CHAPTER 9

Neighborhood and Network Effects

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Abstract

In this chapter, we provide an overview of research on neighborhoods and social networks and their role in shaping behavior and economic outcomes. We include a discussion of empirical and theoretical analyses of the role of neighborhoods and social networks in crime, education, and labor-market outcomes. In particular, we discuss in detail identification problems in peer, neighborhood, and network effects and the policy implications of integrating the social and the geographical space, especially for ethnic minorities.

Keywords

Social networks, Neighborhoods, Group-based policies, Ethnic minorities, Labor economics

JEL Classification Codes

C23, D85, J15, J64, K42, R14, Z13

9.1. INTRODUCTION

Our environment, whether it includes our neighbors, our peers, or more generally, our social contacts, crucially affects many facets of our lives. For example, the decision of an agent of whether or not to buy a new product, study hard, commit a crime, smoke, or find a job is often influenced by the choices of his/her friends and acquaintances, neighbors, classmates, coworkers, professional contacts, etc. Economists—and before them, sociologists—have long recognized the importance of such nonmarket interactions in shaping behavior and outcomes in a large variety of contexts. A long, but only partial, list includes peer effects in the classroom and in the workplace, labor-market referrals, smoking, crime, and other social diseases, consumption externalities, herd behavior, and "contagion" in financial networks, bankruptcy and foreclosure decisions, risk sharing within households, communities, villages, sorting into residential neighborhoods, the adoption and diffusion of new technologies, the role of agglomeration economies in shaping cities and the location decisions of businesses, and the role of human capital externalities in economic growth.

At a very abstract level, we can think of these social interactions as taking place within a "social space," defined by one's reference group—be it one's classmates, peers, neighbors, colleagues, other firms, and so on. There are various ways to model such a social space. Generally speaking, we need to define a set of individual agents (affecting each other), as well as the connections among them. These, in turn, help us define a notion of social or economic distance on the set of locations inhabited by agents in the abstract social space.

One large strand of literature has modeled the social space simply by characterizing the reference group of each agent. For peer effects in education, this is often the set of classmates or schoolmates. For the location decisions of households and firms, it is the set of residential neighbors or other firms in the same industrial district. Interactions are assumed to be symmetric within each reference group, and the various reference groups often define a proper partition of the set of agents. One particular example of this approach consists of the literature on neighborhood effects, which attempts to study how the composition of one's residential neighborhood affects one's outcomes with regard to, for instance, educational achievement, the ability to find a job, or the propensity to engage in crime.

Another strand of the literature has focused on the structure of connections within the abstract social space. This is often modeled using the tools of social network theory. As we describe in more detail in Section 9.3.1, a network is defined as a set of agents and a graph describing who is connected to whom. A growing empirical literature shows that the structure of the network, and the position of individual agents within it, plays an important role in shaping choices and outcomes.

The social space modeled by a network does not necessarily coincide with the physical space. Indeed, an individual may be closely connected to someone residing and working at the other end of the city or even in a different country. The social space—and the distance among agents–may be defined by ethnicity, race, age, nationality, tastes, and many attributes other than physical distance. At the same time, it seems reasonable to think that the costs of interaction increase with physical distance, so interactions may be easier and more frequent among agents who are physically close to each other. Therefore, in general, there will be some partial overlap between the social space modeled as a network and the physical space described by a residential neighborhood.

Finally, there are several mechanisms through which social interactions may affect behavior and outcomes. Social contacts may facilitate the flow of information about, for instance, job openings or the profitability of a new technology, thus influencing the choice set available to agents. Social contacts may also affect one's tastes for a certain good, influencing the likelihood that one will consume that good. One's network or reference group may provide risk-sharing devices and opportunities for cooperation. There may also be complementarities in production or consumption through which social interaction effects operate.

In this chapter, we review the literature on neighborhood effects and the literature on network effects. These two bodies of literature have developed largely separately: the neighborhood effects literature has mostly focused on how residential neighborhoods may shape opportunities, choices, and outcomes of individual agents living in them. This process has implications for urban policy, the evolution of neighborhoods and cities, and the dynamics of segregation and inequality—to mention just a few. The theoretical and empirical study of networks has largely focused on the social space of connections and its implications for outcomes, without including the physical space. We will review these two approaches separately first and then attempt to bring them together in a more unified setting.

It is worth noting here that the neighborhood effects literature has for the most part ignored the microstructure of connections underlying the social interactions occurring within the neighborhood. This is largely because of a data limitation problem: until recently, very few datasets were available that gave researchers information on both network connections and physical locations of agents. We will discuss recent advances in data collection efforts in what follows. Finally, neighborhood effects may arise not just because of social interactions within the neighborhood (or across adjacent neighborhoods) but also because of local shocks or institutions—such as a local business closing, or the presence of churches, clubs, and neighborhood associations. This is analogous to the education setting, where educational outcomes of students may be affected not only by their peers but also by the teacher or the school.

One important issue concerns the identification and estimation of neighborhood or network effects. Because agents are assumed to affect each other—through information exchanges, preferences, or actions—a telltale sign of the presence of such effects is the presence of co-movements in observed outcomes across agents. However, it is extremely difficult to separately identify these effects from other forces that also bring about co-movements. First, there is a simultaneity problem: I affect my social contact, and simultaneously she affects me. This is known in the literature as the "reflection problem," and we will discuss it extensively in Section 9.3.2.1. Second, agents may sort into neighborhoods or networks on the basis of similar tastes or attributes that are unobserved by the econometrician. Again, this poses identification challenges. Finally, agents residing in the same neighborhood or social network may be exposed to similar correlated shocks that are, again, unobserved by the econometrician: for instance, good or bad local institutions, environmental factors that affect an entire set of neighborhoods, or a plant closing and inducing a localized wave of unemployment. In what follows, we will discuss how each of the approaches developed below fares with regard to these identification and estimation challenges.

There exists a rich and long-standing neighborhood effects literature, developed both in the United States and in Europe. We first present the experimental approach, which mostly focuses on immigrants and refugees where the "natural" experiment comes from the fact that their location upon arrival in a new country is arguably "exogenous" because it is imposed by the local authorities of the host country. Other natural or randomized experiments include the relocation of families from public housing projects in poor neighborhoods to low-poverty neighborhoods, via housing vouchers. The Moving to Opportunity (MTO) program is perhaps the most well-known example.

We also present a nonexperimental approach to the analysis of neighborhood effects, where the identification strategy is clever and based on the smallest unit in the city—namely, the city block. By arguing that the assignment of agents to city blocks is quasi-random (i.e., driven by factors orthogonal to possible unobservable attributes), researchers are able to separately identify neighborhood effects from other potential sources of co-movements.

Finally, we develop a structural approach where the theoretical models generate stationary distributions with well-defined properties over space. The parameters of these models can then be estimated by matching moments from the simulated spatial distribution generated by the model with their empirical counterparts from spatial data on neighborhoods or cities.

We then turn to the network literature. We first study settings in which the network is given. The main challenge in studying strategic interactions in social settings is the inherent complexity of networks. If we do not focus on specific structures in terms of the games, it is hard to draw any conclusions. We focus on strategic complementarities so that a player's incentives to take an action (or a "higher" action) increase with the number of his/her friends who take the (higher) action. We look, in particular, at quite tractable "linear-quadratic" settings where agents choose a continuous level of activity. This simple parametric specification permits an explicit solution for equilibrium behavior as a function of the network and thus leads to interesting comparative statics and other results that are useful in empirical work.

We then present the identification strategy based on the best-reply function of these models. This is mostly based on exclusion restrictions arising naturally from the partially overlapping nature of network connections: simply put, my friends' friends may not necessarily be my friends. We also show how identification may survive (and in some cases be strengthened) when one takes into account the endogenous formation of networks. A note of caution is brought by the introduction of nonlinear models of interaction, which may induce multiplicity of equilibria: we discuss some early attempts to estimate network models in the presence of such multiplicity. We conclude this section by reviewing different empirical results for crime, education, labor, health, etc.

In the last part of this chapter, we integrate the two previous bodies of literature by analyzing how the combined effect of neighborhoods and networks affects the outcomes of individuals, focusing mostly on the labor market. This literature is, unfortunately, in its infancy and we review the scarce evidence and theoretical models on this topic.

The rest of this chapter unfolds as follows. In the next section, we look at neighborhood effects, differentiating between the reduced-form empirical literature on neighborhood effects (Section 9.2.1) and the structural approach (Section 9.2.2). Section 9.3 focuses on network effects by first providing some theoretical background (Section 9.3.1), then analyzing the econometric issues related to the empirical study of networks (Section 9.3.2), and finally providing the main empirical results of this literature (Section 9.3.3). In Section 9.4, we study neighborhood and network effects together, looking first at the theoretical models (Section 9.4.1) and then discussing the theoretical results (Section 9.4.2) and the empirical results (Section 9.4.3). Finally, Section 9.5 concludes the chapter.

9.2. NEIGHBORHOOD EFFECTS

In this section, we first review the reduced-form empirical literature that aims at estimating neighborhood effects in a variety of settings. We examine both experimental and nonexperimental approaches. We then turn to more recent structural modeling and empirical work.[1]

9.2.1 Reduced-form empirical literature on neighborhood effects

The reduced-form empirical work on neighborhood effects has a long tradition in both economics and sociology. Much of the early work focused on the effects of growing up in disadvantaged neighborhoods on educational attainment, employment, and other indicators of socioeconomic well-being. Public policy was an important component of this work, with a strong focus on poverty and inequality.[2] However, this work largely suffered from the Manski (1993) critique concerning the reflection problem. Most of the early work used simple regressions of individual outcomes on individual attributes, family and community attributes, and typically mean outcomes in the residential neighborhood. In the absence of an empirical strategy to separately identify the parameters of these models, most of this work suffered from a basic lack of identification.

Cognizant of these challenges, subsequent reduced-form work followed two broad strategies. The first is to exploit some natural variation arising from randomized or quasi-random experiments implemented in various cities to put into effect various policies. The second approach uses some innovative identification strategies to identify neighborhood effects using large datasets with detailed information on geography.

9.2.1.1 Experimental or quasi-experimental evidence

The first set of studies analyzes neighborhood effects by studying various randomized or natural experiments. The majority of these studies exploit housing relocation randomized experiments that allowed residents of low-income neighborhoods or in public housing projects to relocate to different neighborhoods. These experiments in principle allow the researcher to measure the effect of changing neighborhood characteristics on outcomes.

Popkin et al. (1993) study the impact of the Gautreaux program in Chicago, which helped relocate low-income families from public housing to private housing in the Chicago metropolitan area. While the selection of participants into the program was not random, the assignment to city versus suburban neighborhoods was quasi-random and was based on the availability of units. The authors of the study find that moving to a suburban residential location was associated with a significantly higher chance of

[1] For overviews of this literature spanning several decades, see Jencks and Mayer (1990), Durlauf (2004), and Ioannides and Topa (2010).

[2] Jencks and Mayer (1990) and Brooks-Gunn et al. (1997) provide nice surveys of this early literature. Prominent examples include the work of Wilson (1987), Corcoran et al. (1989), and Brooks-Gunn et al. (1992).

being employed than moving to a city location, even conditioning on observed personal characteristics. The employment gains are greater for those who never worked before.

Jacob (2004), on the other hand, exploits the quasi-random closing of high-rise public housing projects in Chicago during the 1990s. Families affected by the closings were offered Section 8 housing vouchers to move anywhere in the metropolitan area. Jacob compares school outcomes for students living in units affected by a closure with those for students in units in the same project that were not closed. Arguably the timing of building closures within a project is uncorrelated with unobserved characteristics of students. Contrary to the Gautreaux experiment, this article finds no evidence of any impact of the demolitions and subsequent relocations on student outcomes.

Oreopoulous (2003) focuses on another source of quasi-random variation in neighborhood quality—namely, the assignment of families to different housing projects in Toronto. By matching project addresses with an administrative panel of Canadians and their parents, this article can examine the impact of neighborhood quality on the long-run outcomes of adults who were assigned as children to different residential projects. Similar to Jacob (2004), Oreopoulous (2003) finds again no effect of neighborhood differences on a wide variety of outcomes, including unemployment, mean earnings, income, and welfare participation. Further, while neighborhood quality does not affect outcomes, family background explains about 30% of the total variation in income and wages.

A large set of studies focuses on the MTO program (Ludwig et al., 2001; Kling et al., 2005, 2007). This was a large, randomized experiment in which participants volunteered for the study, and was randomly assigned to one of three groups: a control group received no new assistance, a Section 8 group received a housing voucher without geographical restrictions, and a third group received a Section 8 voucher to move to a low-poverty neighborhood as well as mobility counseling. Relative to the control group, the two other groups indeed moved to neighborhoods with significantly lower poverty rates, with less crime, and in which residents reported feeling safer.

MTO studies generally find no significant evidence of treatment effects with regard to economic outcomes, such as earnings, welfare participation, or the amount of government assistance. However, these studies do find evidence of large and significant positive treatment effects on a variety of adult mental health measures. For outcomes of teenage youths, an interesting dichotomy appears: in general, treatment effects were positive with regard to mental health and risky behaviors for female youths, but were negative for male youths. These negative impacts for male youths were particularly large for physical health and risky behavior, suggesting that perhaps the neighborhood change induced a severe dislocation and social isolation, or rejection of the prevailing norms in the new neighborhood.

More recently, Ludwig et al. (2012) have studied the long-term effects of the MTO program, 10–15 years after the experiment. They look at intention-to-treat effects for a variety of outcomes, grouped into economic self-sufficiency, physical health, mental health, and subjective well-being. Treatment effects are found not to be significant for economic outcomes, are positive but not statistically significant for physical health, are positive and marginally significant for mental health, and are significantly positive for subjective well-being.[3]

Our reading of this strand of the literature, that by and large employs careful program evaluation approaches, is that the estimated neighborhood effects tend to be small for educational and economic outcomes. Larger effects are found for mental health outcomes. The MTO-related literature represents perhaps the cleanest example of this approach.

However, it is important to note that there are important limitations in the extent to which the treatment effects identified through relocation experiments are informative about the nature of general forms of neighborhood effects *per se*. First, the individuals studied must be eligible for a relocation program in the first place; this typically implies that the resulting sample is somewhat "special" (i.e., so as to be a resident in public housing) and may not be as sensitive to neighborhood effects as other individuals. More generally, even if the eligible population is representative of the target population, the results of an experiment based on a small sample may not scale up to broader populations because of the strong possibility that general equilibrium effects may arise in that case.

Second, the experimental design involves relocation to new neighborhoods that are, by design, very different from baseline neighborhoods. This implies that the identified treatment effect measures the impact of relocating to a neighborhood where individuals initially have few social contacts and where the individuals studied may be very different from the average resident of the new neighborhood. In this way, the treatment effects identified with this design are necessarily a composite of several factors related to significant changes in neighborhoods that cannot be easily disentangled.

Another set of articles uses a different source of quasi-random variation in network composition and location—namely, the resettlement of refugees into various countries. Beaman (2012) studies refugees resettled into various US cities between 2001 and 2005 by the International Rescue Committee—a large resettlement agency. The location decision of the agency for refugees without family already in the United States is arguably exogenous. Beaman posits a dynamic model of labor-market networks inspired by Calvó-Armengol and Jackson (2004), where agents share information about jobs within their individual social networks. The model implies both a congestion effect due to competition for information among job seekers—which leads to negative correlation in

[3] See, however, Bond and Lang (2014) for a discussion of "happiness scales." Depending on the assumptions made regarding the underlying distribution of subjective well-being, the MTO treatment effects may be positive or null with regard to subjective well-being. Still, there is strong evidence that the MTO program reduced various other measures of well-being, such as symptoms of depression.

outcomes within networks—and a positive effect of network connections on employment outcomes, going from older to more recent cohorts. These effects are dynamic: an increase in the size of a given cohort will worsen the expected employment outcomes for subsequent cohorts that arrive immediately afterward, but will gradually improve the outcomes for later cohorts.

The empirical strategy exploits the variation in cohort size for different ethnicities in different cities at different points in time. The possibility of sorting or correlation between network size and unobserved city and ethnicity characteristics (possibly due to the agency's placement strategy) is addressed by controlling for individual characteristics that are observed by the agency, as well as city and nationality-cohort fixed effects. Beaman finds that a one standard deviation increase in the previous year's cohort for a newly arrived refugee lowers his employment probability by 4.9 percentage points. Conversely, an increase in longer-tenured network size improves employment outcomes by 4.3 percentage points. More senior social contacts also have a positive effect on expected wages. This study is notable for its emphasis on *dynamic* neighborhood effects. The model implications provide additional tools for identification.

Edin et al. (2003) and Åslund et al. (2011) exploit a similar source of quasi-random variation from a refugee resettlement program in Sweden during the late 1980s to study neighborhood effects on labor-market and education outcomes, respectively. Both authors argue convincingly that the initial assignment of refugee immigrants to neighborhoods within cities was uncorrelated with unobservable individual characteristics. In particular, "the individual could not choose his/her first place of residence due to the institutional setup, the practical limitations imposed by scarce housing, and the short time frame between the receipt of residence permit and placement." Further, there was no interaction between placement officers and immigrants, so any sorting could take place only on the basis of observable (to both the government officials and the econometrician) attributes.

The first study finds that a larger ethnic enclave in one's initially assigned location has a positive effect on earnings, especially for less-skilled immigrants: a one standard deviation increase in ethnic concentration raises earnings by 13% for less educated immigrants. These positive effects increase with the quality of the enclave as measured by earnings or self-employment rates. The second study focuses on school performance and finds that a one standard deviation increase in the share of highly educated adults (sharing the student's ethnicity) in the neighborhood of residence raises average grades in compulsory school by 0.8 percentile points.[4]

[4] Åslund et al. (2010) also exploit this quasi-random assignment of immigrants to residential locations to revisit the "spatial mismatch" hypothesis. They find that local access to jobs does indeed have a statistically and economically significant impact on employment outcomes.

