Dynamic Properties of Local Interaction Models

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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.

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1 Introduction

Local interactions models in economics can be defined as models in which agents' preferences, information, choices or outcomes are affected by other agents' behavior *directly*, rather than being mediated by markets. A common assumption in these models is that individuals interact *locally*, with a set of neighbors defined by a social or economic distance metric.

The relevance of local interactions 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. (1999) and Ludwig et al. (1999) use the Moving To Opportunity (MTO) program as a natural experiment to evaluate the magnitude of neighborhood effects. Bertrand et al. (1999) find that local social networks have a significant impact on individual welfare participation. Weinberg et al. (forthcoming) find significant neighborhood effects in hours worked using detailed panel data from the NLSY.[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: Aaronson (1996) exploits data on siblings that grew up in different communities; Hanushek et al. (2000) use very detailed data on Texan schools to estimate peer effects in student achievement; Zax and Rees (1999) use a Wisconsin Longitudinal Study to estimate the impact of peer influences during school years on subsequent earnings. Sacerdote (2001) uses a natural experiment (randomized assignment of roommates at Dartmouth college) to find evidence of peer effects in a variety of outcomes.

At a theoretical level, several authors have analyzed the role of local interactions and externalities in models of endogenous growth, income inequality, and neighborhood formation: Benabou (1993), (1996), Durlauf (1996a,b), Fernandez and Rogerson (1996). These models share a common assumption that human capital accumulation is affected by choices and characteristics of local community members. There exists also a rich theoretical literature that considers local interactions in models of information cascades, such as Banerjee (1992) and Bikhchandani et al. (1992); models of learning from neighbors (Bala and Goyal (1998), Gale and Rosenthal (1999), Morris (1997)); the emergence of conformity and social norms (Young (2001), Munshi and Myaux (2002)); and models of inter-dependent preferences as in Becker (1996), Bell

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

(1995), and Kockesen et al. (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.

In more applied work, knowledge spillovers, input-output linkages, and other economies of agglomeration have been used in the new economic geography literature to explain the observed patterns of spatial concentration of firms in a given industry (see Rauch (1993), Audretsch and Feldman (1996), and Ellison and Glaeser (1997)), the observed growth rates in cities (as in Glaeser et al. (1992)), or the presence of temporal "lumping" in the process that determines the spread of a given industry from one country to another (Puga and Venables (1996)). Evidence of local information exchanges and knowledge spillovers determining the adoption and diffusion of new social norms has been reported by Munshi and Myaux (2002), Jaffe et al. (1993), and Kohler (1997).

Finally, the importance of informal contacts and information networks in the job search process has been empirically documented in a growing economics and sociology literature. An early study of the Chicago labor market by Rees and Schultz (1970) finds that informal sources such as referrals from current employees accounts for about half of all white collar hires and for about four fifths of blue collar hires. Granovetter (1974, 1995) finds that roughly 56% of all new jobs are found through neighbors, friends, relatives, or business acquaintances. Corcoran et al. (1980) confirm this basic finding and report, in addition, that informal hiring channels are more prevalent among black workers, as well as younger and less educated workers.

The use of informal channels such as referrals can be rationalized as a means to reduce the uncertainty regarding the quality of a prospective employee. Montgomery (1991) studies a model in which employers find it optimal to use referrals from current employees to reduce the adverse selection problem in hiring: firms are assumed not to perfectly observe a worker's type at the moment of hiring, although the type is subsequently revealed. Further, it is assumed that there exists assortative matching in social networks, so that a high quality worker is more likely to refer someone like herself.[2]

Focusing more closely on the information exchange among workers, Calvo-Armengol and Jackson (2002) analyze an explicit network model of job search in which agents receive random offers and decide whether to use them themselves or pass them on to their unemployed contacts depending on their own employment status and current wage. The model generates very interesting implications that are consistent with the data: for example, positive correlations of unemployment and wages across agents both in a cross-section and over time; long run inequality in expected unemployment rates and wages across groups; dependence duration in unemployment spells; decreasing marginal value of additional employed contacts.

[2]Montgomery (1992) also shows how assortative matching within social networks combined with the presence of informal hiring channels can bring about persistent and widening income inequality, and polarization.

It is worth noting that local interactions have been the subject of numerous studies in social sciences other than economics. Sociologists have theorized, long before economists, that individuals do not exist as isolated entities but are embedded into networks of relations that provide opportunities and constraints, such as information flows, the reduction of transaction costs, the provision and enforcement of norms. Burt (1992) is an excellent introduction to social network theory. Coleman (1988) is the first (to our knowledge) to have introduced the notion of social capital. Geographers and regional scientists have also used the idea that agents are more likely to trade, compete, or exchange information with other agents who reside "close" to them in some metric than with individuals far away, to explain patterns of spatial agglomeration, regional differentiation and inequality, or clustering. Curry (1998) contains a fascinating collection of papers on these themes that are based on stochastic models of local interactions and derive the equilibrium spatial distributions of various outcome variables.

In this chapter, we focus on the study of local interactions in the context of urban unemployment. The main empirical motivation is the observed high variance and clustering in unemployment outcomes across neighborhoods within metropolitan areas. For example, using Chicago Census data, Topa (2001) finds high levels of spatial correlation of unemployment: both in 1980 and in 1990, Census tracts with high levels of unemployment tended to be clustered together in geographically contiguous areas, rather than being spread around in a random fashion. The change in unemployment rates between 1980 and 1990 was also spatially correlated. This geographic "lumping" is consistent with the presence of local interactions and information spillovers. Positive spatial correlations are also present when other socio-economic distance metrics are employed.[3]

We study a "reduced-form" model in which agents' employment probabilities depend on the employment status of their neighbors. Such a role for neighbors' employment status could arise from an underlying exchange of information about job opportunities within social networks. This could occur, for example, in a model where useful tips or referrals are transmitted by currently employed agents to their unemployed contacts, in the expectation of receving similar leads when unemployed. Such information exchanges might be viewed as informal mutual insurance arrangements that are sustainable even in the presence of limited commitment.[4] Our model is defined at the level of individual agents arranged on a set of locations with an explicit distance metric. Agents are heterogeneous with respect to race/ethnicity and education levels. We also 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. Individual networks

[3]See Conley-Topa (2002).

