1975 under this keyword search. The earliest news article is from 1975.

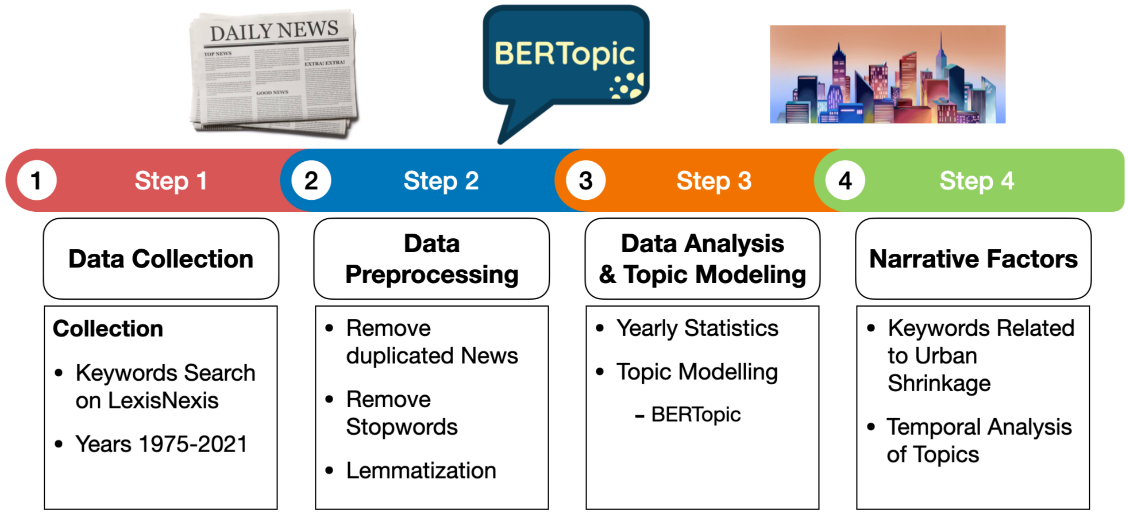

Figure 7.1: Topic Modeling Work Flow.

Hence, the news articles collected for this work are within the time frame starting from Jan 1, 1975, to Oct 1, 2021. As for the data collection, it resulted in 6794 English news articles published by various national and local press organizations (e.g., Forbes, The New York Times, Newsweek, Crain's Detroit Business, The Detroit News, etc.).

7.3 Step 2: Data Preprocessing

Articles collected from Step 1 are further preprocessed by removing the duplicated articles and the articles without the year of publication. The reason to remove the articles without years is that this work aims to reveal the changes of discussion related to urban shrinkage over the years. If there is no publication year, discussions detected in this article cannot mark on the time frame and reflect the discussion changes. After removals, the total number of news articles is 5595. Other than the article's removal, it is also crucial to clean the contents of each news article. Thus, a series of text preprocessing was operated based on previous works [114]. This text preprocessing comprises converting all text to lowercase, expanding contractions, grouping words with the same root (i.e., lemmatization) and removing emojis, numbers, punctuation marks and stopwords (e.g., and, or, not).

7.4 Step 3: Data Analysis & Topic Modeling

7.4.1 Yearly Statistics

Before detecting the topics, this work first counts the number of news articles published each year from 1975 to 2021. Counting the number of news articles may provide the overall trends of how urban shrinkage is covered over time (i.e., 1975 to 2021). Then, these trends can be used to identify several nation-level and city-level historical events (e.g., the 2007 - 2009 US economic recession, the bankruptcy of the city of Detroit, bankruptcy of automobile companies).

7.4.2 Model Utilized for Topic Modeling

```
#generate consistent results
umap_model = UMAP(n_neighbors=15, n_components=5,
                  min_dist=0.0, metric='cosine', random_state=42)

#topic model
topic_model = BERTopic(language = "english",  calculate_probabilities = False,
                       verbose = True,
                       vectorizer_model = vectorizer_model,
                       umap_model = umap_model,
                       embedding_model = 'all-mpnet-base-v2',
                       top_n_words = 15, n_gram_range = (1,2),
                       min_topic_size=15, nr_topics='auto')
```

Figure 7.2: Topic modeling setup.

With respect to topic modeling, BERTopic, a Python-based topic modeling technique, is utilized to detect the topics of all collected news articles. The rationales for selecting BERTopic were its easiness, flexibility in implementation and more options for embedding models [63]. In addition, BERTopic has been proven that it is capable to identify more insights with its embedding approach [115]. As for the model utilized in this work, Figure

Table 7.1: Model Parameter.

Parameter	Value	Description
language	english	News articles collected for this work are in English
calculate_probabilities	False	Less computational efforts
verbose	True	Check the running status of the model
embedding_model	all-mpnet-base-v2	High performance embedding model, allows the model provide a higher quality results
top_n_words	15	Output 15 words word under each topic, allows us to see five more words than the default setting
n_gram_range	(1,2)	Allows the model detect city or state with two words (e.g., New York)
min_topic_size	15	Allows the model generate topics with minimum 15 words
nr_topics	auto	Allows the model combine the similar topic automatically

7.2 shows the model and its parameters used to detect the topics related to urban shrinkage. This model is built using BERTopic along with two embedding models, the Vectorizer model and the UMAP model. The Vectorizer model is used to remove the stop words once more, allowing the model to generate more interpretative topics. While the UMAP model is one of the custom embedding models, setting the *random_state* parameter within the UMAP model allows the model to reproduce consistent results. Other than these two embedding models, the detailed settings of each parameter within the BERTopic model are shown in Table 7.1.

7.5 Step 4: Narrative Factors

In this step, keyword searches on the resulting topics are performed to find the topics based on the different keywords related to the phenomenon of urban shrinkage and its consequences. As for the phenomena of urban shrinkage, two keyword lists are used to find related topics, which are the urban list and the shrinkage list. These two lists consist of

Table 7.2: Keyword of Each Factor Related to Urban Shrinkage

Name	Keywords List
Urban list	urban, city, Detroit, neighborhood, suburban
Shrinkage list	shrink, shrinkage, decline
Population list	population, people, residents
House list	house, housing, mortgage, home, loan
Job list	job, employment, salary, employer, employee, worker, labor
Economy list	economic, stock, industry, tax, car, company, recession

the synonyms of urban and shrinkage, shown by Table 7.2. Turning to the consequences, as summarized in Section 1.1, population loss, increasing unemployment rate, economic decline and housing market collapse are considered as the characteristics of urban shrinkage. Thus, four keyword lists selected for urban shrinkage's consequences are related to the characteristics, which are population, job, economic and house list. As for the population and job list, synonyms of the population and job are selected for these lists (shown by Table 7.2). With respect to the house list, keywords such as loan or mortgage are included, which are related to real-world house purchases. While for the economic and house lists, not only are the synonyms selected for these two lists but the keywords related to these characteristics are also selected. For example, in the economy list (shown in Table 7.2), stock, tax, and recession are chosen to present the economic status. Keywords such as car, industry, and company are selected to represent Detroit's primary industry sector.

The keyword search uses the list shown in Table 7.2. Each keyword within the list is applied to find the top three related topics from the model results by using BERTopic built-in function (i.e., find_topics) [63]. After this, six lists comprising various topics are captured to present each keyword list. Temporal analysis is then conducted on these six lists, aiming to measure each topic's evolution or changes over time as discussed in Section 7.1. For every keywords list, the same topic could be captured multiple times by applying different keywords, this step only keeps one appearance for each topic.

Part III

Results

Chapter 8: Agent-Based Model Results

8.1 Overview

This chapter discusses two agent-based models' results individually. Section 8.2 provides the results of the initial Model, while Section 8.3 introduces the extended model's results. Before detailing the results of each model, efforts related to verification and validation are introduced first. In this work, verification is considered as the process of checking if the model matches its design [92]. The same process is performed to verify both models. The verification process comprises code walkthroughs, visual debugging [116] and sensitivity analysis by conducting a series of control variates experiments on each model's input parameters to ensure the model was working as designed [117]. These tests ensured that no logical errors are made in the translation of the model into code and that there were no programming errors.

For validation, it refers to the process of ensuring the model aligns to the real world, specifically how the two models in this work can capture basic market behavior as it potentially relates to urban shrinkage. In order to do this, three simulation scenarios are presented, which simulate different demand and supply conditions: (1) equal demand and supply; (2) demand exceeds supply; (3) supply exceeds demand. Building on this, the two models can be validated so that the shrinkage can be simulated through the housing trading interactions.

8.2 Initial Agent-Based Model Results

8.2.1 Verification

Verification of the model was performed by conducting code walkthroughs and control variates experiments to ensure the model was working as designed. As discussed in Section 5.3.1, these parameters : 1) D-S; 2) Balance; 3) diffusion rate (DR), thus three sensitivity analysis experiments are performed for three input parameters. To verify D-S, there is no need to run the model, the experiment only set various values D-S(e.g., 0.1, 0.5 and 0.9) and noted each outcome with respect to the number of buyers and sellers at the beginning of the simulation. Various D-S values stand for different demand and supply scenarios, which are discussed in Table 8.1. Also, as shown in Table 8.1, the model is able to generate different numbers of buyers and sellers by modifying the value of D-S.

While Balance controls the initial house price distributions (as discussed in Section 5.3). There is also no need to run the simulation to verify Balance. In this experiment, Balance was set to 0, 50 and 100. As for Balance extreme values (shown in Table 8.2), when set Balance to 0, the average price (AVG) is 55.42, which is lower than the default setting of 80.48 when the Balance is set to 50. When Balance is set at the highest value (i.e., 100), the average house price is 106.05. Therefore, the results show that Balance adds the variations to the house price distributions within our stylized model.

With respect to the experiment of the diffusion rate (DR), DR is set to either 0 or 1. 0 indicates that households can only choose homes within the same sub-market that they are currently living in, while 1 allows households to move to different sub-markets. Hence, this experiment requires running the model and analyzing simulation results to verify DR. The model was run for five time-steps within this experiment and repeated 50 times. As for the parameters' settings, DR values were modified to different values (i.e., 0, 1), and the rest of the parameters were set to default. As shown in Table 8.3, when DR is set to 0, the number of households stays the same as the initialization number as the agents cannot move to different sub-markets. However, when DR is set to 1, the number of households varies drastically from when the model is initialized. Hence, the DR parameter works as expected, which impacts the households' movement between the different sub-markets. After carrying out these verification experiments, it's confident that the model behaves as intended and matches its design.

Table 8.1: Verification of D-S.

D-S Value	Description	Buyer	Seller
0.5	Demand exceeds supply	108	54
1.0	Equal demand and supply	107	107
1.5	Supply exceeds Demand	112	168

Table 8.2: Verification of Balance.

Balance	Description	Average House Price
0	Lower than average prices	55.42
50	Balance average prices	80.48
100	Higher than average prices	106.05

Table 8.3: Verification of Diffusion Rate (DR).

DR Value	Description	Number of Households					
		Downtown		Suburban		Far Suburban	
		Start	End (std.)	Start	End (std.)	Start	End (std.)
0	No movement to another submarkets	446	446 (0)	502	502 (0)	330	330(0)
1	Allow movement to another submarkets	446	428.80 (4.74)	502	515.50 (5.04)	330	333.70 (3.47)

Table 8.4: Validation of D-S.

D-S value	Description	AVG Number of Households		
		Sub-Market	Start	End (std.)
0.5	Demand exceeds supply	Downtown	446	429.20 (5.57)
		Suburban	502	514.80 (5.65)
		Far Suburban	330	334.00 (4.44)
1.0	Equal demand and supply	Downtown	446	429.10 (5.67)
		Suburban	502	515.24 (4.89)
		Far Suburban	330	333.66 (4.16)
1.5	Supply exceeds demand	Downtown	446	429.28 (5.66)
		Suburban	502	514.46 (4.89)
		Far Suburban	330	334.26 (4.16)

8.2.2 Validation

In order to explore how our model can capture market behavior as it relates to urban shrinkage, this section presents several simulation scenarios of different demand and supply conditions for five time steps and run each scenario 50 times; in what follows this work describes the average of these results. Five years is chosen as this avoids longer-term economic and environmental impacts on the housing market. To control the demand and supply, this validation process only changed the D-S parameter in the model and kept all other parameters at their default values. Three scenarios: 1) equal demand and supply; 2) demand exceeds supply; 3) supply exceeds demand, were simulated to explore how the demand and supply condition impacts the number of households in the different sub-markets. Table 8.4 shows the initial number of agents in each sub-market for different D-S settings along with the final numbers after five time steps. As can be seen by altering the D-S parameter, the number of households in the downtown area decreases while the suburbs all see an increase in households.

Building on Table 8.4, Figure 8.1 shows the three scenarios for the number of households for each sub-market. In all three scenarios, downtown shrinkage can be observed in terms of the decreasing number of households from year 0 to 5. Households generally choose to relocate in suburban and far suburban areas leading to a decline in downtown populations.

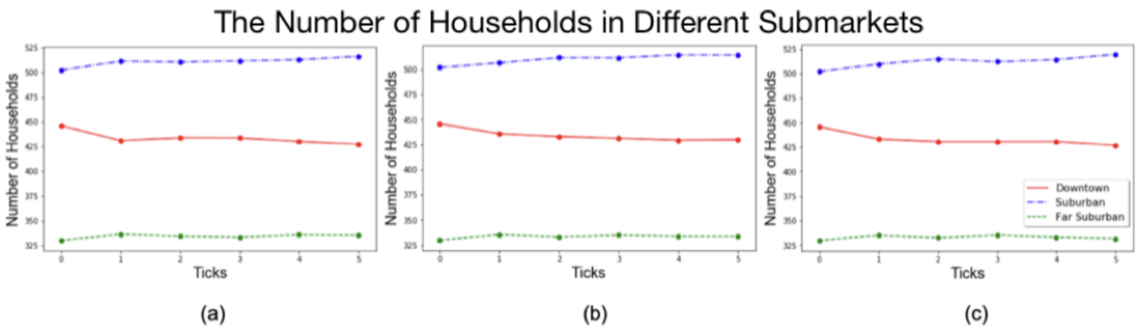

Figure 8.1: Average Results where: (a) demand exceeds supply; (b) equal demand and supply; (c) supply exceeds demand for each different housing sub market.

However, a small number of households did move to the downtown area in one scenario at year 2, that of when demand exceeded supply (as can be seen in Figure 8.1(a)) which can be explained as there are a limited number of houses available in suburban and far suburban sub-markets.

8.2.3 Summary

Section 5 has demonstrated the initial foray into exploring urban shrinkage through housing markets stylized upon the Detroit Tri-county area. Results from the model show that through the buying and selling of houses can lead to a decline in households within the downtown area. This result has implications with respect to urban shrinkage, as discussed in Section 1.1. A decline in households leads to less tax revenue and therefore limits a city's ability to provide services which in turn can lead to more urban decline. In addition, by applying this initial model, a benchmark model has been created for utilizing an agent-based model to simulate the urban shrinkage from the scope of housing trades simulation and captures the dynamics related to the number of households. Building on this, an extended model agent-based model is built in order to capture more dynamics (e.g., household dynamics and house price dynamics) of a shrinking cities housing, which the details are discussed in Chapter 6). The results from the extended model are discussed in the following section (i.e., Section 8.3).

