

Modeling the Effect of Social Contagion in Solar Adoption through Commuter and Socioeconomic Networks

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Article

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Abstract

The widespread adoption of residential solar panels is critical for the global energy transition, yet the social mechanisms driving this process remain poorly understood. Social contagion is a known driver of adoption, but whether it operates primarily through information flow or socioeconomic similarity (homophily) is unclear. Here we use a network science approach to distinguish between these mechanisms for solar adoption across the United States. We constructed and compared three county-level network models: a Socioeconomic Similarity network, a Commuter (information flow) network, and a State-Level baseline. Using Louvain community detection and calibrated Susceptible-Infected-Resistant (SIR) diffusion simulations seeded from every county, we tested which network structure best explains real-world adoption patterns. The Socioeconomic network identified the most homogeneous clusters of existing adopters, but the Commuter network was the only model whose dynamic diffusion patterns produced a statistically significant positive correlation with actual county-level adoption rates. These results suggest a dual mechanism of social contagion, in which commuter-based interaction pathways serve as the primary channels for influence while socioeconomic similarity governs local receptiveness to that influence. Effective solar adoption policies should therefore combine broad, commuter-informed information campaigns with targeted, socioeconomically tailored community engagement rather than relying on either mechanism alone.

Introduction

The growing climate crisis has created an urgent need for a large-scale shift to renewable energy sources. Transitioning away from fossil fuels is a critical factor in reducing global greenhouse gas emissions, and widespread solar power adoption is a key component of this sustainability transition [1]. The global solar power market is projected to grow from \$253.69 billion in 2023 to \$436.36 billion by 2032 [2]. However, this growth faces headwinds; in fact, new solar installations in the U.S. dropped 31% in 2024, the first market contraction since 2017 [3]. Furthermore, high customer acquisition costs remain a significant barrier to the industry's expansion. Understanding the non-economic drivers of adoption is therefore critical to maintaining momentum in the energy transition [4].

Multiple studies have established that social contagion, or “the peer effect,” is a powerful force in the diffusion of solar technology [5, 6]. Additionally, studies have established the use of network theory to analyze socioeconomic data across spatial regions as an effective method of study [7]. The purpose of this study is to better understand the specific mechanisms through which this social contagion operates. It attempts to distinguish between two competing theories: influence driven by the flow of information and influence driven by socioeconomic similarity (homophily).

To distinguish between the mechanisms of influence, we hypothesized that if the principle of homophily is the dominant mechanism in social contagion for solar adoption, then a network model built on socioeconomic similarity will produce communities with more uniform solar adoption rates (lower intra-cluster standard deviation) and its dynamic diffusion patterns will better correlate with real-world

adoption data than a model based purely on information flow, because shared identity is a stronger driver for solar adoption than information exposure.

This research is relevant because it directly informs how to best allocate resources to drive solar adoption. Distinguishing between these two mechanisms has practical implications for designing effective policies. If information flow is the dominant driver, policies should focus on maximizing visibility and broad-based marketing. If socioeconomic similarity is key, a more targeted, community-centric approach that leverages trusted peer groups and local community leaders would be far more effective. A quantitative assessment of which mechanism provides a more reliable model for explaining real-world adoption patterns thus enables a better understanding of how to design more effective campaigns for a rapid and equitable energy transition.

Literature Review

Previous studies have progressively moved from identifying the existence of social contagion in solar adoption to questioning the specific mechanisms that drive it. The foundational work in this area established that peer effects are a quantifiable and significant phenomenon. In a foundational study, Bollinger and Gillingham [5] analyzed the diffusion of solar panels in California and found that a single additional installation in a zip code increased the probability of a subsequent adoption by 0.78 percentage points. This research gave the first robust, quantitative evidence of social contagion in this context. However, the authors acknowledged the inherent difficulty in distinguishing between the specific channels of this influence, such as simple visibility (seeing a neighbor's panels) versus more complex word-of-mouth communication, leaving this open for future investigation.

This phenomenon was further confirmed by Graziano and Gillingham [6], who looked at solar adoption patterns in Connecticut. They found that an additional installation in a census block group increased the probability of another adoption by 0.5 to 0.7 percentage points, corroborating the earlier findings in a different geographical and demographic context. Together, these studies built a strong consensus that peer effects are a real and powerful force. However, like the earlier work, their focus on the general effect did not explicitly differentiate between the channels of influence, reinforcing the need for research that could disentangle these mechanisms.

More recent research has begun to dissect the socioeconomic dimensions of this influence, providing strong support for the theory of homophily. O'Shaughnessy, Grayson and Barbose [8] conducted a comprehensive analysis across the United States and found that while peer effects are a significant driver of adoption across all income levels, they are generally much stronger within the same income group. This work was crucial in highlighting that socioeconomic similarity is a key factor in social contagion and pointed to the need to understand the specific mechanisms at play, particularly in low-income communities where adoption barriers are higher. The authors explicitly suggested further research into the nature of these social interactions; our study tries to address this by directly comparing socioeconomic similarity with information flow.

