Unravelling Network Capital: Exposure and Friending Effects in a network-based model of Moving to Opportunity*

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Abstract

Social capital, from its conceptual roots based in sociology, has since the early 2000s attracted substantial interest in applied economic research. Despite extensive work documenting its significance in determining economic outcomes, the concept remains largely detached from mainstream economic academia and almost entirely absent from economic theory. In this dissertation, I aim firstly to provide an overview of modern empirical literature on social capital and its more analytically tractable component, network capital. To substantiate its importance quantitatively, I develop a stylised network-based model of social capital which extends the Jackson and Rogers (2007) model to incorporate the latest findings of Chetty, Jackson, et al. (2022b). Calibrating my model on data from the latter, I simulate the Moving to Opportunity experiment –a policy aimed at increasing cross-class interaction and decreasing cross-generational inequality– in the presence of biased interaction mechanisms. My model successfully replicates the empirical findings of Chetty et al. and captures a rich variety of endogenous behaviour, most strikingly that of emergent segregation by socio-economic status. My findings indicate that network-based models constitute a promising avenue for future research in both the specific area of social capital and for the field of economics at large, notably with potential incorporations of recent advances in complexity theory and the growing field of complexity economics.

Keywords— Social capital; Network capital; Moving to Opportunity; Network Simulations; Complexity

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Contents

1 Introduction

> *"The science called 'economics' is based on an initial act of abstraction that consists in dissociating a particular category of practices, or a particular dimension of all practice, from the social order in which all human practice is immersed."*

Pierre Bourdieu, *"Les structures sociales de l'économie"*

1.1 Social capital: from sociology to empirical economics

Economic agents do not exist in a vacuum, but are both product and shapers of the societies they inhabit. Although modern economics has traditionally concentrated itself on the actions of individuals pursuing their self-interested goals, a fast-growing strand of literature has since the early 2000s explored the important and underappreciated role played by the quality of individuals' social environment in shaping their economic outcomes. The term "Social capital", popularised by Robert Putnam (2000), broadly encompasses the relationships formed within a society, the societal and communal resources available to those who compose them, and the values and norms which govern their interactions (Durkheim (1893); Bourdieu (1973); Putnam (2000); Lin (2017); Chetty, Jackson, et al. (2022b)). Social capital's arcane definitions have long confined it to theoretical and sociological research, but it has since the early 2000s captured the interest of modern empirical economic research seeking to quantify its manifestations and effects rather than its precise definition. These findings have convincingly established the crucial role of social capital in governing individual outcomes, but have more importantly made evident the degree to which it is unequally distributed across society (Opportunity Atlas, 2020).

Analyses from the past two decades have in particular emphasised the degree to which childhood social capital determines lifelong opportunities and outcomes, and how strongly its quality can vary at the level of the ZIP code, neighbourhood, and even of two adjacent streets. The US-based Opportunity Insights has amassed extensive data showing that this factor, entirely random factor from the point of the view of the child, can reliably predict a wide array of outcomes: secondary and tertiary education outcomes; rates of incarceration, teenage pregnancy, and marriage; adult fertility; adult employment, hours worked, wage, and household income (growing up in one of two adjacent ZIP codes can mean an expected yearly difference of tens of thousands of dollars); geographical and social mobility, and even the probability of obtaining a patent (Bell et al., 2019). Although the rest of the world has not so far been subject to the same level of granular analysis, similar work on Scandinavian countries, a region often praised for its supposedly high degree of social mobility and meritocratic institutions, finds evidence that this pattern is not unique to the United States: although the stronger welfare state vastly decreases the costs associated with inequality and poverty, the degree of cross-generational social inheritance remains strong, particularly when considering skills and lifetime income rather than snapshot income measures (Eshaghnia et al. (2022); Damm and Dustmann (2014); Hedefalk and Dribe (2020)). The importance of childhood social capital is corroborated by natural and controlled experiments wherein children of different ages moving from low-social-capital neighbourhoods to high(er)-social-capital neighbourhoods face vastly improved life outcomes (Bergman et al. (2019); Deutscher (2020); Heckman and Landersø (2021)), most famously the US-based Moving To Opportunity experiment, which I discuss in detail in Section 2.

1.2 Network capital: a tractable component of social capital

This evidence casts doubt on the above interpretation of social capital as a public good freely available to all, and has bolstered the earlier work of Pierre Bourdieu (and Karl Marx before him). Bourdieu analysed "cultural capital" as a finite and unequally distributed rival good guarded by societal elites; a signal of superiority, a means of exerting power, and a beneficial resource whose selective transmission entrenches societal power structures across generations (Bourdieu, 1973). According to this analysis, social capital both governs and is intrinsically manifested in the asymmetric interactions between individuals and their social network, rather than simply being an exogenous public good benefiting all.

The concept of *network capital* provides a valuable framework for understanding this aspect of social capital, by focusing specifically on the unequally distributed *value that individuals or groups derive from* *their position in a network of social relationships and from their connections to others*, rather than their social environment at large. This framework recognizes that the structure and composition of a network can have a significant impact on an individual's ability to access resources and opportunities, impacting eventual outcomes. In particular, the study of social capital from the perspective of networks and interactions provides quantitative network data enabling a tractable economic analysis, contrary to the immaterial concepts of social consciousness (Durkheim, 1893), social public goods (Rupasingha, Goetz, and Freshwater, 2006), or cultural capital (Bourdieu, 1973).

Early studies used survey data to approximate social networks and study the prevalence of homophily (the commonly observed preference for interaction with similar individuals) or the effect of connections to well-connected or otherwise influential individuals in a given network (Espinoza, 1999). The rise of the Internet and online social networks over the past two decades has spurred not only a rise in interest for network-based analysis, but also an exponential growth in primary empirical data available to researchers (for examples, see Norbutas and Corten (2018) or Tóth et al. (2021); see Bailey et al. (2018) for a recent overview). As a result, empirical estimations of network phenomena in economics have been popularised across a range of sub-fields at the macroeconomic level, such as the study of production networks and business cycles (Acemoglu et al., 2012) or of financial contagion (Caccioli, Catanach, and Farmer, 2012). More interestingly, a large range of papers have drawn attention to the importance of social networks in determining micro-level decisions and behaviour: the individual-to-individual diffusion of microfinance (Banerjee et al., 2021), their impact on migration decisions (Foltz, Guo, and Yao (2020); Blumenstock, Chi, and Tan (2021)), or of how job search and wage-setting are enabled by social networks, but are biased by characteristics such as skill, gender, or ethnicity (Sazedj and José Tavares (2021); Sazedj and Jose Tavares (2022), Meurs and Valat (2019)).

Although they underlie the phenomenon studied here, the concepts of social and network capital were rarely, if ever, explicitly mentioned until the ground-breaking work presented in Chetty et al (Chetty, Jackson, et al. (2022b), Chetty, Jackson, et al. (2022a)): the authors use Facebook data to estimate the socio-economic status (SES) of 72 million users and their "economic connectedness" –the degree to which individuals are connected to high-SES individuals within their neighbourhood– as a component of social capital. Linking users' SES to that of their parents, they establish a strong positive relationship between economic connectedness, social mobility, and the variety of other outcomes associated with social capital discussed above. Mirroring the trends in social segregation presented above, they find an extremely uneven distribution of economic connectedness across the United States. This body of work convincingly not only demonstrates the importance of social and network capital, as proxied by social networks and connections, in determining economic outcomes; it also illuminate mechanisms through which these communal resources may be concentrated in certain communities, entrenching inequalities over time.

1.3 Resolving persistent inequalities

Bourdieu's analysis of social capital appears to prevail: large variation in neighbourhood social capital combined with an increasing socioeconomic segregation (Bergman et al. (2019); Sciandra et al. (2013); Ludwig, G. Duncan, et al. (2013)) and low social and geographical mobility has resulted in a consolidation and concentration of socioeconomic advantages in some neighbourhoods, and an entrenchment of disadvantages in others. This self-reinforcing mechanism has contributed to a gradual erosion of social mobility and the meritocratic tenets of the "American Dream", where the circumstances of one's birth matter more than their efforts and choices for success in life (TEDx Talks, 2016).

