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Network Structures and Partisan Dynamics: Examining the Effect of Different Neighborhood Networks on Partisan Homogeneity across the Urban-Rural Divide.

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Abstract

In recent years, polarization in opinions and political preferences has intensified in many societies, driven by complex interactions between interpersonal social influence processes, specific meso-level conditions like network structures, and macro-level outcomes such as partisan polarization. This research examines how meso-level conditions, particularly network structures, influence partisan homogeneity across the urban-rural divide. Using a Bounded Confidence Model, I simulate partisan affiliation convergence and polarization in both urban and rural settings, initializing the simulation with US voter registration data to address criticisms of Agent Based Models for lacking empirical validation. The findings suggest that rural neighborhoods experience a greater increase in partisan homogeneity than urban areas, primarily due to the influence of network structures rather than a narrower socialization process.

Github Repository to replicate the results can be found here:

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1 Introduction

Since Axelrod (1997, p. 203) asked, "if people tend to become more alike in their beliefs, attitudes, and behavior when they interact, why do not all such differences eventually disappear?", various models have explored how diversity in beliefs, attitudes, and political behavior persists despite social influence reducing differences (Macy et al., 2003; Hegselmann & Krause, 2002; Deffuant et al., 2000; Flache et al., 2017; Allport, 1954). Recent research has focused on complex neighborly interactions over time, revealing new mechanisms of social influence (Feliciani et al., 2023; Flache, 2019a). Simultaneously, political behavior research highlights the importance of context in shaping political preferences (Tingsten, 1937).

This research aims to explore how context impacts political behavior, particularly through neighborhood differences across the urban-rural divide. Scholars have long argued that local environment characteristics influence political attitudes (Books & Prysby, 1991; Tingsten, 1937; Butler & Stokes, 1971; Books & Prysby, 1988; Gallego et al., 2016), suggesting mechanisms like contact, interaction, and information flow that depend on local network structures (Allport, 1954; Huckfeldt & Sprague, 1987). Different environments create varied social networks, leading to differences in social influence and opinion convergence, especially across the urban-rural divide, which has recently gained relevance in shaping political behavior (Haffert & Mitteregger, 2023). This leads to the following research question:

How do variations in neighborhood network structures affect partisan convergence and polarization across urban and rural neighborhoods?

New neighborhood and granular geographic data allow researchers to model network structures more accurately, enabling them to examine social influence using real survey and census data. This study utilizes publicly available North Carolina Voter Register Data [1] to build two social influence models simulating partisan affiliation in an urban and a rural part of North Carolina. The focus is on the effect of neighborhood homogeneity and density on partisan convergence by comparing voting behavior from 2016 to 2024.

I argue that voters' partisan conversion will be stronger in rural than urban neighborhoods due

[1] The data can be found here: https://www.ncsbe.gov/results-data/voter-registration-data

to the lower diversity of interactions (Hyp 1) and the narrower socialization process (Hyp 2). The paper is structured as follows: first, I review existing literature, focusing on the urban-rural divide, contextual political behavior, and political socialization. Then, I discuss social influence models and formulate my hypotheses. After that, I describe the North Carolina case, its politics, and the rise of unaffiliated voters. The paper continues with data and design, presenting the model, parameters, and attributes, followed by results and a discussion of the limitations before concluding.

2 Literature Review

2.1 The Urban-Rural Divide in Political Behavior

The urban-rural divide in political behavior has gained relevance in recent years and is considered one of the world's most significant cleavages (Iammarino et al., 2019; Wilkinson, 2019; Huijsmans & Rodden, 2024; Haffert, 2022; Maxwell, 2019; Jennings & Stoker, 2016; Ford & Jennings, 2020; Cramer, 2016). The concept dates back to Lipset and Rokkan (1967), who described the conflict of interests between the rural elite and the entrepreneurial class after the Industrial Revolution (Hegewald & Schraff, 2022; Lipset & Rokkan, 1967).

Today, political science research on the urban-rural divide is based on differences in political behavior across urban and rural populations and their effects on voting behavior. It is argued that the experience of "different types of lives in different types of communities rooted in specific places" is not only physically dividing people but also with regard to their culture, values and preferences (Luca et al., 2023; Jacobs & Munis, 2023, p. 1102). This divide was evident in the last US presidential elections: While Obama, Clinton, and Biden were successful in urban areas, they struggled in rural areas, which are Republican strongholds (Rodden, 2019; Scala & Johnson, 2017). As population density increases, the probability of identifying as a Democrat increases, while Republican identification decreases (Gimpel et al., 2020). Although it is incorrect to view rural areas as homogenous (Scala et al., 2015) or to define the urban-rural divide as a simple dichotomy (Scala & Johnson, 2017), several characteristics can be identified: Rural citizens tend to have more nationalistic attitudes towards immigration and more conservative values regarding cultural diversity (Jennings & Stoker, 2016; Maxwell, 2020; Maxwell, 2019; Hegewald & Schraff, 2022; Huijsmans & Rodden, 2024). They also show lower levels of political

trust and less satisfaction with democracy (García Del Horno et al., 2023; McKay et al., 2021). In contrast, cities often exhibit more progressive, tolerant and liberal values, embodying more diversity and cosmopolitanism (Haffert & Mitteregger, 2023; Maxwell, 2019; Luca et al., 2023). Media coverage tends to focus on cities and their interests rather than rural areas (Cramer, 2016). New ideas about technology, lifestyles, and social issues, such as LGBTQ and religion, are prevalent in cities but must travel from urban to rural areas (Gimpel et al., 2020). However, greater exposure to external ideas increases both the pressure to change and the capacity for tolerance (Allport, 1954; Gimpel et al., 2020).
This exposure to diversity translates into the impact of scale, measured by population density, describing place-based differences in the number of people we encounter daily (Gimpel et al., 2020). This reveals an important attribute describing the different network structures of urban and rural locations. Moreover, space is a primary source of homophily, as we are more likely to have contact with those geographically close to us (McPherson et al., 2001). Urbanites have a larger and more diverse number of people to interact with, though interactions tend to be more superficial than in smaller, more homogenous communities (Gimpel et al., 2020). In sparser communities, frequent interactions within small groups lead to interdependent value distributions and long-standing behavior and thought patterns (Bosworth & Snower, 2019; Knoke & Henry, 1977; Greenfield & Reyes, 2015; Gimpel et al., 2020). Therefore, already in 1987, Madsen argued that urban areas, with greater diversity within a moderate geographic distance, produce networks with higher racial and ethnic heterogeneity (Marsden, 1987). Research has shown that location affects socialization and partisan identification, and there is an increasing psychological distance between urban and rural residents due to differences in political efficacy, responsiveness, morals, and values (Jacobs & Munis, 2023; Kenny & Luca, 2021; García Del Horno et al., 2023; McKay et al., 2021; Gimpel et al., 2020).

Understanding these differences requires examining the theory of contextual political behavior and its impact on political socialization.

2.2 Context vs. Composition

In the political behavior literature, researchers have debated whether similar values and preferences in a geographic area arise from contextual or compositional effects (Maxwell, 2020;

Maxwell, 2019). Similarly, others examined political (dis)agreement in social networks, determining whether it results from selection or influence (Bello & Rolfe, 2014).

Studies on contextual effects argue there is something specific about the experience of living in a certain place that explains political preferences via long-term political socialization (Maxwell, 2019; Enos, 2017). In contrast, literature on compositional effects argues that different areas of residency vary in their demographic makeup resulting in different political preferences (Schelling, 1971; Scala & Johnson, 2017; Maxwell, 2019). Thus, it is assumed that people are increasingly sorting themselves based on their political and cultural affiliations, with individuals with similar opinions living in the same locations. Consequently, those with higher education levels are more likely to reside in cities, primarily due to the available infrastructure and cultural alignment (Schelling, 1971; Maxwell, 2019; Haffert, 2022).

For decades scholars have argued that local environment characteristics affect individual political attitudes (Tingsten, 1937; Allport, 1954; Butler & Stokes, 1971; Books & Prysby, 1988; Gallego et al., 2016). Political scientists generally agree that geographical environments influence political behavior, but methodological issues obscure the mechanisms of this influence (Books & Prysby, 1991, p. 17).

Earlier political geography studies faced challenges in establishing causation within geographic contexts (Sands, 2017; King, 1996). Data limitations led to different measures of contextual effects, mostly either using a narrow definition by restricting the analysis to cases where context is measured as some individual-level variable that is averaged over the contextual units (Boyd & Iversen, 1979; Przeworski, 1974; Huckfeldt & Sprague, 1987) or using a broader definition exploiting characteristics and variables lacking the individual correspondent (Lazarsfeld & Menzel, 1969). However, geographic variables remain statistically significant even after accounting for socio-demographic composition factors, emphasizing the relevance of the social context where people share and reinforce their preferences, values, and beliefs, growing more similar through contact (Maxwell, 2019; McPherson, 2004; Gimpel et al., 2020).

This paper follows the "Interpersonal Interaction Theory," which attributes contextual effects to direct social interaction (Weatherford, 1982). Based on contact theory, which posits that under certain conditions, intergroup prejudices can be reduced through cooperative interaction (Allport, 1954), this perspective emphasizes intergroup relations. Context is crucial, as it can either facilitate integration and contact or foster prejudice and polarization through segregation

(Enos, 2017). As outlined earlier, the scale and diversity of daily contacts differ significantly between urban and rural areas, likely leading to different contextual effects. Therefore, this paper aims to demonstrate the importance of contextual effects and argues for their inclusion in spatial analyses to understand the formation of political preferences and partisan affiliation. The argument is that an essential contextual factor shaping political behavior is the variation in scale and diversity of contacts as well as different socialization and social influence mechanisms between urban and rural regions. The following section will explore this further.

2.3 Social Influence and Political Socialization

Geographic space influences not only the number and presence of interactions but also the "thickness" of relationships, including the frequency and complexity of contact (McPherson et al., 2001, p. 430). It affects socialization processes facilitated by specific environments (Arnett, 1995; McPherson et al., 2001). Socialization is understood as the "process of adaption of an individual to a society which, in turn, shapes each of its members in accordance with the existing culture" (Dubrov & Tatarko, 2018, p. 118). Research on political socialization shows that cultures and contexts differ in the restrictiveness they impose on cultural values and the degree of deviation allowed, leading to narrow and broad socialization forms (Arnett, 1995). Broad socialization encourages individualism, independence, and self-expression, while narrow socialization favors obedience and conformity, discouraging deviation from cultural expectations (Arnett, 1995). Broad socialization allows a wide range of individual differences, whereas narrow socialization restricts variation, pushing individuals toward conformity (Arnett, 1995). Whilst socialization is an interactive process where individuals act as both subjects and objects in their environment, individuals take a more active role in broad socialization (Dubrov & Tatarko, 2018). This interactive nature explains differences and similarities depending on the social context. Dubrov & Tatarko (2018) adapt Arnett's (1995) distinction to urban and rural areas in Russia and argue that broad socialization is more prevalent in cities, while narrow socialization is found in rural areas. The main difference between urban and rural areas is social connections and interactions. Contacts are fewer but more stable in rural areas and numerous but less stable in cities (Dubrov & Tatarko, 2018). Rural areas have "traditional neighborhood community" elements with a permanent population, close kinship, and stronger relations (Dubrov & Tatarko, 2018, p. 120). Social norms and rules are more adhered to in rural areas due to stricter regulations and more acceptance of behavioral deviations in urban areas. This makes it easier for individuals in cities to adopt new ways of thinking or acting, while those in rural areas face greater scrutiny and judgment, making deviation from norms more difficult (Dubrov & Tatarko, 2018).

Thus, citizens in rural areas live in more homogeneous, tightly knit, and smaller communities than urban dwellers. This leads to a lack of cultural and political diversity, resulting in homogeneous political and partisan preferences. I argue that voters' partisan conversion will be stronger in rural neighborhoods, leading them to switch to the majority party. In contrast, I do not expect such an effect in urban areas. The next section will review models of social influence and pave the way for the model used in this paper.

2.4 Models of Social Influence

"**Social Influence:** The tendency to alter one's opinions, attitudes, beliefs, or customs, to more closely resemble those of influential others" (Flache, 2019b).

The starting point for Social Influence Models was the assumption that in many social encounters, individuals modify their opinions, attitudes, beliefs, or behavior towards resembling more those of others they interact with (Flache et al., 2017). On the one hand, research has found that social influences reduces differences between people, making them more similar. Yet, on the other hand, there is no global consensus about the complex dynamics of social influence in interpersonal interactions on the collective level (Flache et al., 2017; Axelrod, 1997). Thus, we face uncertainty about the specific mechanisms that are at play in social influence dynamcis which either lead to assimilation or repulsion in interpersonal influence. This is why Agent-Based Modelling can be fruitful as such models can be built to represent social agents directly when they interact with each other and with their environment (Chattoe-Brown, 2014, p. 2; Flache, 2019b; Flache, 2019a). They can move beyond purely descriptive results of interpersonal dynamics at the micro-level in real-world settings. Instead- and more importantly- they can develop patterns of opinion diversity based on assumptions and their relationship with contextual variables (e.g., group size or initial diversity) observed at the macro-level of a group (Flache, 2019a). Thus, Agent Based Models (ABM) with empirically observed data might be able to transcend conventional correlational empirical research. However, it is required to not only understand but also isolate and disentangle the different factors and mechanisms that potentially affect the outcomes of social influence of interpersonal social interaction in the real world (Flache, 2019b).