The importance of social networks is not a uniquely American phenomenon, which adds to the generalizability of these theories. Using agent-based modeling to study solar home system adoption in India, Rai and Robinson [9] found that social influence, especially from trusted opinion leaders, played a significant role in adoption decisions. While their study focused on a developing country and a different type of solar technology, it still gave evidence of the power of social networks, suggesting that the principles of trust and peer validation are broadly applicable. It also left an open question of how these dynamics operate in a more mature solar market like that of the United States.

While the aforementioned studies identify the key variables of social contagion, they leave open the question of how to best model and compare these competing mechanisms. A methodological framework for this is proposed by Kirkley [7], who used an information-theoretic network approach to analyze spatial socioeconomic correlations. Our study demonstrated that network science provides a quantitative framework for modeling these multi-dimensional similarities between geographic regions. Kirkley's work provided the methodological inspiration for the construction of the Socioeconomic Similarity network.

So, while the previous literature firmly establishes the existence of social contagion in solar adoption and increasingly points toward socioeconomic similarity as key, a clear gap remains in a direct, large-scale comparison between the mechanisms of information flow and homophily. Methodological approaches from network science offer a promising path forward. This study aims to fill this gap by constructing distinct network models for these two mechanisms and using both static and dynamic analyses to determine which provides a more representative explanation for real-world solar adoption patterns.

Methods

To build our networks, the Python libraries of pandas, numpy, networkx, and python-louvain were used. The process consisted of data aggregation, network construction, static community analysis, and then dynamic diffusion modeling.

Datasets & Pre-Processing

The study used two primary datasets. First, the DeepSolar Dataset [10], which provided census tract-level solar panel counts and a rich set of demographic and socioeconomic variables for 2017–2022. Second, the American Community Survey (ACS) 5-Year Commuting Flows Dataset (2016–2020) from the U.S. Census Bureau was used to detail the number of workers commuting between every county pair, serving as a proxy for social and informational linkages [11].

For data aggregation, all census tract-level data was aggregated to the county level. Counts (e.g., population, solar systems) were summed, while rates and continuous variables (e.g., average income, political affiliation) were averaged. The primary outcome measure, solar adoption rate, was calculated for each county as the solar system count divided by the household count. It was also necessary to

standardize county and state names to allow for comparison of networks following network construction. For the dynamic simulation phase, counties with a solar adoption rate at or above the 70th percentile of the national distribution were classified as “adopters.”

Network Construction

Three distinct, undirected networks were constructed, with nodes representing US counties.

The first network created was the Socioeconomic Similarity network. This network was designed to model homophily. An edge was created between two counties if their geographic centroids were within a 1.0-degree threshold (~ 69 miles). The weight of the edge was determined by their socioeconomic similarity, calculated using the Jensen-Shannon Divergence (JSD) across six feature sets: education level, race, occupation, poverty, home ownership, and 2016 voting patterns. The six JSD scores were averaged into a single dissimilarity score, which was then transformed into a similarity weight (weight = $\exp(-\text{dissimilarity})$). To ensure the network was fully connected for the clustering algorithm, a single hub node was added and connected to each disconnected component with an extremely small edge weight.

Then, a Commuter Network was built using the commuting flows data (Fig. 1). This network was designed to model information flow. An edge represents the commuting flow between two counties. To focus on meaningful social and economic ties, commuter links weaker than the 60th percentile of all flows were removed. The edge weight was defined as the natural log of the number of commuters ($\log_{10}$) to normalize the data.

Finally, to allow for comparison and to create a geographic baseline, a state-level network was created. This tested the geographic reach of campaigns. A fully connected component was created for all counties within each state, with a uniform edge weight of 1.0.

Static and Dynamic Analysis

To identify clusters, the Louvain Community Detection algorithm was applied to each network, with resolution parameters tuned for each model (0.8 for Socioeconomic, 1.5 for Commuter) to create meaningful clusters [12]. A post-processing step was implemented to merge any single-member clusters into the community of their strongest neighbor.

To evaluate the effectiveness of the network, the primary evaluation metric was the Weighted Average Intra-Cluster Standard Deviation of solar adoption rates. A lower intra-cluster standard deviation would mean that the model's communities are more homogeneous and thus a better fit for the data.

To move beyond a static analysis and simulate the potential impact of an intervention (e.g., a new solar campaign), a Susceptible-Infected-Resistant (SIR) model was implemented [13]. This allowed for testing of dynamic diffusion properties. The classic SIR epidemiological model was adapted to simulate the

spread of influence for solar adoption. In this context, the “infection” is not a disease but the active social buzz and influence generated by a targeted campaign.

The transmission rate (β) for each network was calibrated such that the average number of “infected” nodes at the end of a simulation matched the 30% of counties identified as “adopters.” The recovery rate (γ) was held constant at 0.05. A full simulation was then run by treating every single county in each network as the starting “seed” of an epidemic – an epidemic that represented the start of a solar influencing campaign. The results from these thousands of simulations were aggregated to calculate an empirical adoption probability for each county, which was then correlated with the actual solar adoption rates.

