Dynamic Properties of Local Interaction Models

Timothy G. Conley, University of Chicago  
Giorgio Topa, New York University*

September 24, 2002

Abstract

This paper analyzes a local interaction model of urban unemployment defined at the level of individual agents. Census tract level data are used to estimate the model parameters by matching empirical moments of the spatial distribution of unemployment in the Los Angeles SMSA with their simulated counterparts. Then, the length of a period in the model is calibrated by matching simulated individual unemployment spells with data from the March CPS. This allows us to study the speed of convergence to the stationary distribution, and the Impulse Response Functions (in time and space) to local shocks.

JEL: J64, R12, C21.

Keywords: Local interactions, spatial econometrics, unemployment.

*The authors are grateful to Ken Arrow, Alberto Bisin, Steven Durlauf, Chuck Manski and participants at the Santa Fe Institute conference on Economy as an Evolving System III for helpful comments. Ryo Nakajima provided excellent research assistance. Conley gratefully acknowledges financial support from the NSF. Giorgio Topa gratefully acknowledges financial support from the NSF and from the C.V. Starr Center for Applied Economics at NYU. The authors are of course responsible for all errors. Corresponding author: Giorgio Topa, Dept. of Economics, New York University, 269 Mercer Street, NY, NY 10003. Giorgio.Topa@nyu.edu.
1 Notes for an Introduction

This paper aims at studying the dynamic behavior of local interaction models in the context of urban unemployment. In general, the existing literature has focused on the cross-sectional properties of the limiting distribution of local interaction models: this is the case, for example, in Glaeser et al. (1996), Brock and Durlauf (1995), Blume and Durlauf (1998). However, little research has been done to study the dynamic properties of the processes generated by these models.

We focus on two sets of issues, using a specific model of local interactions. First, we study several “macro-level” properties of the stochastic process: namely, the speed of convergence to the stationary distribution; Impulse Response Functions (IRFs) – in time and in space – to local shocks; persistence of unemployment clusters. Second, we examine the “micro-level” performance of the model by conducting the following evaluation exercise: having estimated the model using cross-sectional data at the Census tract level, we look at how well the model fits the empirical distribution of unemployment spell durations for individual agents.

These questions are analyzed using the following approach. We propose a model of local information exchanges and social interactions in urban unemployment, defined at the level of individual agents arranged on a set of locations with an explicit distance metric. In the model, agents are heterogeneous with respect to race and ethnicity, and education levels. We also allow information received from one’s own ethnic group to have a differential impact on one’s employment chances than information received from members of other groups. Then, using 1990 Census data for Los Angeles County, we estimate the structural parameters of the model, by matching moments of the empirical cross-sectional distribution of unemployment across Census tracts with their simulated counterparts from the model, at the stationary distribution.

At this stage, we calibrate the length of a period in the model by matching the median length of individual unemployment spells generated by the model at the estimated parameter values, with the actual median spell length from the March Current Population Survey (CPS). Calibration via individual employment spells is necessary here since the actual length of a time period is not identified by the stationary distribution. This is where we perform our evaluation exercise. Having estimated the model using cross-sectional moments only, we use the estimated parameter values to generate a simulated sample of individual level unemployment spells. We then study how well the model performs in matching the properties of the empirical distribution of unemployment spell durations from the March CPS.1

Once we have calibrated the length of a period in the model, we can examine the “macro-level” dynamic properties of our model in three ways. First, we study the speed of convergence of the stochastic process generated by the model towards

---

1As we will discuss in Section 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.
its stationary distribution. It is important to determine how long social interaction effects take to play themselves out, in order (for example) to verify the appropriateness of typical assumptions on fixed covariates over time and on the absence of endogenous mobility by agents. In particular, we use Census information on the mobility rates of neighborhood residents to determine whether or not neighborhood composition remains fairly stable in the time it takes the model to reach its invariant distribution.

Second, we compute IRFs, in time and in space, to study the propagation properties of a given exogenous shock to employment. Different types of shocks can be considered here, e.g. using information on labor demand fluctuations that can be derived from data on cyclical movements in employment at different establishments. These exercises can advance our understanding of the dynamics that govern the rise and fall of neighborhoods, and the way in which social pathologies can spread over neighboring areas in a city.