[4]Limited enforcement contracts of this sort have been analyzed by Thomas and Worrall (1988) in the context of long-term wage contracts, and by Ligon, Thomas and Worrall (1999) in the context of informal credit in developing economies.

are based on physical distance between agents, in the sense that social ties are more likely between agents that are physically close, although long-distance ties may also arise with small but strictly positive probability.[5]

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).[6] Because of the local positive feedback generated by the information exchange, the stationary distribution of unemployment is characterized by positive spatial correlations, that are bounded above by a quantity decreasing in the distance between agents.

This model is closely related to contact processes that are studied in the Interacting Particle Systems literature.[7] 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 is also important in our context: in particular, the number of connections held by each agent and the length of agents' links affect the spatial properties of the stationary distribution of unemployment. Therefore, in our empirical application, we attempt to construct a network structure that is as realistic as possible, drawing heavily from the existing sociological literature on social networks.[8]

We use the stationary distribution implied by our model for estimation. An alternative strategy would be to estimate the model parameters using data on individual transitions in and out of unemployment – this is perhaps more intuitive given that the process is a Markov chain. Unfortunately, this is not feasible because of limitations in the available data. Individual transitions can be estimated from the *CPS* or better

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

[6]In a static framework, Brock-Durlauf (2001) and Glaeser-Scheinkman (2001) 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.

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

[8]See Marsden (1987,1988) and Wellman (1996).

still from longitudinal datasets such as the $NLSY$. However, these data sources lack detailed geographic information on the location of agents: this is problematic because in our model the transitions into employment depend on the state of the agent's social contacts. In the absence of detailed spatial information then, we cannot estimate all the transition rates that are necessary to estimate the model parameters. Therefore, we use Census data on the cross-sectional distribution of unemployment across census tracts.

There are drawbacks to using this approach. First, in the absence of social interactions, not all the model parameters can be identified from the stationary distribution, since the latter is fully defined from the *ratio* of entry and exit rates into unemployment. We use individual transition data from the CPS to calibrate the parameters that are not identified from the stationary distribution. More specifically, we use monthly transitions from employed to unemployed to calibrate the entry rate into unemployment, which does not depend on social interactions in our model. Second, no closed form solution exists for the likelihood function implied by the stationary distribution of our model. Therefore, we use simulation methods for estimation. In particular, the structural parameters of our model are estimated by matching several empirical moments of the cross-sectional distribution of unemployment in the Los Angeles metropolitan area with their simulated counterparts generated by the model.

This chapter's main contributions are an investigation of two aspects of this model's empirical performance. First we attempt to evaluate how well the distribution of agents' unemployment spells from our estimated model compares to Current Population Survey (CPS) data on in-progress unemployment spells.[9] This is important in order to assess the goodness of fit of our model in a dimension that is not used in the estimation. It is also important in a broader research agenda that aims at studying the effects of local shocks not only on unemployment rates over different locations, but also on unemployment durations.

The second aspect we investigate is whether local interactions are really required to explain observed levels of cross-sectional clustering. In particular, we look at agents with heterogeneous employment transition rates but independent transitions and ask whether their sorting across locations is sufficient to explain observed clustering. It is plausible that, e.g., agents with different races or education levels would have differing transition rates. It is also plausible that individuals sort into different neighborhoods on the basis of their neighbors' characteristics or because they have similar preferences over different consumption bundles (see Becker and Murphy (1994)). Such sorting of individuals with different transition rates may induce positive spatial correlation of unemployment even in the absence of any local information spillovers. We allow agents to be heterogeneous with respect to race/ethnicity and

[9]As 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.

education, and we replicate the spatial patterns of these covariates in Los Angeles in our model simulations.[10,11] We then compare cross sectional clustering patterns in the data to those generated by our framework both with and without the presence of dependence across agents.

The rest of this chapter is organized as follows. Section 2 describes the model. Section 3 describes the estimation strategy, the details of the calibration of a subset of parameters, and the evaluation exercise. Section 4 reports the results of the estimation of the model parameters, with and without local interactions. Finally, we offer some conclusions 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 ∞ 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 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 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.[12] 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

[10] In previous work, these two covariates seem to contribute the most to explaining the degree of spatial dependence present in unemployment data. See Conley-Topa (2002).

[11] Other possible identification strategies involve the use of information about local community boundaries, see Topa (2001).

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

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.[13] 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.

Our specification for agents' information networks is based on their locations. Each agent i is randomly assigned links to five 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 4 nearest neighbors of s_i, and the complement of all locations in S other than s_i and its 4 nearest neighbors. Links are drawn in two steps, the first of which is to randomly select among these subsets of S with probabilities 65%, 34%, and 1%, respectively. 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 five 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 the set of five 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 exceeds five contacts (see Marsden (1987,1988)). Further, in a study of Toronto inhabitants in the 1980s, Wellman (1996) finds that a surprisingly high fraction of interactions 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 by Granovetter (1973), who documents the existence and importance of weak ties.