Damm (2009, 2014) and Damm and Dustmann (2014) also exploit a unique natural experiment between 1986 and 1998 when refugee immigrants to Denmark were assigned to neighborhoods quasi-randomly. The first articles focus on labor-market outcomes of ethnic minorities, while the last article looks at the effect of early exposure to neighborhood crime on subsequent criminal behavior of youths. In the latter, the authors find strong evidence that the share of young people convicted of crimes, in particular violent crimes, in the neighborhood increases convictions of individuals residing in the neighborhood later in life.[5] Their findings suggest that social interaction is a key channel through which neighborhood crime is linked to individual criminal behavior. We will return to the issue of social interactions and crime in Section 9.3.3.3.

Finally, we wish to mention a separate strand of literature that also exploits natural experiments to evaluate the extent of residential neighborhood effects, in the context of housing and land prices. As an example, Rossi-Hansberg et al. (2010) examine how nonmarket interactions between residents of a given neighborhood (or across nearby neighborhoods) are reflected in land prices. They exploit a plausibly exogenous source of variation in the attractiveness of a given location provided by an urban revitalization program that was implemented in Richmond, Virginia, between 1999 and 2004. The program gave funding for housing investments in targeted neighborhoods, including demolition, rehabilitation, and new construction of housing. In addition, a "control" neighborhood was selected that was similar to the treated neighborhoods but did not receive any funding.

The study contains information on the location of homes that received funding, and the amount of the funding. Housing prices and characteristics before and after the program are also observed. This allows Rossi-Hansberg et al. (2010) to estimate land prices before and after the policy was implemented, using a hedonic approach. They can, therefore, estimate the spatial extent of neighborhood quality externalities on land prices. In addition, by comparing treated and control neighborhoods, they can compute the magnitude of these externalities. The study finds that increases in land values decline with the distance from the impact areas, as expected: housing externalities decline roughly by half every 1000 feet. Further, the increase in land values arising from externalities brought about by the revitalization ranges between \$2 and \$6 per dollar invested.

9.2.1.2 Nonexperimental evidence

As mentioned above, a more promising approach in our view has relied on very detailed spatial datasets and clever identification strategies to identify neighborhood effects in various settings. Essentially, this set of articles exploits either quasi-random assignment of individual agents to small geographical units (such as census blocks) or careful modeling

[5] See also Jencks and Mayer (1990) and Gould et al. (2011) for the long-term effects of growing up in a poor and low-educated neighborhood.

of the mechanisms underlying social interaction effects that delivers clear testable implications that can be applied to the data.

Bayer et al. (2008) consider spatial clustering of individual work locations for a given residential location as evidence of local referral effects. In order to separately identify labor-market referrals from other spatially correlated effects, they estimate the excess propensity to work together (in a given city block) for pairs of workers who co-reside in the same city block (distinct from their work location), relative to the baseline propensity to work together for residents in nearby blocks (within a reference group of blocks). The key identifying assumption (which is tested on observable characteristics) is that there is no block-level correlation in unobserved attributes among block residents, after taking into account the broader reference group. An additional assumption underlying this research design is that a significant portion of interactions with neighbors are very local in nature—that is, they occur among individuals in the same block.[6] We return to this question in Section 9.4.3. Bayer et al. (2008) find that residing in the same block raises the probability of sharing the work location by 33%, consistent with local referral effects. Inferred referral effects are stronger when they involve at least one individual who is more attached to the labor market, or individuals who are more likely to interact—for example, because they have children of similar ages. The observed variation in the excess propensity to work in the same block is then used to construct a measure of network quality available to each individual in a given neighborhood. A one standard deviation increase in this measure has a positive effect on various labor-market outcomes: labor force participation increases by about 3.4 percentage points for female workers, whereas hours worked increase by 1.8 h per week on average and earnings increase by about 3.4% for male workers.[7]

Hellerstein et al. (2011) build on the identification strategy of Bayer et al. (2008) using matched employer–employee data at the establishment level from the 2000 Decennial Employer–Employee Database. They use census tracts as the geographical unit of analysis, and compute the excess propensity to reside in the same tract for employees in a given *establishment*, relative to the likelihood of residing in the same tract for other

[6] More generally, as discussed in Section 9.1, one important question concerns the extent of overlap between the social space spanned by individual social networks and the geographical space described by neighborhoods. Several sociological studies have examined this question, finding that a significant portion of social interactions occur at very close physical distance among agents. See, for instance, Wellman (1996), Otani (1999), and Lee and Campbell (1999).

[7] Using an identification strategy similar to that of Bayer et al. (2008), Hawranek and Schanne (2014) look at how residential neighborhoods can serve as a pool of information for an informal labor market and investigate the effect of job referrals through one's residential location. They analyze the relationship between living and working together in the context of job referrals in the Rhine-Ruhr metropolitan area in Germany. They find effects very similar to those in Bayer et al. (2008). Indeed, Hawranek and Schanne (2014) find that sharing the same immediate neighborhood raises the propensity to work together by 0.14 percentage points.

employees who work in the same tract but not in the same establishment (which may be due to commuting patterns or the spatial distribution of jobs and workers). Hiring network effects at the neighborhood level can be inferred if the share of residential neighbors among one's coworkers is significantly higher than that predicted by random hiring. They find that indeed the hiring effect of residential networks is significant, and is especially strong for Hispanics and less-skilled workers, and for smaller establishments. They also find that residential labor-market network effects are stronger within than across races, suggesting racial stratification within residential social networks.

Hellerstein et al. (2014) extend this analysis using Longitudinal Employer-Household Dynamics (LEHD) data, which allow longitudinal observation of matched worker–employer pairs. This rich data source enables them to study additional features of labor-market networks, including wage and turnover effects.[8] The main findings are that residence-based networks have a robust effect on worker–employee matches, lowering turnover. This effect is especially strong for neighbors within the same racial or ethnic group. For wages, while overall connectedness with residential neighbors tends to raise wages, within-group connectedness has the opposite effect, lowering wages. This is suggestive of overall residence-based networks being associated with more productive matches, while ethnic or racial residential network effects may capture nonwage amenities. In general, this work highlights the neighborhood-specific nature of social networks, at least in the context of labor-market networks.

Schmutte (2015) also uses matched employer–employee data from the LEHD. Adopting an identification strategy similar to that of Bayer et al. (2008), he studies whether residential labor-market networks lead to matches with higher-paying employers. In particular, he estimates a firm-specific wage premium (following Abowd et al., 1999) and finds that workers who live in neighborhoods with higher-quality networks (measured by the average employer-specific wage premium of network members) are more likely to move to jobs with higher wage premiums. This result holds for both employed individuals and unemployed individuals and is not driven by direct referrals from current employees at a given firm.

This study, together with the articles by Hellerstein et al. (2011) discussed above, brings important empirical insights into the nature of referral effects at the neighborhood level by combining the novel identification strategy of Bayer et al. (2008) with very rich data linking workers to firms at the establishment level. The longitudinal aspect of the LEHD is also important in enabling researchers to study dynamic implications such as turnover—in the case of Hellerstein et al. (2014)—as well as the quality of referral networks as in Schmutte (2015).

[8] Dustmann et al. (2011) and Galenianos (2013) develop predictions for learning models of referrals with regard to wage trajectories and separations as a function of tenure. Datcher (1983) provides empirical evidence on turnover using Panel Study of Income Dynamics data. Brown et al. (2014) provide evidence consistent with learning models of referrals using a unique dataset on a single large US corporation.

In a different setting, Helmers and Patnam (2014) use spatial proximity within villages in Andhra Pradesh, India, to estimate neighborhood effects (spatial peer effects) in the production of cognitive skills for children between the ages of 8 and 12 years. Household locations are precisely mapped within villages, and the authors construct nearest-neighbor adjacency matrices, defined as $\mathbf{G}_r$ in Section 9.3.1.1, to trace the village-level social network. The main idea is then to again use geographical proximity as a proxy for social distance within individual social networks—a theme that appears often in this literature.

The authors use a strategy developed by Bramoullé et al. (2009), among others, to address the reflection problem and to separately identify endogenous from contextual peer effects (see Manski, 1993). This strategy essentially involves exploiting the partially overlapping nature of individual networks to use friends of friends as valid instruments for one's direct social contacts.[9] Helmers and Patnam also use various strategies to address the possibility of correlated unobservables or sorting into networks. They find that, on average, a one standard deviation increase in the growth in cognitive achievement of a child's peers increases cognitive achievement of the child by 0.4 standard deviations. Further, social networks help partially insure against idiosyncratic shocks that hit a household and tend to adversely affect the child's cognitive achievement.

Patacchini and Zenou (2012a) test how social networks affect the labor-market outcomes of ethnic minorities in England. They use a strategy similar to that of Helmers and Patnam (2014) by approximating *social proximity* between individuals by *geographical proximity*. Indeed, since ethnic communities tend to be more socially cohesive, a reasonable conjecture is that the density of people living in the same area is a good approximation for the number of direct friends one has (i.e., *strong ties*), especially if the areas are not too large and if people belong to the same ethnic group.[10] In the same spirit, the density of individuals living in neighboring areas will be a measure of friends of friends (i.e., *weak ties*). Using this framework, Patacchini and Zenou look at the relationship between ethnic employment density and the probability of finding a job through social contacts and use *spatial data analysis techniques* to investigate the spatial scale of these effects. They find that the higher the percentage of a given ethnic group living nearby, the higher the probability of finding a job through social contacts. They also find that such an effect is, however, quite localized. It decays very rapidly with distance, losing significance beyond approximately 60 min travel time.[11]

[9] See Section 9.3.2.2 for a precise description of this identification strategy.

[10] A similar approximation of the social space (approximated by the physical space) is used in Wahba and Zenou (2005) for the case of Egypt.

[11] Conley and Topa (2002) use nonparametric methods to map out several dimensions along which social networks may exist in the context of urban unemployment, using mixtures of geographical, travel time, education, and ethnic distance to characterize social distance.

Conley and Udry (2010) use direct information on farmers' individual social networks in three villages in Ghana to estimate social learning in the adoption of new cultivation technologies. This article contains two important innovations that make it very noteworthy. First, it relies on actual observation of individual networks rather than using spatial proximity as a proxy for them. Second, it lays down an explicit learning model that yields specific implications for the shape of interactions, which enable the authors to identify social effects separately from other, spatially correlated, confounding factors. The sequential nature of plantings and harvests enables the authors to observe how a given farmer reacts to news about his social contacts' choices and outcomes. Consistent with the learning model, the authors find that farmers are more likely to change their fertilizer use when other farmers using similar amounts of fertilizer have lower than expected profits; increase (decrease) their fertilizer use after their social contacts achieve higher profits using more (less) fertilizer than they did; respond more to their neighbors' actions if they only recently started cultivating a particular crop; and respond more to the actions of veteran farmers.

Spatial neighborhood effects also play a role in recent literature on foreclosures, following the recent housing boom and bust cycle in the United States. Campbell et al. (2011) study the effect of sales of foreclosed properties (and more generally, forced sales) on the price of nearby houses in the same neighborhood. They use comprehensive house transactions data from Massachusetts over the 1987–2009 period, matched with information on deaths and bankruptcies of individuals. They find that forced sales in general, and those related to foreclosures in particular, are associated with significant price discounts. Further, local spillover effects from foreclosures are significant (foreclosures lower prices of nearby houses), but decline rapidly with distance. Harding et al. (2009) also find evidence of contagion effects in foreclosures. Several mechanisms can explain such spillovers, ranging from price discovery to the visual impact of rundown or vandalized properties, to a social interaction channel whereby individuals' valuations of their own homes are influenced by their neighbors' valuations (see Ioannides, 2003).

9.2.2 Neighborhood effects estimation using a structural approach

A family of articles uses structural models of social interactions to generate a rich stochastic structure that can be applied to data for estimation. Essentially, these models generate stationary distributions with well-defined properties over space (e.g., excess variance across locations, or positive spatial correlations). The parameters of these models can then be estimated by matching moments from the simulated spatial distribution generated by the model with their empirical counterparts from spatial data on neighborhoods or cities. The model parameters are locally identified (or, in some cases, set identification is attained).

Glaeser et al. (1996) explain the very high variance of crime rates across US cities through a model in which agents' propensity to engage in crime is influenced by neighbors' choices. In doing so, they provide estimates for the range of social interactions. The model is a version of the voter model, in which agents' choices regarding criminal activity are positively affected by their social contacts' choices. One important innovation in this article is to allow for "fixed agents," who are not affected by their neighbors' actions. The variance of crime outcomes across replications of the economy (i.e., cities) is inversely proportional to the fraction of fixed agents in an economy. The distance between pairs of fixed agents in the model yields a measure of the degree of interactions. By matching the empirical cross-city variance of various types of crime with that implied by the model, the authors estimate the extent of neighborhood effects for different types of crime.

Topa (2001) analyzes a structural model of transitions into and out of unemployment to estimate the impact of any local social interaction effects on employment outcomes. The model posits that individuals may receive useful information about job openings from their employed social contacts (the nearest neighbors) but not from their unemployed ones. Formally, the transition probability from employment to unemployment, P_{EU}, depends only on individual attributes and is given by

$$P_{\mathrm{EU}} \equiv \Pr(y_{i,t+1}=0|y_{it}=1;\ X_i)=\alpha(X_i),$$

where y_{it} is the employment status of agent i at time t (1 corresponds to employment and 0 to unemployment) and X_i is a vector of individual characteristics that may affect labor-market outcomes. The reverse probability of finding a job from unemployment, P_{UE}, depends not only on individual characteristics but also on information about job openings transmitted by agent i's employed social contacts:

$$P_{\mathrm{UE}} \equiv \Pr(y_{i,t+1}=1|y_{it}=0;\ y_t,\ X_i)=\beta(X_i)+\phi_2(X_i)I_{it}(y_t),$$

where $I_{it}(y_t)$ is the information received about job openings, which depends on the average employment rate of the neighbors of agent i.

The model generates a first-order Markov process over the set of locations (defined at the census tract level), and the positive local feedback implies that the stationary distribution of unemployment in the simulated city exhibits positive spatial correlations. The model parameters are estimated via indirect inference, comparing the simulated spatial distribution of unemployment generated by the model with the empirical one, using census data for the city of Chicago in 1980 and 1990.

The identification strategy in this article relies on the assumption that neighboring census tracts can affect a given tract's employment outcomes only through their employment levels and not through their own attributes, and on the use of ethnic distance and local community boundaries (as identified by residents) to distinguish local social interactions from other types of spatially correlated shocks. The key assumption is that social spillovers generated by information exchanges within networks are significantly weaker across tracts that are physically close but ethnically very different, or that belong to different local communities; on the other hand, other types of spatially correlated shocks may not be affected by such discontinuities across tracts. Indeed, the spatial correlation in crime outcomes across adjacent tracts does not depend on ethnic distance or on whether the two tracts belong to the same local community. Finally, detailed tract-level controls and fixed effects are also used in the estimation.

Conley and Topa (2007) extend the work of Topa (2001) in several directions, using data for the Los Angeles metropolitan area. First, the model of local interactions and employment transitions is defined at the level of individual agents rather than census tracts. This enables the authors to calibrate a subset of employment transition parameters from retrospective Current Population Survey (CPS) data. Further, the network structure is enriched by allowing for a small number of long "bridging" ties connecting artificial agents in the model that are physically distant from each other. This makes the network structure more realistic, since the sociological literature cited above shows that while many network connections are local in a geographical sense, a sizeable fraction of links occur between locations that are geographically far from each other. Finally, the value of information received about job openings is allowed to vary depending on whether the information is received from members of one's own ethnic group or from members of other groups.

Formally, the probability of transition into unemployment is assumed to depend only on agents' characteristics, race/ethnicity, and education:

$$\Pr(y_{i,t+1}=0|y_{i,t}=1;A_i,H_i,W_i,X_i)$$
$$=\Lambda[(\alpha_{1\mathrm{A}}+\alpha_{2\mathrm{A}}X_i)A_i+(\alpha_{1\mathrm{H}}+\alpha_{2\mathrm{H}}X_i)H_i+(\alpha_{1\mathrm{W}}+\alpha_{2\mathrm{W}}X_i)W_i],$$

where A, H, and W denote African-Americans, Hispanics, and whites, respectively, and $\Lambda(\cdot)=\exp(\cdot)/(1+\exp(\cdot))$. In contrast, the probability that an unemployed agent finds a job depends both on his/her own characteristics and on information flows concerning job opportunities that he/she receives from his/her currently employed social contacts at time t. The article takes the extreme modeling stand of allowing transitions out of unemployment to be affected by one's network contacts, N_i, whereas transitions out of employment are affected by one's personal characteristics alone. This is done in order to calibrate the parameters of the latter transition probabilities with CPS data.

Information received by agent i is assumed to be a function of the number of employed individuals in his/her set of neighbors. The authors distinguish between the number of employed individuals of an individual's own race/ethnicity and those of the other two groups using the notation $I_{i,t}^{\text{Own}}$ and $I_{i,t}^{\text{Other}}$. This allows them to investigate the possibility that information flow may depend on race/ethnicity. The definitions of $I_{i,t}^{\text{Own}}$ and $I_{i,t}^{\text{Other}}$ when agent i is African-American are

$$I_{i,t}^{\text{Own}} \equiv \sum_{k \in N_i} y_{k,t} \times A_k \quad \text{and} \quad I_{i,t}^{\text{Other}} \equiv \sum_{k \in N_i} y_{k,t} \times (1 - A_k).$$

The values of $I_{i,t}^{\text{Own}}$ and $I_{i,t}^{\text{Other}}$ are analogously defined for members of the remaining two racial/ethnic partitions. The probability of transition into employment for African-Americans is defined as

$$\begin{aligned}\Pr(y_{i,t+1} = 1 | y_{i,t} = 0; A_i = 1, X_i, I_{i,t}^{\text{Own}}, I_{i,t}^{\text{Other}}) \\ = \Lambda\left[\beta_{1A} + \beta_{2A} X_i + \phi_{2A}^{\text{Own}} I_{i,t}^{\text{Own}} + \phi_{2A}^{\text{Other}} I_{i,t}^{\text{Other}}\right].\end{aligned}$$

The richer network structure poses an interesting estimation problem: the existence of long ties implies that cross-sectional data will potentially exhibit a strong dependence, with measures such as spatial correlations or mixing coefficients decaying only very slowly as the physical distance increases. This is in contrast to models with only nearest-neighbor interactions, which give rise to a weak cross-sectional dependence. Therefore, even large cross sections should be essentially viewed as a single observation from a vector time series process. Conley and Topa (2007) propose a minimum-distance estimator to obtain point estimates, and a test-statistic inversion method to obtain interval estimates using the minimum distance criterion function as the test statistic.

