# Estimating Dynamic Local Interactions Models

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**Abstract**

This paper presents empirical methods for studying a class of local interactions models in which agents' transitions are affected by their neighbors' states. We consider an application to urban unemployment and social networks in job search using publicly available cross-section and retrospective data. Most links in our model are local, but some span an entire metropolitan area. Our methods are designed to accommodate the presence of strong cross-sectional dependence arising from these few cross-metro area links. We also present simple methods to compare data and model spell distributions and to illustrate the model's dynamic properties.

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# 1 Introduction

The relevance of social interactions, learning from one's network contacts, peer effects, local spillovers, has increasingly been recognized by economists in a variety of contexts. Glaeser et al. (1996) explain the very high variance of crime rates across U.S. cities through a model in which agents' propensity to engage in criminal activities is influenced by neighbors' choices. Case and Katz (1991) explore the role of neighborhood effects on several behavioral outcomes, such as criminal activity, drug and alcohol use, childbearing out of wedlock, schooling, church attendance. Crane (1991) also looks at neighborhood influences on several social pathologies, focusing on non-linearities and threshold effects. Katz et al. (2001) and Ludwig et al. (2001) use the Moving To Opportunity (MTO) program as a natural experiment to evaluate the magnitude of neighborhood effects with respect to crime and educational outcomes.[1] Bertrand et al. (2000) find that local social networks have a significant impact on individual welfare participation. Topa (2001) estimates the magnitude of information spillovers regarding job opportunities using data on the spatial distribution of unemployment rates across Census tracts in the city of Chicago. Weinberg et al. (forthcoming) find significant neighborhood effects in hours worked using detailed panel data from the $NLSY$.[2]

At a theoretical level, several authors have analyzed the role of local interactions and network effects in models of endogenous growth (Benabou (1993, 1996), Durlauf (1996a,b)), information cascades (Banerjee (1992) and Bikhchandani et al. (1992)), social learning (Bala and Goyal (1998), Gale and Rosenthal (1999), Morris (2000)), the emergence of conformity and social norms (Young (2001), Munshi and Myaux (2002)) and job search (Montgomery (1991), Calvo-Armengol and Jackson (forthcoming)). Brock and Durlauf (2001) use random field theory to study generalized logistic models in which each agent's random utility of a given choice is affected by her contacts' outcomes.[3]

In this paper we present empirical methods that are useful in calibrating, estimating, and evaluating a particular type of local interactions models. The crucial feature of this class of models is that, for each agent, the transitions probabilites across states are affected by the state of a finite number of "neighbors". Thus, such models offer a stylized "reduced form" description of situations in which agents' decisions or

[1] In studies concerning education, there is a long tradition starting with the Coleman report (Coleman et al. (1966)) of studying possible peer influences and neighborhood effects on educational outcomes: for instance, Aaronson (1998) exploits data on siblings that grew up in different communities; Zax and Rees (2002) use a Wisconsin Longitudinal Study to estimate the impact of peer influences during school years on subsequent earnings.

[2] Jencks and Mayer (1990) present a survey of empirical work on neighborhood effects. Ioannides and Datcher (1999) and Brock and Durlauf (forthcoming) also give excellent surveys of the existing literature.

[3] Nakajima (2003) represents an early empirical application of Brock and Durlauf's theoretical framework to peer effects in smoking among teenagers.

outcomes are directly affected by other agents' behavior through imitation, learning, information sharing, or social pressure.

The concrete application that we consider here is to urban unemployment. In our model, each agent is directly connected to a few others and their states influence his/her employment transitions. Most of an agents' contacts are in a sense a local group; however, a key feature of our model is that some agents are connected across groups by links that may essentially span the entire economy. This modeling choice is motivated by an attempt to endow our agents in the model with an individual network structure that takes seriously the empirical findings of a rich sociological literature on networks.[4]

Individual networks in the model are based on physical distance between agents, in the sense that social ties are more likely between agents that are physically close; however, ties across large physical distances may also arise with small but strictly positive probability.[5] Specifically, each agent draws contacts from three separate pools of potential contacts – her own Census tract, the neighboring tracts, and the metropolitan area in its entirety. The latter pool allows an agent the possibility of having some "long physical distance connections" or "bridging weak ties" with agents at the other end of the metropolitan area, and is again consistent with the existing sociological evidence.[6]

Granovetter (1973), in a seminal paper, emphasizes the importance of such weak ties in the diffusion of information or innovations, and in acting as a catalyst for social movement. Granovetter (1995) documents the role of weak ties in job search, using data from a sample of job changers in the Boston metro area. He finds that professional, managerial and technical workers were much more likely to find jobs through weak ties than through strong ones. Further, Lin et al. (1981) find that weak ties have a stronger association with higher occupational achievement than strong ties.

In the context of urban communities, Wellman (1996) studies a sample of Toronto residents and finds that a sizeable portion of individual network contacts (roughly one third) occurs with people who live more than five miles away from one's residential location. In this paper, we take a more conservative approach and fix the probability of drawing a network contact from locations "far away" within a metropolitan area

[4]Most of the existing empirical literature in economics uses very stylized network structures: Glaeser et al. (1996) define as one's contacts her immediate neighbor in the space of social connections; Case and Katz (1991) and Topa (2001) use agents in the neighboring tracts; Bertrand et al. (2000) use all other individuals in the SMSA who speak the same language.

[5]In principle other distance metrics may also be used, based on travel time, ethnicity, occupations etc. (see Conley and Topa (2002)).

[6]Formally, two agents $A$ and $B$ are said to have a *weak (strong)* tie if the overlap in their sets of social contacts is small (large). Further, a tie is defined as a *bridge* if it provides the only link between two points in a network. Bridges then assume an important role in the diffusion of information between two largely disconnected sets of agents. Weak ties do not necessarily constitute bridges, but all bridges must be weak ties. See Granovetter (1973) for further details.

as low as one percent. Crucially, however, even such a small probability of long ties dramatically reduces the average path length between any two randomly chosen agents in our model. In other words, even if the majority of ties are local and only a handful are long ties that connect agents at the opposite ends of the metro area, the average number of degrees of separation between any two agents within the metro area is quite small. This is the so-called "small-worlds" feature that has been widely studied and documented, among others, by Travers and Milgram (1969), Lin et al. (1978), Watts and Strogatz (1998), Watts (1999).

We also take a first step towards endogenizing agents' individual networks by letting agents expand their set of social contacts while unemployed. In a fully specified model of job search, agents typically engage in job searching activities while both employed and unemployed. At the same time, it is often the case in such models that search intensity varies according to one's employment status. When considering the role of networks and referrals in job search, one way to endogenize search intensity is to allow agents to vary the number of social contacts (or the frequency of contact) depending on whether they are employed or unemployed. It seems reasonable to assume that workers may use their individual networks less – as a source of information about job openings – in the employed state than in the unemployed one, just as they would choose a lower search intensity in a standard search model.[7] A straightforward way to model this in our context is to assume that agents maintain active links with a smaller number of social contacts while employed than unemployed.