8.3 Extended Model Results

8.3.1 Verification

As discussed in Section 8.1, visual debugging can be carried via the model interface when the model is running. Other than visual verification at the micro-level as discussed above, four plots (e.g., plot A, B, C, D) are used for macro-level visual verification as shown in Figure 8.2. Plot A captures the change in number of households during the simulation. Plot B outputs some generic results (e.g., total household number, number of bank agents), but the main purpose of this plot is to show the households' employment statuses are updating (i.e., changing) over the simulation, which was discussed in Section 6.4.2. As for Plots C and D, they show the median and average house prices during the simulation. With these plots updating during the simulation, what can be ensured is that the model does not have programming errors that stop the simulation instantly. But further sensitivity analysis experiments are needed to test the impacts of the input parameters, which is not possible to capture through visual debugging alone and this work turn to this next.

As discussed in Section 6.3.1, three input parameters were used in the model: 1) D-S; 2) HAVE-BANK?; and 3) Price-Drop-Rate. To test these three input parameters, a series of control variates experiments were designed for sensitivity analysis within the verification purposes. For instance, when verifying D-S, only the value of D-S was modified and kept the other two parameters set to default values as shown in Table 6.2. Each experiment is run 50 times, and in what follows, this work reports only the average results.

To verify D-S (see Section 6.3.1), one does not need to run the model, as D-S is only used when the model is being initialized to set the number of buyers and sellers. Therefore this work tested various D-S values (e.g., 0.1, 0.5 and 0.9) and noted its outcome with respect to the number of buyers and sellers. Various D-S values stand for different demand and supply scenarios, which will be discussed further below. As shown in Table 8.5, the model is able to generate different numbers of buyers and sellers by modifying the value of D-S. As for the other two parameters (i.e., price-drop-rate and HAVE-BANK?), because they are used

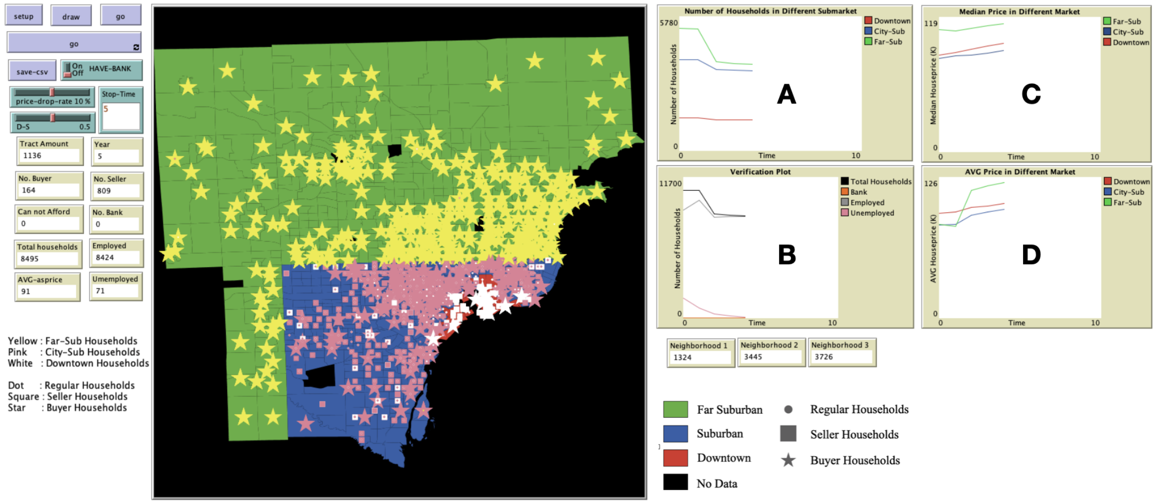

Figure 8.2: Model Verification, including input parameters, monitors (left) and the study area (middle) and charts recording key model properties (A: Number of households in different sub-markets; B: Verification plot for total household numbers (e.g., total household number, number of bank agents, the number of employed and unemployed households); C and D show the median and average house price changes during the simulation).

during the simulation, the following verification experiments were undertaken.

To test price-drop-rate parameter, a series of extreme value tests were carried. Within the test, by setting the parameter to 0, 5, and 10 which represents how much of a percentage of the ask-price will be decreased in each time step if the house is not sold. In this experiment, the bank agent is not added, (i.e., HAVE-BANK is False). The rationale for this is that the purpose here is to test the impacts of Price-Drop-Rate on ask-price. Hence, capturing the average ask-price changes throughout a simulation gains sufficient evidence for this stage of verification. As Figure 8.3(A) shows, when increasing the value of Price-Drop-Rate, the average ask-price decreases more, which indicates that Price-Drop-Rate parameter does have an impact on the average ask-price and this parameter works as intended.

Moving to the verification of HAVE-BANK?, as discussed in Section 6.3.1, HAVE-BANK? allows the model to add a bank agent. Unlike that of regular sellers, bank agent's ask-price drop rate is doubled (seen Section 6.4.2). Hence, the assumption is that with the increasing number of bank-owned properties, the average ask-prices may decrease more than those in a scenario where there is no bank agent. Table 8.6 captures an average of 932.42 bank-owned proprieties by the end of the simulation, which indicates HAVE-BANK? is capable to add a bank agent when the need arises. Figure 8.3 (B) shows that the average ask-price drops with the increasing number of properties owned by the bank agent, and the average ask-price is lower compared to the no bank scenario. This suggests that the bank agent is added properly by the model. After carrying out these tests, it's confident that the model behaves as it is intended and matches its design and thus is verified.

Table 8.5: Verification of D-S.

D-S Value	Description	Buyer (std.)	Seller (std.)
0.1	Demand exceeds supply	3633.78 (30.92)	403.24 (3.47)
0.5	Equal demand and supply	3018.70 (17.78)	2018.28 (17.92)
0.9	Supply exceeds Demand	404.10 (2.78)	3632.30 (25.72)

Table 8.6: Verification of Input Parameter.

HAVE-BANK?	Total Household		Buyer		Seller		Bank	
	Start	End (std.)	Start (std.)	End (std.)	Start (std.)	End (std.)	Start	End (std.)
True	10601	7007.02 (59.44)	2016.82 (16.29)	129.48 (10.86)	2016.34 (16.20)	134.72 (8.65)	0	932.42 (50.12)
False	10601	7952.06 (20.49)	2016.48 (19.19)	143.56 (9.2)	2016.02 (19.13)	1056.84 (52.9)	0	0

8.3.2 Validation

Now turning to model results and validation, validation refers to the process of ensuring the model aligns with the real world, specifically how the model can capture basic market behavior as it potentially relates to urban shrinkage. In order to do this, this work presents three simulation scenarios of different demand and supply conditions for a period of 20 (year) time steps. Each scenario is run 50 times and in what follows, only the average results are reported. Twenty years is chosen as the simulation time period, which covers the years of 1990, 2000 and 2010 where we have census data for, which in turn can be used to validate the model. To control the demand and supply scenarios within the model, only the D-S parameter is changed and all other parameters are kept at their default values (e.g., Table 6.2). Three different scenarios were simulated to explore how different demand and supply conditions impact on median and average house prices in the different sub-markets: 1) equal demand and supply; 2) demand exceeds supply; 3) supply exceeds demand. Table 8.7 shows the final median and average house prices in each sub-market for different D-S settings which are the same values described in Section 8.5.

Building on Table 8.7, Figure 8.4(A) shows the three scenarios with respect to the number of households in each sub-market. As Figure 8.4(A) shows, the overall trend of household numbers in all three scenarios is decreasing, which can be considered as population loss in a shrinking city or the whole metropolitan area. However, one can see that around time step 5, there is a drop in the number of households. This drop is due to the bank agent entering the simulation and taking over sellers' houses which were unsold (as discussed in Section 6.4.2). While Figures 8.4 (B) and (C) demonstrate how median and average house prices change over the simulation scenarios. The results indicate that among all three simulation scenarios, the median and average house prices in different sub-markets turn out to be increasing. This is due to inflation that is included in our model (as discussed in Section 6.4.3). The simulated increasing house price trends are similar to that of the empirical data which was shown in Figure 8.4.

In demand exceeds supply scenarios, although all buyers are attempting to find sellers

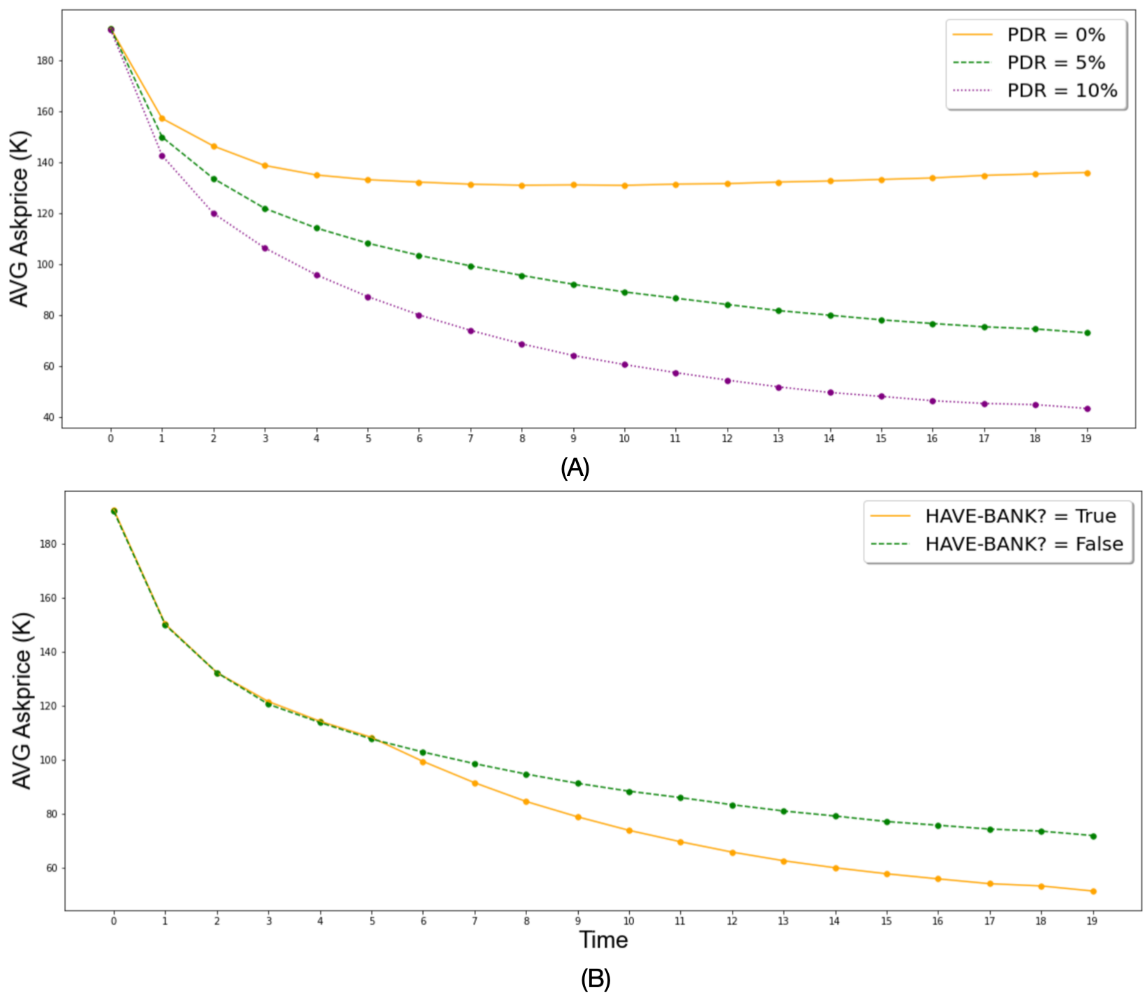

Figure 8.3: Average ask-price changes with Different values of HAVE-BANK?.

and complete trades (i.e., buy a house), due to insufficient sellers generated at initialization of the model, the number of relocating households is the lowest among all scenarios. However, as shown in Table 8.7, the model captures the highest median house price in the far suburban sub-market (which is approximately 60% more than that of downtown), which is due to the sellers flooding this area as discussed in Section 6.4.1 and is similar to what one sees in the "real world" (i.e., Figure 6.5). This suggests the model captures the correct market behavior.

Table 8.7: Median and Average House prices (K) in Different sub-markets at the End of the Simulation.

D-S Value	Description	Median House Price (std.)			Average House Price (std.)		
		Downtown	Suburban	Far Suburban	Downtown	Suburban	Far Suburban
0.1	Demand exceeds supply	124.85 (2.06)	112.66 (1.63)	187.62 (1.83)	119.48 (1.50)	116.43 (1.23)	191.10 (2.12)
0.5	Equal demand and supply	127.68 (2.33)	116.60 (1.80)	146.60 (1.81)	116.22 (1.74)	101.75 (1.170)	163.07 (1.26)
0.9	Supply exceeds Demand	127.19 (2.29)	119.76 (1.16)	155.22 (1.90)	108.06 (1.57)	87.46 (0.70)	137.83 (1.13)

Table 8.8: Median House prices (K) from Different Scales and Differences (%) in Different sub-markets.