2.5 Classic Assimilation Model

The earliest model of social influence and collective opinion formation dynamics was inspired by conformity experiments in the 1950-60s (French, 1956; Abelson, 1964).
Abelson (1964) argued that in interaction between two group members "each member of the group changes his attitude position towards the other by some constant fraction of the 'distance' between them", so that repeated social influence would always reduce opinion differences and lead to consensus in well connected group settings (Flache et al., 2017, §1.6). This was explained by social balance theories arguing for the human tendency to reduce dissonance from disagreement with others and thus seeking to be similar to people they like or respect (Festinger, 1962; Heider, 1946). However, this view has become outdated as empirical work contradicts a societal tendency for consensus and instead shows increasing dissimilarity and polarization. Thus, the way was paved for the Bounded Confidence, also called Similarity Bias Model, that tried to address such shortcomings.

2.6 Bounded Confidence Model

Bounded Confidence Models (Hegselmann & Krause, 2002; Deffuant et al., 2000; Deffuant, 2002) argue that the degree of social influence between connected individuals is dependent on their similarity. It assumes that if opinion disagreement between agents i and j is too big, interaction will not lead to opinion assimilation as agent i will lose "confidence." They define a Confidence Threshold ϵ based on different personal, contextual, or social factors, with μ representing the Opinion Convergence Rate. Thus, influence from another actor j can only affect i's opinion if their disagreement $|o_i - o_j|$ does not exceed this threshold.

$$\text{Opinion Update} = o_{i,t+1} = o_{it} + \Delta o_{it} = o_{it} + f_w(o_{it}, o_{jt})(o_{jt} - o_{it}) \tag{1}$$

$$\text{Assimilation Weights} = f_w(o_i, o_j) = \begin{cases} \mu, \text{ if } |o_i - o_j| \leq \epsilon \\ 0, \text{ otherwise} \end{cases} \tag{2}$$

Bounded Confidence Models are drawing from the principle of homophily (McPherson, 2004; McPherson et al., 2001; Lazarsfeld & Menzel, 1969), stating that people are more likely to connect and interact with similar others. Homophily implies that distance in terms of social characteristics translates into network distance, the number of relationships through which a piece of information must travel to connect two individuals (McPherson et al., 2001). It can be derived from structural patterns of social interactions, sorting similar people into similar spaces where they meet, communicate and influence each other such as neighborhoods or workplaces (Flache et al., 2017; McPherson et al., 2001). There are different ways to model homophily which will be explained in detail in section 5.3.

2.7 Repulsive Influence Model

The third strand of social influence models are called Repulsive Influence Model. They are combining assimilation with differentiation following the assumption that some interactions lead to a "boomerang" effect in such a way that individuals adjust their opinions to become more dissimilar to people they disagree with (Feliciani et al., 2023; Flache et al., 2017; Flache, 2019a). Also this model family derives its theoretical foundation from Social Balance and Cognitive Dissonance Theories (Festinger, 1962; Heider, 1946) but unlike Bounded Confidence Models, they argue that social influence is not only caused by homophily but also by xenophobia (Flache & Macy, 2011; Flache, 2019a). This is motivated by social identity and group theory (Tajfel et al., 1979) leading individuals to change their opinions to promote their ingroup position or to distance themselves from the outgroup opinions (Flache, 2019a).

Using a Bounded Confidence Model, I will simulate partisan convergence and polarization in urban and rural environments by initializing the simulation model with US voter registration data to explore the hypotheses outlined in the next section.

3 Hypotheses

The differences in socialization and interaction patterns between urban and rural locations as reviewed in the previous section, lead me to the following hypotheses:

The number of interaction is higher in urban areas and lower in rural. Moreover, the diversity of interaction is different, with urbanites interacting with more different people than rural citizens. Over time, this will lead to a higher partisan affiliation convergence in rural areas compared to urban areas.

Hypothesis 1 [H1] The network structures in urban and rural environments differ. Urban areas, characterized by higher diversity in interactions and smaller individual influence, will exhibit greater partisan diversity over time. Conversely, rural areas, with lower diversity of interactions and stronger individual influence, will show higher convergence towards a single partisan affiliation.

To model this I use a different parameters for the number of interactions, which likely results in urban citizens interacting with a more diverse and varied group of people, while rural citizens will interact more frequently with the same individuals. Moreover, I am using a Bounded Confidence Model in which the influence weight of interpersonal interactions is based on their similarity which will likely lead to differences in the influence of interactions between urban and rural areas.

Hypothesis 2 [H2] The type of socialization differs significantly between urban and rural areas. Urban environments, with broad socialization networks, facilitate diversity in partisan affiliation. In contrast, rural areas, characterized by narrower socialization networks promote convergence towards a single affiliation.

To model this, I use the Blau Index to measure the homogeneity of the context as well as the local partisan exposure. In rural areas where the Blau Index indicates high partisan homogeneity, the influence of interactions is amplified by a constant C and a penalty parameter p, leading to stronger convergence towards a single partisan affiliation. This adjustment reflects the greater impact of homogeneous social interactions in rural areas, reinforcing the tendency towards partisan uniformity.

By running an ABM over the specified period of 400 epochs, I aim to observe these dynamics and validate my hypothesis that urban environments foster partisan diversity in partisan affiliations while rural areas foster homogeneity.

Defining Homogeneity and Diversity:

Homogeneity or convergence in partisan behavior and social interactions refers to the degree to which a group shares similar characteristics or affiliations (Bishop & Cushing, 2008; McPherson et al., 2001). Specifically, partisan homogeneity indicates the extent to which individuals within a network align with the same political party. In homogeneous contexts, there is high similarity and low variance, with most individuals sharing the same partisan affiliation.

Diversity, on the other hand, refers to the presence of diverse and often competing characteristics or affiliations within a group (Putnam, 2007). In partisan behavior, it is indicated by a wide range of political affiliations and opinions among individuals.

4 The Case: North Carolina

"Both Democrats and Republicans agree: Victory in 2020 runs through North Carolina. Whichever party wins in NC will likely prevail on Election Day." North Caroline Republican Mailer, May 2020

In this paper, I will focus my analyses on the case of North Carolina (NC) which has a number of attributes that make it the ideal case study to study political behavior in the US. The next section will discuss the case of NC.

4.1 Politics of North Carolina

North Carolina's distinctive voting patterns and political landscape have established its pivotal role in US elections. But why is that the case?

After the breakup of the Democratic South in the late 1960s, there was a consistent bifurcate dynamic in the politics of NC: while the presidential and senate level was generally dominated by Republicans, the state level mostly stayed Democratic. Both dynamics could change due to specific campaigns, with Democrats occasionally winning at the federal level or Republicans taking various state offices (Bullock & Rozell, 2021; Bitzer et al., 2022).

Then, in 2008, Democrats were successful in federal and state elections, ultimately resulting in the "nationalization" of voting patterns in the years to come, where federal and state elections were more consistent (Bullock & Rozell, 2021, p. 116). Since then, NC has been considered a swing state for a number of election cycles (Cooper, 2024; Bitzer et al., 2022) with intense partisan competition whilst simultaneously retaining an average distribution across most demographic and political attributes (Bitzer et al., 2022; Bullock & Rozell, 2021; Cooper, 2024). Yet, as of 2020 there are more Unaffiliated registrants than registered Republicans or Democrats in North Carolina (Bitzer et al., 2022), making it not just one purple state "but one that is large and purple" (see: Primary Primers).[2] Thus, NC could able to provide a difference between losing and winning in the presidential elections which is known by the parties.

4.2 The Unaffiliated Voters

The large number of unaffiliated voters in the US in general, but in North Carolina specifically, must be addressed to understand the unique political dynamics and their influence in the ABM. Since the 1970s, a not negligible part of Americans have identified as independent or unaffiliated (Klar & Krupnikov, 2016).[3] This phenomenon gained attention in 1992, when Keith et al. thoroughly analyzed the independent voters and found they often exhibit clear and consistent partisan preferences. (Keith et al., 1992). Moreover, research has shown that there are no strong demographic or ideological differences between partisan and independent citizens except for their stance on expressing a clear partisan affiliation (Klar et al., 2022).

As of 2024, a large number of voters identify as independent, with 80-90 percent leaning towards Democrats or Republicans. These "leaners" engage in politics and vote for their preferred party but do not openly express a party affiliation, which has led them to be labeled as "closet Democrats and Republicans" (Keith et al., 1992). The reason for concealing their political affiliations lies in the increasingly hostile and affectively polarized nature of partisan politics in the US (Klar & Krupnikov, 2016). Hence, unaffiliated or independent voters often choose to remain "undercover" with their partisan affiliation, thereby avoiding public displays of partisanship, such as advocating for a party in conversations with friends or coworkers or wearing political signs or showing campaign posters (Klar & Krupnikov, 2016). Another incentive for being unaffiliated is specific to NC's semi-closed primaries, allowing unaffiliated voters to choose

[2] In U.S. elections, the color purple is often used to represent a political region or state that is neither strictly Democratic (blue) nor strictly Republican (red), but rather a mix of both.

[3] In the following, the terms independent and unaffiliated are being used interchangeably.

to vote in either party's primary. Despite this flexibility, many unaffiliated voters consistently vote in one party's primary, supporting the notion of independent voters as "shadow partisans" (Bitzer et al., 2022).

Development of Partisan Afilliations

Figure 1 illustrates an increase in partisan homogeneity in the rural area from 2014 to 2024, evidenced by the rise in Republican and the decline in Democratic voteshare. This results in a more homogeneous partisan distribution, with the majority of rural voters supporting the Republican party. In contrast, urban areas exhibit a different trend: the partisan voteshare distribution becomes more balanced over time, leading to a more equal representation of different partisan affiliations and thus a more fragmented partisan landscape.
However, in both contexts in North Carolina, we also see an increase in unaffiliated voters, which makes it more difficult to measure partisan polarization or homogeneity. Thus, one has to accurately account for unaffiliated voters and their influence in the model.

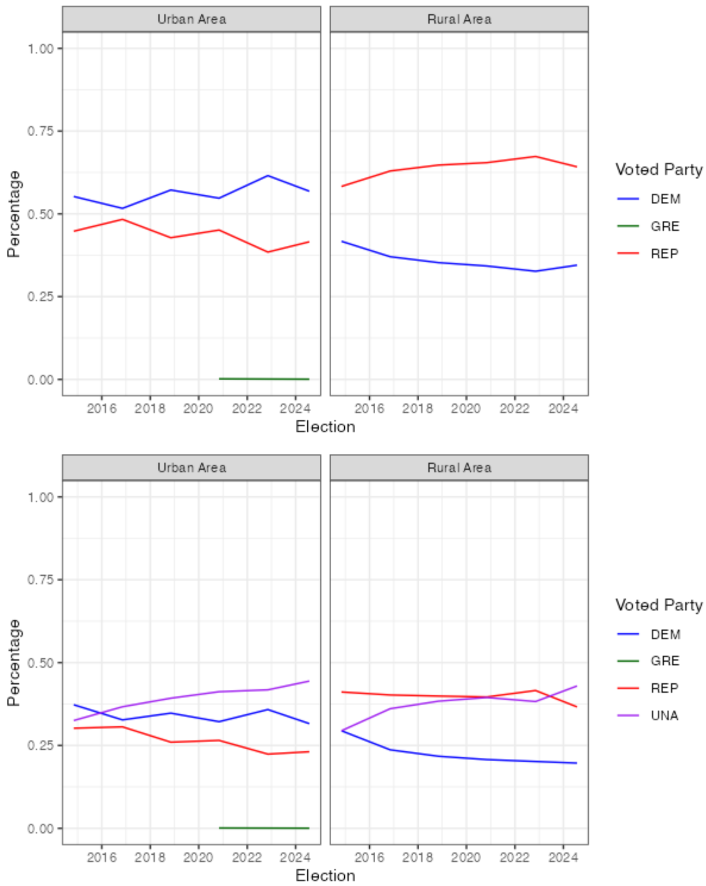

Figure 1. Partisan Affiliation in singular Urban and Rural ZIP Codes as chosen in the ABM

Descriptive results of party affiliations in the rural as found in Figure 1 might be partly explained by the risk aversion of former Democratic rural residents who find themselves in increasingly homogeneous Republican neighborhoods (Werner, 2016). Consequently, the rise in unaffiliated voters may reflect former Democrats' efforts to navigate the intense political landscape of their neighborhoods by opting for unaffiliation rather than continuing to identify as Democrats. This mechanism is less pronounced in urban areas, where the rise of the unaffiliated voters could reflect a more gradual shift in party affiliation in a more fragmented political landscape. This needs to be accurately modeled in the ABM as discussed in 5.3.3.
I assume that the rise in unaffiliated voters in both urban and rural contexts can be explained by people's tendency for risk aversion which is more pronounced in homogeneous contexts, thus leading to a stronger increase in Unaffiliated voters coupled with a decrease of Democrats in the rural neighborhood.

The general trends shown in the ZIP Codes chosen for the ABM are replicated using data across all urban and rural neighborhoods in North Carolina and are found in the Appendix in table 15.

4.3 Urban and Rural Dynamics of North Carolina

I am using the US Department of Agriculture's Rural-Urban Commuting Areas codes (RUCA) which have been found to perform well in classifying urban and rural areas (Mulrooney & McGinn, 2022). The RUCA codes are derived from the 2010 census and American Community Survey data, using criteria such as population density, urbanization, and commuting patterns to identify urban cores and their adjacent economically integrated territories. By applying these criteria to census tracts and ZIP Codes instead of counties, RUCA codes provide a more detailed geographic pattern of urban and rural areas than other classifications.[4] Figure 2 shows the distribution of the RUCA Classification in North Carolina. To determine one rural and one urban neighborhood, I employed a mixture of indicators as I wanted to display the complexity of rural areas adequately. Firstly, I used the USDA's RUCA indicator which is available on ZIP Codes level and classifies urbanity and rurality based on scale from 1 to 10, 10 being the most

[4]Since the decennial update of the RUCA Codes 2020 is still under development and expected in fall 2024, I have to use the 2010 Codes.

rural ZIP Codes. I chose all ZIP Codes with either 1 or 10 as RUCA value and then examined the population density, size and overall demographics.