Thanks to the richer model structure, the parameter estimates can be used to evaluate how well unemployment spell distributions simulated from the model match the empirical ones from the CPS data. The authors find that the model generates too many long unemployment spells (with the estimated parameter values) relative to the data. They further present descriptive methods to illustrate model properties by simulating impulse response functions, in time and in space, to localized unemployment shocks that hit certain neighborhoods in the Los Angeles metropolitan area. They find that, at the stationary distribution, negative employment shocks take a long time to be fully absorbed (more than 2 years), but travel relatively little in space.

Finally, before turning to the literature on social network effects, we wish to mention the work of Bayer et al. (2007) that provides a framework for analyzing the extent and impact of sorting into neighborhoods on the basis of their socioeconomic composition and school quality. Their basic model is a rich discrete-choice model of household location decisions across residential neighborhoods, where household preferences are defined over housing and neighborhood characteristics. This model nests hedonic price regressions as well as traditional discrete-choice models.

The article addresses the endogeneity of school and neighborhood attributes by embedding a boundary discontinuity design into the model.[12] The idea is to use the geographical boundaries of school catchment areas to compare characteristics of households residing on opposite sides of a given boundary. Assuming that the underlying distribution of unobserved attributes affecting location choices is continuous, any observed discontinuity at the boundary in, say, household education or income enables the researcher to estimate the value of school quality.

The boundary discontinuity design is also used to identify and estimate the full distribution of household preferences over schools and neighbors. Household sorting across boundaries generates variation in neighborhood attributes that is related to an observable variable—namely, schools. Therefore, by controlling for differences in school quality on either side of the boundary, one can estimate the value to households of such neighborhood attributes. Thus, by embedding the boundary discontinuity design into a full sorting model, the article provides a strategy to estimate household preferences for housing and neighborhood attributes. This approach can be potentially very useful to jointly model sorting and social interaction effects, allowing the researcher to separately identify both channels.

9.3. NETWORK EFFECTS

We have seen the importance of neighborhood effects on different outcomes (crime, labor, etc.), using both natural experiments and a structural approach. We will now look at the network effects on different outcomes. Here the network will be modeled as a graph where nodes will be agents (workers, consumers, firms, etc.) and links will represent friendship relationships, R&D alliances, criminal interactions, etc.[13]

9.3.1 Network theory

We would like to develop some network theory that will be useful for the empirical estimation of network effects. There is a growing network literature in economics where researchers have been looking at both *network formation* and *games on networks*—that is, games in efforts for which the network is fixed. Here we will mainly describe the main results of games on networks—that is, when the network is taken as given, since there are

[12] This approach builds on the earlier work by Black (1999) and is a special case of the general regression discontinuity design developed by Hahn et al. (2001).

[13] For overviews of the literature on the economics of networks, see, in particular, the surveys by Jackson (2003, 2004, 2005, 2011), Ioannides and Datcher-Loury (2004), De Martí and Zenou (2011), Zenou (2015a), Jackson and Zenou (2015), and Jackson et al. (2015), as well as the books by Vega-Redondo (2007), Goyal (2007), Jackson (2008), Benhabib et al. (2011), and Jackson and Zenou (2013).

no clear-cut results in the network formation literature. We will, however, return to network formation when we deal with the estimation of peer and network effects in economics.

Although there are many forms that games on networks can take, there are two prominent and broadly encompassing classes of games.[14] The distinction between these types of games relates to whether a given player's relative payoff from taking an action versus not taking an action is *increasing* or *decreasing* in the set of neighbors who take the action. The first class of games on networks, of which coordination games are the canonical example, are games of *strategic complements*. In games of strategic complements, an increase in the actions of other players leads a given player's higher actions to have relatively higher payoffs compared with those of the player's lower actions. Examples of such games include the adoption of a technology, a search in the labor market, R&D efforts, human capital decisions, criminal efforts, smoking behaviors, etc. Games of *strategic substitutes* are such that the opposite is true: an increase in other players' actions leads to relatively lower payoffs from higher actions of a given player. Applications of strategic substitutes include local public good provision and information gathering.

We will here mainly describe games with strategic complements since their empirical applications are the most important in economics.[15] There are two distinct models. In the first one, the *local-aggregate model*, it is the sum of active links that matters. In the second one, the *local-average model*, it is the average sum of active links that matters.

9.3.1.1 The local-aggregate model

Following Calvó-Armengol and Zenou (2004) and Ballester et al. (2006, 2010), we examine a simple model that can encompass any social network. For that, consider a game where $N_r = \{1, \ldots, n_r\}$ is a finite set of agents in network $\mathbf{g}_r$ ($r = 1, \ldots, \overline{r}$), where $\overline{r}$ is the total number of networks.[16] We represent these social connections by a graph $\mathbf{g}_r$, where $g_{ij,r} = 1$ if agent i is connected to agent j, and $g_{ij,r} = 0$ otherwise. Links are taken to be reciprocal, so $g_{ij,r} = g_{ji,r}$.[17] By convention, $g_{ii,r} = 0$. We denote by $\mathbf{G}_r$ the $n_r \times n_r$ adjacency matrix with entry $g_{ij,r}$, which keeps track of all direct connections. For example, if we consider criminal activities, then agents i and j share their knowledge of delinquent activities if and only if $g_{ij,r} = 1$. For the labor market, a link will indicate the exchange of job information between the individuals. Each agent i decides how much

[14] For a complete overview on the literature on games on networks, see Jackson and Zenou (2014).

[15] We refer to Allouch (2012), Bramoullé and Kranton (2007), Bramoullé et al. (2014), and Jackson and Zenou (2014) for an exposition of the games on networks with strategic substitutes.

[16] Even though we consider only one network in the theoretical analysis, we keep the subscript r because it facilitates the transition to the econometric analysis.

[17] This is only for the sake of the exposition. All the results go through with a directed and weighted network.

effort to exert in some activity, denoted $y_{i,r} \in \mathbb{R}_+$. This could be crime, education, labor search, R&D activities, etc. The utility of each agent i providing effort $y_{i,r}$ in network $\mathbf{g}_r$ is given by

$$u_{i,r}(\mathbf{y}_r, \mathbf{g}_r) = (a_{i,r} + \eta_r + \varepsilon_{i,r})y_{i,r} - \frac{1}{2}y_{i,r}^2 + \phi_1 \sum_{j=1}^{n_r} g_{ij,r} y_{i,r} y_{j,r}, \tag{9.1}$$

where $\phi_1 > 0$ and $\mathbf{y}_r$ is an n_r-dimensional vector of efforts. This utility has two parts. An individual part, $(a_{i,r} + \eta_r + \varepsilon_{i,r})y_{i,r} - \frac{1}{2}y_{i,r}^2$, where the marginal benefits of providing effort $y_{i,r}$ are given by $(a_{i,r} + \eta_r + \varepsilon_{i,r})y_{i,r}$ and increase with own effort $y_{i,r}$. $a_{i,r}$ denotes the *exogenous heterogeneity* of agent i that captures the *observable* characteristics of individual i (e.g., sex, race, age, parental education) and the observable *average* characteristics of individual i's best friends—that is, the average level of parental education of i's friends, etc. (*contextual effects*). To be more precise, $a_{i,r}$ can be written as

$$a_{i,r} = \sum_{m=1}^{M} \beta_m x_{i,r}^m + \frac{1}{g_{i,r}} \sum_{m=1}^{M} \sum_{j=1}^{n_r} g_{ij,r}\, x_{j,r}^m \gamma_m, \tag{9.2}$$

where $g_{i,r} = \sum_{j=1}^{n_r} g_{ij,r}$ is the number of direct links of individual i, x_i^m is a set of M variables accounting for observable differences in individual characteristics of individual i, and β_m and γ_m are parameters. In the utility function, η_r denotes the unobservable network characteristics—for example, the prosperous level of the neighborhood/network $\mathbf{g}_r$—and $\varepsilon_{i,r}$ is an error term, which captures other uncertainty in the proceeds from the effort. Both η_r and $\varepsilon_{i,r}$ are observed by the agents (when choosing the effort level) but not by the econometrician.

The second part of the utility function, $\phi_1 \sum_{j=1}^{n_r} g_{ij,r} y_{i,r} y_{j,r}$, corresponds to the local-aggregate effect since each agent i is affected by the sum of the efforts of the agents for which he/she has a direct connection. The higher the number of active connections, the higher the marginal utility of providing his/her own effort. This is a game with strategic complementarities since

$$\frac{\partial^2 u_{i,r}(\mathbf{y}_r, \mathbf{g}_r)}{\partial y_{i,r} \partial y_{j,r}} = \phi_1 g_{ij,r} \geq 0.$$

At equilibrium, each agent maximizes his/her utility (9.1), and the best-reply function, for each $i = 1, \ldots, n$, is given by

$$y_{i,r} = \phi_1 \sum_{j=1}^{n_r} g_{ij,r} y_{j,r} + a_{i,r} + \eta_r + \varepsilon_{i,r}. \tag{9.3}$$

Denote by $\mu_1(\mathbf{g}_r)$ the largest eigenvalue of network $\mathbf{g}_r$ and $\alpha_{i,r} \equiv a_{i,r} + \eta_r + \varepsilon_{i,r}$, with the corresponding nonnegative n_r-dimensional vector $\boldsymbol{\alpha}_r$. It can be shown that if

$\phi_1\mu_1(\mathbf{g}_r) < 1$, the peer effect game with payoffs (9.1) has a unique Nash equilibrium in pure strategies given by

$$\mathbf{y}_r^* \equiv \mathbf{y}_r^*(\mathbf{g}_r) = \mathbf{b}_{\boldsymbol{\alpha}_r}(\mathbf{g}_r, \phi_1), \tag{9.4}$$

where $\mathbf{b}_{\boldsymbol{\alpha}_r}(\mathbf{g}_r,\phi_1)$ is the weighted Katz–Bonacich centrality, a well-known measure defined by Katz (1953) and Bonacich (1987). Formally,

$$\mathbf{b}_{\boldsymbol{\alpha}_r}(\mathbf{g}_r, \phi_1) = (\mathbf{I}_{n_r} - \phi_1\mathbf{G}_r)^{-1}\boldsymbol{\alpha}_r = \sum_{k=0}^{\infty}\phi_1^k\mathbf{G}_r^k\boldsymbol{\alpha}_r, \tag{9.5}$$

where $\mathbf{I}_{n_r}$ is the $(n_r \times n_r)$ identity matrix, $\boldsymbol{\alpha}_r = \mathbf{a}_r + \eta_r\mathbf{1}_{n_r} + \boldsymbol{\varepsilon}_{i,r}$, and $\mathbf{1}_{n_r}$ is an n_r-dimensional vector of ones. In words, the Katz–Bonacich centrality of agent i counts the total number of paths (not just the shortest paths) in $\mathbf{g}_r$ starting from i, weighted by a decay factor that decreases with the length of these paths. This is captured by the fact that the matrix $\mathbf{G}_r^k$ keeps track of the indirect connections in the network—that is, $g_{ij,r}^{[k]} \geq 0$ measures the number of paths of length $k \geq 1$ in $\mathbf{g}_r$ from i to j. This result shows that more central agents in the network will exert more effort. This is intuitively related to the equilibrium behavior, as the paths capture all possible feedbacks. In our case, the decay factor depends on how the effort of others enters into one's own effort's payoff. It is then straightforward to show that, for each individual i, the equilibrium utility is

$$u_{i,r}(\mathbf{y}_r^*, \mathbf{g}_r) = \frac{1}{2}\left[b_{\alpha_{i,r}}(\mathbf{g}_r, \phi_1)\right]^2,$$

so the equilibrium utility of each criminal is proportional to his/her Katz–Bonacich centrality. It is important to understand that there are magnifying or *social multiplying* effects due to network relationships, which are captured by the Katz–Bonacich centrality. To understand this last point, consider the case of a dyad for which $n_r = 2$ and, for simplicity, assume that $\alpha_{1,r} = \alpha_{2,r} = \alpha_r$. If there were no interactions—that is, $g_{12,r} = g_{21,r} = 0$—then the unique Nash equilibrium would be $y_{1,r}^* = y_{2,r}^* = \alpha_r$. With social interactions (i.e., $g_{12,r} = g_{21,r} = 1$), if $\phi_1 < 1$, the unique Nash equilibrium is given by

$$y_{1,r}^* = y_{2,r}^* = \frac{\alpha_r}{1 - \phi_1}. \tag{9.6}$$

In the dyad, complementarities lead to an effort level above the equilibrium value for an isolated player. The factor $1/(1 - \phi_1) > 1$ is often referred to as a *social multiplier*. An important part of the empirical analysis of network effects would be to estimate ϕ_1. If, for example, the estimated value of ϕ_1 is 0.5, then the social multiplier is equal to 2. Take the example of crime. This means that if a criminal would commit crimes alone, then he/she will commit α_r crimes, and this will be determined only by his/her observable characteristics. Now, if this criminal has only one criminal friend, compared with the case where he/she operates alone, he/she will increase his/her crime effort by 100%—that is, he/she will commit $2\alpha_r$ crimes. This is not due to his/her characteristics but only to the fact that he/she interacts with another criminal.

9.3.1.2 The local-average model

Following Patacchini and Zenou (2012b), let us now develop the *local-average* model, where the *average effort level* of direct links affects utility. For that, let us denote the set of individual *i*'s direct connections as

$$N_{i,r}(g_r) = \{j \neq i, g_{ij,r} = 1\},$$

which cardinality is $g_{i,r}$. Let $g^*_{ij,r} = g_{ij,r}/g_{i,r}$ for $i \neq j$, and set $g^*_{ii,r} = 0$. By construction, $0 \leq g^*_{ij,r} \leq 1$. Note that $\mathbf{g}^*_r$ is a row-normalization of the initial network $\mathbf{g}_r$, as illustrated in the following example, where $\mathbf{G}_r$ and $\mathbf{G}^*_r$ are the adjacency matrices of $\mathbf{g}_r$ and $\mathbf{g}^*_r$, respectively.

Example 9.1. Consider the following network $\mathbf{g}_r$:

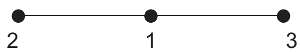


Figure 9.1 A star network.

Then,

$$\mathbf{G}_r = \begin{bmatrix} 0 & 1 & 1 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{bmatrix} \text{ and } \mathbf{G}^*_r = \begin{bmatrix} 0 & 1/2 & 1/2 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{bmatrix}.$$

As above, $y_{i,r}$ denotes the effort level of individual *i* in network *r*. Denote by $\overline{y}_{i,r}$ the average effort of individual *i*'s best friends. It is given by

$$\overline{y}_{i,r} = \frac{1}{g_{i,r}} \sum_{j=1}^{n_r} g_{ij,r} y_{j,r} = \sum_{j=1}^{n_r} g^*_{ij,r} y_{j,r}. \tag{9.7}$$

Each individual *i* selects an effort $y_{i,r} \geq 0$ and obtains a payoff given by the following utility function:

$$u_{i,r}(\mathbf{y}_r, \mathbf{g}_r) = \left(a^*_{i,r} + \eta^*_r + \varepsilon^*_{i,r}\right) y_{i,r} - \frac{1}{2} y^2_{i,r} - \frac{\lambda_2}{2} \left(y_{i,r} - \overline{y}_{i,r}\right)^2, \tag{9.8}$$

with $\lambda_2 > 0$. All the parameters have the same interpretation as in (9.1). Let us now interpret the peer-effect part of this utility function since it is the only aspect that differs from (9.1). Indeed, the last term, $\frac{\lambda_2}{2}\left(y_{i,r} - \overline{y}_{i,r}\right)^2$, reflects the influence of the individual's friends' behavior on the individual's own action. It is such that each individual wants to minimize the *social distance* between himself/herself and his/her reference group, where λ_2 is the parameter describing the *taste for conformity*. Here, the individual loses utility $\frac{\lambda_2}{2}(y_{i,r} - \overline{y}_{i,r})^2$ from failing to conform to others. This is the standard way economists have been modeling conformity (see, among others, Kandel et al., 1992; Bernheim, 1994; Akerlof, 1997; Fershtman and Weiss, 1998; Glaeser and Scheinkman, 2001).

Observe that beyond the idiosyncratic heterogeneity, $a^*_{i,r}$, there is a second type of heterogeneity, referred to as *peer heterogeneity*, which captures the differences between individuals due to network effects. Here it means that individuals have different types of friends and thus different reference groups $\overline{y}_{i,r}$. As a result, the social norm each individual i faces is endogenous and depends on his/her location in the network as well as the structure of the network. Indeed, in a star-shaped network (as the one described in Figure 9.1) where each individual is at most distance 2 from each of the other individuals, the value of the social norm will be very different from a circle network, where the distance between individuals can be very large.

We now characterize the Nash equilibrium of the game where agents choose their effort level $y_{i,r} \geq 0$ simultaneously. When $\phi_2 < 1$, the peer effect game with payoffs (9.8) has a unique interior Nash equilibrium in pure strategies for each $i = 1, \ldots, n_r$ given by

$$y_{i,r} = \phi_2 \sum_{j=1}^{n_r} g^*_{ij,r} y_{j,r} + a_{i,r} + \eta_r + \varepsilon_{i,r}, \tag{9.9}$$

where $\phi_2 \equiv \lambda_2/(1+\lambda_2)$, $a_{i,r} \equiv a^*_{i,r}/(1+\lambda_2)$, $\eta^*_r \equiv \eta^*_r/(1+\lambda_2)$, and $\varepsilon_{i,r} \equiv \varepsilon^*_{i,r}/(1+\lambda_2)$. In matrix form, (9.9) can be written as

$$\mathbf{y}_r = \left(\mathbf{I}_{n_r} - \phi_2 \mathbf{G}^*_r\right)^{-1} \boldsymbol{\alpha}_r. \tag{9.10}$$

9.3.1.3 Local aggregate or local average? theoretical considerations

In the local-aggregate model, it is the *sum of the efforts of his/her peers* that affects the utility of individual i. So the more individual i has active (i.e., providing effort) friends, the higher is his/her utility. In contrast, in the *local-average* model, it is the deviation from the *average of the efforts of his/her peers* that affects the utility of individual i. So the closer individual i's effort is to the average of his/her friends' efforts, the higher is his/her utility.