	Census Median House Value (K)		Simulation 1:10 Median House Value (K)		% of Difference vs Simlation 1:10		Simulation 1:100 Median House Value (K)		% of Difference vs Simlation 1:100	
Year	2010	2020	2010	2020	2010	2022	2010	2020	2010	2022
Downtown	84.74	181.12	108.76	140.51	28.34	-22.42	99.00	127.68	16.83	-29.51
City Suburban	127.13	135.34	119.03	154.00	-6.37	13.71	90.21	116.60	-29.04	-13.85
Far Suburban	216.59	228.08	162.80	207.16	-24.83	-9.17	122.00	146.50	-43.67	-35.77

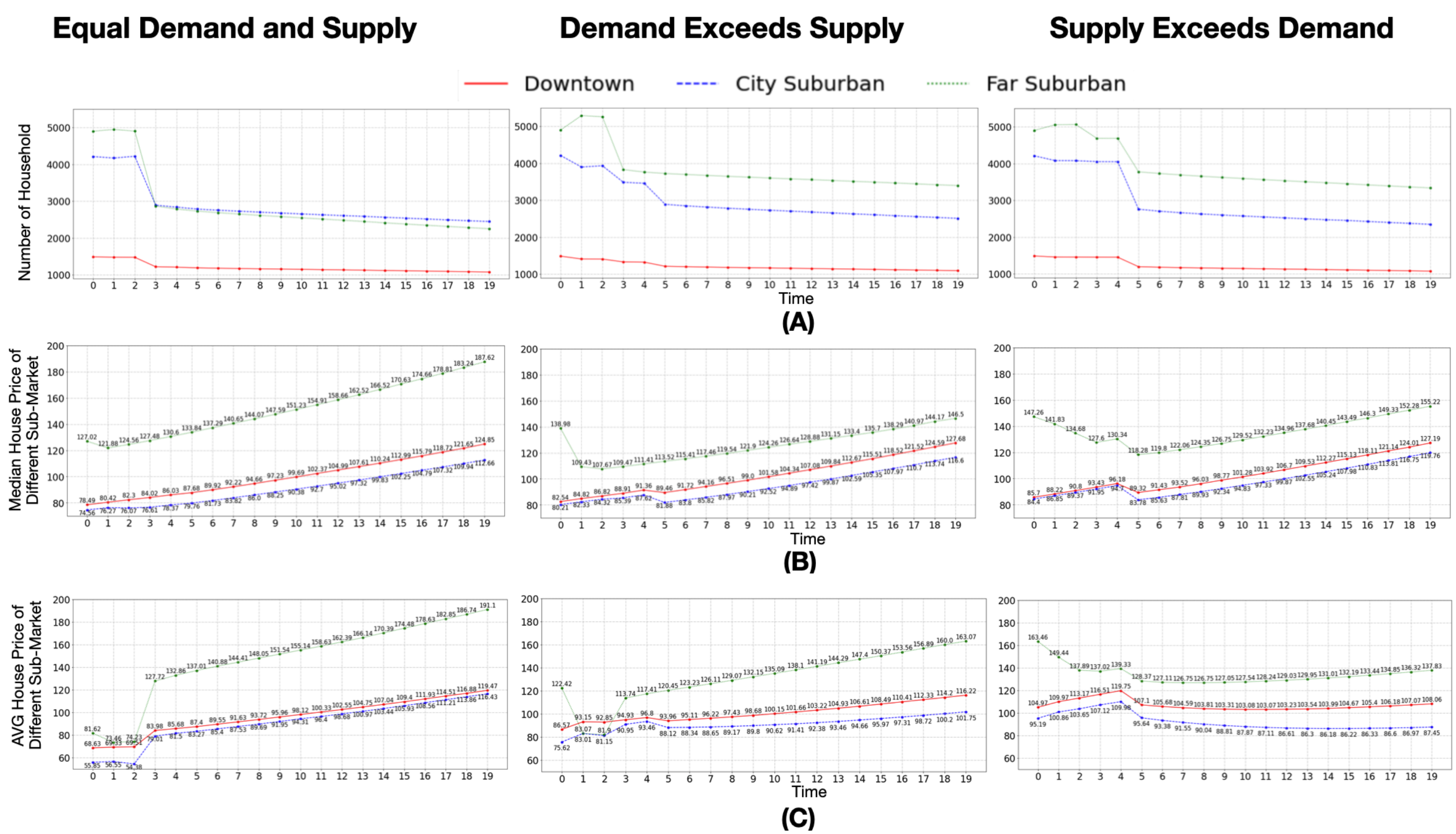

Figure 8.4: Validation of Market Behaviors.

While in demand equals to supply scenario, due to a relatively balanced market, we witness the most household relocations being captured, along with the lowest median house prices in suburban and far suburban sub-markets (i.e., suburban: 116.60; far suburban: 146.50). However, the median house price in the downtown sub-market is not the lowest among all scenarios (i.e., 127.68). This result might sound counter-intuitive because one would expect the lowest median house price in the supply exceeds demand scenario. However, the average house price for all three sub-markets in this scenario is in the middle of all the scenarios, which suggests there are nuances in how one should record and report the results of the model. One reason for this result could be because all buyers have the preferences to purchase houses in far suburban and suburban (as discussed in Section 6.4.1), which leads to a relatively competitive market. In addition, all sub-markets average house prices are the lowest among all scenarios.

8.3.3 Scaling Experiments

As discussed in Section 6.3, other than using one agent to represent 100 households, experiments using one agent to represent ten households are carried out to determine the scale's impacts on the final simulation results. Table 8.8 illustrates the caparisons of simulation results of 1:10 and 1:100 scales to Census data from the aspect of median house value in aggregated sub-market level. Also, Figure 8.5 illustrates the percentage of difference between simulation results (i.e., 1:10, 1:100) and census data in the middle (i.e., Figure 8.5 (a) and (c)) and the end of the simulation (i.e., Figure 8.5 (b) and (d)). The results from both 1:10 and 1:100 scales models capture a prosperous far suburban sub-market. The results from 1:100 capture an initial collapsing and gradually growing downtown sub-market. Comparing the simulation results to census data, the differences between census data and the 1:10 model results are smaller than the results from the 1:100 model. However, the same up-warding trends for the median prices from every sub-market are captured by both models, which aligns with census data (as shown in Table 8.8). Although the 1:10 model can capture the results with fewer differences compared to the real census data, the ideal scenario is to run

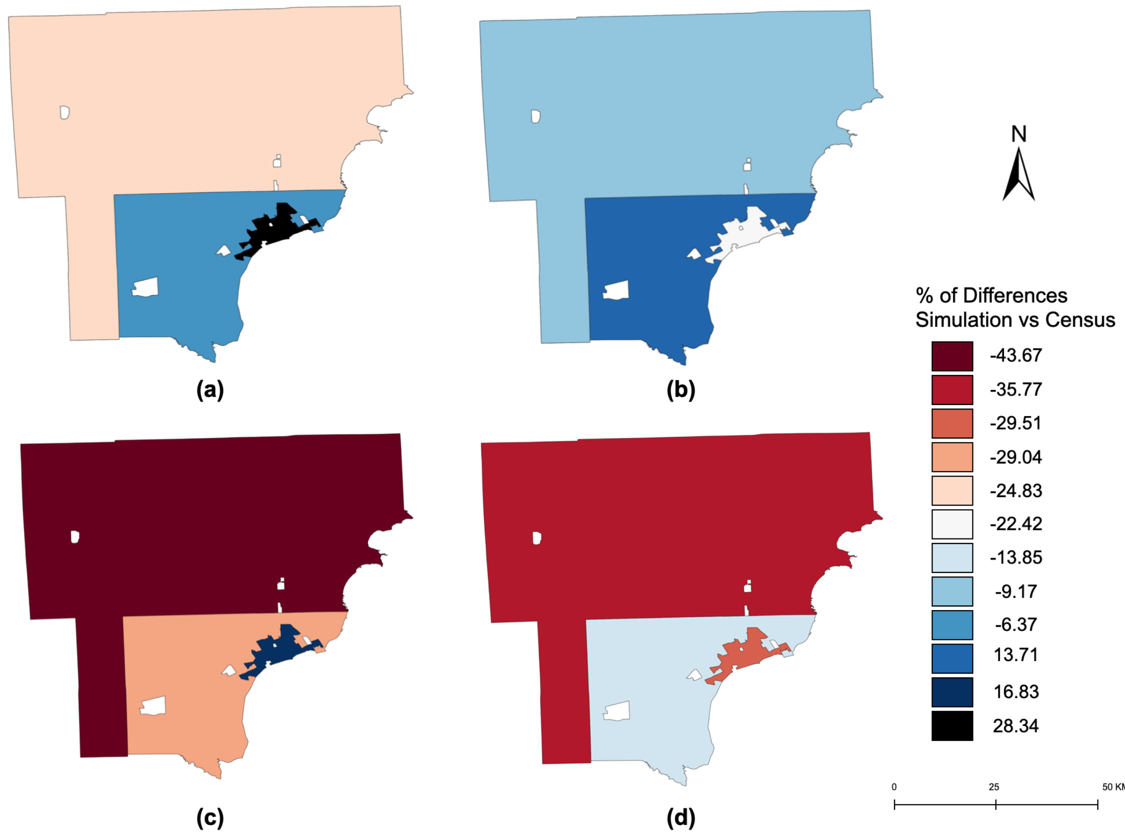

Figure 8.5: Median House Prices Differences between Simulation Results and Census Data: (a) 2010 (b) 2020 (c)2010 (d) 2020 .

a one-to-one model to simulate the urban shrinkage. Due to the constrain of the NetLogo platform, the 1:10 model takes 6.5 hours to simulate one run (i.e., 20 time steps) with a MacBook Pro M1 Max chip with 32G memory. Thus, running a one-to-one model would be more computationally intensive and time-consuming. With respect to time and the purpose of this model, 1:100 is a reasonable scale for this model to explain Detroit's shrinkage by capturing decreasing numbers of households and collapsing downtown and city suburban housing markets.

8.3.4 Summary

By discussing the results above from the three scenarios and the scaling experiments, it is clear to the reader that our model captures urban shrinkage from the aspect of decreasing numbers of households in the downtown sub-market using 1:100 scale. Also, the results of the extended model are similar to empirical data shown in Figure 6.5. Even without inflation, house prices are still increasing even in a well-known shrinking city and our model captures similar trends in the three scenarios (as shown in Figure 8.4). To some extent one could consider such results as level 2 validation in terms of Axtell and Epstein [118] schema of classification of model validation. In the sense, quantitative agreements of emerging macro-structures (e.g., declining number of households and increasing house prices) can be attained by utilizing the model building from the bottom-up.

Chapter 9: Topic Modeling Results

9.1 Overall

This chapter illustrates the results of the topic modeling. Section 9.2 first presents the overall trend that is measured from the yearly statistics by reporting the number of news articles published each year. In Section 9.3, the resulting topics from the topic modeling are presented. Next, Section 9.4 turns to the keywords search for each keyword list related to the phenomena of urban shrinkage and its consequences, as discussed in Section 7.5.

9.2 Yearly Statistics

This section illustrates the results of the statistics on the number of published news articles each year. This section is meant to provide the overall trends of how newspapers cover the urban shrinkage. Figure 9.1 illustrates the general trend of news articles related to urban shrinkage. Generally, it can be measured as an increasing trend until 2013. The overall trend slightly calmed down and fluctuated from 2012 to 2013. Until 2021, the number of news articles covering urban shrinkage shows a decreasing trend. With respect to the number of newspaper articles published yearly, two peaks are measured 2008 to 2009 and 2012 to 2013.

From 2008 to 2009, national and city-level historical events happened, including the 2007-2009 recession and Chrysler's bankruptcy. Turning to the 2012-2013 peak, a notable city-level event occurred in 2013: the city of Detroit's bankruptcy. Other than these two significant peaks, the 1981-82 recession can also be measured by the small peak of 1981 and 1982. Turning to the other small peak measured in 1991 and 1992, two city-level events can be linked to these two years. Detroit's crime rate peaked in 1991 [119], and Chrysler opened a new plant inside the city of Detroit [120]. Through the yearly statistics on the collected

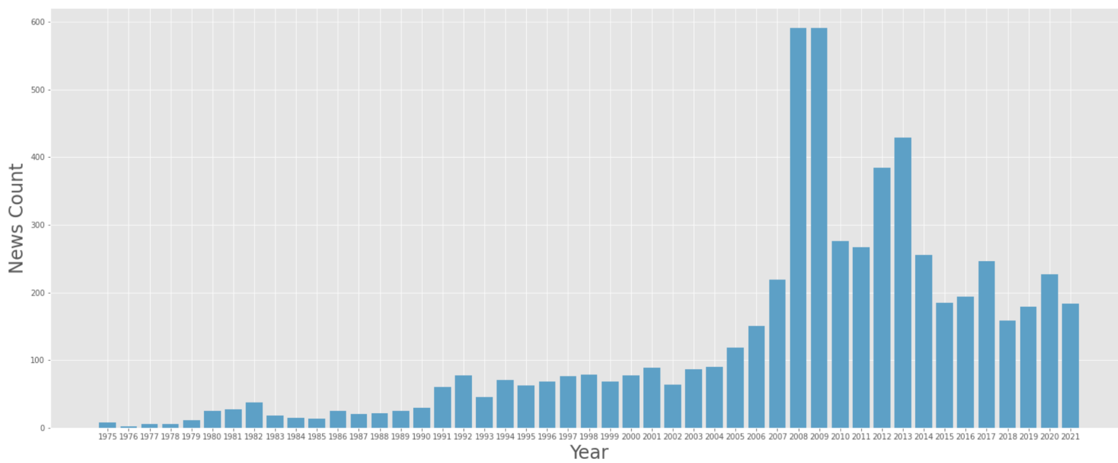

Figure 9.1: News Article Published Each Year (1975 to 2021)

news articles, this work can measure that the urban shrinkage has drawn a lot of attention, which can be reflected by the increasing number of yearly published news articles. Other than this, several national and city-level historical events can be linked to the peaks that are measured from the yearly statistics. However, this analysis is still rough and further analysis is needed to gain insights related to how urban shrinkage is discussed over time by news articles, which will be discussed next.

9.3 Resulting Topics

With respect to the resulting topics generated by the model utilized in this work, Table 9.1 illustrates the resulting topics along with their names and the frequency. The model has detected a total of 42 topics, but firstly some irrelevant or outlier topics (i.e., Topic -1) and topics with frequencies are equally less than 20 times (i.e., Topic 33, 34, 35, 36, 37, 38, 40) are removed. The rationale for removing Topic -1 is that the model automatically detects the irrelevant topic as an outlier topic for us. As for the topics with frequencies that are equally less than 20 times, they are not directly related to the urban shrinkage. But, there is one exception: Topic 39. This topic comprises fhfa (i.e., Federal Housing Finance Agency), fha (i,e., Federal Housing Administration) and loan, which might be related to the housing

Table 9.1: Resulting Topics.

Topic	Frequency	Name
-1	2195	-1_state_united_president_said
0	565	0_city_county_detroit_buffalo
1	509	1_know_going_think_right
2	390	2_business_think_going_year
3	253	3_job_american_economy_america
4	167	4_price_home_housing_market
5	161	5_mln_consensus_share_rev
6	148	6_chrysler_auto_sale_automaker
7	143	7_trump_vote_election_ballot
8	128	8_bank_credit_financial_think
9	103	9_tax_stock_stimulus_income
10	101	10_cent_canadian_canada_word
11	82	11_energy_oil_climate_gas
12	73	12_airline_travel_air_airport
13	69	13_trade_rep_japan_agreement
14	68	14_board_election_employer_hearing
15	65	15_covid_coronavirus_case_health
16	64	16_percent_economy_said_market
17	57	17_film_street_min_scene
18	47	18_school_student_district_education
19	45	19_stock_percent_moneyline_company
20	37	20_tdb_btd_store_sale
21	36	21_team_game_hockey_player
22	35	22_housing_hud_program_community
23	34	23_drug_crime_police_enforcement
24	33	24_border_immigration_immigrant_patrol
25	32	25_percent_sale_tuesday_fell
26	27	26_station_redwing_wgclusa_wjbkdetroit
27	26	27_newspaper_news_editor_daily
28	26	28_health_care_insurance_research
29	25	29_comey_supra_clinton_information
30	23	30_democracy_obama_american_america
31	21	31_austerity_britain_liverpool_london
32	21	32_newspaper_news_editor_said
33	20	33_tuesday_price_yang_paulson
34	20	34_black_church_white_ross
35	19	35_swine_flu_tuesday_economy
36	18	36_cent_australian_point_index
37	18	37_defense_dod_military_navy
38	18	38_hospital_health_reg_nurse
39	17	39_fhfa_fha_loan_freddie
40	16	40_museum_art_corcoran_barnes

Table 9.2: Keywords Search Results.