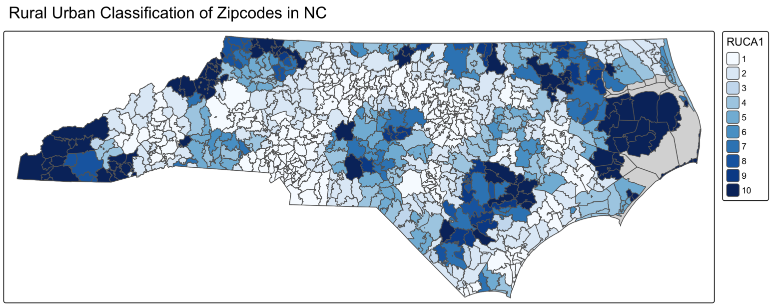

Figure 2. Map of North Carolina

To minimize the noise and effects of bordering neighborhoods, I selected an urban ZIP Code based on its high population density of 6,213 people per square mile, significant infrastructure development, and diverse demographic composition, which collectively represent stereotypical urban characteristics. For the rural ZIP Code I decided to chose a neighborhood that is partly isolated from the mainland North Carolina, has a population density of 98 people per square mile and a size of 7.95 square miles.[5]

Metric	**Urban Neighborhood**	**Rural Neighborhood**
Population	11,195	777
Population Density	6,213 people per sq mi	98 people per sq mi
Size	1.80 sq mi	7.95 sq mi

Table 1. Statistics for both Neighborhoods

I have intentionally varied the number of citizens in different neighborhoods to demonstrate the impact of diversity in interactions. Consequently, with the same probability and proximity threshold, interactions in urban areas are more likely to involve different individuals, whereas interactions in rural areas are more likely to occur with the same individuals.

[5]Due to data protection, I can not give further information regarding the name and location of both ZIP Codes.

5 Data and Design

5.1 Overview

The following sections describe the model and data used in this project, following the ODD (Overview, Design concepts, Details) protocol for describing Individual- and Agent Based Models (Grimm et al., 2006).

Purpose of ABM:

The purpose of this Agent-Based Model (ABM) is to simulate neighborhood interactions in two different network contexts, aiming to analyze their impact on partisan affiliation and the underlying mechanisms influencing these interactions. Given the literature on the urban-rural divide, which suggests distinct contextual effects and patterns in urban and rural settings, this ABM aims to explore these differences. The model is designed to incorporate various mechanisms as distinct parameters and functions, and therefore allowing for a detailed examination of these different influences. The ABM shows probabilistic behavior in a set geographic space but also includes stochastic elements. All parameter and elements will be explained in more detail in section 5.3.

Input Data and Ethics Approval

Voter Registration Files, maintained by each US county, include details of individuals registered to vote in a specific jurisdiction. This paper uses the 2024 North Carolina Voter Registration Data, which provides up-to-date information on voter registration status, demographics, party affiliation, name, and address for over 7 million voters. While individual voter history data for the past 10 years is available, it limits the analysis to this time frame. The data, publicly accessible without requiring personal information or data safety measures, can be downloaded here:

Since the required voter registration data is publicly available in North Carolina, obtaining Ethics Approval was straightforward. In consultation with my supervisor, I took several measures to protect and anonymize the data. After receiving approval from the Ethics Committee, I securely stored the data in a password-protected folder. To ensure voter anonymity, I removed the name variable from the dataset and focused only on the two selected ZIP Codes, deleting all other data. I used the addresses to derive coordinates and create proximity matrices but deleted the address variable once this was done.

For the analysis, I ensured that data plots did not display ZIP Codes, street names, or other spatial identifiers that could reveal the neighborhoods. Apart from summary statistics and spatial shapes, no other information can be derived to identify the neighborhoods. These steps were taken to ensure the privacy and protection of the voters involved in this project.

I will run two models in total: the first for the rural and the second for the urban ZIP Code.

Process Overview and Scheduling

The model starts with an initial network with a set configuration of agents, their location and attributes based on the voter registration data. At the beginning of each epoch, exposure values for each agent are recalculated, updating agents' exposure to in- and outgroup partisans based on their k nearest neighbors. For each agent (ego), I am using a Poisson distribution to calculate their number of interactions per epoch which ranges between 0 and 7 interactions based on empirical data from PEW (PEW, 2018). For each interaction, a potential interaction partner (alter) is selected from agents within the proximity threshold. The ABM then calculates partisan and demographic similarities between interacting agents. If the similarity is strong enough and the interaction thus falls below the confidence threshold of 0.6, the influence (delta_P) of the interaction is defined and influence occurs. The influence is mitigated by each agent's level of stubbornness, a concept that will be explained later, affecting how much their political views are susceptible to change during the interaction. Moreover, if alter belongs to the majority party within ego's proximity and ego's outgroup exposure is high, a penalty p is applied to the probability change. If ego and alter belong to the same party, their vote probabilities are increased based on the interaction weight μ, or decreased if they have different partisan affiliations. After each interaction, the party with the highest vote probability for ego and alter is determined and their voting behavior is updated accordingly. The Blau index for each agent is recalculated based on the updated party proportions of their nearest neighbors. At the end of each epoch, the voting probabilities for all agents are logged. This iterative process continues for 400 epochs, and captures the dynamic interactions between agents and their impact on partisan affiliation.

Figure 3 shows a basic social interaction between two agents ego and alter who are similar enough to influence each other's partisan vote probabilities.

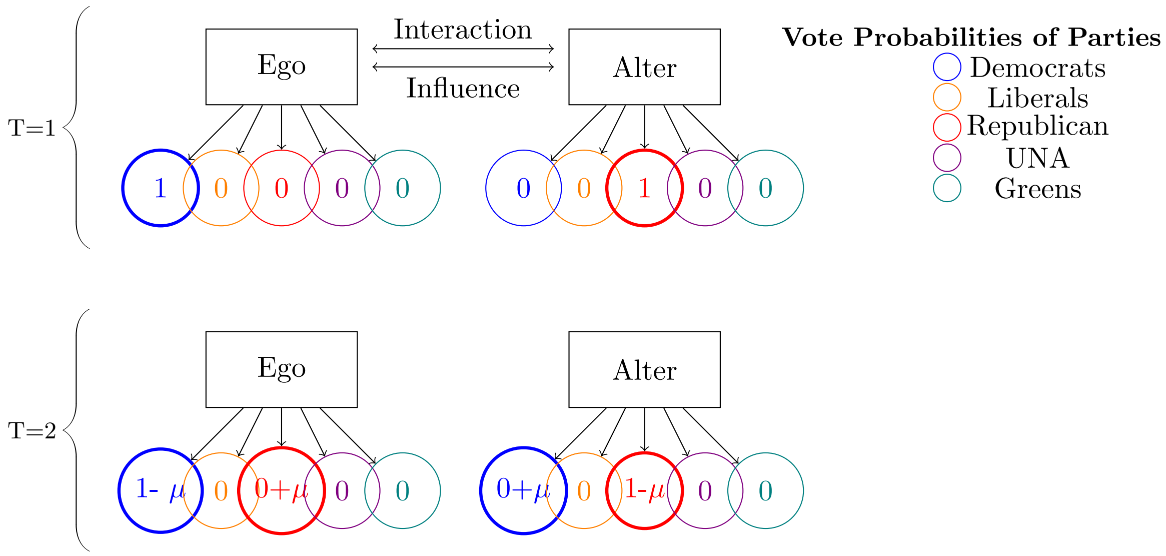

Figure 3. Interaction between two Agents with $W_{\text{ego,alter}}$ < Confidence Threshold
Note: Ego and Alter mutually influence their Vote Probabilities based on the interaction weight μ.
Specific model details are left out.

5.2 Design Concepts and Agents' Attributes

Since the aim of this model is to simulate a realistic model of human behavior, most of the parameter and model decisions have been derived from either empirical data sources or theoretical insights. Agents (ZIP Code residents) are the only entities in this ABM. Following is a list of agent attributes and global variables.

Geographic Location:

The voter registration data gave me access to the voters' addresses. I retrieved the addresses' coordinates using the Google Maps API and then converted them to WGS 84 coordinates.

Partisan Affiliation:

This is a variable that indicates which party the agent has voted for or intends to vote for. The parties in both ZIP Codes that have been voted for are Democratic (DEM), Republican (REP), Liberals (LIB), Greens (GRE), No Labels Party (NLB) or Unaffiliated (UNA).

Race Group, Gender and Age:

The race variable categorized Asian (A), Black or African American (B), American Indian or Alaska Native (I), Two or more Races (M), Other (O), White (W), Native Hawaiian or Pacific Islander (P), Undesignated (U). The gender variable had three categories: Male (M), Female (F) or Undisclosed (U).

The Age variable was derived from the year of birth and then binned into 10 year categories

Vote Probability:

These probability variables represent the likelihood of an individual voting for a specific party. For the party, agents registered with in 2016, the probability is set to 1, for all other probabilities it is calculated as the proportion of times they voted for that party out of their total votes.

Stubbornness:

Previous studies on voting behavior have identified the strength of partisan preferences as an important factor since loyal partisans are less likely to change their vote choice in interaction then people with weaker political identities (Bello & Rolfe, 2014). Therefore, I encoded a variable measuring partisan loyalty called 'stubbornness', counting the length of the initial sequence of identical party values. This length represents the number of consecutive votes for the same party before switching. The raw stubbornness is then normalized dividing it by the total number of votes by that voter.

$$\begin{aligned} L_i &= \text{length of consecutive identical votes in } V_i \\ S_i &= \frac{L_i}{N_i} \end{aligned} \tag{3}$$

where V_i is the votes of voter i in previous elections recorded in dataset and N_i is the length of V_i. This provides a measure of how strongly a voter is aligned with a particular party, using their previous voting behavior to examine the loyalty and stability to that party. If the longest run was unaffiliated, the second longest run was used instead because unaffiliated values were excluded from the stubbornness calculation. This exclusion is based on the assumption that being unaffiliated represents a lack of strong partisan preference, which could distort the measurement of a voter's loyalty to a specific party. Additionally, switching votes from a party to unaffiliated was considered a break in the run, just like switching votes to another party, to accurately reflect changes in voter loyalty.

Blau Index

Blau's Index of Heterogeneity calculates group demographic diversity for nominal or ordinal variables. It is used here to calculate the heterogeneity in race and partisan distribution within each grid. It ranges from 0 to 1, 0 being total homogeneity and 1 total heterogeneity.

$$\text{Blau Index} = (1 - \Sigma p_i^2) \tag{4}$$

where p_i is the proportion of each category across the neighbors. As described before, I calculated the Blau Index and Partisan Exposure for individuals in both neighborhoods using the KNN Algorithm to find the nearest neighbors of an individual i. Due to the differences in agent size in both environments, I decided on 50 neighbors for rural individuals and 200 for urbanites. Figure 4 illustrates the Blau Index. As for the partisan exposure, I used k nearest neighbors and calculated the Blau Index based on the sum of their partisan affiliations. It can be seen that the urban and rural neighborhoods differ significantly in terms of their homogeneity. Whilst the Blau Index ranges from 0.55 to 0.67 in rural areas, it ranges from 0.84 to 0.85 in the urban context, illustrating higher heterogeneity in partisan affiliation.

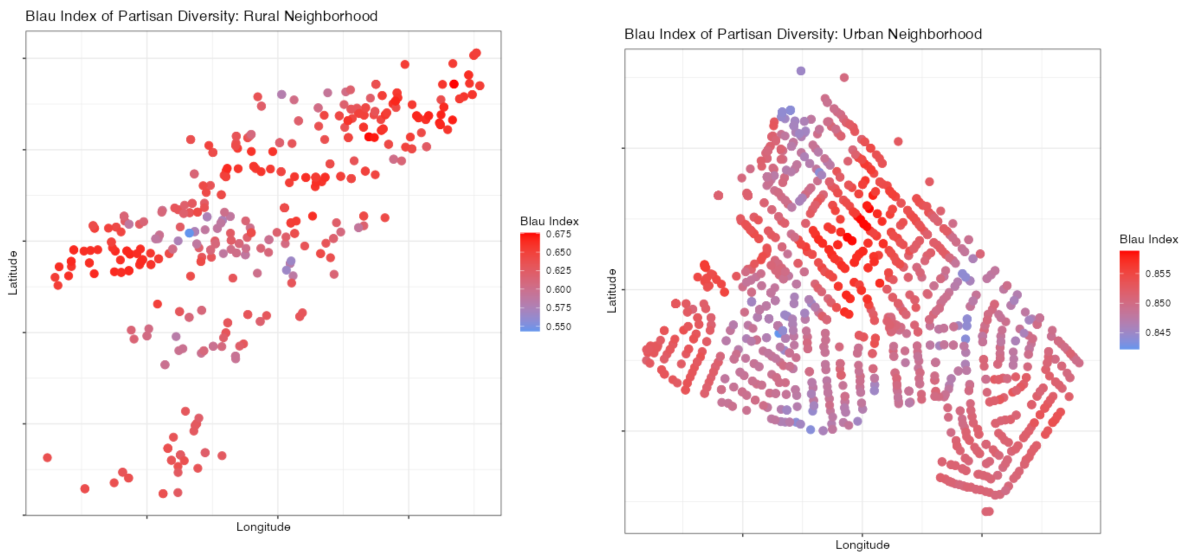

Figure 4. Blau Index Partisan Distribution

The partisan affiliation and the Blau Index are both used in the simulation model as interaction parameter. But also, the homogeneity with regard to other characteristics such as race, gender and age plays an important role. As interaction influence is dependent on agents' similarity, other socio-demographic attributes play a role.