Consequently, the two models are quite different from an economic viewpoint, even though, from a purely technical point of view, they are not that different (compare the best-reply functions (9.3) and (9.9)). In particular, the adjacency matrix $\mathbf{G}_r$ of direct links of the network totally characterizes the peer effects in the *local-aggregate* model, whereas it is a transformation of this matrix $\mathbf{G}_r$ to a weighted stochastic matrix $\mathbf{G}^*_r$ that characterizes the peer effects in the *local-average* model. This means that, in equilibrium, in the former model, individuals are positively affected by the sum of their friends' effort (non-row-normalized $\mathbf{G}_r$), while in the latter, they are positively affected by the average effort of their friends (row-normalized $\mathbf{G}_r$).

From an economic viewpoint, in the *local-aggregate* model, even if individuals were *ex ante* identical (in terms of $a_{i,r}$ and $\varepsilon_{i,r}$), different positions in the network would imply different effort levels, because it is the sum of the efforts that matter. This would not be true in the *local-average* model since, in that case, the position in the network would not matter since it is the deviation from the average effort of friends that affects the utility.

9.3.2 Empirical aspects of social networks: Structural approach

We now use the previous models from Section 9.3.1 to estimate the empirical effects of networks. We will first start with the econometric issues and then state some empirical results, especially those relevant for policy issues.

9.3.2.1 Linear-in-means model: The reflection problem

In the standard *linear-in-means model*, each agent is affected by the average action of his/her reference group. This is the standard *peer-effect* model (see Section 9.2), where the reference group is the same for all individuals. For example, in crime, the criminal activity of individual i will depend on the average criminal activity of the neighborhood where he/she lives. As a result, the right-hand side of this equation will be same for all individuals living in the same neighborhood (typically a census tract in the United States). In education, this would mean that the grades of each student i will be determined by the average grades in the school or in the classroom to which that student belongs. Implicitly, when talking about neighborhood effects, we assume that each delinquent interacts in the same way with everybody in his/her neighborhood (if we think of a census tract then, on average, this would mean that individual i interacts with 4000 people). Similar assumptions have to be made for the classroom or school example. In contrast, in a network approach where the dyad is the unit of interest, one assumes that each individual interacts with only his/her direct friends. As we have seen in (9.4), the individual is also influenced by indirect links but he/she puts a lower weight on them. In (9.4), we showed that the weight is proportional to the distance in the network as captured by the Katz–Bonacich centrality of each individual. If an individual is five links away from individual i, then the weight is ϕ_1^5, which is small given than ϕ_1 is less than 1.

Let us return to the linear-in-means model. From an econometric viewpoint, the simultaneity in behavior of interacting agents (i.e., the endogenous action of each agent is affected by the average endogenous action of the reference group) introduces a perfect collinearity between the expected mean outcome of the group and its mean characteristics. Therefore, it is difficult to differentiate between the effect of peers' choice of effort and peers' characteristics that do impact on their effort choice (the so-called *reflection problem*; Manski, 1993). Basically, the reflection problem arises because, in the standard approach, individuals interact in groups—that is, individuals are affected by all individuals belonging to their group and by nobody outside the group. In other words, groups do not overlap. Let us explain formally the reflection problem in the linear-in-means model.

The reflection problem (Manski, 1993) arises when it is not possible to disentangle the endogenous effects from the contextual effects. The basic linear-in-means model can be written as

$$y_{i,r} = \phi_2\, \mathbb{E}(y_r) + \gamma\, \mathbb{E}(x_r) + \beta\, x_{i,r} + \varepsilon_{i,r}, \tag{9.11}$$

where, as above, $y_{i,r}$ is the effort or outcome (e.g., education, crime, etc.) of individual i belonging to group r, $x_{i,r}$ is an observable characteristic of individual i's (i.e., i's characteristics such as his/her gender, age, education, etc.)[18] in group r, $\mathbb{E}(y_r)$ denotes the average of the efforts/outcomes in the peer group r of individual i, $\mathbb{E}(x_r)$ denotes the average of the characteristics (or characteristics specific to group r) in the peer group r of individual i, and $\varepsilon_{i,r}$ is an error term. We want to identify $\phi_2 > 0$ (i.e., the *endogenous peer effect*) and separate it from $\gamma > 0$, the *exogenous contextual effect*. Observe that, contrary to (9.1) or (9.8), r refers to a group (i.e., neighborhood, school, class, etc.) and not to a network. Assume $\mathbb{E}(\varepsilon_{i,r}|y_r, x_r) = 0$. If we take the average over peer group r of Equation (9.11) and solve this equation, we obtain

$$\mathbb{E}(y_r) = \left(\frac{\gamma + \beta}{1 - \phi_2}\right) \mathbb{E}(x_r).$$

Plugging the value of $\mathbb{E}(y_r)$ into (9.11) yields

$$y_{i,r} = \left(\frac{\phi_2(\gamma + \beta) + \gamma(1 - \phi_2)}{(1 - \phi_2)}\right) \mathbb{E}(x_r) + \beta\, x_{i,r} + \varepsilon_{i,r}.$$

If one estimates this equation, there is an identification problem since ϕ_2 (endogenous peer effects) and γ (exogenous contextual effects) cannot be separately identified. There are three estimated coefficients and four structural parameters, and thus identification fails. This is the *reflection problem* (Manski, 1993). In terms of policy implications of peer effects, it is of paramount importance to *separately* identify peer or endogenous effects from contextual or exogenous effects (Manski, 1993, 2000; Moffitt, 2001) because endogenous effects generate a *social multiplier*, while contextual effects do not. Consider, for example, peer effects in crime. A special program targeting some individuals will have multiplier effects: the individual affected by the program will reduce his/her criminal activities and will influence the criminal activities of his/her peers, which, in turn, will affect the criminal activities of their peers, and so on. In contrast, any policy affecting

[18] For the sake of the presentation, we consider only one characteristic of individual i and not the sum of characteristics $\sum_{j=1}^{n_r} x_{j,r}^m$ as in (9.2). The extension to more than one characteristics is straightforward.

contextual effects will have no social multiplier effects (e.g., improving the gender composition of students at school).

Let us show now that in the case of social networks the reflection problem nearly never arises because the reference group is the set of network contacts each individual has. Following Bramoullé et al. (2009), let us show how using a network approach, we can solve the reflection problem. We will also show how it can help solve the problem of endogenous network formation and, more generally, correlated effects.

9.3.2.2 Social networks: The local-average model

So far the reference group was the same for all individuals (the neighborhood, the class, etc.) since peer effects are an average intragroup externality that affects identically all the members of a given group. In particular, the group boundaries are arbitrary and at a fairly aggregate level. In contrast, social networks use the smallest unit of analysis for cross influences: the dyad (two-person group). In that case, the reference group of individual i is his/her direct links (e.g., friends). Furthermore, the reference group of individual j, who is a best friend of individual i, is not the same as for individual i because individual j may have some best friends that are not individual i's best friends. As a result, Equation (9.11) can now be written as

$$y_{i,r_i} = \phi_2\, \mathbb{E}(y_{r_i}) + \gamma\, \mathbb{E}(x_{r_i}) + \beta\, x_{i,r_i} + \varepsilon_{i,r_i}, \tag{9.12}$$

where r_i is *now* the reference group of individual i (see (9.7)), so $y_{i,r_i} \equiv y_{i,r}$ and $\mathbb{E}(y_{r_i}) \equiv \overline{y}_{i,r}$ where $\overline{y}_{i,r}$ is defined by (9.7). Similarly, if we consider more than one characteristics for individual i, then, using (9.2), we have $\gamma\mathbb{E}(x_{r_i}) + \beta\, x_{i,r_i} \equiv a_{i,r}$. As a result, adding the network fixed effect η_r, we find Equation (9.12) is exactly equivalent to (9.9), which corresponds to the unique Nash equilibrium of the *local-average model* where the utility function is given by (9.8).

Let us write (9.12) or (9.9) in matrix form (with network fixed effect). We have

$$\mathbf{Y}_r = \phi_2 \mathbf{G}_r^* \mathbf{Y}_r + \beta \mathbf{X}_r + \gamma \mathbf{G}_r^* \mathbf{X}_r + \eta_r \mathbf{l}_{n_r} + \boldsymbol{\varepsilon}_r, \tag{9.13}$$

where $\overline{r}$ is the total number of networks in the sample, n_r is the number of individuals in the rth network, $n = \sum_{r=1}^{\overline{r}} n_r$ is total number of sample observations, $\mathbf{Y}_r$ is an $n \times 1$ vector of observations on the dependent (decision) variable, $\mathbf{G}_r^*$ is the $n \times n$ row-normalized matrix of $\mathbf{G}_r$, $\mathbf{X}_r$ is an $n \times 1$ vector of observations on the exogenous variables, $\mathbf{l}_{n_r}$ is an n_r-dimensional vector of 1, and $\varepsilon_{i,r}$'s (whose corresponding vector is $\boldsymbol{\varepsilon}_r$) are independent and identically distributed innovations with zero mean and variance σ^2 for all i and r. Assume $E\left[\boldsymbol{\epsilon} | \mathbf{G}_r, \mathbf{X}_r\right] = 0$. Then (9.13) is similar to a spatial autoregressive model (Anselin, 1988).

The network-specific parameter η_r is allowed to depend on $\mathbf{G}_r$, $\mathbf{G}_r^*$, and $\mathbf{X}_r$ as in a fixed effect panel data model. To avoid the incidental parameter problem when the number of groups $\overline{r}$ is large, we eliminate the term $\eta_r \mathbf{l}_{n_r}$ using the deviation from group mean projector $\mathbf{J}_r = \mathbf{I}_{n_r} - \frac{1}{n_r}\mathbf{l}_{n_r}\mathbf{l}_{n_r}^{\mathrm{T}}$. This transformation is analogous to the *within* transformation for a fixed effect panel data model. As $\mathbf{J}_r\mathbf{l}_{n_r} = 0$, the transformed network model is

$$\mathbf{J}_r\mathbf{Y}_r = \phi_2\mathbf{J}_r\mathbf{G}_r^*\mathbf{Y}_r + \beta\mathbf{J}_r\mathbf{X}_r + \gamma\mathbf{J}_r\mathbf{G}_r^*\mathbf{X}_r + \mathbf{J}_r\varepsilon_r. \tag{9.14}$$

If $\phi_2\beta + \gamma \neq 0$, Bramoullé et al. (2009) demonstrates that identification of the local-average model is possible since $[\mathbf{J}_r\mathbf{G}_r^{*2}\mathbf{X}_r, \mathbf{J}_r\mathbf{G}_r^{*3}\mathbf{X}_r, \ldots]$ can be used as instrumental variables for the endogenous effect. Note, in a natural network, if individuals i and j are friends and individuals j and k are friends, it does not necessarily imply that individuals i and k are also friends. The *intransitivity in social connections* provides an exclusion restriction such that the characteristics of the friends' friends $\mathbf{G}_r^{*2}\mathbf{X}_r$ may not be perfectly correlated with the own characteristics $\mathbf{X}_r$ and the characteristics of the friends $\mathbf{G}_r^*\mathbf{X}_r$. Thus, one can use instrumental variables like $\mathbf{J}_r\mathbf{G}_r^{*2}\mathbf{X}_r$ to identify endogenous and contextual effects. On the basis of this important observation, Bramoullé et al. (2009) have shown that if the matrices $\mathbf{I}_{n_r}$, $\mathbf{G}_r^*$, and $\mathbf{G}_r^{*2}$ are linearly independent, social effects are identified. Thus, the natural exclusion restrictions induced by the network structure (existence of an intransitive triad) guarantee identification of the model.[19]

Although this setting allows us to solve the reflection problem, the estimation results might still be flawed because of the presence of unobservable factors affecting both individual and peer behavior. It is thus difficult to disentangle the *endogenous peer effects* from the *correlated effects*—that is, from effects arising from the fact that individuals in the same group tend to behave similarly because they face a common environment. If individuals are not randomly assigned into groups, this problem might originate from the possible sorting of agents. If the variables that drive this process of selection are not fully observable, potential correlations between (unobserved) group-specific factors and the target regressors are major sources of bias. In our case, two types of possibly correlated effects arise—that is, at the network level and at the peer group level.

The use of *network fixed effects* proves useful in this respect. Assume, indeed, that agents self-select into different networks in a first step, and that link formation takes place within networks in a second step. Then, as Bramoullé et al. (2009) observe, if linking decisions are uncorrelated with the observable variables, this two-step model of link formation generates network fixed effects. Assuming additively separable network heterogeneity, a within-group specification is able to control for these correlated effects. Indeed, by subtracting from the individual-level variables the network average, one can identify social effects and disentangle endogenous effects from correlated effects.

Bramoullé et al. (2009) also deal with this problem in the context of networks. They show that if the matrices $\mathbf{I}_{n_r}$, $\mathbf{G}_r$, $\mathbf{G}_r^2$, and $\mathbf{G}_r^3$ are linearly independent, then by subtracting from the variables the network component average (or the average over neighbors, i.e.,

[19] Cohen-Cole (2006) and Lee (2007) present a similar argument—that is, the use of out-group effects—to achieve the identification of the endogenous group effect in the linear-in-means model.

direct friends), one can again identify social effects and disentangle endogenous effects from correlated effects. The condition is more demanding because some information has been used to deal with the fixed effects.[20]

A number of articles using network data have used this strategy to deal with the identification and estimation of peer effects of (9.13) with correlated effects (e.g., Lee, 2007; Bramoullé et al., 2009; Calvó-Armengol et al., 2009; Lee et al., 2010; Lin, 2010; Liu and Lee, 2010; Liu et al., 2012; Patacchini and Zenou, 2012b; Boucher et al., 2014). As stated above, these articles exploit the architecture of network contacts to construct valid instrumental variables for the endogenous effect (i.e., the characteristics of indirect friends) and to use network fixed effects as a remedy for the selection bias that originates from the possible sorting of individuals with similar unobserved characteristics into a network. The underlying assumption is that such unobserved characteristics are common to the individuals within each network.

9.3.2.3 Social networks: The local-aggregate model

We have seen so far that the local-average model is well identified under some conditions on the adjacency matrix. Most researchers have used this model to estimate peer or network effects. However, in some cases, the local-aggregate model also seems to be a natural outcome of a game. In that case, do the identification conditions proposed by Bramoullé et al. (2009) still apply? Liu et al. (2012) show that they do not.

If we now consider the local-aggregate model presented in Section 9.3.1.1, then the matrix equivalent of the best-reply functions (9.3) in the theoretical model is

$$\mathbf{Y}_r = \phi_1 \mathbf{G}_r \mathbf{Y}_r + \beta \mathbf{X}_r + \gamma \mathbf{G}_r^* \mathbf{X}_r + \eta_r \mathbf{l}_{n_r} + \varepsilon_r, \tag{9.15}$$

where the only difference from the local-average model is that, for the endogenous effect, $\mathbf{G}_r$ is not row normalized.

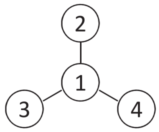
Liu et al. (2012) demonstrate that the identification conditions for the *local-aggregate* model are weaker than those for the *local-average* model because one can use the sum of rows from the adjacency matrix as an additional instrument in the local-aggregate model, while this is not possible in the local-average model since it is always equal to 1. To be more precise, Liu et al. (2012) show that when $\mathbf{G}_r$ has *nonconstant row sums* for some network r, then if $\mathbf{I}_{n_r}$, $\mathbf{G}_r$, $\mathbf{G}_r^*$, and $\mathbf{G}_r\mathbf{G}_r^*$ are linearly independent and $|\beta| + |\gamma| + |\eta_r| \neq 0$, the model is identified.[21]

Figure 9.2 gives an example where identification is possible for the local-aggregate model but fails for the local-average model. Consider a dataset where each network is represented by the graph in Figure 9.2 (a star-shaped network). For the row-normalized adjacency matrix $\mathbf{G}_s^*$, it is easy to see that $\mathbf{G}_s^{*3} = \mathbf{G}_s^*$. Therefore, it follows from Bramoullé

[20] See Blume et al. (2011) for an overview of these econometric issues.

[21] They also have some conditions for identification when $\mathbf{G}_r$ has *constant row sums*.

et al. (2009) that the local-average model (9.13) is not identified. On the other hand, as $\mathbf{G}_r$ in Figure 9.2 has *nonconstant row sums* and $\mathbf{I}_{n_r}$, $\mathbf{G}_r$, $\mathbf{G}_r^*$, and $\mathbf{G}_r\mathbf{G}_r^*$ are linearly independent, it follows that the local-aggregate model (9.15) can be identified for this network.



$$\mathbf{G}_r = \begin{bmatrix} 0 & 1 & 1 & 1 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{bmatrix} \quad \text{and} \quad \mathbf{G}_r^* = \begin{bmatrix} 0 & 1/3 & 1/3 & 1/3 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{bmatrix}$$

Figure 9.2 An example where the local-aggregate model can be identified but the local-average model cannot be identified.

9.3.2.4 Testing the local-average model against the local-aggregate model

Liu et al. (2014) propose a test to evaluate whether the local-average model is more relevant in some activities than the local-aggregate model, and vice versa. For that, they first develop a theoretical model by considering the following utility function:

$$u_{i,r}(\mathbf{y}_r, \mathbf{g}_r) = \underbrace{(\alpha^*_{i,r} + \lambda_1 \sum\nolimits_{j=1}^{n_r} g_{ij,r} y_{j,r}) y_{i,r}}_{\text{benefit}} - \underbrace{\frac{1}{2}[y^2_{i,r} + \lambda_2 (y_{i,r} - \sum\nolimits_{j=1}^{n_r} g^*_{ij,r} y_{j,r})^2]}_{\text{cost}}. \tag{9.16}$$

This is the so-called *hybrid model* because it includes both local-aggregate and local-average aspects of preferences. The best-reply function of each individual i is given by

$$y_{i,r} = \phi_1 \sum\nolimits_{j=1}^{n_r} g_{ij,r} y_{j,r} + \phi_2 \sum\nolimits_{j=1}^{n_r} g^*_{ij,r} y_{j,r} + \alpha_{i,r}, \tag{9.17}$$

where $\alpha_{i,r} \equiv \alpha^*_{i,r}/(1+\lambda_2)$, $\phi_1 \equiv \lambda_1/(1+\lambda_2)$, and $\phi_2 \equiv \lambda_2/(1+\lambda_2)$. It is easily verified that when $\lambda_1 = 0$, we are back to the local-average model (see (9.3)), while when $\lambda_2 = 0$, we are back to the local-aggregate model (see (9.9)).