Keywords	Resulting Topics
Urban	0, 6, 22, 31
Shrinkage	2, 9, 14, 25, 28
Population	0, 3, 22, 28, 30
House	4, 8, 22, 39
Job	2, 3, 4, 9, 14, 16, 31
Economy	2, 3, 6, 9, 16, 19, 22

market. Thus, Topic 33, 34, 35, 36, 37, 38, and 40 are removed. Topic 39 is kept for further analysis of this work.

A rough classification of the resulting topic (i.e., Topics 0 to 32 and 39) can be done by simply using their names. For instance, it's straightforward to find that topics related to economy (e.g. Topic 3, 8, 13, 19), politics (e.g., 7, 29, 30), sports (e.g.,Topic 21, 26), film (e.g., Topic 17), traveling (e.g. Topic 12), public health (e.g., 3, 15), public safety (e.g., 23), education (e.g., 18) and housing market (e.g., 22, 39). However, it's challenging to reveal more insights related to urban shrinkage by classifying the resulting topic using the name of each topic. Therefore, as discussed in Section 7.5, keyword search and temporal analysis on each set of resulting topics are conducted to find relevant insights related to urban shrinkage.

9.4 Keywords Search

As discussed in Section 7.5, the six lists of keywords are used for the search of topics related to the phenomena of urban shrinkage and its consequences. The six lists of keywords are urban, shrinkage, population, house, job and economy. This section introduces all six sets of the resulting topics from the keyword searches. Then, temporal analysis is carried out for every set of keyword search results.

With respect to the keywords search results, Table 9.2 shows the resulting topics for all six keyword lists. Five topics are found for Urban, Population and House keywords list. For Shrinkage, Job and Economy keywords list, seven topics are captured for each keywords

Figure 9.2: Keywords and Related Topics

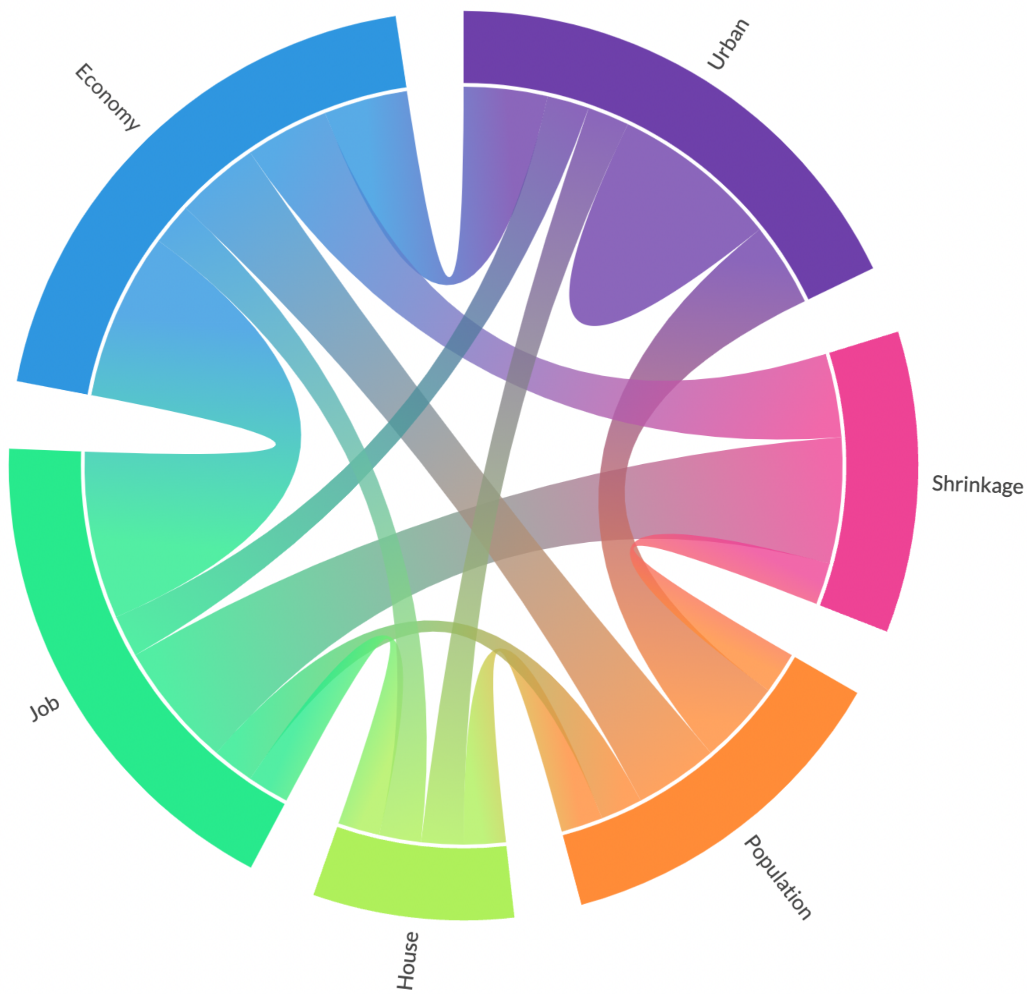

Figure 9.3: Topic Intersection for Each Keyword

Table 9.3: Keywords Search Resulting Topics Overlaps.

	Urban	Shrinkage	Population	House	Job	Economy
Urban	4	0	2	1	1	2
Shrinkage	0	5	1	0	3	2
Population	2	1	5	1	1	2
House	1	0	1	4	1	1
Job	1	3	1	1	7	4
Economic	2	2	2	1	4	7

list. Figure 9.2 shows the relationships among different keywords list and the resulting topics. The reader may notice that there are only 17 unique topics instead of 42 resulting topics shown by Table 9.1 in Section 9.3. This is because the keywords search filters out the topic that is not directly related to urban shrinkage (e,g, politics, sport, film, travel). In Figure 9.2, the number under each keyword indicates how many topics are included in a specific keyword. For example, the number 5 means five topics are found under Urban keywords. At the same time, the number under each topic indicates the frequency of a specific topic. For example, the number 4 under Topic 22 means that Topic 22 appears four times among all keywords searches. The lines within the circle connect the topics and keywords, which refer to the relationship between topic and keywords. Using Topic 22 as an example again, the four lines indicate that Topic 22 is found as the resulting topic for Urban, Population, House and Economy keywords search. Table 9.3 shows the number of intersected topics among different keywords, which is visualized by Figure 9.3. The largest number of intersections (i.e., 4) is found between Job and Economy keywords, which means the resulting topics of the Job and Economy keyword searches share the same four topics (i.e., Topic 2, 3, 9, 16).

After introducing the resulting topic of the keywords searches, the next Section turns to the temporal analysis for each set of resulting topics. For each set of resulting topics, the same analysis is conducted to explore how the resulting topics' frequency change over time and how the words under each resulting topic change over time. By showing the frequency changes through multiple line graphs, it allows us to identify the most discussed topic in a specific year and link the most discussed topic with certain national and city-level historical events. In the following section, each set of results topics is discussed individually.

9.4.1 Urban Keywords Resulting Topics

Table 9.2 shows four topics that are captured for urban keywords, which are Topics 0, 6, 22 and 31. Figure 9.4 shows each topic's frequency change over time. The peak of Topic 0 is detected in the year 2013, which is the year that the city of Detroit went into bankruptcy (as discussed in Section 2.1). In Topic 0, other cities such as Buffalo are detected, which is another shrinking city located in the Great Lake Area. Similarly, Topic 31 also detects some cities' names. For example, Liverpool is a city that has automobile manufacturers in Britain. However, the peak detected for Topic 31 is in the year 2012. Several events can be linked to this peak, which is the 2012 London Olympics, increasing productivity of Liverpool's car manufacturing and the UK's GDP shrank in the year 2012 [121,122]. Topic 6 contains terms such as automaker and Chrysler, and its peak is captured in 2008, which is during the 2007-2009 recession. In addition, Chrysler's bankruptcy in 2008 and the 2008-2010 automotive manufacturing crisis can also be linked to this peak.

No peak is detected for Topic 22, but this topic is related to urban housing status and it fluctuates starting from 1989. Within this topic, hud (i.e., Housing and Urban Development) created the Consolidated Plan to support the local urban and community planning in 1995 and a large number of programs had been applied for the urban housing development [123]. In addition, 1995 is the first high point of the Topic 22 discussion. Starting from 2007, Topic 22 is discussed due to the city's 2007-2009 recessions, 2013 bankruptcy, and the Covid-19 pandemic in 2020. These events also change the housing market and communities of Detroit. For example, hud has made efforts to deal with the increasing number of low-price and long-term abandoned houses, including the house demolitions and renovations [124].

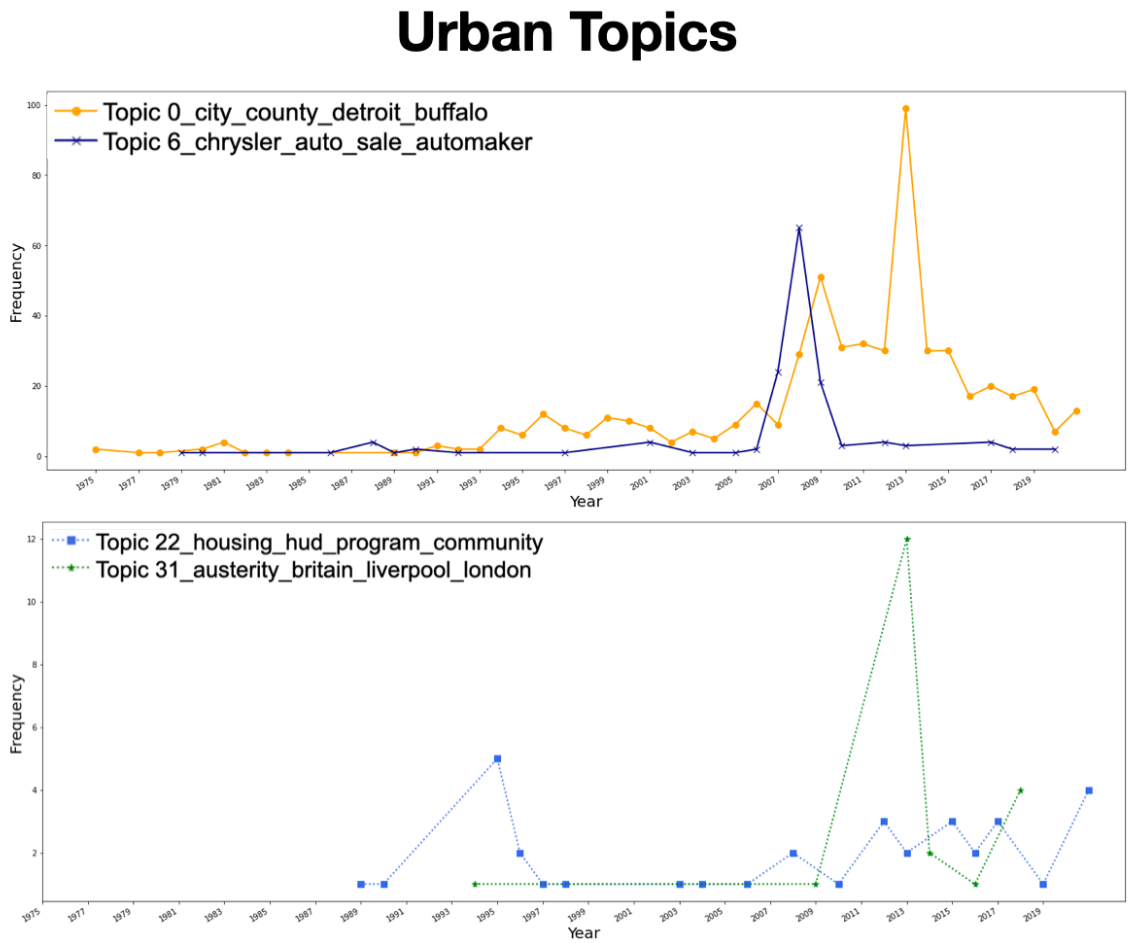

Figure 9.4: Urban Topic Over Time

9.4.2 Shrinkage Keywords Resulting Topics

Within the resulting topics of shrinkage keywords, five topics are captured: Topics 2, 9, 14, 25 and 28 (as shown in Table 9.2). Figure 9.5 shows how the results topics' frequencies change over time. Topic 2 is related to business and the peak measured in 2008 during the recession. By that time, all types of businesses and companies shrank, including the automobile industry and finance market [125]. As a result, the tax revenue also shrank. Topic 9 is captured to support the shrinkage of the finance market during the 2007-2009 recession. However, the peak of Topic 9 is measured in the year 2020. The reason behind this

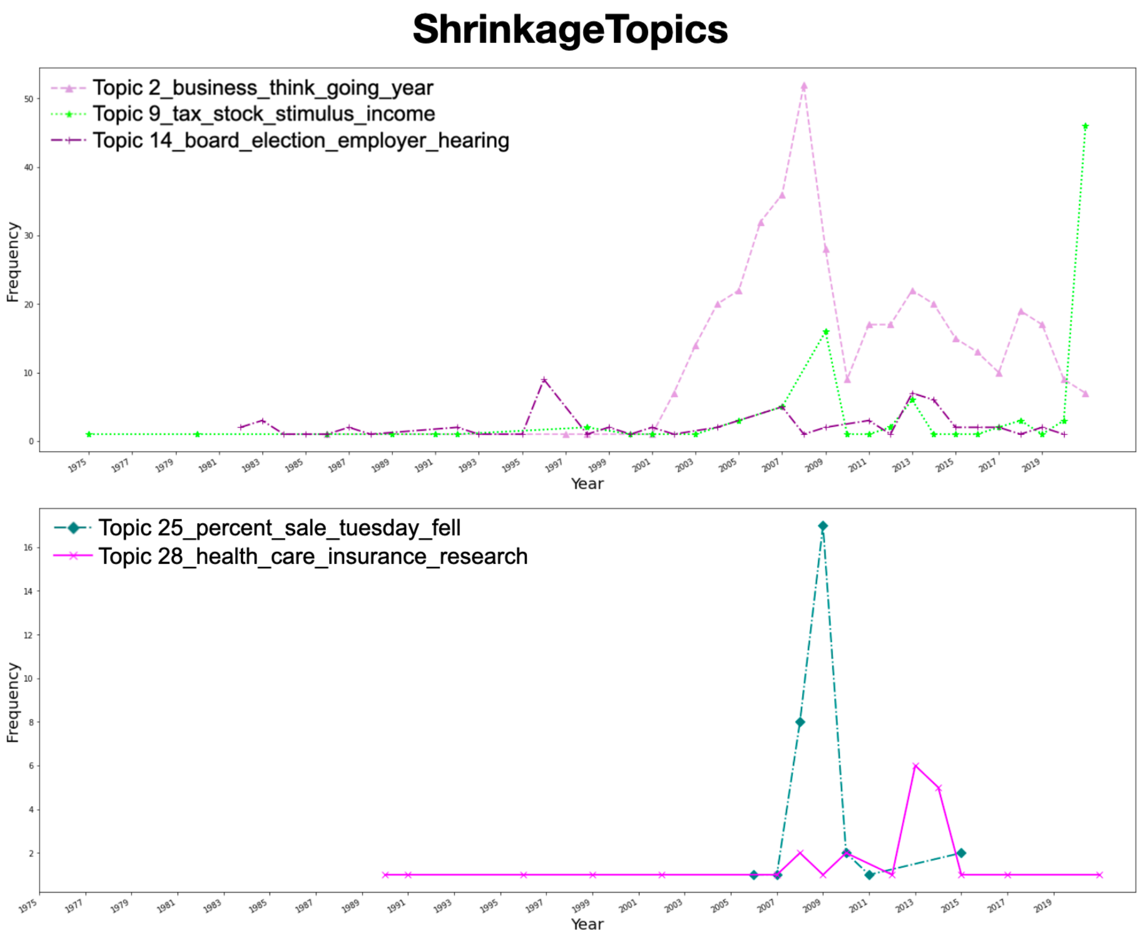

Figure 9.5: Shrinkage Topic Over time

is that due to the global pandemic, the stock market witnessed some turbulence [126]. In addition, people's income was impacted and the federal government distributed the stimulus. Within Topic 25, terms like "sale", "profits", "loss", "fell", indicate the shrinkage of business along with its peak measured in 2009. Due to the shrinkage of different types of business, especially, the automobile industry during the recession, terms within Topic 14 such as, board, nlrb (i.e., National Labor Relations Board), employer, employee, union indicate that the federal agency and union stepped into the role of solving the relations between the employer and employee [127].