In a fully endogenous model, such behavior would result from the solution of a choice problem, and would be optimal given that *(a)* a larger network is likely to be more valuable during an unemployment spell, and *(b)* the costs of maintaining individual social links is lower while unemployed due to a lower cost of time. For the sake of computational feasibility, our treatment in this paper is to have agents automatically switch to a larger network when unemployed: while mechanical, this feature still lets us begin to explore the consequences on employment outcomes of having a variable network size in response to one's employment status. In fact, in this paper we take the simplest possible approach by assuming that agents' transition rates out of the employed state are not affected by the state of their social contacts. While extreme, this first step has the advantage of making our calibration and estimation choices very simple, as we discuss in more detail in Section 3. However, employed agents still affect their contacts' transitions into jobs. Finally, we allow employment status of neighbors from an agent's own racial/ethnic group to have a differential impact on her employment chances than employment status of neighbors who belong to other groups.

In addition to network specification, we try to make a contribution in the way in which we construct a model defined at the level of individuals. Unlike Glaeser et al. (1996) and Topa (2001), our model allows for individual covariates. We calibrate

[7]See, for example, Burdett and Mortensen (1980). They model a continuous search intensity parameter that varies endogenously between on- and off-the-job search.

agents' covariate distributions using education and demographic data from the Los Angeles metropolitan area. This allows some potential for empirical patterns in spatial correlation of education and demographics to explain clusters in unemployment in the model. Clearly, clustering in outcomes need not arise only through interactions between agents, but may be due also to spatial correlation in agent characteristics (typically induced by sorting).[8]

Formally, the model generates a first-order Markov process over a very large but finite state space, where the state of the system at each point in time is a configuration of individual employment outcomes. It is straightforward to show that a stationary distribution exists and is unique, for a given distribution of individual characteristics (that are assumed to be fixed over time).[9] Because of the local positive feedback generated by the information exchange, the stationary distribution of unemployment is characterized by spatial correlations across agents.

This model is closely related to contact processes that are studied in the Interacting Particle Systems literature.[10] These are typically continuous time Markov processes defined on infinite integer lattices in $\mathcal{Z}^d$, where particles can be in one of two states at each instant. The transition rates between states are affected by the state of a finite set of nearest neighbors on the lattice. For the contact process, there exists a critical value of a parameter governing the strength of interactions between neighbors such that nondegenerate distributions over the set of configurations only exist for parameter values above this threshold. Model properties can vary according to the graph structure connecting agents. For example, when agents are connected on tree structures, the contact process has two distinct critical values: i.e., an intermediate phase appears where the process survives globally, but dies out locally (see Liggett (1999)).

The graph structure of our network is also critical in our context: in particular, the number of connections held by each agent and the network distance (degrees of separation) between agents affect the cross sectional properties of the stationary distribution of unemployment. The existence of ties between agents that are very distant in physical location implies that agents throughout the economy will often be close in terms of network distance, which is the appropriate metric for measuring dependence in their random variables. We argue that the most appropriate way to think about taking limits in the cross section as the size of the network grows

[8] The possibility of correlated unobservables further complicates the estimation of social effects. Topa (2001) employs various strategies to address this problem in a similar setting. Here we abstract from this issue entirely for computational limitations.

[9] In a static framework, Brock-Durlauf (2001) and Glaeser-Scheinkman (2003) analyze local interactions models in which multiple equilibria are possible, depending on the strength of the 'social multiplier' brought about by the local interactions. Estimation of the model parameters is problematic in this case, although Brock-Durlauf (forthcoming) and Bisin et al. (2003) present estimators that are consistent and efficient even in the presence of multiple equilibria.

[10] The contact process was first introduced by Harris (1974). See Liggett (1985,1999) for a very rigorous and thorough introduction to Interacting Particle Systems.

should preserve the feature that a small proportion of links ought to be potentially economy-wide. If this feature persists, then the maximum network distance – degrees of separation – between agents should be viewed as either being fixed or growing very slowly as the number of agents in the network increases.

Therefore, we argue that the cross section should be viewed as exhibiting strong dependence across observations. In particular, this strong dependence will result in large-sample cross sectional averages not approaching integrals with respect to the stationary distribution. Even cross sections with an arbitrarily large number of agents will exhibit randomness over time and we view them as a single observation from a time series process. In this sense, we are in a very different situation than Glaeser et al. (1996), Brock and Durlauf (2001), Topa (2001), Conley and Topa (2003) (to mention but a few), in which interactions are strictly local or "nearest neighbor" and there is weak cross-sectional dependence. In all of these papers, it is possible to do inference based on a single cross section of data that is not feasible given our setting. The particular network structure that we adopt thus poses some unique challenges in terms of the empirical analysis, but has the advantage of being a richer and more realistic depiction of workers' actual social networks.

We present empirical methods aimed at those using publically available cross section and retrospective data. We calibrate transition parameters that depend only on the individual's characteristics from retrospective $CPS$ data. However, this $CPS$ data and available panel datasets, e.g. the $NLSY$, lack enough information for us to specify the relevant state variables for each agent's transitions in our model when they depend on the state of his/her social contacts. Even with the assumption that agents' social networks are largely defined by the physical location of their residence, there is either insufficient detail in agents' locations or sampling rates are too low to capture many individuals living very close together in these data sets.[11] Therefore, we use Public Use Census data on the cross-sectional distribution of unemployment across census tracts. This provides information on tract-level aggregates of agents' outcomes which, while far from ideal, provides more information about geography-based social network outcomes than the $NLSY$ and $CPS$.

Our basic situation is perhaps best described as needing to draw inference about a time series data generating process (DGP) from a single observation of a vector time series.[12] We will not be able to get consistent estimates, taking limits as the size of the cross section grows. However, there is still substantial information in a single realization of a vector process whose DGP has a relatively small number of parameters. We present two ways to obtain estimates: a mimimum distance estimator that we use to obtain point estimates and a test-statistic inversion method to directly obtain interval estimates using the minimum distance criterion function as our test

[11] The lack of location information can be largely overcome by working with confidential data as done by, e.g., Weinberg, Reagan, and Yankow (forthcoming). We focus on publically available data as the costs of accessing such data will be prohibitive for many researchers.

[12] We also use retrospective data to calibrate certain model parameters as described below.

statistic. Both methods use simulation methods to construct a minimum distance criterion function. In addition, the test-statistic inversion method uses simulation to acquire parameter-dependent critical values for the inversion exercise. In other words, for a given parameter value, we simulate the process to determine the distribution of our criterion function test statistic and hence the critical value for that parameter value. Our interval estimator then consists of the set of parameter values whose associated test statistics (when constructed with the real data) are less than the parameter-specific critical value.

We also present methods to investigate how well the individual-level dynamics implied by our estimated model match those of individuals. We evaluate how well the individual spell distributions implied by our point estimate of the model match those from retrospective $CPS$ data.[13] In addition to being of interest in their own right, individual-level spell distributions are a good diagnostic to understand the shortcomings of the model. They are more informative than measures of model fit in the cross section as they are more transparently related to model parameters than cross-sectional statistics. We also present descriptive methods to illustrate the implications of model estimates by computing Impulse Response Functions (IRFs), both in time and in space, to local adverse employment shocks. This allows us to study, for instance, how long it takes for a certain neighborhood to climb out of a high unemployment situation, or how much a negative shock can propagate to nearby areas.