Finally, we analyze the persistence properties of the unemployment clusters generated by the stationary distribution of our process. Do these clusters tend to remain localized in certain portions of the map of the city over time, or do they move around? Once a given geographic area enters a high unemployment state, does the area tend to remain “locked” in this situation for a long time? Moreover, one would expect that the local feedback caused by social interactions makes such clusters more persistent than if local interactions were absent. The model permits one to isolate the portion of the expected duration of a given cluster that is due purely to social interactions.

Preliminary estimation results suggest that positive local spillovers are present. Further, these local spillovers appear to be stronger within than across ethnic communities: information received from neighbors of a different ethnic group has a much smaller impact than information received by neighbors of the same group. This is again consistent with a social interaction story, given the extent of assortative matching in social networks that has been widely documented. Finally, the effectiveness of additional social contacts in generating employment opportunities exhibits decreasing returns.

The model evaluation exercise indicates that while the model does very well at matching the cross-sectional moments of unemployment across Census tracts, it performs less well on another dimension, namely at matching the empirical distribution of individual unemployment spells. Nonetheless, the model is able to reproduce the qualitative features of this distribution. Finally, the simulated IRFs seem to indicate that a local negative labor demand shock travels fairly little in space (up to about two kilometers away from the initial area), and is absorbed within about two quarters from the end of the negative shock.

\[2\] See, for example, Marsden (1987), (1988).
2 Model

The model is an extension of the information exchange model in Topa (2001). Agents are assumed to exchange information about job opportunities within their social networks. In particular, useful tips or referrals are transmitted by currently employed agents to their unemployed contacts, in the expectation of receiving similar tips when unemployed. Such information exchanges may be viewed as informal mutual insurance arrangements that are sustainable even in the presence of limited commitment.

There is a finite set of agents $M$ in the model, residing in a finite set of locations $s \in S \subset \mathbb{R}^2$. A subset $M_s$ of agents resides at each location $s$; these subsets form a partition of $M$. Locations are fixed, in the sense that agents cannot move from one location to another over time. Each agent $i$ in location $s$ is characterized by a type $f_i = 1, \ldots, k, \ldots, K$ (denoting race or ethnicity), and by a vector of characteristics $X_{ks}$ that are assumed to be constant over time. Notice that characteristics vary by agent type and/or location, so all agents of type $k$ in location $s$ are ex-ante identical, and will vary only with respect to their employment outcomes.

Time flows discretely from 0 to $\infty$ in the model. The state of each agent at time $t$, $y_{it}$, is her employment status: $y_{it} \in E \equiv \{1, 0\}$, where 1 represents the employed state and 0 the unemployed state. Therefore, the state of the system at each point in time is a configuration of employment states $y_t \in Y \equiv E^M$.

A distance metric $d(r, s)$ is defined over the set of locations $S$ for any pair of locations $(r, s)$. In this paper, we focus on physical distance between agents, but in general one can use other metrics that take into account, for example, travel time between locations, differences in language spoken, religious affiliation, ethnicity, or occupation between agents, along the lines of Conley and Topa (2002). For each agent $i$ in location $s$ the set of neighbors $N_s$ is defined as $N_s \equiv \{j : d(s, s_j) \leq d\}$, where $s_j$ denotes the location where agent $j$ lives. Notice that $N_s$ includes other agents in the same location $s$ as agent $i$.

The evolution of the system is ruled by the following conditional transition probabilities for the state of each agent $i$ of type $k$ in location $s$, given the configuration of the system in the previous period. An individual can become unemployed with a probability that depends on her characteristics and possibly on characteristics of the

---

3Essentially, the model is a version of the contact process, which was first studied by Harris (1974) and belongs to a large family of Interacting Particle Systems. See Liggett (1985), (1999) for an excellent mathematical treatment of this and other models, including the Ising model, the voter model and the exclusion process.

4In the empirical application, these locations correspond to Los Angeles PMSA Census tracts, and agents in $M_s$ are assumed to all reside at the centroid of tract $s$ (since we do not have information about individual locations within a tract).

