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Who Joins and How? Sociodemographic Pathways into Reddit's Political and Conspiracy Communities

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Abstract

Social media platforms have been increasingly scrutinized for their role in facilitating the growth of echo chambers and fringe communities, yet less is known about how users from different sociodemographic backgrounds are drawn into these spaces. This study investigates how Reddit users—categorized by inferred age, gender, affluence, and partisanship—enter political and conspiracy-related communities on the platform. Building on the attention-flow graph—a network that quantifies how users shift their attention from one subreddit to another over time—we construct a stratified network of subreddit transitions to measure both the likelihood of entry and the specific pathways taken by users from different sociodemographic groups. We find that alt-right and conspiratorial subreddits are disproportionately entered by older, masculine users, whereas younger and feminine users are underrepresented. Radical left spaces, by contrast, attract more left-wing and less affluent individuals. While entry points to conspiracy subreddits are broadly shared across groups, the bridges connecting users to these communities diverge: young and feminine users often pass through esoteric subreddits, whereas older and masculine users take more overtly political routes. Analysis of shared URLs further reveals differing media diets, with young, poor users preferring niche outlets and masculine users more likely to share partisan right-wing sources. These findings shed light on how sociodemographic sorting shapes exposure to polarized and conspiratorial content online, and offer methodological tools for understanding and potentially mitigating these dynamics.

Keywords: Social media · Network science · Conspiracy · Sociodemographics

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Chapter 1

Introduction

Although still widely debated, social media has been often blamed for exacerbating selective exposure—the tendency of users to prefer information sources that align with their own views—by enabling the creation of so-called *echo chambers* (Cinelli et al., 2021; Bail et al., 2018) that prevent users from being exposed to information contradicting its previous beliefs. Echo chambers serve as breeding grounds for conspiracy theories and far-right extremism, providing extremists with a platform to shape the worldview of users sympathetic to their ideologies (Cinelli et al., 2022; Neo, 2018). Research shows that users who join conspiracy communities tend to radicalize over time, increasing their engagement with conspiracy content while disengaging from other communities (Samory and Mitra, 2018). This can lead to important real-world consequences, such as QAnon's involvement in the January 6th attack on the U.S. Capitol (Lee et al., 2022). It is thus critical to study how and where users are first drawn into conspiratorial spaces, as well as who is most vulnerable to enter this kind of spaces. Understanding these pathways and user characteristics is essential for developing effective strategies to counter online extremism and mitigate its real-world impact.

Political extremism has been often linked to conspiratorial belief (van Prooijen et al., 2015; Hopp and Vargo, 2019). However, partisan individuals tend to sort not only in terms of ideological identity but also because of demographics (Mason, 2015, 2018). Democrats are frequently associated as the party of women, non-white people, and residents of urban areas, while Republican voters are associated with older people, white men, and residents of rural areas. This demographic sorting transforms political orientation into a *mega-identity* that perceives opposing partisans as radically different from who they are (Finkel et al., 2020). The demographic entanglement of political identity underscores the need to go beyond ideological labels and consider how social, economic, and identity-based factors shape the way individuals encounter and engage with conspiracy and political content online, as there is evidence of demographic segregation of users even without explicitly observing demographic attributes (Monti et al., 2023). In this context, it is of interest to examine how and where individuals from different sociodemographic groups enter politicized or conspiratorial spaces on social media. Prior research on Reddit, one of the most popular social media platforms worldwide, has explored these pathways, showing, for instance, that men-centered online communities—collectively referred to as "the manosphere"—can serve as gateways to far-right movements such as the alt-right (Mamié et al., 2021).

Self-described as the "front page of the internet", Reddit is a news and discussion platform organized into topical forums known as subreddits—each focused on a specific subject—where users commonly subscribe to and engage with multiple communities. Reddit has been consistently associated with the proliferation of far-right and conspiratorial communities (Massachs et al., 2020; Phadke et al., 2021a). Moreover, several studies on Reddit have explored how users participate in these types of communities on the platform. For instance, Phadke et al. (2021b) show that direct interactions with members of conspiracy communities are strong predictors of individuals subsequently joining those communities. Furthermore, Russo et al. (2024) find that interactions with fringe-community members increase the likelihood of joining fringe communities. Additionally, Hickey et al. (2025) observe that users that actively join a hate subreddit have a high likelihood of actively joining additional hate subreddits. More generally, Rollo et al. (2022) develop the *attention-flow graph* framework to quantify how users shift their focus between subreddits over time and to explore which subreddits act as *gateways* or *bridges* to political and conspiratorial communities.

Our work adopts a similar perspective to that of Rollo et al. (2022), examining which subreddits act as entry points and precursors to conspiratorial and politicized communities on Reddit. However, our focus extends beyond identifying these gateway or bridge forums: we investigate how these pathways differ across users with varying sociodemographic profiles. In particular, we ask ourselves which sociodemographic groups are more likely to be drawn into these communities, and whether certain forums disproportionately attract users from specific demographic backgrounds. This approach allows us to expand upon prior research on user trajectories into fringe spaces by uncovering patterns of demographic sorting among users who become active participants in conspiratorial or extremist political communities. To this end, we formulate a main research question and two sub-questions that will guide our analysis throughout this work:

Main Research Question (RQ). How do different sociodemographic groups enter political and conspiracy communities on Reddit?

RQ1: How likely are different sociodemographic groups to enter political and conspiracy communities on Reddit?

RQ2: Which paths do different sociodemographic groups use to enter such communities, and how different are they?

To answer these questions, we propose a methodology based on the Attention-Flow Graph (AFG), proposed by Rollo et al. (2022) to identify the main communities of subreddits within Reddit by analyzing the user attention-flow between them and to detect key subreddits along these pathways such as *gateways* or *bridges* to other communities. We extend the work of Rollo et al. (2022) by inferring users' sociodemographics (age, gender, affluence, partisanship) from their posting activity (Waller and Anderson, 2021; Monti et al., 2023) and constructing a *stratified-AFG* that quantifies the attention-flow of users depending on sociodemographic traits. Within this framework, we assess how likely it is for users from different sociodemographic groups to enter political/conspiracy communities and what are the different pathways they take to arrive at them by identifying the subreddits that act as key entry-points and bridges from different communities.

This work is organized in four main parts. In Chapter 2 we introduce the relevant theoretical background necessary to understand the presented methodology and is intended to be consulted or skipped by the reader whenever deemed appropriate. In Chapter 3 we present the data processing pipeline and main methodology used to perform our analysis. In Chapter 4 we present the main results of the analysis and their discussion. In Chapter 5 we highlight the main conclusions of our work and future directions.

Chapter 2

Background

2.1 Network Science

A network or graph (Barabási and Pósfai, 2016; Newman, 2010), is defined as a collection of elements called *nodes*, connected by a set of edges. The edges of a network can be *directed* or *undirected* and a network is called directed when all its edges are directed, and undirected when all its edges are undirected. Mathematically, an undirected (directed) network $G = (\mathcal{N}, \mathcal{L})$ is defined by two sets $\mathcal{N}$ (nodes) and $\mathcal{L}$ (edges), such that $\mathcal{N} \neq \emptyset$ and $\mathcal{L} \subseteq \mathcal{N} \times \mathcal{N}$ is a set of pairs of elements of $\mathcal{N}$. We define the cardinality of these sets as $|\mathcal{N}| = n$ and $|\mathcal{L}| = m$.

The fundamental mathematical representation of a network is given by its *adjacency matrix* $\mathcal{A}$, a square matrix of $n \times n$ such that A_{ij} $(i, j = 1, \ldots, n)$ is equal to one when there exists an edge l_{ij} and zero otherwise. The diagonal of this matrix is composed by zeros for networks without self-edges and its symmetric for undirected networks. In the case when relations between nodes have differences in strength, we can define a *weighted* network through its adjacency matrix such that:

$$A_{ij} = \begin{cases} w_{ij}, & \text{an edge from } i \text{ to } j \text{ exists} \\ 0, & \text{otherwise} \end{cases},$$

where $w_{ij} \in \mathbb{R}^+$ represents the strength of the relationship between i and j. In the case where w_{ij} has a sign, we call the network a *signed* network. We can also define the *transpose* of a network by switching the direction of its edges or equivalently transposing its adjacency matrix.

2.1.1 Node Degree and Degree Distribution

A fundamental property for any network is its *degree* k, this is the number of edges that have a relationship with a node. In the case of directed networks, we distinguish between the in-degree k_{in} and out-degree k_{out}, which are respectively the number of ingoing and outgoing edges for a given node. We can also define the *degree distribution* of a network, which is given by the fraction $P(k)$ of nodes in the network that have a certain degree k. Mathematically, for a network with n nodes this is:

$$P(k) = \frac{n_k}{n} \quad ; \quad \sum_{k=1}^{\infty} P(k) = 1,$$

where n_k is the number of nodes with degree k. For directed networks, we distinguish between the in-degree distribution and the out-degree distribution. Since $P(k_{\text{in/out}})$

is a probability distribution, we can obtain the expected or average degree of the network as:

$$\left\langle k_{\text{in/out}} \right\rangle = \sum_{k=0}^{\infty} kP(k_{\text{in/out}}).$$

Complex networks, network representations of complex systems, tend to have heterogeneous degrees, presenting values in different orders of magnitude without a characteristic scale (Albert and Barabási, 2002). In this case, the degree distributions are known as *scale-free*, presenting a power-law behavior with the majority of nodes having small degree and a few nodes, known as *hubs* with very high degree values.

2.1.2 Network Connectivity

We define a *walk* between two nodes n_0 and n_k in a network G as an alternating sequence of nodes and edges $n_0, l_1, n_1, l_2, \dots, n_{k-1}, l_k, n_k$ with $l_i = (n_{i-1}, n_i)$. A *trail* is a walk in which all edges are distinct; a *path* is a trail in which all nodes are distinct. We say an undirected network G is connected if there exists a path between each pair of distinct nodes of the network (van Steen, 2010). In the case of a directed network we distinguish between *weakly connected* and *strongly connected*, where the former has the same meaning as in the undirected case (ignoring the direction), and the latter means there exists a directed path between each pair of distinct nodes of the network.

Networks divide naturally into "pieces" known as *connected components*, defined as maximal subsets $\mathcal{S} \subseteq \mathcal{N}$ of nodes such that they are connected (weakly/strongly connected in the directed case). The largest connected component in a network is known as the *giant component.* A simple algorithm to find the connected components (and thus, giant component) derives as an application of the Breadth-First-Search algorithm (Roughgarden, 2022). In Algorithm 1 we show a pseudocode implementation of this algorithm with time complexity of $\mathcal{O}(|\mathcal{N}| + |\mathcal{L}|)$.

Algorithm 1: Pseudocode that applies the Breadth-First-Search algorithm to find the (weakly) connected components of a network G.

```
Input: G = (N, L) in adjacency-list format^1, where n = |N|
Output: ∀u, v ∈ N, cc(u) = v iff u, v are in the same connected component.
        numCC the number of connected components.
set all nodes as unexplored;
for i := 1 to n do
    if i is unexplored then
        numCC := numCC + 1;
        Q := a queue^2, initialized with i;
        while Q is not empty do
            remove the node from the front of Q, named v;
            cc(v) := numCC;
            for each (v, w) in v's adjacency list do
                if w is unexplored then
                    set w as explored;
                    add w to the end of Q;
```

[1]A data structure such that objects are removed from the front and added from the back in constant time.

2.1.3 Random Walks on Networks

Given a directed (weighted) network G with adjacency matrix A_{ij}, we define a discrete-time random walk (DTRW) on the network as a random process where a walker located at $v_i \in \mathcal{N}$ at a timestep t has a probability of moving in the next step to an out-neighbor v_j that is proportional to A_{ij} (Masuda et al., 2017). We can thus define a transition-probability matrix T such that each element T_{ij} contains the probability for a walker to move from v_i to v_j. The most natural choice is the normalized adjacency matrix:

$$T_{ij} = \frac{A_{ij}}{s_i^{out}}; \quad \sum_{j=1}^{n} T_{ij} = 1,$$

where s_i^{out} is the out-strength of a node, i.e., the sum of the weights of all its outgoing nodes. DTRW's can be visualized as Markov chains, where the probability $p_i(t)$ that a node v_i is visited at a discrete time t evolves as:

$$p_j(t+1) = \sum_{i=1}^{n} p_i(t) T_{ij}; \quad \sum_{i=1}^{n} p_i(t) = 1,$$

for any t. We can also consider the *stationary distribution* $\mathbf{p}^* = (p_1^*, \ldots, p_n^*)$ of the chain such that $p_i^* = \lim_{t\to\infty} p_i(t)$, where the following eigenvalue problem holds:

$$\mathbf{p}^* = \mathbf{p}^* T.$$

For directed networks that are strongly connected (or undirected networks that are connected), the chain is irreducible, i.e. it's possible to reach every state from any other state within a finite number of steps, and $\mathbf{p}^*$ is unique (Norris, 1997).

PageRank

Random walks on networks can be used measure the relative *importance* of nodes in a network and therefore, to compute a ranking for every node based solely on the structure of the network. This is the case of the PageRank scores (Page et al., 1999; Gleich, 2015), a scoring system created by Google that uses the link structure of the web to determine the importance of pages. The PageRank score vector is defined as the stationary distribution of a DTRW on a network with a slight modification to ensure the existence and uniqueness of this distribution.

Empirical directed networks are not usually strongly connected, compromising the uniqueness of the random walk stationary distribution since it depends on the initial condition of the random walk when there are multiple absorbing states[3]. In order to ensure the uniqueness of the PageRank vector, random walkers are allowed to "teleport" to other nodes with a given probability and thus render the network strongly connected. In this case, the probability $p_i(t)$ that a node v_i is visited at a discrete time t evolves as (Masuda et al., 2017):

$$p_j(t+1) = \alpha \sum_{i=1}^{n} p_i(t) T_{ij} + (1-\alpha) u_j,$$

[2] A way to represent a network such that each node stores a list of its connected nodes (neighbors).
[3] States that, once entered, cannot be left.

where u_i is a "personalization" vector satisfying the constraint $\sum_i u_i = 1$. This vector determines the conditional probability for a random walker to teleport to a given node u_i when it teleports. The probability to teleport from a node with at least one out edge is $1 - \alpha$, whereas teleporting from nodes without out edges has always probability 1. If $u_i > 0$ for all nodes in the network, the random walk is *ergodic*[4] and therefore converges to a unique stationary distribution $\mathbf{p}$ such that it satisfies the recurrence relation:

$$\mathbf{p} = \alpha \cdot T\mathbf{p} + (1 - \alpha)\mathbf{u}$$

.
The idea behind PageRank is to use the stationary distribution $\mathbf{p}$ as a centrality measure for nodes. The above equation implies that a node v_i is central if it has a large in-degree and the source nodes of the edges that enter v_i are also central with small out-degree. This last condition ensures that the total centrality score of source nodes entering v_i is shared among its out-neighbors.

Personalized PageRank

The *damping factor* α is usually set to 0.85 in order to allow the walk to capture the network's structure while ensuring the uniqueness of $\mathbf{p}$. The *personalization* vector $\mathbf{u}$ is usually set to $u_i = 1/n$ for all nodes in the network. Another option for u_i is a *personalized PageRank*, where this vector is localized around one node or a group of nodes. In this case, the Personalized PageRank (PPR) score measures node centrality in a localized region of the network, with a random walker always teleporting back to the same subset of nodes.

2.1.4 Community Detection

In many cases, complex networks divide themselves in *communities* (Guimera et al., 2007; Fortunato, 2010) according to a given characteristic inherent to the represented system. These communities are defined as sets of nodes where the edge density within node members of a same community is greater than the edge density within node members of different communities (see Figure 2.1).

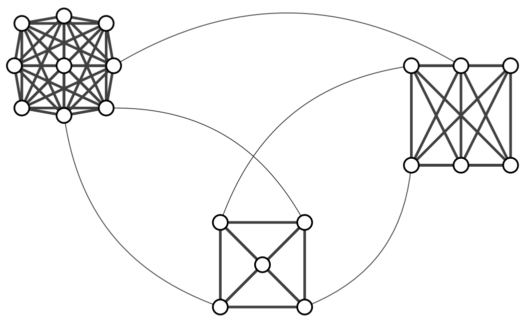

Figure 2.1. Network with community structure composed by different modules, where each node is strongly connected with members of its same community and weakly connected with members of a different community.

[4]The probability of transitioning from one state to another is independent of when the transition takes place (Norris, 1997).