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. In keeping with our interpretation of social interactions as reflecting information about new job opportunities, 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 con-

[13] 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.

cerning 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. We will 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 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:[14]

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

The transitions for the other two racial/ethnicity groups are parameterized analogously with group-specific $\beta, \gamma, \lambda^{Own}$ and λ^{Other}, with the only common parameter across groups being σ. This parameter is also the only deviation from the typical logistic functional form as $I_{i,t}^{Own}$ is allowed to enter into the logit index only after being raised to the power σ. We use this power function to allow for additional flexibility (beyond that in in the logit functional form) in fitting nonlinear effects of information as there is evidence that such nonlinear information effects may be important. For example, Bandiera and Rasul (2002) study farmer networks and the adoption of new crops in Mozambique, and find that the informational value of an additional contact is decreasing in the number of contacts. This concavity is also found by Jackson and Calvo-Armengol (2002) in simulations of their theoretical model. [15]

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 shown that a stationary distribution exists and is unique, for any choice of agents' characteristics. 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.

[14]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.

[15]For example, for σ close to zero $I_{i,t}$ simply becomes an indicator for whether any of i's contacts are currently employed.

3 Empirical Methodology

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 α and γ parameters are not separately identified for given values of λ and σ. In particular, these parameters are not separately identified for the natural base case with no social interactions for any racial/ethnic group, $\lambda^{Own} = \lambda^{Other} = 0$. Therefore we use individual spell data to calibrate the α parameters for each of the six race and education combination. We maintain this calibration of α parameters when we allow for social interactions to be present, even though we conjecture that these parameters may be identified due to the model's nonlinearity of the model and the addition of a continuous regressor. Calibrating the α parameters in both models is motivated by a desire to limit the number of parameters estimated with the cross sectional distribution and to better isolate the marginal contribution of the social interaction terms.

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.[16] The data contains an indicator of whether the respondent was employed or unemployed during the week prior to each interview.[17] 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 δ 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

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

We separately calibrate δ 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.

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

[17] 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.*

Estimation of γ and σ parameters

After calibrating α, we use a simulation method to estimate the remaining parameters. We estimate two specifications: the full parameterization of zero to one transition rates with local interactions in equation (3) and for comparison a restricted version of that model without local interactions present (λ parameters set to zero). For the specification with local interactions, the vector of model parameters θ_0 is defined as $\theta_0 \equiv \left[\beta_A, \gamma_A, \lambda_A^{Own}, \lambda_A^{Other}, \beta_H, \gamma_H, \lambda_H^{Own}, \lambda_H^{Other}, \beta_W, \gamma_W, \lambda_W^{Own}, \lambda_W^{Other}, \sigma\right]$ and is assumed to be in the interior of some compact parameter space $\Theta \subset \Re^{13}$.

For each candidate parameter value, we use simulations to determine a vector of cross sectional moments for tract-level unemployment rates by racial/ethnic groups: $\psi(\theta)$.[18] There are three sets of moments in the vector $\psi(\theta)$, one for each group: African Americans, Hispanics, and Whites. For each group, the moments are: the expected value of the tract-level unemployment rate; the variance of the tract-level unemployment rate; and the average 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. Thus there are a total of 15 elements in $\psi(\theta)$.

θ_0 is estimated by minimizing the (quadratic form or chi-squared) distance between the simulated moments $\psi(\theta)$ and their sample analogs: $\widehat{\psi}$.[19] The estimator $\widehat{\theta}$ is defined as:

$$\widehat{\theta} = \arg\min_{\Theta} \left(\widehat{\psi} - \psi(\theta)\right)^{\top} \Omega^{-1} \left(\widehat{\psi} - \psi(\theta)\right), \tag{6}$$

where Ω is an estimate of the asymptotic covariance matrix of the empirical moment conditions.[20]

The restricted specification without local interactions is estimated in the same fashion, using the same 15 moments. The logit index specification for 0 to 1 transitions is restricted by omitting the I^{Own} and I^{Other} terms for all racial/ethnic groups from

[18] For a given value of θ, the model is simulated starting from a configuration with all agents employed for 100 periods, to attempt to reach the stationary distribution. Then, a simulated configuration of employment y is sampled and simulated moments $\psi(\theta)$ are computed for that θ. We use a simulated annealing algorithm to minimize the objective criterion over Θ. This algorithm is particularly robust to the possible presence of multiple local optima and/or discontinuities in the objective function. We thank Bill Goffe for kindly providing the Matlab SIMANN code to us.

[19] It is difficult to formally show that the model parameters θ are identified as the solution to the limiting form of this criterion function given our choice of moments ψ. 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.

[20] Ω is a nonparametric estimate constructed via the method in Conley (1999), which is analogous to Bartlett (Newey-West) covariance matrix estimators for time series. The estimate is a weighted sum of cross products of tract-level observations with a weight function that declines linearly from one at distance 0km to zero at distance 20km.

equation (3). Thus the σ and λ parameters vanish leaving only 6 parameters to estimate: $[\beta_A, \gamma_A, , \beta_H, \gamma_H, \beta_W, \gamma_W]$.

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.[21] 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.

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.[22] Figure 3 reports non-parametric estimates of the spatial Auto-Correlation Function (ACF) for total unemployment, as well as for unemployment conditional on race. 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 findings for the city of Chicago reported in Conley and Topa (2002).

Table 2 presents our results for the model without local interactions. Column A reports our calibrated transition probabilities from employment (1) to unemployment (0), for our six racial/ethnic group and college education category combinations. Column B reports the corresponding estimates of 95% confidence intervals for the transition back to employment, 0 to 1. For comparison with estimates for the full specification with interactions, we also present these results in terms of parameters in the logit indices in equation (1) and equation (3) with its λ parameters set to zero. Column C reports the calibrated parameter values for the intercept and coefficient on education for each racial/ethnic group in the logit index for the 0 to 1 transition, equation (1). Similarly, Column D presents estimated intercepts and slopes for the logit index in the 0 to 1 transition, equation (3). Column E reports standard errors.