Other than business shrinkage, health care service's shrinkage is also captured by Topic 28, and the discussion peak is measured at 2014 [128]. In addition, several discussions related to health care (i.e., Obamacare) are detected in 2008 and 2010. With respect to these two years, 2008's discussion is related to presidential candidates' health reform proposals, while Obamacare was effective in 2010 [129].

9.4.3 Population Keywords Resulting Topics

Resulting topics of population keywords contains five topics (i.e., Topics 0, 3, 22, 28, 30), which is shown by Table 9.2. Topic 0 and 22 are two intersection topics with urban keywords resulting topics. Details related to these two topics were discussed in Section 9.4.1. The urban area is made of population and houses. Thus these two topics are intersected with urban topics. Health care is also connected to the population. As a result, Topic 28 is captured within the population resulting topics, which is discussed in Section 9.4.2.

Topic 3 is firstly captured, which is related to job and employment status. For example, two low points in the American employment rate during the two recessions (i.e., 1981-1981 and 2007-2009) [130], where two discussions of Topic 3 are measured by Figure 9.6. This topic is under population keyword resulting topics because Topic 3 reveals the overall American employment status, including employment growth and decline. As a result, few discussions revealing the employment growth status are captured, such as the discussion in 2017 when unemployment reached a 17-year low [131]. Topic 30 is another topic captured for the first

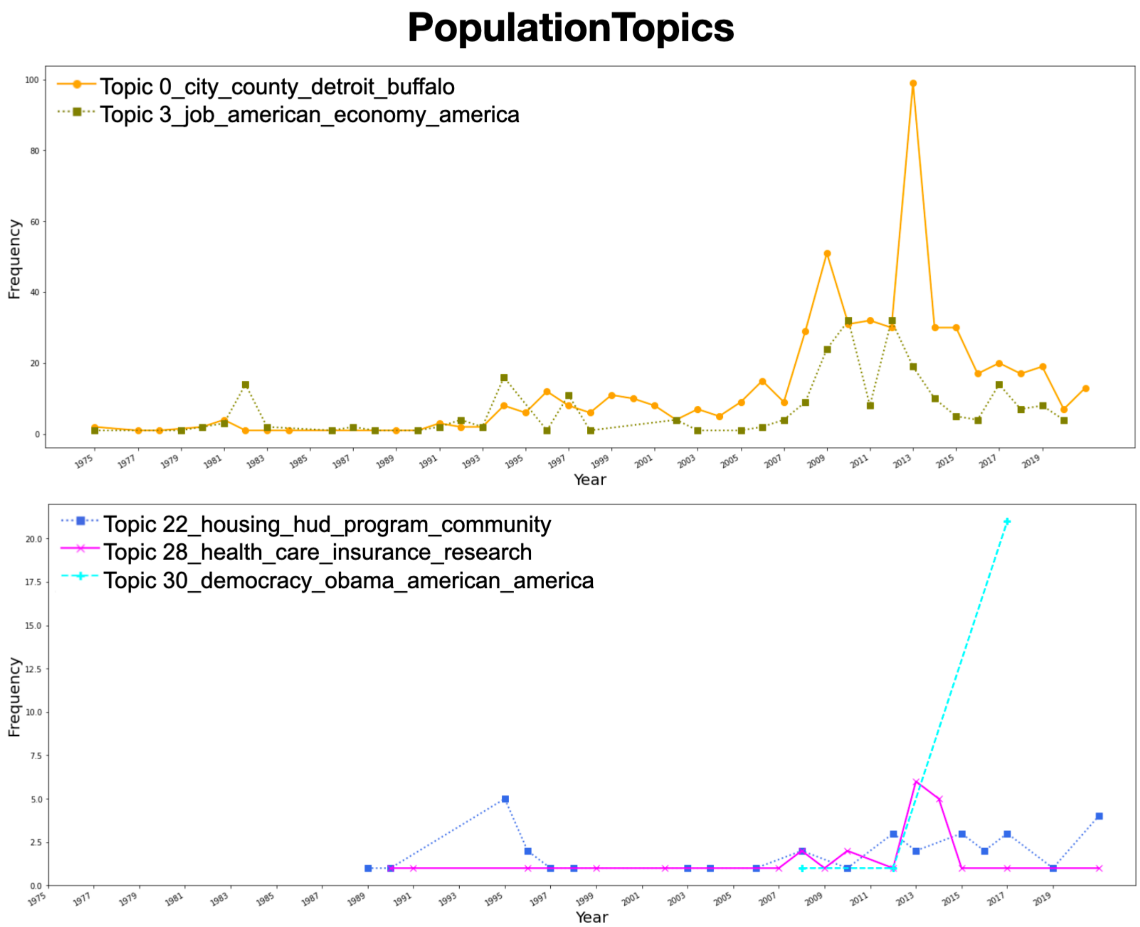

Figure 9.6: Population Topic Over time

time and this topic is related to immigration, which is an essential branch of the population. The peak is measured in 2017 because several immigration programs from the Obama era were terminated by the Trump administration [132].

9.4.4 House Keywords Resulting Topics

Four resulting topics are captured by using the house keywords, which are Topics 4, 8, 22 and 39, shown in Table 9.2. Topic 22 is intersected with urban and population keywords resulting topics. Details related to Topic 22 is discussed in Section 9.4.1. As for the rest of the resulting topics, Topic 4 is related to the housing market, especially the housing price.

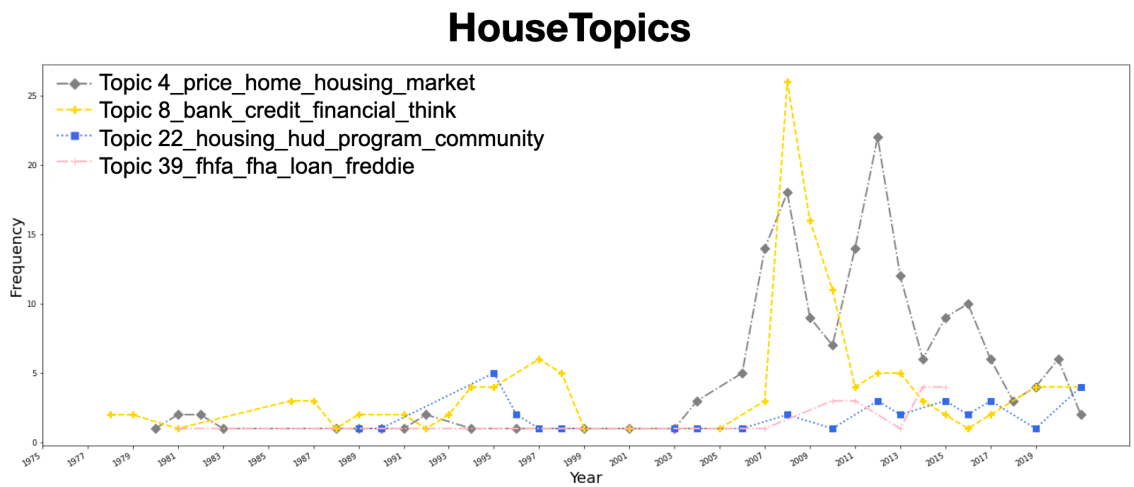

Figure 9.7: House Topic Over time

Topic 8 and 39 are related to bank, loan and financial organizations. Two peaks are measured for Topic 4; one is captured during the 2008-2009 recession, and the other is captured in 2013 (i.e., Detroit bankruptcy). By that time, the housing prices had reached a low point at both national and city levels [124]. With respect to Topic 8, the peak discussion of Topic 8 is measured in 2008 during the recession, which was led by the subprime mortgage crisis related to housing trades[133]. Thus, the discussion related to the mortgage and financial organizations (i.e., Topic 8, 39) comes along with the housing market prices discussions (i.e., Topic 4).

9.4.5 Job Keywords Resulting Topics

With respect to job keywords resetting topics, seven topics are captured, which are Topics 2, 3, 4, 9, 14, 16 and 31. Topics 2, 9 and 14 are intersected with shrinkage resulting topics. To summarize, the shrinkage of different businesses during the 2007-2009 rescission led to the job market shrinkage and specific organizations managed to solve issues brought by that, which are discussed in Section 9.4.2. Topic 3's detail is presented in Section 9.4.3, which indicates the discussion of the overall American employment status. As discussed in Section 9.4.1, Topic 31 refers to the increasing productivity of Liverpool's car manufacturers,

Figure 9.8: Job Topic Over time

which indicates the increase in job demands [121]. Although Topic 4 is related to the housing market, it's rational to infer that people cannot afford houses due to the change in unemployment status. By the names of Topic 16, it's hard to find the connections between Topic 16 to the job keywords. However, this topic can be connected to Topic 9, which refers to how stock market changes impact the job markets.

9.4.6 Economy Keywords Resulting Topics

As for the seven resulting topics extracted by economy keywords, most of them have already captured by other keywords, for example, Topic 2, 9 discussed in shrinkage (Section 9.4.2),

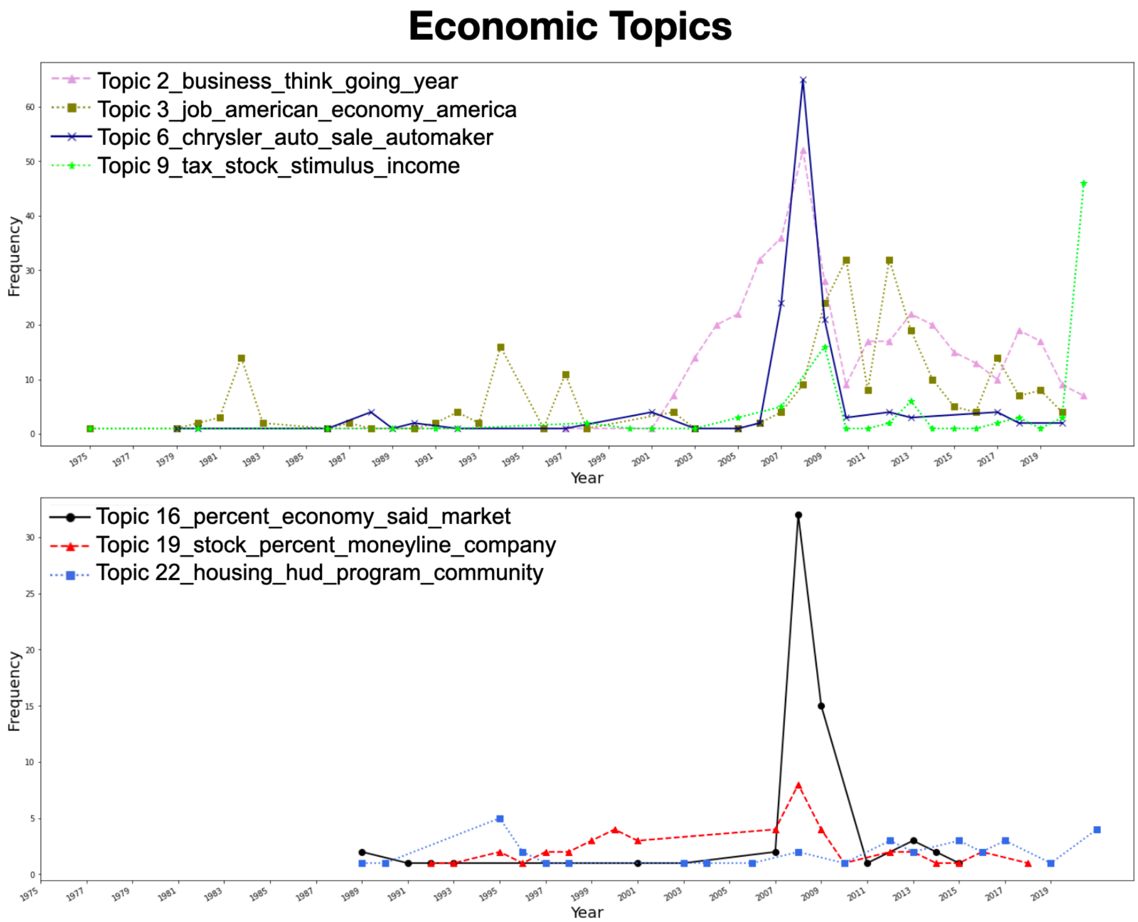

Figure 9.9: Economy Topic Over time

Topic 3 in population (Section 9.4.3), Topic 6, 22 in urban (Section 9.4.1), Topic 16 in job (Section 9.4.5). Only Topic 19 is the newly captured topic using economic keywords, which are also related to the stock market. Topics 2, 3, 9, 16 and 19 represent the nation-level economic status, including the stock market turbulence and stimulus to both the stock market and the public during the recession and pandemic [125,126]. While Topic 6 indicates how Detroit's local economy is impacted by the nation-level economy status, for instance, the recession's impact on the automobile industry (i.e., automotive manufacturing crisis) [134]. The discussion related to housing (i.e., Topic 22) is due to the Consolidated Plan created by hud (i.e., Housing and Urban Development) has the potential to boost an urban area's economy through urban developments [123].