Figure 5 shows the Blau Index for the racial distributions in both neighborhoods. The racial distribution in both locations is much more homogeneous with range from 0 to 0.2 in the rural context and 0.1 to 0.3 in the urban area. Thus, people are much more similar in both ZIP Codes in terms of their race than their partisan affiliation. However, in both figures, it is clearly shown that the rural location is much more homogeneous than its urban counterpart.

Figure 5. Blau Index Racial Distribution

Exposure to Outgroup Partisans:

I determined each agent's exposure to in- and outgroup partisans by assessing their k nearest neighbors, with local outgroup exposure values ranging from 0 to 1. A score of 1 implies that an agent interacts predominantly with outgroup members, while a score of 0 indicates primary exposure to ingroup members. Figure 6 presents these local partisan exposure statistics. Using methods from Brown and Enos (2021), I calculated exposure by weighing the proportion of neighbors from each party equally for 50 rural and 200 urban nearest neighbors. Consequently, rural exposures are more homogeneous, typically Republican, with some unaffiliated. Urban exposures, however, predominantly feature Democrats and unaffiliated voters, with only a small fraction exposed significantly to Republicans. This aligns with the expectation outlined in Hypothesis 2.

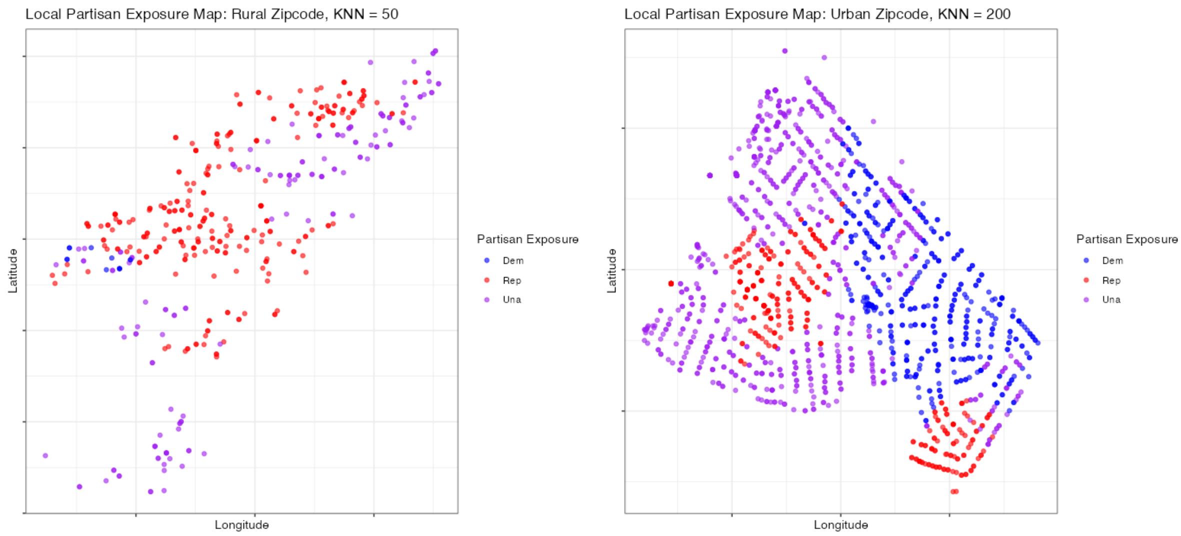

Figure 6. Local Partisan Exposure

5.3 Details: The Bounded Confidence Model

I will be using a **Bounded Confidence Model** where interaction and its influence is not only determined by spatial proximity but also homophily, partisan stubbornness and contextual factors.

5.3.1 Interaction and Influence

Interactions are modeled as dyadic (between pairs of neighbors) and follow a multi-step process, that involves stochastic as well as probabilistic elements. This model does not follow the Hegelsman & Krause (2002; 2015) approach who assume that all agents in the population influence each other simultaneously, that is every agent i adopts in one time step the average opinion of all those whose fulfill the conditions of the Bounded Confidence Model, thus not exceeding the Confidence Threshold. Instead, I follow Deffuant et al. (2000; 2002) and their pairwise interaction mechanism but include a proximity threshold to limit interaction to those agents that are within a defined proximity threshold. However, research has shown that both interaction mechanisms lead to very similar simulation results (Urbig & Lorenz, 2007).

5.3.2 Interaction Frequency

The range for the frequency of interactions for each agent is based on empirical insights from US neighborhood data. Specifically, I used the PEW 2018 Survey Data (PEW, 2018), that asked respondents how often they interact with their neighbors in a month and how much they trust them. As shown in Figure 24 and 25, the number of interaction differs across urban and rural neighborhoods. While rural citizen have a higher mean interaction frequency of 6.75 times per month, ruralites interact on average 5.3 times per month. However, they trust their neighbors more than urban individuals.

To implement this, I use a Poisson distribution function to simulate the number of daily interactions for each agent, based on the specified mean (λ), which represents the average monthly interactions per neighborhood context divided by 4 to obtain a weekly average. The number of interactions ranges between 0 interactions per epoch and a maximum of 7, corresponding to the lowest and highest values observed in the PEW survey.

Spatial Proximity and Interaction Range

Based on Abelson (1964) who argued that interpersonal contacts vary due to factors like proximity, interests, and social networks, I argue that interactions primarily occur within defined spatial proximities. For each interaction, potential alters are identified within a 300m proximity threshold using a proximity matrix, and one is randomly selected, whilst ensuring the ego does not interact with itself. This proximity threshold is consistent across urban and rural areas. Agents within 300m are eligible for interaction, with urban areas naturally having more potential interaction partners as shown in Figure 7 due to their population density. This number does not change throughout the model, reflecting the static nature of neighbor proximity.

Figure 7 shows the variation in neighbor count within a 300m range between urban and rural settings. Urban residents generally have more neighbors, leading to more diverse interactions, aligning with the network dynamics outlined in Hypothesis 1 for the ABM.

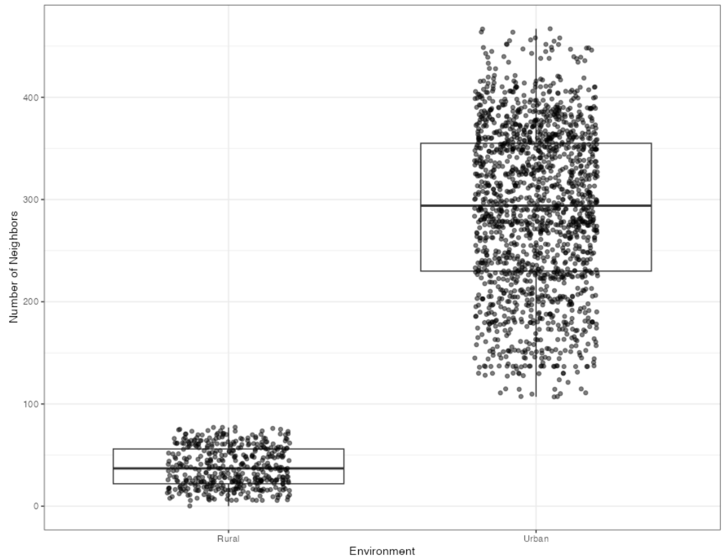

Figure 7. Number of Neighbors within 300m Distance

Similarity Bias and Homphily Assumptions

Based on the literature on Bounded Confidence Models (Deffuant et al., 2000; Deffuant, 2002; Hegselmann & Krause, 2002; Hegselmann & Krause, 2015) and the homophily condition that it entails, the influence of interaction only happens between agents if they are similar enough. There are different ways to integrate homophily into models of opinion dynamics. I will use threshold mechanisms which is referred to as bounded confidence and commonly used in models with continuous opinions (Fortunato, 2005; Deffuant et al., 2000; Hegselmann & Krause, 2002; Urbig & Lorenz, 2007). The first homophily assumption is based on opinion similarity, in my case, partisan affiliation, suggesting that two agents i and j will influence each other if they share the same party affiliation: $\text{party}_i = \text{party}_j$ (Byrne, 1971). As a second homophily mechanism, I argue that agents influence each other if they share enough demographic attributes D (McPherson et al., 2001).

Based on this, the following equation describes the homophilious selection:

$$\text{W\_dem}_{i,j} = \frac{\sum_{d=1}^{D} I(c_{i,d} = c_{j,d})}{D} \tag{5}$$

where I is the indicator function that equals 1 if the condition is true and 0 otherwise, $c_{i,d}$ is the value of the d-th demographic attribute for agent i, and D is the total number of demographic attributes.

$$\text{W\_party}_{i,j} = \frac{\sum_{p=1}^{P}(1 - |v_{i,p} - v_{j,p}|)}{P} \tag{6}$$

where $v_{i,p}$ is the value of the p-th voting probability for agent i, and P is the total number of parties.

$\text{W\_dem}_{i,j}$ and $\text{W\_party}_{i,j}$ is then calculated as the average of both similarities, providing an overall measure of similarity between ego and alter which is then used to determine the influence of their interaction.

$$\text{W}_{i,j} = \frac{\text{W\_dem}_{i,j} + \text{W\_party}_{i,j}}{2} \tag{7}$$

Blau Index Adjustment Factor C:

Moreover, I implemented a Blau Index Adjustment factor for rural neighbors to emphasize the impact of similarity in homogenous settings, thus effectively implementing a context-depending parameter.

$$\text{W}_{i,j} = \begin{cases} \text{W}_{i,j} \times C & \text{if } B_i \leq 0.3 \\ \text{W}_{i,j} & \text{otherwise} \end{cases} \tag{8}$$

Here, B_i represents the Blau Index for agent i, and C is an adjustment factor greater than 1 that enhances the influence of similarity in less diverse settings. The factor C adjusts the similarity score Wi, j when the Blau Index of ego's k nearest neighbors is 0.3 or less, indicating a highly homogeneous environment that could amplify the effect of similarity in interactions. In urban areas, however, C is set to 1, effectively neutralizing this adjustment. Consequently, in rural neighborhoods, the similarity weight Wij is calculated by aggregating similar demographic and voting attributes and then multiplying by the Blau Index if it indicates substantial partisan homogeneity in agent i's neighborhood.

Penalty Factor p:

Lastly, I included a context-specific parameter for the tolerance of aversion in partisan affiliation to Neighbors. As argued before, I assume that there is a more narrow political socialization network at play in rural areas that penalizes partisan diversion and promotes convergence. I implemented that theoretical expectation by including the penalty factor p. It is calculated using the local partisan exposure of ego's k nearest neighbors and amplifies the influence weight of the interaction between ego and alter when they belong to different parties and alter belongs to the majority partisan group that ego is exposed to. In this case of high partisan outgroup exposure for ego, the influence of that interaction is enhanced by p to model the narrow socialization network in rural contexts.

$$\mathrm{W}_{i,j} = \begin{cases} \mathrm{W}_{i,j} \times p, & \text{if party\_diff} = 1 \text{ and exposureOutgroup}_i > 0.5 \\ \mathrm{W}_{i,j} & \text{otherwise} \end{cases} \tag{9}$$

5.3.3 Update Vote Probability Equation:

For agents interacting, the change in voting probability is defined as follows:

Determine Party Difference δ

$$\delta = 1\{\mathrm{ego}_p \neq \mathrm{alter}_p\} \tag{10}$$

Update voting probability based on party difference δ and similarity weight W

$$\Delta P\_vote_{it} = \begin{cases} -\mu \times \mathrm{W}_{i,j} & \text{if } \delta = 1 \text{ and } \mathrm{W}_{i,j} < \text{ confidence threshold} \\ \mu \times \mathrm{W}_{i,j} & \text{if } \delta = 0 \text{ and } \mathrm{W}_{i,j} < \text{ confidence threshold} \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

where μ represents the influence factor which determines the strength of the interaction between agents, while the confidence threshold is set to $-exp(0.6)$, indicating that two agents must have at least 60 percent similarity for their interaction to influence each other's opinions.

Influence factor μ and Stubbornness value S

The change in voting probability is scaled by the influence weight μ which is determining the strength of scoial influence, thus controlling the speed of opinion change in an interaction. Based on prior research, I selected a small μ value of 0.05 to reflect that individuals rarely completely change their opinions due to a single interaction (Schweighofer & Garcia, 2024).[6] The robustness of μ is typically tested by varying its values, with results displayed in Figure 12 supporting the chosen value. Additionally, voting probability changes are multiplied by the Stubbornness variable S_{it}, which ranges from 0 to 1—0 indicating least stubborn with frequent partisan switches, and 1 indicating high stubbornness with consistent party voting. Due to data constraints, most values skew towards 1; this is mitigated by applying an exponential function to scale the stubbornness effect, lessening influence as stubbornness increases, whereas agents with low stubbornness are minimally affected. This formula is shown in Equation 12.

$$\Delta P\_vote_{it} = \Delta P\_vote_{it} \times \exp(-S_{it}) \tag{12}$$

Figure 8 shows the scaling of the influence and stubbornness values.