The model without local interactions performs quite badly in terms of producing

[21] 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.

[22] 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.

sensible transition rates back to employment. For Whites for example, the probability of finding a job within a week is almost one for persons without college, whereas it is close to zero for persons with college. So the model implies that whites with college experience especially long unemployment spells, which is clearly at odds with the empirical evidence in labor economics. We conjecture that the reason for this result is that the model tries to fit the observed spatial correlation patterns in unemployment by imposing long unemployment histories on college educated agents, who are characterized by positive spatial sorting. Finally, the test of the over-identifying restrictions yields a resounding rejection of the model, with a p-value practically equal to 0.

Table 3 presents our results for the model with local interactions. For ease of comparison, column A repeats calibrated parameters in the logit index for the 1 to 0 transitions, equation (1). Column B reports the estimated parameter values for the terms in the logit index for the 0 to 1 transition, equation (3). Column C again reports standard errors. With respect to the model without interactions, the estimates now imply reasonable transition probabilities back into employment, with a positive effect of education and of information, both from one's own group and from others. However, 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. We conjecture that one explanation might be the possibility that inter-group social ties tend to be "weak", whereas intra-group ties tend to be "strong": Granovetter (1973) has argued that weak ties are more effective at transmitting useful information than strong ones. Finally, the estimated σ is about 0.8, indicating the presence of strong concavity in the effectiveness of additional contacts. This is consistent with independent findings in Bandiera and Rasul (2002). A note of caution is introduced by the test of the over-identifying restrictions: while the test statistic is significantly lower than that for the model without interactions (702.9 vs. 974.5, respectively), the model with interactions is still overwhelmingly rejected.

Table 4 illustrates the marginal benefit of allowing for local interactions in terms of matching the estimated spatial correlations. A comparison of columns C and D reveals that the model with interactions performs much better than that without interactions in fitting the observed spatial correlation patterns. Therefore, there is a strong indication that sorting without local interactions is not sufficient to explain the unconditional spatial correlations of unemployment.

Finally, Table 5 and Figures 4 – 6 provide a measure of how well these local interactions models can fit the distribution of in-progress spells measured with CPS data. As is quite clear from a visual inspection of Figures 4 and 5, again the model with interactions performs much better in terms of fitting the observed distribution. Figure 6 confirms this impression by comparing the deciles of the empirical distribution (not conditioning on race) with those from the simulated distribution, for both models. In Table 5, we make this comparison more rigorous by comparing the simulated proportions of spells falling within four separate ranges with the 95% confidence intervals for the actual proportions. While the model without interactions is able to match only four out of the sixteen proportions under consideration, the model with interactions can match ten out of sixteen.

The model with interactions still generates spells that tend to be longer than the empirical ones: in particular, the right tail is fatter for the distribution of simulated spells. This is suggestive of duration dependence, and is consistent with the theoretical implications of the search model with network effects analyzed by Calvo-Armengol and Jackson (2002). They find that the presence of information networks alone is able to generate duration dependence in unemployment spells, even in the absence of unobserved heterogeneity.

5 Summary and Conclusions

In this chapter we have studied a model of local interactions, defined at the level of individual agents, in the context of urban unemployment. Our objective was on the one hand to investigate whether or not local interactions are really required to explain observed spatial patterns of unemployment. On the other, we wanted to evaluate the plausibility of the model with respect to a dimension of the data not used in the estimation, namely the distribution of in-progress individual unemployment spells.

With respect to the first objective, the results show that indeed the model with interactions performs much better than the one without in two areas: first, it is better able to replicate the spatial correlation patterns present in the data. Second, it is able to do so while still producing meaningful individual transition rates back into employment.

With respect to the second exercise, again the model with interactions performs much better than the model which only takes into account sorting along observed characteristics, although the former still tends to generate too many very long spells relative to the empirical distribution. This is quite interesting on various dimensions. First, it is consistent with a set of theoretical results in Calvo-Armengol and Jackson (2002), who show that network interactions in job search are sufficient to generate duration dependence in unemployment. Second, it suggests that one cannot just fit cross-sectional moments to provide a plausible model of unemployment, but rather must develop a richer model in order to better capture the duration dimension as well. This is in our opinion an important avenue for future research.

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TABLE 1

Summary Statistics by Census Tract, Los Angeles County, 1990 Census

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

N = 1,643 Census Tracts, Los Angeles County (Los Angeles PMSA)

TABLE 2

Estimates for Model Without Local Interactions

		A	B	C	D	E
		Calibrated 1 to 0 Probabilities*	95% CI for 0 to 1 Probabilities**	Calibrated 1 to 0 Index Parameters	Estimated 0 to 1 Index Parameters	S.E. for the Estimated 0 to 1 Index Parameters
African American	No College	1.67	51.0530 - 95.7462			
	College	0.28	2.1781 - 97.0038			
Hispanic	No College	0.57	15.4947 - 17.3246			
	College	0.29	0.0000 - 100.0000			
White	No College	0.44	99.8030 - 99.9511			
	College	0.35	0.4592 - 6.9287			
African American	Intercept			-4.078	1.578	0.784
	Education			-1.802	-1.742	1.074
Hispanic	Intercept			-5.157	-1.630	0.034
	Education			-0.672	1.316	8.665
White	Intercept			-5.421	6.925	0.356
	Education			-0.218	-10.913	0.354

* Weekly Probabilities of Entering Unemployment, in Percentage Points.