To adapt the SIR model for this study, β was not held as a global constant. Instead, the probability of transmission between two counties was made proportional to the strength of their connection in the network. The transmission probability for a specific edge was calculated as Eq. (1):

$$P(u,v) = \beta_{base} \times (\text{edge_weight}(u,v) / \text{max_possible_weight}) \quad (1)$$

Results

Before building our networks, exploratory data analysis was used to determine a threshold of meaningful adoption. The percentage of counties with zero adoption was 8.66%. The top 30% of counties had adoption by 0.2% of households, while the top 10% of counties had an adoption rate of 0.5% of households (Fig. 2). This was out of a total of 3,108 counties in the DeepSolar data. The maximum adoption rate within a county was 15.56%.

Network Homogeneity Analysis

The static analysis evaluated which network model best grouped counties into homogeneous clusters based on their real-world solar adoption rates. The primary metric was the Weighted Average Intra-Cluster Standard Deviation, where a lower standard deviation indicates a better fit. The results are shown in Fig. 4.

To confirm that the efficacy of the socioeconomic and commuter models could not be attributed to chance, these models were also compared to random network models. The performance of each model was compared against a null model consisting of 50 randomized networks generated to have the exact same number of nodes and the same degree distribution as the original network, but with the edges completely reshuffled. Figure 5 shows the Weighted Average Intra-Cluster Standard Deviation for the actual Socioeconomic model (blue star) and the actual Commuter model (green star), plotted against the distribution of scores from their respective randomized counterparts (blue and green scattered dots). The results show a clear and significant difference, with the networks that modeled Socioeconomic and Commuter trends actively having lower standard deviations.

Table 1
Network characteristics of the socioeconomic and commuter network.

Metric	Socioeconomic	Commuter
Weighted std dev	0.00431	0.00535
Density	0.0039	0.0134
Avg. clustering coeff.	0.5451	0.0908
Adoption assortativity	0.0053	0.0007

Beyond the homogeneity measure, other network characteristics were also analyzed. Density, which measures the proportion of actual connections out of all possible connections, was much lower for the Socioeconomic network (0.0039) than the Commuter network (0.0134), meaning the Socioeconomic network had a sparser, more clustered structure.

The average clustering coefficient, which measures the degree to which nodes in a graph tend to cluster together, was dramatically higher for the Socioeconomic network (0.5451 vs. 0.0908). This shows that counties in the Socioeconomic model are organized into tightly-knit local communities of peers.

Adoption assortativity measures the tendency of high-adoption nodes to connect to other high-adoption nodes. The Socioeconomic network exhibited a significantly stronger positive assortativity for solar adoption (0.0053 vs. 0.0007). This indicates that in the socioeconomic similarity-based network, high-adoption counties are much more likely to be structurally connected to other high-adoption counties, forming distinct peer clusters. These metrics show that the Socioeconomic network not only creates more homogeneous groupings but also has a structure that is more representative of clustered, peer-driven social phenomena.

Dynamic Network Analysis: SIR Diffusion Model

The dynamic analysis tested the predictive power of each network's structure. Simulating the spread of influence and correlating the results with real-world data makes it possible to determine which network better models the process of solar adoption diffusion from one community to the next. The results are summarized in Table 2.

Table 2
Correlation between simulated adoption probability and actual adoption rates.

Model	Unconditional correlation	Conditional correlation
Socioeconomic	-0.2434	-0.2307
Commuter	0.1801	0.1808
State-Level	-0.1484	0.5494

The unconditional correlation represents the correlation between a county's actual solar adoption rate and its probability of being “infected” (influenced) in a simulation starting from any random county in the network. This metric assesses how well a network's overall connectivity can predict a county's general susceptibility to influence, regardless of where the influence originates. Conditional correlation looks at the correlation between a county's actual solar adoption rate and its probability of being infected in only those simulations that were started from a known “adopter” county (a county in the top 30% of actual adoption). This is a more targeted metric that specifically evaluates how well a network models the spread of influence from existing, established areas of high adoption.

The dynamic analysis shows a notable difference in the performance of the models. The Commuter Network model demonstrated the strongest and only consistently positive correlation with observed county-level solar adoption rates (correlation = 0.1801). This indicates that the structure of inter-county commuter flows provides a statistically significant framework for predicting the real-world diffusion patterns of solar adoption.

In contrast, the Socioeconomic Similarity Network yielded a negative correlation, implying a mismatch between its diffusion dynamics and real-world outcomes. The State-Level Network's high conditional correlation is an artifact of its structure; it effectively models intra-state diffusion but inherently fails to account for any inter-state influence, limiting its general predictive power.

Discussion

The study's primary hypothesis – that a network model based on socioeconomic similarity would better predict solar adoption patterns than one based on information flow – is partially refuted by the dynamic analysis, though it is supported by the static analysis of cluster standard deviation.

The static analysis, based on cluster homogeneity, offered partial support for the socioeconomic model, showing that communities defined by local, similar peers are indeed more uniform in their adoption behavior. The standard deviation within clusters from the socioeconomic network was 0.00431, about 20% smaller than the 0.00535 standard deviation in the commuter network. This finding aligns with the principle of homophily, which posits that individuals are more likely to trust and adopt behaviors from those they perceive as peers [14]. For a high-cost, high-visibility innovation like solar panels, the social

validation that comes from a similar individual is important in reducing uncertainty, which is a key step in the adoption process as described in the 'Diffusion of Innovations' theory [15].