5The underlying assumption is that the process through which individuals lose and find jobs takes place at a higher frequency than the process that rules agents’ locational choices. This issue will be discussed further in what follows.
area in which she resides, $X_{ks}$:  

$$p_d \equiv \Pr(y_{i,t+1} = 0|y_{it} = 1; X_{ks}) = \frac{\exp \left[ \alpha_0^k + \alpha_1 X_{ks} \right]}{1 + \exp \left[ \alpha_0^k + \alpha_1 X_{ks} \right]}. \quad (1)$$

On the other hand, the probability of finding a job depends both on own characteristics $X_{ks}$ and on information flows $I_{st}^k$ and $I_{st}^{-k}$, concerning job opportunities, that she receives from her currently employed social contacts at time $t$. Formally, information received by a type $k$ agent in location $s$ is assumed to be a strictly increasing and concave function $f(\cdot)$ of the number of employed individuals in her set of neighbors $N_s$: 

$$I_{st}^k \equiv f \left( \sum_{j \in N_s, f_j = k} y_{jt} \right); \quad I_{st}^{-k} \equiv f \left( \sum_{j \in N_s, f_j \neq k} y_{jt} \right) \quad (2)$$

where $f(0) = 0$, $f'(\cdot) > 0$, $f''(\cdot) < 0$. In the empirical implementation, we will use a power function: $f(x) = x^\xi$, $\xi \in (0, 1)$. We distinguish between $I_{st}^k$ and $I_{st}^{-k}$ to allow for the possibility that an agent of type $k$ may be affected differentially by information received from neighbors of the same type $k$ as opposed to neighbors of a different type ($-k$).

Then, we define the transition probability into employment as:  

$$p_u \equiv \Pr(y_{i,t+1} = 1|y_{it} = 0; y_{-i,t}, X_{ks}) = \frac{\exp \left[ g \left( I_{st}^k, I_{st}^{-k}, X_{ks} \right) \right]}{1 + \exp \left[ g \left( I_{st}^k, I_{st}^{-k}, X_{ks} \right) \right]}, \quad (3)$$

where 

$$g \left( I_{st}^k, I_{st}^{-k}; X_{ks} \right) \equiv \gamma_0^k + \gamma_1 X_{ks} + \lambda_0^k \left( I_{st}^k + \delta \cdot I_{st}^{-k} \right)$$

and $\delta$ measures the extent to which information from other groups $I_{st}^{-k}$ affects one’s employment chances differently than information from one’s own group $I_{st}^k$. We assume that $\delta$ is common across groups to limit the number of parameters to be estimated.

Notice that we are letting the intercepts $\alpha_0^k$ and $\gamma_0^k$ vary across groups, but we are constraining the slope parameters $(\alpha_1, \gamma_1)$ to be the same across groups. In principle, we could also allow the $\lambda$ contagion parameter to depend on individual/area characteristics $X_{ks}$. All these restrictions are imposed for computational ease and may be relaxed and tested in the future.

---

6In practice, we are going to use the education level of agents of type $k$ at location $s$.

7These 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.
The model defined above generates a first-order Markov process $y_t$ with state space $Y$ of configurations over the set of locations. It is straightforward to show that a stationary distribution exists and is unique, for a given choice of individual and local characteristics $X_{ks}$. The stationary distribution of unemployment is characterized by positive spatial correlations, that are bounded above by a quantity decreasing in the distance between agents. However, it is hard to characterize the invariant distribution analytically: that is why one uses simulation-based estimation methods, such as Simulated Method of Moments or an indirect inference methodology.

In the estimation, one takes as given the spatial distribution of the $X$ covariates, as determined by sorting of individuals across locations, and simulates the model conditionally on this until the system reaches its invariant distribution. Then the structural parameters are estimated by comparing the empirical distribution of unemployment in the data with simulated realizations of the stationary distribution of the model. Simulations are performed by drawing every period a vector $\zeta_t$ of shocks from $M$ uniform distributions on $[0, 1]$. Then the state of each agent in the model is updated according to the realization of $\zeta_{it}$, using the conditional transition probabilities in equations (1) and (3). These random shocks to employment may be modeled as spatially independent, or may follow a spatially auto-regressive structure, to mimic the potential effects of correlated unobservables.

3 Data

We use two separate data sets in the empirical exercise. The first comes from the Census Bureau 1990 decennial census, Summary File STF3a, while the second is drawn from the 1988 - 90 March file of the Current Population Survey (CPS). Both data sets refer to the same geographic area, namely the Los Angeles Primary Metropolitan Statistical Area (PMSA), which coincides with Los Angeles County.

The first data set contains summary statistics, at the Census tract level, for Los Angeles County, based on the 100% count data. There are 1643 Census tracts in Los Angeles County. These data are used to estimate the structural parameters of the model. For each tract, we have detailed information on a variety of socio-demographic characteristics, including: number of tract residents by race and ethnicity; age distribution by race and ethnicity; employment rate by race and ethnicity; education by race and ethnicity; characteristics of the housing stock, including median housing values and median gross rents. It is crucial that, even though these are summary statistics, employment and education information is broken down by race and ethnicity, since in our model agents are characterized by type-$k$-specific covariates, and may be affected differentially by their neighbors’ employment outcomes, depending on whether or not they are members of the same group.