Although neighbourhoods are a large determinant of adult outcomes, they are not exogenously assigned at birth, but rather an endogenous, systemic outcome resulting from strategic choices. Leveraging lifelong Danish data on tax and residence, Heckman and Landersø (2021) and Eshaghnia et al. (2022) reveal the high degree of sorting present in the choice of childhood neighbourhood: certain parents choose to move to higher-quality neighbourhoods around the time of their children's birth, so that they can throughout their childhood benefit from exposure to better schools (Gensowski et al., 2020), public services, and higher-quality connections (in terms of economic outcomes). However, this is only possible for parents whose permanent income is high enough to afford the move, and disadvantaged families end up priced out of the higher-quality neighbourhoods. Over generations, sorting of neighbourhoods by the level of advantage they provide results in high-quality neighbourhoods increasingly being inhabited by families already in the upper portion of the income distribution, and families in the process of reaching it. Although growing up in better environments improves the social mobility of children, this is made inaccessible to those they would benefit the most: the poorest and least socially mobile. Even within a given neighbourhood, more advantaged families are better able to access and utilise locally provided public goods, further strengthening divisions over time.

The confirmation of the existence of this sorting mechanism corroborates previous evidence that although disadvantaged individuals are aware of the benefits of moving to a better neighbourhood for themselves as well as for their children and would indeed prefer to do so, they are barred from doing so by both economic and administrative barriers (Bergman et al., 2019). Being exposed to a high-social-capital environment early in life leads to compounding advantages during individuals' formative years, and to vastly improved adult outcomes. Correcting these inequalities ex post, e.g., through progressive tax systems, can be costly and inefficient. This has important implications for how we can aim to correct inequality-reinforcing mechanisms in societies, and suggests a role for policy intervention to correct what may be perceived as a market failing to provide equal opportunities, to allow disadvantaged families to gain these same benefits (Gensowski et al., 2020). The effects of early and sustained interventions aiming at correcting early-life inequalities can ripple and multiply across generations, greatly increasing their effectiveness.

1.4 Outlook and objectives

Despite recent empirical advances, social capital remains largely on the fringe of mainstream economics, and its implications absent from considerations linked to the creation and evaluation of policies aimed at redressing inequalities. This dissertation has so far provided an overview of the modern literature on social capital to establish its crucial and so far, largely omitted, importance, to spur future work on this promising avenue of research. In particular, the study of social capital from the perspective of networks and interactions provides quantitative data enabling a somewhat more tractable economic analysis than the more arcane concept of social capital. To substantiate this claim and motivate future research, the rest of this dissertation aims to examine a specific policy aimed at redressing inequalities –the Moving to Opportunity (MTO) experiment– through the lens of network capital. Specifically, I build a stylised network-based model of MTO inspired by Jackson and Rogers (2007) which captures the most recent findings of Chetty, Jackson, et al. (2022b) on inequality in social capital, and test it using their original data. This is done, firstly, to highlight how considerations of network capital can illuminate previously ambiguous findings on the MTO experiment. Secondly, and more importantly, this provides a framework to guide future research and acts as a proof-of-concept that this new variety of model is tractable in practice including with the usage of real data, can enrich the current literature linking social networks and inequality, and can capture richer behaviours than classical economic models.

The rest of this dissertation is organised as follows. In section 2, I argue that considerations of network capital and individuals' social networks can explain inconsistencies in the results of experiments such as Moving to Opportunity, and motivate the usage of network-based models to analyse this. In section 3, I give an overview of the literature on network formation models and extend the Jackson and Rogers (2007) model to create counterfactual MTO experiments in the presence of systemic biases. In section 4, I present my simulation results. Finally. In section 5, I discuss my results, their importance, and conclude with an outlook on possible future avenues of research aiming to utilise advances in complexity theory to refine current economic models.

2 Moving to Opportunity and Network Capital

2.1 Moving to Opportunity: an overview

The US-wide Moving to Opportunity (henceforth MTO) experiment, launched in 1994, treated 4600 low-income families with children living in public housing located in high-poverty neighbourhoods ($\geq 40\%$ of the population below the federal poverty line). These families were randomly assigned to one of three groups: the first received vouchers to move to public housing in a low-poverty neighbourhood ($< 10\%$ of the population below the federal poverty line) of their choice; the second also received public housing vouchers, but without the requirement of moving to low-poverty neighbourhoods; the third served as control group, staying in their disadvantaged neighbourhood. Moves occurred between 1994-1998, with extensive follow-up interviews and surveys organised in 2003 (after 5-9 years) and 2011 (after 13-17 years) to assess short- and long-term outcomes (Bergman et al., 2019).

MTO participants overall experienced improvements in subjective well-being (Ludwig, G. Duncan, et al., 2013) and physical as well as mental health (Ludwig, G. J. Duncan, Gennetian, et al., 2012). Children below the age of 13 at assignment saw their earnings increase by 31% relative to the control mean of \$11,270, had a higher college attendance rate, and, importantly, were themselves less likely to live in low-poverty neighbourhoods as adults (Bergman et al., 2019): MTO seemingly succeeded in "breaking the cycle" of remaining in low-social-capital environments. However, the effects of MTO have since its first evaluations consistently been shown to be largely dependent on age at assignment. Adults see little to no significant improvement in economic self-sufficiency (Ludwig, G. J. Duncan, and Pinkston (2005); Ludwig, G. Duncan, et al. (2013)), and, if any, a negative impact on earnings (Chetty, Hendren, and Katz, 2015). Compared to their younger peers, older children (aged 13-18) saw, at best, no significant impact on their welfare and future earnings, with evidence pointing to net losses in the latter (-\$967 per annum as per Chetty, Hendren, and Katz (ibid.)).

Well-recognised evaluations of MTO have tended to focus on its overall effects, rather than trying to understand the underlying factors causing this type of scheme to succeed or fail. Considering age as the main differentiating factor, most evaluations posit that MTO's failures can be explained by a simple model where disruption costs associated with moving are outweighed by cumulative exposure to a high-social-capital environment only for young enough children (Bergman et al., 2019). However, this hypothesis has not been thoroughly tested due to intrinsic limitations of the data generated by the experiment[1] (ibid.), and only provides an imperfect analysis of the observed heterogeneity in treatment effects, such as the vastly different outcomes experienced by boys and girls, or by individuals of different races[2].

2.2 Network Capital: a plausible driver

I hypothesise that these results may be illuminated by more recent studies into the ways social capital manifests itself through the network of relations which individuals form. I argue that network capital is an overlooked key component of social capital, and a crucial driver of the empirical observations outlined above.

The fact that girls and boys tend to experience vastly different outcomes has often been attributed to gender-associated differences in peer groups and their differing aversion to criminal behaviour (Scian-

[1] Specifically, the MTO experimental design cannot separate an age-invariant disruption cost coupled with an exposure effect from age-dependent disruption/exposure effects, since age at time of moving is perfectly correlated with cumulative time lived in the new neighbourhood.

[2] An often-criticised aspect of policies such as MTO is that they only "move the problem around" and do not aim to resolve the issues underlying segregation in social capital (Geronimus and Thompson, 2004). Although similar small-scale experiments in different settings have yielded similarly positive results (Deutscher (2020), Chyn (2018)), the theoretical effectiveness of MTO at a large scale is also cast into doubt by general equilibrium effects: Derenoncourt (2022) examines the effect of the Great Migration, wherein substantial African American migration towards cities in the Northern United States during the 20th century. This led to "White Flight" from neighbourhoods which still today suffer from poorer schooling, policing, criminality, and which remain largely ghettofied or generally segregated by both race and SES.

Nonetheless, their examination as a policy can provide crucial experimental evidence on the relation between social capital, childhood environment, and a variety of life outcomes. This may in turn be applied to design and implement policies which stand better chances at resolving these underlying issues.

dra et al., 2013), and to the fact that boys and girls across age groups differ in their ability to construct a new peer group to replace the one they lost by moving (Chetty, Hendren, and Katz, 2015). Beyond aggregate neighbourhood effects, the networked nature and importance of peers in criminal behaviour has often been documented in the literature (most recently in Dustmann, Mertz, and Okatenko (2023)), but lack of data makes directly validating this hypothesis in the case of MTO impossible. Deutscher (2020) furthers earlier analyses of MTO and specifically examines the effect of different peer groups in a similar Australian natural experiment, enriched with cohort-specific data: their findings corroborate MTO's overall positive impact and the role of peers. However, they conclude that aggregate neighbourhood and peer group characteristics cannot conclusively explain outcomes, and underline the need for more detailed data on peer networks to estimate the effects of peers on outcomes more accurately.