The state-level network's standard deviation was the least, at 0.00395. This indicates that state-level policy is extremely telling of solar adoption: state-level policy that supports adoption can drive a state as a whole to a similar adoption level, even over wide geographic or socioeconomic groups. This shows that the homogenizing effect of state-level policies and incentives can create similar adoption conditions across diverse socioeconomic groups within a state's borders [16].

However, the dynamic diffusion analysis using SIR revealed a distinction in predictive power for the spread of adoption. The Commuter Network emerged as the superior model for predicting how influence travels and propagates through the population. Its strong and statistically significant positive correlation with real-world adoption rates (unconditional correlation = 0.1801) demonstrates that the pathways of daily human interaction, as proxied by commuter flows, are fundamental to the diffusion process. The Socioeconomic Similarity Network, despite its static homogeneity, yielded a negative correlation, indicating that its structure, as modeled, does not effectively predict the dynamic spread of adoption.

These combined results suggest that social contagion can be quantified on two levels: information flow (proxied by commuter ties) provides the essential channels and opportunities for influence to travel, while socioeconomic similarity acts as the filter for receptivity of a new campaign. The initial decision to adopt may be heavily influenced by homophily, which is why existing socioeconomic clusters are internally consistent. However, for that peer influence to be felt across a region and lead to broad diffusion, there must be structural pathways – like daily commuter routes – for the information to travel from one peer group to another.

The findings are supported by the theory on “the strength of weak ties” [17]. Information flow moves novel information through weak ties. Our commuter network models these weak ties – the connections between different social clusters. Commuter routes represent the bridges between communities that allow new information and social proof about solar adoption to travel from one distinct cluster to another [18]. This explains why the Commuter network does well at predicting the dynamic spread of adoption across the nation.

On the other hand, socioeconomic similarity acts as the filter for acceptance through strong ties, with our socioeconomic network modeling these kinds of ties that are derived from characteristics like income and educational level. So, while weak ties can introduce an idea, the decision to actually adopt and pursue a significant investment like solar requires validation from one's peers [19]. This explains why the Socioeconomic clusters are so internally consistent after adoption has occurred.

Our findings can inform more targeted future solar campaigns and the disbursement of incentives in a more effective way. Rather than relying on broad, geographically-based campaigns, policymakers should prioritize a strategy rooted in socioeconomic targeting to ensure program efficacy. The evidence that adoption occurs in distinct socioeconomic clusters suggests that resources – whether for marketing or

financial incentives – should be directed toward specific, well-defined peer groups. This approach moves beyond simply targeting neighborhoods to engaging in group-based incentives for these identified clusters. Moreover, to ensure that this influence spreads, policymakers should target areas of already high adoption; additionally, they can use information flow to predict future diffusion of solar panels, helping plan infrastructure and future campaigns.

This study is limited by its use of proxies; commuter flows do not capture all forms of social interaction, and the socioeconomic model is a simplified representation of many socioeconomic factors. Future work could incorporate data from social media networks or analyze the temporal evolution of these networks over time.

Additionally, to further explore the social contagion, richer networks for information flow can be created by incorporating additional data, such as social media connections or friendship networks. This would allow not only a more robust information network but also the comparison of different information channels themselves. Moreover, to track how the social contagion evolves over time, a model that analyzes adoption patterns with two snapshots of solar adoption data could be created. Specifically, modeling the diffusion of solar from 2017 to 2022 using new DeepSolar data can reveal whether the diffusion better follows the commuter or the socioeconomic model [20, 21].

Conclusion

This study reveals that social contagion in solar adoption acts as a dual-process mechanism where information flow and socioeconomic influence play different roles. While the Socioeconomic Similarity network successfully identified the homogeneous communities where adoption takes root, indicating that strong ties act as validation, it was the Commuter Network – representing daily information flow – that accurately predicted the dynamic spread of solar technology across the United States. Ultimately, effective adoption strategies must be hybrid, leveraging high-volume commuter corridors to maximize awareness diffusion through weak ties while simultaneously tailoring incentives to specific socioeconomic peer groups to ensure final receptivity.

Abbreviations

ACS

American Community Survey

IPCC

Intergovernmental Panel on Climate Change

JSD

Jensen–Shannon Divergence

SIR

Susceptible–Infected–Resistant

U.S. / US

Declarations

Competing interests:

The author declares no competing interests.

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Author Contribution

A.R. conceived the study, curated and analyzed the data, constructed and ran the network models and simulations, interpreted the results, and wrote the manuscript.

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Data Availability

The DeepSolar dataset from Stanford University is publicly available at http://web.stanford.edu/group/deepsolar/deepsolar_tract.csv. The 2016–2020 5-year ACS commuting flows data from the U.S. Census Bureau are publicly available at <https://www.census.gov/data/tables/2020/demo/metro-micro/commuting-flows-2020.html>.