In order to quantify how strong the community structure in a given network is, Newman and Girvan (2004) propose the *modularity* measure Q, the difference between the fraction of intra-community edges in a network and the expected value of this fraction in a network with the same number of communities but random edges between nodes. Mathematically this is:

$$Q = \frac{1}{2m} \sum_{i,j} \left[A_{ij} - \frac{k_i k_j}{2m} \right] \delta(C_i, C_j),$$

where m is the number of edges in the network, k_i the degree of node i, A_{ij} the adjacency matrix and $\delta(C_i, C_j)$ the Kroenecker delta with $\delta(C_i, C_j) = 1$ when nodes i and j are in the same community ($C_i = C_j$) and zero otherwise. We can notice that the modularity Q can have different values for different community partitions and that such values can be high or low depending on how well-connected the communities are in the network. Finding an *optimal* partition that maximizes the value of Q in a network (modularity optimization) is impossible due to the number of possible ways to partition a network in communities, and due to the fact that modularity optimization has been proven to be an NP-complete problem (Brandes et al., 2006). Moreover, it is known that modularity optimization suffers from the so-called *resolution limit* problem (Barabási and Pósfai, 2016), since in this case we fail to identify communities smaller than a certain scale, thereby inducing a resolution limit on the community detected by a pure modularity optimization approach. Finally, modularity is not well-defined for directed networks, constraining modularity optimization algorithms to work only with the undirected version of networks and therefore losing important information.

The Infomap Algorithm

One of the most popular algorithms for community detection in complex networks is the Infomap Algorithm (Rosvall and Bergstrom, 2007). This algorithm is based on the code-description of a random walk in a network using information theory, capturing the flux of information in the network such that communities are defined as groups of nodes where the flux of information persists for a long period of time. Although the core problem behind this algorithm is equivalent to the modularity maximization problem, one important advantage is that it's naturally well-defined for directed (and weighted) networks since it's entirely based on the idea of a directed random walk. It has also been shown that the resolution limit for the Infomap algorithm depends on the total weight of edges between communities rather than on the total weight of all edges in the whole network (Kawamoto and Rosvall, 2015), making it less likely to be affected by it in comparison with modularity maximization algorithms.

Rosvall and Bergstrom (2008) propose to quantify the information content of a random walk using a chain of *bits*, a unique binary chain describing exactly the random walk (see Figure 2.2(A)). In order to do this, they consider a possible partition of the network in communities and assign two labels (in bit-chain form) to each community: one "entry" label and one "exit" label. Every time the random walk enters or exits a community these labels are registered. In the same way, for the random walk *within* the communities, they assign binary labels to the nodes and register every time the random walk goes through a node. The set of the entry, exit, and node labels represents the random walk in bit-chain form.

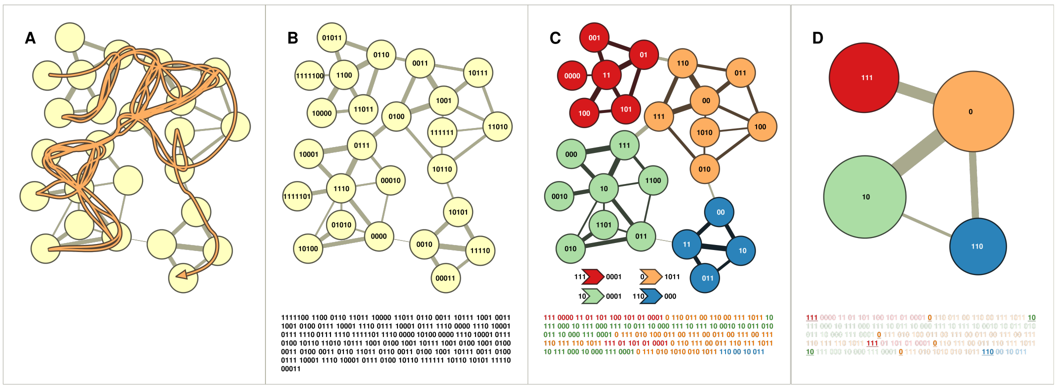

Figure 2.2. A. Trajectory of a random walk in a given network. **B.** Node labeling in the network using Huffman's coding method and chain-bit description of the random walk. **C.** Community structure identified by finding the random walk with the shortest-length bit description among all possible partitions. **D.** Visual description of the Infomap Algorithm. Original figure from Rosvall and Bergstrom (2008).

To assign labels to each possible partition, Rosvall and Bergstrom (2008) use the *Huffman coding* (see Figure 2.2(B)), the optimal way of describing a stationary distribution of frequencies in binary code. This coding associates a shorter chain of bits (*codeword*) to random variables that are more frequent. In this way, if a node or a community are visited frequently during a random walk, they have a shorter associated codeword. Therefore, within this framework, the random walk with the *shortest* bit-chain description is the one that optimally describes the most relevant communities within the network and in consequence, the best community partition of the network. Since each random walk has an associated partition M, finding the random walk with the *shortest* bit-chain description is equivalent to finding the partition M_{opt} that minimizes the description of a random walk in bits among all possible partitions (see Figure 2.2(C)). This is, finding the partition that minimizes the *Map Equation* (Rosvall et al., 2009):

$$L(M) = q_{\curvearrowright} H(\mathcal{Q}) + \sum_{i=1}^{m} p^i_{\circlearrowright} H(\mathcal{P}^i).$$

The equation above is derived from Shannon's coding theorem (Shannon, 1948), which establishes that for the shortest-length description of a random walk in bits, the average number of bits per step L is equal to the entropy[5] of the walk. The first term of this equation is the entropy of the random walk movements *among* communities, while the second term is the entropy of the random walk movements *within* communities. $q_{\curvearrowright}$ is the probability of transitioning between communities at a given step, and $\mathcal{Q}$ the normalized probability distribution of movements between each one of the m communities. Analogously, $p^i_{\circlearrowright}$ is the fraction of within-community movements that occurred in community i along with the probability of exiting community i [6], with $\mathcal{P}_i$ the normalized probability distribution of within-community movements within every community.

In this way, the problem of community detection in a network can be seen as an

[5]Shannon's entropy is defined as the average information level associated to the possible results of a random variable. Mathematically, for a probability distribution: $H(\mathcal{Q}) = -\sum_i q_i \log_2(q_i)$.

[6]Such that $\sum_i^m p^i_{\circlearrowright} = 1 + q_{\curvearrowright}$

optimization problem with the objective of minimizing $L(M)$, the optimal description of bits of a given random walk in a network. A greedy heuristic algorithm to solve this problem is given by the Infomap algorithm defined by the following procedure (see Figure 2.2(D)):

1. **Stage 1:** At the initial step, each node is assigned to its own community. Afterwards, in a random sequential order, each node is moved to the nearest community such that the quantity $L(M)$ has a maximum decrease. If there's no movement that decreases $L(M)$, the node remains in its original community. This step is repeated until no movement can decrease $L(M)$.

2. **Stage 2:** After the initial stage, a new network is built with the newly found communities as new nodes and weighted edges between with weights proportional to the number of edges between member nodes of each community. Afterwards, the first stage is repeated on the new network, joining nodes in new *super-modules*. This hierarchical network construction is repeated until $L(M)$ remains constant.

Despite its relative theoretical complexity, the Infomap algorithm is a very popular choice for community detection since it's fast and applicable to all types of networks. This algorithm is comparable to other efficient algorithms that maximize modularity, such as the Louvain algorithm (Blondel et al., 2008), with both algorithms having a time complexity of $\mathcal{O}(m)$, where m is the number of edges.

2.1.5 The Disparity Filter

The Disparity Filter is a network edge-pruning method that takes advantage of the local weight fluctuations on the outgoing and incident edges of single nodes. In complex networks with heavy-tailed weight distribution $P(\omega)$ and strength distribution $P(s)$ a small fraction of edges carry the largest proportion of a give node's total strength. In order to measure this (for an undirected network), Serrano et al. (2009) propose normalizing the weights of edges from node i to its neighbors as $p_{ij} = \omega_{ij}/s_i$, where s_i is the node strength, and defining the *disparity function*:

$$\Upsilon_i(k) \equiv kY_i(k) = k\sum_j p_{ij}^2.$$

The function $Y_i(k)$ characterizes the level of local heterogeneity in a node. In the case of perfect homogeneity, where all the network edges share the same amount of strength of a node, $\Upsilon_i = 1$. In the case of perfect heterogeneity, $\Upsilon_i = k$. Most real systems are observed in an intermediate behavior, with $\Upsilon_i \sim k^\alpha$ with $\alpha \equiv 1/2$. In this case, the weights associated to a node are carried by a small fraction of edges, while the remaining edges carry just a small fraction of a node's strength.

With the above function in mind, Serrano et al. (2009) propose the disparity function as a way to measure the fluctuations of the weights attached to a given node at a local level, in a way that we can asess the importance of a node's edges independently. However, local node heterogeneities could simply be produced by random fluctuations, highlighting the importance of defining a *null model* to obtain the random expectation for the weight distribution associated with each node. To this end, they propose a null model under the following null hypothesis: "the normalized weights which correspond to the edges of a certain node of degree k are produced by a random assignment from a uniform distribution". The probability density function for one of the normalized weights taking a particular value x can be shown to be:

$$\rho(x) = (k-1)(1-x)^{k-2}.$$

In in analogous way, it can obtained that the probability that the normalized weight p_{ij} of each edge for a given node is compatible with the null hypothesis is simply given by the complement of the cumulative distribution function (CDF) of $\rho(x)$:

$$\alpha_{ij} = \mathbb{P}(X \geq p_{ij}) = 1 - (k-1)\int_0^{p_{ij}} (1-x)^{k-2} dx.$$

The probability α_{ij} is equivalent to a p-value in statistical inference, since it is the probability to obtain a value larger or equal than the observed one considering the null hypothesis as true. By imposing a significance level α, the Disparity Filter considers all edges satisfying $\alpha_{ij} < \alpha$ as significant heterogeneities due to the fact that they reject the null hypothesis, all the other edges are discarded. Since the significance level α is constant, the Disparity Filter uses an homogeneous criterion to compare local inhomogeneities in nodes with different degrees and strengths.

In the case of directed networks the previous discussion can be extended by distinguishing between ingoing and outgoing edges and calculating for each ingoing (outgoing) edge the probability α_{ij}^{in} (α_{ij}^{out}) that its normalized weight p_{ij}^{in} (p_{ij}^{out}) satisfies the null hypothesis. Therefore, all the incoming (outgoing) edges with $\alpha_{ij}^{in} < \alpha$ ($\alpha_{ij}^{out} < \alpha$) reject the null hypothesis and can be considered as significant heterogeneities. The multi-scale backbone of weighted directed networks is then obtained by preserving all the incoming and outgoing edges that satisfy the threshold for at least one of the two nodes at the ends of the edge, while discarding the rest.

2.2 Inferring Social Dimensions on Reddit

Reddit is a social media platform organized in topical communities or forums called *subreddits*. Users interact with each other by either making or commenting a *post* on a given subreddit. Additionally, users can *up-vote* (*down-vote*) a post to show agreement (disagreement) or approval (disapproval). The *score* of a post is the number of up-votes minus the number of down-votes.

Interaction data in Reddit can be used to quantify the positioning of subreddits along different social dimensions. Waller and Anderson (2021) use the commenting data of the 10,000 most popular subreddits, accounting for 95.4% of the comments and 93.2% of the users in a 14-year period, to represent subreddits using community embeddings (Martin, 2017). To generate these embeddings, they apply the word2vec algorithm (Mikolov et al., 2013) to the commenting data by treating subreddits as "words" and users as "contexts"[7] and training the model using the skip-gram with negative sampling method (SGNS).

2.2.1 Word2Vec and the SGNS method

Word2Vec is a neural network-based model used to learn vector embeddings to represent words such that words with similar meanings are close together in vector

[7]Every comment in a subreddit becomes a word-context (subreddit-user) pair in the training data with repetition.

space. One of the most popular architectures for learning these vector representations is the skip-gram model. The training objective of the skip-gram model is to predict surrounding words (context) within a window given a target current word. SGNS does this by comparing the observed word-context pairs with randomly generated non-observed pairs (negative samples) and maximizing the probability of the actual word-context pairs while minimizing the probability of the negative pairs (Landgraf and Bellay, 2017).

Since the subreddit-user data used by Waller and Anderson (2021) is generated without using a context window of any kind, all word-context pairs are included in the training of the word2vec model, equivalently to using an infinite-size window to obtain data. The training procedure of the SNGS maximizes the dot product of word-context pairs that frequently co-occur and minimizes the dot product of randomly generated word-context pairs. This ensures that subreddits with a similar user membership end up with similar vector embeddings. In fact, the cosine similarity between two subreddits embeddings is strongly related with the similarity of the user-base of these subreddits.

2.2.2 Defining Social Dimensions

To generate a social dimension corresponding to a particular social construct (e.g. age), Waller and Anderson (2021) first select a pair of seed subreddits that are extremely similar but differ primarily in the social construct[8]. To ensure the robustness of the social dimensions, the seeds are algorithmically augmented with additional similar pairs of communities by performing the following steps:

1. Let (s_1, s_2) be the original pair of seeds, k be the desired total number of seed pairs, and $\mathcal{C} = \{(c_i, c_j)\}_{i \neq j}$ be the set of all pairs of subreddits where c_j is one of the 10 nearest-neighbours of c_i. Vector differences between the original and new seed pairs are obtained by calculating the difference between the corresponding embedding vectors of each pair, i.e., calculating $\mathbf{s}_1 - \mathbf{s}_2$ and $\mathbf{c}_i - \mathbf{c}_j$ for all $c \in \mathcal{C}$.

2. Afterwards, all subreddit pairs are ranked based on the cosine similarity of their vector differences in comparison with the vector difference of the original pair of seeds. Mathematically this is:

$$\cos(\mathbf{s}_1 - \mathbf{s}_2, \mathbf{c}_i - \mathbf{c}_j) = \frac{(\mathbf{s}_1 - \mathbf{s}_2) \cdot (\mathbf{c}_i - \mathbf{c}_j)}{||\mathbf{s}_1 - \mathbf{s}_2|| \cdot ||\mathbf{c}_i - \mathbf{c}_j||}, \quad \forall c \in \mathcal{C}.$$

3. Finally, the most similar subreddit pair to the original seed pair that has no overlap in subreddits with any of the previous seed pairs is selected. This process is repeated greedily until $k-1$ additional pairs are selected having k seed pairs in total.

The social dimension corresponding to a given social construct is then defined as the average of the vector differences of all the k pairs of seeds. Waller and Anderson (2021) select $k = 10$ pairs having as primary pairs: `r/AskMen` and `r/AskWomen` for the gender dimension, `r/teenagers` and `r/RedditForGrownups` for the age dimension, `r/democrats` and `r/Conservative` for the partisan dimension, and `r/vagabond` and `r/backpacking` for the affluence dimension. In Table B.2 we present the full list of

[8] For example, `r/AskMen` vs `r/AskWomen` for the gender dimension.

seed pairs generated for these dimensions.

In Figures 2.3(a)) and 2.3(b) we show a summary of subreddit embedding and social dimension creation process described above. It is important to mention that while the initial seed choice in this process is a key determinant of the social dimension, similar initial seed choices generate similar dimensions as demonstrated by Waller and Anderson (2021).

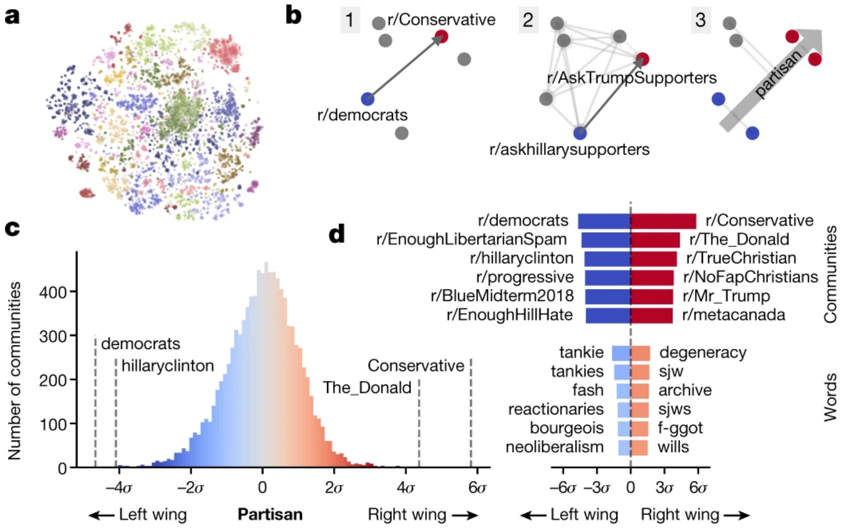

Figure 2.3. **a.** Two-dimensional projection of the vector embedding of the 10,000 most popular subreddits as defined by Waller and Anderson (2021) colored by topical clusters. **b.** Seed generation process used to define social dimensions illustrating social dimensions in vectorial form. **c.** Distribution of partisan scores for the 10.000 most popular subreddits. The x-axis shows the number of standard deviations from the mean partisan score. **d.** Top communities in the poles of the partisan dimension and their most frequent word usage. Original figure from Waller and Anderson (2021)

2.2.3 Social Dimension Scores

Once a social dimension has been obtained, Waller and Anderson (2021) assign a score on that dimension to a given subreddit by projecting its normalized embedding vector $\mathbf{c}_s$ onto the social dimension vector $\mathbf{d}$:

$$F_s^d = \mathbf{c}_s \cdot \mathbf{d}.$$

A subreddit's score on a given dimension is a measure of how similar its member users are with the seeds at either sides of the axis. A subreddit that its more similar to one seed than the other will have a score near the extremes of the axis, while a subreddit that is equally similar to both seeds will fall in the middle (see Figure 2.3(c)). Waller and Anderson (2021) obtain the scores of the 10,000 most popular subreddits during a 14-year period for social dimensions including age, gender, partisanship, and affluence.