The second data set is used to calibrate the length of a period in the model. In

---

*It is easy to show that the Markov chain is irreducible and aperiodic.
particular, we use information on the length of current unemployment spells for respondents who are currently unemployed, sampled at a given point in time. Note that this does not yield the empirical distribution of unemployment spell durations, since only spells in progress are sampled, and individuals with longer spell durations tend to be oversampled. However, this is not a problem since we can sample “artificial” spells in exactly the same way in our model simulations. Again, we supplement unemployment spell information with demographic information about respondents, specifically race, ethnicity and educational attainment.

4 Empirical Methodology

We take the following steps in order to empirically implement the model. First, locations $S$ are taken to correspond to Los Angeles PMSA Census tracts, and agents in each subset $M_s$ are assumed to all reside at the centroid of tract $s$ (since we do not have information about individual locations within a tract). The physical distance in kilometers between the centroids of any two tracts $r$ and $s$ is used as a measure of the distance $d(r,s)$. The radius $\bar{d}$ that determines the set of neighbors $N_s$ for agents in tract $s$ is set at two kilometers.\(^{10}\)

Agent types $f_i$ are assumed to represent race and ethnicity. To reduce the computational burden, we focus on three groups ($K = 3$): Asians and Non-Hispanic Whites, Blacks, Hispanics. A finer classification may be used in future work. Also for computational ease, we use a single covariate $X_{ks}$, namely the percentage of tract residents with at least a college degree (for each group $k$).

From model simulations, it appears that one cannot separately identify the $\{\alpha_k^0\}_{k=1}^K$ and the $\{\gamma_0^k\}_{k=1}^K$ intercepts in the probabilities of entering and exiting unemployment. Therefore, we calibrate the $\{\alpha_k^0\}_{k=1}^K$ parameters using individual level data from the CPS.\(^{11}\) Thus, the vector of model parameters $\theta$, defined as $\theta \equiv \left[ \alpha_1, \{\gamma_0^k\}_{k=1}^K, \gamma_1, \{\lambda_0^k\}_{k=1}^K, \delta, \xi \right]$ has 10 elements: $\theta \in \Theta \subset \mathbb{R}^{10}$.

The model is defined at the level of individual agents within each location $s$. In order to simulate the model, we create a set of “artificial agents” $\bar{M}$ and distribute them over the set of actual Census tracts according to the empirical distribution of

\(^9\)We use three separate waves, 1988, 1989, and 1990, 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, 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.

\(^{10}\)A histogram of the distribution of pairwise distances between tracts for LA County is reported in the top panel of Figure 1. The bottom panel reports the distribution of the number of neighboring tracts included in $N_s$, for agents residing in each tract $s$: the median number of tracts is 7.

\(^{11}\)More specifically, we use a sample of respondents for whom we have employment information for two consecutive months in order to compute the empirical probability of being unemployed at $t+1$, conditional on being employed at $t$.\(^7\)
persons (16 years and older) over Los Angeles County, by race and ethnicity. Each artificial agent in our simulations represents about 100 real people. So, for example, tract number 2317, in South Central LA, had 5921 residents over 16 years of age (from the 1990 Census): 63 Asians and Non-Hispanic Whites, 1788 Blacks, 4070 Hispanics. In our simulated world, the same tract has 60 artificial agents: one of type \( k = 1 \), 18 of type \( k = 2 \), and 41 of type \( k = 3 \). The median number of artificial agents (across simulated tracts) is 39, and the distribution of agents across tracts ranges from one to a maximum of 203.\(^{12}\) Each agent of type \( k \) in location \( s \) is endowed with the level of educational attainment \( X_{ks} \) obtained from the 1990 Census data.