The rest of this paper is organized as follows. Section 2 describes the model. Section 3 describes our calibration, estimation, and model evaluation strategies. Section 4 reports our empirical results for this application. Finally, we offer some conclusions and suggestions for future research in Section 5.

# 2 Model

Our model is an extension of the information exchange model in Topa (2001). There is a finite set of agents $M$ in the model, residing in a finite set of locations $s \in S \subset \Re^2$. A subset $M_s$ of agents resides at each location $s$; and they remain at these locations over time. Agents are allowed to be heterogeneous in race/ethnicity and education. We allow three racial/ethnic groups corresponding to a partition of the population into African American, with indicator $A_i$; Hispanic with indicator $H_i$; and White (includes Asian and all others) with indicator $W_i$. An indicator $X_i$ of high/low education status further characterizes each agent and corresponds to college education status. Time flows discretely from 0 to $\infty$ in the model. The state of agent $i$ at time $t$, $y_{i,t}$, is her employment status: $y_{i,t} \in \{1, 0\}$, where 1 represents the employed state and 0

[13] As we will discuss in Section 3.3, the data provide information on the length of in-progress unemployment spells for respondents who are currently unemployed, sampled at a given point in time. We replicate this sampling scheme in our simulations.

the unemployed state. Therefore, the state of the system at each point in time is a configuration of employment states $y_t \in \mathcal{Y} \equiv \{1, 0\}^M$.

The evolution of the system is ruled by the following conditional transition probabilities for the state of each agent $i$, given the configuration of the system in the previous period. As mentioned above, in principle one would like to allow agents to receive information from her social contacts while both employed and unemployed, but with a varying intensity of network use in each state. In particular, one could assume that agents expand their set of social contacts while unemployed. In a fully endogenous model of network choice, agents would optimally choose to broaden their individual networks for two reasons: first, the value of an additional referral is higher while unemployed;[14] second, the individual agent's cost of time is likely to be lower while unemployed.[15]

In the present paper, we take the extreme modeling stand of reducing the number of active contacts (from whom agent $i$ could receive referrals) to zero while employed. Specifically, we only allow transitions out of unemployment to be affected by one's network contacts, whereas transitions out of employment are affected by one's personal characteristics alone. We do so in order to be able to calibrate the parameters of the latter transition probabilities with $CPS$ data, as detailed in Section 3. In fact, were we to allow both transitions to depend on the state of an agent's contacts, it would be much harder to separately identify the parameters involved in each set of transition probabilities, and at the same time it would be impossible to calibrate a subset of these parameters (as we do here) with $CPS$ data because the latter lack any information about individual networks.

Therefore, we specify probabilities for transitions into unemployment as depending only on agents' characteristics, race/ethnicity and education:

$$\begin{aligned}\Pr(y_{i,t+1} &= 0|y_{i,t} = 1; A_i, H_i, X_i) = \\ &\Lambda\left[(\alpha_{1A} + \alpha_{2A}X_i)A_i + (\alpha_{1H} + \alpha_{2H}X_i)H_i + (\alpha_{1W} + \alpha_{2W}X_i)W_i\right].\end{aligned} \tag{1}$$

where $\Lambda(\cdot) = \exp(\cdot)/(1 + \exp(\cdot))$.

In contrast, the probability that an unemployed agent finds a job depends both on own characteristics and on information flows concerning job opportunities, that she receives from her currently employed social contacts at time $t$. Formally, information received by agent $i$ in location $s$ is assumed to be a function of the number of employed individuals in her set of neighbors $N_i$. The details of the individual network construction are described in Section 3.1. We distinguish the number of employed individuals of an individual's own race/ethnicity from those of the other two groups using the notation $I_{i,t}^{Own}$ and $I_{i,t}^{Other}$. This allows us to investigate the possibility that

[14] Even allowing for on-the-job search, an additional link is likely to be more valuable while unemployed if one's reservation wage while unemployed is lower than while currently holding a job.

[15] Granovetter (1995) contains empirical evidence in support of our assumption. He finds that many new jobs were found through contacts that were activated specifically during one's job search while unemployed.

information flow may depend on race/ethnicity. The precise definitions of $I_{i,t}^{Own}$ and $I_{i,t}^{Other}$ when agent $i$ is African American are:

$$I_{i,t}^{Own} \equiv \sum_{j \in N_i} y_{jt} \times A_j \text{ and } I_{i,t}^{Other} \equiv \sum_{j \in N_i} y_{jt} \times (1 - A_j). \tag{2}$$

The values of $I_{i,t}^{Own}$ and $I_{i,t}^{Other}$ are analogously defined for members of the remaining two racial/ethinic partitions. We define the transition probabilities into employment for African Americans as:[16]

$$\begin{aligned} \Pr(y_{i,t+1} &= 1 | y_{i,t} = 0; A_i = 1, X_i) = & (3) \\ & \Lambda\left[\beta_A + \gamma_A X_i + \lambda_A^{Own} \cdot I_{i,t}^{Own} + \lambda_A^{Other} \cdot I_{i,t}^{Other}\right] & (4) \end{aligned}$$

The transitions for the other two racial/ethnicity groups are parameterized analogously with group-specific $\beta, \gamma, \lambda^{Own}$ and $\lambda^{Other}$.

The model defined above generates a first-order Markov process $y_t$ with state space $\mathcal{Y}$ of configurations over the set of locations. It can be easily shown that a stationary distribution exists and is unique, for any choice of agents' characteristics. However, we do not have a closed form solution for it. The stationary distribution of unemployment is characterized by positive spatial correlations.

# 3 Empirical Methods

We use a mix of calibration and estimation in our analysis. We estimate the model parameters using its implications for the stationary distribution of cross-sectional tract-level unemployment rates. Using only the information in the stationary distribution, the model's $\alpha$ and $\gamma$ parameters are not separately identified for certain values of $\lambda$. In particular, these parameters are not separately identified for the natural base case with no social interactions for any racial/ethnic group, $\lambda^{Own} = \lambda^{Other} = 0$. With $\lambda$ non-zero we conjecture that $\alpha$ and $\gamma$ are identified due to the model's nonlinearity and the addition of a continuous regressor. However, we think it would likely be too much to ask of our cross section to estimate $\alpha$ and $\gamma$ in practice. Our intuition that job-loss transitions are likely to depend much less on social contacts than job-finding transitions makes the calibration of $\alpha$ from individual-level data the natural choice for a calibration.

Therefore we use individual spell data from the $CPS$ to calibrate the $\alpha$ parameters for each of the six race and education combinations. Notice that in order to do so it is

[16] These transition probabilities implicitly assume that labor demand in the city is perfectly elastic. When labor demand is less than perfectly elastic, the total number of vacancies should affect the probability of exiting unemployment. So for example, if a group is largely unemployed, this makes it easier for another group to find jobs (abstracting from skill differentials, job types, etc). We thank Ken Arrow for pointing this out to us.

crucial that the transition probabilities while employed be only a function of individual characteristics and not of the state of agents' contacts. In fact, if the transition probabilities in (1) included a social interactions term, two intertwined difficulties would arise: on the one hand, separate identification of the $\alpha$, $\gamma$ and $\lambda$ parameters would become much more tenuous; on the other hand, it would be impossible to calibrate the $\alpha$ parameters from the $CPS$ (or, say, the publicly available version of the $NLSY$) because such data would lack any information on the composition and current state of individual networks.