We can map subreddit scores onto individual Reddit users by leveraging their posting and commenting activity, along with the precomputed subreddit scores for each social dimension. For each user u, we define an activity vector $\mathbf{n}_u$, where each entry represents the number of times the user has posted/commented in a specific subreddit s. Similarly, we define a social dimension vector $\mathbf{s}_d$, where each entry corresponds to the score F_s^d of subreddit s on a particular social dimension. The user's score on that social dimension is then given by the normalized projection of their activity vector onto the social dimension vector (Monti et al., 2023):

$$F_u^d = \frac{\mathbf{s}_d \cdot \mathbf{n}_u}{\mathbf{1} \cdot \mathbf{n}_u}.$$

In this case, users that tend to participate in subreddits that are at the extreme of a social dimension, they will be assigned a larger probability of being in that extreme as well (e.g. a user is male if it frequents subreddits associated with male users).

2.3 The Attention-Flow Graph

Rollo et al. (2022) define the Attention-Flow Graph (AFG) framework to study the flow of users across Reddit communities using network theory. The AFG is a network that summarizes how users shift their attention from one subreddit to another over time, naturally capturing Reddit's topical community structure.

2.3.1 Network Definition

The AFG is a weighted and directed network, where a link between subreddits represents how much of a user's attention migrated from a subreddit i to a subreddit j on average for a given time period. Given a timestep t (a given month), a set $\mathcal{U}$ of users and a set $\mathcal{S}$ of subreddits, the AFG for the Redddit environment is constructed by performing the following steps:

1. We obtain $c_{u,s}^{(t)}$, the number of interactions of user $u \in \mathcal{U}$ with subreddit $s \in \mathcal{S}$ at time t. We define $\mathbf{b}_u^t$ as the *attention vector* of user u at time t, where each entry of the vector is given by the normalized value of $c_{u,s}^{(t)}$.

2. For each user u and subreddit s, we quantify how much of the user's attention changes between t and $t' = t - 1$ by obtaining:

$$\Delta\mathbf{b}_{u,s}^t = \begin{cases} \mathbf{b}_{u,s}^t - \mathbf{b}_{u,s}^{t'}, & \text{if } \mathbf{b}_{u,s}^t \cdot \mathbf{b}_{u,s}^{t'} = 0 \\ 0, & \text{otherwise} \end{cases}.$$

   We distinguish between the positive flow vector $\Delta^+\mathbf{b}_u^t$, that highlights adopted subreddits, and the negative flow vector $\Delta^-\mathbf{b}_u^t$, that highlights abandoned subreddits.

3. We define the *attention flow* of user u at time t as the outer product $\mathbf{F}^{(t,u)} = \hat{\Delta^-}\mathbf{b}_u^t \otimes \Delta^+\mathbf{b}_u^t$, where $\hat{\Delta^-}\mathbf{b}_u^t$ is the l_1-normalized form of the absolute values in $\Delta^-\mathbf{b}_u^t$. In this step, $f_{i,j}^{(t,u)}$ represents how much of the attention of user u was transferred from subreddit i to subreddit j between the time-steps t' and t.

4. By aggregating over users, we obtain the overall user's attention that migrated from subreddit i to subreddit j between the timesteps t' and t:

$$\mathbf{F}^{(t)} = \sum_{u \in \mathcal{U}} \mathbf{F}^{(t,u)}.$$

5. We refer to the AFG as the aggregated network over multiple time-steps $\mathcal{F} = \frac{1}{T}\sum_{t=1}^{T}\mathbf{F}^{(t)}$.

Between steps 4 and 5, Rollo et al. (2022) perform a *weight rescaling* step, since the network weights, representing user flow, depend on the popularity of the source and target subreddits. Therefore, to dampen this dependency, it is suggested to rescale the network weights by the geometric mean of their in/out node strengths [9]:

$$F'_{ij} = \frac{F_{ij}}{\sqrt{\sum_k F_{ik} \cdot \sum_k F_{kj}}} = \frac{F_{ij}}{\sqrt{s_i^{out} \cdot s_j^{in}}}.$$

The AFG is normally a *dense* graph with relatively low-weights. Rollo et al. (2022) show that by performing a last pre-processing step and setting a threshold to prune low-weight edges reduces noise and can be beneficial for detecting communities in the network at low computational cost.

2.3.2 Communities, Gateways and Bridges

The definition of the AFG provides a direct way to find topical *communities* of subreddits within Reddit's environment since a community found in the AFG (using any community detection network) can be interpreted as a group of subreddits where the user's attention migrates regularly from one to another, while migrating to external subreddits is rare. Users belonging to the same community can be seen as users that are usually interested in similar topics. Moreover, assuming that users on Reddit reads the same subreddits it posts in, communities can be seen as an example of *echo chambers*, where users are exposed only to the content inside their own communities and the interactions between users of different communities is less probable.

The definition of communities in the AFG also enable the possibility to understand which are the likely pathways an active user takes to enter or to move from a given community. To do this, Rollo et al. (2022) operationalize the concepts of *gateways* to, and *bridges* from a given community X. By modeling Reddit users' as discrete-time random walkers[10] (with the weighted adjacency matrix $\mathcal{F}$ of the AFG acting as the transition matrix of the Markov chain process defined by the discrete-time random walk), the stationary distribution of walkers that have a probability of (re)-start in a given community (or group of communities) is given by the Personalized PageRank (Page et al., 1999; Gleich, 2015) of nodes in the network. Thus, Rollo et al. (2022) use this metric to quantitavely determine which are the subreddits that are more likely to act as entry-points (gateways) for a community X for users coming from outside the community, and which subreddits are more likely to act as bridges for users transitioning from X to another community Y.

Definition 1 (Bridge node). A subreddit s belonging to a community Y is a bridge from the community X (with $X \neq Y$) if it has a high probability of being reached by a DTRW with uniform probability of (re)-starting in any $s' \in X$. This is equivalent to saying that $s \in Y \neq X$ is a bridge from X if it has a high Personalized PageRank (PPR) value, where the PPR is a random walk with uniform probability

[9] The in (out) strength of a node $s_i^{in/out}$ is defined as the sum of the ingoing (outgoing) weights to that node.

[10] See Subsection 2.1.3 for more details.

of re-(start) in any $s' \in X$.

The above definition requires a pair of starting-arrival communities and is intended to highlight subreddits that act as *transition points* for users that migrate from a community X towards a community Y. Bridge nodes can be seen as subreddits which users usually transit while migrating their attention from one community to another. Rollo et al. (2022) propose a complementary definition in order to capture subreddits that act as *attracting points* or *entry points* to a given community X for users that migrate from outside of the same community X.

Definition 2 (Gateway node). A subreddit $s \in X$ is a gateway for the community X if it has a high probability of being reached by a DTRW with uniform probability of (re)-starting in any $s' \notin X$. This is equivalent to saying that $s \in X$ is a gateway for X if it has a high PPR value, where the PPR is a random walk with uniform probability of re-(start) in any $s' \notin X$.

Chapter 3

Methodology

This chapter describes our methodology based on extending the Attention-Flow Graph framework (see Section 2.3). We first identify the main topical communities of subreddits within Reddit and then study the user pathways between political and conspiracy communities in Reddit while accounting for different sociodemographics, e.g. if users are old/young, masculine/feminine, poor/affluent, etc. Our main methodology can be summarized in the following steps:

1. We build a novel dataset consisting on user posts on the most active subreddits in the Reddit environment during the 2019-2023 period and use it to construct the Attention-Flow Graph (AFG) between these subreddits in order to quantify the migration of users' attention between subreddits. In contrast with the original AFG framework, we apply the Disparity Filter to extract the backbone of this network and use the Infomap algorithm to find political/conspiracy communities of subreddits, where users belonging to the same community can be seen as users interested in similar topics.

2. We quantify the positioning of every user in the dataset along social dimensions (age, gender, affluence, partisanship) as introduced in Section 2.2 and compare it with the positioning of users that entered a given community calculated using only the subset of posts before entering that community. We thus identify which sociodemographic groups are more likely to enter a particular community by assessing the social dimensions that are under or over-represented before entering a community with respect to the user scores of our general population[1].

3. As a novel contribution, we introduce a *stratified* version of the AFG that incorporates the social dimension positioning of every user in the dataset, where the signed edges between subreddits represent attention migration of users from an associated sociodemographic (young/old, masculine/feminine, poor/affluent, left-wing/right-wing). We then study the paths different sociodemographic groups take to enter a given community by identifying key subreddits that act as *gateways* or *bridge* subreddits in the stratified-AFG distinguishing between the positive and negative edges of the network.

The aforementioned methodology is not limited only to the study political/conspiracy communities in Reddit but it can be used to study any topical community of interest both from a general and a sociodemographic perspective. In the following, we describe in detail each of the steps of the methodology. In Sections 3.1 and 3.2, we describe

[1] All the Reddit users present in our dataset.

the steps followed to build the AFG and find topical communities within Reddit. In Section 3.3 we introduce the methodology used to infer the sociodemographic traits of users in Reddit by projecting the social dimension scores defined by Waller and Anderson (2021). Finally, in Section 3.4 we describe the process to build the stratified version of the AFG and the definitions of gateway and bridges used for comparing the pathways followed by users with different sociodemographic characteristics.

3.1 Data Preprocessing

We build a new dataset with more recent data than Rollo et al. (2022) by obtaining all Reddit posts[2] from 2019 to 2023 from the PushShift dataset (Baumgartner et al., 2020). Since Reddit's user activity and posts have significantly increased throughout time, leading to a more computationally expensive analysis for recent years, we take a random sample of users, selecting $\sim 10\%$ of all the total participant users that made a post during the 2019-2023 period. To ensure users are positively engaged with a community, we maintain posts with a score greater than one. We also exclude inactive subreddits by selecting only subreddits that have at least one month with at least 50 distinct users publishing a post on it during the considered time period. Finally, we also take care of *bots* by filtering out users who posted on more than 50 distinct subreddits for at least one month and users with bot in their username. We obtain a dataset with 50,360,619 posts submitted by 4,536,459 unique users in 89,157 unique subreddits.

3.2 Attention Flow Graph

We build the Attention-Flow Graph (see Section 2.3) using the previously obtained data and we use the resulting network to find groups of subreddits (communities) where users' attention migrates regularly. As suggested by Rollo et al. (2022), we rescale the network weights by the geometric mean of their in/out node strengths to avoid too much weight dependence on subreddits' popularity (see Figure B.1 comparing different approaches).

3.2.1 The Disparity Filter

The obtained AFG is *dense*, with 2,273,667 edges among 65,612 nodes and with high degrees for each node ($\langle k^{in} \rangle \approx 182$) making computationally expensive both the analysis and eventual community detection on the network. Thus, we pre-process the network by pruning non-significative edges following a different approach as the one made by Rollo et al. (2022). In the original paper, given that edges have relatively low weights (median $\sim 10^{-4}$), the authors decide to set a threshold and prune low-weight edges. However, one important drawback of this approach is its dependence on the overall structure of the network and its weight distribution, $P(\omega)$.

For many complex networks this distribution is heavy-tailed and spans several orders of magnitude implying a lack of characteristic scale, whereas any thresholding method introduces a characteristic scale from the beginning by removing all edges with a weight below a given value ω_c. While this issue is not a major drawback in networks where the weights of all the edges are independently and identically

[2] We focus only on posts made by users (rather than comments) since posts act as a stronger proxy of *involvement* of a user in a given subreddit (Datta and Adar, 2019).

distributed (iid), cutting off the tail of the $P(\omega)$ would destroy the multiscale nature of more realistic networks by systematically ignoring nodes with small strengths.

We prune edges from the AFG according to the Disparity Filter method proposed by Serrano et al. (2009). This method extracts the multi-scale backbone of complex weighted networks by preserving the edges that are statistically significant[3] with respect to a null model that locally assigns normalized weights to edges by random assignment from a uniform distribution (see Subsection 2.1.5 for more details). The disparity filter is an efficient methodology whenever weight heterogeneity is high since it maintains the multi-scale property of the network and doesn't ignore nodes with small strengths. However, it works also for more homogeneous networks, since in this case the filtering loses its hierarchical properties and becomes analogous to the global thresholding method mentioned before.

After applying the disparity filter to the AFG with a significance value of $\alpha = 0.01$ we obtain a final pruned network with a giant component containing 62 139 nodes with 779 021 directional edges. In Figure B.2(a) we show the weight distribution of the network before and after pruning, highlighting the method's efficiency in maintaining the distribution's overall structure.

3.2.2 Community Detection

We use the final AFG to detect topical communities on Reddit using the Infomap algorithm[4] (Rosvall and Bergstrom, 2007) to extract the underlying community structure of the AFG. We chose this algorithm over the more robust Stochastic Block Model (SBM), originally used by Rollo et al. (2022), given its computational efficiency in large networks. Even though community detection methods involving statistical methods such as the SBM (Peixoto, 2017) have less probability of *overfitting* (mistaking stochastic noise with actual community structure) and *underfitting* (modularity optimization cannot find more than $\sqrt{2m}$ communities, this is the so-called *resolution limit*) than greedy methods involving modularity optimization (Guimerà et al., 2004), the Infomap algorithm gives a good trade-off between accuracy and complexity being more robust than simple modularity optimization. The algorithm's resolution limit depends only on the total weight of edges between communities and it has an almost-linear time complexity even on large networks (Kawamoto and Rosvall, 2015). Moreover, this algorithm is naturally applicable to weighted and directed networks in contrast with other popular methods like the Louvain algorithm (Blondel et al., 2008).

3.3 Incorporating Sociodemographics

We quantify users' positions along social dimensions by leveraging the *subreddit embedding* scores obtained by Waller and Anderson (2021) for different social dimensions (age, gender, affluence, partisanship) and projecting them onto users using their subreddit posting activity. Waller and Anderson (2021) quantify the positioning along social dimensions of $10,060$ of the most popular subreddits over a 14-year period in Reddit using community embeddings that position subreddits in a d-dimensional space such that subreddits with a similar user-base are close together in this space (see Section 2.2 for more details). They find social dimensions

[3] Given a significance value α such that $p_{val} < \alpha$.
[4] See Subsection 2.1.4 for more details.

corresponding to specific social constructs by identifying a pair of seed subreddits that differ in a given target construct but are similar in other aspects[5] and averaging together the vector differences of the top-k pairs of subreddits with the most similar vector difference to the difference of the original seeds. The average difference of these pairs is then the final dimension corresponding to the target construct.

Waller and Anderson (2021) position every subreddit along the axes of a social dimension by projecting its vector embedding onto the particular dimension vector. Subreddits with similar user-base as the extreme axes of a given social dimension (negative or positive), end up near those extremes, whereas communities that are equally similar to any extreme fall in the middle. It is important to mention that these scores measure social associations and not individual characteristics (hard measured socio-demographics of a user). For example, a subreddit's position on the partisan axis is not a direct measure of the political leaning of the members of the subreddit, but it is considered an association with the constructs of left-wing and right-wing partisanship as expressed on Reddit.

3.3.1 User Projected Scores

We project subreddit scores onto users by considering the activity of each user in the Reddit environment. We define the score F_u^d of a user u with respect to a given dimension d as the weighted average of all his posts in each subreddit (Monti et al., 2023):

$$F_u^d = \frac{\sum_s N_{u,s} F_s^d}{\sum_s N_{u,s}},$$

where $N_{u,s}$ is the number of posts of a user u in a subreddit s and F_s^d the subreddit score on a given dimension.

We obtain the user scores F_u^d of all the participating users of the $89,157$ subreddits considered in this study for the age, gender, affluence, and partisanship social dimensions. We do this by considering the subreddit scores F_s^d obtained by Waller and Anderson (2021) for the same social dimensions and for the subreddits that remain popular for our considered time period ($8,296$ from the original $10,060$). In order to avoid noise, we consider only users that posted at least 5 times in one of the subreddits for which the subreddit scores are available.

We also obtain the user scores F_u^d of all the participating users of the communities found in Section 3.2 before they entered a particular community. This is, we calculate their scores taking into account only the posts shared before posting for the first time in a given community [6]. This allows us to study which sociodemographic groups are more likely to enter a given community, with a specific focus on political and conspiracy communities. In this case, we also ensure that users posted at least 5 times in one of the subreddits for which the subreddit scores are available to avoid having users without scores.