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Figures

Major Commuter Flows (> 1,000 workers) into Massachusetts

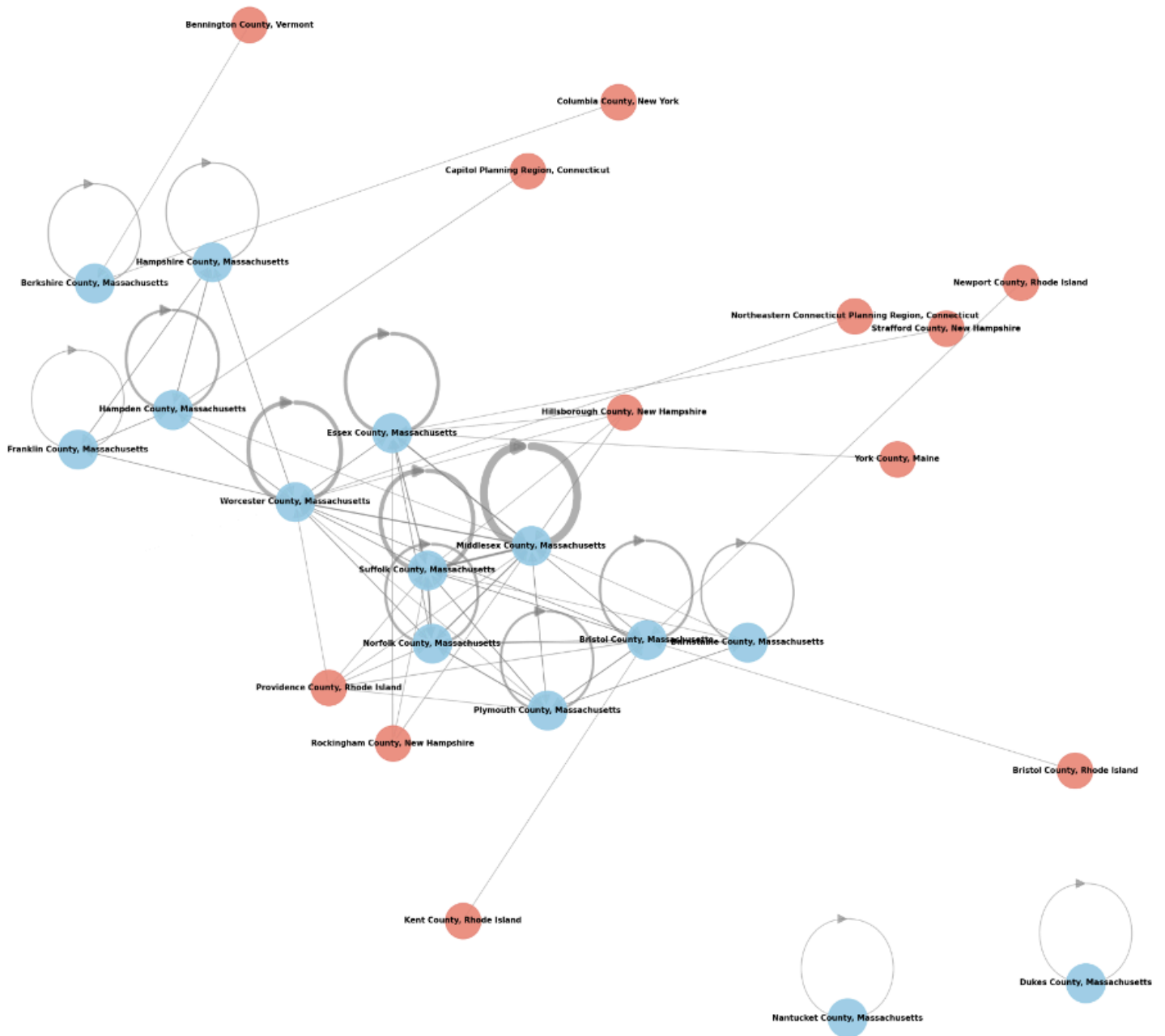


Figure 1

A visualization of the Commuter Network in Massachusetts. Edge weights represent relative commuter flow; blue nodes represent counties within the state, while red nodes represent counties outside the state.