The structural parameters \( \theta \) are estimated using a minimum distance criterion: essentially, we minimize the distance (according to a statistical metric) between a set of empirical moments \( \hat{\psi} \) from the empirical spatial distribution of employment across Census tracts and the corresponding simulated moments \( \tilde{\psi}(\theta) \). The estimator \( \hat{\theta} \) is defined as:

\[
\hat{\theta} = \arg \min_{\theta} \left( \hat{\psi} - \tilde{\psi}(\theta) \right)^\top \Omega \left( \hat{\psi} - \tilde{\psi}(\theta) \right),
\]

where \( \Omega \) is a weighting matrix.\(^{13}\)

In practice, for a given value of \( \theta \), the model is simulated starting from a configuration with all agents employed (the initial condition does not matter since the stationary distribution is unique) for 100 periods, to attempt to reach the stationary distribution. Then, a simulated configuration of employment \( \tilde{y} \) is sampled and simulated moments \( \tilde{\psi}(\theta) \) are computed for that \( \theta \). 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.\(^{14}\)

With respect to our choice of moments for \( \psi \), we have chosen a set of first and second order moments of the spatial distribution of employment rates \( Y_{sk} \) across tracts \( s \) and types \( k \), defined as \( Y_{sk} \equiv \frac{1}{|M_s|} \sum_{i \in M_s, f_i = k} y_i \). In particular, we use the mean and variance of \( Y_k \) across tracts, and the spatial correlation of \( Y_k \) evaluated at specific distances. Thus, the vector of moments to be matched is

\[
\psi \equiv \left[ \mu(Y_k), \sigma(Y_k), \rho_{d_1}(Y_k), \rho_{d_2}(Y_k) \right],
\]

where \( \rho_{d_j}(Y_k) \) denotes the spatial correlation of employment rates \( Y_{sk} \) for tracts at distance \( d_j \) from each other.\(^{15}\)

---

\(^{12}\)Overall, there are a little over 68,000 artificial agents in our simulated world. Figure 2 compares the distribution of artificial agents across tracts with that of actual persons 16 years and older.

\(^{13}\)The optimal weighting matrix is \( \Omega^* = V^{-1} \), where \( V \) is the covariance matrix

\[
E \left\{ \left[ \hat{\psi} - \tilde{\psi}(\theta) \right] \left[ \hat{\psi} - \tilde{\psi}(\theta) \right]^\top \right\}.
\]

For this preliminary draft, we have used the simplest weighting matrix possible, \( \Omega = I \).

\(^{14}\)We thank Bill Goette for kindly providing the Matlab SIMANN code to us.

\(^{15}\)These spatial correlations are estimated non-parametrically using a Gaussian kernel (see Conley...
It is difficult to formally show that the model parameters $\theta$ are identified, given our choice of moments $\psi$. However, Conley and Topa (forthcoming) examine the question of local identification for a similar local interaction model (albeit a simpler one), defined at the level of individual agents, when the data used for estimation are only available at the level of spatial aggregates, such as tracts or zip codes: this is exactly the situation we face in this paper. Numerical simulations are strongly suggestive that local identification is attained in this case. Therefore, we are confident that local identification is preserved in the present setup.

Finally, we calibrate the length of a period in our simulations in the following way. We simulate the process generated by our model at the estimated parameter values $\hat{\theta}$. We draw a random sample of artificial agents, after the process has reached its invariant distribution, isolate the currently unemployed agents, and record for each agent $i$ the number of periods $w_i$ for which $i$ has been unemployed. This procedure yields a distribution of unemployment spells in progress that corresponds to the empirical one derived from the March CPS data set, given its sampling scheme. We then calibrate the length of a period by comparing the median simulated spell length with its empirical counterpart.\(^{16}\)

\section{Estimation 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, Asians and Non-Hispanic Whites have the lowest median unemployment rate and the highest education levels. Figure 3 contains histograms of the distribution of unemployment rates across tracts, by race and ethnicity.

Figure 4 reports non-parametric estimates for the spatial Auto-Correlation Functions (ACFs) of the employment rate, by ethnic group, as a function of physical distance across tracts.\(^{17}\) For all groups, there exists a positive amount of spatial correlation at distances close to zero, that decays towards zero as distance increases. One can also test for the null hypothesis of spatial independence using a bootstrap technique. These positive spatial correlations are consistent with our local information exchange model.

Table 2 reports the estimation results from the minimization of (4). These are very

---

\(^{16}\)Notice that because the process generated by our model is a first-order, finite-state Markov chain, the invariant distribution is independent of the time scale. In other words, we do not need to define a time scale for our process to estimate $\theta$.