[5]For example `r/teenagers` and `r/RedditForGrownups` for the age dimension.

[6]We don't use the member subreddits of the community to obtain the score, since we only use posts shared in subreddits before entering the community.

3.4 Stratified Attention Flow Graph

As a main contribution to study the different pathways users take depending on their sociodemographic traits, we extend the AFG framework (see Section 2.3) to stratified (signed) versions of the original network, where edge weights capture attention flow conditioned on a specific social dimension (e.g., age, gender, etc.) and the sign of the weights indicates users' positions along that dimension (e.g., old vs young, masculine vs feminine, etc.).

3.4.1 Network Construction

Given the scores F_u^d for each user and social dimension, we construct a *stratified* version of the AFG for each social dimension by aggregating the attention flow of users (step 4 of subsection 2.3.1) as a weighted sum of their social dimension scores:

$$\mathbf{F}_d^{(t)} = \sum_{u \in \mathcal{U}} \mathbf{F}^{(t,u)} \cdot F_u^d.$$

We then refer to the stratified-AFG for each dimension d (age, gender, affluence, partisanship) as the aggregated network over multiple time-steps:

$$\mathcal{F}_d = \frac{1}{T} \sum_{t=1}^{T} \mathbf{F}_d^{(t)}.$$

In order to give more importance to edges with a high quantity of user-attention migration, we multiply the signed network weights with the weights of the original AFG (see Section 3.2) in case the edge exists in both networks. When an edge doesn't exist for the original AFG, we consider it non-existent for the stratified version. We notice that the stratified-AFG is a *signed* network since users can have negative scores representing their association to the negative axis of a given social dimension (e.g. negative scores on the gender axis associates user with the masculinity axis). We distinguish the positive (negative) version of $\mathcal{F}_d$ by only keeping edges that are positive (negative) on the original network. The edges of the positive (negative) network $\mathcal{F}_d^{\pm}$ for a given social dimension represent how much of a user's attention migrated from a subreddit i to a subreddit j given that this user is associated with the positive (negative) axis of the social dimension. For example, the edges of $\mathcal{F}_{\text{age}}^{+}$ represent how much of an old-age-associated user's attention migrated between subreddits.

The definition of the stratified-AFG $\mathcal{F}_d$ allows us to get a notion of how the pathways into subreddit communities vary across social dimensions (age, gender, affluence, partisanship) and which subreddits are more relevant as entry points or transition points depending on a user's particular social and demographic association. In other words, we are interested in finding which subreddits act as *gateways* or *bridges* where users enter to or transition from a given community depending on their sociodemographic association.

3.4.2 Gateways and Bridges

We define gateways and bridges in an analogous way as Rollo et al. (2022) by modeling Reddit users as discrete-time random walkers (see Subsection 3.4.2 for more details), with the weighted adjacency matrix $\mathcal{F}^{\pm}$ as the transition matrix of the Markov chain process defined by the random walk. The discrete-time random walk (DTRW) has a probability of (re)-start in a given community (or group of communities) and therefore its stationary distribution is given by the Personalized PageRank (Page et al., 1999; Gleich, 2015) of nodes in the network (PPR).

A gateway node (*to* a community X), as defined in Subsection 3.4.2, can be seen as a subreddit that has a high probability (given by the PPR of the node) of being an *entry-point* for Reddit users coming from outside X. On the other hand, a bridge node *from* X to Y, as defined in Subsection 3.4.2, is a subreddit that acts as a *transition point* where Reddit users arrive after exiting X. However, in this work we are interested in identifying subreddits that act as bridges *to* a given community X after exiting any other different community, since we aim to uncover the pathways different user groups take to enter given political/conspiracy communities. Therefore, to find bridges *to* a given community X, we mantain the same definition of bridge given by Rollo et al. (2022) but we perform the random walk (and obtain the PPR) on the transpose of the stratified-AFG, i.e. the network with all the edges in reverse direction. In this way, we ensure that the bridge nodes (to X) with highest PPR are subreddits that have several pathways to X and thus act as transition points to X from outside the community.

By applying the aforementioned definitions to the stratified-AFG $\mathcal{F}^{\pm}$, we can rank the top gateway and bridge nodes in the network for a given axis of a given social dimension, i.e. for users of different sociodemographic groups. In this way, we can compare the role that particular subreddits play, as attracting or transition points between communities, when users navigate the Reddit environment and how this role changes when accounting for different sociodemographic associations, uncovering the different pathways users take according to their sociodemographic traits.

Chapter 4

Results and Discussion

This chapter illustrates the results obtained by applying our methodology with a particular focus on political/ conspiracy communities. First, we discuss some structural properties of the final AFG and the communities found using the Infomap algorithm (Section 4.1). Then, we assess which sociodemographics are more representative of users before entering the previously identified political/conspiracy communities (Section 4.2) by obtaining each users' social dimension scores using their sharing activity before entering a community. Finally, we restrict our attention to the stratified-AFG and the induced subgraph spanned by the political/conspiracy communities (Section 4.3) to study the possible pathways followed by users when accounting for sociodemographics, focusing on key subreddits that act as gateways and bridges for a given community and their differences when accounting for sociodemographic traits.

4.1 Attention Flow Graph

As mentioned in Section 3.2, the AFG is a dense graph; thus, to reduce noise and facilitate its analysis, we prune its edges using the disparity filter by removing the less significant edges ($p_{val} < 0.01$) with respect to a uniform null model on the weight distribution $P(\omega)$. As a result, we obtain a final pruned network, with a giant component[1] containing $62,139$ nodes and $779,021$ directed edges. We use this network to find topical communities in Reddit's environment by applying the Infomap community detection algorithm, finding a total of $4,083$ communities with a median size of 10 nodes each. In Figure B.2(b) we observe that the community size distribution exhibits a power-law-like behavior, with most communities having size ~ 10 and a few communities having large sizes $\sim 10^3$. To empirically validate the resulting communities, we manually compare selected communities of interest with those identified by Rollo et al. (2022) via the Stochastic Block Model (SBM), observing a successful general topical alignment.

4.1.1 Degree Distribution

In Figure 4.1 we show the complementary cumulative distribution function (CDF), $P_c(k)$, of the (in/out)-degree of the AFG along with exponential, power-law, and log-normal fits. Each fit was tested against each other using a likelihood-ratio test, with a log-normal fit being favored over the other two cases for both degrees. This result suggests that the degree distribution of the AFG lies between the thin-tailed exponential and the heavy-tailed power-law cases. An exponential degree distribution

[1] Largest (weakly) connected component.

implies a characteristic scale, with most nodes having similar degrees and hubs being rare. A power-law distribution, by contrast, implies a scale-free structure with a small number of highly connected hubs dominating the network. The log-normal distribution, which falls between these two extremes, allows for significant variability in node degrees but a moderately heavy tail, indicating some presence of hubs but without the extreme concentration of connectivity seen in pure power-law networks.

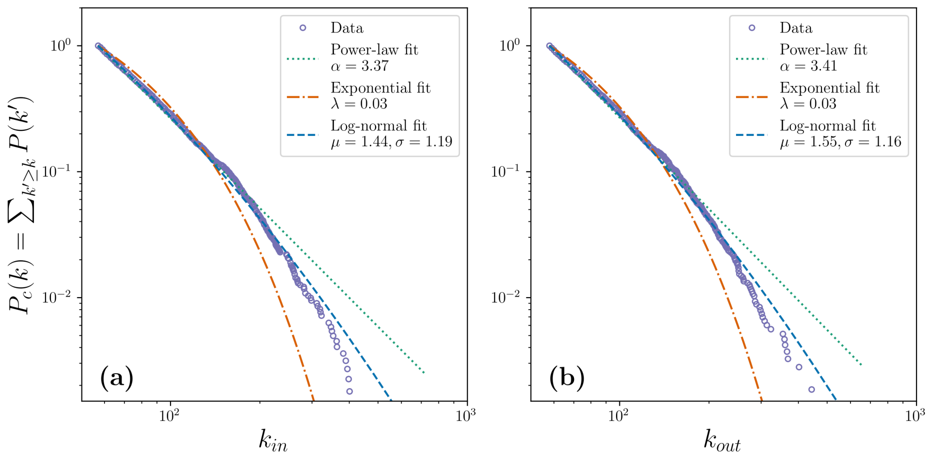

Figure 4.1. **(a)** Complementary CDF of the in-degree of the pruned AFG along with exponential, power-law, and log-normal fits. **(b)** Complementary CDF of the out-degree of the pruned AFG, with a log-normal fit being favored over an exponential and a power-law fit.

The form of the degree distribution of the AFG follows from its definition. When constructing the network, we rescale the edge weights to dampen the dependency of the weights with subreddit popularity, giving the possibility to less popular subreddits to participate meaningfully in the attention flow. After pruning less-significant edges, the consequence of edge rescaling is reducing the dominance of very popular subreddits, resulting in a broader but not excessively heavy-tailed degree distribution, consistent with a log-normal rather than power-law structure.

4.1.2 Political and Conspiracy Communities

Building on the work of Rollo et al. (2022), we focus on topical communities associated with politics and conspiracy theories. In particular, we examine the communities formed around five seed subreddits of special interest, which center on discussions about the environment, left-wing and right-wing politics, and conspiracy or esoteric topics. In Figure 4.2 we present the subgraph of the AFG spanned by the member subreddits of these communities.

Radical Left (seed: `r/socialism`). This community contains mainly left-wing oriented subreddits. In fact, among the subreddits with most subscribers we can find `r/AOC` dedicated to left-wing politician Alexandria Ocasio-Cortez, along with more radical subreddits such as `r/LateStageCapitalism` (dedicated anti-capitalist satire) or `r/Anarchism` (dedicated to the anarchic social movement). A member of interest for this community is `r/ChapoTrapHouse`, a subreddit dedicated to a popular radical left podcast banned from Reddit during the so-called *The Great Ban* (Cima et al., 2024) due to "the promotion of hate of groups based on identity and vulnerability"[2].

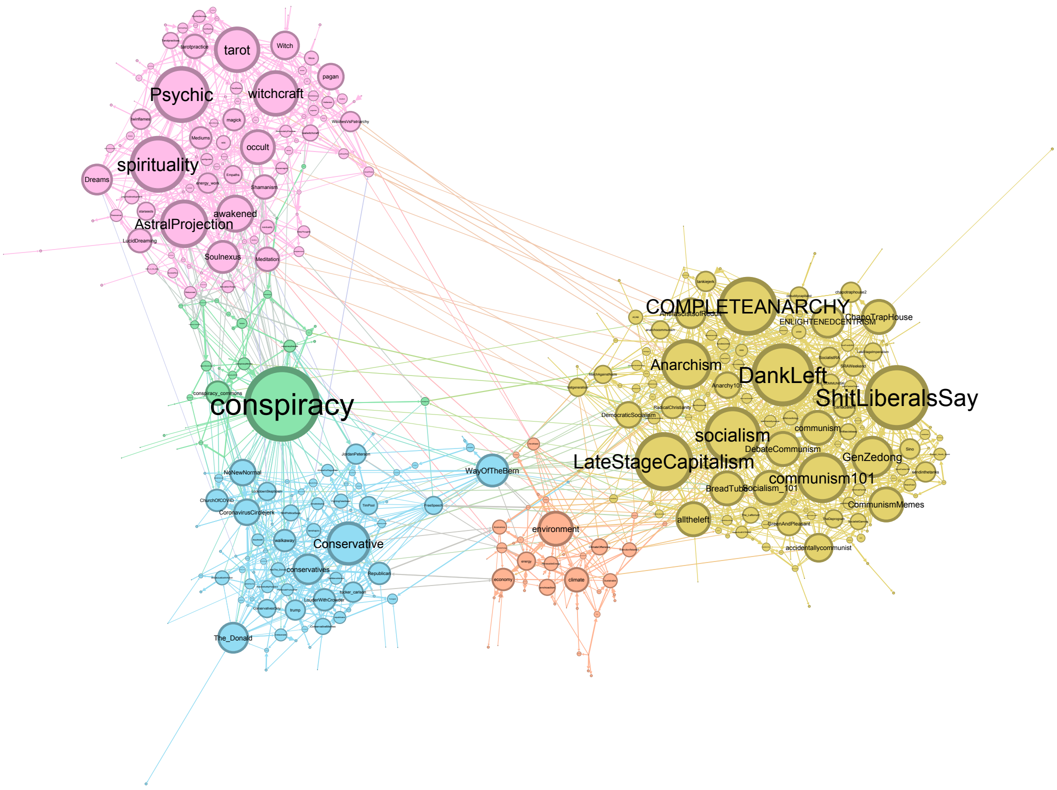

Figure 4.2. Subgraph of the AFG highlighting the selected conspiracy and political communities of the Reddit environment. Each community is represented by a color: Conspiracy (green), Esoterism (pink), Alt-Right (blue), Radical Left (yellow), and Environment (orange). The size of the nodes represents the in-degree centrality of the subreddits and the width of the edges is proportional to edge weight.

Alt-Right (seed: `r/Conservative`). This community hosts a majority of right-wing oriented subreddits such as `r/Republican` or `r/trump`, dedicated to U.S. president Donald Trump. The community also contains more radical subreddits aligned with the "alt-right" movement and conspiracy theories, such as `r/The_Donald`, a forum associated with the success of Donald Trump's presidential campaign in 2016 (Massachs et al., 2020) also banned from Reddit during The Great Ban due to its involvement in planning the 2021 US Capitol invasion (Washington Post, 2020), `r/HillaryForPrison` (anti-democrat subreddit) or `r/ChurchOfCOVID` (satirical COVID-19-skeptic forum).

Conspiracy (seed: `r/conspiracy`). This community mainly contains discussion forums for conspiracy theories. Among the subreddits with most subscribers we find general discussion forums dedicated to all kind of conspiracy theories like `r/conspiracy` or `r/conspiracytheories`, along with conspiracy theories for specific topics like `r/EscapingPrisonPlanet` (reincarnation conspiracy theory) or `r/unvaccinated` (anti-vax discussion forum). Some of the subreddits in this community are been involved with QAnon theory[3] (Engel et al., 2022).

[2] Reddit's update to its content policy (accessed 23/06/2025).
[3] A far-right conspiracy theory whose core belief is that a secret group of powerful elites operates

Esoterism (seed: r/spirituality). This community is not directly related to political topics. However, we can observe from Figure 4.2 that the conspiracy community acts as a "bridge" between this community and alt-right-related subreddits. Indeed, this community is tightly-related with conspiracy theories in the spiritual/paranormal sphere. Examples of popular subreddits within this community are: r/Paranormal, r/Glitch_in_the_Matrix, or r/witchcraft.

Environment (seed: r/environment). This community is characterized by discussion forums related to climate change, environmental issues and economics. Most member subreddits of this community are positively-engaged with climate change (r/ZeroWaste, r/ClimateActionPlan, or r/Sustainable) in contrast with subreddits in the conspiracy and alt-right communities (e.g. r/climateskeptics).

The subgraph induced by the five identified communities in the AFG includes a total of 403 subreddits with $2,072$ directed edges between them. In Table B.1 we report the number of nodes and edges between members of each community. The Radical Left and Esoterism communities are the biggest comunities, having around 10^2 nodes in contrast with the Environment and Conspiracy communities having less than 50 nodes. Figure B.3 shows the probability for a random-walk on the AFG with restart on a source community s reaches a target community t (as calculated by the PPR) as a measure of community *closeness*. We observe that the Radical Left community is close to the Alt-Right and Esoterism communities. Conspiracy exhibits greater proximity to the Esoterism and Alt-Right communities than the converse case, suggesting that individuals engaged with conspiracy subreddits are more likely to transition into esoteric or alt-right subreddits than vice versa. We also observe that the Environment community is significantly closer to the Radical Left community than to other communities, which is expected given that its constituent subreddits are predominantly focused on liberal and climate change–related topics.

4.2 Who Enters Political and Conspiracy Communities?

Following the methodology outlined in Section 3.4 we obtain the "general" user scores F_u^d of all the participating users of the $89,157$ subreddits considered in this study for each social dimension d (age, gender, affluence, and partisanship). In Figure B.4 we report the user score distribution for each social dimension along with the subreddit score distribution of the subreddits used to calculate the user scores. We consider these user scores as the baseline of our Reddit population, as we aim to uncover significant differences (if any) between this baseline and the distribution of scores before users enter political/conspiracy communities. To this end, we also obtain the scores of all the users that entered any of the communities found in subsection 4.1.2 obtaining such scores as in section 3.3 using only the posts made *before* entering such communities. We consider that a user entered a community if it made a post with a score greater than one in such community in any moment during the studied time period.

In Figure 4.3, we show the distribution of general user scores along each social dimension (first row), transformed into percentiles and represented as a uniform distribution $U(0,100)$. This uniform distribution serves as a null hypothesis, reflecting the fact that percentiles, by definition, divide sorted data into equally sized groups.

a global child-trafficking ring and that President Donald Trump is secretly working to expose and defeat them.