## 3.1 Calibration

**Agents and Individual Networks**

The configuration of agents and their characteristics are calibrated to 1990 Census data for the Los Angeles Primary Metropolitan Statistical Area (PMSA), which coincides with Los Angeles County. The set $S$ contains 1622 locations determined by the latitude and longitude coordinates for centroids of 1622 of the 1643 census tracts in this PMSA.[17] The number of agents of each race/ethnicity at location $s$ corresponds to the population of adults (16+ years of age) of that race/ethnicity in the 1990 census divided by 100, rounded up. So, for example, tract number 2317, in South Central Los Angeles had 5921 adult residents: 63 Whites, 1788 African Americans, and 4070 Hispanics. In our model, the corresponding location has 60 agents: 1 White, 18 African American, and 41 Hispanic. The distribution of $X_i$ across agents is separately calibrated within each tract–level race/ethnicity group. For each racial/ethnic group in each tract, the fraction of agents with $X_i = 1$ is set equal to the reported proportion of those with college attainment in the 1990 census, if it can be expressed using the available integer ratios. If available integer ratios could not match the proportion exactly, we randomized between the two closest integer ratios to the census data proportion so that the expected proportion of college-educated agents matched the census data proportion.[18] This calibration resulted in a total of $69,832$ agents. The number of agents across tracts ranges from 8 to a maximum of 203, with a median of 39. Figure 1 reports histograms of the distribution of persons (16+ years) and artificial agents across tracts.

Our specification for agents' information networks, $N_i$, is based on their locations. Each agent $i$ is randomly assigned links to ten other agents, based upon the following algorithm. The set $S$ of all locations is partitioned into three subsets: the agent's own location $s_i$, the four nearest neighbors of $s_i$, and the complement of all locations in $S$ other than $s_i$ and its four nearest neighbors. Each individual link is drawn

[17] We dropped 21 of the 1643 census tracts in the Los Angeles PMSA due to their very low populations.

[18] For example, if 21 of the 63 whites in tract 2317 had a college education, then the 1 white agent in the corresponding model location would have been randomly assigned X=1 with probability 1/3 and X=0 with probability 2/3.

in two steps, the first of which is to randomly select among these subsets of $S$ with probabilities 65%, 34%, and 1%, respectively. This amounts to choosing the candidate pool of contacts from which this link will be established. Then an agent from the selected subset is drawn with a uniform probability and linked with agent $i$. Links are drawn without replacement and considered to be unidirectional so each agent has exactly ten links and when agent $i$ is linked with agent $j$, $j$ will not always be linked with $i$. We use the notation $N_i$ to refer to the set of ten agents linked to agent $i$. Agents' employment transitions are assumed to depend only upon the states of the first-order neighbors in $N_i$.

The motivation for this choice of network structure comes from a rich sociology literature on social networks. Evidence from the General Social Survey strongly suggests that individual networks used to discuss important matters rarely exceed a size in the single digits (see Marsden (1987,1988)). We use ten contacts as a rough approximation. Further, in a study of Toronto inhabitants in the 1980s, Wellman (1996) finds that a surprisingly high fraction of interactions (about two thirds) took place among people who lived less than 5 miles apart. We use his findings to roughly calibrate the parameters used in our network algorithm. Finally, allowing agents to draw contacts from locations far away with small probability is motivated both by Wellman (1996) and by Granovetter's work. Granovetter (1973) lays out a theoretical argument for the importance of weak bridging ties for the diffusion of information and the birth of successful social movements.[19] Granovetter (1995) empirically documents the importance of such weak ties in job finding, using data for a sample of workers in the Boston metropolitan area.

As mentioned in the Introduction, even if a majority of social ties are local and only a few are long ties, the median path length is quite small in our model. Here path length is defined as the minimum number of "steps" that are necessary in order to reach agent $B$ starting from agent $A$, using individual social contacts at each step. Figure 2 reports the histogram of the distribution of path lengths for a sample of $3,000$ pairs drawn from our set of individual agents. The median path length turns out to be six, and the maximum is ten. This 'small worlds' feature is crucial in our setting in that it induces strong dependence across observations in the cross section.

**One to Zero Transition Calibration**

We calibrate the model parameters $(\alpha_{1A}, \alpha_{2A}, \alpha_{1H}, \alpha_{2H}, \alpha_{1W}, \alpha_{2W})$ using individual transition data from the $CPS$. Each household in the $CPS$ is interviewed once per month during two sets of four consecutive months, usually during the third week of the month.[20] The data contains an indicator of whether the respondent was em-

[19] In a striking example, Granovetter studies two working-class communities in Boston in their attempts to mobilize against urban renewal projects: the one in which weak ties were more prevalent was much more successful at reaching effective social coordination.

[20] Each month, $CPS$ field representatives attempt to collect data from the sample units during the week of the 19th.

ployed or unemployed during the week prior to each interview.[21] We treat months as though they have exactly 4 weeks and proceed as though each pair of consecutive months provides data on an individual's employment state at week $t$ and week $t+4$. We calibrate a weekly transition rate from employment to unemployment from this data, ignoring potential quick transitions back to employment between $t$ and $t+4$. In effect, we assume that no unemployment to employment transitions occur between $t$ and $t+4$. With this imposed, letting $\delta$ denote the weekly employed to unemployed transition probability, the conditional probability of an individual being unemployed in week $t+4$ given she was employed at $t$ is

$$\delta + \delta(1-\delta) + \delta(1-\delta)^2 + \delta(1-\delta)^3 . \tag{5}$$

We separately calibrate $\delta$ for all six race/ethnicity and college education combinations so that expression (5) equals the sample frequency of unemployed individuals at $t+4$ who were employed at $t$.

## 3.2 Estimation

**Point Estimation**

After calibrating $\alpha$, we use a simulation method to obtain point estimates of the remaining parameters.[22] We estimate the full parameterization of zero to one transition rates with local interactions in equation (3). Therefore, the vector of model parameters $\theta_0$ is defined as $\theta_0 \equiv \left[\beta_A, \gamma_A, \lambda_A^{Own}, \lambda_A^{Other}, \beta_H, \gamma_H, \lambda_H^{Own}, \lambda_H^{Other}, \beta_W, \gamma_W, \lambda_W^{Own}, \lambda_W^{Other}\right]$ and is assumed to be in the interior of some compact parameter space $\Theta \subset \Re^{12}$.