\(^{17}\)Essentially, the autocovariance at distance $d_j$ is estimated by a local average of cross-products of de-meaned observations that are close to $d_j$ units apart. See Conley and Topa (2002) for details.
preliminary results, and no standard errors have been computed yet. The estimated parameter values seem quite reasonable. First, $\hat{\alpha}_1$ is negative and $\hat{\gamma}_1$ is positive, suggesting that an increase in education levels lowers the probability of entering unemployment and increases the probability of finding a job. Second, the estimated “contagion” parameters $\hat{\lambda}_k^0$ are positive for all $k$.

A third interesting result is that $\hat{\delta}$ is roughly two thirds, i.e. less than unity: this parameter measures the extent to which information received from members of a different racial/ethnic group have a differential impact on one’s probability of finding a job than information received from one’s own group. Therefore, the local interaction effect is weaker across ethnic communities than within them: this is consistent with our interpretation of the local spillovers as being generated by social interactions, as opposed to other possible correlated effects. Finally, $\hat{\xi}$ is equal to about one third: this implied that $f(\cdot)$ in equation (2) is quite concave, i.e. that there are decreasing returns in the effectiveness of one additional social contact in raising one’s probability of finding a job.

Figure 5 compares ACF estimates using the actual data $y$ with those derived from simulated $\tilde{y}$ at the estimated parameter values $\hat{\theta}$: the fit is quite good. Overall, the model seems to fit the spatial moments of the cross-sectional distribution of unemployment across Census tracts very well.

6 Calibration and Simulations

In this Section, we first calibrate the actual length of a period in the model by matching the median unemployment spell length from the 1988 – 90 March CPS for the Los Angeles PMSA with the median simulated spell length, at the estimated parameter values. We then proceed to evaluate the micro-level performance of the model in fitting the empirical distribution of individual spells. Finally, we examine the macro-level dynamic properties of the model through simulations at the estimated parameter values.

Table 3 reports summary statistics for the empirical distribution of unemployment spell durations obtained from the 1988 – 90 March CPS data (as defined in Section 3). Overall, the median spell length is six weeks, whereas the mean length is 11.9 weeks. For all groups, the distribution of spell lengths is very skewed to the right. Blacks have the highest mean and median spell lengths.

In order to calibrate the length of a period in our model, we simulate the process for 1,000 periods, at the estimated parameter values $\hat{\theta}$. We then draw 14,490 agents at a given period, broken down by race and ethnicity using the same proportions as the CPS sample we try to match. Within the simulated sample, 1441 agents are currently unemployed: we measure the length of their current unemployment spell up to the period in which they were sampled. The median simulated spell length for our artificial agents is 44 periods. Therefore, using the median length, our calibration
suggests that one period in the model corresponds to roughly one day in ‘real’ time.

6.1 Micro-level Model Evaluation

Figure 6 compares the distributions of actual and simulated unemployment spells, both in total and broken down by ethnic group. The model seems to be able to reproduce the qualitative features of the empirical distribution fairly well, although the shape of the overall distribution (and that for Asians and NH Whites) is still quite far from the empirical one. In later drafts this comparison will be made more formally using non-parametric tests. Therefore, while the model does quite well in matching cross-sectional moments of the tract-level distribution of unemployment, it performs less well in this other dimension, namely in fitting individual level unemployment spell lengths. This is perhaps not surprising given the relatively simple structure of the employment-unemployment transition probabilities.

6.2 Macro-level Dynamic Properties

6.2.1 Speed of Convergence

[...TO BE CONTINUED...]

6.2.2 Impulse Response Functions to Local Shocks

Local unemployment shocks are simulated in the following way. We take as initial area all census tracts whose centroids are within one kilometer of the centroid of tract #2317, in South Central LA: there are 13 such tracts. We then draw four concentric rings around this initial area, defined as follows. The first ring includes all tracts at distance between one and two Km. from the central tract (18 tracts), the second ring includes all tracts at distance between two and three Km. from the central tract (25 tracts), and so on. The last ring includes tracts up to five Km. away from the initial tract.

We simulate the process generated by our model, at the estimated parameter values, for 200 iterations. Then, we start tracking employment rates in the initial area and in the four concentric rings for 420 periods: given our calibration, this corresponds to roughly 60 weeks. After four weeks, we hit the initial area with a negative unemployment shock of varying length (four and twenty-six weeks, respectively): in other words, all agents within this initial area are unemployed during these periods. After these temporary shocks, the process is allowed to run until the end of the sixty weeks. Thus, we can plot IRFs to the temporary negative shock both over time and over space, as it propagates to the outer rings.