We then compare this baseline distribution to the distribution of scores for users *prior* to entering each of the previously identified communities. This comparison allows us to highlight which percentiles are overrepresented or underrepresented among users who enter a given community, providing a way to quantify, among all the users that entered a community, the likelihood that those users belong to a specific sociodemographic group. We particularly focus on the extreme quartiles of each distribution as they represent users that are strongly associated with a specific sociodemographic.

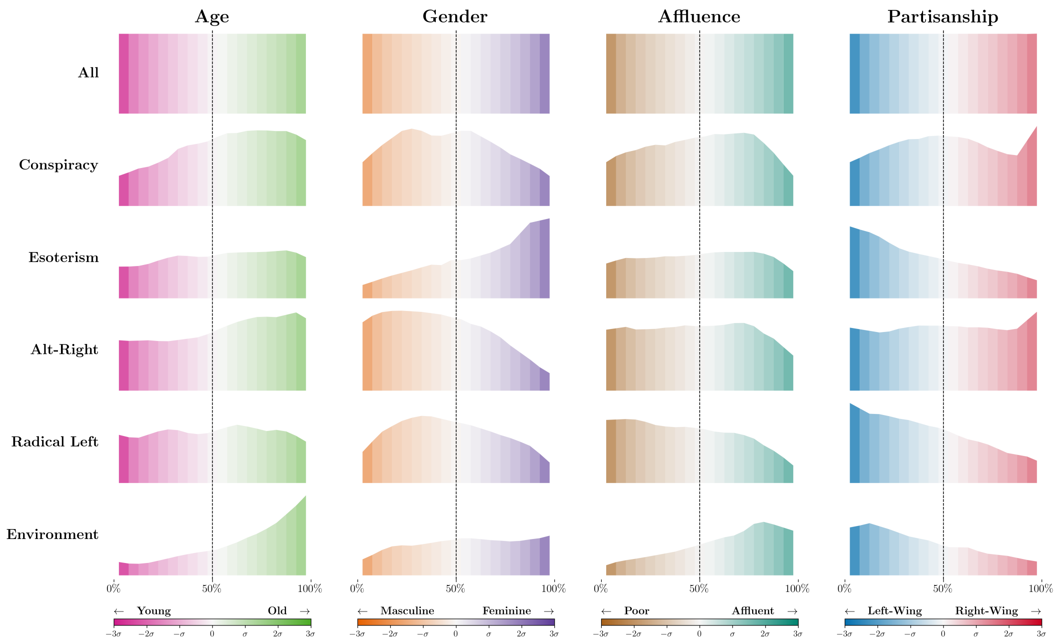

Figure 4.3. User score distributions along the age, gender, affluence and partisanship dimensions before entering each of the communities of interest. The x-axis represents the user scores transformed into percentiles (e.g. a user with a gender score greater than 60% of other communities is positioned at the 60th percentile), and color corresponds to the z-scores of the distribution. Each bin contains a total of 5 percentiles (e.g. the first bin contains percentiles 0-5, the second contains percentiles 5-10, etc.). The distribution for all users (top row) by definition is the uniform distribution $U(0, 100)$, while the distributions for each community highlight which percentiles are underrepresented or overrepresented within the community. The dotted line indicates the 50th percentile.

Qualitatively, we observe that users prior to entering the Conspiracy community (second row) tend to skew towards the older end of the age dimension and the masculine end of the gender dimension. While the distribution along the partisanship axis appears relatively diffuse, a notable peak in the 95th percentile suggests a concentration of strongly right-wing-associated users who are more likely to enter this community. In contrast, users entering the Esoterism community (third row) display a pronounced skew towards the feminine axis of the gender dimension and a clear tilt towards the left-wing end of the political spectrum.

For users entering the Alt-Right community (fourth row), we observe a strong skew towards masculinity and a more moderate skew towards older age. The partisanship distribution reveals elevated peaks at both extreme percentiles, indicating that this community attracts users from both ends of the political spectrum, albeit in a more polarized manner. Users entering the Radical Left community (fifth row) show a clear skew towards left-wing political alignment and lower affluence, with a milder tendency towards the masculine end of the gender axis.

Finally, users entering the Environment community (sixth row) are notably skewed towards the older end of the age dimension. Smaller but still noticeable skews are observed towards affluence and left-wing partisanship, suggesting a more moderate but consistent profile across these dimensions.

4.2.1 RQ1: How Likely Are Different Groups to Enter Political and Conspiracy Communities?

The percentile distributions observed in Figure 4.3 allow us to quantify the likelihood for different sociodemographic groups to enter political/conspiracy communities. To obtain this likelihood, we divide each distribution in quartiles[4] and calculate p_q, the probability that a user score falls in a given quartile for users before joining a given political/conspiracy community. We focus on the likelihood ratio between p_{75} and p_{25}, since these probabilities represent the relative density of users in the upper and lower quartiles of a given sociodemographic dimension. A ratio greater than 1 indicates an overrepresentation of users from the top quartile (e.g., older, more affluent, more right-wing), while a ratio below 1 indicates a relative overrepresentation from the lower quartile. Moreover, conditional on entering the community, this ratio tells us how much more (or less) likely is a user to come from a specific sociodemographic group. Figure 4.4 summarizes the results for each community and social dimension.

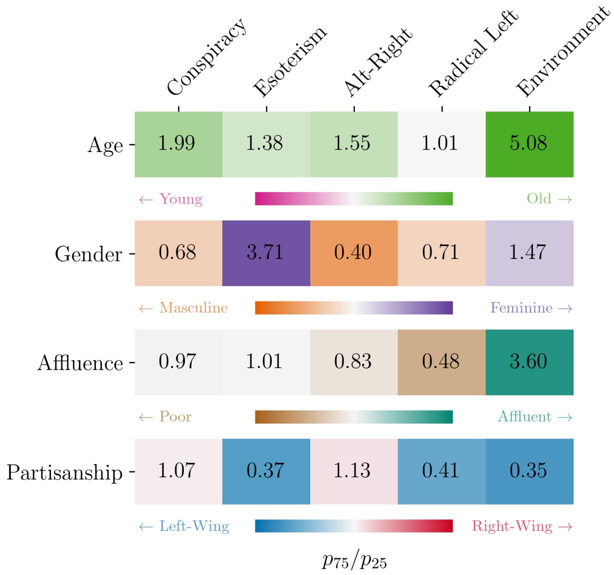

Figure 4.4. Likelihood ratio between the probabilities of having a user score in the first and third quartiles (25th and 75th percentiles) of the general user scores of a given social dimension for users before entering a political/conspiracy community. A ratio lower than one means users belonging to the first quartile are more likely to enter a given community. A ratio greater than one associates more likelihood to enter a given community for users belonging to the third quartile. Colors are associated with the log-likelihood ratio in order to highlight which sociodemographic group is more represented when entering a community.

[4] These are always the quartiles obtained from the general user scores.

Users associated with older age are approximately twice as likely to enter the Conspiracy community compared to their younger counterparts. Similarly, male users are about 1.5 times more likely to enter than users associated with the feminine end of the gender spectrum[5]. This is also the case for the Alt-Right community, with male users about 2.5 times more likely to enter than users aligned with the feminine axis, while older users being approximately 1.5 times more likely to enter than younger ones. We observe a weak effect on the partisanship dimension, with right-wing users being only 1.2 times more likely to enter this community.

In the case of the Esoterism community, users aligned with the feminine gender axis are approximately 3.7 times more likely to enter than their masculine counterparts. These users are also 2.7 times more likely to come from the left-wing end of the political spectrum compared to right-leaning users. Users entering the Radical Left community are roughly twice as likely to come from the lower end of the affluence distribution, indicating a disproportionate representation of economically disadvantaged individuals. These users are also around 2.5 times more likely to be left-leaning in their political alignment, with a weaker but notable skew toward masculinity—being approximately 1.4 times more likely to enter than feminine users.

Finally, in the case of the Environment community, older users are nearly five times more likely to enter compared to younger ones. Users associated with high affluence are also substantially overrepresented, being about 3.6 times more likely to enter than those from the lower end of the affluence spectrum. Left-leaning users are similarly overrepresented, with a likelihood approximately 2.7 times greater than that of right-leaning users.

4.3 Pathways Into Political And Conspiracy Communities

Once we characterize the users that enter political/conspiracy communities, it is of interest to study the pathways they take to enter these communities. To this end, using the general user scores found in the previous section, we construct the stratified-AFG $\mathcal{F}^{\pm}$, where the weight of each (signed) edge represents how much of a user's attention-flow migrated from a subreddit i to a subreddit j weighted by the user's associated score for a social dimension. For example, for the gender dimension the positive stratified-AFG $\mathcal{F}^{+}$ contains edges representing the attention-flow of users associated with the "feminine" construct, whereas the negative stratified-AFG $\mathcal{F}^{-}$ contains edges representing the attention-flow of users associated with the "masculine" construct.

4.3.1 Community Closeness

Using the stratified-AFG, we re-examine the closeness between communities distinguishing between the positive and negative versions of the network. This allows us to highlight how community closeness changes depending on a user's socio-demographic traits, i.e. how probable it is for a user of a given demographic group to arrive from one community to another. In Figure 4.5, we model users as random walkers and we compare the probability for a random-walk on the (positive and negative)

[5] $1/1.5 \approx 0.68$

stratified-AFG to reach a target community t if (re)-starting on a source community s. It is important to notice that this random walk is always done on the complete stratified-AFG and not just on the induced subgraph, giving the opportunity to the random walker to take any possible path. Visiting probabilities are then re-normalized to the space defined by the nodes in the induced subgraph.

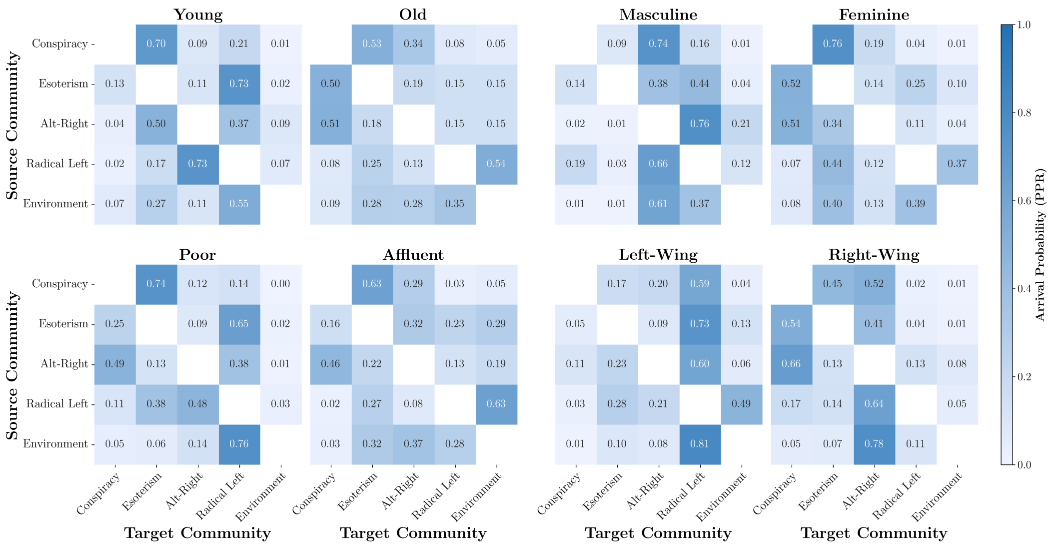

Figure 4.5. Probability that a random-walk (with restart) on the AFG reaches a target community t if starting from a source community s, distinguishing by the positive and negative axes of each social dimension: Age (upper-left), Gender (upper-right), Affluence (lower-left), and Partisanship (lower-right).

Age Dimension (upper-left). The Conspiracy and Esoterism communities are closely connected across age groups, though transitions from Conspiracy to Esoterism are more pronounced among younger users. Younger users also show stronger links between Esoterism, the Radical Left, and the Alt-Right, suggesting greater ideological crossover in this group. In contrast, older users show tighter connections between the Alt-Right and Conspiracy, with little interaction involving Esoterism or the Radical Left. Among older users, transitions between the Radical Left and Environment communities are more prominent, reflecting a different axis of movement that also appears, though to a lesser extent, among the young.

Gender Dimension (upper-right). Among male users, all communities show strong connectivity with the Alt-Right, suggesting that this group often acts as a convergence point regardless of users' starting communities. In contrast, users aligned with the feminine axis display a consistently high probability of transitioning into the Esoterism community, no matter where they begin. For male users, both Esoterism and the Alt-Right are also closely linked to the Radical Left, indicating potential transitions across ideological lines. On the feminine axis, however, these same communities are more strongly connected to Conspiracy, reflecting a different pattern of movement that may be shaped by gender-associated identity traits.

Affluence Dimension (lower-left). The Conspiracy and Esoterism communities are strongly connected across both low- and high-affluence users. Among less affluent users, we also observe a strong connection between Conspiracy and the Radical Left. The Alt-Right is consistently linked to Conspiracy regardless of affluence, but among low-affluence users, it also shows a strong mutual connection with the Radical Left. Additionally, the Radical Left and Environment communities maintain a strong, bidirectional relationship across both affluence groups.

Partisanship Dimension (lower-right). Among left-wing users, all communities show strong connectivity with the Radical Left, as it could be expected since this community is a focus point for left-wing-associated users. In contrast, right-wing users are most strongly connected to the Alt-Right community. We also observe distinct patterns of mutual connections: Esoterism and Conspiracy are closely linked among right-wing users, while Radical Left and Environment communities share strong ties among left-wing users.

4.3.2 RQ2: How Do Entry Paths Differ Across Sociodemographic Groups?

The definition of the stratified-AFG allow us to operationalize the definition of *bridges* and *gateways* to the previously found communities (see subsection 3.4.2). In particular, we obtain the ranking of gateways and bridges for both the negative $\mathcal{F}^-$ and positive $\mathcal{F}^+$ versions of the stratified-AFG and compare them obtaining the weighted Kendall Tau index[6] between them, a correlation index that compares rankings with ties giving more weight to changes in the top elements of the rank. Using this framework, we compare how the entry pathways towards a given community differ across sociodemographic groups.

In Figure 4.6 we report the values for the weighted Kendall-Tau $\hat{\kappa}_\tau$ between the bridge/gateway rankings obtained for both versions (positive and negative) of the stratified-AFG for each social dimension. Moreover, in Figure 4.7 we present the values for the weighted Kendall-Tau κ_τ between the rankings of the positive (or negative) stratified-AFG and the normal AFG acting as a baseline, in order to not only compare how the pathways to each community differ for each sociodemographic, but which sociodemographic has the most *peculiarity* in their pathways with respect to the general population.

Gateways And Bridges To Conspiracy

We observe no substantial differences in the gateway subreddits leading to the Conspiracy community across social dimensions—that is, subreddits that serve as entry points to the community. As shown in Table B.3, the top three gateways are consistently `r/conspiracy`, `r/conspiracy_commons`, and `r/conspiracytheories`. These are broad-topic subreddits centered on conspiracy theories, suggesting they serve as common gateways into the conspiracy ecosystem across all sociodemographic groups. Indeed, we observe no significant deviations from the rankings derived from the baseline AFG, reinforcing the idea that these subreddits function as universal entry points, independent of users' social attributes.

In contrast to gateways, we observe notable *peculiarity* in the bridges to the Conspiracy community across sociodemographic groups, particularly among young, masculine, and left-wing users (Table B.4). While most bridges originate from esoteric subreddits—such as `r/AstralProjection`, `r/LucidDreaming`, and `r/Retconned`—the specific patterns differ by group. Young users often arrive through spirituality- and

[6] See Appendix A.1 for a detailed description of this metric.

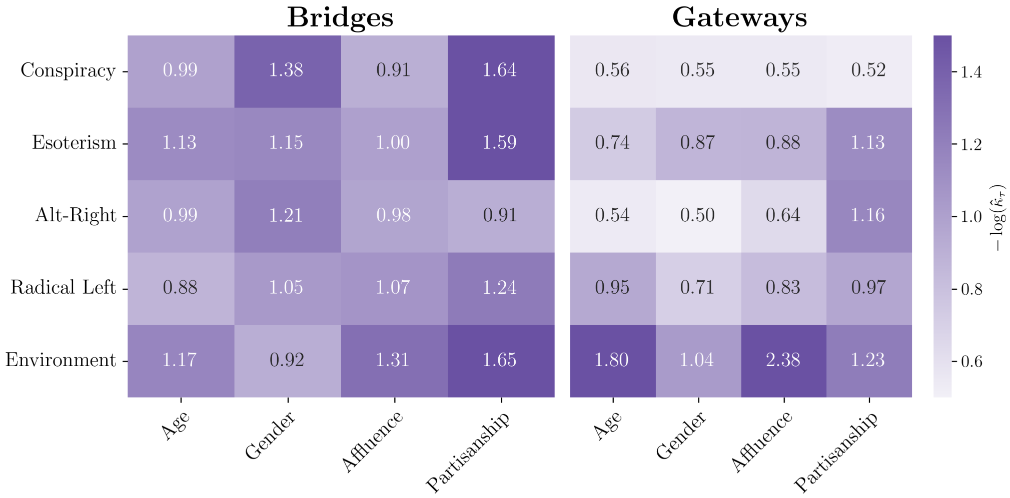

Figure 4.6. Negative logarithm of the weighted Kendall-Tau ($\hat{\kappa}_\tau$) values between the bridge/gateway rankings of the positive and negative versions of the AFG for each social dimension. Higher values are assigned to higher ranking difference between social dimension axes, and viceversa.

religion-focused communities like `r/Wicca`, whereas older users also pass through politically oriented forums, such as the alt-right subreddit `r/DescentIntoTyranny`, a subreddit discussing the idea of the US becoming a "tyrannic state". Gender differences follow a similar pattern: male users more frequently enter through political subreddits (e.g., `r/CoronavirusCirclejerk`, `r/thebakery`), while feminine users tend to pass through esoteric spaces. Along the partisanship axis, both left- and right-wing users primarily transition into Conspiracy via esoteric subreddits, though the particular themes discussed vary.