We obtain minimum distance parameter estimates using three sets of moments, one for each group: African Americans, Hispanics, and Whites. For each group, we use these cross sectional empirical moments: the average of the tract-level unemployment rate; the sample variance of the tract-level unemployment rate; and the average sample covariances of tract-level unemployment rates between tracts whose centroids are between .25 to 1.75, 2.25 to 3.75, and 5.25 to 6.75 km apart. We stack these empirical cross-sectional moments in a vector $\Psi_t$ with a total of 15 elements. For each candidate parameter value $\theta$, we use simulations to determine the expectation of $\Psi_t$ with respect to its stationary distribution when $\theta$ is the true parameter value: $E_\theta \Psi$.[23] We then obtain a point estimate of $\theta_0$ by minimizing the (quadratic form or

[21] The precise wording of the employment question is: "Last week, did you do any work for either pay or profit? Did you have a job either full or part time? Include any job from which you were temporarily absent." If the respondent answers 'Yes' to either, she is counted as *employed*. The precise wording of the unemployment question is: "Last week, were you on layoff from a job? Have you been doing anything to find work during the last 4 weeks?" If the respondent answers 'Yes' to both, she is counted as *unemployed*.

[22] There exists a vast literature on simulation-based estimation methods. Two excellent examples are Gourieroux et al. (1993) and Tauchen (1997).

[23] For a given value of $\theta$, the model is simulated starting from a configuration with all agents em-

chi-squared) distance between $E_\theta \Psi$ and $\Psi_t$. The estimator $\widehat{\theta}$ is defined as:

$$\widehat{\theta} = \arg\min_{\Theta} J(\theta) \equiv (\Psi_t - E_\theta \Psi)^\top \Omega(\theta)^{-1} (\Psi_t - E_\theta \Psi), \tag{6}$$

where $\Omega(\theta)$ is an estimate of the variance-covariance matrix of $\Psi_t$ under the stationary distribution implied by $\theta$.We use a simulated annealing algorithm to minimize the objective criterion over $\Theta$. This algorithm is particularly robust to the possible presence of multiple local optima and/or discontinuities in the objective function.[24]

**Interval Estimation**

The usual large-sample approximations taking limits as the time span grows are of course infeasible with only one observation $\Psi_t$. However, a test-statistic inversion approach can still deliver valid confidence interval estimates.[25] Under the null hypothesis that the true value of the parameter is $\theta$, we can simulate the distribution of $\Psi$, construct the analog of $J(\theta)$ for each of a large number of simulated draws of $\Psi$, and hence obtain an approximation of the stationary distribution of the test statistic $J(\theta)$ that is arbitrarily precise. Let $c_\theta$ denote an appropriate critical value from this simulated $J(\theta)$ distribution, e.g. its 95th percentile. A confidence set for $\theta_0$ can then be defined as the set of all $\theta$ values in the parameter set where $J(\theta)$ using the real data is less than its corresponding critical value $c_\theta$. Of course we only approximate this confidence set using a finite number of $\theta$ values and for this method to work well in practice, $c_\theta$ and $J(\theta)$ will need to be smooth in $\theta$. Given the relatively large dimension of our parameter space, a simple grid search would be quite costly. Instead, we compute test statistics and critical values along the path of $\theta$ values considered by our simulated annealing algorithm in its search for $\widehat{\theta}$ which should provide good coverage of the areas of the parameter space with low $J(\theta)$. These points are augmented with randomly drawn points from the areas of the parameter space not frequented by the annealing algorithm, those with relatively high values of $J(\theta)$.[26]

It is important to note that our confidence set need not contain $\widehat{\theta}$. One way this could happen is because the confidence set itself is empty, none of the points in the parameter space appear consistent with the data (this is in fact what happens in our application). It can also happen however, when the confidence set is nonempty. Because we have parameter-specific critical values, it is possible that $J(\widehat{\theta}) > c_{\widehat{\theta}}$ even though the test statistic is below its critical value for other values of $\theta$.

ployed for 200 periods, to attempt to reach the stationary distribution. Then, a total of 50 simulated configurations of employment $y$ are skip-sampled every 12 periods thereafter and the resulting $\Psi$ are averaged to approximate $E_\theta \Psi$. The skip-sampling is done to obtain plausibly independent draws so as to keep down the number of $\Psi$ that need to be computed from $y$ realizations since this is quite costly.

[24] We thank Bill Goffe for kindly providing the Matlab SIMANN code to us.

[25] Examples of confidence interval estimation via inversion of this type of test statistic in situations with large-sample results include Hansen, Heaton, and Yaron (1996) and Hu (2002).

[26] In practice, we use 14 intermediate $\theta$ values along the path followed by the simulated annealing algorithm, augmented by 512 randomly drawn values close to the edges of the "hypercube" formed by considering a lower and an upper bound for each element of $\theta$.

Obtaining confidence sets by inverting this test statistic would still be our our prefered method even if we had access to a long time series of $\Psi_t$. This is because it works even withouth point identification of $\theta_0$ and it is difficult to formally show that the moment equations $E_\theta \Psi$ identify $\theta_0$. If there are solutions to the moment equations other than $\theta_0$, then asymptotically the confidence interval will not converge to a point $\theta_0$ but rather to a set of all the solutions. Nevertheless, this confidence set can still be very informative. See Hu (2002) for an application of this test statistic approach in a very different application where parameters may not be point identified.

## 3.3 Evaluation and Illustration

**Evaluation Based on Individuals' Employment Spells**

We use data from the $1988-90$ March files of the Current Population Survey ($CPS$) for individuals in the Los Angeles PMSA to investigate the empirical plausibility of our models' estimated spell distributions.[27] In particular we compare the distributions of in-progress unemployment spells for agents in each racial/ethnic group from our model with spells for observations from the corresponding racial/ethnic group in the $CPS$.

The first set of comparisons we perform consists of plotting specific moments of the empirical distribution of spells in progress against the histogram of the distribution of those moments generated by 400 simulations of the model at the point estimates. In particular, we consider the percentage of spells that last between 1 and 4 weeks, 5 to 9 weeks, 10 to 18 weeks, and 19 weeks or more. These fractions are defined as a vector of moments $\xi$. We perform a very long simulation of our model at the estimated parameter values and draw 400 separate samples of spells (drawn sufficiently apart as to ensure independence across draws). We then compute the above moments both for the empirical spell distribution derived from the $CPS$ data $(\widehat{\xi})$, and for each simulated distribution (indexed by $k$) generated by our model $(\widetilde{\xi}_k)$. Finally, we plot each element of $\widehat{\xi}$ against the histogram generated by the distribution of the corresponding element of $\widetilde{\xi}_k$, $k = 1, ..., 400$. These plots provide a visual test of whether the selected moments of the empirical unemployment spell distribution can be plausibly generated by our model at the point estimates.