Figure 7 shows the results of this experiment (again, these are very preliminary
results). Figures 8 and 9 report the results using alternative ‘rings’ configurations.\textsuperscript{18} The initial unemployment shock seems to travel fairly little in space: a negative employment response relative to the “no shock” situation is present only up to about two Km from the edge of the initial area. In time, the negative shock seems to be absorbed within two quarters from the end of the shock.

6.2.3 Persistence of Unemployment Clusters

[... TO BE CONTINUED... ]

\textsuperscript{18}The initial area has a radius of two Km, and each concentric ring has a width of 0.5 and 0.3 Km, respectively.
References


<table>
<thead>
<tr>
<th>Statistic</th>
<th>Mean</th>
<th>Median</th>
<th>Std. Dev.</th>
<th>Min. Value</th>
<th>Max. Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Persons 16 Years and Older</td>
<td>4123.2</td>
<td>3890</td>
<td>1812.5</td>
<td>2</td>
<td>20294</td>
</tr>
<tr>
<td>Percentage Asians &amp; Non-Hispanic Whites</td>
<td>57.77</td>
<td>67.46</td>
<td>31.06</td>
<td>0.00</td>
<td>100.00</td>
</tr>
<tr>
<td>Percentage Blacks</td>
<td>11.66</td>
<td>2.84</td>
<td>20.57</td>
<td>0.00</td>
<td>94.65</td>
</tr>
<tr>
<td>Percentage Hispanics</td>
<td>32.13</td>
<td>23.60</td>
<td>26.26</td>
<td>0.00</td>
<td>100.00</td>
</tr>
<tr>
<td>Unemployment Rate (Total)</td>
<td>7.49</td>
<td>6.42</td>
<td>4.74</td>
<td>0.00</td>
<td>47.07</td>
</tr>
<tr>
<td>Unemployment Rate (Asians &amp; N.H. Whites)</td>
<td>5.75</td>
<td>4.60</td>
<td>5.31</td>
<td>0.00</td>
<td>59.09</td>
</tr>
<tr>
<td>Unemployment Rate (Blacks)</td>
<td>9.42</td>
<td>6.43</td>
<td>12.67</td>
<td>0.00</td>
<td>100.00</td>
</tr>
<tr>
<td>Unemployment Rate (Hispanics)</td>
<td>8.07</td>
<td>7.93</td>
<td>5.52</td>
<td>0.00</td>
<td>50.57</td>
</tr>
<tr>
<td>Percent with at least College Degree (Total)</td>
<td>22.10</td>
<td>18.33</td>
<td>16.31</td>
<td>0.00</td>
<td>100.00</td>
</tr>
<tr>
<td>Percent with at least College Degree (Asians &amp; N.H. Whites)</td>
<td>28.15</td>
<td>25.43</td>
<td>16.04</td>
<td>0.00</td>
<td>100.00</td>
</tr>
<tr>
<td>Percent with at least College Degree (Blacks)</td>
<td>24.14</td>
<td>18.16</td>
<td>24.23</td>
<td>0.00</td>
<td>100.00</td>
</tr>
<tr>
<td>Percent with at least College Degree (Hispanics)</td>
<td>11.90</td>
<td>7.10</td>
<td>12.88</td>
<td>0.00</td>
<td>100.00</td>
</tr>
</tbody>
</table>

N = 1,643 Census Tracts, Los Angeles County (Los Angeles PMSA)
# TABLE 2a
Structural Estimation Results

<table>
<thead>
<tr>
<th>Estimate</th>
<th>S.E.</th>
<th>P - value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prob. of losing one's job: alpha_0 (AW)</td>
<td>-4.026 *</td>
<td></td>
</tr>
<tr>
<td>Prob. of losing one's job: alpha_0 (BL)</td>
<td>-2.666 *</td>
<td></td>
</tr>
<tr>
<td>Prob. of losing one's job: alpha_0 (HO)</td>
<td>-3.761 *</td>
<td></td>
</tr>
<tr>
<td>Prob. of losing one's job: alpha_1</td>
<td>-14.352</td>
<td></td>
</tr>
<tr>
<td>Prob. of finding a job: gamma_0 (AW)</td>
<td>-17.570</td>
<td></td>
</tr>
<tr>
<td>Prob. of finding a job: gamma_0 (BL)</td>
<td>-9.954</td>
<td></td>
</tr>
<tr>
<td>Prob. of finding a job: gamma_0 (HO)</td>
<td>-11.694</td>
<td></td>
</tr>
<tr>
<td>Prob. of finding a job: gamma_1</td>
<td>12.985</td>
<td></td>
</tr>
<tr>
<td>Own-group information: lambda_0 (AW)</td>
<td>7.392</td>
<td></td>
</tr>
<tr>
<td>Own-group information: lambda_0 (BL)</td>
<td>4.690</td>
<td></td>
</tr>
<tr>
<td>Own-group information: lambda_0 (HO)</td>
<td>5.624</td>
<td></td>
</tr>
<tr>
<td>Other-groups information: delta</td>
<td>0.693</td>
<td></td>
</tr>
<tr>
<td>Information parameter: xi</td>
<td>0.320</td>
<td></td>
</tr>
</tbody>
</table>