This ambition was eventually realised in Chetty, Jackson, et al. (2022b) and Chetty, Jackson, et al. (2022a): their tour-de-force lies in their decomposition of EC into two further measures: exposure effect, and friending effect. The former measures the degree to which below-median SES individuals encounter above-median SES individuals in their neighbourhood (extensive margin). The latter measures the degree to which individuals actually form friendships with above-median SES individuals, conditional on exposure (intensive margin), or, in other words, the strength of their bias against befriending below-median SES individuals. Leveraging data at the ZIP code level across several high school cohorts, they find that exposure and friending bias can differ significantly in adjacent neighbourhoods, and that in many cases high performance in one metric is not correlated with high performance in the other: environments may have any combination of high or low exposure effect and high or low friending effect, determining overall economic connectedness and correlations with other economic outcomes. High-quality connections are concentrated in high-social-capital neighbourhoods, a higher-quality environment to which MTO-participants are able to move. However, these findings decisively show that better environment alone is not enough to ensure improved outcomes. Low-SES individuals (i.e., MTO participants) and high-SES individuals are often members of entirely disjointed groups in society, and may thus never actually encounter each other to a significant degree (ibid.): this leads to a low exposure level for low-SES individuals, an effect which can be compounded by friending biases which further limit the number of high-quality connections formed (in term of future outcomes). Promoting cross-class exposure through mixing policies, such as the ones examined in Chetty, Jackson, et al. (ibid.), Mayer and Puller (2008), or Derenoncourt (2022), is unlikely to have a strong positive effect on its own, due to underlying biases.

This is supported by more precise empirical evidence based on within-school-and-university segregation. Mayer and Puller (2008) examine segregation on university campuses across the US and find strong evidence of both the exact exposure effects described in Chetty et al –students of different SES, genders, ethnicities, political leanings, campus activities, and academic results tend to participate in different groups, and thus encounter those outside their own to a smaller extent– but also of friending biases: students exhibit preferences against befriending those who differ from them in terms of these factors. In particular, they find that policies aimed at increasing cross-group exposure (such as specially-designed housing allocation) are by themselves largely ineffective at increasing cross-group connections. Campigotto, Rapallini, and Rustichini (2022) and Diemer (2022) find similar results when considering schools throughout Europe and in Sweden, respectively. On a related, albeit smaller scale, Michelman, Price, and Zimmerman (2022) leverages random room assignment at Harvard University in the 1920s-30s to show that exposure to high-SES peers leads to significant improvements in future outcomes: increased probability of membership at the university's prestigious "Old Boys' clubs" and subsequent membership at high-profile country clubs, higher probability of prestigious finance careers, and higher average adult income. However, this is only true for students already stemming from prestigious (and expensive) private feeder schools; minority and high-achieving students from other backgrounds see no effect at all from being exposed to "high-quality" peers. Both this link and the compounding gains for high-SES students are found to persist throughout the 20th century, indicating that Harvard's random room policy aimed at promoting cross-class osmosis failed (corroborating Mayer and Puller (2008)'s simulated results), and that Chetty et al's distinction between exposure and friending effects is crucial in practice.

These findings support the hypothesis that heterogeneity in the social and network capital which MTO participants faced in their new environments can help explain the heterogeneous estimated treatment effects. More generally, MTO-type policies may not succeed if they fail to take into account the role of both of these effects: decreasing friending biases alone has little chance to improve outcomes if there is no cross-class exposure; decreasing exposure biases alone cannot hope to improve outcomes if individuals still have strong preferences for within-class connections. Investigating how these differences translate into outcomes is a relatively fruitless exercise without access to detailed panel data linking social capital to life outcomes, but could enrich existing work on human capital production functions (Conti, Mason, and Poupakis, 2019). Instead, I aim to explore how aspects of individuals' interactions can lead to structural and qualitative differences in their social networks, and how such mechanisms can reinforce existing inequalities. This idea is not captured well by traditional economic models and methods: the analysis of networks requires specialised econometric techniques (Paula, 2020), and network-based models, even in economic contexts, typically rely on stochastic processes rather than the analysis of optimising behaviour and general equilibrium (Asano et al., 2021). Although some theoretical (Bowles and Carlin, 2020) and experimental (Nishi et al., 2015) work investigating inequality in games on networks exists, none that I have been able to find has attempted to do so using data in the context of policy interventions.

3 Building a network-based model of MTO

The remainder of this paper is devoted to building a simplified network-based model of MTO where agents' SES impacts their integration into the environment, and the success of the scheme. This requires, firstly, having a model which can generate counterfactual social networks on which to simulate MTO-type schemes. I now provide an overview of the literature on models of social network formation before specifying the exact model I apply, and detail a highly stylised implementation of MTO, whose theoretical and simulated results are provided in the next section.

3.1 An overview of network formation models

3.1.1 Modelling philosophies

Models dealing with networks in an economic context lie at the intersection of two fields with vastly different modelling philosophies. On one hand, graph theory derives from a mathematical analysis of networks' characteristics and algorithms generating them, generally based on random or stochastic processes. Economic literature, which characteristically focuses on the role of agents' strategic choices, has instead traditionally analysed network formation through a game theoretical lens, in which agents form connections to maximise an individual or communal utility function (Bala and Goyal, 2000), typically under the assumption of perfect information regarding every agent on the network. These assumptions are typical in game theory to simplify analysis once the number of agents considered is non-trivial. However, they are generally unsuitable for realistically describing many real-life processes of network formation which concern more than a very small number of agents, or in settings where game theoretical assumptions of perfect information or utility maximisation do not accurately describe agents' information sets and behaviour.

Network formation models differ largely in the situations they aim to describe and their mechanics, but can broadly be classified according to their degree of "rationality" (Huggins, 2010): the degree to which they are governed by inherent randomness as opposed to strategic decisions made by the agents composing them. This leads to a loose classification along a spectrum of models ranging from "stochastic" (entirely random) to "strategic" (entirely rational/game theoretical) (Jackson and Rogers, 2007). Note that in this context, an "unstrategic" model does not preclude the use of preferences (Iranzo, Pablo-Martí, and Aguirre, 2020) or utility-based concerns (Mayer and Puller, 2008), but simply that friendships are generally formed ad hoc based on the outcome of a random meeting process (Jackson and Rogers, 2007), rather than one involving strategic search of the best possible connections (Bala and Goyal (2000), Melguizo (2022), Marti and Zenou (2011)) under perfect information.

Testing which mechanism dominates in a given setting is a difficult and somewhat tautological process , as outlined in Jackson and Rogers (2007): the prevalence of randomness versus that of strategy as well as their definition depends on the algorithm considered, making comparisons across models and result validation difficult. Nonetheless, the existing evidence points to a relatively intuitive and obvious empirical division. Strategic processes tend to dominate in competitive settings where strategy is rewarded, such as international trade (Atkin, Khandelwal, and Osman, 2017), academic citation networks (Jackson and Rogers (2007); Iranzo, Pablo-Martí, and Aguirre (2020)), or the diffusion of financial institutions (Banerjee et al., 2021); random processes tend to dominate in my setting of interest: non-competitive or social settings, such as friendship formation (Bailey et al. (2018), Jackson and Rogers (2007), Marti and Zenou (2011)). This indicates that a parsimonious, mostly random model would best serve my objective in addition to greatly simplifying analysis.

Taking a more stylised and high-level approach has the added benefit of not requiring the specification of utility-relevant concerns: preferences and compatibility between different agents, or utility-cost functions which might depend on the number of connections, their quality, or the compatibility between agents (Currarini, Jackson, and Pin, 2009). These considerations would vastly increase the difficulty of the exercise considered, with very little marginal gain without data to calibrate the model or estimate the underlying parameters.

3.1.2 Modelling systemic biases

Chetty, Jackson, et al. (2022b)'s findings substantiate the fact that homophily arises not only as a consequence of preferences, but also as a consequence of underlying biased exposure mechanisms. Individuals do not sample their encounters independently and identically from the entire underlying population, but are more likely to encounter, for instance, those who are more similar to themselves in terms of their SES. This results in large qualitative and quantitative differences in social networks for individuals of different SES. As a result, the assumption of perfect information is obviously unsuitable to describe real social network formation processes.

Discarding assumptions of perfect information necessarily entails the inclusion of some kind of exposure mechanism through which agents are made aware of each other's existence, where the possibility of forming a connection between two agents hinges on them being exposed to each other, and where both of these depend on both nodes' characteristics. This is not uncommon in the literature, but formulations are generally made ad hoc with the aim of capturing perceived or observed real life patterns in a certain setting (Currarini, Jackson, and Pin (2009), Mayer and Puller (2008); Calvó-Armengol and Jackson (2004); Iranzo, Pablo-Martí, and Aguirre (2020); Meurs and Valat (2019)). A specific relevant example is Mayer and Puller (2008), which models the gradual exposure of new students on university campuses to other students on their dorm, degree, who participate in the same campus activities, and to friends of friends. The importance of second-degree connections (friends of friends) is a key characteristic of social networks, and must be incorporated to form realistic social networks.