Denote by $g_r^{\max}$ the highest degree in network r—that is, $g_r^{\max} = \max_i g_{i,r}$. If $\phi_1 \geq 0$, $\phi_2 \geq 0$, and $g_r^{\max}\phi_1 + \phi_2 < 1$, then the network game with payoffs (9.16) has a unique interior Nash equilibrium in pure strategies given by

$$\mathbf{Y}_r = \left(\mathbf{I}_{n_r} - \phi_1 \mathbf{G}_r - \phi_2 \mathbf{G}_r^*\right)^{-1} \boldsymbol{\alpha}_r. \tag{9.18}$$

In terms of econometrics, with network fixed effects, (9.17) can be written in matrix form as

$$\mathbf{Y}_r = \phi_1 \mathbf{G}_r \mathbf{Y}_r + \phi_2 \mathbf{G}_r^* \mathbf{Y}_r + \beta \mathbf{X}_r + \gamma \mathbf{G}_r^* \mathbf{X}_r + \eta_r \mathbf{l}_{n_r} + \varepsilon_r. \tag{9.19}$$

Liu et al. (2014) then test the local-aggregate model against the local-average model, and vice versa. For that, they extend Kelejian's (2008) J test for spatial econometric models to differentiate between the local-aggregate and the local-average endogenous peer effects in an econometric network model with network fixed effects. The idea of the J test is as follows. If a given model contains the correct set of regressors, then including the fitted values of an alternative model (or of a fixed number of competing models) into the null model should provide no significant improvement.

9.3.2.5 Endogenous network formation

The instrumental variable strategy proposed by Bramoullé et al. (2009) and developed above, however, works if the network is exogenous (i.e., it works conditional on the exogeneity of the adjacency matrix $\mathbf{G}_r$), which is not usually the case unless one has a controlled field experiment so that the network was formed exogenously (e.g., see Carrell et al., 2009, 2013). Alternatively, one needs to be able to plausibly rule out unobserved factors or develop instruments that are clearly exogenous to the interaction structure, or else model network formation and try to account for factors that could have substantial influences on both behavior and network formation.[22]

An approach to dealing with this comes from Goldsmith-Pinkham and Imbens (2013). Under homophily, linked individuals are likely to be similar not only in terms of *observed characteristics* but also in terms of *unobserved characteristics* that could influence their behavior. By failing to account for similarities in (unobserved) characteristics, one might mistakenly attribute similar behaviors to peer influence when they simply result from similar characteristics. In order to highlight the problem, let us write the model (9.13) as follows[23]:

$$\mathbf{Y}_r = \phi_2 \mathbf{G}_r^* \mathbf{Y}_r + \beta \mathbf{X}_r + \gamma \mathbf{G}_r^* \mathbf{X}_r + \eta_r \mathbf{l}_{n_r} + \underbrace{\zeta \mathbf{v}_r + \mathbf{e}_r}_{\boldsymbol{\varepsilon}_r}, \tag{9.20}$$

where $\mathbf{v}_r = (v_{1,r}, \ldots, v_{n_r,r})^{\mathrm{T}}$ denotes a vector of *unobserved characteristics* at the individual level and $\mathbf{e}_r = (e_{1,r}, \cdots, e_{n_r,r})^{\mathrm{T}}$ is a vector of random disturbances. Let us consider a network formation model where the variables that explain the links between individuals i and j belonging to network r (i.e., $g_{ij,r}$) are the distances between them in terms of observed and unobserved characteristics—that is,

$$g_{ij,r} = \alpha + \sum_{m=1}^{M} \delta_m |x_{i,r}^m - x_{j,r}^m| + \theta\, |v_{i,r} - v_{j,r}| + \eta_r + u_{ij,r}. \tag{9.21}$$

Homophily behavior in the unobserved characteristics implies that $\theta < 0$—that is, the closer two individuals are in terms of unobservable characteristics, the higher is the

[22] Observe that this problem can be mitigated if one observes the network at different points in time. For example, König et al. (2014a) study R&D collaborations between firms for over 20 years and use time and firm fixed effects. In that case, if the unobservables that make firms create R&D collaborations do not change over time, this method should be satisfactory.

[23] For the argument, it does not matter if we apply the local-average or the local-aggregate model.

probability that they are friends. If ζ is different from zero, then the network $\mathbf{G}_r$ in model (9.20) is endogenous.

A testable implication of this problem would be to find a negative correlation between the predicted probability of forming a link (based on observable characteristics), as measured by $\widehat{g_{ij,r}}$, and the unobserved similarity in pairs, as measured by the difference in residuals from Equation (9.20), $|\hat{\varepsilon}_{i,r} - \hat{\varepsilon}_{j,r}|$.[24] Evidence against network endogeneity would be the finding of a zero correlation.[25]

Another way of dealing with this problem is to simultaneously (or sequentially) estimate (9.21) and (9.20) as in Goldsmith-Pinkham and Imbens (2013). For example, König et al. (2014a) propose a three-stage least squares estimation, where in the first stage, a network formation model similar to (9.21) is estimated.[26] Then, using the *predicted value of the adjacency matrix*, the authors perform the other stages using a similar instrumental variable approach as in Bramoullé et al. (2009) and described above.[27]

One of the challenges of the approach of Goldsmith-Pinkham and Imbens is that modeling network formation on a link-by-link basis is not very realistic because one must account for interdependencies (Chandrasekhar and Jackson, 2013; Jackson, 2013; Jackson et al., 2015). There is a powerful and natural formulation of network formation models that takes these interdependencies into account. They are known as *exponential random graph models*.[28] However, because the number of possible networks on a given number of nodes is an exponential function of the number of nodes, it is practically impossible to estimate the likelihood of a given network, and thus there is an important computational hurdle (see the discussion in Chandrasekhar and Jackson, 2013). Another possible approach is to model the network as an evolving process (see, e.g., Snijders, 2001; Christakis et al., 2010; Mele, 2013; König et al., 2014b) as such models allow for dependencies in that new links form on the basis of the network existing at the time.

9.3.2.6 Multiple equilibria

Whereas the previous sections focus mainly on linear models, we now consider nonlinear models of social interactions, which typically generate multiple equilibria, as they induce externalities.[29] Bisin et al. (2011a) use the Brock and Durlauf (2001) model of social interactions to study network effects in smoking, using National Longitudinal Survey of

[24] Under dissortative matching (i.e., heterophily), the correlation should be positive.

[25] See Patacchini et al. (2014), who perform such a test.

[26] The idea to use the *predicted* adjacency matrix $\mathbf{G}_r^*$ to construct instruments can also be found in Kelejian and Piras (2014) and Comola and Prina (2014).

[27] In Section 9.4.3, we discuss the article by Del Bello et al. (2014), who also simultaneously estimate (9.21) and (9.20).

[28] See Jackson (2008) for background on these models.

[29] Glaeser and Scheinkman (2001) derive sufficient conditions on the strength of interactions to generate multiplicity.

Adolescent to Adult Health (Add Health) data on high schools. (For a description of the Add Health data, see Section 9.3.3.2). The model is an extension of the canonical random utility discrete choice model, where the utility of each choice is affected not only by individual attributes and a random term but also by a term that captures influences from network contacts. Thus, agents solve the following program:

$$\max_{y_i \in \{-1,1\}} U(y_i, X_i, \pi_i, \varepsilon_i) = y_i(\beta X_i + \phi_2 \pi) + \varepsilon_i(y_i), \tag{9.22}$$

where π_i captures either average smoking among agent i's direct social contacts (in the case of local interactions) or average smoking in the school as a whole (if we consider global interactions). The random term ε_i depends on the smoking choice y_i and follows an extreme value distribution:

$$\Pr(\varepsilon_i(-1) - \varepsilon_i(1) \leq z) = \frac{1}{1 + \exp(-z)}. \tag{9.23}$$

From the first-order conditions, the probability that agent i smokes is given by

$$\Pr(y_i = 1) = \frac{1}{1 + \exp(-2(\beta X_i + \phi_2 \pi_i))}. \tag{9.24}$$

Assuming that the number of agents in each school is large enough, then a law of large numbers argument applies and the following characterization of equilibrium is obtained for the case of global interactions:

$$\pi = \sum_{i \in I} \tanh(\beta X_i + \phi_2 \pi). \tag{9.25}$$

It is easy to show that very nonlinear effects may arise. Depending on which equilibrium a given school starts from, an increase in the utility cost of smoking (brought about, for instance, by a tobacco tax) may induce an increase or a decrease in equilibrium average smoking in the school. Similarly, an increase in the strength of social interactions or in the initial number of friends smoking in individual networks may cause—depending on the initial equilibrium—an increase or a decrease in eventual smoking. This is important from a policy perspective, since it emphasizes that a given policy may have counterintuitive effects because of the nonlinear feedbacks induced by network effects.

The model can be estimated using the techniques developed by Moro (2003).[30] As discussed in Manski (1993), the reflection problem is mitigated in nonlinear models; further, the possible presence of correlated unobservables can be addressed using a Heckman-style approach to correct for selection into networks. Moro (2003) developed a two-step approach to tackle the issue of estimating equilibrium models with multiple equilibria. In the first stage, summary statistics of the equilibrium for each school are

[30] See also Aguirregabiria and Mira (2007).

estimated, using nonparametric methods. In the second stage, the model parameters are estimated via maximum likelihood, conditioning the likelihood of the data on the first-stage estimates of the equilibrium. This allows the likelihood to be a well-behaved function, as opposed to a correspondence—as would be the case given the presence of multiple equilibria. This reduces the computational burden enormously.

Bisin et al. (2011a) find evidence of strong network effects in smoking, both school-wide and at the level of individual friendship networks. The parameter estimates are consistent with the widespread presence of multiple equilibria among the schools considered in the Add Health sample. As mentioned earlier, simulations of the model with the parameter estimates indicate that changes in attributes, the shape of networks, or various policies can have highly nonlinear and sometimes counterintuitive effects, with the possibility of large shifts in smoking prevalence because of the presence of multiple equilibria.

9.3.3 Empirical results

Let us describe the empirical results obtained on the basis of the theoretical models presented in Section 9.3.1 and discuss the policy implications.

9.3.3.1 Local-average model

This is the most tested model in the literature. Researchers have tested Equation (9.9) using the method developed in Section 9.3.2.2. There is usually no theoretical model for the microfoundation of Equation (9.9). Researchers have estimated this equation because it is similar to the one used in spatial econometrics (Anselin, 1988) and it is easier to test. The empirical results indicate that peer effects and network effects are important in education (Calvó-Armengol et al., 2009; De Giorgi et al., 2010; Lin, 2010; Bifulco et al., 2011; Boucher et al., 2014; Patacchini et al., 2014), crime (Patacchini and Zenou, 2012b), labor (Patacchini and Zenou, 2012a), consumption (De Giorgi et al., 2014), smoking (Fletcher, 2010; Bisin et al., 2011a), alcohol consumption (Fletcher, 2012), and risk sharing (Angelucci et al., 2014).[31]

Equation (9.9) has also been tested using another instrumental variable approach. The idea is to treat the composition of students in a given grade within a school as quasi-random and to isolate this quasi-random variation in the friendship network formation process. Using this approach, Fletcher and Ross (2012) find that students who have friends who smoke or drink are more likely to smoke or drink even when comparing observationally similar students who belonged to different cohorts in the same school and made exactly the same friendship choices on key student demographics. Fletcher et al. (2013) find that girls have higher grade point averages (GPAs) than very similar

[31] There are also some tests of the local-average model (games played on networks) in laboratory settings (see Kosfeld, 2004; Jackson and Yariv, 2011; Charness et al., 2014 for additional background). There are also various field experiments that effectively involve games on networks (see, for example, Centola, 2010).

students in the same school when they belong to a cohort that implies more friends with a higher level of maternal education even after controlling for aggregate peer effects associated with maternal education. Finally, Patacchini and Zenou (2014) find strong peer effects in religion practice. They use the fraction of religious students of the same gender, religious affiliation, and ethnic group in the same grade and school as an instrument for the individual fraction of religious friends.

9.3.3.2 Local-aggregate model

There are very few tests of the local-aggregate model. Two notable exceptions are those provided by Liu et al. (2012) and Lindquist and Zenou (2014), who test peer and network effects in crime. Both estimate Equation (9.3) or its econometric equivalent (9.15) with instrumental variables and network fixed effects (Section 9.3.2.3). Liu et al. (2012) use Add Health data to estimate these network peer effects.[32] The Add Health database has been designed to study the impact of the social environment (i.e., friends, family, neighborhood, and school) on adolescents' behavior in the United States by collecting data on students in grades 7–12 from a nationally representative sample of roughly 130 private and public schools in the 1994–1995 school year (wave I). Every pupil attending the sampled schools on the interview day was asked to compile a questionnaire (in-school data) containing questions on respondents' demographic and behavioral characteristics, education, family background, and friendships. This sample contains information on roughly 90,000 students. A subset of adolescents selected from the rosters of the sampled schools, about 20,000 individuals, were then asked to complete a longer questionnaire containing more sensitive individual and household information (in-home and parental data). Those subjects were interviewed again in 1995–1996 (wave II), in 2001–2002 (wave III), and in 2007–2008 (wave IV).

From a network perspective, the most interesting aspect of the Add Health data is the friendship information, which is based upon actual friend nominations. Indeed, pupils were asked to identify their best friends from a school roster (up to five males and five females). This information was collected in wave I and 1 year after, in wave II. As a result, one can reconstruct the whole geometric structure of the friendship networks. The Add Health dataset also contains information on 15 delinquency items, and the survey asked students how often they participated in each of these delinquent activities during the previous year.

Using the Add Health data, Liu et al. (2012) have estimated ϕ_1 for wave I for 1297 criminals distributed over 150 separate networks, with network size ranging between 4 and 77. They find an estimated value of ϕ_1 of 0.0457, which gives a social multiplier of 1.048 in the case of the dyad (see (9.6)). If we consider an average group of four best friends (linked to each other in a network), a standard deviation increase in the level

[32] This dataset has also been used by Calvó-Armengol et al. (2009), Fletcher (2010), Lin (2010), Bifulco et al. (2011), Fletcher (2012), and Patacchini et al. (2014).

of delinquent activity of each of the peers translates into a roughly 17% increase of a standard deviation in the individual level of criminal activity.

Lindquist and Zenou (2014) also estimate ϕ_1 from Equation (9.15) with a very different dataset. They look at individuals in Sweden who are over 16 years old and who have been suspected (and convicted) of committing at least one crime. For that, they have access to the official police register of all people who are suspected of committing a crime in Sweden. In this register, the police keeps records of who is suspected of committing a crime with whom. In this context, a (criminal) link exists between two individuals if they are suspected of committing a crime together. Both the convictions data and the suspects data include crime type, crime date, and sanction received. One advantage of this dataset over the Add Health one is that links are not self-reported and are thus less subject to measurement errors. Another advantage is that information on links is available at each moment of time over a period of 20 years. As a result, Lindquist and Zenou (2014) can add individual lagged crime as one of the individual-level control variables.

They find an estimate of ϕ_1 of 0.167. For one individual, this means that having only one friend increases crime by 20%. If we consider the case of four individuals (their smallest network), then individual crime will increase by 100% compared with the case when the individual is committing crime alone.

9.3.3.3 *Local-aggregate versus the local-average model*

Instead of testing each model separately, one can test one model against the other using the method developed in Section 9.3.2.4. Using the Add Health data, Liu et al. (2014) find that for "studying effort" (i.e., how hard students study in schools), students tend to *conform* to the social norm of their friends (local-average model), while for sport activities, both the social multiplier (local-aggregate model) and the social norm effect (local-average model) matter. In contrast, for criminal activities, the local-aggregate model seems to be more appropriate (Liu et al., 2013). In terms of policy implications, an effective policy for the *local-average* model would be to change people's perceptions of "normal" behavior (i.e., their social norm) so that a *group-based policy* should be implemented, while for the *local-aggregate* model, this would not be necessary, and an *individual-based policy* should be implemented instead.

9.3.3.3.1 Individual-based policies: Key players

Consider the case of crime, where we can show that the local-aggregate model is at work, at least for the Add Health data. In that case, a key-player policy (Ballester et al., 2006), whose aim is to remove the criminal whose removal reduces total crime in a network the most, would be the most effective policy since the effort of each criminal and thus the sum of one's friends' crime efforts will be reduced. In other words, the removal of the key player can have large effects on crime because of feedback effects or "social multipliers" (see, in particular, Glaeser et al., 1996; Verdier and Zenou, 2004; Kleiman, 2009). That is, as the fraction of individuals participating in a criminal behavior increases, the impact on others is multiplied through social networks. Thus, criminal behaviors can be magnified, and interventions can become more effective.