9.5 Summary

By analyzing the newspaper articles by applying yearly statistics (i.e., Section 9.2) and topic modeling techniques (i.e., Section 9.3), several national and city level historical events related to urban shrinkage (e.g., 2007-2009 recession and Chrysler bankruptcy) are identified by the number of news published each year and the keywords search results. With respect to the insights of Detroit's shrinkage, it can be summarized by the combined impacts of economic environment change, decline of the automobile industry, employment status change and housing market crash. Specifically, Detroit's economy is bonded with the automobile industry. Through the discussions in Section 9.4.1 and 9.5, it's clear that national-level economy recessions impacted the automobile industry (i.e., 2007 -2009), which led to the automotive manufacturing crisis. As a result, the shrinkage of the automotive industry leads to an increase in the unemployment rate, as discussed in Section 9.4.2 and 9.4.5. The housing market collapse is also captured by the resulting topic discussed in Section 9.4.4.

Chapter 10: Discussion and Conclusion

In this Chapter, each model's findings and contributions are presented in Section 10.1. Then, the limitations and potential future works for both agent-based modeling and topic modeling are identified and discussed in Section 10.2. Section 10.3 addresses the overall conclusion of this work.

10.1 Discussion

While we are witnessing a global growth of the urban population which raises concerns about urban sustainability (e.g., [8, 135, 136]), not all cities are growing (Section 1). Some, like Detroit are actually shrinking, which has drawn a lot of discussion from the research and practice communities globally as it causes population loss, economic decline and a growth in crime due to vacant properties and housing market contraction (e.g., [6,12,13,38]). However, few efforts have been made to explore this phenomenon from the CSS domains of the social simulation modeling and social information extraction.

With respect to the field of social simulation modeling, two agent-based models significantly add to this nascent field of inquiry by specifically capturing how the buying and selling of houses can lead to urban shrinkage from the bottom-up through a case study of the cit of Detroit. Results from the two models (i.e., Chapter 8) have implications concerning urban shrinkage. For example, both of the agent-based models built in this work show how household decline in an area which potentially could lead to less tax revenue and therefore limits a city's ability to provide services which in turn can lead to more urban decline as discussed in Section 1.1. The extended model results show an upward trend for median and average house prices, which seems inconsistent with the intuitive results of the contracting housing market (i.e., the decreasing of house prices). This was due to the inflation over the simulated years (see Chapter 6.4.3 and 8.3).

As for the social information extraction, the topic modeling from this work has extended the field of text-contents analysis by identifying the insights related to the urban shrinkage phenomenon from a large number of newspapers. The results from the topic modeling (i.e., Chapter 9) have disclosed insights related to the shrinkage of the city of Detroit. The topic model results capture the economic environment change (i.e., 2007- 2009 recession), which led to the decline of the automobile industry, employment status change and housing market crash as discussed in Section 1.1.

10.2 Limitations & Future Works

10.2.1 Agent-Based Modeling

While our agent-based models can capture urban shrinkage, like all models there are limitations and there is always room for improvement. One area of improvement could be to extend the model to represent more types of housing stock (e.g., apartments, single family homes, etc.) which could be sourced from the American Community Survey or local government property records along with home sales data. This work did not choose to go this route here as the purpose of the model was to act as a prototype to explore how urban shrinkage might emerge from the bottom-up through the interactions of buying and selling houses. Another area of further work could be to characterize new incoming populations better. In the current models, new households are not introduced based on their heterogeneous financial and demographic backgrounds due to data limitations (i.e., the census data is not continuous between 2000 and 2010). In addition, instead of letting the two model generate all households within the study area, two model use the 1 agent to 100 households to scale the model, which may lead to the scaling issues during initialization (e.g., insufficient number of households, reductions of agents' heterogeneities on house value). The reason of selecting one agent to represent 100 households is due to it would be computationally intensive and time-consuming if running a one-to-one model on NetLogo and details are provided in Section 8.3.3. As a result, the final simulated household numbers and house values may be lower than the empirical data. With this being said, the declining trend in the number of households for the whole study area is captured successfully by the model, which aligns to the empirical data. One way to better capture new households entering the study area and mitigate the scaling issues during the model initialization is to use techniques from synthetic population generation such as those seen in micro-simulation models and geographically-explicit agent-based models (e.g., [137, 138]). This would potentially allow us to better capture how changes in demographics impact on residents' ability to stay in an area and their preferences for certain types of neighborhoods but that beyond the scope of this current paper as this would be a large undertaking and most agent-based models like the ones cited in Section 3.2.2 only look at one aspect (i.e., subsystem) such as the land market rather than the entire urban system itself [92].

Building upon this idea, the models presented in this word only explored the buying and selling of properties; however, as we noted in the introduction (Section 1.1), urban shrinkage is a complex issue and we don't specifically model the economic environment comprehensively (rather we simply consider inflation as an only aspect of the economic environment). This simulation could be improved by incorporating time series data with respect to the economy, such as unemployment rates or economic growth. Alternatively, one could couple this model with a more macro economic model to account for such factors (e.g., [139, 140]). Other than incorporating more data into the simulation, the model could capture more nuanced residential dynamics if the time step was deceased from a year to say monthly. This would allow for a slower incremental price dropping of house values if they remained unsold. It would also be interesting to experiment with multiple space-time scales in order to explore the equifinality of the urban shrinkage from different temporal and spatial scales (e.g., [141]). Another area of work, especially with respect to urban sustainability, would be to explore what would it take to stop urban shrinkage, or how do neighborhoods go from declining to growing such as through gentrification. Gentrification in Detroit has been discussed is the literature (e.g., [142–145]). Hence, another direction to extend the model would be to explore gentrification and segregation in Detroit through modeling and simulation. Similar to urban shrinkage, there is a growing body of models exploring gentrification (e.g., [86, 87, 146]) which show promise in capture such phenomena. For segregation status, previous works (e.g., [92, 147, 148]) provide potentials to integrate agent-based model with real census data to further study the segregation within the city of Detroit.

10.2.2 Topic Modeling

With topic modeling results revealing the insights of Detroit's shrinkage, similar to all modeling works, limitations can be founded, and there is always room to improve current topic modeling. One direction to improve it would be introducing the news earlier than 1975. Due to the constrain of the current platform used to collect newspaper articles, this work does not include historic newspapers before 1975. Even though some resources or platforms offer such newspaper articles, the copyrights and usage regulations of the newspapers collected from such platform emerges as another issue. As a result, current topic model results capture more insights related 2007-2009 recession other than insights related to the 1968 Detroit riots [149]. To further capture more insights related to urban shrinkage in Detroit, one way would be searching news articles from various sources to collect newspapers before 1975. Another way to improve is from the visualization perspective, which is considered a challenging part of topic modeling due to the constraints of visualization tools [114]. This work also ran into this challenging scenario, in which the evolution of the topics (i.e., changes of words within each topic) are not presented to disclose each topic's insights that can be possibly liked to the shrinkage of Detroit.

As for the topic modeling utilized in this work, the social information or insight related to Detroit's shrinkage is extracted from newspaper articles. Moving from urban shrinkage to other urban or social phenomena, with a substantial of works analyzing newspapers using topic modeling techniques (e.g., public health and urban study [49,150]), news articles shows promise to act as a data source for topic modeling techniques to disclose insights related to various social phenomena. At the same time, social media text-data is another source to extract social information within today's urban study. Thus, one direction of future work would be to collect social media and newspaper articles within the same time frame for topic modeling to detect the variations of discussions related to urban shrinkage from different data sources.

10.3 Conclusion

Moving the focus point from Detroit to other urban areas, the agent-based models presented in this work could be generalized across different urban areas by integrating more data and adding new types of agents (e.g., investors whose behaviors are different from households and banks). This is one reason we provide the code and the data to the model (see Chapter 5 and 6), to allow other researchers to extend and explore the model as they see fit. The topic modeling research framework introduced in **??** could be utilized to conduct such analysis on a large number of newspapers to study urban shrinkage across different urban areas. This research framework also provides the potential to explore other social phenomena by conducting such an analysis on newspapers. Even with these limitations and areas of further work discussed in Section **??**, this work has demonstrated how agent-based modeling integrated with geo-spatial data provides a promising method to explore urban shrinkage and the contribution to the CSS fields of the social simulation modeling. In addition, the text content analysis on a large number of newspaper through topic modeling techniques has shown that newspaper text-data is an alternative data source to gain insights related to urban shrinkage. If further developments and adaptions could be added to both agent-based models and topic models, this work would offer the potential to test policies to mitigate issues brought by urban shrinkage.

Bibliography

Bibliography

[1] Y. D. Wei, H. Li, and W. Yue, "Urban land expansion and regional inequality in transitional china," *Landscape and Urban Planning*, vol. 163, pp. 17–31, 2017.

[2] D. Haase, S. Lautenbach, and R. Seppelt, "Modeling and simulating residential mobility in a shrinking city using an agent-based approach," *Environmental Modelling & Software*, vol. 25, no. 10, pp. 1225–1240, 2010.

[3] Y. Long and K. Wu, "Shrinking cities in a rapidly urbanizing China," *Environment and Planning A: Economy and Space*, vol. 48, no. 2, pp. 220–222, 2016.

[4] W. J. V. Neill, "Carry on Shrinking?: The Bankruptcy of Urban Policy in Detroit," *Planning Practice & Research*, vol. 30, no. 1, pp. 1–14, 2015.

[5] C. Couch, J. Karecha, H. Nuissl, and D. Rink, "Decline and sprawl: An evolving type of urban development–observed in Liverpool and Leipzig," *European Planning Studies*, vol. 13, no. 1, pp. 117–136, 2005.

[6] K. Großmann, M. Bontje, A. Haase, and V. Mykhnenko, "Shrinking cities: Notes for the further research agenda," *Cities*, vol. 35, pp. 221–225, 2013.

[7] D. Reckien and C. Martinez-Fernandez, "Why do cities shrink?" *European Planning Studies*, vol. 19, no. 8, pp. 1375–1397, 2011.

[8] O. Slach, V. Bosák, L. Krtička, A. Nováček, and P. Rumpel, "Urban shrinkage and sustainability: Assessing the nexus between population density, urban structures and urban sustainability," *Sustainability*, vol. 11, no. 15, p. 4142, Jan. 2019.

[9] M. Bontje, "Facing the challenge of shrinking cities in East Germany: The case of Leipzig," *GeoJournal*, vol. 61, no. 1, pp. 13–21, Sep. 2004. [Online]. Available: https://doi.org/10.1007/s10708-005-0843-2

[10] C. Deng and J. Ma, "Viewing urban decay from the sky: A multi-scale analysis of residential vacancy in a shrinking US city," *Landscape and Urban Planning*, vol. 141, pp. 88–99, 2015.

[11] J. M. Shane, *Abandoned Buildings and Lots*. Washington, D.C.: U.S. Dept. of Justice, Office of Community Oriented Policing Services, 2012, oCLC: 951617158.

[12] C. Martinez-Fernandez, I. Audirac, S. Fol, and E. Cunningham-Sabot, "Shrinking cities: Urban challenges of globalization," *International Journal of Urban and Regional Research*, vol. 36, no. 2, pp. 213–225, 2012.

[13] Y. Xie, H. Gong, H. Lan, and S. Zeng, "Examining shrinking city of Detroit in the context of socio-spatial inequalities," *Landscape and Urban Planning*, vol. 177, pp. 350–361, 2018.

[14] D. Reckien and C. Martinez-Fernandez, "Why Do Cities Shrink?" *European Planning Studies*, vol. 19, no. 8, pp. 1375–1397, 2011.

[15] J. P. Steil, L. Albright, J. S. Rugh, and D. S. Massey, "The social structure of mortgage discrimination," *Housing Studies*, vol. 33, no. 5, pp. 759–776, Jul. 2018.

[16] G. D. Squires, R. Dewolfe, and A. S. Dewolfe, "Urban Decline or Disinvestment: Uneven Development, Redlining and the Role of the Insurance Industry," *Social Problems*, vol. 27, pp. 79–95, 1979.

[17] A. Power, "Social exclusion and urban sprawl: Is the rescue of cities possible?" *Regional Studies*, vol. 35, no. 8, pp. 731–742, 2001.

[18] E. Kneebone, "Job Sprawl Stalls: The Great Recession and Metropolitan Employment Location," 2013, https://www.brookings.edu/research/job-sprawl-stalls-the-great-recession-and-metropolitan-employment-location/ accessed 2021-2-7.

[19] X. Yuan, R. Mahabir, A. Crooks, and A. Croitoru, "Achieving situational awareness of drug cartels with geolocated social media," *GeoJournal*, May 2021. [Online]. Available: https://doi.org/10.1007/s10708-021-10433-2

[20] B. Shapiro and A. Crooks, "Kinetic Action and Radicalization: A Case Study of Pakistan," in *2021 International Conference on Social Computing, Behavioral-Cultural Modeling & Prediction and Behavior Representation in Modeling and Simulation*. Washington DC: Thomson, R., Hussain, M.N., Dancy, C.L. and Pyke, A. (eds), 2021, pp. 321–330.

[21] C. Cioffi-Revilla, *Introduction to computational social science*. London, UK: Springer, 2014.

[22] D. M. J. Lazer, A. Pentland, D. J. Watts, S. Aral, S. Athey, N. Contractor, D. Freelon, S. Gonzalez-Bailon, G. King, H. Margetts, A. Nelson, M. J. Salganik, M. Strohmaier, A. Vespignani, and C. Wagner, "Computational social science: Obstacles and opportunities," *Science*, vol. 369, no. 6507, pp. 1060–1062, Aug. 2020, publisher: American Association for the Advancement of Science. [Online]. Available: http://www.science.org/doi/10.1126/science.aaz8170

[23] J. F. McDonald, "What happened to and in Detroit?" *Urban Studies*, vol. 51, no. 16, pp. 3309–3329, 2014.

[24] W. J. Neill, "Carry on shrinking?: The bankruptcy of urban policy in Detroit," *Planning Practice and Research*, vol. 30, no. 1, pp. 1–14, 2015.

[25] A. Bergesen, "Race riots of 1967: An analysis of police violence in detroit and newark," *Journal of Black Studies*, vol. 12, no. 3, pp. 261–274, 1982.

[26] C. J. Wurdock, "Neighborhood racial transition: A study of the role of white flight," *Urban Affairs Quarterly*, vol. 17, no. 1, pp. 75–89, 1981.

[27] T. J. Sugrue, *The origins of the urban crisis: Race and inequality in postwar detroit-updated edition.* Princeton, NJ: Princeton University Press, 2014.

[28] P. Eisinger, "Is Detroit Dead?" *Journal of Urban Affairs*, vol. 36, no. 1, pp. 1–12, 2014.

[29] J. Rappaport *et al.*, "Us urban decline and growth, 1950 to 2000," *Economic Review-Federal Reserve Bank of Kansas City*, vol. 88, no. 3, pp. 15–44, 2003.

[30] E. Poethig, J. Schilling, L. Goodman, B. Bai, J. Gastner, R. Pendall, and S. Fazili, *The Detroit Housing Market: Challenges and Innovations for a Path Forward.* Washington DC: Urban Institute, 1964.

[31] US Census Bureau, *Decennial Census (2010, 2000)*, 2010, https://www.census.gov/data/developers/data-sets/decennial-census.html. Accessed Sep. 09, 2019.