** Weekly Probabilities of Exiting Unemployment, in Percentage Points.

TABLE 3

Estimates for Model With Local Interactions

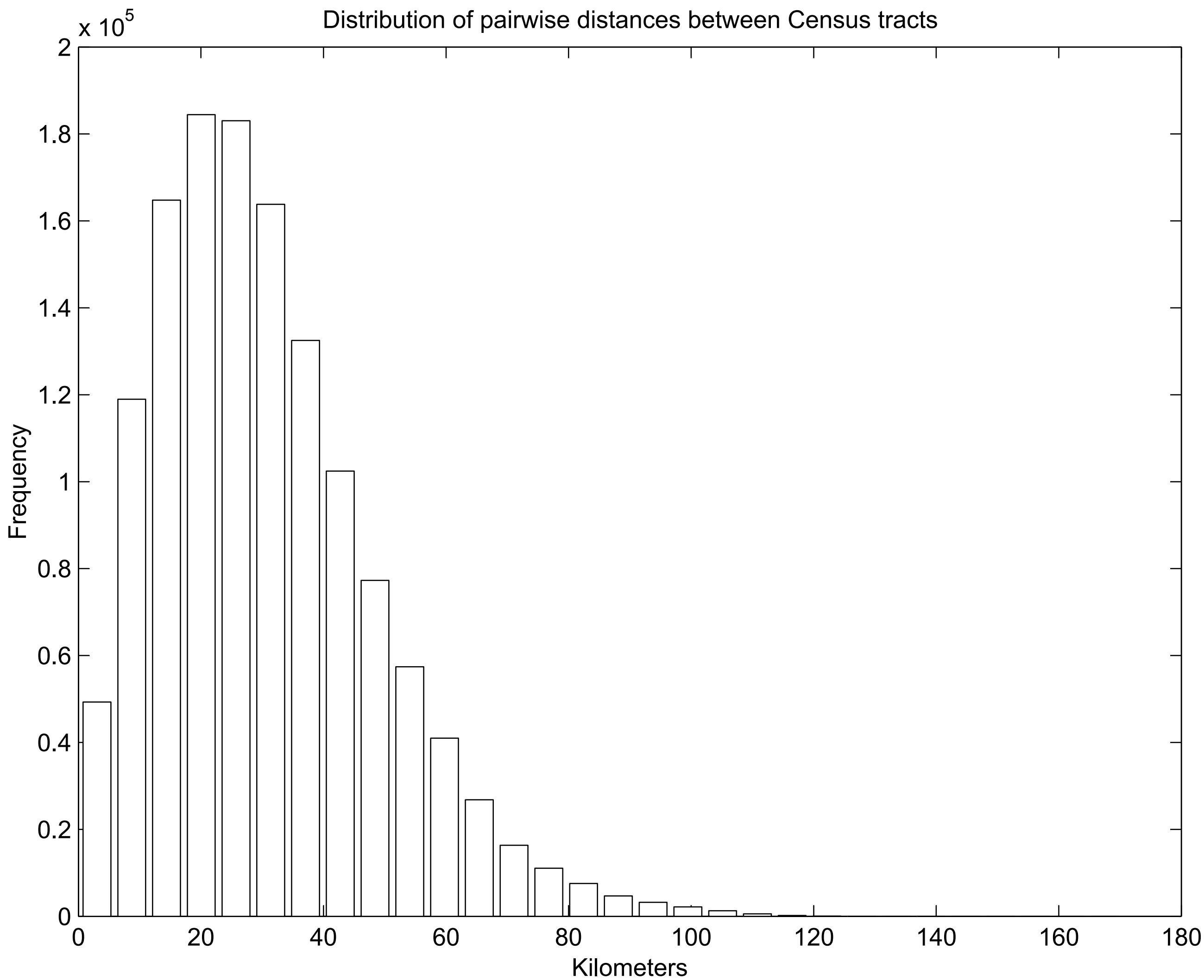
		A Calibrated 1 to 0 Index Parameters	B Estimated 0 to 1 Index Parameters	C S.E. for the Estimated 0 to 1 Index Parameters
African American	Intercept	-4.078	-4.106	1.980
	Education	-1.802	1.745	12.596
	Own Race Info	.	0.081	0.828
	Other Race Info	.	1.524	1.063
Hispanic	Intercept	-5.157	-3.995	0.095
	Education	-0.672	0.133	0.888
	Own Race Info	.	0.085	0.015
	Other Race Info	.	1.009	0.063
White	Intercept	-5.421	-5.711	0.163
	Education	-0.218	5.370	29.175
	Own Race Info	.	0.561	0.057
	Other Race Info	.	1.274	0.113
Nonlinearity Parameter Sigma		.	0.812	0.016

TABLE 4
Spatial Correlations of Unemployment Rates (Total and By Race)

	Tract Distance Range	A Empirical Correlation	B S.E. for Empirical Correlation	C Model Correlation Without Interactions	D Model Correlation With Interactions
Total	.25 to 1.75 km	0.535	0.035	0.395	0.410
	2.25 to 3.75 km	0.400	0.033	0.276	0.207
	5.25 to 6.75 km	0.282	0.024	0.167	0.068
African Americans	.25 to 1.75 km	0.123	0.027	0.016	0.156
	2.25 to 3.75 km	0.080	0.013	0.011	0.108
	5.25 to 6.75 km	0.029	0.010	0.007	0.048
Hispanics	.25 to 1.75 km	0.249	0.032	0.143	0.306
	2.25 to 3.75 km	0.208	0.022	0.107	0.207
	5.25 to 6.75 km	0.148	0.016	0.069	0.114
Whites	.25 to 1.75 km	0.158	0.033	0.023	0.130
	2.25 to 3.75 km	0.118	0.020	0.017	0.097
	5.25 to 6.75 km	0.077	0.014	0.012	0.054