The second set of comparisons uses the same set of 400 simulated spell distributions but focuses on $CDFs$. Here we compute the $CDF$ corresponding to the empirical spell distribution $\left(\widehat{F}(x) \equiv \Pr(\widehat{x} < x),\ x = 1, ..., 99\right)$ – where $x$ denotes the spell length in weeks – to the $CDFs$ derived from each of the 400 simulated

[27] We use three separate waves of the CPS in order to have a sufficient number of currently unemployed persons in our sample. The total sample size is 14,490 observations: out of these, a total of 389 were unemployed at the time of the interview. The overall unemployment rate in the Los Angeles area was roughly the same (around 5.3%) during this period, suggesting that business cycle conditions were fairly stable.

distributions $\left(\widetilde{F}_k(x) \equiv \Pr(\widetilde{x}_k < x),\ x = 1, ..., 99\right)$.[28] Then, for each of the values of $x$ at which the $CDFs$ are computed, we calculate $\widetilde{F}_{\min}(x) \equiv \min_k \widetilde{F}_k(x)$ and $\widetilde{F}_{\max}(x) \equiv \max_k \widetilde{F}_k(x)$. We then plot the empirical $CDF$, $\widehat{F}(\cdot)$, against the lower and upper bounds $\widetilde{F}_{\min}(\cdot)$ and $\widetilde{F}_{\max}(\cdot)$ generated by our simulations. Again, the purpose is to see whether the empirical spell distribution can be plausibly generated by our model.

**Illustration Via Impulse Response Functions ($IRFs$)**

In order to better illustrate the implications of our parameter estimates, we also report simulations of $IRFs$ to various kinds of localized negative shocks to employment. The thought experiment consists of forcing employment rates to zero in a given area for either four or 26 weeks, and recording the contemporaneous and subsequent responses both in the initial area and in a sequence of four concentric rings around that area. The initial shock area is defined as all Census tracts within $r$ Km. of the centroid of a previously selected tract, $s_0$. The first concentric ring is defined as all tracts whose centroids lie at a distance $r < d < r + \rho$ from the centroid of $s_0$; the second ring includes all tracts at distances $r + \rho < d < r + 2\rho$, and so on.

The employment rates over tracts in the initial shock area and in all concentric rings are recorded for a total of 112 weeks (two years following the end of the shorter shock). The $IRFs$ are computed as averages of these employment rates across 30 independent simulation runs of the same shock, using the estimated parameter values. We try different kinds of shocks, by varying the size of the initial affected area and the location of the area itself: in particular, we use areas with different education levels to see whether they respond differently to negative employment shocks.

# 4 Results

Table 1 reports summary statistics. There is a large Hispanic presence in Los Angeles, accounting for about one third of the population over 16 years of age. Hispanics tend to have the highest median unemployment rate (by Census tract), and the lowest percentage of adults (25 years and older) with at least a college degree. Conversely, Whites have the lowest median unemployment rate and the highest education levels.[29] Figure 3 reports non-parametric estimates of the spatial Auto-Correlation Function (ACF) for total unemployment, as well as for unemployment conditional on race.[30] There is a substantial amount of spatial correlation in the data. Interestingly, the correlation is much lower once one conditions on race: this is consistent with our

[28] The spell length $x$ is top-coded at 99 weeks in the $CPS$.

[29] Notice that the average unemployment rate is 7.5%, which is higher that the average unemployment rate for individuals reported in the CPS. This is because we are taking the average over tract-level unemployment rates.

[30] The autocovariance at distance $\delta$ is estimated by a local average of cross-products of de-meaned observations that are close to $\delta$ units apart. See Conley and Topa (2002) for details.

findings for the city of Chicago reported in Conley and Topa (2002).

Table 2 reports our point estimates for the model parameters, $\theta$. Column A reports our calibrated parameters in the logit index for the transitions from employment (1) to unemployment (0), for our six racial/ethnic group and college education category combinations (equation (1)). Column B reports the estimated parameter values for the terms in the logit index for the 0 to 1 transition, equation (3). The point estimates imply reasonable transition probabilities from unemployment into employment, with a positive effect of education and of information, both from one's own group and from others. The estimates of $\left(\lambda_i^{Own}, \lambda_i^{Other}\right)$, $i = A, H, W$, indicate that agents are affected more by information received by members of different groups than by information from one's own group: for African Americans and Hispanics this may suggest that members of these groups benefit more from interactions with Whites than with members of their own group, but the result is implausible for Whites given their overall attachment to the labor force.[31] We conjecture that one explanation might be the possibility that inter-group social ties tend to be of the weak sort, whereas intra-group ties tend to be strong: as we have argued, there is ample evidence that weak ties are more effective at disseminating new information than strong ones.

Our interval estimation results indicate that the model is rejected by the data. The confidence set is empty: at our point estimates $\widehat{\theta}$, the critical values $c_{\widehat{\theta}}$ are 81.74, 102.3, and 171.61 for the $90th$, $95th$, and $99th$ percentiles of the simulated distribution of $J\left(\widehat{\theta}\right)$. In contrast, the value of the minimized criterion $J\left(\widehat{\theta}\right)$ using the real data is 743.65. The gap between the critical values and the $J(\cdot)$ statistic is similar or higher at all other points in the parameter space that we sample. Nevertheless, the point estimates are still interesting as they are the closest model to the data. In what follows, we wish to understand what specific aspects of the model are incompatible with the data. Therefore, we compare additional aspects of the data to those of the model at $\widehat{\theta}$.

The empirical correlations of unemployment across tracts are compared to their simulated counterparts in Table 3. We compute the simulated spatial moments generated by the model at each of 50 independent draws from the stationary distribution at the estimated parameter values. We then compare the empirical correlations with the lower and upper bounds of the corresponding simulated moments across the 50 samples. While the range of model correlations can bracket the empirical ones for Whites and African Americans, it cannot for Hispanics or total unemployment.

Our evaluation and illustration exercises are reported in Figures $4-6$ and $7-8$, respectively. The left column of Figure 4 shows the empirical distribution of in-progress unemployment spells measured with $CPS$ data. The right column reports a representative model realization at the estimated parameter values. As is quite clear simply from a visual inspection, the model generates too few short spells and too

[31] Our point estimates are consistent with the own-information effect being strongest for Whites, and with the other-information effect being strongest for African Americans.

many long spells, with the possible exception of African Americans.

Figure 5 contains our first set of comparisons described above. For total unemployment, the empirical moments of the spell distribution are consistent with the distribution of simulated moments from the model for intermediate length spells (5 to 9 and 10 to 18 weeks), but are definitely inconsistent for both very short and long spells. Again, the model generates too few short spells and too many long spells relative to the data. The same pattern holds true for White and Hispanic unemployment. For African Americans on the other hand, all four empirical moments could have been conceivably drawn from the corresponding marginal distribution generated by the model.

Figure 6 contains the second set of comparisons and confirms our previous results. The empirical CDF is stochastically dominated by both the lower and the upper bounds of the simulated CDFs for total unemployment, Whites, and Hispanics. On the other hand, the simulated bounds contain the empirical CDF of unemployment spells for Blacks.

With regard to our illustration of the model's properties via IRFs to negative local shocks, we have performed several experiments, varying the location and the size of the initial shock area within the Los Angeles $PMSA$. We report here two such experiments: one involves a shock area centered around a very poor Census tract in South Central Los Angeles; the other is based on an initial shock area centered around a middle-class Census tract in the North Western part of the metropolitan area. The former area has much lower education levels than the latter. The two shock areas contain approximately the same number of tracts and the width of each concentric ring is set at 300 meters.