[32] U. C. Bureau, "American Community Survey Data," 2020. [Online]. Available: https://www.census.gov/programs-surveys/acs/data.html

[33] Z. Ma, C. Li, and J. Zhang, "Understanding urban shrinkage from a regional perspective: Case study of northeast china," vol. 146, no. 4, p. 05020025. [Online]. Available: https://ascelibrary.org/doi/abs/10.1061/%28ASCE%29UP.1943-5444.0000621

[34] M. Hartt, "The diversity of north american shrinking cities," vol. 55, no. 13, pp. 2946–2959, publisher: SAGE Publications Ltd.

[35] C. Martinez-Fernandez, T. Weyman, S. Fol, I. Audirac, E. Cunningham-Sabot, T. Wiechmann, and H. Yahagi, "Shrinking cities in australia, japan, europe and the USA: From a global process to local policy responses," vol. 105, pp. 1–48.

[36] L. Van den Berg, R. Drewett, L. H. Klaassen, A. Rossi, and C. H. VIjVERBERG, *A study of growth and decline.* Elsevier, 1982, vol. 1.

[37] S. Scheuer, D. Haase, and M. Volk, "On the Nexus of the Spatial Dynamics of Global Urbanization and the Age of the City," *PLOS ONE*, vol. 11, no. 8, p. e0160471, Aug. 2016, publisher: Public Library of Science. [Online]. Available: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0160471

[38] Y. Li and Y. Xie, "A New Urban Typology Model Adapting Data Mining Analytics to Examine Dominant Trajectories of Neighborhood Change: A Case of Metro Detroit," *Annals of the American Association of Geographers*, vol. 108, no. 5, pp. 1313–1337, 2018.

[39] X. Meng and Y. Long, "Shrinking cities in China: Evidence from the latest two population censuses 2010–2020," *Environment and Planning A: Economy and Space*, vol. 54, no. 3, pp. 449–453, 2022, publisher: SAGE Publications Sage UK: London, England.

[40] L. Mao, Z. Zheng, X. Meng, Y. Zhou, P. Zhao, Z. Yang, and Y. Long, "Large-scale automatic identification of urban vacant land using semantic segmentation of high-resolution remote sensing images," *Landscape and Urban Planning*, vol. 222, p. 104384, Jun. 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0169204622000330

[41] Y. Zhou, C. Li, Z. Ma, S. Hu, J. Zhang, and W. Liu, "Identification of Shrinkage and Growth Patterns of a Shrinking City in China Based on Nighttime Light Data: A Case Study of Yichun," *Sustainability*, vol. 11, no. 24, p. 6906, Jan. 2019.

[42] P. Propastin and M. Kappas, "Assessing Satellite-Observed Nighttime Lights for Monitoring Socioeconomic Parameters in the Republic of Kazakhstan," *GIScience & Remote Sensing*, vol. 49, no. 4, pp. 538–557, Jul. 2012.

[43] X. Yuan, R. J. Schuchard, and A. T. Crooks, "Examining Emergent Communities and Social Bots Within the Polarized Online Vaccination Debate in Twitter," *Social Media + Society*, vol. 5, no. 3, p. 2056305119865465, Apr. 2019, publisher: SAGE Publications Ltd.

[44] J. R. Hawks, H. Madanat, E. R. Walsh-Buhi, S. Hartman, A. Nara, D. Strong, and C. Anderson, "Narrative review of social media as a research tool for diet and weight loss," *Computers in Human Behavior*, vol. 111, p. 106426, Oct. 2020.

[45] S. Y. Han, M.-H. Tsou, E. Knaap, S. Rey, and G. Cao, "How Do Cities Flow in an Emergency? Tracing Human Mobility Patterns during a Natural Disaster with Big Data and Geospatial Data Science," *Urban Science*, vol. 3, no. 2, p. 51, Jun. 2019. [Online]. Available: https://www.mdpi.com/2413-8851/3/2/51

[46] Z. Wang, X. Ye, and M.-H. Tsou, "Spatial, temporal, and content analysis of Twitter for wildfire hazards," *Natural Hazards*, vol. 83, no. 1, pp. 523–540, Aug. 2016.

[47] A. Crooks, A. Croitoru, A. Stefanidis, and J. Radzikowski, "#Earthquake: Twitter as a Distributed Sensor System," *Transactions in GIS*, vol. 17, no. 1, pp. 124–147, 2013, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1467-9671.2012.01359.x.

[48] P. Martí, L. Serrano-Estrada, and A. Nolasco-Cirugeda, "Social Media data: Challenges, opportunities and limitations in urban studies," *Computers, Environment and Urban Systems*, vol. 74, pp. 161–174, Mar. 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0198971518302333

[49] T. Okuhara, H. Ishikawa, M. Okada, M. Kato, and T. Kiuchi, "Newspaper coverage before and after the HPV vaccination crisis began in Japan: a text mining analysis," *BMC Public Health*, vol. 19, no. 1, p. 770, Jun. 2019. [Online]. Available: https://doi.org/10.1186/s12889-019-7097-2

[50] S. B. Meyer, S. K. Lu, L. Hoffman-Goetz, B. Smale, H. MacDougall, and A. R. Pearce, "A Content Analysis of Newspaper Coverage of the Seasonal Flu Vaccine in Ontario, Canada, October 2001 to March 2011," *Journal of Health Communication*, vol. 21, no. 10, pp. 1088–1097, Oct. 2016, publisher: Taylor & Francis _eprint: https://doi.org/10.1080/10810730.2016.1222038. [Online]. Available: https://doi.org/10.1080/10810730.2016.1222038

[51] S. De Benedictis, S. Orgad, and C. Rottenberg, "#MeToo, popular feminism and the news : A content analysis of UK newspaper coverage," *European Journal of Cultural Studies*, vol. 22, no. 5-6, pp. 718–738, Oct. 2019, publisher: SAGE Publications Ltd. [Online]. Available: https://doi.org/10.1177/1367549419856831

[52] L. Costelloe, "Discourses of sameness: Expressions of nationalism in newspaper discourse on French urban violence in 2005," *Discourse & Society*, vol. 25, no. 3, pp. 315–340, May 2014, publisher: SAGE Publications Ltd. [Online]. Available: https://doi.org/10.1177/0957926513519533

[53] C. Brozek, "Newspaper coverage of selected urban problems in metropolitan detroit: A content analysis," 1971.

[54] M. Munro, "House price inflation in the news: a critical discourse analysis of newspaper coverage in the UK," *Housing Studies*, vol. 33, no. 7, pp. 1085–1105, Oct. 2018, publisher: Routledge _eprint: https://doi.org/10.1080/02673037.2017.1421911. [Online]. Available: https://doi.org/10.1080/02673037.2017.1421911

[55] IBM, "What is Natural Language Processing?" 2020. [Online]. Available: https://www.ibm.com/cloud/learn/natural-language-processing

[56] D. Khurana, A. Koli, K. Khatter, and S. Singh, "Natural Language Processing: State of The Art, Current Trends and Challenges," Aug. 2017, arXiv:1708.05148 [cs].

[57] R. Sandhiya, A. M. Boopika, M. Akshatha, S. V. Swetha, and N. M. Hariharan, "A Review of Topic Modeling and Its Application," in *Handbook of Intelligent Computing and Optimization for Sustainable Development*. John Wiley & Sons, Ltd, 2022, pp. 305–322, section: 15 _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/9781119792642.ch15. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1002/9781119792642.ch15

[58] S. Boon-Itt and Y. Skunkan, "Public Perception of the COVID-19 Pandemic on Twitter: Sentiment Analysis and Topic Modeling Study," *JMIR Public Health and Surveillance*, vol. 6, no. 4, p. e21978, Nov. 2020, company: JMIR Public Health and Surveillance Distributor: JMIR Public Health and Surveillance Institution: JMIR Public Health and Surveillance Label: JMIR Public Health and Surveillance Publisher: JMIR Publications Inc., Toronto, Canada. [Online]. Available: https://publichealth.jmir.org/2020/4/e21978

[59] N. C. Lindstedt, "Structural Topic Modeling For Social Scientists: A Brief Case Study with Social Movement Studies Literature, 2005–2017," *Social Currents*, vol. 6, no. 4, Aug. 2019, publisher: SAGE Publications Inc. [Online]. Available: https://doi.org/10.1177/2329496519846505

[60] S. S. Chawathe, "Topic analysis of climate-change news," in *2020 10th Annual Computing and Communication Workshop and Conference (CCWC)*, 2020, pp. 0543–0549.

[61] L. Liu, L. Tang, W. Dong, S. Yao, and W. Zhou, "An overview of topic modeling and its current applications in bioinformatics," *SpringerPlus*, vol. 5, no. 1, p. 1608, Sep. 2016. [Online]. Available: https://doi.org/10.1186/s40064-016-3252-8

[62] D. M. Blei, A. Y. Ng, and M. I. Jordan, "Latent Dirichlet Allocation," *Journal of Machine Learning Research*, vol. 3, no. Jan, pp. 993–1022, 2003. [Online]. Available: https://jmlr.csail.mit.edu/papers/v3/blei03a.html

[63] M. Grootendorst, "Bertopic: Neural topic modeling with a class-based tf-idf procedure," *arXiv preprint arXiv:2203.05794*, 2022.

[64] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding," May 2019, arXiv:1810.04805 [cs]. [Online]. Available: http://arxiv.org/abs/1810.04805

[65] M. V. Koroteev, "BERT: A Review of Applications in Natural Language Processing and Understanding," Mar. 2021, arXiv:2103.11943 [cs]. [Online]. Available: http://arxiv.org/abs/2103.11943

[66] M. Batty, *Cities and complexity: understanding cities with cellular automata, agent-based models, and fractals*, Cambridge, MA, 2007.

[67] W. R. Tobler, "A Computer Movie Simulating Urban Growth in the Detroit Region," *Economic Geography*, vol. 46, pp. 234–240, 1970, publisher: [Clark University, Wiley]. [Online]. Available: https://www.jstor.org/stable/143141

[68] G. K. Ingram, J. F. Kain, and J. R. Ginn, "The NBER Urban Simulation Model," in *The Detroit Prototype of the NBER Urban Simulation Model*. NBER, 1972, pp. 1–8. [Online]. Available: https://www.nber.org/books-and-chapters/detroit-prototype-nber-urban-simulation-model/nber-urban-simulation-model

[69] A. J. Heppenstall, A. T. Crooks, L. M. See, and M. Batty, *Agent-based models of geographical systems*. New York, NY: Springer, 2011.

[70] I. Benenson and P. M. Torrens, *Geosimulation: Automata-Based Modelling of Urban Phenomena*. London, UK: John Wiley & Sons, 2004.

[71] M. Batty, Y. Xie, and Z. Sun, "Modeling urban dynamics through GIS-based cellular automata," *Computers, Environment and Urban Systems*, vol. 23, no. 3, pp. 205–233, 1999.

[72] K. C. Clarke and L. J. Gaydos, "Loose-coupling a cellular automaton model and gis: Long-term urban growth predictions for San Francisco and Baltimore," *International Journal of Geographic Information Science*, vol. 12, no. 7, pp. 699–714, 1998.

[73] K. C. Clarke, N. Gazulis, C. K. Dietzel, and N. C. Goldstein, "A decade of SLEUTHing: Lessons learned from applications of a cellular automaton land use change model," in *Classics from IJGIS: Twenty Years of the International Journal of Geographical Information Science and Systems*, P. Fisher, Ed. Boca Raton, FL: Taylor & Francis, 2006, pp. 413–426.

[74] G. Chaudhuri and K. Clarke, "The SLEUTH land use change model: A review," *Environmental Resources Research*, vol. 1, no. 1, pp. 88–105, 2013.

[75] J. Lv, Y. Wang, X. Liang, Y. Yao, T. Ma, and Q. Guan, "Simulating urban expansion by incorporating an integrated gravitational field model into a demand-driven random forest-cellular automata model," *Cities*, vol. 109, p. 103044, Feb. 2021.

[76] Y. Zhai, Y. Yao, Q. Guan, X. Liang, X. Li, Y. Pan, H. Yue, Z. Yuan, and J. Zhou, "Simulating urban land use change by integrating a convolutional neural network with vector-based cellular automata," *International Journal of Geographical Information Science*, vol. 34, no. 7, pp. 1475–1499, 2020.

[77] D. C. Parker, S. M. Manson, M. A. Janssen, M. J. Hoffmann, and P. Deadman, "Multi-agent systems for the simulation of land-use and land-cover change: A review," *Annals of the Association of American Geographers*, vol. 93, no. 2, pp. 314–337, 2003.

[78] N. Gilbert and K. G. Troitzsch, *Simulation for the Social Scientist*, 2nd ed. Milton Keynes, UK: Open University Press, 2005.

[79] A. Crooks, "Cellular automata," in *The International Encyclopedia of Geography: People, the Earth, Environment, and Technology*, D. Richardson, N. Castree, M. F. Goodchild, A. L. Kobayashi, W. Liu, and R. Marston, Eds. Wiley Blackwell, 2017, pp. 1–9.

[80] A. T. Crooks, C. J. E. Castle, and M. Batty, "Key challenges in agent-based modelling for geo-spatial simulation," *Computers, Environment and Urban Systems*, vol. 32, no. 6, pp. 417–430, 2008.

[81] Y. Xie, M. Batty, and K. Zhao, "Simulating emergent urban form using agent-based modeling: Desakota in the suzhou-wuxian region in china," *Annals of the Association of American Geographers*, vol. 97, no. 3, pp. 477–495, 2007.

[82] I. N. S. Djenontin, L. C. Zulu, and A. Ligmann-Zielinska, "Improving Representation of Decision Rules in LUCC-ABM: An Example with an Elicitation of Farmers' Decision Making for Landscape Restoration in Central Malawi," *Sustainability*, vol. 12, no. 13, p. 5380, Jan. 2020, number: 13 Publisher: Multidisciplinary Digital Publishing Institute.

[83] A. Malik and R. Abdalla, "Agent-based modelling for urban sprawl in the region of Waterloo, Ontario, Canada," *Modeling Earth Systems and Environment*, vol. 3, no. 1, p. 7, 2017.

[84] D. Pumain and L. Sanders, "Theoretical principles in interurban simulation models: A comparison," *Environment and Planning A*, vol. 45, no. 9, pp. 2243–2260, 2013.

[85] I. Benenson, I. Omer, and E. Hatna, "Entity-based modeling of urban residential dynamics: the case of Yaffo, Tel Aviv," *Environment and Planning B*, vol. 29, no. 4, pp. 491–512, 2002.

[86] D. O'Sullivan, "Toward micro-scale spatial modeling of gentrification," *Journal of Geographical Systems*, vol. 4, no. 3, pp. 251–274, 2002.

[87] P. M. Torrens and A. Nara, "Modeling gentrification aynamics: A hybrid approach," *Computers, Environment and Urban Systems*, vol. 31, no. 3, pp. 337–361, 2007.