Gateways And Bridges To Alt-Right

We observe the highest peculiarity and difference in the gateway subreddits leading to the Alt-Right community when accounting for partisanship, as expected, since this community is highly associated with right-wing politics. Indeed, Table B.5 shows that left-wing users enter the Alt-Right community through subreddits such as `r/WayOfTheBern`[7], a bipartisan subreddit associated with the spreading of conspiracy theories (Phadke et al., 2021a), or `r/Trumpgret`, a subreddit dedicated to discussing voting regret of Donald Trump's supporters. On the other hand, right-wing users enter the Alt-Right community through more "traditional" gateway subreddits related with conservative politics and the alt-right movement, such as `Conservative`, `The_Donald` or `JordanPeterson`, a subreddit related to conservative public figure Jordan Peterson associated with the so-called manosphere and in spreading climate change conspiracy theories[8].

We observe the highest peculiarity in the bridges to Alt-Right for the young, masculine, and poor users. Table B.6 shows that young users mostly arrive to Alt-Right

[7] Subreddit once dedicated to US senator Bernie Sanders and now dedicated to discuss politics rejecting the traditional left-right political spectrum.
[8] Scientists slam Joe Rogan's podcast episode with Jordan Peterson as 'absurd' and 'dangerous' (accessed 01/07/2025).

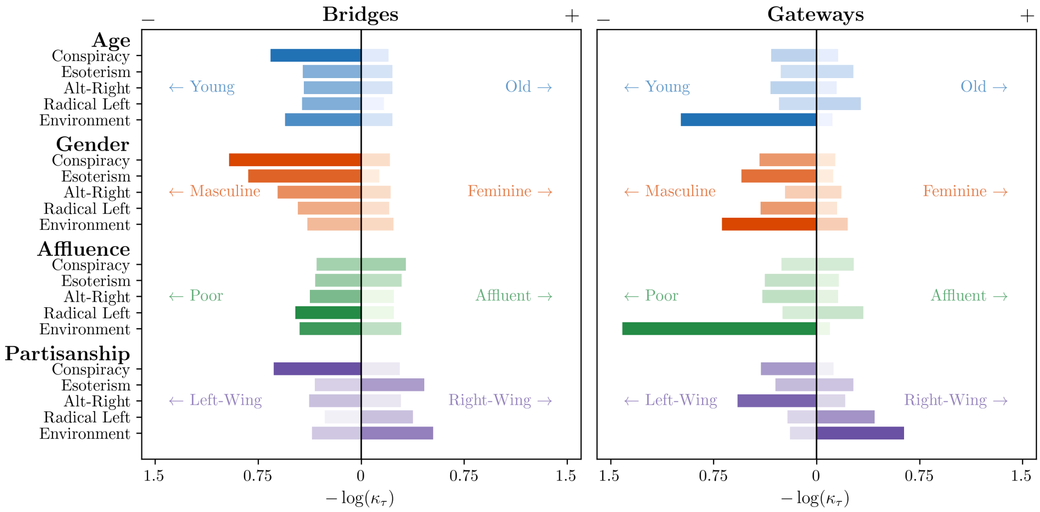

Figure 4.7. Negative logarithm of the weighted Kendall-Tau (κ_τ) values between the bridge/gateway rankings of the signed-AFG's $\mathcal{F}^{\pm}$ and the baseline AFG $\mathcal{F}$. The values are colored by social dimension and the colors are normalized by the values of each dimension. Higher values are assigned to higher ranking difference with the baseline and viceversa.

through Radical Left fringe subreddits such as `r/ShitLiberalsSay` (satirical anti-liberal forum) or `r/MoreTankie196` (socialist meme subreddit). On the other side, old users tend to arrive through conspiracy-related subreddits such as `r/conspiracy` or more pragmatic subreddits like `r/energy`, which hosts general discussions on energy policy, infrastructure, and geopolitics. On the gender dimension, male users tend to reach the Alt-Right through ideologically diverse subreddits such as `r/economy`, `r/unvaccinated`, and `r/ChapoTrapHouse`. These subreddits range from policy-focused economic discourse to conspiratorial anti-establishment content and satirical far-left critique. In contrast, female users more often arrive via consistently anti-establishment and conspiratorial subreddits such as `r/conspiracy`, `r/ConspiracyMemes`, and `r/ShitLiberalsSay`. When accounting for affluence, we notice that `r/conspiracy` acts as the most important bridge to Alt-Right for both poor and affluent users. Nevertheless, poor users tend to consistently arrive through fringe and conspiratorial forums (e.g. `r/ConspiracyMemes` or `r/ShitLiberalsSay`), while affluent users tend to arrive through more pragmatic and general subreddits related to geopolitics and economy (e.g. `r/energy` or `r/economy`).

Gateways And Bridges To Environment

There are clear differences in the pathways leading to environmental communities across nearly all sociodemographic dimensions (see Figures 4.7 and 4.6), with the most pronounced deviations from the baseline observed among young, masculine, poor, and right-wing users. Table B.7 shows that for young users, top entry points often include subreddits unrelated to environmental topics—such as `r/KillingStalking`, a forum for Korean manhwa, and `r/facts`, which focuses on general fact posting. Still, `r/climatechange` emerges as a key gateway, reflecting a more activist-oriented engagement. In contrast, older users tend to enter through more pragmatic subreddits that approach environmental issues through economic and policy lenses, such as `r/environment` and `r/energy`. A similar divide is observed along the gender axis: masculine users are more likely to arrive via general-interest subreddits that frame environmental topics in economic terms (e.g., `r/Economics`, `r/oil`), while feminine users often engage through more climate-conscious and lifestyle-oriented communities like `r/ZeroWaste`. These patterns extend to affluence and partisanship as well—affluent and right-wing users tend to access environmental discourse through economically focused subreddits, whereas poor and left-wing users more often enter through explicitly climate-focused forums.

Table B.8 shows the top three bridges to Environment communities by social dimension. For age, users commonly enter through socialism-related subreddits such as `r/Socialism_101` and `r/socialism`. Younger users also show entry points from esoteric forums like `r/Meditation` and climate-skeptic subreddits such as `r/climateskeptics`, while older users primarily arrive via Radical Left communities focused on critiques of capitalism, including `r/LateStageCapitalism` and `r/lostgeneration`. Regarding the affluence social dimension, users generally come from radical left and esoteric subreddits like `r/ChapoTrapHouse` and `r/Meditation`, but affluent users notably also transition through `r/Conservative`, a prominent Alt-Right subreddit. A similar pattern emerges along the partisanship axis: left-wing users primarily enter from radical left forums, whereas right-wing users often bridge from Alt-Right and conspiracy-oriented communities such as `r/conspiracy`.

Gateways And Bridges To Radical Left

Similarly to Alt-Right, we find the highest peculiarity and difference between the gateway subreddits to Radical Left when accounting for partisanship, given that this is a community associated with left-wing politics. Table B.9 shows that both left-wing and right-wing users mainly enter the Radical Left community through subreddits related to communism, such as `r/communism` or `r/communism101`, with an apartisan debate forum (`r/DebateCommunism`) as the main entry point for right-wing users. Moreover, we observe also popular fringe subreddits as entry points, such as `r/ChapoTrapHouse` or `r/LateStageCapitalism`.

In the case of bridges to Radical Left, we observe the highest peculiarity and differenence between sociodemographic groups when accounting for the affluence and partisanship social dimensions. Table B.10 shows a stark difference between the bridges for poor and affluent users. Less-affluent users arrive to Radical Left through radicalized conspiracy and alt-right subreddits, such as `r/Freespeech` or `r/C_S_T`, abbreviation for "Critical Shower Thoughts" and a subreddit associated with "politically incorrect" content and the roots of alt-right movements (Massachs et al., 2020). On the other hand, affluent users arrive to Radical Left from pragmatic subreddits mainly coming from Environment discussing political topics from an economic perspective (`r/Economics`, `r/energy`, `r/environment`). Regarding the partisanship dimension, we observe that esoteric forums play an important role as bridges to Radical Left, although right-wing users mainly arrive through conspiracy communities (`r/C_S_T`, `r/conspiracy`, etc.) while left-wing users arrive through forums including members from both parts of the political spectrum such as `r/WayOfTheBern` and `r/environment`.

Gateways And Bridges To Esoterism

We observe the most peculiarity and difference between sociodemographic groups for both the gateways and bridges to Esoterism when accounting for the gender and partisanship dimension. Regarding the gateways, Table B.11 shows that `r/Dreams`, a subreddit dedicated to sharing dream anecdotes, is an important entry point for both masculine and feminine users. Nevertheless, masculine users particularly enter through "self-help" related subreddits (`r/GetMotivated` or `r/confidence`) while feminine users enter through more esoteric subreddits such as `r/witchcraft` or `r/tarot`. In the case of partisanship, we observe that esoteric topics are the main entry point to the community for both political extremes although topics may change depending on political leaning.

In the case of the bridges to Esoterism, Table B.12 shows a clear separation both in the gender and the affluence dimensions. While masculine users arrive to Esoterism from mainly Radical Left fringe subreddits (e.g. `r/LateStageCapitalism` or `r/SocialistRA`), feminine users arrive from conspiracy-related forums (e.g. `r/conspiracy` or `r/C_S_T`). Regarding partisanship, we observe an expected behavior since left-wing users mainly arrive to Esoterism through left-wing-related forums and viceversa. Nevertheless, we notice that they both arrive from quite radical forums such as `r/LateStageCapitalism` and `r/Anarchism` for the left-wing side, and `r/conspiracy` and `r/HillaryForPrison` for right-wing users.

4.3.3 Pathways Outside Of Reddit: URL Sharing

In the previous sections, we examined which users are more likely to enter political or conspiracy communities on Reddit, focusing on their sociodemographic profiles and the subreddits that serve as gateways or transition points. Equally important, however, are the pathways that bring users to these communities from outside Reddit. While we cannot directly trace a user's broader online behavior, we can gain valuable insight by analyzing the URLs they share. These links offer a proxy for the information ecosystems users engage with before arriving at the communities identified earlier. Though indirect, this approach allows us to explore the external influences shaping the diverse trajectories into Reddit's political and conspiratorial spaces.

In Figure 4.8 we report the top-5 most shared URL domains on Reddit posts by users from each sociodemographic group *before* entering a given community. To avoid noise, we define a sociodemographic group in this case as users on the first or third quartile of the scores for each social dimension. For example, we consider users as "males" if their user scores on the gender dimension fall on the first quartile of the distribution. In Figure B.6 we report the most shared domains without filtering out the users by score, observing a considerable overlap in the overall results.

Figure 4.8 reveals a clear generational divide in information sources. Younger users tend to diverge from mainstream outlets, instead favoring streaming platforms like Twitch, Discord, and SoundCloud. In contrast, older users predominantly rely on more "traditional" news sources—such as The Guardian, Reuters, and CNN—as well as mainstream social media channels like Twitter and YouTube, though the specific domains vary somewhat by community of interest. We observe a similar behavior for the affluence dimension, where affluent users mostly share the same previously mentioned mainstream news source outlets[9], whereas *poor* users share more alternative or niche domains depending on the topics discussed in each community.

[9] This behavior doesn't apply to affluent users entering Esoterism and Alt-Right communities, where both sociodemographic groups share alternative information outlet.

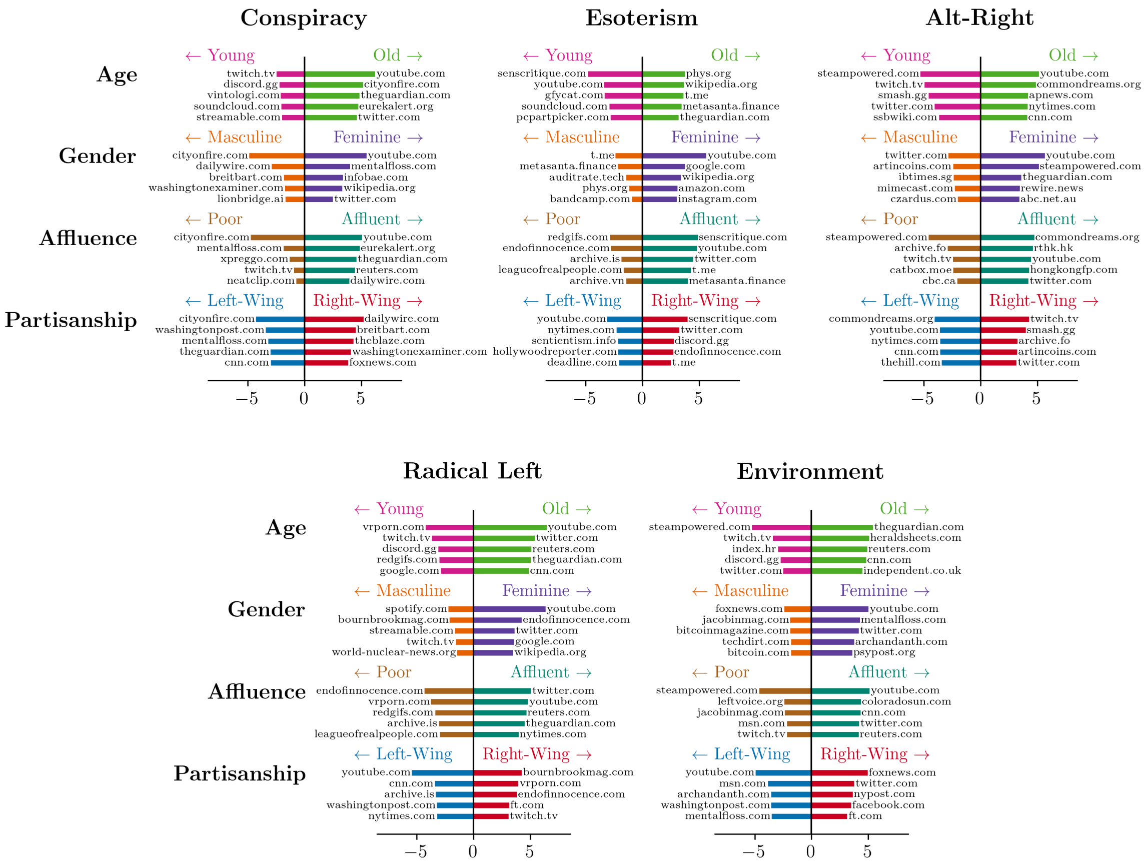

Figure 4.8. Top-5 most shared URL domains by sociodemographic group before entering political/conspiracy communities. We obtain the ranking r_i^d of each domain i for a given social dimension d by making a weighted sum of the sharing frequency of each domain for each user, multiplied by the user's score in the social dimension, and then applying the logarithm to reduce the influence of outliers and skewed distributions. We report the results for users that are within the first and third quartiles of each social dimension to reduce noise.

We also observe a sharp divide within the Conspiracy community along both gender and partisan lines. Masculine users tend to share politically charged domains, particularly those with a right-wing bias—such as The Daily Wire, Breitbart, and The Washington Examiner (Media Bias Fact Check, 2025). In contrast, feminine users largely avoid political sources, instead favoring mainstream platforms like YouTube, Twitter, and Wikipedia. A similar polarization appears along the partisan dimension: left-leaning users predominantly share left-leaning outlets such as The Washington Post, The Guardian, and CNN, while right-leaning users concentrate on right-wing sources including The Daily Wire, Fox News, and more overtly ideological sites like Breitbart and The Blaze. This pattern holds across most communities, though the specific domains shared vary widely. In less overtly political communities, the content of shared URLs shifts away from politics altogether, reflecting the interests of the group without a consistent ideological tilt.