Figure 7 reports the IRFs for the South Central shock. The first thing to notice is that both the 4 week and the 26 week shocks take about two years to be fully absorbed. The second observation is that the negative shock does not travel very far to adjacent areas: the fourth concentric ring (which lies approximately one Km. away from the edge of the initial shock area) is hardly affected by the negative shock. On the other hand, the first three rings do register an increase in expected unemployment rates, ranging from a little less than two to about three percentage points.

The IRFs for the North Western shock are depicted in Figure 8. Again it takes roughly two years for the shocks to be fully absorbed in the initial area, and the surge in unemployment does not travel far on average in physical space. Further, the size of the response in the adjacent rings is smaller than in the South Central area. This is consistent with the asymmetric nature of the information spillovers found by Topa (2001). Since college education has a positive effect on the index that determines the probability of exiting unemployment, the relative size of the social interaction effect is smaller for higher educated workers. Therefore, an area that has relatively more college educated workers will tend to be relatively less affected by a nearby negative labor shock, at least with respect to the information spillover propagation channel that we explore here.

# 5 Conclusion

In this paper we present a set of calibration, estimation and evaluation methods that are useful to empirically assess a particular class of local interactions models. Agent in these models have transition probabilities that depend on the state of a finite number of neighbors. We consider a specific application to urban unemployment, where agents receive information about job opportunities from their employed social contacts. Our model endows agents with a fairly rich individual network structure that takes seriously the empirical findings of a large sociological literature on social networks. We also take a first step at endogenizing agents' networks by allowing agents to vary the number of contacts across employment states: this is consistent with the job search literature with endogenous search effort.

A key feature of our network structure is that agents may have ties with other agents that do not live close to them within the metro area. Even a low probability of such long ties implies that the median path length between any two agents in the model is very small. An important consequence of this feature is that a cross section of data should be modeled as having strong dependence across observations in the limit. Thus our task is to draw inference about a time series DGP from a single observation of a vector time series. We present a minimum distance estimator to obtain point estimates, and a test-statistic inversion method to directly obtain interval estimates.

Our estimation results indicate that the model is rejected by the data. Therefore, we also present evaluation and illustration methods that can be used to analyze the performance of the model at the point estimates, and to highlight the dimensions along which the model fails to match the data. In particular, we study the spatial correlations of unemployment across tracts and the distribution of individual in-progress unemployment spells. The main results are that the model generates weaker spatial correlations among Hispanics than in the data and it tends to produce too few short spells and too many long spells relative to the data.

Finally, we perform an illustration exercise to describe the IRFs to localized negative employment shocks, again at the point estimates. Here the main result is that negative shocks take a fairly long time (roughly two years) to be fully absorbed, but travel relatively little in space. Interestingly, the size of the spillover effect to contiguous areas is smaller for areas with relatively more educated workers, since this type of workers is less dependent on information exchanges to find employment. This exercise is meant only as an illustration of the sort of propagation analyses that one could carry out if information were available on the size and the duration of actual local shocks, and on the segments connecting place of residence and place of work for all workers.

We plan to extend the present work in several ways. We plan to study the way in which the model behavior changes as one varies several parameters of the network construction algorithm. More formally, we wish to search over network parameters, such as the size of the individual networks or the probability of drawing contacts from each of the three candidate pools. In addition, we need to better understand the nature of the long unemployment spells implied by the model at the point estimates; in particular, the extent to which they are spatially clustered and/or recurrent in relatively isolated areas of the network.

One important possible reason for the over-abundance of long spells generated by the model is that in the model we only allow transitions between employment and unemployment, but not into and out of the labor force. In the data, a worker who is experiencing a very long unemployment spell is likely to exit the labor force. This transition tends to reduce the length of the actual spells observed in the data. We plan to estimate this model with employed and not-employed states with the latter being the union of unemployed and out of the labor force. While maintaining a two-state representation of labor force outcomes, this definition of the two states might be preferable as it aggregates rather than omit the out of the labor force state.

Finally, we would like to move away from our extreme assumption regarding the number of social contacts while employed and unemployed. However, this is not a straightforward extension as it involves allowing for social interaction effects in the transition into unemployment as well as into employment, which complicates the analysis with regard to the identification and estimation of the model parameters.

# References


[1] Aaronson, Daniel (1998), "Using Sibling Data to Estimate the Impact of Neighborhoods on Children's Educational Outcomes", *Journal of Human Resources*, Vol. 33 (4), 915-46.

[2] Bala, Venkatesh and Sanjeev Goyal (1998), "Learning from Neighbours", *Review of Economic Studies,* Vol. 65, 595-622.

[3] Banerjee, Abhijit V. (1992), "A Simple Model of Herd Behavior", *Quarterly Journal of Economics,* Vol. 107, 797-817.

[4] Benabou, Roland (1993), "Workings of a City: Location, Education, and Production", *Quarterly Journal of Economics,* Vol. 108, 619-652.

[5] Benabou, Roland (1996), "Equity and Efficiency in Human Capital Investment: The Local Connection", *Review of Economic Studies*, Vol. 63, 237-264.

[6] Bertrand, Marianne, Erzo F.P. Luttmer and Sendhil Mullainathan (2000), "Network Effects and Welfare Cultures", *Quarterly Journal of Economics,* Vol. 115 (3), 1019-55.

[7] Bikhchandani, Sushil, David Hirshleifer and Ivo Welch (1992), "A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades", *Journal of Political Economy,* Vol. 100, 992-1026.

[8] Bisin, Alberto, Andrea Moro and Giorgio Topa (2003), "On the Empirical Implications of Models with Multiple Equilibria", unpublished manuscript, NYU.

[9] Brock, William A. and Steven N. Durlauf (2001), "Discrete Choice with Social Interactions", *Review of Economic Studies,* Vol. 68, pp. 235-260.

[10] Brock, William A. and Steven N. Durlauf (forthcoming), "Interactions-Based Models", in *Handbook of Econometrics,* Vol. V, James J. Heckman and Edward Leamer, Eds.

[11] Burdett, Kenneth and Dale T. Mortensen (1980), "Search, Layoffs, and Labor Market Equilibrium", *Journal of Political Economy,* Vol. 88 (4), 652-72.

[12] Calvo-Armengol A. and MO Jackson (forthcoming), "Social Networks in Determining Employment and Wages: Patterns, Dynamics and Inequality", *American Economic Review.*

[13] Case, Anne C. and Lawrence F. Katz (1991), "The Company You Keep: the Effects of Family and Neighborhood on Disadvantaged Youths", NBER Working Paper no. 3705.

[14] Coleman, James S., E. Campbell, J. Hobson, J. McPartland, A. Mood, F. Weinfeld, and R. York (1966), *Equality of Educational Opportunity,* Washington D.C.: US Government Printing Office.

[15] Conley, Timothy G. (1999), "GMM Estimation with Cross Sectional Dependence", *Journal of Econometrics,* Vol. 92, pp. 1-45.

[16] Conley, Timothy G. and G. Topa (2002), "Socio-Economic Distance and Spatial Patterns in Unemployment", *Journal of Applied Econometrics,* Vol. 17 (4), 303-27.