3.2 Extending the Jackson and Rogers (2007) Model

I base myself on the model proposed by Jackson and Rogers (2007). The mechanics of the Jackson and Rogers (JR) model lead it to generate artificial networks with characteristics close to that of naturally occurring networks, with the goal of applying these for realistic simulations of MTO. This model is also simple to implement in code, and its mechanics map intuitively to a policy such as MTO, in which new agents are added to an existing network, for reasons which I make evident shortly.
I explain the extensions I add to the model to better suit my objective, before covering its mechanism in detail and addressing some caveats.

3.2.1 Model extensions

I extend the JR model to include agents' socio-economic status and allow it to impact their interactions in two ways. A given agent or node i is characterised by its socio-economic status SES_i: either "High" ($SES_i = 1$) or "Low" ($SES_i = 0$). This allows an intuitive mapping from this model to the work of Chetty, Jackson, et al. (2022b), where individuals are likewise classified into two groups: below-median SES (Low), and above-median SES (High). In a given network, let p_H denote the share of High agents, T_t the set of nodes in the network at time t, and $T_t(i)$ the neighbours of node i at time t.

Firstly, I incorporate a simple mechanism of biased exposure. Encountered nodes are sampled without replacement from the list of possible node encounters, but weighted by their SES. The weights are determined by the parameter ϵ, which describes how much less likely nodes of different SES are to meet: Chetty, Jackson, et al. (2022a) show that individuals tend to form most of their connections in settings which depend on their SES (see Figure 1, 2a in their paper for details).
If there are k nodes in t's encounterable population, the probability of meeting a given node t' is $(k)^{-1}$ if $SES_t = SES_{t'}$, and $(k * \epsilon)^{-1}$ if $SES_t \neq SES_{t'}$.
Following this procedure, m parent nodes are drawn from T_{t-1}, and n parent neighbour nodes are drawn from $\bigcup_{i \in M} T_{t-1}(i)$ to form the encounters.

Secondly, I incorporate a simple mechanism of friending bias favouring within-class connections. I allow the probability of two nodes i, j forming a connection conditional on encounter to be dependent on both nodes' SES.. Hence, p_0 is the probability of a within-class link ($SES_i = SES_j$) being formed, and p_x is the probability of a cross-class link ($SES_i \neq SES_j$) being formed, conditional on encounter. I define $\rho = p_o/p_x$ as the ratio of these two probabilities, where $\rho = 1$ if there is no friending bias, and

$\rho > 1$ if there is a friending bias *against* cross-class friendships.

This extension brings three new parameters to the JR model to straightforwardly integrate the main findings of Chetty et al: p_H, ϵ, ρ. The first two determine the degree of exposure in a given setting by governing how likely agents are to be exposed to high-SES agents, the latter determines the friending bias.
Although four new parameters are added in total $(p_H, \epsilon, p_o, p_x)$, only two degrees are freedom are effectively added in my formulation: if we follow Chetty, Jackson, et al. (2022b) in being most concerned with an agent's relation to the median SES, we can keep fixed $p_H = 0.5$, such that individuals are either above-median SES or below-median SES; taking either p_o or p_x as given in the original JR model, we only need to further specify ρ to determine the strength of friending bias, and ϵ to determine the strength of exposure bias, precisely our two main parameters of interest.

Apart from these changes, the social network generation algorithm follows exactly from Jackson and Rogers, outlined below[3].

3.2.2 The network generation model

This is an iterative model, which proceeds as follows.
At each time t:

- A new node t is added to the network, with $P(SES_t = 1) = p_H$.
- The node t encounters a set M of m parent nodes in T_{t-1}, and a set N of n parent neighbour nodes in $\bigcup_{i \in M} T_{t-1}(i)$.
- The node t befriends each parent node i with probability p_{mo} if $SES_i = SES_t$, and with probability p_{mx} if $SES_i \neq SES_t$.
- The node t befriends each parent neighbour node j with probability p_{no} if $SES_j = SES_t$, and with probability p_{nx} if $SES_j \neq SES_t$.
- Repeat T times.

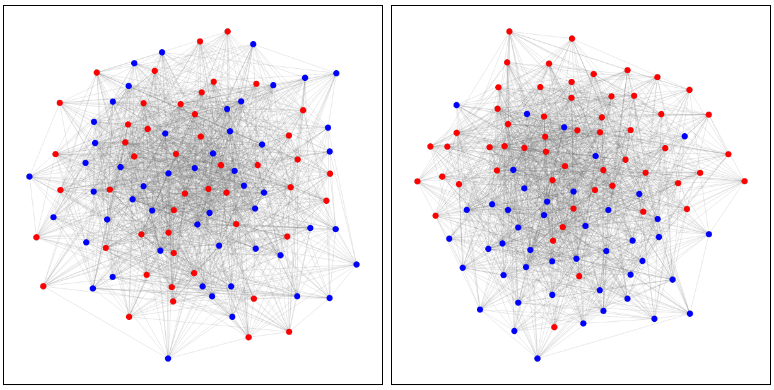
This procedure results in a network of size T. This can be described by a $T * T$ adjacency matrix A where $A_{ij} = A_{ji} = 1$ if there is a link between nodes i, j, and $A_{ij} = 0$ otherwise[4].

3.2.3 Model showcase

Before performing more extensive quantitative testing of my model in the next section, I provide a qualitative overview of the effect of the parameters ϵ, ρ on overall network characteristics.
4 samples networks are showcased in Figure 1 with varying degrees of Exposure and Friending biases. Showing low-SES nodes in blue and high-SES nodes in red, the emergence of segregation can be visually ascertained even for relatively small values of ρ and/or ϵ: the model appears to succeed in capturing the emergence of macro-level segregation from small changes in micro-level interactions.

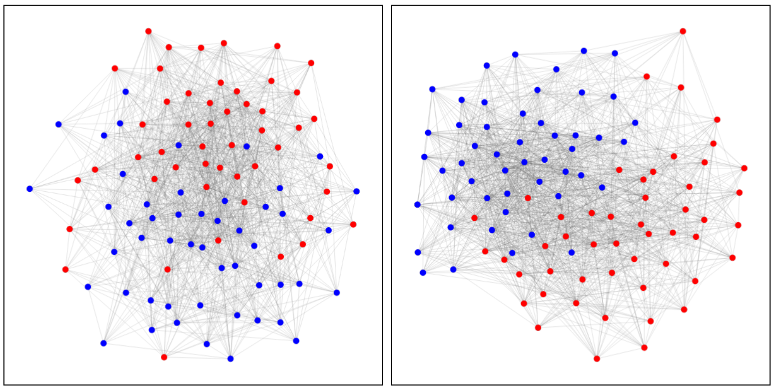
[3] I largely simplify the analysis by focusing on exactly two SES. Although allowing for more than two socio-economic "classes" may allow for more realistic behaviour and accurate predictions, it is certain that this would vastly increase the complexity of the model and the data required to calibrate it. Likewise, I also assume that the probability of two nodes forming a connection only depends on whether they are of the same SES, not the type of their common SES: without empirical evidence that High-SES individuals are more likely than Low-SES individuals to become friends conditional on exposure, this only complexifies the model.

[4] Note that the JR model can be applied to both directed and undirected networks, depending on the context. Here, friendships/connections/links are assumed to be reciprocal, hence I utilise the undirected version which results in a symmetric adjacency matrix.



(a) Unbiased: $\epsilon = 1, \rho = 1$

(b) Only exposure bias: $\epsilon = 1.75, \rho = 1$



(c) Only friending bias: $\epsilon = 1, \rho = 1.75$

(d) *Both* biases: $\epsilon = 1.5, \rho = 1.5$

Figure 1: Extended JR model: Exposure and Friending Bias compound, leading to segregation.

3.3 Modelling MTO

In the context of Moving to Opportunity, the JR model is convenient as the exact same iterative algorithm can intuitively be reapplied to simulate MTO[5]: a MTO node is added to the network, and encounters a set of parent nodes and parent neighbour nodes, mimicking how a new arrival in a new social environment may encounter other individuals in different groups (Chetty, Jackson, et al. (2022b), similar to the model of Mayer and Puller (2008)[6].

3.4 Model behaviour

I now formulate some simple theoretical predictions regarding the model's expected behaviour. I assume for now that each node in the network has a large number of neighbours of both types[7]. From the perspective of the MTO node, each parent node it can encounter then has functionally the same neighbourhood on average, in terms of the number of H and L nodes (I shortly show why this will rarely hold in reality, nor in simulated models). Hence, the MTO node's "search" for connections is constrained only by our chosen parameters (m, n, ϵ) rather than the network, which we do not control.