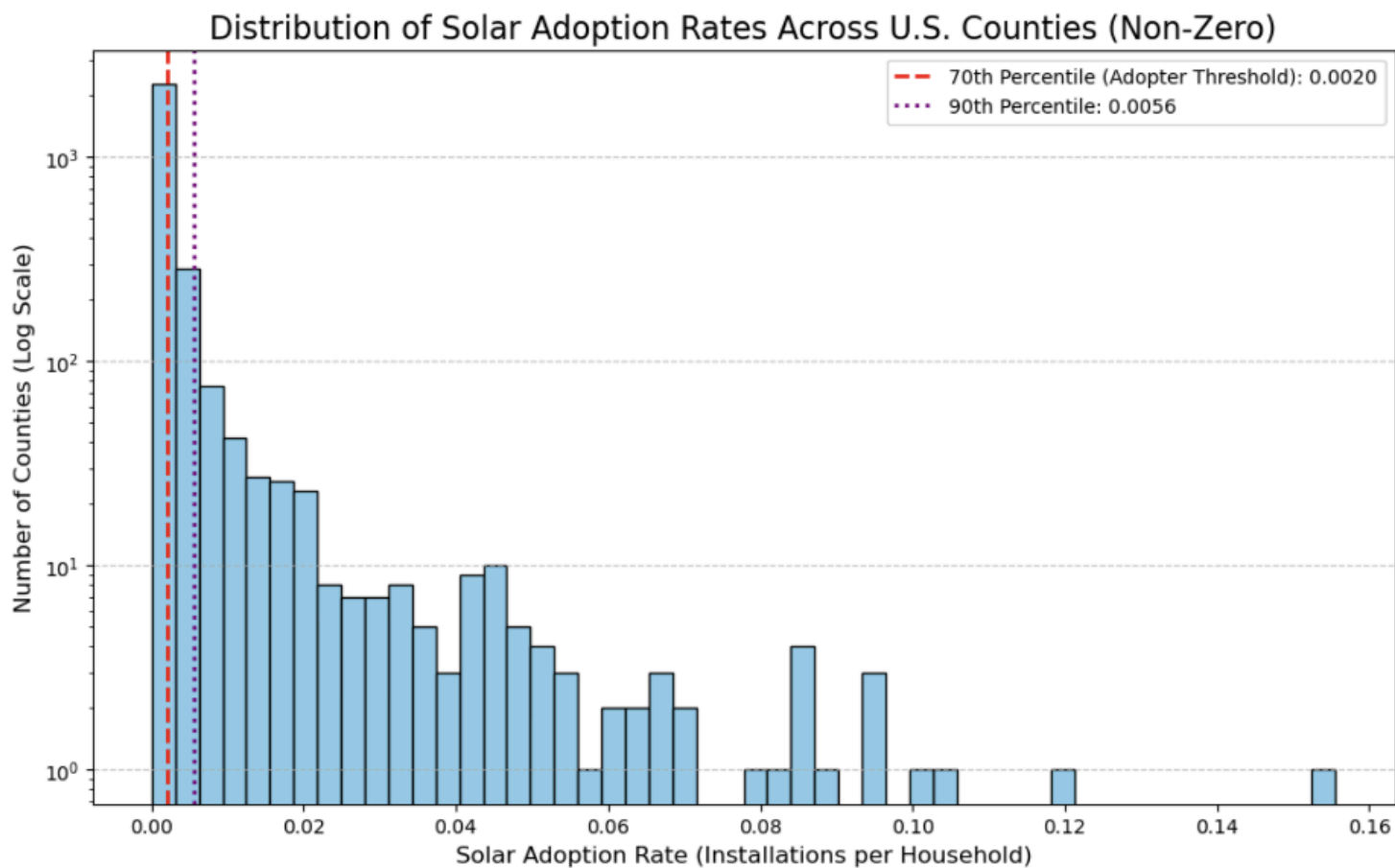


Figure 2

Distribution of solar adoption rates across U.S. counties. The histogram shows the number of counties (log scale) by solar adoption rate (installations per household). Most counties have a minimal adoption rate.