TABLE 5
In-Progress Unemployment Spell Distribution Comparison

	Spell Length Range	A 95% CI for Actual Proportion	B Model Proportion Without Interactions	C Model Proportion With Interactions
Total	4 Weeks or Less	0.4004 - 0.4993	0.2992	0.2569
	5 to 9 Weeks	0.1536 - 0.2320	0.1615	0.1783
	10 to 18 Weeks	0.1465 - 0.2237	0.1325	0.1858
	19+ Weeks	0.1347 - 0.2098	0.4027	0.3668
African Americans	4 Weeks or Less	0.1580 - 0.4871	1.0000	0.3655
	5 to 9 Weeks	0.0110 - 0.2470	0.0000	0.1928
	10 to 18 Weeks	0.1305 - 0.4501	0.0000	0.1526
	19+ Weeks	0.1040 - 0.4121	0.0000	0.2851
Hispanics	4 Weeks or Less	0.4077 - 0.5412	0.4955	0.2638
	5 to 9 Weeks	0.1591 - 0.2688	0.3042	0.2012
	10 to 18 Weeks	0.1340 - 0.2381	0.1461	0.1794
	19+ Weeks	0.0813 - 0.1699	0.0512	0.3414
Whites	4 Weeks or Less	0.3565 - 0.5185	0.1359	0.2196
	5 to 9 Weeks	0.1117 - 0.2355	0.0754	0.1433
	10 to 18 Weeks	0.1058 - 0.2275	0.1300	0.2031
	19+ Weeks	0.1543 - 0.2901	0.6538	0.4227



Distribution of pairwise distances between Census tracts
x 10^5
2
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
Frequency
0
20
40
60
80
100
120
140
160
180
Kilometers