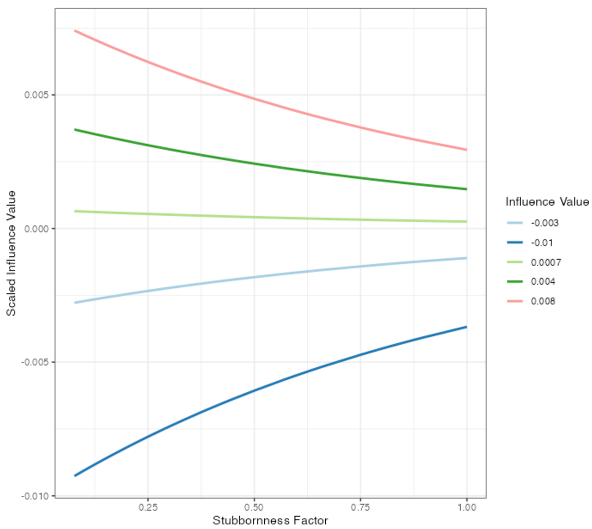

Figure 8. Exponential Scale of Influence Values by Stubbornness Factor

Unaffiliated Influence

As previously discussed, UNA voters lack influence over others' political views but are still susceptible to influence. Figure 1 showed an increase in UNA vote shares from 2016 to 2024, suggesting a need to model this rise in the ABM.

Based on my theoretical assumption that unaffiliated voting probabilities might have increased due to the risk aversion of former Democratic rural residents in increasingly homogeneous Republican neighborhoods, I attempt to model this political drift. By allowing unaffiliated proba-

[6] Schweighöfer and Garcia used a μ value of 0.05.

bilities to increase for Democrats when they interact with Republicans, this simulates a scenario where exposure to Republicans may lead to increased unaffiliated sentiments among Democrats. I apply a reduced influence weight for 'delta_UNA' to ensure the shift toward unaffiliation is less pronounced than intra-party influence. For the urban ZIP Code I use the same reduced influence weight, but unlike in the rural context, it applies to both Democrats and Republicans. Thus, whenever a Republican and a Democrat interact, both are influenced not only towards the other agent's party but also, with a decreased weight, towards unaffiliation.

Finally, the agents' voting probabilities for the different parties are updated based on the influence values from the previous interaction. Moroever, the Blau Index values for each agent and their k nearest neighbors as well as the local partisan exposure values are both dynamically updated after each interaction. After that, the next interaction takes place. Table 12 in the Appendix sums up the different parameter and their implementation for the urban and rural ZIP Codes.

6 Results

This section will depict the results of the simulation model and compare it to the empirical data. To examine Hypotheses 1 and 2, I first measure the aggregate level of homogeneity in both neighborhoods and analyze individual partisan affiliations to evaluate the accuracy of the simulation models against empirical data. Following this, I explore variations in parameter settings to identify the specific mechanisms that influenced the outcomes.

6.1 Aggregate Level: Measuring Neighborhood Partisan Homogeneity

I calculated the initial aggregate homogeneity for each ZIP Code using 2016 data and the homogeneity for 2024, applying the same measures to the simulation results. I adjusted the election data variable to align with the epoch timeframe used in the simulation model, where every 100 epochs correspond to 2 years in the empirical data.

6.1.1 Empirical Data

Figure 9 shows the Blau Index across several election dates from 2016 to 2024, comparing urban and rural areas. It is calculated with and without considering unaffiliated voters and measures diversity based on political affiliations. Higher values indicate greater diversity.

The urban ZIP Code consistently exhibits higher values than the rural one, indicating greater diversity. While both areas show a general decline in diversity from 2016 to 2022, there is a sharp increase in 2024. This may be because 2024 registration is still open, leading to greater variability in the data.

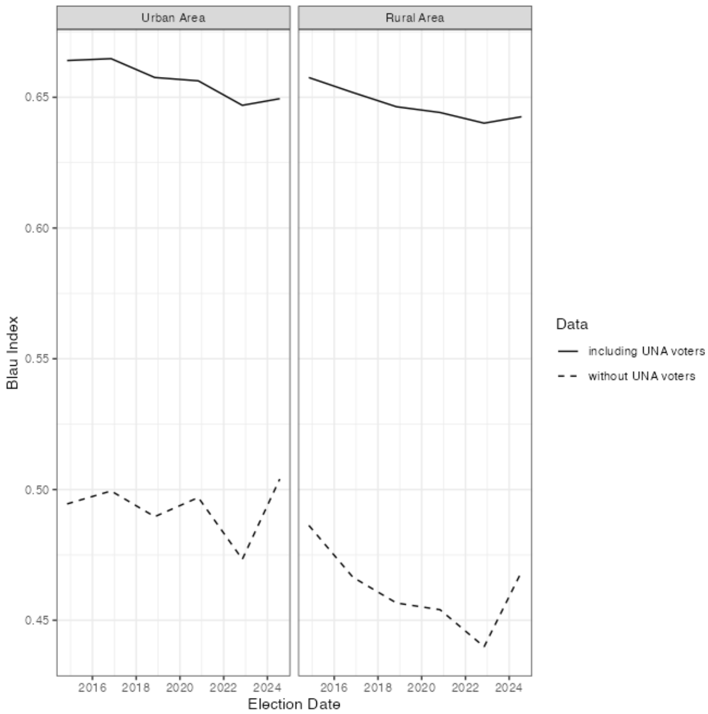

Figure 9. Blau Index for Empirical Data

6.1.2 Simulation Data

Blau Index Simulation vs. Empirical Data

Both simulation models closely align with the empirical data, successfully replicating the Blau Index and demonstrating high accuracy. However, the rural model slightly overestimates the increase in homogeneity by the end of the period.

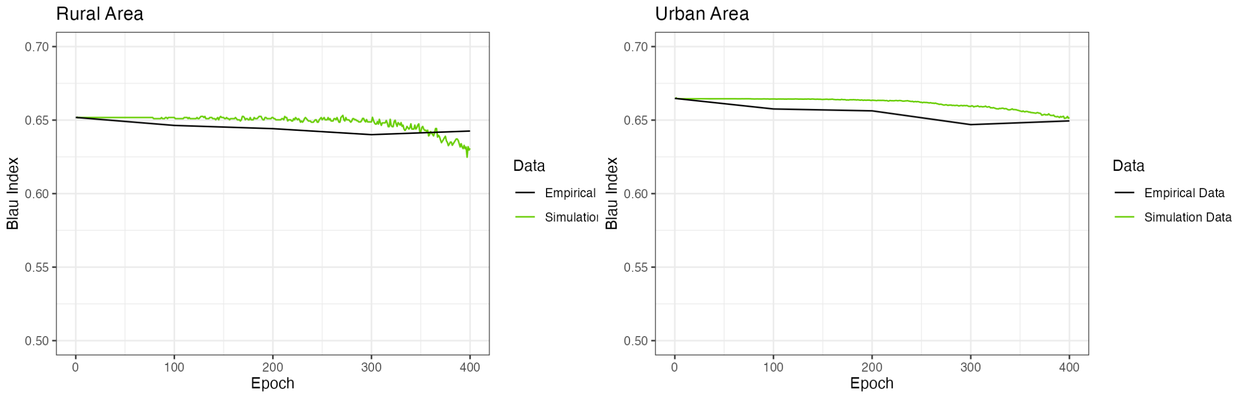

Figure 10. Blau Index Simulation vs. Empirical Data

Whilst I found that the aggregate partisan homogeneity increases over time in the rural neighborhood, which is replicated by the rural model, the urban location also shows an increase in homogeneity in both empirical data and the simulation model. This contradicts the initial assumption that urban areas lead to more partisan diversity. To examine this further, I will analyze the change in partisan affiliation.

Change in Partisan Affiliation

I plotted the predicted partisan affiliations across the epochs and compared them with the empirical data in Figure 11. Both models closely replicate the empirical trends, though there are slight discrepancies across epochs. While the overall patterns align well with real-world data, some nuanced dynamics are simplified in the models.

The rural model underestimates the increase in unaffiliated voters and slightly overestimates the decline in Democratic voters. Additionally, it fails to replicate the dip in Republican affiliation after 2022, suggesting that some parameters may overestimate Republican influence and underestimate that of Democratic voters. The figures also indicate that partisan vote shares are more evenly distributed in the urban area, reflecting greater partisan diversity compared to the rural area, where Republicans and unaffiliated voters dominate.

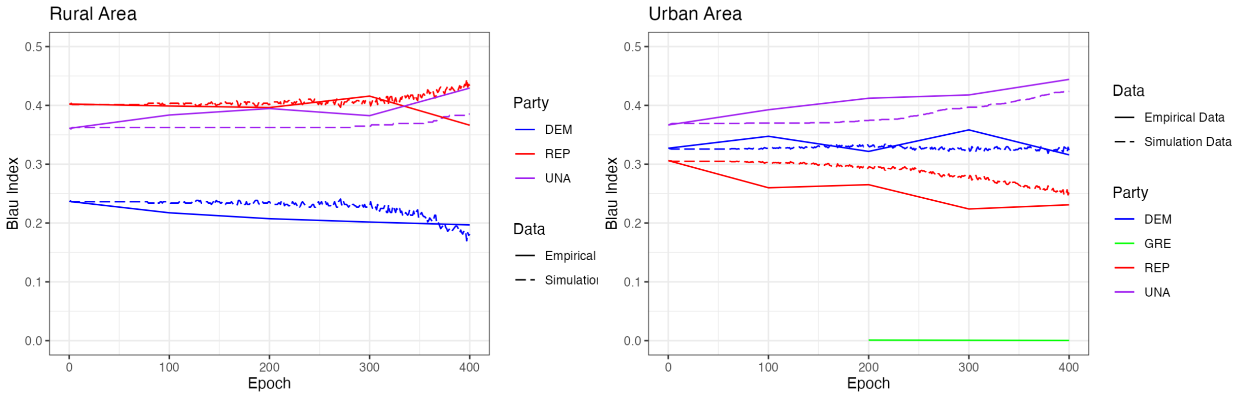

Figure 11. Partisan Affiliation Simulation vs. Empirical Data

As seen, the results indicate that homogeneity increases slightly more in the rural environment. However, I want to assess how accurate the models predict correct voter partisan affiliation.

6.2 Individual Level: Predicting Individual Partisan Affiliation:

To test if my model also performs well on the individual level, I will examine how many of the vote switches are correctly modeled by the ABM. I conducted accuracy tests comparing each agent's predicted partisan affiliation after 400 epochs with the empirical results after 8 years. The accuracy of predicting the partisan affiliation for 2024 is **0.86** for the rural model and **0.87** for the urban model. To evaluate the models' predictions of partisan switches, I employed machine learning metrics commonly used in classification tasks, where binary outcomes are predicted (e.g., 0 = No Party switch, 1 = Party Switch). I calculated Specificity, Sensitivity, Precision and Accuracy, with the detailed results presented in Table 10 in the Appendix.[7] Table 2 shows the Accuracy metric for both simulation models. Moreover, confusion matrices for both models can be found in the Appendix in section 9.3. Both models show strong accuracy, with rates above 85%, demonstrating their predictive reliability.

Data Type	**Partisan Affiliation Accuracy**	**Vote Switch Accuracy**
Rural Model	0.86	0.86
Urban Model	0.87	0.87

Table 2. Accuracy for Party Affiliation and Vote Switches for Rural and Urban Models

[7] A detailed explanation for the different metrics are also found in the Appendix.

6.3 Examining Different Parameter Choices

We have established that rural areas exhibit stronger homogeneity over time compared to urban areas and that both models show a high accuracy. However, the underlying mechanisms driving these results remain unclear. To explore these mechanisms, I conducted simulations using different input parameters, as shown in the figures below. I will evaluate the impact of these parameters by comparing the simulation results with the empirical data.

6.3.1 Tuning Influence Strength μ and the Proximity Threshold

I used different μ values in the ABMs to accelerate or decelerate convergence processes. Figure 12 illustrates how different μ values, representing the strength of social influence, affect the speed and pattern of convergence among agents over 400 epochs. As shown in both neighborhoods, a higher μ value leads to a higher level of convergence after 400 epochs, a result that aligns with previous research (Schweighofer & Garcia, 2024). In rural areas initial partisan homogeneity is higher, and the smaller, more homogeneous population does not converge anymore after a certain point. With higher μ values, convergence stabilizes as interactions occur within an already aligned group, leaving little room for additional alignment. In contrast, urban areas begin with greater diversity. Higher μ values lead to stronger convergence, as the larger, more varied population leaves room for broader alignment.

Thus, while μ accelerates convergence in both contexts, the rural area's high initial homogeneity constrains the effect, whereas urban areas with greater diversity converge more with higher μ.