[5]It is important to note that the JR model itself should not be interpreted as a dynamic model mimicking a real, ongoing process of social network creation where nodes are iteratively added. Rather, the output of the model should itself be interpreted as a realised social network on which to conduct analysis (in our case, MTO simulations).

[6]Further, for large m and n, the MTO simulation considered here is functionally identical to Mayer and Puller's model

[7]More specifically, the first results presented require that each H node has at least $\frac{n}{1+\epsilon}$ H neighbours and $\frac{n*\epsilon}{1+\epsilon}$ L neighbors, and that each L node has at least $\frac{n*\epsilon}{1+\epsilon}$ H neighbours and $\frac{n}{1+\epsilon}$ L neighbors.

3.4.1 Exposure and Friending Effect

In Chetty, Jackson, et al. (2022a), Exposure and Friending effects are defined as:

$$\text{Exposure} = \frac{\text{Share H in group encountered}}{\text{Share H in population}}$$

$$\text{Friending Effect} = 1 - \frac{\text{Share H of friends}}{\text{Share H in group encountered}}$$

A new Low (High) node encounters $m + n$ nodes, of which $\frac{m+n}{1+\epsilon}$ will be High (Low), and $\frac{\epsilon(m+n)}{1+\epsilon}$ will be Low (High). The share of High nodes in the population is defined by p_H, hence in my model we can naively predict average Exposure effect for a low SES and High SES node to be, respectively:

$$\text{Exposure}_L = \frac{1}{p_H(1+\epsilon)}; \quad \text{Exposure}_H = \frac{\epsilon}{p_H(1+\epsilon)} \tag{1}$$

A new Low (High) node befriends each encountered Low (High) node with probability p , and each encountered High (Low) node with probability p/ρ. It should then have $\frac{p}{\rho} * \frac{m+n}{1+\epsilon}$ High (Low) friends, and $p * \frac{\epsilon(m+n)}{1+\epsilon}$ Low (High) friends. Hence we can naively predict average Friending Effect effect for a low SES and High SES node to be, respectively:

$$\text{Friending Effect}_L = \frac{\epsilon(\rho-1)}{\epsilon\rho+1}; \quad \text{Friending Effect}_H = \frac{1-\rho}{\epsilon\rho+1} \tag{2}$$

In the presence of exposure bias ($\epsilon > 1$) and friending bias ($\rho > 1$), we should indeed observe a stronger exposure effect and a positive friending effect for High nodes, and a weaker exposure effect and negative friending effect for Low nodes (mirroring Chetty, Jackson, et al. (ibid.)).

It is interesting to note there that the Exposure and Friending biases considered by Chetty et al essentially correspond to the network-wide realisation of the underlying exposure and friending biases, serving as a useful and *observable* metric for an estimation of such biases in a given setting. In section 4.4, I specifically test whether these estimated aggregate values can be used to reliably estimate underlying biases by comparing simulation results with those observed by Chetty et al. at the county level.

3.4.2 Network segregation and assortativity

I also calculate network-level measures of segregation. The definition of network segregation depends on the context considered and is a widely studied subfield of graph theory. In my case, its most intuitive assessment is to measure proxies of assortativity: the propensity of nodes to connect to similar nodes, i.e., nodes of the same SES.

A simple proxy for this is to compare the share of High SES friends possessed by High and Low SES nodes: if this share differs largely between SES, this indicates a strong presence of segregation. As stated just above, we can naively predict that a Low SES node should have a share $\frac{p}{\rho} * \frac{1}{1+\epsilon}$ of Low friends, and a share $\frac{1}{\rho} * \frac{1}{1+\epsilon}$ of High friends. Conversely, a High SES node should have a share $\frac{p}{\rho} * \frac{1}{1+\epsilon}$ of High friends, and a share $\frac{1}{\rho} * \frac{1}{1+\epsilon}$ of Low friends.

A slightly more involved proxy is attribute assortativity, as defined in Newman (2003). The attribute assortativity r is equal to 1 if the network is perfectly assortative (all edges connect two nodes of the same SES), -1 if the network is perfectly dissassortative (all edges connect two nodes of different SES), and 0 if connection is independent of SES (nodes are equally likely to connect to same and different SES).

Precisely predicting the strength of assortativity is a complex process due to the non-linear network effects. Advanced techniques such as mean-field analysis can be used to estimate its likely distribution (as seen in Jackson and Rogers (2007)), but is vastly beyond the scope of an undergraduate dissertation. As such, I simply calculate this measure.

3.4.3 Non-linear network effects

However, the naive formulas laid out above will underestimate the realised impact of the underlying biases, as they do not take into account the fact that nodes are more likely to be connected to nodes of the same type. This results in nodes' neighbourhoods not being functionally identical, as previously assumed, and the above assumption is very unlikely to hold.

As an example, consider the network laid out in Figure 2, and suppose we are simulating MTO with the following parameters: $m = 2, n = 10, p_H = 1/6, p = 1, \epsilon = 3, \rho = 3$. We should then expect an Exposure Effect of $[\frac{1}{6}(1+3)]^{-1} = 1.5$ and a Friending Effect of $1 - \frac{3(2-1)}{3*2+1} \approx 0.57$.
Suppose the two parent nodes chosen are the two at the centre of the "stars" (with a thicker border), in which case all 12 nodes presented are encountered. In this case, the MTO node encounters 2 H nodes and 10 L nodes, leading to a lower realised Exposure Effect of 1.2 and a higher realised Friending Effect of 0.625. This exemplifies how the non-linearities inherent to many network-based systems can amplify micro-scale interactions (such as preferences) to create macro-scale patterns (here, segregation).

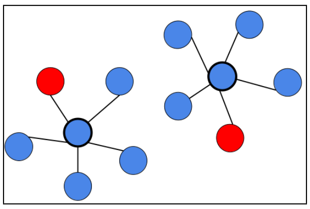


Figure 2: An example of why underlying systemic biases lead to underestimates of Friending and Exposure Effects.

Having constructed a model to generate realistic counterfactual social networks and a simplified approach to modelling MTO-type experiments, I now simulate MTO outcomes in the presence of exposure and friending biases for a range of parameter combinations.

4 Simulations

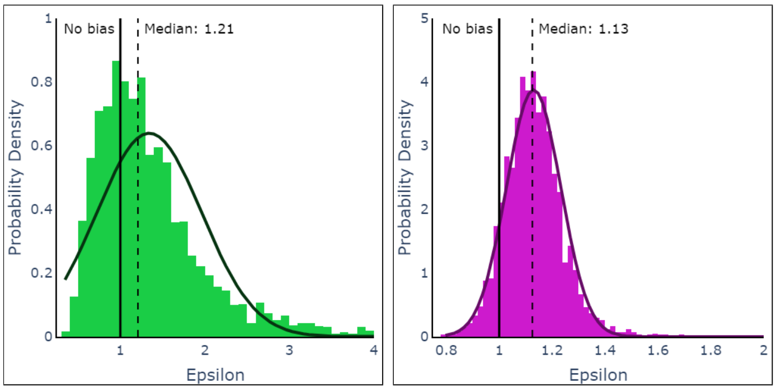
4.1 Data

Chetty et al estimate exposure and friending effects for both High and Low SES individuals in a representative sample of 3012 counties in the United States (Chetty, Jackson, et al., 2022b). I now use this data to estimate the distribution of parameters that I will sample from to run the simulations: note that equations 1 and 2 can be rearranged to yield the following expressions for ρ and ϵ, our two parameters of interest.

$$\hat{\epsilon} = \frac{1}{p_H * \text{Exposure}_L} - 1 \tag{3}$$

$$\hat{\rho} = \frac{\hat{\epsilon} + \text{Friending Effect}_L}{\hat{\epsilon}(1 - \text{Friending Effect}_L)} \tag{4}$$

Hence, given values of Exposure and Friending effect, we can estimate an approximate value of ϵ, which can in turn be applied to estimate ρ. Since the interpretation of the Exposure and Friending Effects differ somewhat in the model from what they are as observed by Chetty et al, the correspondence in parameters is not exact. However, this does provide an idea of the values from which to sample. Descriptive statistics for the values of $\hat{\epsilon}, \hat{\rho}$ calculated based on this data are shown in Table 3c. Distributions are shown in Figures 3a and 3b.