Chapter 5

Conclusions

This study investigates how different sociodemographic groups enter communities on Reddit, focusing on political and conspiracy communities. We first identify five topical political and conspiratorial communities of interest using the attention-flow graph—a network of subreddits where edges represent the flow of user attention from one subreddit to another. We then investigate how likely are users from different sociodemographic groups to enter these communities by inferring individual user sociodemographics based on their Reddit activity and previously computed social dimension scores for the platform's most popular subreddits. We find that users entering alt-right and conspiratorial subreddits are more likely to be older and masculine, while younger and more feminine users are underrepresented in these spaces. Interestingly partisanship is not a relevant sociodemographic to consider when users enter these communities. On the other hand, we find that subreddits associated to the so-called radical left have an overrepresentation of left-wing users along with less-affluent or *poor* users. We also explore different communities, observing that esoteric subreddits are more likely to be visited by feminine and left-wing users and that subreddits related to environmental discussion are more likely to be joined by old, affluent, and left-wing users.

By extending the attention-flow graph framework, we quantify the flow of user attention specific to sociodemographic groups and analyze the structure of this network to identify key subreddits that act as gateways and bridges into the previously identified political and conspiratorial communities. We find, for instance, no substantial differences in the gateways to conspiracy subreddits across sociodemographic groups, suggesting that these entry points are broadly shared and do not disproportionately channel specific types of users. In contrast, we observe notable differences for bridge subreddits, where young and feminine users mainly arrive to conspiracy subreddits through esoteric communities while old and masculine users arrive through politically-oriented subreddits. Additionally, we analyze the external information ecosystems that precede entry into these communities, using shared URLs as a proxy. This reveals distinct media consumption patterns across sociodemographic groups—highlighting how young and poor users tend to diverge from mainstream outlets and instead favor alternative or niche domains in contrast with their old and affluent counterparts. Moreover, we identify a divide within users entering conspiracy communities: masculine users disproportionately share politically charged right-wing media outlets, while feminine users avoid political sources and instead favor mainstream online platforms.

Our work provides a concrete methodology for studying the sociodemographic composition of users entering communities on Reddit and offers insight into the pathways they take to reach these communities. By illuminating how different groups navigate the platform, our findings contribute to a deeper understanding of the formation and growth of conspiracy and fringe communities on social media. This framework lays the groundwork for future research aimed at establishing causal relationships, such as how external media exposure, platform design, or user attributes influence entry into these communities. Further exploration in this direction could inform the development of targeted interventions, moderation strategies, or public policy efforts to mitigate the spread of harmful or conspiratorial content online.

Appendix A

Appendix of Theory

A.1 Weighted Kendall-Tau Index

In the field of social networks, it is common to obtain different scores for different measures such as degree centrality, clustering coefficient, PageRank, etc. It is thus natural to induce a *ranking* of these scores, assuming there are no ties. Several correlation statistics such as Kendall's τ (Kendall, 1938) and Spearman's rank correlation (Spearman, 2015) can be used to compare and evaluate the similarity between different rankings. Kendall formulates his correlation index considering two real-valued vectors $\mathbf{r}$ and $\mathbf{s}$ representing the ranking of elements given by scores and defining:

$$\langle \mathbf{r}, \mathbf{s} \rangle := \sum_{i<j} \mathrm{sgn}(r_i - r_j)\mathrm{sgn}(s_i - s_j),$$

where

$$\mathrm{sgn}(x) = \begin{cases} 1, & \text{if } x > 0; \\ 0 & \text{if } x = 0; \\ -1 & \text{if } x < 0. \end{cases}$$

This is, for each pair of elements (i, j), this sum quantifies whether the rank difference of the elements agree in sign. If both are positive or negative, the product is $+1$ and we have a *concordant* pair. If one is positive and one is negative, the product is -1 and we have a *discordant* pair. If either is 0 (tie), the product is 0 and there is no contribution. Since $\langle \mathbf{r}, \mathbf{s} \rangle$ represents an inner product in a high-dimensional space, we can define the norm $||\mathbf{r}|| := \langle \mathbf{r}, \mathbf{r} \rangle$ and use it to define Kendall's τ as the normalized inner product (Kendall, 1945):

$$\tau(\mathbf{r}, \mathbf{s}) := \frac{\langle \mathbf{r}, \mathbf{s} \rangle}{||\mathbf{r}|| \cdot ||\mathbf{s}||}.$$

Kendall's τ index ranges from -1 (perfect inverse agreement), to 0 (perfect disagreement), to $+1$ (perfect agreement) and is proportional to the number of pairwise adjacent swaps needed to transform one ranking into the other. One of the main drawbacks of this index is that even perfect agreement may yield $\tau < 1$ if there are many *ties* in the rankings as the index underestimates correlation on tied data. Moreover, even when the top elements of different rankings are almost identical, τ can be quite low due to the fact that elements in rankings, specially low-ranking elements, can be ranked in slightly different ways and thus introduce a lot of noise to the index.

In order to solve some of the aforementioned problems of the original Kendall τ index, Vigna (2015) propose to obtain a weighted correlation index by naturally extending the previously defined inner product to a *weighted* inner product:

$$\langle \mathbf{r}, \mathbf{s} \rangle_w := \sum_{i<j} \operatorname{sgn}(r_i - r_j) \operatorname{sgn}(s_i - s_j) w(i, j),$$

where $w(\cdot, \cdot) : n \times n \to \mathbb{R}^{+ \cup \{0\}}$ is a non-negative symmetric weight function that associates different weights to different rankings. In this case, by equivalently defining the norm associated to the inner product, we define the weighted Kendall τ index as:

$$\tau_w(\mathbf{r}, \mathbf{s}) := \frac{\langle \mathbf{r}, \mathbf{s} \rangle_w}{||\mathbf{r}||_w \cdot ||\mathbf{s}||_w}.$$

For computational reasons, Vigna (2015) restricts to a class of weighting functions in which w is obtained by *additively* combining a one-argument weighting function $f : n \to \mathbb{R}^{+ \cup \{0\}}$ applied to each element of a pair. In particular, they focus on the *hyperbolic* weight function $f(r) = 1/(r + 1)$ as this function gives more importance to exchanges for elements with high rank and weights zero only pairs in which both indexes have infinite rank.

Appendix B

Supporting Figures

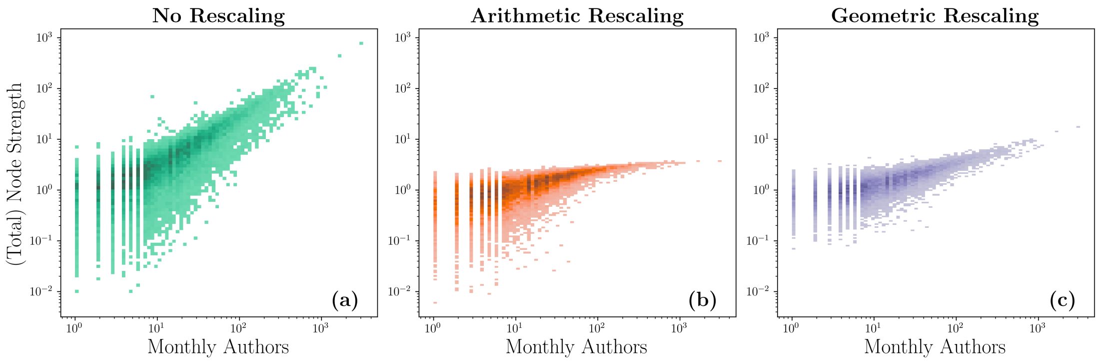

Figure B.1. Distribution of all subreddits in a given month (January 2023) in the space defined by their number of monthly users and their total node strength $s_i^t = s_i^{in} + s_i^{out}$. In **(a)** we show the distribution before weight rescaling, whereas in **(b)** and **(c)** we show the distribution after rescaling the network weights by the arithmetic and geometric mean of their in/out node strengths. We observe that we can effectively dampen the correlation between node strength and subreddit popularity with both of these approaches, with the latter mantaining the structure while dampening the dependence.

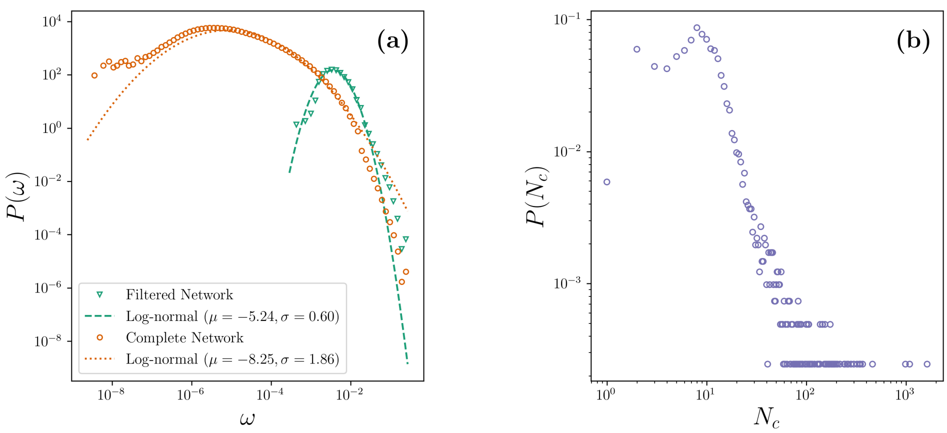

Figure B.2. **(a)** Weight distribution before and after applying the Disparity Filter with a likelihood-ratio test favoring a log-normal distribution over a power-law distribution in both cases. **(b)** Community size distribution after finding communities in the network using the Infomap Algorithm. We observe that this distribution is power-law-like, with most communities having ~ 10 subreddits, and a few having higher community size.

Community	$\lvert\mathcal{N}\rvert$	$\lvert\mathcal{L}\rvert$
Radical Left	133	817
Esoterism	108	543
Alt-Right	83	335
Environment	43	115
Conspiracy	36	67

Table B.1. Number of nodes $\lvert\mathcal{N}\rvert$ and intra-community edges $\lvert\mathcal{L}\rvert$ for each community.

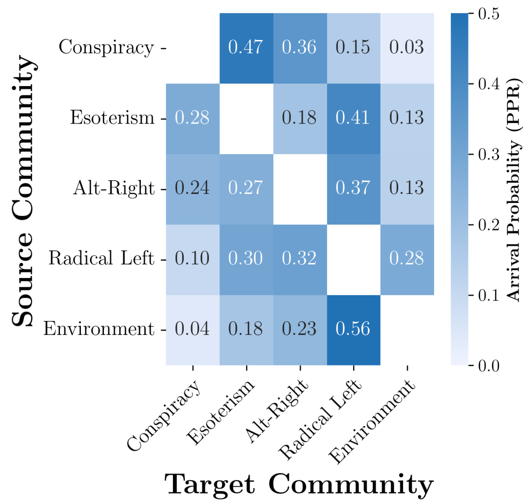

Figure B.3. Probability that a random-walk (with restart) on the AFG reaches a target community t if starting from a source community s (with $t \neq s$).

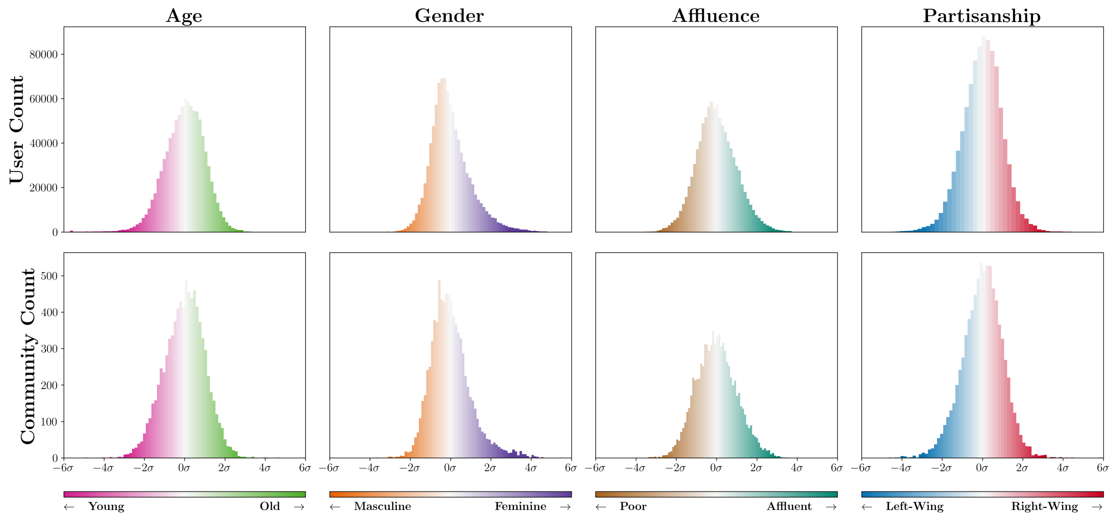

Figure B.4. Subreddit score distributions (bottom row) and the corresponding projected user score distributions (top row) on the age, gender, affluence, and partisanship social dimensions. The x-axis and the colors shows the number of standard deviations from the mean score of each dimension (z-score). We observe similar results as in Waller and Anderson (2021), with more subreddits (and users) being associated with the feminine axis of the gender dimension, for example.

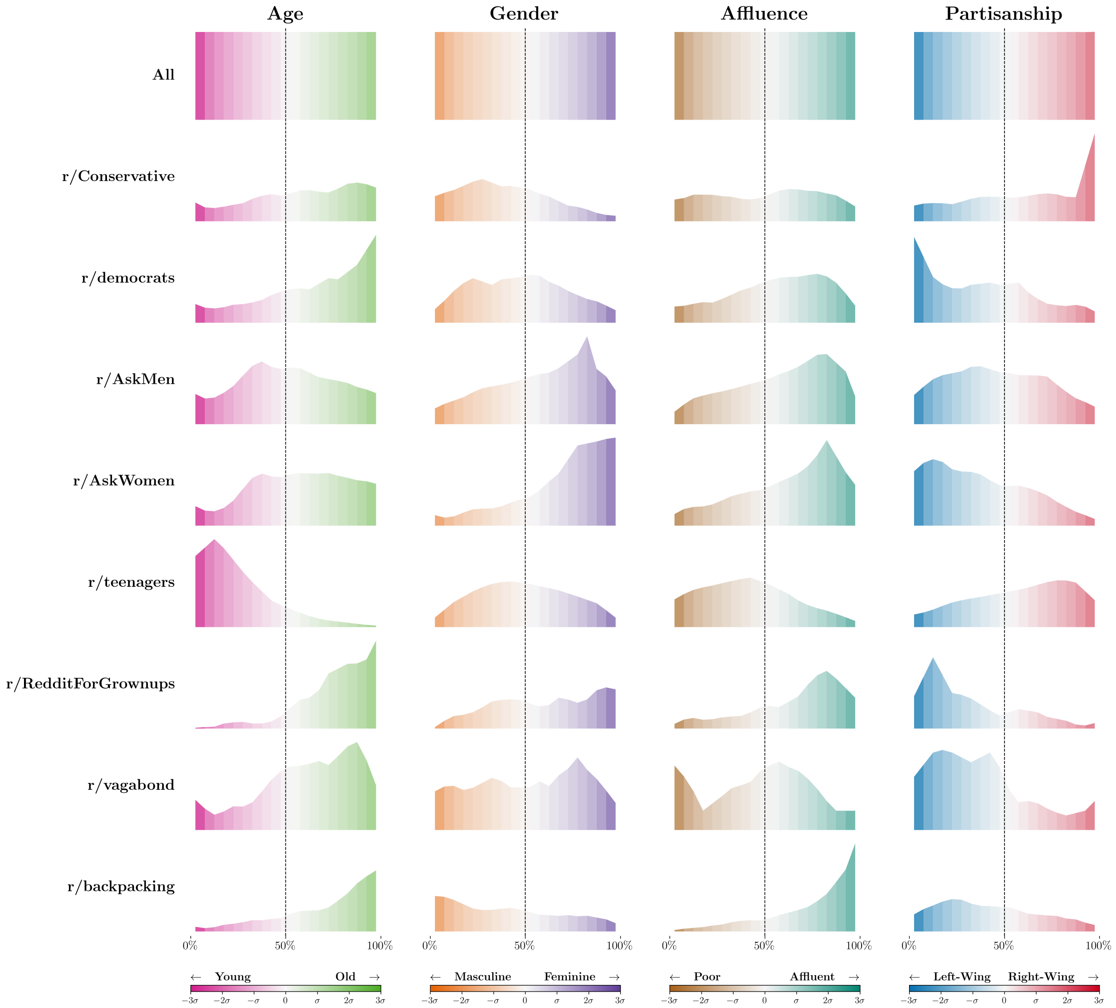

Figure B.5. User score distributions along the age, gender, affluence and partisanship dimensions before joining the main seed subreddits for each social dimension. The x-axis represents the user scores transformed into percentiles and color corresponds to the z-scores of the distribution. The distribution for all users (top row) by definition is the uniform distribution $U(0, 100)$. For each subreddit we qualitatively assess its *quality* as a seed by observing how well-under-or-over-represented a particular axis of a social dimension is. For the age dimension, we observe a clear separation between `r/teenagers` and `r/RedditForGrownups`, as well as between `r/democrats` and `r/Conservative` for the partisan dimension. We don't observe the same behavior for the gender and affluence dimension, with `r/AskMen` not having a clear overrepresentation of *masculine* users and `r/vagabond` not having a clear overrepresentation of *poor* users.