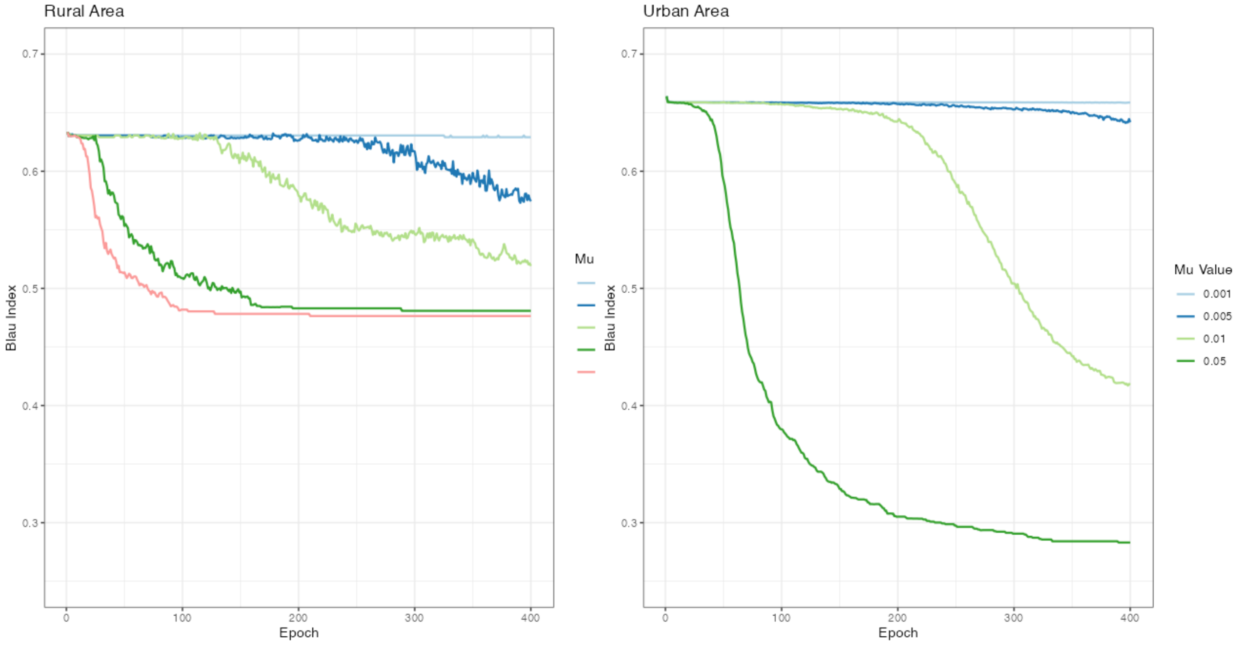

Figure 12. Impact of Social Influence Strength (μ) on Partisan Convergence

Figure 13 illustrates the impact of different proximity threshold settings on partisan convergence over 400 epochs, emphasizing the role of spatial closeness in social convergence dynamics. The results indicate that a lower proximity threshold, reflecting a closer spatial arrangement of individuals, generally accelerates the convergence process. However, this also limits interactions to a smaller group, particularly in sparsely populated rural areas. This suggests that while proximity influences the extent and speed of social influence among residents, its impact diminishes when the neighborhood size is already small.[8]

[8]Due to the long running time of the urban simulation models ($\approx$ 30 hours per model), I was not able to test different proximity threshold values for the urban model. However, as the urban neighborhood is very small, covering only 1.80 square miles, I do not expect significant changes across different proximity values.

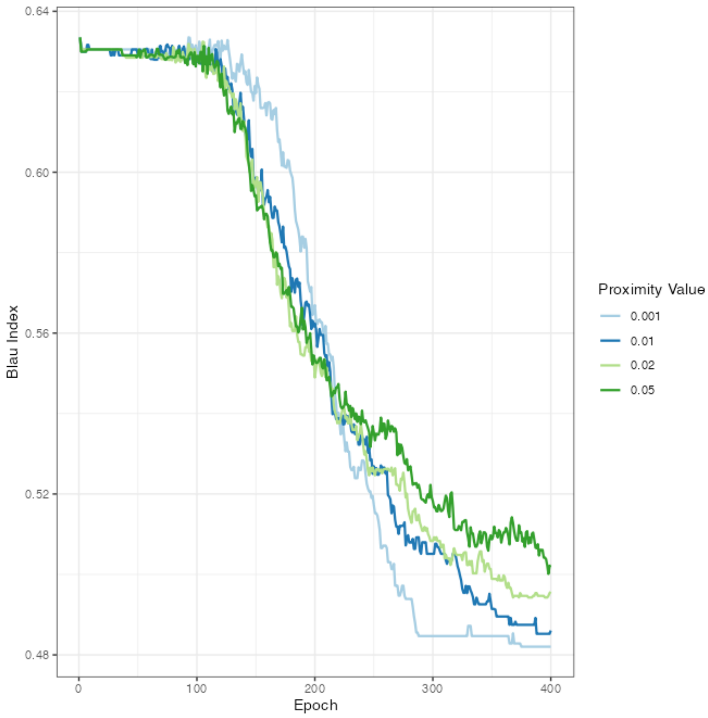

Figure 13. Influence of Proximity Threshold on Partisan Convergence

6.3.2 Effect of Context: The Effect of Context Parameter C and p

Both C and p parameters were designed to enhance interaction influence in homogeneous contexts, modeling the narrow socialization process typical of rural settings. However, removing the context parameter from the rural model increased the accuracy of the simulation's predictions, achieving a value of **0.89**. Additionally, the model without the context parameter more closely replicated the homogeneity level observed in the empirical data, resulting in a smaller increase in homogeneity compared to when the context parameter was included. This outcome contradicts Hypothesis 2, which argued that narrow socialization in homogeneous rural areas would increase overall homogeneity. This suggests that the real-life processes in such contexts may not be adequately captured by the current context parameters in the model.

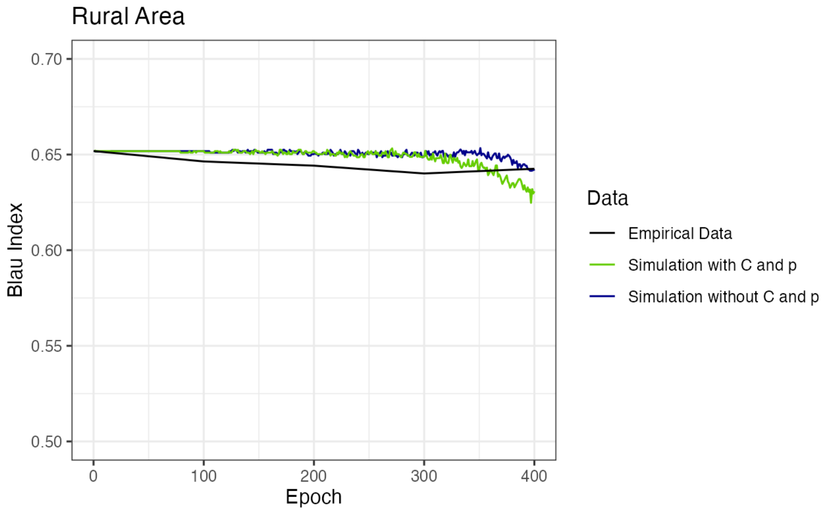

Figure 14. Comparison of Simulation Models with and without Context Parameters in Rural Areas

I also implemented the context parameter in a model for the urban area to assess its impact on the urban neighborhood. As expected, this modification did not significantly change the results and only slightly reduced accuracy. This is likely due to the fact that the initial conditions required for these parameters—such as high partisan homogeneity and strong partisan out-group exposure—were infrequently present in the urban setting. Detailed results are provided in Section 9.4.2 of the Appendix.

However, removing the context parameter from the rural model implies that the distinct network structures between urban and rural areas are relevant for understanding the greater increase in homogeneity observed in rural areas. This finding supports Hypothesis 1, which posited that rural neighborhoods would exhibit higher aggregate levels of partisan homogeneity due to the lower diversity of interactions. In rural areas, where interactions occur within smaller, more homogeneous groups, the absence of diverse social networks naturally leads to stronger convergence towards a single partisan identity. Therefore, the increase in homogeneity can be attributed to the limited diversity in rural social networks, confirming Hypothesis 1 that network settings significantly influence partisan convergence.

7 Limitations and Alternative Explanations

Having discussed the previous results, a very important caveat has to be named: this paper only focuses on the effect of neighborly interactions. Whilst there exist many other forms of social interaction and social influence that affect partisan affiliation, the aim and thus also the significance of this paper are limited to the effect of neighborhood interactions only. When attempting to generalize this work, one has to be aware of that limitation. For this reason, the following section will describe further avenues of social influence that might have been at play in the models without being explicitly included.

7.1 Alternative Explanations

7.1.1 Commuting to Work

Type of Commute	Rural ZIP Codes	Urban ZIP Codes
Employed in the Selection Area, Live Outside	537	14663
Live in the Selection Area, Employed Outside	157	7138
Live and Employed in the Selection Area	41	544

Table 3. Inflow/Outflow Analysis for 2016

Source: Data from the U.S. Census Bureau's OnTheMap https://onthemap.ces.census.gov on 08/06/2024

As shown in Table 3, over 90% of workers in both neighborhoods live outside the area, indicating strong external influences through interactions beyond their neighborhood. Similarly, a significant portion of residents work outside the neighborhood (around 80% in the rural community and less than 90% in the urban area), suggesting they are influenced by experiences in other neighborhoods. While my model doesn't explicitly capture these external influences due to data limitations, it's common in ABM literature to include a noise parameter ϵ to account for such effects indirectly.

7.1.2 Party Campaigning

Another influence could stem from party mobilization during campaigns. North Carolina, being a crucial Swing State, has likely seen significant efforts from both parties focused on neighborhoods like those studied in this paper. Campaigns often target voters and neighborhoods using low-level geographic data, potentially increasing local homogeneity (Brown, 2023; Hersh, 2015). In recent years, parties have increasingly used data analysis to identify, categorize, and target specific voters and neighborhoods, enhancing their outreach efforts (Hersh, 2015). However, incorporating campaigning data into the simulation models is beyond the scope of this paper.

7.1.3 Social Media

A third factor is social media, which increasingly shapes how people perceive their political environment (Barberá, 2020; Kubin & Von Sikorski, 2021). Social media transcends the spatial proximity needed for interactions in traditional ABMs, allowing connections and interactions on a global level. It also contributes to political polarization by creating echo chambers, where like-minded individuals reinforce each other's views in a homogenous digital context through filter bubbles, ranking algorithms and group chats(Barberá, 2020; Sunstein, 2018). However, social media also offers exposure to diverse perspectives (Barnidge, 2017; Fletcher & Nielsen, 2018). The inconsistent research on social media's effects complicates modeling these influences in the simulation.

In order to attempt to account for aforementioned alternative influence mechanisms, one could implement a noise parameter ϵ, to examine the robustness of my results in light of alternative effects. However, due to the long running time of the simulation models ($\approx$ 30 hours per model), I was not able to do so in time anymore.

7.2 Further Limitations

For all simulation models attempting to replicate complex systems like a society, the validity and generalizability of the results depend on the assumptions made (Feliciani et al., 2023). To model political behavior, I made simplifying assumptions which, as the results indicate, might have been too "simple" and not accurately simulated real-world micro-level mechanisms.
One criticism of the paper could be the assumed number of interactions where neighbors discuss politics. Although I derived my parameter choices from empirical data, the data described overall contact and communication, not specifically neighborly political conversations. This might have led to an overestimation of political interactions and their influence. Previous research shows that contextual effects on neighborhood influence on partisan affiliation are small and occur over a long period. Brown (2023) found that a "10 percentage point increase in exposure to Democratic or Republican neighbors between presidential elections increases the likelihood of switching to that party by 0.3-2.5 percentage points" (Brown, 2023, p. 3). Thus, the actual effect size of neighborhood influence might be too small to model within an 8-year period.

Furthermore, the assumption about unaffiliated voters in the models can be challenged, as they are more difficult to understand and model compared to partisans. The rise in unaffiliated voters might have occurred exogenously due to individual frustration with party performance rather than neighborhood influence. Given the unexploited and varied literature on unaffiliated voters in the US, this was my best effort for this project. However, the way I modeled the unaffiliated increase might not reflect the real-world mechanism accurately.

Additionally, incorporating different parameters into an ABM can enhance its complexity and realism, but it risks overstimulating the model, making it difficult to isolate single parameter effects. When too many variables act simultaneously, it becomes challenging to isolate which parameters influence specific outcomes, mixing up causal relationships within the model. Therefore, I used sensitivity analyses, systematically varying parameters one at a time, to identify their impacts and interactions, aiding in understanding how complex influences interweave within the model.

Another limitation is related to data availability. While recent voter registration data is complete, it becomes less comprehensive further back in time. Choosing 2016 voter data, rather than 2020, for a longer modeling period sacrificed data thoroughness, resulting in a smaller sample size than the original 2024 data. This means both models lack completeness in initialization, and potential neighbors and their influences are not modeled due to data unavailability.

8 Conclusion

This paper examined how variations in neighborhood network structures influence partisan convergence and polarization across urban and rural neighborhoods by using two different ABMs for rural and urban ZIP Codes in North Carolina.

The results suggest that while rural neighborhoods do exhibit a slightly stronger increase in partisan homogeneity compared to urban areas, this effect is overestimated in the rural model when a narrow socialization process is modeled, indicating that current context parameters in the model do not capture the real-life contextual effects. Thus, I have to reject Hypothesis 2. Although both models performed well in terms of accuracy, they encountered challenges in accurately depicting partisan switches, highlighting the complexity of simulating real-world political behavior, particularly in contexts where changes are gradual and occur over extended periods. However, after removing the context parameter from the rural model—effectively running the same model for both urban and rural neighborhoods with the only difference being their network structures—the rural model improved in replicating homogeneity and partisan switches. This finding supports Hypothesis 1, which argued that rural neighborhoods would exhibit higher aggregate levels of partisan homogeneity due to the lower diversity of interactions. These findings underscore the challenges of modeling social influence and partisan convergence, particularly in environments where interactions are diverse and socialization processes complex. The overestimation of homogeneity in rural areas indicates the need for more nuanced models that better capture the slow and subtle nature of contextual effects on political behavior.

In conclusion, while this study provides valuable insights into the dynamics of partisan convergence across different neighborhood contexts, it also highlights the limitations of current modeling approaches in fully capturing the intricacies of real-world social and political interactions. Future research should continue to refine these models, incorporating longer time frames and more detailed interaction data to better understand the mechanisms driving political behavior in diverse environments. For instance, utilizing the Social Connectedness Index from Meta, available for US ZIP Codes could offer more insights into neighborhood connectedness and help fine-tune model parameters. Additionally, it will be important to develop new ways to model unaffiliated voters and their influence on partisans, as trends in US politics suggest their numbers are likely to increase.