[88] N. Schwarz, D. Haase, and R. Seppelt, "Omnipresent sprawl? A review of urban simulation models with respect to urban shrinkage," *Environment and Planning B*, vol. 37, no. 2, pp. 265–283, 2010.

[89] L. An, M. Linderman, J. Qi, A. Shortridge, and J. Liu, "Exploring complexity in a human–environment system: An agent-based spatial model for multidisciplinary and multiscale integration," *Annals of the Association of American Geographers*, vol. 95, no. 1, pp. 54–79, 2005.

[90] S. Manson, L. An, K. Clarke, A. Heppenstall, J. Koch, B. Krzyzanowski, F. Morgan, D. O'Sullivan, B. Runck, E. Shook, and L. Tesfatsion, "Methodological issues of spatial agent-based models," *Journal of Artificial Societies and Social Simulation*, vol. 23, no. 1, p. 3, 2019.

[91] D. C. Parker and T. Filatova, "A conceptual design for a bilateral agent-based land market with heterogeneous economic agents," *Computers, Environment and Urban Systems*, vol. 32, no. 6, pp. 454–463, 2008.

[92] A. Crooks, N. Malleson, E. Manley, and A. Heppenstall, *Agent-based modelling and Geographical Information Systems: A Practical Primer*. London, UK: Sage, 2019.

[93] N. Magliocca, E. Safirova, V. McConnell, and M. Walls, "An economic agent-based model of coupled housing and land markets (CHALMS)," *Computers, Environment and Urban Systems*, vol. 35, no. 3, pp. 183–191, 2011.

[94] D. K. Gode and S. Sunder, "Allocative efficiency of markets with zero-intelligence traders: Market as a partial substitute for individual rationality," *Journal of Political Economy*, vol. 101, no. 1, pp. 119–137, 1993.

[95] R. L. Axtell and J. D. Farmer, "Agent-based modeling in economics and finance: Past, present, and future," Computational Social Science Working Paper, Tech. Rep., 2017.

[96] T. Filatova, D. Parker, and A. van der Veen, "Agent-based urban land markets: Agentś pricing behavior, land prices and urban land use change," *Journal of Artificial Societies and Social Simulation*, vol. 12, no. 1, p. 3. [Online]. Available: http://jasss.soc.surrey.ac.uk/12/1/3.html

[97] W. Alonso, *Location and land use : toward a general theory of land rent*, ser. Publications of the Joint Center for Urban Studies of the Massachusetts Institute of Technology and Harvard University. Cambridge, Mass: Harvard University Press, 1964.

[98] D. Haase, A. Haase, N. Kabisch, S. Kabisch, and D. Rink, "Actors and factors in land-use simulation: The challenge of urban shrinkage," *Environmental Modelling & Software*, vol. 35, pp. 92 – 103, 2012.

[99] V. Grimm, U. Berger, F. Bastiansen, S. Eliassen, V. Ginot, J. Giske, J. Goss-Custard, T. Grand, S. K. Heinz, G. Huse, A. Huth, J. U. Jepsen, C. Jørgensen, W. M. Mooij, B. Müller, G. Pe'er, C. Piou, S. F. Railsback, A. M. Robbins, M. M. Robbins, E. Rossmanith, N. Rüger, E. Strand, S. Souissi, R. A. Stillman, R. Vabø, U. Visser, and D. L. DeAngelis, "A standard protocol for describing individual-based and agent-based models," *Ecological Modelling*, vol. 198, no. 1-2, pp. 115–126, 2006.

[100] U. Wilensky, *NetLogo. http:// ccl.northwestern.edu/ netlogo*. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL., 1999.

[101] City of Detroit Open Data Portal, "Detroit's Open Data Portal," 2019, https://data.detroitmi.gov/ accessed 2019-12-13.

[102] A. Patel, A. Crooks, and N. Koizumi, "Slumulation: An agent-based modeling approach to slum formations," *Journal of Artificial Societies and Social Simulation*, vol. 15, no. 4, p. 2, 2012.

[103] U. C. Bureau, "Decennial Census (2010, 2000)," 2000, https://www.census.gov/data/developers/data-sets/decennial-census.html accessed 2019-12-13.

[104] R. Bourne, "Government and the Cost of Living: Income-Based vs. Cost-Based Approaches to Alleviating Poverty," 2018, https://www.cato.org/publications/policy-analysis/government-cost-living-income-based-vs-cost-based-approaches accessed 2019-11-19.

[105] C. Brinkley-Badgett, "Comparing average property taxes for all 50 states and D.C." 2017, https://www.usatoday.com/story/money/personalfinance/2017/04/16/comparing-average-property-taxes-all-50-states-and-dc/100314754/ accessed 2019-12-14.

[106] ValuePenguin, "Michigan Mortgage Rates for June 2019," ValuePenguin, Tech. Rep., Jun. 2019, https://www.valuepenguin.com/mortgages/michigan-mortgage-rates.

[107] P. Pant, "How much you should budget for home maintenance," 2019, https://www.thebalance.com/home-maintenance-budget-453820.

[108] CNNMoney, "Buying a home in 10 steps," May 2015, https://money.cnn.com/pf/money-essentials-home-buying/index.html accessed 2019-06-11.

[109] R. Jordan, M. Birkin, and A. Evans, "An agent-based model of residential mobility assessing the impacts of urban regeneration policy in the EASEL District," *Computers, Environment and Urban Systems*, vol. 48, pp. 49–63, 2014.

[110] Y. Xie and S. Fan, "Multi-city sustainable regional urban growth simulation—MSRUGS: A case study along the mid-section of Silk Road of China." *Stochastic Environmental Research and Risk Assessment*, vol. 28, no. 4, pp. 829–841, 2014.

[111] T.-N. Nelson, "Advantages and Disadvantages of Buying a Foreclosure," 2020, https://www.hgtv.com/lifestyle/real-estate/advantages-and-disadvantages-of-buying-a-foreclosure accessed 2020-12-07.

[112] D. Knowles, "Forsaken Detroit homes for sale for as little as $1," 2013, urlhttps://www.nydailynews.com/life-style/real-estate/1-buy-house-detroit-article-1.1415014 accessed 2019-12-13.

[113] Coin News, "Inflation Calculator | Find US Dollar's Value from 1913-2020," 2020, https://www.usinflationcalculator.com/ accessed 2020-11-19.

[114] P. Kherwa and P. Bansal, "Topic Modeling: A Comprehensive Review," *EAI Endorsed Transactions on Scalable Information Systems*, vol. 7, no. 24, 2020, number: 24 Publisher: European Alliance for Innovation.

[115] R. Egger and J. Yu, "A Topic Modeling Comparison Between LDA, NMF, Top2Vec, and BERTopic to Demystify Twitter Posts," *Frontiers in Sociology*, vol. 7, p. 886498, May 2022. [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9120935/

[116] V. Grimm, "Visual debugging: A way of analyzing, understanding and communicating bottom-up simulation models in ecology," *Natural Resource Modeling*, vol. 15, no. 1, pp. 23–38, 2002.

[117] J.-S. Lee, T. Filatova, A. Ligmann-Zielinska, B. Hassani-Mahmooei, F. Stonedahl, I. Lorscheid, A. Voinov, G. Polhill, Z. Sun, and D. C. Parker, "The Complexities of Agent-Based Modeling Output Analysis," *Journal of Artificial Societies and Social Simulation*, vol. 18, no. 4, p. 4, 2015.

[118] R. Axtell and J. M. Epstein, "Agent-based modelling: Understanding our creations," *The Bulletin of the Santa Fe Institute*, pp. Winter, 28–32, 1994.

[119] M. Friedman, A. C. Grawert, and J. Cullen, *Crime Trends, 1990-2016*. Brennan Center for Justice at New York University School of Law New York, NY, 2017.

[120] D. P. Levin, "Chrysler Opens Plant, Makes a Point," *The New York Times*, Apr. 1992. [Online]. Available: https://www.nytimes.com/1992/04/01/business/chrysler-opens-plant-makes-a-point.html

[121] G. Fitzgerald, "Land Rover's Halewood Factory - History in Liverpool," Tech. Rep., 2020. [Online]. Available: https://www.roverparts.com/roverlog-news-blog/halewood-factory/

[122] B. News, "UK GDP: Economy shrank at end of 2012," *BBC News*, Jan. 2013. [Online]. Available: https://www.bbc.com/news/business-21193525

[123] H. Exchange, "Consolidated Plan Regulations and Federal Register Notices," 2006. [Online]. Available: https://www.hudexchange.info/programs/consolidated-plan/consolidated-plan-regulations-and-federal-register-notices

[124] D. Philp, *A $500 House in Detroit: Rebuilding an Abandoned Home and an American City*. Simon and Schuster, Apr. 2017.

[125] N. Reid, M. C. Carroll, and X. Ye, "The Great Recession of 2007-2009," *Economic Development Quarterly*, vol. 27, no. 2, pp. 87–89, May 2013, publisher: SAGE Publications Inc. [Online]. Available: https://doi.org/10.1177/0891242413485633

[126] N. A. Sansa, "The Impact of the COVID-19 on the Financial Markets: Evidence from China and USA," Rochester, NY, Apr. 2020. [Online]. Available: https://papers.ssrn.com/abstract=3567901

[127] R. Milkman and S. Luce, "Labor Unions and the Great Recession," *RSF: The Russell Sage Foundation Journal of the Social Sciences*, vol. 3, no. 3, pp. 145–165, 2017, publisher: Russell Sage Foundation. [Online]. Available: https://muse.jhu.edu/article/659928

[128] D. U. Himmelstein and S. Woolhandler, "Public Health's Falling Share of US Health Spending," *American Journal of Public Health*, vol. 106, no. 1, pp. 56–57, Jan. 2016. [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4695931/

[129] Davalon, "History of the Affordable Care Act (Obamacare) | eHealth," 2022. [Online]. Available: https://www.ehealthinsurance.com/resources/affordable-care-act/history-timeline-affordable-care-act-aca

[130] C. J. Goodman and S. M. Mance, "Employment loss and the 2007-09 recession: An overview," *Monthly Lab. Rev.*, vol. 134, p. 3, 2011.

[131] M. Dunn and A. Blank, "Job market continued to improve in 2017 as the unemployment rate declined to a 17-year low : Monthly Labor Review: U.S. Bureau of Labor Statistics," 2018. [Online]. Available: https://www.bls.gov/opub/mlr/2018/article/job-market-continued-to-improve-in-2017-as-unemployment-rate-declined-to-a-17-year-low.htm

[132] D. Nakamura, "Trump administration announces end of immigration protection program for 'dreamers'," *Washington Post*, 2017. [Online]. Available: https://www.washingtonpost.com/news/post-politics/wp/2017/09/05/trump-administration-announces-end-of-immigration-protection-program-for-dreamers/

[133] Y. Demyanyk and O. Van Hemert, "Understanding the subprime mortgage crisis," *The Review of financial studies*, vol. 24, no. 6, pp. 1848–1880, 2011.

[134] G. H. Popescu, "The consequences of the automotive sector crisis on the US manufacturing system," *Journal of Self-Governance and Management Economics*, vol. 2, no. 4, pp. 107–115, 2014, iSBN: 2329-4175 Publisher: Addleton Academic Publishers.

[135] D. Simon, G. Corrie, and N. Harini, "Rethinking Urban Sustainability and Resilience," in *Urban Planet: Knowledge towards Sustainable Cities*. Cambridge: Cambridge University Press, 2018, pp. 149–162.

[136] National Academies of Sciences, Engineering, *Pathways to Urban Sustainability: Challenges and Opportunities for the United States*, Oct. 2016.

[137] M. Birkin and B. Wu, "A review of microsimulation and hybrid agent-based approaches," in *Agent-Based Models of Geographical Systems*, A. J. Heppenstall, A. T. Crooks, L. M. See, and M. Batty, Eds. New York, NY: Springer, 2012, pp. 51–68. [Online]. Available: https://doi.org/10.1007/978-90-481-8927-4_3

[138] N. Jiang, A. T. Crooks, H. Kavak, A. Burger, and W. G. Kennedy, "A method to create a synthetic population with social networks for geographically-explicit agent-based models," *Computational Urban Science*, vol. 2, no. 1, p. 7, Feb. 2022. [Online]. Available: https://doi.org/10.1007/s43762-022-00034-1

[139] A. Ford, S. Barr, R. Dawson, J. Virgo, M. Batty, and J. Hall, "A multi-scale urban integrated assessment framework for climate change studies: a flooding application," *Computers, Environment and Urban Systems*, vol. 75, pp. 229–243, 2019.

[140] K. Happe, K. Kellermann, and A. Balmann, "Agent-based Analysis of Agricultural Policies: an Illustration of the Agricultural Policy Simulator AgriPoliS, its Adaptation and Behavior," *Ecology and Society*, vol. 11, no. 1, 2006.

[141] J.-Y. Kang and J. Aldstadt, "Using multiple scale spatio-temporal patterns for validating spatially explicit agent-based models," *International Journal of Geographical Information Science*, vol. 33, no. 1, pp. 193–213, 2019.

[142] G. C. Galster, "Gentrification as Diversification: Why Detroit Needs It and How It Can Get It Symposium," *Journal of Law in Society*, vol. 4, no. 1, pp. 29–44, 2002.

[143] J. J. Betancur, "Can Gentrification Save Detroit - Definition and Experiences from Chicago Symposium," *Journal of Law in Society*, vol. 4, no. 1, pp. 1–12, 2002.

[144] T. Pride, "Resident-Led Urban Agriculture And The Hegemony Of Neoliberal Community Development: Eco-Gentrification In A Detroit Neighborhood," p. 174, 2016.

[145] B. Doucet, "Deconstructing Dominant Narratives of Urban Failure and Gentrification in a Racially Unjust City: The Case of Detroit," *Tijdschrift voor economische en sociale geografie*, vol. 111, no. 4, pp. 634–651, 2020.

[146] N. Bagheri-Jebelli, A. Crooks, and W. G. Kennedy, "Capturing the effects of gentrification on property values: An agent-based modeling approach," in *The 2019 Computational Social Science Society of Americas Conference*, Santa Fe, NM, 2019.

[147] T. C. Schelling, "Dynamic models of segregation," *The Journal of Mathematical Sociology*, vol. 1, no. 2, pp. 143–186, 1971.

[148] R. Farley, C. Steeh, T. Jackson, M. Krysan, and K. Reeves, "Continued racial residential segregation in detroit: "chocolate city, vanilla suburbs" revisited," *Journal of Housing Research*, vol. 4, no. 1, pp. 1–38, 1993.

[149] J. T. Darden and R. W. Thomas, *Detroit: Race Riots, Racial Conflicts, and Efforts to Bridge the Racial Divide.* Michigan State University Press, 2013. [Online]. Available: http://www.jstor.org/stable/10.14321/j.ctt7ztb49

[150] F. de Oliveira Capela and J. E. Ramirez-Marquez, "Detecting urban identity perception via newspaper topic modeling," *Cities*, vol. 93, pp. 72–83, Oct. 2019.

Curriculum Vitae

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