FIGURE 1

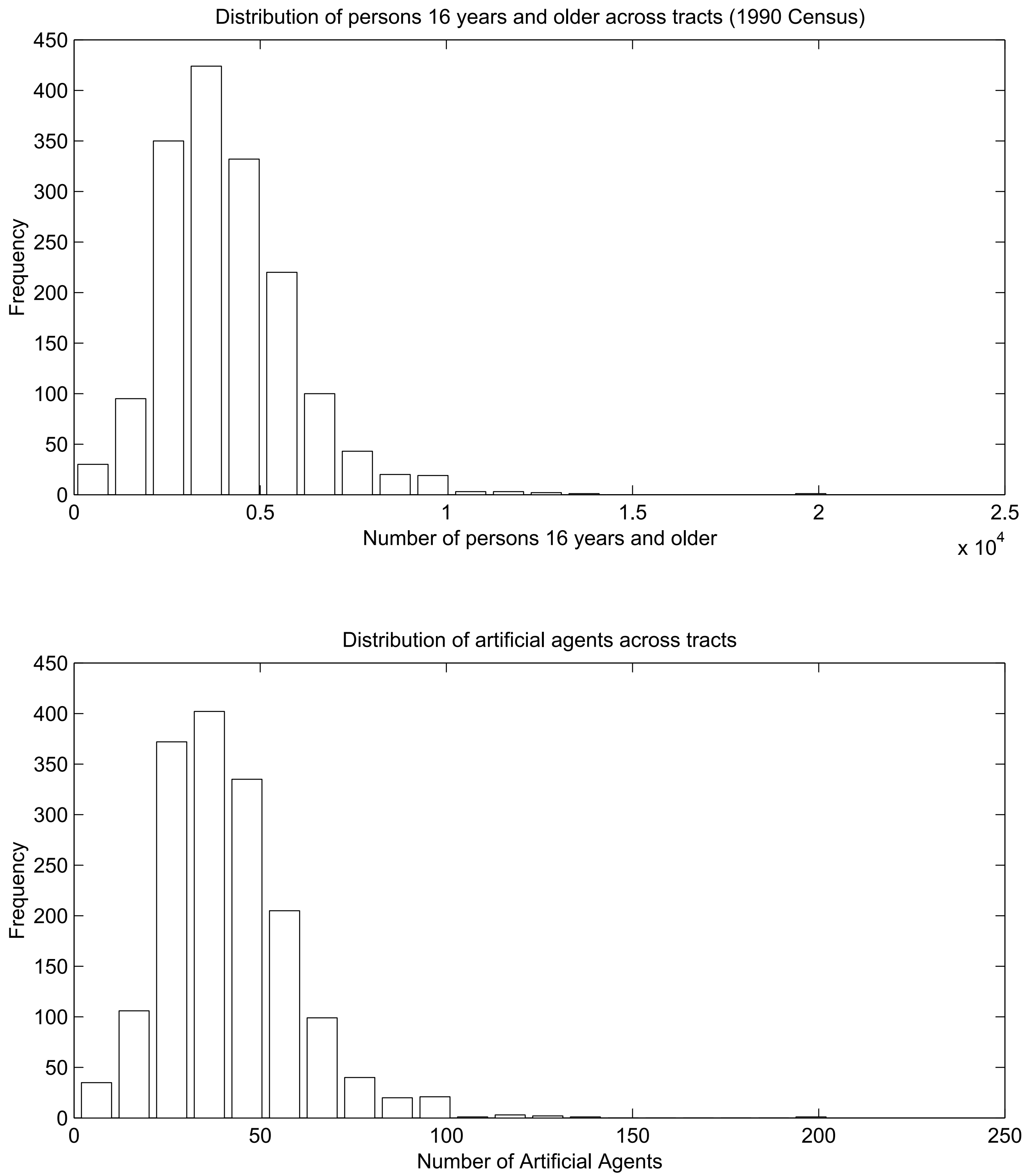


FIGURE 2: Comparison of Persons and Agents By Tract

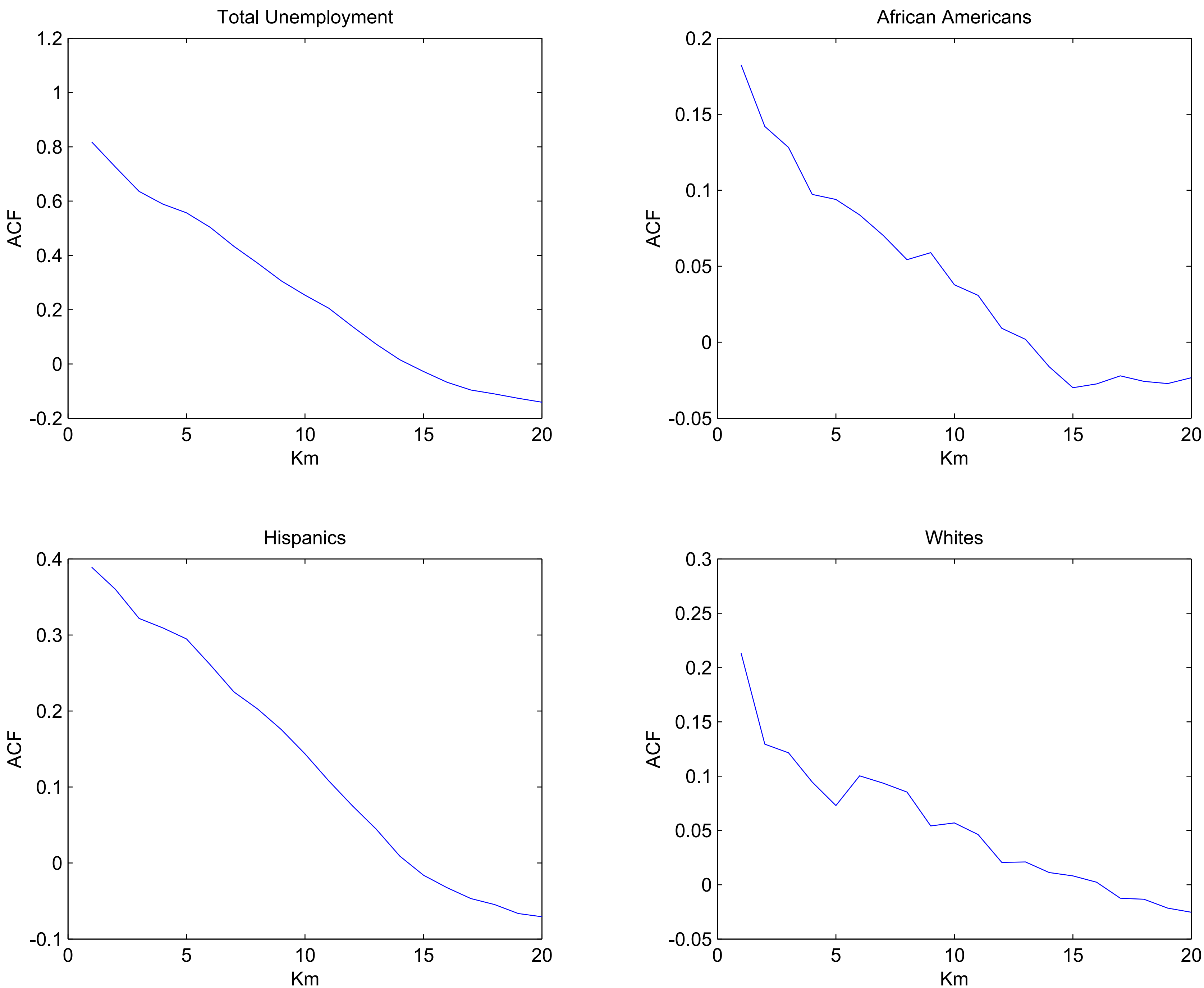