*: Calibrated from CPS data

# TABLE 2b
Empirical vs. Simulated Moments

<table>
<thead>
<tr>
<th></th>
<th>Empirical</th>
<th>Simulated</th>
</tr>
</thead>
<tbody>
<tr>
<td>Own Auto-Correlation (3 Km.): AW</td>
<td>0.120</td>
<td>0.123</td>
</tr>
<tr>
<td>Own Auto-Correlation (6 Km.): AW</td>
<td>0.098</td>
<td>0.076</td>
</tr>
<tr>
<td>Mean(Employment Rate): AW</td>
<td>0.942</td>
<td>0.950</td>
</tr>
<tr>
<td>Std. Dev.(Employment Rate): AW</td>
<td>0.053</td>
<td>0.088</td>
</tr>
<tr>
<td>Own Auto-Correlation (3 Km.): BL</td>
<td>0.127</td>
<td>0.134</td>
</tr>
<tr>
<td>Own Auto-Correlation (6 Km.): BL</td>
<td>0.082</td>
<td>0.083</td>
</tr>
<tr>
<td>Mean(Employment Rate): BL</td>
<td>0.905</td>
<td>0.943</td>
</tr>
<tr>
<td>Std. Dev.(Employment Rate): BL</td>
<td>0.127</td>
<td>0.158</td>
</tr>
<tr>
<td>Own Auto-Correlation (3 Km.): HO</td>
<td>0.313</td>
<td>0.313</td>
</tr>
<tr>
<td>Own Auto-Correlation (6 Km.): HO</td>
<td>0.266</td>
<td>0.264</td>
</tr>
<tr>
<td>Mean(Employment Rate): HO</td>
<td>0.919</td>
<td>0.954</td>
</tr>
<tr>
<td>Std. Dev.(Employment Rate): HO</td>
<td>0.055</td>
<td>0.079</td>
</tr>
</tbody>
</table>
TABLE 3  
Unemployment Spell Lengths, Los Angeles PMSA, 1988-90 March CPS

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Unemployment Spell Length (Total)</td>
<td>11.86</td>
<td>16.71</td>
<td>3</td>
<td>6</td>
<td>12</td>
<td>1</td>
<td>99</td>
<td>389</td>
</tr>
<tr>
<td>Unemployment Spell Length (Asians &amp; N.H. Whites)</td>
<td>13.50</td>
<td>18.66</td>
<td>3</td>
<td>6</td>
<td>16</td>
<td>1</td>
<td>99</td>
<td>144</td>
</tr>
<tr>
<td>Unemployment Spell Length (Blacks)</td>
<td>16.07</td>
<td>19.61</td>
<td>4</td>
<td>12</td>
<td>20</td>
<td>2</td>
<td>99</td>
<td>31</td>
</tr>
<tr>
<td>Unemployment Spell Length (Hispanics)</td>
<td>10.17</td>
<td>14.58</td>
<td>3</td>
<td>6</td>
<td>12</td>
<td>1</td>
<td>99</td>
<td>215</td>
</tr>
</tbody>
</table>

Sample of in-progress unemployment spells, measured at a given point in time. Each cell reports spell lengths in weeks. Spell lengths are top-coded at 99 weeks.
Distribution of pairwise distances between Census tracts

Distribution of the number of neighboring tracts in $N_s$, for each tract $s$
Distribution of persons 16 years and older across tracts (1990 Census)

Distribution of artificial agents across tracts
Distribution of Unemployment Rate across Census tracts: Asians & N.H. Whites

Distribution of Unemployment Rate across Census tracts: Blacks

Distribution of Unemployment Rate across Census tracts: Hispanics