Formally, consider the local-aggregate model presented in Section 9.3.1.1 and denote by $Y_r^*(\mathbf{g}_r) = \sum_{i=1}^{n} y_{i,r}^*$ the total equilibrium level of crime in network $\mathbf{g}_r$, where $y_{i,r}^*$ is the Nash equilibrium effort given by (9.4). Also denote by $\mathbf{g}_r^{[-i]}$ the network $\mathbf{g}_r$ without individual i. Then, in order to determine the key player, the planner will solve the following problem:

$$\max\{Y^*(\mathbf{g}_r) - Y^*(\mathbf{g}_r^{[-i]}) i = 1, \ldots, n\}.$$

When the original delinquency network $\mathbf{g}_r$ is fixed, this is equivalent to

$$\min\{Y^*(\mathbf{g}_r^{[-i]}) i = 1, \ldots, n\}. \tag{9.26}$$

Ballester et al. (2006) and Ballester and Zenou (2014) have shown that if $\phi_1 \mu_1(\mathbf{g}_r) < 1$, then the key player that solves (9.26) is individual i^* if and only if he/she is a delinquent with the highest *intercentrality* in $\mathbf{g}_r$—that is, $d_{i^*}(\mathbf{g}_r, \phi_1) \geq d_i(\mathbf{g}_r, \phi_1)$, for all $i = 1, \ldots, n$, where[33]

$$\begin{aligned} d_i(\mathbf{g}_r, \phi_1) &= \mathbf{1}_{n_r}^{\mathrm{T}} \mathbf{M}(\mathbf{g}_r, \phi_1) \boldsymbol{\alpha}_r - \mathbf{1}_{n_r}^{\mathrm{T}} \mathbf{M}(\mathbf{g}_r, \phi_1) \boldsymbol{\alpha}_r^{[i]} + \mathbf{1}_{n_r}^{\mathrm{T}} \mathbf{M}^{[i]}(\mathbf{g}_r, \phi_1) \boldsymbol{\alpha}_r^{[i]} \\ &= B(\mathbf{g}_r, \phi_1) - B(\mathbf{g}_r^{[i]}, \phi_1) + \frac{b_{\boldsymbol{\alpha}_r^{[i]}, i}(\mathbf{g}_r, \phi_1) \sum_{j=1}^{n} m_{ji}(\mathbf{g}_r, \phi_1)}{m_{ii}(\mathbf{g}_r, \phi_1)}. \end{aligned} \tag{9.27}$$

The intercentrality measure (9.27) highlights the fact that when a delinquent is removed from a network, two effects are at work. The first effect is the *contextual effect*, which indicates the change in the contextual effect $\boldsymbol{\alpha}_r$ (from $\boldsymbol{\alpha}_r$ to $\boldsymbol{\alpha}_r^{[i]}$) after the removal of the key player while the network $\mathbf{g}_r$ remains unchanged. The second effect is the *network*

[33] To understand (9.27), let $\mathbf{M}(\mathbf{g}_r, \phi_1) = (\mathbf{I}_{n_r} - \phi_1 \mathbf{G}_r)^{-1}$ and let its entries be $m_{ij}(g, \phi)$, which count the number of walks in $\mathbf{g}_r$ starting from i and ending at j, where walks of length k are weighted by ϕ_1^k. Then, we know from (9.5) that the Katz–Bonacich vector of centralities is simply $\mathbf{b}_{\boldsymbol{\alpha}_r} = \mathbf{M}(\mathbf{g}_r, \phi_1)\boldsymbol{\alpha}_r$. Thus, $b_{i,r}(\mathbf{g}_r, \phi_1)$ is the Katz–Bonacich centrality of i in network $\mathbf{g}_r$, $B(\mathbf{g}_r, \phi_1)$ is the *sum* of the Katz–Bonacich centralities in network $\mathbf{g}_r$—that is, $B(\mathbf{g}_r, \phi_1) = \mathbf{1}_{n_r}^{\mathrm{T}} \mathbf{M}(\mathbf{g}_r, \phi_1) \boldsymbol{\alpha}_r$ (where $\mathbf{1}_{n_r}$ is an n-dimensional vector of ones and $\mathbf{1}_{n_r}^{\mathrm{T}}$ is its transpose)—and $B(\mathbf{g}_r^{[-i]}, \phi_1) = \mathbf{1}_{n_r}^{\mathrm{T}} \mathbf{M}^{[-i]}(\mathbf{g}_r, \phi_1) \boldsymbol{\alpha}_r^{[-i]}$ is the *sum* of the Katz–Bonacich centralities in network $\mathbf{g}_r^{[-i]}$, where $\boldsymbol{\alpha}_r^{[-i]}$ is an $(n_r - 1) \times 1$ column vector in which $\boldsymbol{\alpha}_{i,r}$ has been removed and $\mathbf{M}^{[-i]}(\mathbf{g}_r, \phi_1) = (\mathbf{I}_{n_r} - \phi_1 \mathbf{G}_r^{[-i]})^{-1}$ is an $(n-1) \times (n-1)$ matrix in which the ith row and ith column corresponding to i have been removed from $\mathbf{M}^{[-i]}(\mathbf{g}_r, \phi_1)$. Finally, let $\boldsymbol{\alpha}_r^{[i]}$ be an $(n \times 1)$ column vector where all entries but i are defined as $\boldsymbol{\alpha}_r^{[-i]}$, while entry i contains the initial $\alpha_{i,r}$, and let $\mathbf{M}^{[i]}(\mathbf{g}_r, \phi_1)$ be the $n \times n$ matrix such that each element is $m_{jk}^{[i]} = m_{ji} m_{ik} / m_{ii}$ so that $B(\mathbf{g}_r^{[i]}, \phi_1) = \mathbf{1}_{n_r}^{\mathrm{T}} \mathbf{M}(\mathbf{g}_r, \phi_1) \boldsymbol{\alpha}_r^{[i]}$ and

$$\mathbf{1}_{n_r}^{\mathrm{T}} \mathbf{M}^{[i]}(\mathbf{g}_r, \phi_1) \boldsymbol{\alpha}_r^{[i]} = b_{\boldsymbol{\alpha}_r^{[i]}, i}(\mathbf{g}_r, \phi_1) \sum_{j=1}^{n} m_{ji}(\mathbf{g}_r, \phi_1) / m_{ii}(\mathbf{g}_r, \phi_1).$$

effect, which captures the change in the network structure when the key player is removed. More generally, the intercentrality measure $d_i(\mathbf{g}_r, \phi_1)$ of delinquent i accounts both for one's exposure to the rest of the group and for one's contribution to every other exposure.

Liu et al. (2012) were the first to test the key-player policy using the Add Health data. As mentioned above, they find an estimate value of ϕ_1 of 0.0457. They then calculate the key player for each network using the intercentrality measure (9.27). They find that the key player is *not* necessarily the most active criminal in the network. They also find that it is *not* straightforward to determine which delinquent should be removed from a network by observing only his/her criminal activities or position in the network. Compared with other criminals, the key players are less likely to be a female, are less religious, belong to families whose parents are less educated, and have the perception of being more socially excluded. They also feel that their parents care less about them, are more likely to come from single-parent families, and have more trouble getting along with their teachers.

Lindquist and Zenou (2014) also test the key-player policy but with different data (the co-offending networks mentioned above). While Liu et al. (2012) observed the network at only one point in time, Lindquist and Zenou (2014) consider two periods of 3 years each (2000–2002 and 2003–2005). The period 1 dataset includes 15,230 co-offenders who are suspected of committing (on average) 5.91 crimes each and who are distributed over 1192 separate networks. The period 2 dataset includes 15,143 co-offenders who are suspected of committing (on average) 5.92 crimes each and who are distributed over 1185 networks. Their data also include 3881 individuals who are members of a network with four or more people in *both* periods. They show that 23% of all key players are not the most active criminals in their own networks, 23% do not have the highest eigenvector centrality, and 20% do not have the highest betweenness centrality.[34]

As stated above, their estimate of peer effects ϕ_1 is 0.167. They show that the key-player model predicts that the (average) reduction in crime for the mean network (with size 80) is equal to 30%. Second, this reduction in crime is negatively related to network size. If one looks at a network that is twice as large as the mean network (i.e., with size 160), then the predicted percentage reduction in crime is 26%, while the predicted decrease for the smallest networks (with size 4) is 35%.

Given that the key-player policy can be controversial and can be costly to implement, we want to know by how much the key-player policy outperforms other reasonable policies. Because they have two periods of time (2000–2002 and 2003—2005), Lindquist and Zenou (2014) can test the prediction of crime reduction following the key-player policy against the true outcome observed in period 2 data. For that, they look at the

[34] Eigenvector centrality and betweenness centrality are well-known measures of centrality. See Wasserman and Faust (1994) and Jackson (2008) for a complete overview of the different existing centrality measures.

relative effect of removing the key player in those cases in which the key player is no longer a part of the active network. To do this, they create an indicator variable for each person indicating whether or not that person died during the relevant time period and if that person was put in prison. Their results indicate that, in the real world, the key-player policy outperforms the random-player policy by 9.58%. The key-player policy also outperforms the policy of removing the most active player by 3.16% and outperforms the policies of removing the player with the highest eigenvector and the highest betweenness centrality by 8.12% and 2.09%, respectively.[35]

9.3.3.3.2 Group-based policies

As stated above, if the *local-average model* is at work, then a key-player policy would have a much smaller effect since it will not affect the social norm of each group of friends in the network. To be effective, one would have to change the social norm for each of the criminals, which is clearly a more difficult objective. In that case, one needs to target a group or gang of criminals to drastically reduce crime. It is indeed clearly much more complicated to implement a group policy than an individual policy since it is very difficult to change the social norm of a group. Consider education. Then, since the local-average model seems important (at least in the Add Health data), we should change the social norm in the school or the class and try to implement the idea that it is "cool" to work hard at school.[36] An example of a policy that has tried to change the social norm of students in terms of education is the *charter-school* policy. The charter schools are very good at screening teachers and at selecting the best ones. In particular, the "no excuses policy" (Angrist et al., 2010, 2012) is a highly standardized and widely replicated charter model that features a long school day, an extended school year, selective teacher hiring, and strict behavior norms, and emphasizes traditional reading and mathematical skills. The main objective is to change the social norms of disadvantaged children by being very strict on discipline. This is a typical policy that is in accordance with the local-average model

[35] Other articles have tested the key-player policies for other activities. For R&D networks, König et al. (2014a) calculate the key firms, which are the firms for which their removal will reduce total welfare the most. Banerjee et al. (2013) study a problem related to the key-player issue. Their data come from a survey on 75 rural villages in Karnataka, India, that they conducted to obtain information on network structure and various demographics. They look at the diffusion of a microfinance program in these villages and show that if the bank in charge of this program had targeted individuals in the village with the highest eigenvector centrality (a measure related to the Katz–Bonacich centrality), the diffusion of the microfinance program (i.e., take-up rates) would have been much higher. For an overview of key-player policies, see Zenou (2015c).

[36] This is related to the "acting white" literature where it is argued that African-American students in poor areas may be ambivalent about studying hard in school because this may be regarded as "acting white" and adopting mainstream identities (Fordham and Ogbu, 1986; Delpit, 1995; Ainsworth-Darnell and Downey, 1998; Austen-Smith and Fryer, 2005; Battu et al., 2007; Battu and Zenou, 2010; Fryer and Torelli, 2010; Bisin et al., 2011b; De Martí and Zenou, 2012).

since its aim is to change the social norm of students in terms of education. Angrist et al. (2012) focus on special needs students that may be underserved. Their results show average achievement gains of 0.36 standard deviations in mathematics and 0.12 standard deviations in reading for each year spent at a charter school called Knowledge is Power Program (KIPP) Lynn, with the largest gains coming from the limited English proficiency, special education, and low-achievement groups. They show that the average reading gains were driven almost entirely by special education and limited English proficiency students, whose reading scores rose by roughly 0.35 standard deviations for each year spent at KIPP Lynn.

Boarding schools could also be a way of changing the social norm in terms of education. For example, the SEED schools are boarding schools serving disadvantaged students located in Washington, DC, and Maryland. The SEED schools, which combine a "no excuses" charter model with a 5-day-a-week boarding program, are America's only urban public boarding schools for the poor. The SEED schools serve students in grades 6–12. Like other "no excuses" charter schools—for example, KIPP or the Harlem Children's Zone, SEED schools have an extended school day, provide extensive after-school tutoring for students who need support, rely heavily on data to alter the scope, pace, and sequence of instruction, and maintain a paternalistic culture with high expectations. Curto and Fryer (2014) provide the first causal estimate of the impact of attending SEED schools on academic achievement. Using admission lotteries, they show that attending a SEED school increases achievement by 0.211 standard deviations per year in reading and 0.229 standard deviations per year in mathematics.

9.4. NEIGHBORHOOD AND NETWORK EFFECTS

So far, we have described separately the literature on neighborhood and network effects. We have seen that there are some similarities, especially when researchers do not have data on the social space and approximate them by the geographical space (see, in particular, Bayer et al., 2008; Patacchini and Zenou, 2012a,b; Helmers and Patnam, 2014). However, these two spaces are different, and we need an explicit analysis of both of them in order to better understand their relationships and how they affect outcomes. For example, if we want to understand the adverse labor-market outcomes of ethnic minorities, we need to analyze each space and see how they reinforce each other. Unfortunately, this branch of the literature is still in its infancy and most research has been done from a theoretical perspective, with only a few empirical tests. Let us describe this research.[37]

[37] In economics, Ioannides (2012) is a good starting point even though few analyses incorporate the two spaces. In sociology, there are some discussions of these issues. See, in particular, Guest and Lee (1983), Wellman (1996), Otani (1999), and Mouw and Entwisle (2006).

9.4.1 Theory: Spatial models with social networks

We will describe different models that integrate the urban and social space. We start with models with social interactions, then consider weak and strong ties, and end up with explicit networks using graph theory. As we enrich the social space, we model the urban space in a simpler way from a general urban model to a model with only two locations.

9.4.1.1 Spatial models with social interactions

In this section, the social network is not explicitly modeled, but is captured through social interactions. In contrast, the geographical space is explicitly modeled as in the standard urban economics literature (Fujita, 1989; Zenou, 2009; Fujita and Thisse, 2013). There is an early body of literature that deals with the endogenous location of firms and workers and the formation of cities by explaining why cities exist, why cities form where they do, and why economic activities agglomerate in a small number of places (Fujita and Thisse, 2013). The key articles in this literature are those of Ogawa and Fujita (1980) and Fujita and Ogawa (1982), who solve a more general model that includes both firms and households (see also Beckmann, 1976; Borukhov and Hochman, 1977; Papageorgiou and Smith, 1983). Their articles model the emergence of urban centers brought about by household and firm location decisions in the context of spatially differentiated labor and land market interactions. Consider, for example, the model of Fujita and Ogawa (1982). The key aspect of this model is to assume that productivity in a location is a function of the density of economic activity at various locations weighted by a decay function. In other words, the agglomeration force is the existence of informational spillovers among firms. An important characteristic of information is its public good nature: the use of a piece of information by a firm does not reduce its content for other firms. Hence, the diffusion of information within a set of firms generates *externality-like* benefits to each of them. Provided that the information owned by firms is different, *the benefits of communication generally increase as the number of firms involved rises*. Furthermore, since the quality of information involves distance-decay effects, the *benefits are greater if firms locate closer to each other*. Therefore, all other things being equal, each firm has an incentive to be close to others, thus fostering the agglomeration of firms. This is the social interaction aspect of these types of models (Beckmann, 1976 provides a similar model but for individuals rather than firms). Of course, there are also disagglomeration effects because the clustering of many firms in a single area increases the average commuting distance for their workers, which in turn increases the wage rate and land rent in the area surrounding the cluster. Consequently, the equilibrium distributions of firms and households are determined as the balance between these opposite forces.

In Fujita and Ogawa (1982), this type of specification yields a rich set of possible outcomes. Depending on the importance of the spatial decay function relative to commuting costs, many urban configurations are possible, from a purely monocentric city to complete dispersion.[38] None of these articles, however, offer much detail regarding the information externality nor the spatial decay function.[39]

Helsley and Strange (2007) propose an interesting spatial model of urban interactions where agents choose to visit a particular location to interact with others.[40] A critical component of the model is the decision taken by a city's firms or households to visit a particular location to interact with others. The greater the aggregate number of visits, the greater is the value derived from any given visit. Visits involve transportation costs, however, and this generates downward-sloping equilibrium housing rent, land rent, and population density functions. In equilibrium, all of these must be consistent with the interactions that take place in the center.

To be more precise, consider the location space as a long, narrow strip of land where there is one unit of land at each location. All interactions occur at a single location, the central business district (CBD). Locations are completely characterized by their distance from this CBD, given by the variable x. Consumers are identical and derive utility from residential (or commercial) space q, other goods z (the numeraire), and interaction according to the additively separable utility function:

$$u(y_i, S) = q_i + z_i + v(y_i, S),$$

where y_i is the number of visits to the center for agent i and S measures the quality of interactions there. Assume that $v(y_i, S)$ is increasing and strictly quasi-concave in both arguments, with $\partial^2 v(y_i, S)/\partial y_i \partial S > 0$. This last assumption means that the marginal value of a visit to the center increases with the quality of the interactions there. There are two costs associated with a visit to the center: a fixed cost T and transportation cost tx, $t > 0$. Since consumers are assumed to be all identical and have the same income w, we can skip the subscript i. The budget constraint for a consumer with income w at location x is

$$z = w - R(x)q - (T + tx)y, \tag{9.28}$$

where $R(x)$ is the rent per unit of space at distance x from the CBD. We assume that each consumer occupies one unit of space—that is, $q = 1$. Combining these two equations, the consumer chooses y that maximizes

$$u(y, S) = 1 + w - R(x) - (T + tx)y + v(y, S).$$

Solving this equation leads to a unique $y^* \equiv y(S, x)$ and it easily verified that the optimal number of visits y^* made to the center increases with the quality of interactions S and

[38] This type of model has been extended by Helsley (1990), Ota and Fujita (1993), Lucas (2001), Berliant et al. (2002), and Lucas and Rossi-Hansberg (2002).
[39] See Duranton and Puga (2004) for a critical overview of these issues.
[40] See also Brueckner et al. (2002) and Brueckner and Largey (2008).

decreases with distance x. The key new element here is to specify interaction quality, S. Helsley and Strange (2007) assume that the equilibrium level of interaction quality satisfies

$$S = \int_0^{x_f(S)} F(\gamma(S,x))n(S,x)\mathrm{d}x, \tag{9.29}$$

where $x_f(.)$ is the city fringe and $F(.)$ is increasing and strictly concave, and $F(0) = 0$. Since each consumer occupies one unit of space, and there is one unit of land at each location, $n(.)$ equals the population, population density (persons per unit land), and structural density (units of residential or commercial space per unit land). Here, each agent has the potential to benefit from interacting with any other agent. However, the value of interacting with any particular agent exhibits a diminishing marginal impact, captured by the concavity of $F(.)$. In this model, the interdependence between agents arises from the endogeneity of interactions: agents choose jointly both how much to contribute to a location and how much to make use of that location. It is easily seen that the solution of S is a fixed point. The model is then easily closed by considering an open city with free migration and having a free-entry condition for builders.