(a) Distribution of $\hat{\epsilon}$

(b) Distribution of $\hat{\rho}$

	Epsilon	Rho
mean	1.3546	1.1316
std	0.6755	0.1136
min	0.3456	0.7967
25%	0.8999	1.0595
50%	1.2082	1.1255
75%	1.6126	1.1929
max	6.8370	2.5296
skew	1.8287	1.2903
$\% \geq 1$	0.6630	0.9017

(c) Descriptive statistics: $\hat{\epsilon}, \hat{\rho}$

Figure 3: Distributions of $\hat{\epsilon}, \hat{\rho}$ estimated based on Chetty, Jackson, et al. (ibid.)

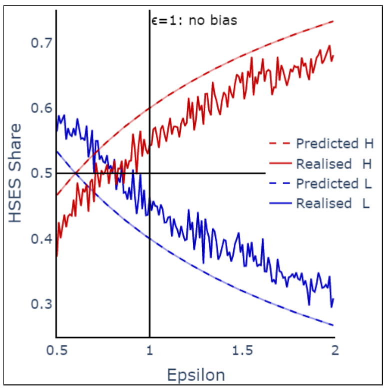
Both parameters are highly normally distributed, although with a relatively high positive skewness for ϵ. In both cases, a large share of values are greater than 1 (66% for ϵ, 90% for ρ), indicating an extensive presence of both exposure and friending biases in most US counties. We can also see that the values' ranges differ: whereas nearly all ρ values are between 0.8 and 1.5[8], a significant share of the ϵ values are greater than 2. The larger dispersion in ϵ is likely due to this parameter being less precisely defined, and its single value in my model captures a large variety of real life situations. This nonetheless provides some reassurance that my model specification is not irrelevant, as it is able to match these effects observed with actual data. Additionally, this somewhat corroborates my earlier hypothesis that systemic randomness dominates strategic behaviour in this network formation setting, as i) "random" exposure imposes a stronger bias than "random" friendship formation conditional on exposure, and ii) there is greater variance in exposure bias random overall. The Pearson correlation coefficient is of -0.011, with a p-value of 0.552, hence we cannot reject the hypothesis that ρ, ϵ are uncorrelated. An additional caveat is that in reality, it is highly unlikely that the share of High SES individuals in a given

[8]Note that for values of $\rho < 1, p_o = 1$, calculated p_x in my model are not bounded by [0,1]. Whenever this is the case, I impose that $p_x \in [0,1]$. As a result, the model behaviour is ill-defined: nodes always befriend nodes of the opposite SES, and never befriend those of the same SES. This can result in a bipartite network, with no within-class links.

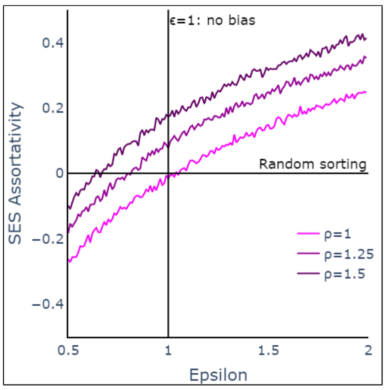
population p_H is uncorrelated with that setting's exposure and friending biases. However, Chetty et al perform their calculations with the assumption that $p_H = 0.5$, hence there is no data with which to investigate this relationship.

I do not provide any testing of the other model parameters, which, unless specified, take the following values: $T = 100$, $m = 10$, $p_{mo} = 1$, $n = 10$, $p_{no} = 1$, $p_H = 0.5$. As mentioned earlier, taking $p_H = 0.5$ allows for a division of agents into either below-median or above-median SES, in line with Chetty, Jackson, et al. (2022a). I follow Jackson and Rogers (2007) in choosing the within-class friending probability to be equal to 1 to simplify analysis and choosing $m = n = 10$ as a baseline. The network size of 100 is smaller than the typical group size ranging between 500 and 1500 considered in Chetty et al (due to computational time constraints), but of the same order of magnitude (10^2). As I have no data on which to calibrate these parameters, it is more sensible to take broadly realistic baseline values, and focus on the impact of ρ, ϵ. The rest of this section is dedicated to creating networks and running simulations of MTO, first with arbitrary parameter combinations, and finally with values estimated based on the data on Chetty et al to compare simulated and realised values of Exposure and Friending effects and test the accuracy of my model in replicating observed outcomes.

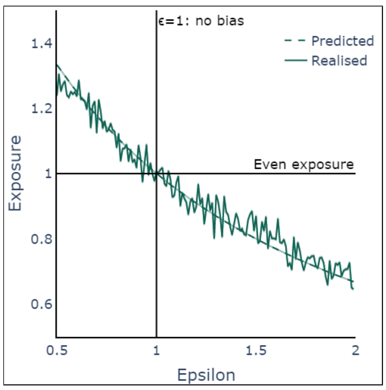
4.2 Varying ϵ, ρ individually



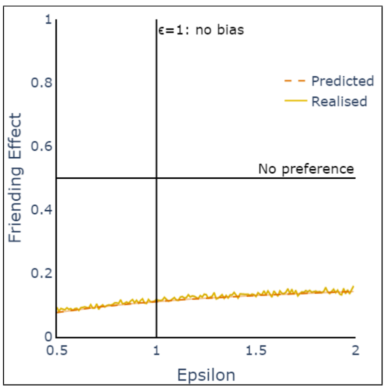
(a) Network-average share of HSES friends for a LSES node



(b) Network-level SES assortativity



(c) MTO Exposure effect



(d) MTO Friending Effect

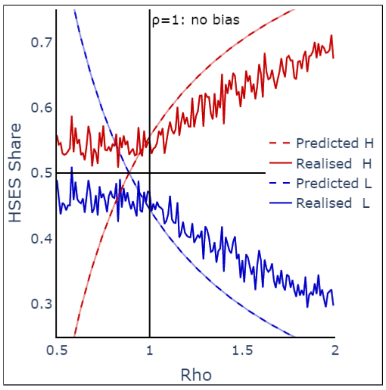
Figure 4: Effect of varying ϵ on network characteristics and simulated MTO outcomes. Unless specified otherwise, $\rho = 1.25$.

First, we can observe the effect of varying ϵ, ρ individually in intervals of 0.01 from 0.5 (nodes are twice as likely to encounter/befriend nodes of the opposite SES) to 2 (nodes are half as likely to encounter/befriend nodes of the opposite SES), holding the other fixed at values of 1, 1.25, and 1.5. For each parameter combination, I generate 10 networks following the process outlined above, and run

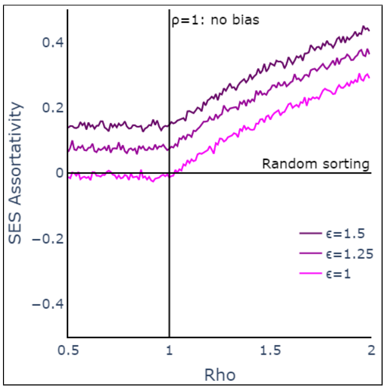
MTO simulations 100 times on each. For each of ρ, ϵ, this makes for a total of $3*150*10*100 = 450,000$ simulations. Simulation results for varying ϵ are presented in Figure 4, those for varying ρ in Figure 5. "Predicted" lines are calculated on the basis of Equations 1, 2.

Firstly, we can see that the effect of increasing either of ϵ, ρ individually is as predicted: SES assortativity (Figures 4b, 5b) and the difference in share of High SES friends between High and Low nodes (Figures 4a, 5a) both increase, and are greater than 0 for bias values greater than 1. It is noteworthy that the point at which the segregation curves cross the no-segregation horizontal line depends on both parameters. If $\epsilon > 1$, a value of $\rho < 1$ can still lead to overall segregation (and vice-versa). Importantly, the naive predictions (dashed lines in Figures 4a, 5a) for the share of friends in each SES are, as expected, inaccurate: the share of HSES friends for a LSES node is overestimated in both cases, due to network effects increasing the importance of LSES nodes being more likely to have LSES connections.

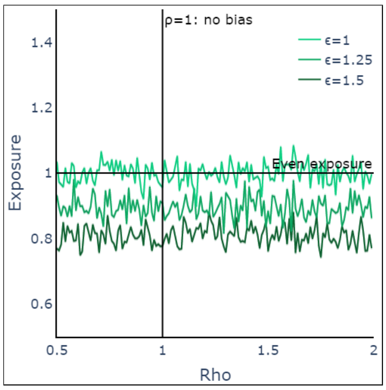
For $\epsilon < 1$, assortativity is (as predicted) negative (Figure 4b): nodes are more likely to befriend others of the opposite SES. However, for $\rho < 1$, friending is essentially random, leading to assortativity to be roughly constant around a low value proportional to ϵ (Figure 5b).