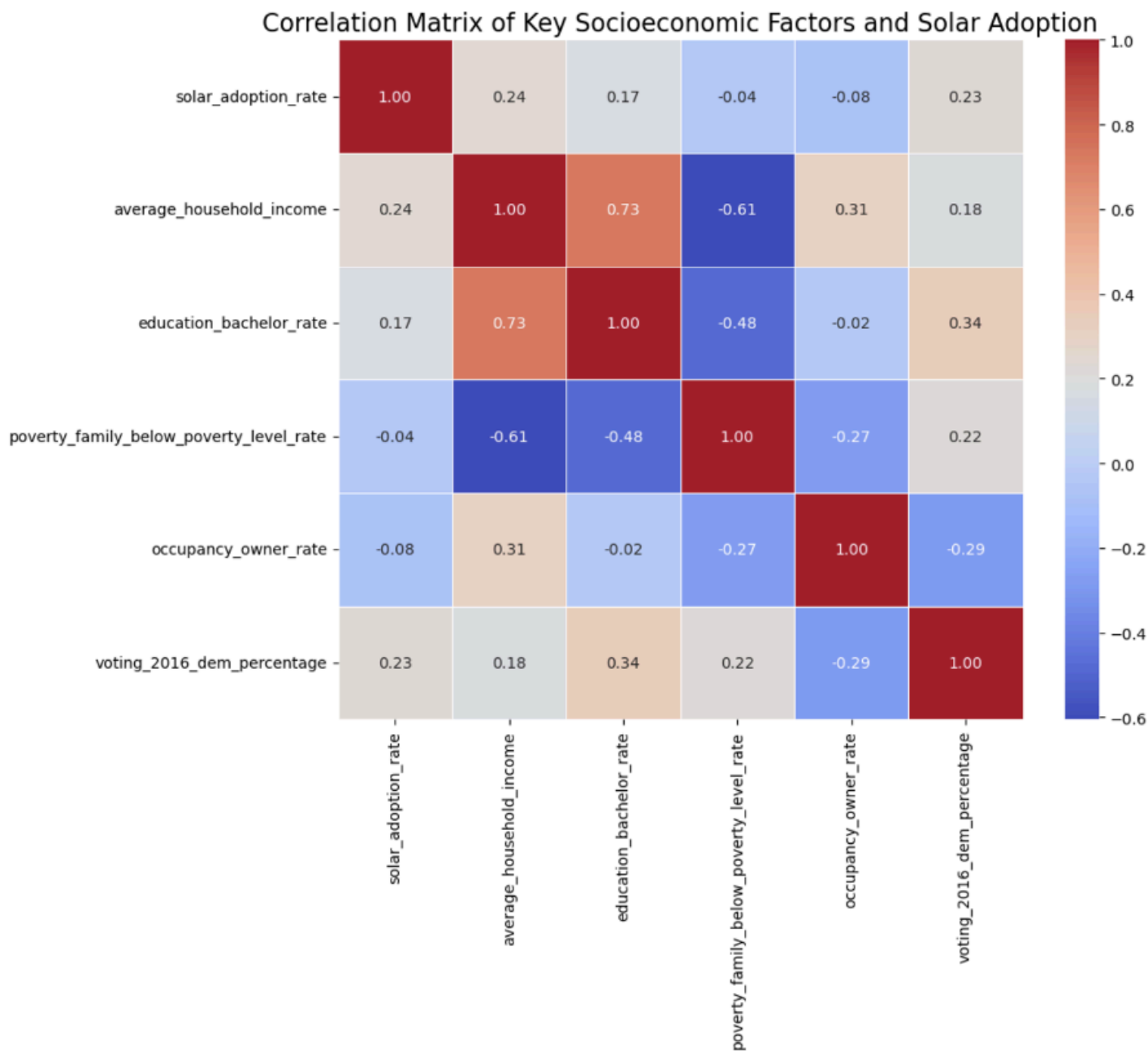


Figure 3

Correlation matrix of socioeconomic factors and solar adoption. A Pearson correlation matrix for various socioeconomic factors and the solar adoption rate.