Mossay and Picard (2011, 2013) propose a model in the same vein where the utility function is given by

$$u(q,z,S) = z + S(x) - \frac{\beta}{2q},$$

where β is the preference for residential space and where social interactions are given by

$$S(x) = A - \int n(x')T(x - x')\mathrm{d}x',$$

where A denotes the total return from interacting with other agents and $\int n(x')T(x-x')\mathrm{d}x'$ reflects the cost of reaching other agents from location x, where $n(x)$ is the population density with $\int n(x)\mathrm{d}x = 1$. In this formulation of social interactions, the authors consider a linear cost function $T(x - x') = 2\tau|x - x'|$, where τ measures the intensity of traveling costs. In this model, each agent *interacts with all other agents* and A is assumed to be large enough so as to ensure that $S(x) \geq 0$, for any location x. Mossay and Picard have a similar budget constraint as in (9.28)—that is, $z = w - R(x)q$ so that consumers choose q and z that maximize $u(q,z,S)$. They then calculate a spatial equilibrium in a monocentric city so that no agent has an incentive to relocate. They show that there is a unique spatial equilibrium under the assumption of global social interactions where each agent interacts with all other agents residing in the same city.

In all these models, the interactions between the social and geographical spaces are explicitly modeled. However, apart from their residential location, the outcome of workers is *not* taken into account. Picard and Zenou (2014) extend the previous models to introduce the labor-market outcomes of workers where it is assumed that social interactions are the main channel for finding employment. Indeed, consider two populations and assume that each individual of type i (i.e., belonging to population $i = 1, 2$) located at a distance x from the CBD can only *socially* interact with the members of his/her own population but must decide with how many of them he/she wants to interact, given that each social interaction implies a travel cost τ (per unit of distance) but leads to job information.

In this context, the expected utility of an individual of type i residing at location x is given by

$$u_i(x) = e_i(x)(w - t|x|) - T_i(x) - R(x), \tag{9.30}$$

where $e_i(x)$ is the individual's employment probability, $T_i(x)$ is the total travel cost at a distance x due to social interactions, and $R(x)$ is the land rent at a distance x from the CBD.[41] In this expression, all individuals from the same group, employed and unemployed, socially interact with each other. The steady-state employment rate is

$$e_i(x) = \frac{\pi_i(x)}{\pi_i(x) + \delta}, \tag{9.31}$$

where δ is the exogenous destruction rate and $\pi_i(x)$ is the probability of finding a job at a distance x from the CBD for a worker from population i.

Let us be more precise about the meeting process between agents. Each individual of type i residing at x meets $n_i(x)$ individuals from his/her own population to socially interact with them. This means that each individual meets $n_i(x)$ times all his/her population mates in a deterministic way during the period considered in the model. Since social interactions occurs at the place of residence of the potential information holder, the cost of those social interactions is given by $T_i(x) = n_i(x)c_i(x)$, where

$$c_i(x) = \frac{1}{P_i}\int_{D_i} \tau|x - y|\mathrm{d}y \tag{9.32}$$

measures the average cost of a single social interaction and P_i is the total population of individuals of type i. Observe that it is assumed that there is a uniform distribution of workers in the city, and this is why (given that each worker consumes one unit of land) the density of workers at each location is given by $1/P_i$. As a result, each worker i residing at x socially interacts with all members of his/her own population and each of these interactions implies a commuting cost of τ per unit of distance. Observe also that the location x of a worker i is crucial to determine $c_i(x)$. If, for example, a worker i lives close to the CBD, then his/her cost $c_i(x)$ will be relatively low since this worker will be at the same distance from the left and the right of x. But, if this worker is located at one end of the city, then $c_i(x)$ will be very high.

[41] Unemployment benefits are normalized to zero.

Since each social interaction leads to job information, the individual's probability of finding a job for a worker of type i residing at x is given by

$$\pi_i(x) = \alpha n_i(x)\frac{E_i}{P_i}, \tag{9.33}$$

where α is a positive constant and E_i/P_i denotes the employment rate for workers of type i. This equation captures the fact that each individual i located at x meets $n_i(x)$ individuals from his/her own population, but only those who are employed provide some information about jobs. This highlights the random search process since the probability of employment of each person met by worker i is just E_i/P_i and is not specific to the person met. Quite naturally, the individual's probability of finding a job increases with the number of social interactions $n_i(x)$ and with the employment rate in his/her own population.

In this model, each individual chooses $n_i(x)$ that maximizes (9.30), which is obtained by plugging (9.33) into (9.31) and then into (9.30) and plugging (9.32) into $T_i(x) = n_i(x)c_i(x)$ and then into (9.30). When deciding the optimal level of social interactions, an individual i located at x trades off the benefits of an increase in $n_i(x)$, which raises his/her chance of obtaining a job with its costs, since more social interactions imply more traveling and thus higher $c_i(x)$.

Consider first a homogenous population. Then, in a monocentric city, one can easily close the model by solving for the land and labor equilibrium conditions and check that everything is consistent. In that case, it is easy to show that $c(x) = \frac{\tau}{P}(b^2 + x^2)$ on the city support $D = [-b, b]$, where b is the city border and $x = 0$ is the CBD. Picard and Zenou (2014) show that the employment probability $\pi(x)$ and the optimal number of social interactions $n(x)$ decrease with x, the distance from the city center.

If we now consider two populations that do not socially interact with each other, then it can be shown that there exists a spatially segregated equilibrium where population 1 resides around the city center, while population 2 is located at both ends of the city. In this equilibrium, the employment rate of population 1 is always higher than that of population 2 whatever their relative sizes, E_1/P_1 and E_2/P_2. It can also be shown that each worker's employment probability $e_i(x)$ and the number of social interactions $n_i(x)$ decrease with x. Indeed, a residential location further away from the city center reduces the net gain from employment for both populations as well as each individual's average access to his/her social network. As a result, individuals have fewer incentives to find a job. This result is interesting because it highlights the feedback effect of space and segregation on labor-market outcomes. If we take two populations identical in all possible characteristics, then employment differences between these populations will result from the existence of spatial segregation and the resulting spatial organization of workers' social networks. Workers obtain job information through their social contacts that belong to the same type but organize in a different way through the urban area.

9.4.1.2 Spatial models with weak and strong ties

In the previous section, the modeling of social networks was implicit and was captured through social interactions. For example, in Picard and Zenou (2014), workers were interacting with all other workers of the same type in the city and each social interaction could lead to job information if one met someone who already had a job. We now enrich the social network aspect by differentiating between job information from strong ties (close and regular relationships such as family and friends) and from weak ties (random and irregular relationships). The notion of weak and strong ties was initially developed by Granovetter (1973, 1974, 1983),[42] who stipulates and shows that weak ties are superior to strong ties for providing support in getting a job. Indeed, in a close network where everyone knows each other, information is shared and so potential sources of information are quickly shaken down, and so the network quickly becomes redundant in terms of access to new information. In contrast, Granovetter stresses the *strength of weak ties* involving a secondary ring of acquaintances who have contacts with networks outside the individual's network and therefore offer new sources of information on job opportunities.

Montgomery (1994), Calvó-Armengol et al. (2007), Patacchini and Zenou (2008), and Zenou (2013, 2015b) propose modeling the impact of weak and strong ties on workers' outcomes using a dyad model so that the social network is very simplified but keeps the interaction between the two types of ties. Formally, consider a population of individuals of size 1 and assume that individuals belong to mutually exclusive two-person groups, referred to as *dyads*. We say that two individuals belonging to the same dyad hold a *strong tie* to each other. We assume that dyad members do not change over time. A strong tie is created once and forever and can never be broken. Individuals can be in either of two different states: employed or unemployed. Dyads, which consist of paired individuals, can thus be in three different states,[43] which are the following: both members are employed—we denote the number of such dyads by d_2; one member is employed and the other is unemployed (d_1); and both members are unemployed (d_0). By denoting the employment rate and the unemployment rate at time t by $e(t)$ and $u(t)$, where $e(t), u(t) \in [0,1]$, we have

$$\begin{cases} e(t) = 2d_2(t) + d_1(t), \\ u(t) = 2d_0(t) + d_1(t). \end{cases} \tag{9.34}$$

[42] In his seminal articles, Granovetter (1973, 1974, 1983) defines *weak ties* in terms of lack of overlap in personal networks between any two agents—that is, weak ties refer to a network of acquaintances who are less likely to be socially involved with one another. Formally, two agents A and B have a weak tie if there is little or no overlap between their respective personal networks. Vice versa, the tie is *strong* if most of agent A's contacts also appear in agent B's network.

[43] The inner ordering of dyad members does not matter.

The population normalization condition can then be written as

$$e(t) + u(t) = 1, \tag{9.35}$$

or, alternatively,

$$d_2(t) + d_1(t) + d_0(t) = \frac{1}{2}. \tag{9.36}$$

Let us explain how social interactions are modeled. Time is continuous and individuals live forever. Matching can take place between dyad partners. At time t, each individual can meet a weak tie with probability $\omega(t)$ (thus $1 - \omega(t)$ is the probability of meeting the strong-tie partner at time t).[44] These probabilities are constant and exogenous, do not vary over time, and thus can be written as ω and $1 - \omega$. We refer to matchings inside the dyad partnership as *strong ties*, and to matchings outside the dyad partnership as *weak ties* or random encounters. Within each matched pair, information is exchanged in the following way. Each job offer is taken to be received only by employed individuals, who can then direct it to one of their contacts (through either strong or weak ties). This is a convenient modeling assumption, which stresses the importance of on-the-job information.[45] To be more precise, employed individuals hear of job vacancies at the exogenous rate λ, while they lose their job at the exogenous rate δ. All jobs and all workers are identical (*unskilled labor*), so that all employed individuals obtain the same wage. Therefore, employed individuals, who hear about a job, pass this information on to their current matched partner, who can be a strong or a weak tie. It can be readily checked that the net flow of dyads from each state between t and $t + \mathrm{d}t$ is given by

$$\begin{cases} \dot{d}_2(t) = [1 - \omega + \omega\, e(t)]\lambda d_1(t) - 2\delta d_2(t), \\ \dot{d}_1(t) = 2\omega\, e(t)\lambda d_0(t) - \delta d_1(t) - [1 - \omega + \omega\, e(t)]\lambda d_1(t) + 2\delta d_2(t), \\ \dot{d}_0(t) = \delta d_1(t) - 2\omega\, e(t)\lambda d_0(t). \end{cases} \tag{9.37}$$

Take, for example, the first equation. Then, the variation of dyads composed of two employed individuals ($\dot{d}_2(t)$) is equal to the number of d_1 dyads in which the unemployed individual has found a job (through either his/her strong tie with probability $(1 - \omega)\lambda$ or his/her weak tie with probability $\omega e(t)\lambda$) minus the number of d_2 dyads in which one of the two employed individuals has lost his/her job. Observe that the urban spatial structure will be less rich here because, in all the models in Section 9.4.1.1, the social interactions were localized and individuals had to commute to each other person in order to interact with him/her. In equilibrium, the choice of social interactions for each person had to be consistent with the global level of interactions in the city (see, e.g., Equation 9.29).

[44] If each individual has one unit of time to spend with his/her friends, then $\omega(t)$ can also be interpreted as the percentage of time spent with weak ties.

[45] Zenou (2015b) relaxes this assumption by studying a model where jobs can be found through social networks but also directly by unemployed individuals.

In the present model, social interactions or social networks are not localized. Workers meet their strong ties without commuting because either they live with them (e.g., if they are a couple) or they are close relatives or friends who can be reached without commuting (e.g., by telephone). Workers also meet their weak ties without having to pay extra commuting costs because they meet in common places (e.g., in the gym or at the tennis club or in a bar). As a result, if an individual is unemployed in a d_1 dyad, this means that, without commuting, he/she will meet his/her strong tie $1-\omega$ percent of his/her time, and to obtain a job, it has to be that the strong tie has heard about a job, which occurs at rate λ. He/she will also meet his/her weak tie (without commuting) ω percent of his/her time, and to obtain a job this weak tie has to be employed and have heard about a job, which occurs with probability $e(t)\lambda$.

By solving the system of Equation (9.37) in the steady state, one can show that there exists an interior equilibrium where the employment rate is given by

$$e^* = \frac{\sqrt{\lambda[\lambda + 4\delta(1-\omega)]} - 2\delta + 2\lambda\omega - \lambda}{2\lambda\omega}. \tag{9.38}$$

Moreover, it is easily verified that increasing ω, the time spent with weak ties, raises the steady-state employment rate e^*, confirming the initial idea of Granovetter that weak ties are superior to strong ties in providing information about jobs. Here, it is because workers stuck in a d_0 dyad can never find a job through their strong tie (who is unemployed) but only via their weak ties, while this is not true in a d_1 dyad.

Following Zenou (2013), we can then close the model by locating all workers in a monocentric city and assuming that they have an expected utility similar to (9.30)—that is,[46]

$$u(x) = e^*(w - tx) - (1-e^*)stx - T(x) - R(x), \tag{9.39}$$

where it is assumed that the employed individuals commute more to the CBD than the unemployed individuals ($0 < s < 1$ is the fraction of time the unemployed individuals commute to the CBD) and e^* is given by (9.38). The cost of social interaction $T(x)$ is defined as

$$T(x) = \omega(x)\int \tau|x-y|\mathrm{d}y.$$

If social interactions ω are endogenized so that workers choose ω that maximizes (9.39) minus the social interaction costs, then workers face a trade-off between higher ω, which increases their chance of finding a job, and lower ω because of higher social interaction costs. It is straightforward to see that the optimal ω decreases with x, the distance to the CBD. This is because it is always more expensive to commute to the CBD when

[46] This utility function is similar to that of Picard and Zenou (2014). See (9.30).

employed than when unemployed (i.e., $t > st$), so the marginal gain of interacting with weak ties is higher for workers residing closer to jobs than for those located further away from the CBD.

This model can then be extended by introducing two populations, say black and white workers, where *strong ties* are always of the same race (family, best friends) and there are no spatial costs of interacting with them because they tend to live in the same neighborhood. In contrast, *weak ties* can be of either race, and meeting them implies a commute to the center of activities, here the CBD. Black and white workers are totally identical (in terms of characteristics, skills, etc.). If there is discrimination in the housing market (which is well documented; see, e.g., Yinger, 1986, 1997) against blacks so that they tend to reside further away from jobs than whites, then it can be shown that the former will experience a higher unemployment rate than the latter. Indeed, because black workers reside far away from the CBD, they will tend to interact less with weak ties, especially whites, and more with their strong ties. Weak ties are an important source of job information, and when black individuals do not obtain this information, they end up having a higher unemployment rate than whites. This is a vicious circle since blacks experience a higher unemployment rate and mostly rely on other blacks, who also experience a high unemployment rate, for example. Since jobs are mainly found through social networks via employed friends, black individuals are stuck in their location with no job. In particular, those residing far away from jobs will mainly rely on their strong ties. As a result, when they find themselves in a d_0 dyad, they have nearly no chance of leaving it since the only way out is to meet an employed weak tie. In the model, the lack of social contacts between blacks and whites[47] thus explains why the social network of black workers is not of good quality and why blacks experience high unemployment rates.[48]

To summarize, in this framework, ethnic minorities experience higher unemployment rates because they are *separated both in the urban space and in the social space*.[49]

9.4.1.3 Spatial models with explicit social networks

In this section, we describe an even richer structure of social networks by modeling them as in Section 9.3.1. The seminal article of Jackson and Wolinsky (1996) was the first

[47] Mouw and Entwisle (2006) show empirically that about one-third of the level of racial friendship segregation in schools is attributable to residential segregation. Most of this effect is the result of residential segregation across schools rather than within them.

[48] American metropolitan areas are segregated by race, both by neighborhood and across jurisdiction lines. In 1980, after a century of suburbanization, 72% of metropolitan blacks lived in central cities, compared with 33% of metropolitan whites (Boustant, 2010).

[49] Sato and Zenou (2015) investigate the impact of urban structure on the choice of social interactions. They show that in denser areas, individuals choose to interact with more people and meet more weak ties than in sparsely populated areas.

article to model network formation in a game-theoretical framework. In their model, individuals benefit from direct links and also indirect links but with a decay. They pay, however, an exogenous cost for creating a link. Johnson and Gilles (2000) and Jackson and Rogers (2005) extend this model by assuming that the cost of creating a link is proportional to the *geographical distance* between two individuals so that agents living further away are less likely to form links because the costs are higher. These are interesting models that mainly show that geographical distance can hinder relationships and social interactions between agents. However, in these models, equilibrium networks are difficult to characterize and the focus is on network formation and not on individuals' outcomes.

Following Helsley and Zenou (2014), we develop a simple model where the impact of network structure and urban space on workers' outcomes is analyzed. On contrast to the previous models, there are only two locations, the center located at 0, where all interactions occur, and the periphery located at 1 (*geographical space*). Each agent is also located in a social network (*social space*), where, as in Section 9.3.1, a network is captured by the $n \times n$ adjacency matrix $\mathbf{G}$ with entry g_{ij}, which keeps track of all direct connections so that $g_{ij} = 1$ if agent i is connected to agent j, and $g_{ij} = 0$ otherwise.[50]

We study a two-stage game where the n agents first choose their geographical location and then, as in as Helsley and Strange (2007),[51] the number of visits to the center. Consider the local-aggregate model described in Section 9.3.1.1 so that individuals in network $\mathbf{g}$ derive utility

$$U_i(y_i, \mathbf{y_{-i}}, \mathbf{g}) = w + \alpha_i y_i - \frac{1}{2} y_i^2 + \phi_1 \sum_{j=1}^{n} g_{ij} y_i y_j, \tag{9.40}$$

where $\phi_1 > 0$ and where w stands for income, y_i is the number of visits that agent i makes to the center, and $\mathbf{y_{-i}}$ is the corresponding vector of visits for the other $n-1$ agents. Agents located in the periphery must travel to the center to interact with others. If we let t represent the marginal transport cost, then $\alpha_i = \alpha - tx_i$. Thus, for each agent i residing in the periphery (i.e., $x_i = 1$), $\alpha_i = \alpha - t$, while for agents living in the center (i.e., $x_i = 0$), $\alpha_i = \alpha$. We assume $\alpha > t$, so $\alpha_i > 0$, $\forall x_i \in \{0,1\}$, and hence $\forall i = 1, 2, \ldots, n$. We imagine that each visit results in one interaction, so the aggregate number of visits is a measure of aggregate interactivity. As in (9.1), utility (9.40) imposes additional structure on the interdependence between agents; under (9.40), the utility of agent i depends on his/her own visit choice and on the visit choices of the agents with whom he/she is directly connected in the network—that is, those for whom $g_{ij} = 1$.