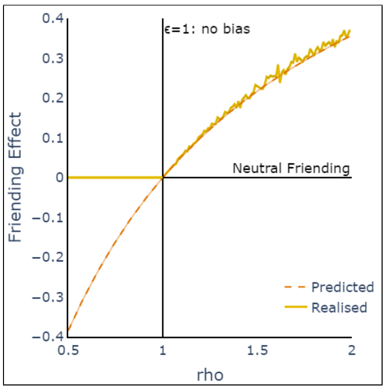
(a) Network-average share of HSES friends for a LSES node



(b) Network-level SES assortativity



(c) MTO Exposure effect



(d) MTO Friending Effect

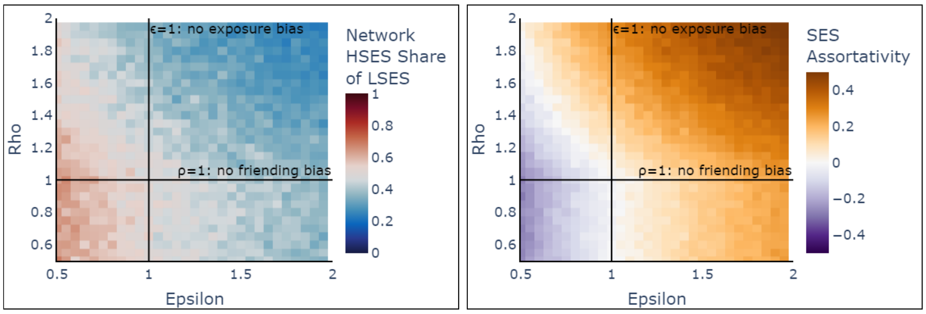
Figure 5: Effect of varying ρ on network characteristics and simulated MTO outcomes. Unless specified otherwise, $\epsilon = 1.25$.

The MTO outcomes also both follow predictions. Exposure is decreasing in ϵ (Figure 4c), and random in ρ (Figure 5c), since exposure is independent of friending bias. Friending Effect is increasing (i.e., higher segregation) in both, although much more strongly in ρ (Figures 4d, 5d). Note that the predictions are highly inaccurate for values of $\rho < 1$: I believe this is due to the model then behaving near-randomly, rather than due to nodes having a preference for befriending opposite-SES nodes.

Importantly, we can see that both determinants of Chetty et al's Economic Connectedness indicate segregation: Exposure effect is less than 1, Friending effect is greater than 0. This model then succeeds in capturing the importance of exposure and friending biases in determining aggregate network outcomes, which may influence the success of schemes such as MTO.

4.3 Varying ϵ, ρ jointly

Then, I vary both parameters together in the same range of $[0.5, 2]$ in intervals of 0.05, for a total of $30^2 * 10 * 100 = 900,000$ simulations. Most results are analogous to those in section 4.2, but plotting average outcomes as a function of both ϵ, ρ leads to better illustrations of how the two biases can interact to both compound and counteract each other, and to how accurate our predictions are.

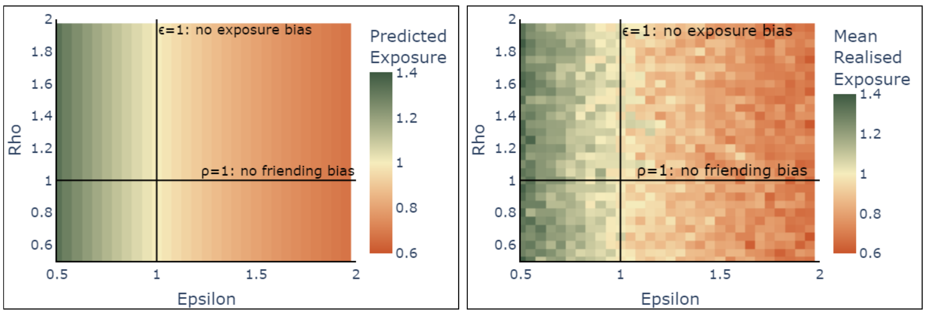


(a) Network-average share of HSES friends for a LSES node

(b) Network-level SES assortativity

Figure 6: Network segregation when varying both ρ, ϵ.

Firstly, we can see in Figure 6 that both measures of segregation depend on both biases. There is a clear phase transition with no segregation in the $\epsilon - \rho$ space, roughly following the downwards diagonal where $\rho * \epsilon = 1$: the two biases are roughly equally important in determining outcomes, although this is likely due to choosing to set $m = n$, and may change depending on the degree to which random parent connections matter relative to biased neighbour connections. As expected, this indicates that the two biases can counteract or compound each other: if $\rho > 1$, a value of $\epsilon < 1$ can still result in weak or no segregation. Segregation is also stronger overall when both biases increase together than when a single of them increases by more on its own (assortativity varies more along the diagonal than either horizontally or vertically).



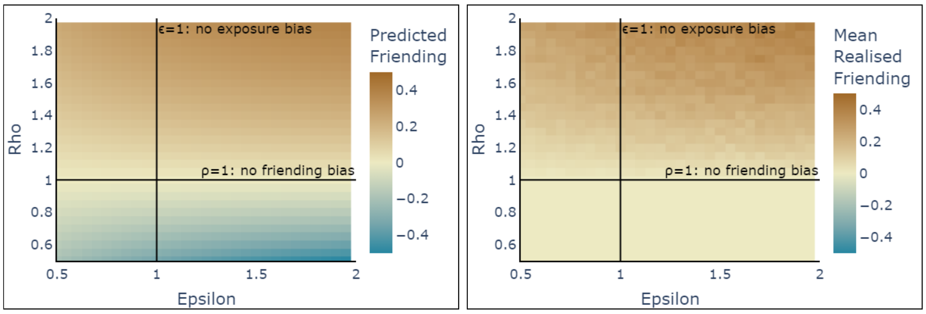
(a) Predicted exposure effect (Equation 1)

(b) Average realised exposure effect

Figure 7: Exposure effect when varying both ρ, ϵ.

Results for exposure effect are shown in Figure 7. Overall, they confirm the earlier hypothesis that exposure is decreasing ϵ and largely independent of ρ. Of key importance is the $\epsilon = 1$ line, which separates environments with high-exposure (left) and low-exposure (right).

Results for friending effect are shown in Figure 8. For values of ρ close to or below 1, friending effect is roughly neutral, rather than negative (i.e., prone to cross-SES friendships). Friending effect is



(a) Predicted friending effect (Equation 2)

(b) Average realised friending effect

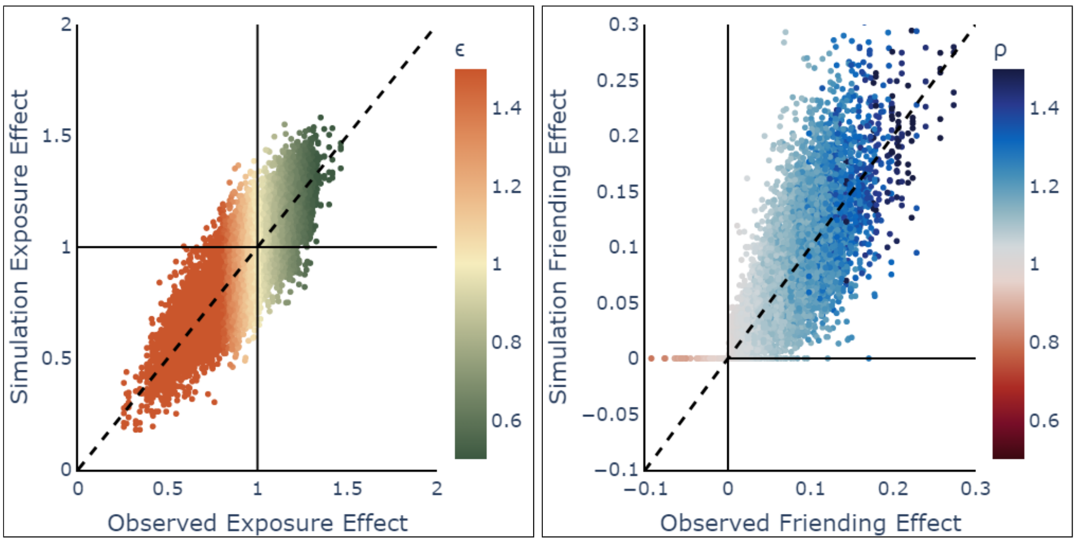
Figure 8: Friending effect when varying both ρ, ϵ.

increasing (i.e., higher segregation) in ρ and to a lesser degree in ϵ. Contrary to predictions, simulated results do not include the presence of negative Friending Effect (i.e., preference towards cross-class connections).