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9 Appendix

9.1 Descriptive Partisan Affiliation North Carolina

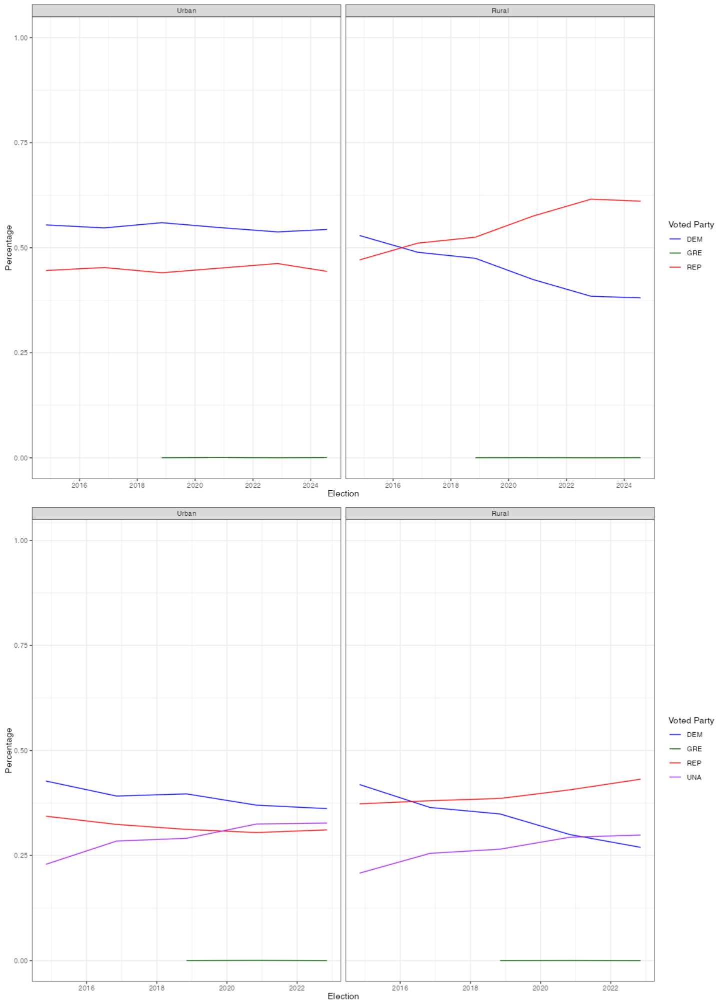


Figure 15. Partisan Affiliation in Urban and Rural ZIP Codes in North Carolina

Year & Data Type	DEM	GRE	LIB	REP	UNA
2016 Empirical Data	103	—	1	175	157
2016 Simulation Data	103	—	—	175	158
2024 Empirical Data	101	—	2	170	163
2024 Simulation Data	79	—	—	189	168

Table 4. Party Affiliation in Rural Area

9.2 Change in Party Voting Probabilities

I calculated the change in voting probabilities to examine the general trends of the simulation model. Across both models, it is seen that there is an increase in vote probabilities to identify as Unaffiliated which matches the empirical trends. For Democrats and Republicans, the probabilities remain stable.

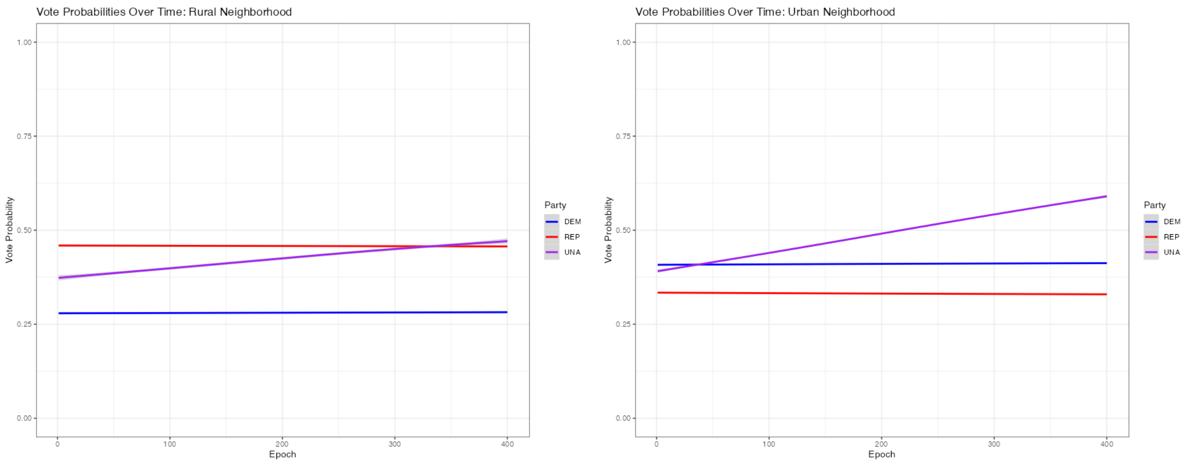


Figure 16. Party Voting Probabilities Simulation

Year & Data Type	DEM	GRE	LIB	REP	UNA
2016 Empirical Data	529	—	13	495	593
2016 Simulation Data	532	—	—	500	598
2024 Empirical Data	554	1	9	393	673
2024 Simulation Data	525	—	—	410	695

Table 5. Party Affiliation in Urban Area

9.3 Confusion Matrix of Predicted Vote Switches

In the confusion matrix, 0 indicates no vote switches, and 1 indicates a vote switch. The positive class is 1.

	0	1
0	346	44
1	35	11

Table 6. Confusion Matrix Rural Area

	0	1
0	1324	39
1	162	105

Table 7. Confusion Matrix Urban Area

Data Type	**Partisan Affiliation**	**Vote Switches Metrics**			
	Accuracy	**Precision**	**Specificity**	**Accuracy**	**Sensitivity**
Rural Model	0.86	0.33	0.91	0.86	0.33
Urban Model	0.87	0.72	0.89	0.87	0.72

Table 8. Metrics for Party Affiliation and Vote Switches for Rural and Urban Models

Table 10 shows that the urban model performs better with overall higher scores than the rural model. Precision, the proportion of positive predictions that are actually correct, and Sensitivity, the True Positive Rate, are very low for the rural model, indicating that the model is not very good at correctly identifying switches both due to False Negatives (Precision), effectively not identifying correct positives, and False Positives (Sensitivity), predicting negative values as positive. However, Specificity, the True Negative Rate, and Accuracy, the ratio of correctly predicted observations to the total observations are both very high for the rural model.

The urban model performs very well with high values for all metrics, specifically for Accuracy and Specificity.

9.4 Effect of Context: The Effect of Context Parameter: C and p:

9.4.1 Removing Context Parameter from Rural Model

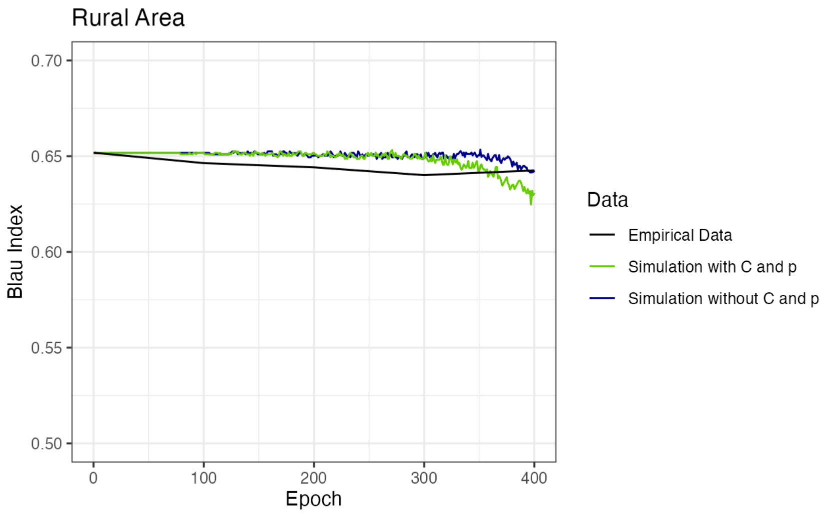


Figure 17. Blau Index Comparison

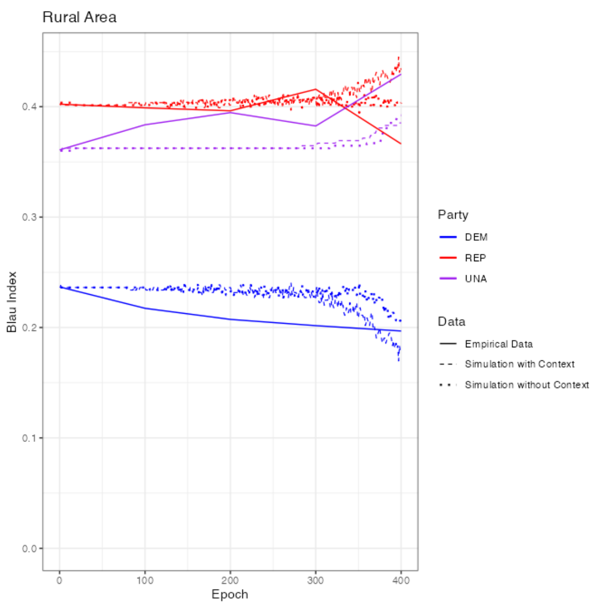


Figure 18. Partisan Affiliation Comparison

Data Type	Partisan Affiliation	Vote Switches Metrics			
	Accuracy	Precision	Specificity	Accuracy	Sensitivity
Rural Model	0.89	0.45	0.91	0.89	0.45

Table 9. Metrics for Rural Model without Context Parameter

9.4.2 Implementing Context Parameter into Urban Model

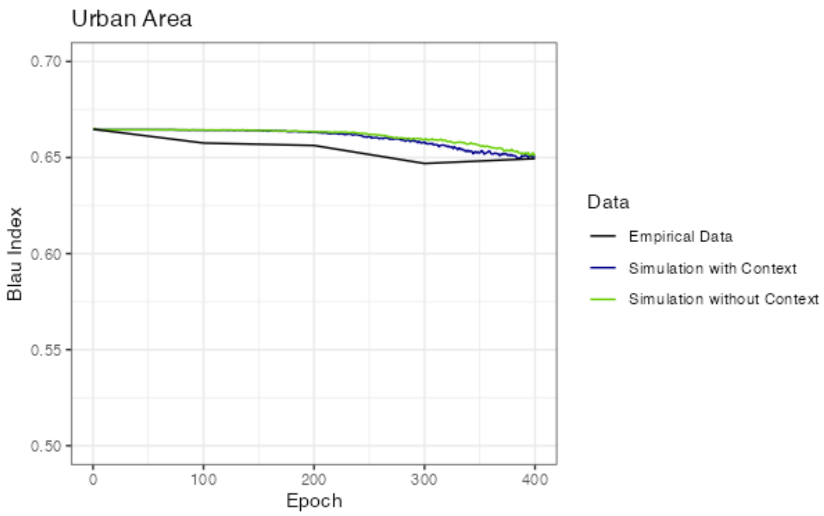


Figure 19. Blau Index Comparison

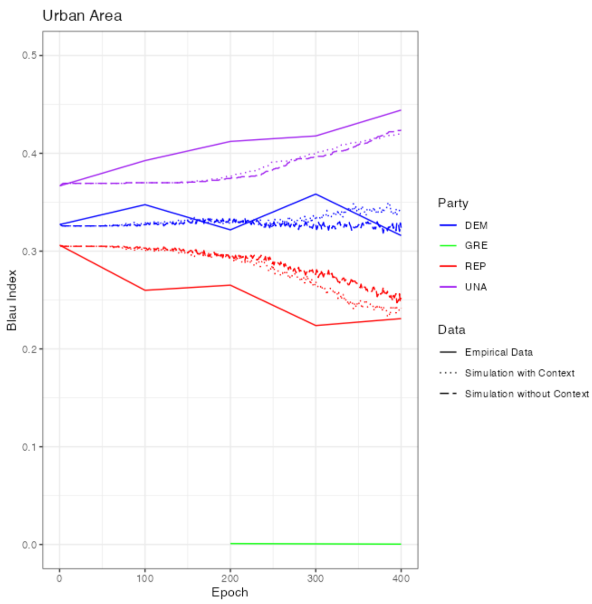


Figure 20. Partisan Affiliation Comparison

Data Type	Partisan Affiliation	Vote Switches Metrics			
	Accuracy	Precision	Specificity	Accuracy	Sensitivity
Urban Model	0.84	0.55	0.89	0.85	0.55

Table 10. Metrics for Urban Model with Context Parameter

9.5 Parameter Descriptions

Parameter in ABM	Concept	Network Attribute
Number of Agents per square mile	Density of Network	Network-Specific
Total Number of Agents	Size of Neighborhood	Network-Specific
Range of Interaction	Frequency of Interaction	Network-Specific
Sociodemographic Values of Agents	Neighborhood Similarity	Network- and Node-Specific
Homophily Parameter H	Homophily in Neighborhood	Network-Specific
Weight of Social Influence μ	Strength of Interaction (superficial or influential)	Edge-Specific
Size of Penalty Parameter	Tolerance/Rejection of Aversion	Network-Specific
Stubbornness S	Loyalty of Agent i's voting behavior	Node-specific
Blau Index S	Heterogeneity of i's nearest neighbors	Node- and Network-specific
Local Partisan Exposure S	Partisan Exposure of i's nearest neighbors	Node- and Network-specific