[50] We skip subscript r since we consider only one network.
[51] See Section 9.4.1.1.

Each agent i chooses y_i to maximize (9.40) taking the structure of the network and the visit choices of other agents as given. With use of the results in Section 9.3.1.1, it is straightforward to see that if $\phi_1\mu(\mathbf{G}) < 1$, there is a unique Nash equilibrium in visits to the center given by

$$\mathbf{y}^* = (\mathbf{I}_n - \phi_1\mathbf{G})^{-1}\boldsymbol{\alpha} = \mathbf{M}\alpha = \mathbf{b}_{\boldsymbol{\alpha}}(\mathbf{g}, \phi_1), \tag{9.41}$$

where $\mathbf{b}_{\boldsymbol{\alpha}_r}(\mathbf{g}_r, \phi_1)$ is the weighted Katz–Bonacich centrality defined in (9.5). The Nash equilibrium visit choice of agent i is thus

$$y_i^*(x_i, \mathbf{x_{-i}}, \mathbf{g}) = \sum_{j=1}^{n} m_{ij}\alpha_j = \sum_{j=1}^{n}\sum_{k=0}^{+\infty}\phi_1^k g_{ij}^{[k]}\alpha_j, \tag{9.42}$$

where $\mathbf{x_{-i}}$ is the vector of locations for the other $n - 1$ agents. The Nash equilibrium number of visits $y_i^*(x_i, \mathbf{x_{-i}}, \mathbf{g})$ depends on the position in the social network and the geographical location. An agent who is more central in the social network, as measured by his/her Katz–Bonacich centrality, will make more visits to the interaction center in equilibrium. Intuitively, agents who are better connected have more to gain from interacting with others, and so exert higher interaction effort for any vector of geographical locations.

Using the best-response function (see Section 9.3.1.1), we can write the equilibrium utility level of agent i as

$$U_i(y_i^*, \mathbf{y}_{-\mathbf{i}}^*, \mathbf{g}) = w + \frac{1}{2}\left[y_i^*(x_i, \mathbf{x_{-i}}, \mathbf{g})\right]^2 = w + \frac{1}{2}\left[b_{\alpha_i}(\mathbf{g}, \phi_1)\right]^2, \tag{9.43}$$

where $y_i^*(0, \mathbf{x_{-i}}, \mathbf{g})$ and $y_i^*(1, \mathbf{x_{-i}}, \mathbf{g})$ are the equilibrium effort of individual i if he/she lives in the center and in the periphery, respectively.

This was the second stage. In the first stage, each agent i chose to live either in the center ($x_i = 0$) or in the periphery ($x_i = 1$) anticipating the utility (9.43) that agent will obtain at each location. There is an exogenous cost differential $c > 0$ associated with the central location. Assuming that the center has more economic activity generally, this cost differential might arise from a difference in location land rent from competition among other activities for center locations. Helsley and Zenou (2014) totally characterize the subgame-perfect Nash equilibria and show that this characterization depends on c, t, α, and the centralities of the agents determined by their m_{ii} and m_{ij} (i.e., their Katz–Bonacich centralities). In particular, more central agents always reside closer to the center than less central agents. If we define the type of an agent by his/her position in the network (in terms of Katz–Bonacich centrality), then it can be shown that the number of equilibria is equal to the number of types of agents plus one. For example, in a star network, there are two types of agents (the star and the peripheral agent) and thus, depending of the values of the parameters, there will be three equilibria: a central equilibrium, where all agents live in the center; a peripheral equilibrium, where all agents live in the periphery; and a core-periphery equilibrium, where the stars live in the center and the peripheral agents reside in the periphery of the city.

An interesting result is that there is much more clustering in the center of the city in denser networks than in sparse networks. This is because there are many more interactions in a denser network and thus it is more beneficial for agents to live in the center and interact with other agents.

9.4.2 Discussion

In this theoretical presentation, we have seen how the urban space and the social space interact with each other and how they affect the labor-market outcomes of workers. We use this framework to explain the adverse labor-market outcomes of ethnic minorities, especially for black workers in the United States.

If we consider only *neighborhood effects* as in Section 9.2, then there is an important literature in urban economics showing that the distance to jobs is harmful to workers, in particular, black workers. This is a particular form of neighborhood effects, in which the physical location of the neighborhood in relation to jobs, rather than the composition of the neighborhood, generates adverse effects. This is known as the "spatial mismatch hypothesis" (Kain, 1968; Ihlanfeldt and Sjoquist, 1998; Gobillon et al., 2007; Zenou, 2009). In other words, it is because ethnic minorities reside in *neighborhoods* that are disconnected from jobs that they experience high unemployment rates. In the US context, where jobs have been decentralized and blacks have stayed in the central parts of cities, the main conclusion of the spatial mismatch hypothesis is that the distance to jobs is the main cause of their high unemployment rates.

If we consider only *network effects* as in Section 9.3, then it is because ethnic minorities have "low"-quality social networks that they experience adverse labor-market outcomes.[52] This is clearly shown by Calvó-Armengol and Jackson (2004),[53] where jobs can be found both directly and through other workers linked to each other in the social network. They show that a steady-state equilibrium with a clustering of workers with the same status is likely to emerge since, in the long run, employed individuals tend to be mostly friends with other employed individuals, and unemployed individuals tend to be mostly friends with other unemployed individuals. As a result, if because of some

[52] There is strong evidence that indicates that labor-market networks are partly race based, operating more strongly within than across races (Ioannides and Datcher-Loury, 2004; Hellerstein et al., 2011) and that the social network of black workers is of lower quality than that of whites (Frijters et al., 2005; Fernandez and Fernandez-Mateo, 2006; Battu et al., 2011).

[53] See also Calvó-Armengol (2004), Calvó-Armengol and Zenou (2005), Calvó-Armengol and Jackson (2007), and Galenianos (2014).

initial conditions, black individuals are unemployed, then in the steady state they will still be unemployed because both their strong and their weak ties will also be unemployed.

Here, we argue that both the neighborhood and the social network are important in explaining the high unemployment rates of blacks. Let us explain why this is so by considering the model of Helsley and Zenou (2014) (Section 9.4.1.3) and interpreting it in the following way. There are two locations, a center, where all jobs are located and all interactions take place, and a periphery. Here an interaction between two individuals means that they exchange job information with each other and thus each visit to the center implies a job-information exchange with someone else. As above, y_i is the number of visits that individual i makes to the center in order to obtain information about jobs, and each visit results in one interaction. As a result, the higher is the number of interactions, the higher is the quality of job information and the higher is the probability of being employed. There are two types of workers: black and white, and the only difference between them is their position in the network. We assume that whites have a more central position (in terms of Katz–Bonacich centrality) in the network than blacks. This captures the idea of the "old boy network" where whites grew up together, went through school together, socialized together during adolescence and early adulthood, and entered the labor force together (Wial, 1991).

In this interpretation of the model, it is straightforward to see that black workers will make fewer visits to the center and thus will interact less with other workers in the network, in particular, with very central agents such as white workers. Moreover, the black workers will also choose to locate further away from jobs than white workers because they interact less with central workers. At the extreme, we could have an equilibrium where all white workers live in the center of the city, while all black workers reside in the periphery. This would imply that whites will interact more with whites and less with black workers. Blacks will interact less and mostly with blacks and thus will have much less information about jobs. This will clearly have dramatic consequences in the labor market and will explain why blacks experience a lower employment rate than whites. In other words, the *lack of good job contacts would be here a structural consequence of the social isolation of inner-city neighborhoods*. Importantly, the *causality goes from the social space to the geographical space*, so it is the *social mismatch* (i.e., their "bad" location in the social network) of black workers that leads to their *spatial mismatch* (i.e., their "bad" location in the geographical space).

We saw in Section 9.4.1.2 that the causality can go the other way. Indeed, in Zenou (2013), it is the spatial mismatch of black workers (due to housing discrimination) that leads to their social mismatch (i.e., less interaction with white weak ties) and thus their adverse labor-market outcomes.

For the policy implications of each model, it is crucial to know the sense of causality. If it is the geographical space that causes the social mismatch of black workers, then the policies should focus on workers' geographical location, as in the spatial mismatch literature. In that case, *neighborhood regeneration policies* would be the right tool to use. Such policies have been implemented in the United States and in Europe through the enterprise zone programs and the empowerment zone programs (e.g., Papke, 1994; Bondonio and Greenbaum, 2007; Ham et al., 2011; Busso et al., 2013). The enterprise zone policy consists in designating a specific urban (or rural) area, which is depressed, and targeting it for economic development through government-provided subsidies to labor and capital.

The aim of the empowerment zone program is to revitalize distressed urban communities, and it represents a nexus between social welfare policy and economic development efforts. By implementing these types of policies, one brings jobs to people and thus facilitates the flows of job information in depressed neighborhoods. Another way of reducing the spatial mismatch of black workers would be to implement a transportation policy that subsidizes workers' commuting costs (Pugh, 1998). In the United States, a number of states and counties have used welfare block grants and other federal funds to support urban transportation services for welfare recipients. For example, programs helping job takers (especially African-Americans) obtain a used car—a secured loan for purchase, a leasing scheme, a revolving credit arrangement—may offer real promise and help low-skilled workers obtain a job by commuting to the center where jobs are located.

If, in contrast, it is the social space that causes the spatial mismatch of black workers, then the policies should focus on workers' social isolation. Policies that promote social integration and thus increase the interracial interactions between black and white workers would also have positive effects on the labor-market outcomes of minority workers. Such policies, like the MTO program described in Section 9.2.1.1, have been implemented in the United States. Another way of reducing the unemployment rate of minorities in the context of our model is to observe that *institutional connections* can be engineered to create connections between job seekers and employers in ways that parallel social network processes. For example, scholars such as Granovetter (1979) and Wilson (1996) have called for poverty reduction programs to "create connections" between employers and poor and disadvantaged job seekers.[54]

This is ultimately an empirical question of causality—whether people who are central in the network move to the city, or whether people who are less connected move to the city and then become more central. Such an empirical test is crucial, but one would need either a natural experiment with an exogenous shock or convincing instruments to break the sense of causality. In the labor-market interpretation, the key issue is whether black workers first choose to live in geographically isolated neighborhoods (or are forced to live

[54] This is related to the policy issues highlighted in Section 9.3.3.3, where we advocated a *group-based policy* for individuals who had preferences according to the *local-average* model and an *individual-based policy* for individuals who had preferences according to the *local-aggregate* model. Clearly, the MTO program, which gives vouchers to individual families, is an individual-based policy, while the enterprise zone program is a group-based policy.

there because of housing discrimination) and then become isolated in the social space because of the lack of contacts with white workers, or whether black workers prefer to interact mainly with other black individuals and as a consequence locate in areas where few whites live, which are isolated from jobs. In any case, we believe that the social and the geographical space are intimately related and policies should take into account both of them if they are to be successful.

9.4.3 Empirical results

Unfortunately, there are very few empirical studies that explicitly test the interactions between the urban space and the social space and their impact on the outcomes of individuals. We saw in Section 9.2.1.2 that a significant portion of *social interactions with neighbors* are very local in nature—that is, occur among individuals in the same block.[55] Bayer et al. (2008) find that residing in the same block raises the probability of sharing the work location by 33%, which is consistent with a social network effect. Similarly, Hellerstein et al. (2011) and Hellerstein et al. (2014) also find that the hiring effect of *residential networks* is significant and is especially strong for Hispanics and less-skilled workers, and for smaller establishments. All this evidence highlights the neighborhood-specific nature of social networks, at least in the context of labor-market networks. Ananat et al. (2013) find that blacks get a higher return in wages from local agglomeration and human capital spillovers when more of the surrounding workers are black, suggesting that information flows occur along racial lines.

Del Bello et al. (2014) propose one of the few tests that aim to explicitly estimate the effect of the social and geographical space on two outcomes: education and crime. They use the Add Health data described above, which provides information on friendship networks for students in grades 7–12. This dataset also allows them to separate students in different census block groups and thus can determine whether two students who are friends (*social space*) also reside in the same neighborhood or not (*geographical space*). They consider two types of peers: *peers at school*, who are peers nominated at school but who do *not* live in the same neighborhood, and *peers in the neighborhood*, who are peers nominated at school and who also live in the same neighborhood. Using the local-aggregate model presented in Section 9.3.2.3, they estimate Equation (9.15), which we rewrite for the sake of the exposition:

$$\mathbf{Y}_r = \phi_1 \mathbf{G}_r \mathbf{Y}_r + \beta \mathbf{X}_r + \gamma \mathbf{G}_r^* \mathbf{X}_r + \eta_r \mathbf{l}_{n_r} + \varepsilon_r.$$

[55] See also Arzaghi and Henderson (2008), Rice et al. (2006), and Rosenthal and Strange (2003, 2008), who show that interaction or agglomeration effects decay very quickly.

Del Bello et al. (2014) decompose the $\mathbf{G}_r$ matrix so that $\mathbf{G}_r = \mathbf{G}_{r,\mathrm{S}} + \mathbf{G}_{r,\mathrm{N}}$, where $\mathbf{G}_{r,\mathrm{S}}$ keeps track only of peers at school in network r and $\mathbf{G}_{r,\mathrm{N}}$ accounts for peers in the neighborhood in network r. Thus, the model estimated is

$$\mathbf{Y}_r = \phi_{1\mathrm{S}}\mathbf{G}_{r,\mathrm{S}}\mathbf{Y}_r + \phi_{1,\mathrm{N}}\mathbf{G}_{r,\mathrm{N}}\mathbf{Y}_r + \beta\mathbf{X}_r + \gamma_{\mathrm{S}}\mathbf{G}^{*}_{r,\mathrm{S}}\mathbf{X}_r + \gamma_{\mathrm{N}}\mathbf{G}^{*}_{r,\mathrm{N}}\mathbf{X}_r + \eta_r\mathbf{l}_{n_r} + \varepsilon_r. \tag{9.44}$$

As in Section 9.3.2.3, Del Bello et al. (2014) estimate this equation using the characteristics of friends of friends as instruments for the endogenous peer effects and network fixed effects. However, as stated in Section 9.3.2.5, this empirical strategy works only if $\mathbf{G}_{r,\mathrm{S}}$ and $\mathbf{G}_{r,\mathrm{N}}$ are conditionally exogenous. If students sort themselves into neighborhoods and then into friendships according to some unobserved characteristics correlated with the error term, peer effects $\phi_{1\mathrm{S}}$ and $\phi_{1,N}$ in (9.44) are not identified. In order to address this issue, following the discussion in Section 9.3.2.5, one can simultaneously estimate Equation (9.44), the outcome equation, and Equation (9.21), the network formation equation.

Del Bello et al. (2014) find that the effect of peers (friends) on own education (measured by the average GPA of the student) are strong for both *peers at school* and *peers in the neighborhood*, although the effect of school friends is more than twice that of neighborhood peers. They obtain the opposite for the crime outcome, where only *peers in the neighborhood* appear to exhibit an endogenous multiplier effect on criminal activity. This suggests that friends at school (social space) are key for educational outcomes, while friends residing in the same neighborhood (social and geographical space) are the most important determinant of own criminal activities.

These results are important in light of our policy discussion in Section 9.4.2. According to these results, it seems that a key-player policy (see Section 9.3.3.3) as well as neighborhood policies (such as the neighborhood regeneration policies mentioned in Section 9.4.2) are crucial in reducing juvenile crime, while group-based policies at the school level such as the *charter-school* or *boarding-school* policies mentioned in Section 9.3.3.3 are the most efficient ones for improving education for young students.

9.5. CONCLUDING REMARKS

In this chapter, we have reviewed the literature on neighborhood effects, network effects, and neighborhood and network effects. We have seen that for the experimental evidence based on relocations or resettlements of individuals, the neighborhood effects are quite limited in the United States and Canada, while they are important in Europe, especially in Scandinavian countries. In the latter, we showed that ethnic enclaves can have positive effects on labor-market outcomes and education of immigrants, both in Sweden and in Denmark, especially for the less-skilled ones. Unfortunately, they seem to have a positive effect also on crime since growing up in a neighborhood with many criminals has a long-term effect on crime for immigrants. Interestingly, when we look at nonexperimental evidence at the city block level in the United States, then there are strong neighborhood effects since workers who co-reside in the same city block are more likely to work together compared with residents in nearby blocks. In other words, a significant portion of interactions with neighbors are very local in nature—that is, they occur among individuals in the same block. This effect is especially strong for neighbors within the same racial or ethnic group. We also discussed the structural approach to the estimation of neighborhood effects: here the literature finds evidence of important neighborhood effects for crime and in the labor market.

We then turned to network effects and focused only on studies for which the network was explicitly studied and modeled as a graph. We mainly described (quasi) structural approaches where a model was first written and then tested. For that, we first developed a simple model where agents embedded in a network choose efforts in some activity (education, crime, labor, etc.) where the network is given,[56] the utility is linear-quadratic, and there are strategic complementarities in efforts. In one version of the model, the network effects of each individual i are captured by the sum of efforts of the agents who are directly connected to individual i (local-aggregate model) and, in the other, they are captured by the distance to the social norm from each agent i (local-average model). We calculated the Nash equilibrium of each of these models and showed the importance of the position in the network with regard to the outcomes of the agents. We then discussed the different empirical tests based on these models and their identification strategies. The results indicate that there are very strong network effects in different activities (education, crime, health, etc.) and that policies should take into account which model is more appropriate for the data. One interesting policy is the key-player policy, which aims to target an agent in a network in order to maximize total activity or welfare.

In the last part of this chapter, we studied the interaction between neighborhood and network effects. We first developed some models where the urban and the social space are integrated, and analyzed how the interaction between these two spaces affects the labor-market outcomes of workers, especially ethnic minorities. We then turned to the empirical tests and found that very few studies include both spaces in their analysis. This is clearly what should be done in the future since we are starting to have better data that can encompass both spaces. This will be very important for policies since it will help us understand the relative role of neighborhood versus peer and network effects on outcomes such as crime, education, and labor.

[56] There is an important literature on network formation that we do not survey here because these models are usually plagued by multiple equilibria, which are clearly difficult to test empirically. See Jackson (2008) for an overview.

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