A key result in all cases is that we can observe that inherent randomness in the network generation algorithm and MTO simulation leads to a larger variance in Exposure and Friending Effects rather than the smooth progression predicted, despite values shown being averaged over 10 networks with 100 MTO simulations each. This highlights the importance of network structure and how much minute differences in them can impact outcomes, the importance of examining network structure more exactly.

4.4 Values of ϵ, ρ from Chetty et al (2022)

Finally, I run MTO simulations using the data collected in Chetty et al. For each county, I first use observed Exposure and Friending effects to estimate $\hat{\epsilon}, \hat{\rho}$ (as described in section 4.1). For each, I then generate a corresponding networks and run MTO simulations, and calculate realised Exposure and Friending Effects. This exercise allows me to compare Exposure and Friending effects resulting from the simulation with the actual values observed by Chetty et al, serving as an indication as to whether my model is realistic and can replicate observed outcomes.



(a) Simulated and observed exposure effect

(b) Simulated and observed friending effect

Figure 9: Comparing simulated values of Exposure and Friending Effects with observed values. Simulation parameters estimated based on observed values in Chetty et al.

The results are shown in Figure 9, with the 45-degree line indicating a perfect matching of simulated to observed data. Overall, it would appear that my model is highly accurate in replicating observed Exposure and Friending effects: a simple linear regression obtains coefficients of 0.942 with an R^2 for

Exposure, and a coefficient of 0.945 with an R^2 of 0.639 for Friending (Table 1), both very close to a perfect fit of 1. Additionally, the goodness of this fit does not appear to depend on either ϵ or ρ, although values of ρ equal to or lower than 1 result in the model being ill-behaved, and simulated friending bias being equal to 0, rather than negative as observed.

	Simulated Exposure	Simulated Friending
Intercept	0.056***	0.008***
	(0.006)	(0.001)
Observed Friending		0.945***
		(0.007)
Observed Exposure	0.942***	
	(0.006)	
Observations	9,640	9,640
R^2	0.723	0.639
Adjusted R^2	0.723	0.639
Residual Std. Error	0.124	0.034
F Statistic	25214.724***	17086.102***
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 1: Simulated versus Observed values of Exposure and Friending Effects

5 Discussions

5.1 Results

Given the evidence on the importance of social capital presented in Section 1, the main addition this dissertation aimed to provide to the existing literature was a simple framework for future research into network-based models of social and network capital, and to investigate how this could be applied to better understand, evaluate, and predict treatment outcomes.

The simulation results outlined in Section 4 indicate that this avenue of research is promising. Even a simple network-based model of MTO is able to capture a rich variety of emergent behaviour, most notably that of segregation and heterogeneity in network structure. This is done taking a micro-founded approach, leaving room for future refinements *a la* Mayer and Puller (2008) where utility from connections (and thus, friending decisions) are dependent on more detailed characteristics, and for precise model calibration on such data. Lacking such data myself, I have instead focused on outlining how a model can, at the micro level, incorporate biases which result in the aggregate heterogeneity in individual-specific network capital observed in Chetty, Jackson, et al. (2022b). Crucially, I am able to calibrate my two model parameters (ϵ, ρ) using this data, and am highly successful in replicating observed values of proxies for network capital. Future research with access to more precise data on network structure and individual characteristics could push this even further and obtain more accurate and trustworthy results, by specifying based on data the remaining model parameters which I have left undiscussed. Although still considered the workhorse social network generation model, the JR model considered here is also relatively simple and does not leverage more recent advances in graph theory drawing on e.g. the explosion of social network data over the last decade. Modern recreations of the survey-based work of Espinoza (1999) should also attempt to provide more specific analysis of networks in the precise setting considered, that is social network construction in high-poverty or segregated urban environments, to hopefully achieve more accurate results and a better understanding of network structures in such environments.

Chetty et al utilise their revolutionary measures of Exposure and Friending effects to propose improvements to policies aimed at increasing social mixing, but their results are only descriptive insofar as they make no attempt to study the individual-level mechanisms leading to the aggregate outcomes they study. The policies they discuss only affect the aggregate networks *through their direct effect on individuals and their interactions*: for instance, the policy involving creating a joint common room for students of all ethnicities to avoid them segregating themselves into separate rooms is *not* directly impacting Exposure Effect. Rather, it aims to lower (on average) students' exposure bias (ϵ), which in turn leads to an emergent increase in Exposure Effect for the average student. Although I do not claim that the model I have built enables anything resembling causal evaluations in its current state, a better approach would involve estimating the change in bias parameters resulting from such a policy, and in turn estimate the emergent change in aggregate network characteristics. This takes the approach of using micro-founded data advanced by Chetty et al further, by specifying a micro-founded model.

The model I have built is limited due to its simplicity and lack of data to calibrate it exhaustively, and cannot conclusively be applied in policy evaluation. However, I believe I have succeeded in providing a framework for such an approach to be refined in future research following the most recent advances, and a convincing showcase for why such an approach is tractable (contrary to what lack of current work on this topic suggests), and how it could be fruitful in generating new insights and better methods.

5.2 Looking forward: Social Capital, Complexity, and Economics

> *"Just as the organised activity of an ants' nest cannot be understood from the behaviour of a "representative ant" so macroeconomic phenomena should not be assimilated to those associated with the "representative agent". You would not imagine looking at the behaviour of a representative ant if you wanted to predict the evolution of the activity of the nest."*

Alan Kirman, *"Complex economics: individual and collective rationality"*

A recurring thread throughout this dissertation is the idea that economic agents do not exist in a vacuum: their knowledge, opportunities, choices, and eventual outcomes are all governed by fundamental mechanisms and structures whose very existence is assumed away by currently standard economic models. One simple example is a fundamental building block of economic models: the exchange between a representative buyer and a representative seller on a market. As pointed out by Kirman (2010), these two agents only interact through a price: differences in market structures or competition power exist only insofar as demand and supply curves are able to differ. In reality, markets for buyers and sellers much more closely resemble a network than the abstract black box in which representative agents interact: consumers only know of a specific subset of firms and other individuals, and are only able to interact with an even more limited number of them. Market structures, competition, and equilibrium are phenomena which *emerge* from these interactions and their underlying structure, rather than being assumed into existence (for recent work on this example, see Fleiner et al. (2019)). Similar mechanisms exist in numerous other economic fields of study, including migration, job search, social learning, institutional adoptions, firm-to-firm production networks, financial contagion, or consumption decisions (refer to Section 1.2 for recent examples of work on these examples). In addition to the numerous empirical examples mentioned throughout, a growing literature attempts to capture such mechanisms in theoretical models. The endogenous emergence of segregation in the model outlined above extends the seminal work of Schelling (1969), which pioneered an agent-based approach to study patterns in urban segregation, to include network effects. This has since been refined to consider relevant economic factors, such as inequal outcomes emerging from a combination of heterogenous agents and preferences over neighbourhoods (Sridhar, 2022). However, these mechanisms remain largely disregarded by mainstream economic theory in favour of a black box containing any number of representative agents.

This traditional perception of economics fails to represent the economy as a complex or emergent system: a system whose aggregate behaviour and outcomes are not solely determined by the properties of its individual components, but instead emerge from the complex interactions and feedback loops between those components. Economics as a field has failed to innovate and keep up with the explosion of Big Data which has accompanied advances in network science and complexity theory over the last two decades. I do not attempt to claim that developing this approach to economics is certain to be successful and to improve upon current models. However, the promising avenue of research that some have dubbed *complexity economics* has the potential to provide fascinating new insights and tools to consider the fundamental building blocks of economic theory, and deserves to be pursued further.

6 Appendix

6.1 Code and data repository

My simulations are coded in Python 3.8 using the NetworkX library. Python enables a streamlined implementation of network simulations using NetworkX jointly with other data analysis, but is not the most efficient coding language. Although I have strived to optimise my code somewhat, it remains unsuitable for analysing very large networks or a large number of simulations. Here, I constrain myself to a relatively small network size (order of 10^2) and number of simulations (order of 10^6), for a running time of a few hours. This code can serve as guidance for similar future work, but more extensive simulations would greatly benefit from being rewritten in more low-level or specialised languages such as C or MatLab.

The code for both simulations and data analysis, as well as the simulation data underlying analysis and figures appearing in this dissertation, are all available on my public GitHub repository at the following link: https://github.com/RassssD/Diss-model.

6.2 Bibliography

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