Table 11. Network Parameters for Urban and Rural Settings

Table 12. Global Parameter

Name	Description	Static/ Dynamic	Urban	Rural
Proximity Threshold	The maximal proximity of two agents to still have a probability of interaction.	Static	500m	500m
Epoch	Time Unit in Weeks	Dynamic	1- 400	1- 400
N	Total Number of Agents	Static	1630	436
num_interactions	Range of Interaction for each agents	Dynamic	[0-7], $\lambda = 1.3$	[0-7], $\lambda = 1.7$
potential_alters	List of all agents that fall within the proximity threshold and could thus interact with ego.	Dynamic	[0,N-1]	[0,N-1]
Penalty Parameter p	Context-specific parameter for the Tolerance or Rejection of Aversion in Partisan Affiliation to Neighbor	Static	1.5	1
C	Blau Index Adjustment Factor	Static	1.1	1

Table 13. Agent Specific Parameter

Name	Description	Static/ Dynamic	Range
Geographic Location	An agent's location in the neighborhood expressed as WGS 84 coordinates.	Static	
Partisan Affiliation	This is a variable that indicates which party the agent has voted for or intends to vote for. The parties in both zip-codes that have been voted for are Democratic (DEM), Republican (REP), Liberals (LIB), Greens (GRE) and No Labels Party (NLB).	Static	Nominal
Vote Probability	These probability variables represent the likelihood of an individual voting for a specific party, calculated as the proportion of times they voted for that party out of their total votes. For instance, DEM_prob indicates the probability of voting Democratic, UNA_prob for unaffiliated, LIB_prob for Libertarian, GRE_prob for Green, and REP_prob for Republican.	Dynamic	[0,1]
delta_P	Change in Vote Probability	Dynamic	[0,1]
Race Group	Race of Agent: Asian (A), Black or African American (B), American Indian or Alaska Native (I), Two or more Races (M), Other (O), White (W), Native Hawaiian or Pacific Islander (P), Undesignated (U).	Static	Nominal

Gender	Gender of Agent: Male (M), Female (F) or Undisclosed (U)	Static	Nominal
Age	Age of Agents which is derived from the year of birth and then binned into 10 year categories.	Static	[18-99]
Stubbornness	The stubbornness variable was created using Run Length Encoding (RLE). This method encodes consecutive identical elements. For each voter (ncid), it counts the length of the initial sequence of identical party values. This length represents the number of consecutive votes for the same party before switching. The raw stubbornness is then normalized by dividing the RLE length by the total number of votes by that voter. L_i = length of consecutive identical votes in V_i $S_i = \frac{L_i}{N_i}$ where V_i is the votes of voter i in previous elections recorded in the dataset and N_i is the length of V_i.	Static	[0,1]

	This provides a measure of how strongly a voter is aligned with a particular party, using their previous voting behavior to examine the loyalty and stability to that party. If the longest run was "UNA" (unaffiliated), the second longest run was used instead because "UNA" values were excluded from the stubbornness calculation. This exclusion is based on the assumption that being unaffiliated represents a lack of strong partisan preference, which could distort the measurement of a voter's loyalty to a specific party. Additionally, switching votes from a party to "UNA" was considered a break in the run, just like switching votes to another party, to accurately reflect changes in voter loyalty.		
Blau Index	Blau's Index of Heterogeneity calculates group demographic diversity for nominal or ordinal variables. It is used to calculate the heterogeneity in race and partisan distribution within each grid. It ranges from 0 to 1, 0 being total homogeneity and 1 total heterogeneity. Formula: $(1 - \Sigma p_i^2) = 1 - \text{total}$	Dynamic	[0,1]
Exposure to Outgroup	I calculated exposure by weighing the proportion of neighbors from each party equally for 50 rural and 200 urban nearest neighbors.	Dynamic	[0,1]

9.6 Interaction Mechanism Visualization

Figure 21. Interaction between two Agents with W < Confidence Threshold

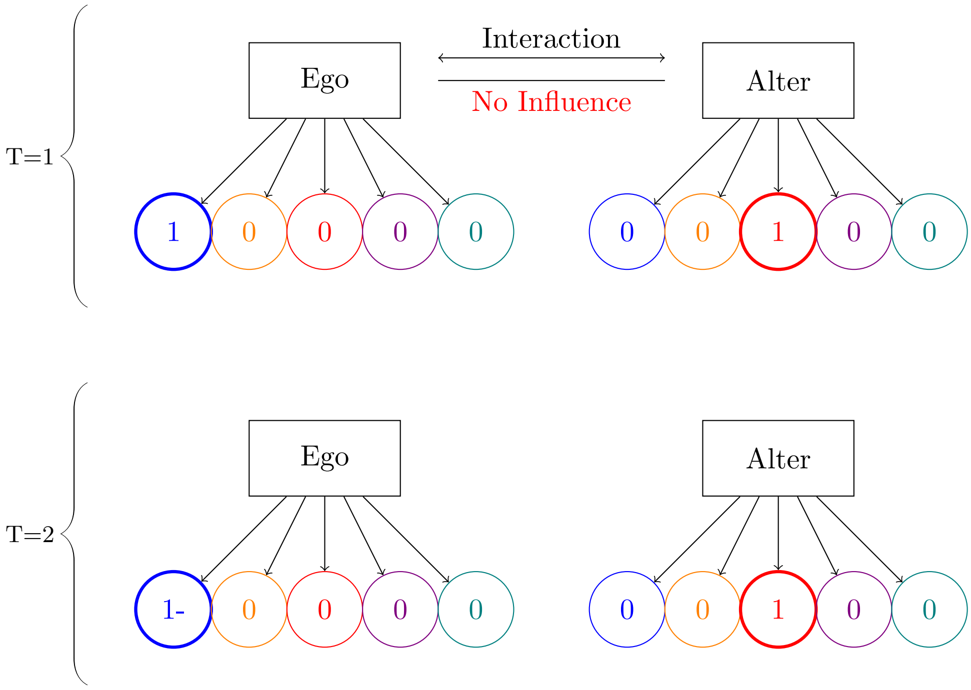
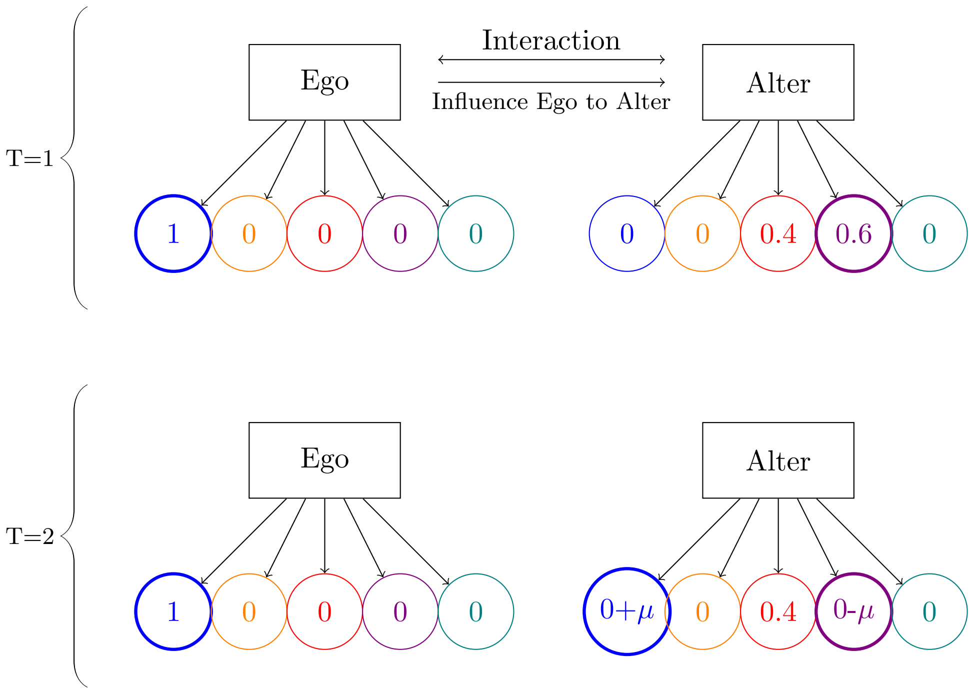


Figure 22. Interaction between two Agents with Alter being Unaffiliated



9.7 Partisan Development across Urban and Rural Areas in NC

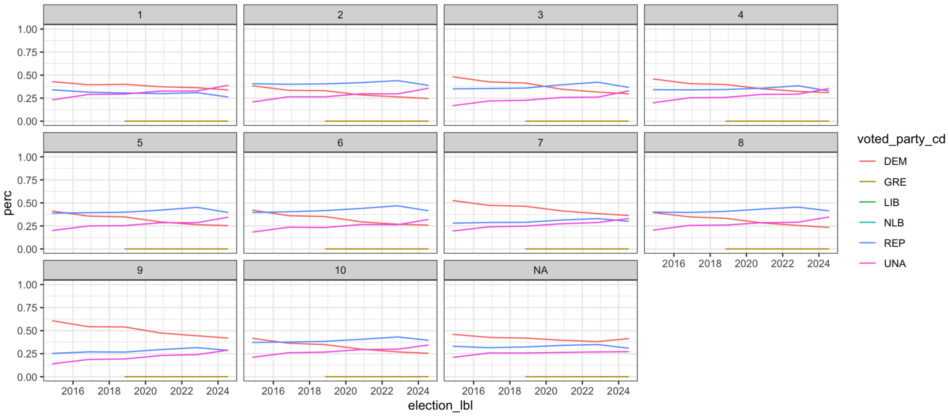


Figure 23. Partisan Development across Urban and Rural Areas in NC

9.8 Interactions with neighbors in Rural and Urban Areas

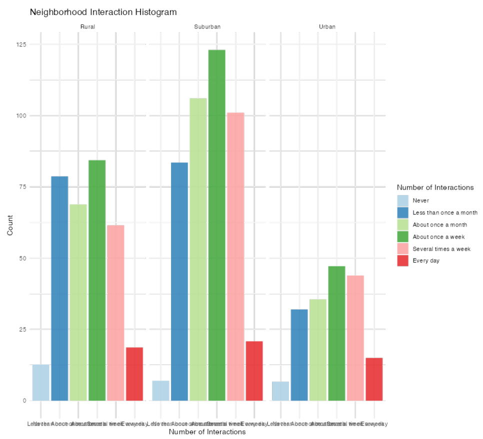


Figure 24. Source: PEW 2018

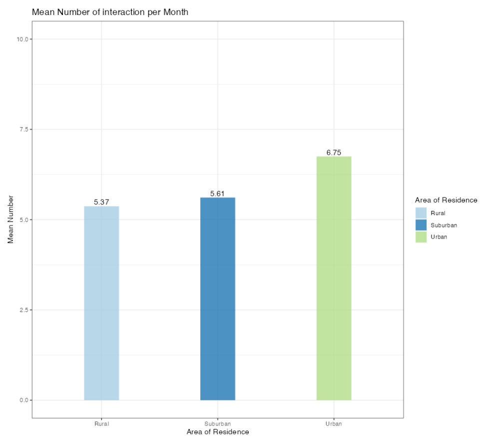


Figure 25. Source PEW 2018

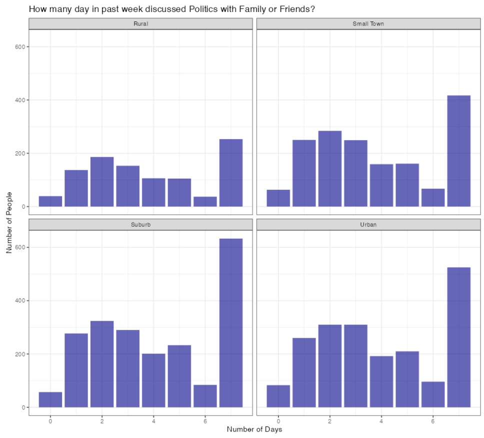


Figure 26. Source: ANES

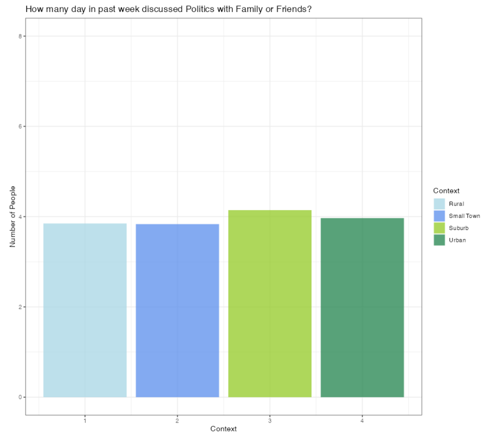


Figure 27. Source: ANES

9.9 Summary Statistics

Table 14. Summary Statistics Urban Area

Variable	N	Perc(%)	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Gender	1630							
... F	717	44%						
... M	767	47%						
... U	146	9%						
Race	1630							
... A	49	3%						
s ... B	451	28%						
... I	4	0%						
... M	9	1%						
... O	58	4%						
... U	140	9%						
... W	919	56%						
Party	1630							
... DEM	748	46%						
... GRE	2	0%						
... LIB	13	1%						
... REP	250	15%						
... UNA	617	38%						
Age	1630		40	16	18	27	52	96

Table 15. Summary Statistics Rural Area

Variable	N	Perc (%)	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Gender	599							
... F	276	46%						
... M	291	49%						
... U	32	5%						
Race	599							
... A	3	1%						
... B	1	0%						
... I	1	0%						
... O	7	1%						
... U	35	6%						
... W	552	92%						
Party	599							
... DEM	119	20%						
... LIB	2	0%						
... REP	231	39%						
... UNA	247	41%						
Age	599		55	16	18	43	67	93