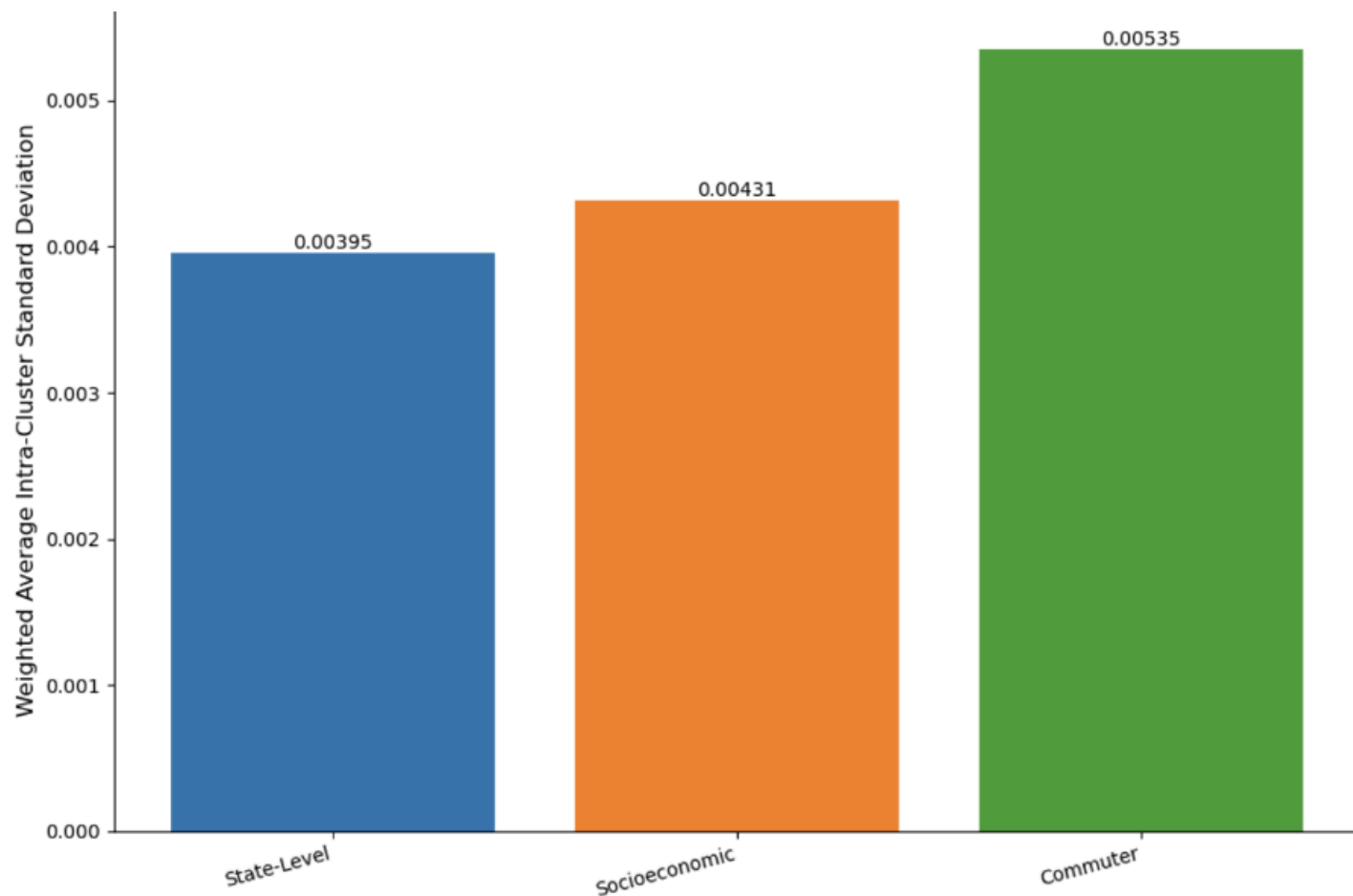


Figure 4

Comparison of model homogeneity. Lower standard deviation indicates that more uniform clusters are created.

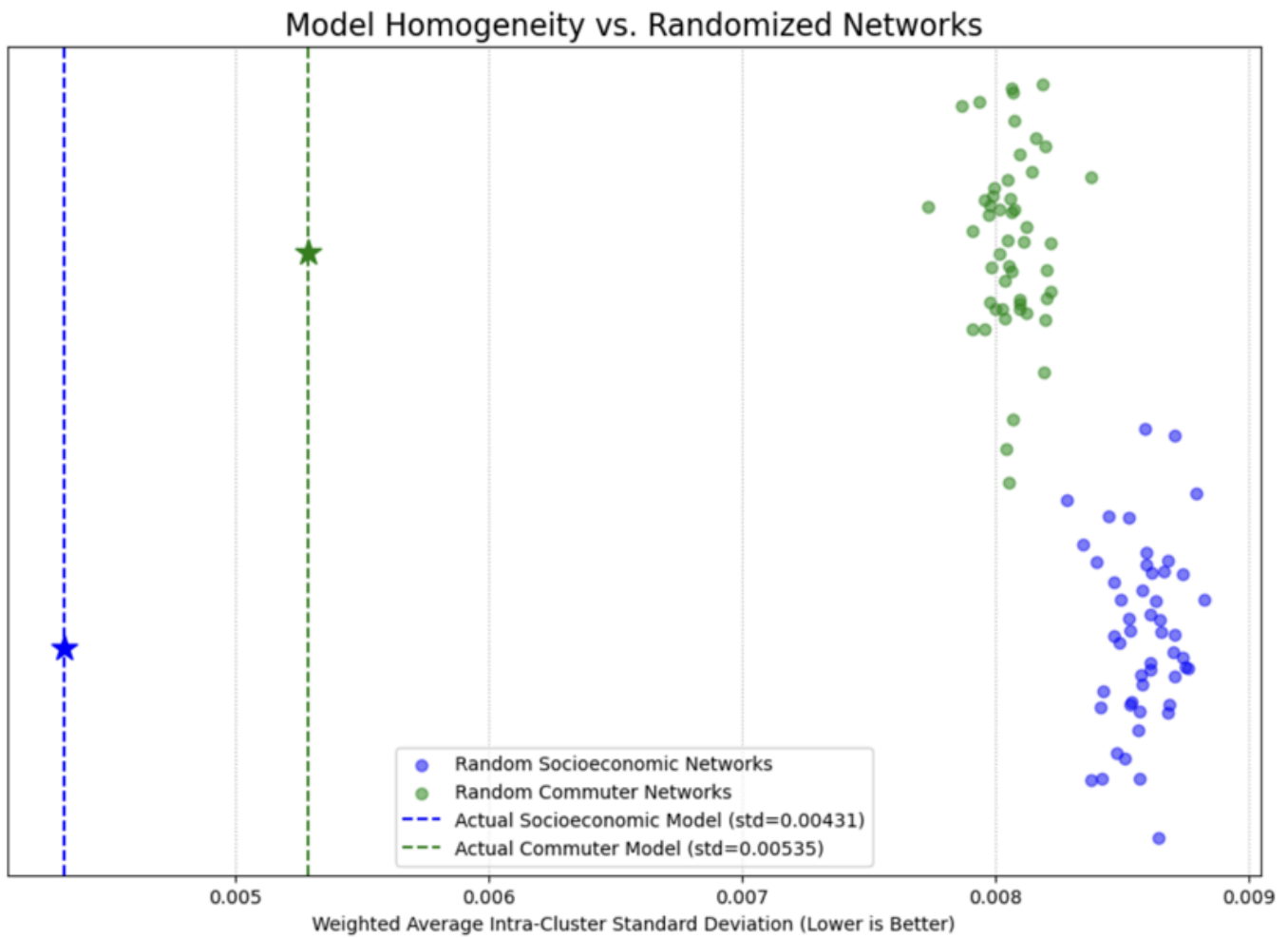


Figure 5

Comparison to random network models. The intra-cluster standard deviation of random network models was far greater than that of the tuned socioeconomic and commuter models. The x-axis shows the standard deviation; the y-axis is arbitrary.