[17] Conley, Timothy G. and G. Topa (2003), "Identification of Local Interaction Models with Imperfect Location Data", *Journal of Applied Econometrics.*

[18] Corcoran, Mary, Linda Datcher and Greg Duncan (1980), "Information and Influence Networks in Labor Markets", in *Five Thousand American Families: Patterns of Economic Progress*, edited by Greg Duncan and James Morgan, vol. 7, pp. 1-37, Ann Arbor, MI: Institute For Social Research.

[19] Crane, Jonathan (1991), "The Epidemic Theory of Ghettos and Neighborhood Effects on Dropping Out and Teenage Childbearing", *The American Journal of Sociology,* vol. 96, no. 5, 1226-1259.

[20] Durlauf, Steven N. (1996a), "A Theory of Persistent Income Inequality", *Journal of Economic Growth,* Vol. 1, 75-93.

[21] Durlauf, Steven N. (1996b), "Neighborhood Feedbacks, Endogenous Stratification, and Income Inequality", in *Dynamic Disequilibrium Modelling: Proceedings of the Ninth International Symposium on Economic Theory and Econometrics,* W. Barnett, G. Gandolfo, and C. Hillinger, eds., Cambridge University Press.

[22] Gale, Douglas and Robert W. Rosenthal (1999), "Experimentation, Imitation, and Stochastic Stability", *Journal of Economic Theory,* Vol. 84 (1), 1-40.

[23] Glaeser, Edward L., Bruce Sacerdote, and José A. Scheinkman (1996), "Crime and Social Interactions", *Quarterly Journal of Economics,* vol. 111, 507-548.

[24] Glaeser, Edward L. and José A. Scheinkman (2003), "The Social Multiplier", *Journal of the European Economic Association,* Vol. 1 (2-3), 345-53.

[25] Gouriéroux, C., A. Monfort, and E. Renault (1993), "Indirect Inference", *Journal of Applied Econometrics,* vol. 8, S85-S118.

[26] Granovetter, Mark S. (1973), "The Strength of Weak Ties", *American Journal of Sociology,* Vol. 78 (6), 1360-1380.

[27] Granovetter, Mark S. (1995), *Getting a Job: A Study of Contacts and Careers,* Cambridge, MA: Harvard University Press.

[28] Hansen Lars, John Heaton and Amir Yaron (1996), "Finite Sample Properties of Some Alternative GMM Estimators", *Journal of Business and Economic Statistics*, Vol. 14, 262-280.

[29] Harris, Theodore E. (1974), "Contact Interactions on a Lattice", *The Annals of Probability,* vol. 2, 969-988.

[30] Hu, Luojia (2002), "Estimation of a Censored Dynamic Panel Data Model", *Econometrica,* Vol. 70, No. 6, 2499-2517.

[31] Ioannides, Yannis M. and Linda Datcher Loury (1999), "Job Information Networks, Neighborhood Effects and Inequality", unpublished manuscript, Dept. of Economics, Tufts University.

[32] Jencks, Christopher and Susan E. Mayer (1990), "The Social Consequences of Growing Up in a Poor Neighborhood", in *Inner-City Poverty in the United States,* edited by L. Lynn and M. McGeary, Washington, D.C.: National Academy Press, 111-186.

[33] Katz, Lawrence F., Jeffrey Kling and Jeffrey Liebman (2001), "Moving To Opportunity in Boston: Early Results of a Randomized Mobility Experiment", *Quarterly Journal of Economics,* vol. 116 (2), 607-54.

[34] Liggett, Thomas M. (1985), *Interacting Particle Systems,* New York: Springer Verlag.

[35] Liggett, Thomas M. (1999), *Stochastic Interacting Systems: Contact, Voter and Exclusion Processes,* New York: Springer Verlag.

[36] Lin, Nan, Paul Dayton and Peter Greenwald (1978), "Analyzing the Instrumental Use of Relations in the Context of Social Structure", *Sociological Methods and Research,* Vol. 7 (2), 149-166.

[37] Lin, Nan, Walter M. Ensel and John C. Vaugh (1981), "Social Resources and Strength of Ties: Structural Factors in Occupational Status Attainment", *American Sociological Review,* Vol. 46, 393-405.

[38] Ludwig, Jens, Greg J. Duncan and Paul Hirschfield (2001), "Urban Poverty and Juvenile Crime: Evidence from a Randomized Housing-Mobility Experiment", *Quarterly Journal of Economics,* vol. 116 (2), 655-79.

[39] Manski, Charles F. (1993), "Identification of Endogenous Social Effects: the Reflection Problem", *Review of Economic Studies,* Vol. 60, pp. 531-542.

[40] Marsden, Peter V. (1987), "Core Discussion Networks of Americans", *American Sociological Review*, Vol. 52, pp. 122-131.

[41] Marsden, Peter V. (1988), "Homogeneity in Confiding Relations", *Social Networks,* Vol. 10, pp.57-76.

[42] Montgomery, James D. (1991), "Social Networks and Labor-Market Outcomes: Toward an Economic Analysis", *The American Economic Review,* vol. 81, no. 5, pp. 1408-1418.

[43] Morris, Stephen (2000), "Contagion", *Review of Economic Studies,* Vol. 67 (1), 57-78.

[44] Munshi, Kaivan and Jacques Myaux (2002), "Social Change and Individual Decisions: With an Application to the Demographic Transition", unpublished manuscript, University of Pennsylvania.

[45] Nakajima, Ryo (2003), "Measuring Peer Effects in Youth Smoking Behavior", unpublished manuscript, New York University.

[46] Rees, Albert and George P. Schultz (1970), *Workers and Wages in an Urban Labor Market,* Chicago: Univ. of Chicago Press.

[47] Tauchen, George (1997), "New Minimum Chi-Square Methods in Empirical Finance", in *Advances in Economics and Econometrics: Theory and Applications: Seventh World Congress,* D.M. Kreps and K.F. Wallis, eds., Cambridge University Press.

[48] Topa, Giorgio (2001), "Social Interactions, Local Spillovers, and Unemployment", *Review of Economic Studies,* Vol. 68, pp. 261-295.

[49] Travers, Jeffrey and Stanley Milgram (1969), "An Experimental Study of the Small World Problem", *Sociometry,* Vol. 32 (4), 425-443.

[50] Watts, Duncan J. (1999), *Small Worlds: The Dynamics of Networks between Order and Randomness*, Princeton: Princeton University Press.

[51] Watts, Duncan J. and Steven H. Strogatz (1998), "Collective Dynamics of 'Small-World' Networks", *Nature,* 393, 440-442.

[52] Weinberg, Bruce, Patricia Reagan and Jeffrey Yankow (forthcoming), "Do Neighborhoods Affect Hours Worked: Evidence from Longitudinal Data", *Journal of Labor Economics.*

[53] Wellman Barry (1996), "Are Personal Communities Local? A Dumptarian Reconsideration", *Social Networks,* Vol. 18, 347-354.

[54] Young, H. Peyton (2001), "The Dynamics of Conformity", in *Social Dynamics,* S.N. Durlauf and H.P. Young, eds., Cambridge, MA: MIT Press.

[55] Zax, Jeffrey S. and Daniel I. Rees (2002), "IQ, Academic Performance, Environment, and Earnings", *Review of Economics and Statistics,* Vol. 84 (4), 600-616.