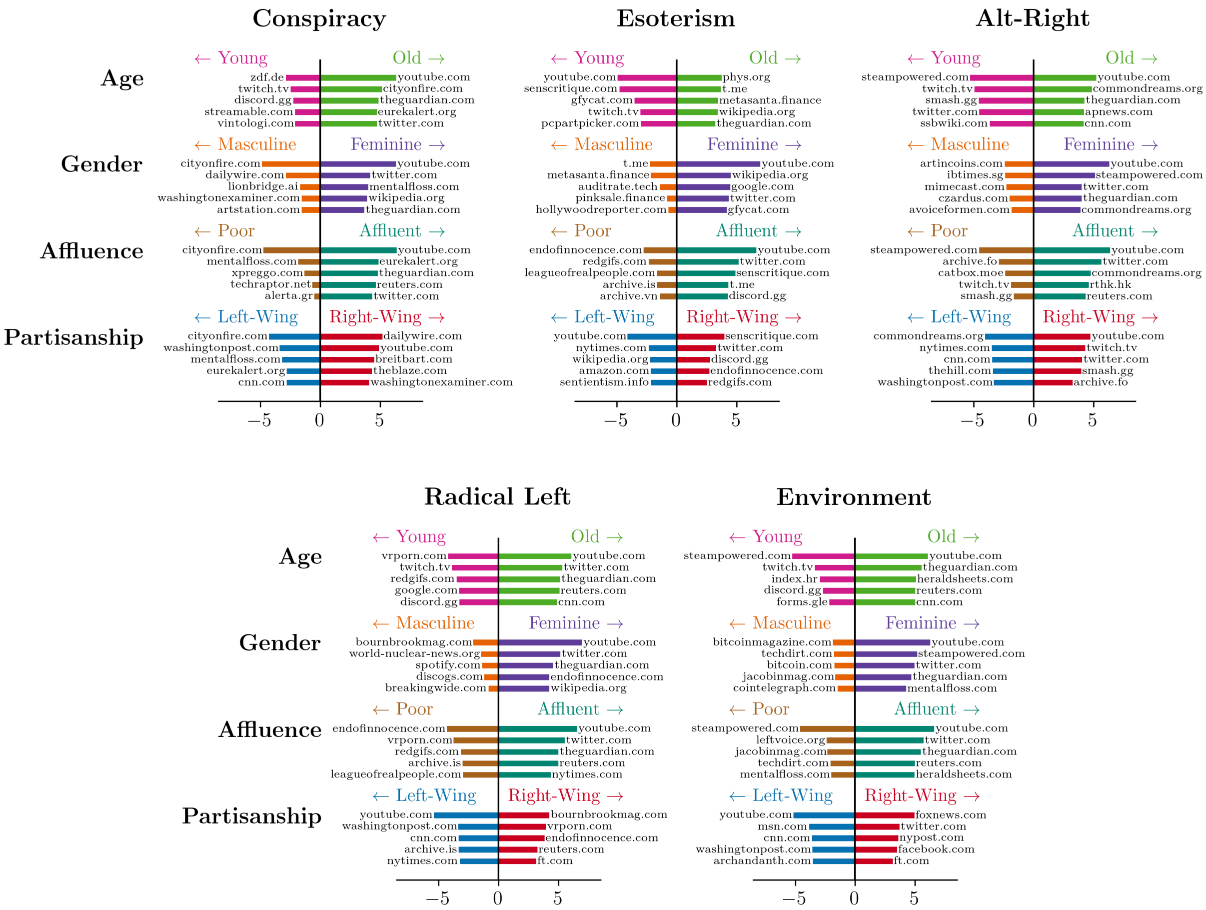

Figure B.6. Top-5 most shared URL domains by sociodemographic group before entering political/conspiracy communities. We obtain the ranking r_i^d of each domain i for a given social dimension d by making a weighted sum of the sharing frequency of each domain for each user, multiplied by the user's score in the social dimension, and then applying the logarithm to reduce the influence of outliers and skewed distributions.

Social Dimension	Seed Pairs	
	Negative Axis	Positive Axis
Age (Young - Old)	**r/teenagers**	**r/RedditForGrownups**
	r/AskMen	r/AskMenOver30
	r/trackandfield	r/trailrunning
	r/RedHotChiliPeppers	r/pearljam
	r/youngatheists	r/TrueAtheism
	r/saplings	r/eldertrees
	r/TeenMFA	r/MaleFashionMarket
	r/teenrelationships	r/relationship_advice
	r/hsxc	r/running
	r/bapccanada	r/canadacordcutters
Gender (Masculine - Feminine)	**r/AskMen**	**r/AskWomen**
	r/OneY	r/Women
	r/ROTC	r/USMilitarySO
	r/predaddit	r/BabyBumps
	r/TrollYChromosome	r/CraftyTrolls
	r/TallMeetTall	r/bigboobproblems
	r/FierceFlow	r/HaircareScience
	r/AskMenOver30	r/AskWomenOver30
	r/daddit	r/Mommit
	r/malelivingspace	r/InteriorDesign
Affluence (Poor - Affluent)	**r/vagabond**	**r/backpacking**
	r/almosthomeless	r/personalfinance
	r/Nightshift	r/fitbit
	r/FolkPunk	r/IndieFolk
	r/hitchhiking	r/hiking
	r/AskACountry	r/travel
	r/alaska	r/CampingandHiking
	r/DumpsterDiving	r/Frugal
	r/KitchenConfidential	r/Cooking
	r/fuckolly	r/gameofthrones
Partisan (Left-Wing - Right-Wing)	**r/democrats**	**r/Conservative**
	r/GamerGhazi	r/KotakuInAction
	r/AskAnAmerican	r/askaconservative
	r/lastweektonight	r/CGPGrey
	r/GunsAreCool	r/progun
	r/excatholic	r/Catholicism
	r/askhillarysupporters	r/AskTrumpSupporters
	r/OpenChristian	r/TrueChristian
	r/EnoughLibertarianSpam	r/ShitRConservativeSays
	r/liberalgunowners	r/Firearms

Table B.2. Subreddit seeds used by Waller and Anderson (2021) when defining social dimensions (age, gender, affluence and partisanship) using the community embedding of these seed subreddits. Each element of the subreddit pair represents a given axis (positive or negative) of the social dimension. In bold we highlight the original pair of seeds used to generate the rest of them based on the similarity of their vector differences.

Social Dimension	Top-3 Gateways	
	Negative	Positive
Age (Young - Old)	r/conspiracytheories r/ConspiracyMemes r/conspiracy	r/conspiracy r/conspiracy_commons r/conspiracytheories
Gender (Masculine - Feminine)	r/conspiracy_commons r/conspiracytheories r/conspiracy	r/conspiracy r/conspiracytheories r/conspiracy_commons
Affluence (Poor - Affluent)	r/conspiracy r/conspiracy_commons r/ConspiracyMemes	r/conspiracy r/conspiracytheories r/conspiracy_commons
Partisan (Left-Wing - Right-Wing)	r/EscapingPrisonPlanet r/conspiracy_commons r/holofractal	r/conspiracy r/conspiracy_commons r/conspiracytheories

Table B.3. Top-3 Gateways ranked by PPR for the Conspiracy community for each social dimension axis.

Social Dimension	Top-3 Bridges	
	Negative	Positive
Age (Young - Old)	r/AstralProjection (Esoterism) r/LucidDreaming (Esoterism) r/Wicca (Esoterism)	r/Retconned (Esoterism) r/DescentIntoTyranny (Alt-Right) r/awakened (Esoterism)
Gender (Masculine - Feminine)	r/CoronavirusCirclejerk (Alt-Right) r/thebakery (Radical Left) r/Paranormal (Esoterism)	r/Retconned (Esoterism) r/Wicca (Esoterism) r/AstralProjection (Esoterism)
Affluence (Poor - Affluent)	r/Retconned (Esoterism) r/DescentIntoTyranny (Alt-Right) r/AstralProjection (Esoterism)	r/CoronavirusCirclejerk (Alt-Right) r/Meditation (Esoterism) r/FreeSpeech (Alt-Right)
Partisan (Left-Wing - Right-Wing)	r/Wicca (Esoterism) r/tarot (Esoterism) r/enlightenment (Esoterism)	r/AstralProjection (Esoterism) r/LucidDreaming (Esoterism) r/Retconned (Esoterism)

Table B.4. Top-3 Bridges ranked by PPR for the Conspiracy community for each social dimension axis. We report each subreddit's community membership below its name.

Social Dimension	Top-3 Gateways	
	Negative	Positive
Age (Young - Old)	r/The_Donald r/LouderWithCrowder r/JordanPeterson	r/Conservative r/JordanPeterson r/WayOfTheBern
Gender (Masculine - Feminine)	r/JordanPeterson r/Conservative r/The_Donald	r/CoronavirusCirclejerk r/Conservative r/WayOfTheBern
Affluence (Poor - Affluent)	r/The_Donald r/WayOfTheBern r/ShitPoliticsSays	r/Conservative r/JordanPeterson r/Republican
Partisan (Left-Wing - Right-Wing)	r/WayOfTheBern r/Trumpgret r/jimmydore	r/Conservative r/The_Donald r/JordanPeterson

Table B.5. Top-3 Gateways ranked by PPR for the Alt-Right community for each social dimension axis.

Social Dimension	Top-3 Bridges	
	Negative	Positive
Age (Young - Old)	r/ShitLiberalsSay (Radical Left) r/MoreTankie196 (Radical Left) r/GenZedong (Radical Left)	r/conspiracy (Conspiracy) r/ConspiracyMemes (Conspiracy) r/energy (Environment)
Gender (Masculine - Feminine)	r/economy (Environment) r/unvaccinated (Conspiracy) r/ChapoTrapHouse (Radical Left)	r/conspiracy (Conspiracy) r/ShitLiberalsSay (Radical Left) r/ConspiracyMemes (Conspiracy)
Affluence (Poor - Affluent)	r/conspiracy (Conspiracy) r/ShitLiberalsSay (Radical Left) r/ConspiracyMemes (Conspiracy)	r/conspiracy (Conspiracy) r/energy (Environment) r/economy (Environment)
Partisan (Left-Wing - Right-Wing)	r/ShitLiberalsSay (Radical Left) r/GenZedong (Radical Left) r/LateStageCapitalism (Radical Left)	r/conspiracy (Conspiracy) r/ConspiracyMemes (Conspiracy) r/environment (Environment)

Table B.6. Top-3 Bridges ranked by PPR for the Alt-Right community for each social dimension axis. We report each subreddit's community membership below its name.

Social Dimension	Top-3 Gateways	
	Negative	Positive
Age (Young - Old)	r/facts r/KillingStalking r/climatechange	r/environment r/energy r/business
Gender (Masculine - Feminine)	r/Economics r/economy r/oil	r/ZeroWaste r/environment r/climate
Affluence (Poor - Affluent)	r/KillingStalking r/climate r/climatechange	r/environment r/energy r/ZeroWaste
Partisan (Left-Wing - Right-Wing)	r/environment r/ZeroWaste r/climate	r/economy r/Economics r/oil

Table B.7. Top-3 Gateways ranked by PPR for the Environment community for each social dimension axis.

Social Dimension	Top-3 Bridges	
	Negative	Positive
Age (Young - Old)	r/Meditation (Esoterism) r/Socialism_101 (Radical Left) r/climateskeptics (Alt-Right)	r/LateStageCapitalism (Radical Left) r/socialism (Radical Left) r/lostgeneration (Radical Left)
Gender (Masculine - Feminine)	r/ChapoTrapHouse (Radical Left) r/chapotraphouse2 (Radical Left) r/DankLeft (Radical Left)	r/LateStageCapitalism (Radical Left) r/Socialism_101 (Radical Left) r/FreeSpeech (Alt-Right)
Affluence (Poor - Affluent)	r/energy_work (Esoterism) r/ChapoTrapHouse (Radical Left) r/Anarchism (Radical Left)	r/LateStageCapitalism (Radical Left) r/Meditation (Esoterism) r/Conservative (Alt-Right)
Partisan (Left-Wing - Right-Wing)	r/LateStageCapitalism (Radical Left) r/ChapoTrapHouse (Radical Left) r/socialism (Radical Left)	r/Conservative (Alt-Right) r/conspiracy (Conspiracy) r/canadaleft (Radical Left)

Table B.8. Top-3 Bridges ranked by PPR for the Environment community for each social dimension axis. We report each subreddit's community membership below its name.

Social Dimension	Top-3 Gateways	
	Negative	Positive
Age (Young - Old)	r/communism r/communism101 r/ShitLiberalsSay	r/LateStageCapitalism r/lostgeneration r/PropagandaPosters
Gender (Masculine - Feminine)	r/ChapoTrapHouse r/chapotraphouse2 r/leftistvexillology	r/LateStageCapitalism r/communism r/Anarchy101
Affluence (Poor - Affluent)	r/communism r/Anarchy101 r/communism101	r/LateStageCapitalism r/Sino r/GreenAndPleasant
Partisan (Left-Wing - Right-Wing)	r/ChapoTrapHouse r/communism r/communism101	r/DebateCommunism r/CommunismMemes r/LateStageCapitalism

Table B.9. Top-3 Gateways ranked by PPR for the Radical Left community for each social dimension axis.

Social Dimension	Top-3 Bridges	
	Negative	Positive
Age (Young - Old)	r/FreeSpeech (Alt-Right) r/conspiracyNOPOL (Conspiracy) r/AstralProjection (Esoterism)	r/conspiracy (Conspiracy) r/WayOfTheBern (Alt-Right) r/C_S_T (Conspiracy)
Gender (Masculine - Feminine)	r/Meditation (Esoterism) r/JordanPeterson (Alt-Right) r/jimmydore (Alt-Right)	r/conspiracy (Conspiracy) r/C_S_T (Conspiracy) r/WayOfTheBern (Alt-Right)
Affluence (Poor - Affluent)	r/C_S_T (Conspiracy) r/FreeSpeech (Alt-Right) r/conspiracy (Conspiracy)	r/Economics (Environment) r/energy (Environment) r/environment (Environment)
Partisan (Left-Wing - Right-Wing)	r/WayOfTheBern (Alt-Right) r/environment (Environment) r/WitchesVsPatriarchy (Esoterism)	r/conspiracy (Conspiracy) r/C_S_T (Conspiracy) r/Meditation (Esoterism)

Table B.10. Top-3 Bridges ranked by PPR for the Radical Left community for each social dimension axis. We report each subreddit's community membership below its name.

Social Dimension	Top-3 Gateways	
	Negative	Positive
Age (Young - Old)	r/Dreams r/LucidDreaming r/AstralProjection	r/spirituality r/Meditation r/tarot
Gender (Masculine - Feminine)	r/Dreams r/GetMotivated r/confidence	r/Dreams r/witchcraft r/tarot
Affluence (Poor - Affluent)	r/AstralProjection r/Retconned r/occult	r/Meditation r/spirituality r/WitchesVsPatriarchy
Partisan (Left-Wing - Right-Wing)	r/tarot r/witchcraft r/WitchesVsPatriarchy	r/LucidDreaming r/AstralProjection r/Paranormal

Table B.11. Top-3 Gateways ranked by PPR for the Esoterism community for each social dimension axis.

Social Dimension	Top-3 Bridges	
	Negative	Positive
Age (Young - Old)	r/alltheleft (Radical Left) r/EscapingPrisonPlanet (Conspiracy) r/conspiracytheories (Conspiracy)	r/conspiracy (Conspiracy) r/C_S_T (Conspiracy) r/AntifascistsofReddit (Radical Left)
Gender (Masculine - Feminine)	r/LateStageCapitalism (Radical Left) r/SocialistRA (Radical Left) r/ChapoTrapHouse (Radical Left)	r/conspiracy (Conspiracy) r/C_S_T (Conspiracy) r/EscapingPrisonPlanet (Conspiracy)
Affluence (Poor - Affluent)	r/conspiracy (Conspiracy) r/ConspiracyMemes (Conspiracy) r/alltheleft (Radical Left)	r/AntifascistsofReddit (Radical Left) r/C_S_T (Conspiracy) r/habitica (Conspiracy)
Partisan (Left-Wing - Right-Wing)	r/lostgeneration (Radical Left) r/LateStageCapitalism (Radical Left) r/Anarchism (Radical Left)	r/conspiracy (Conspiracy) r/HillaryForPrison (Alt-Right) r/JordanPeterson (Alt-Right)

Table B.12. Top-3 Bridges ranked by PPR for the Esoterism community for each social dimension axis. We report each subreddit's community membership below its name.

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