FIGURE 3: AutoCorrelations of Unemployment

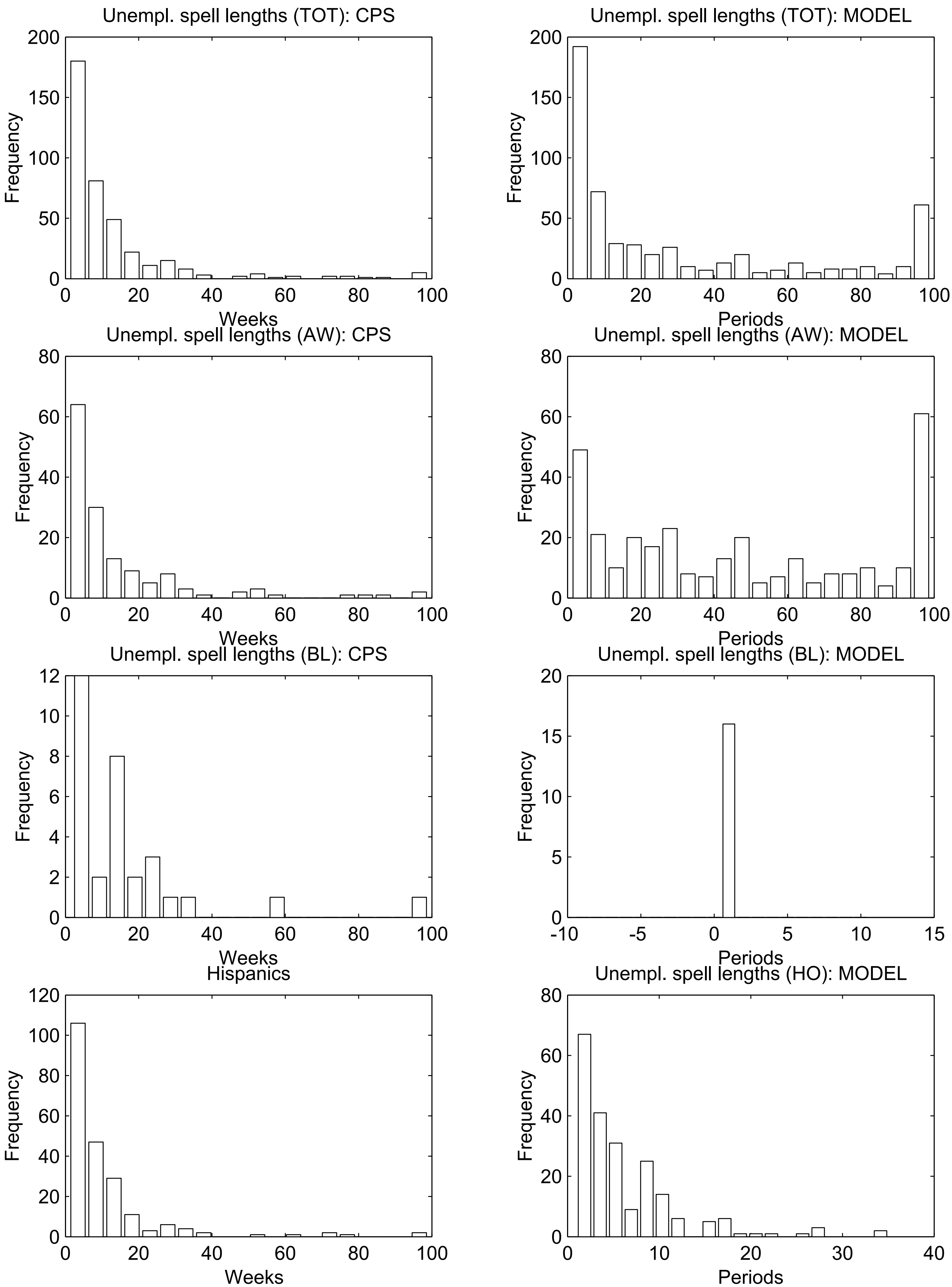


FIGURE 4: Spells, Model WITHOUT Interactions

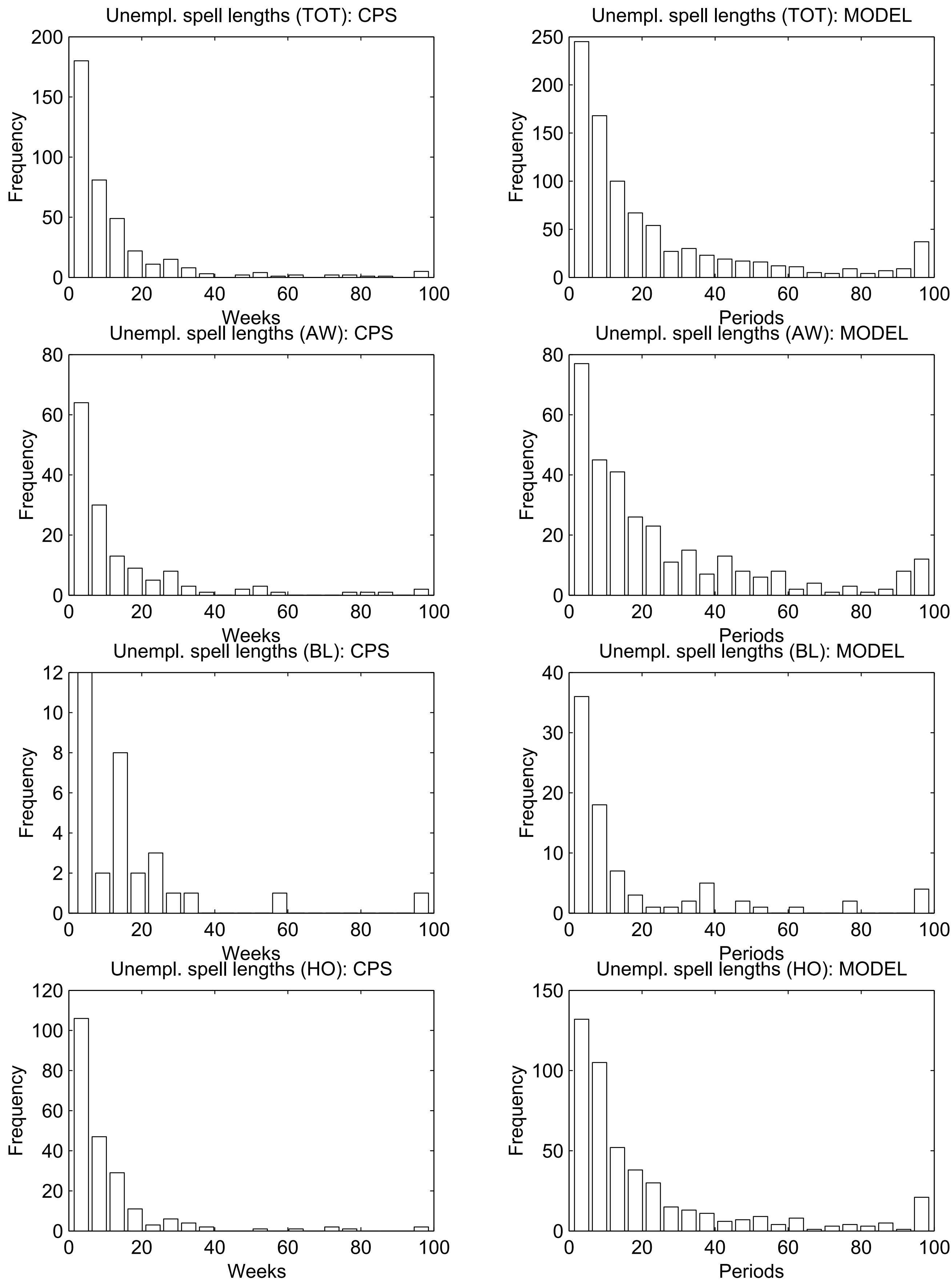
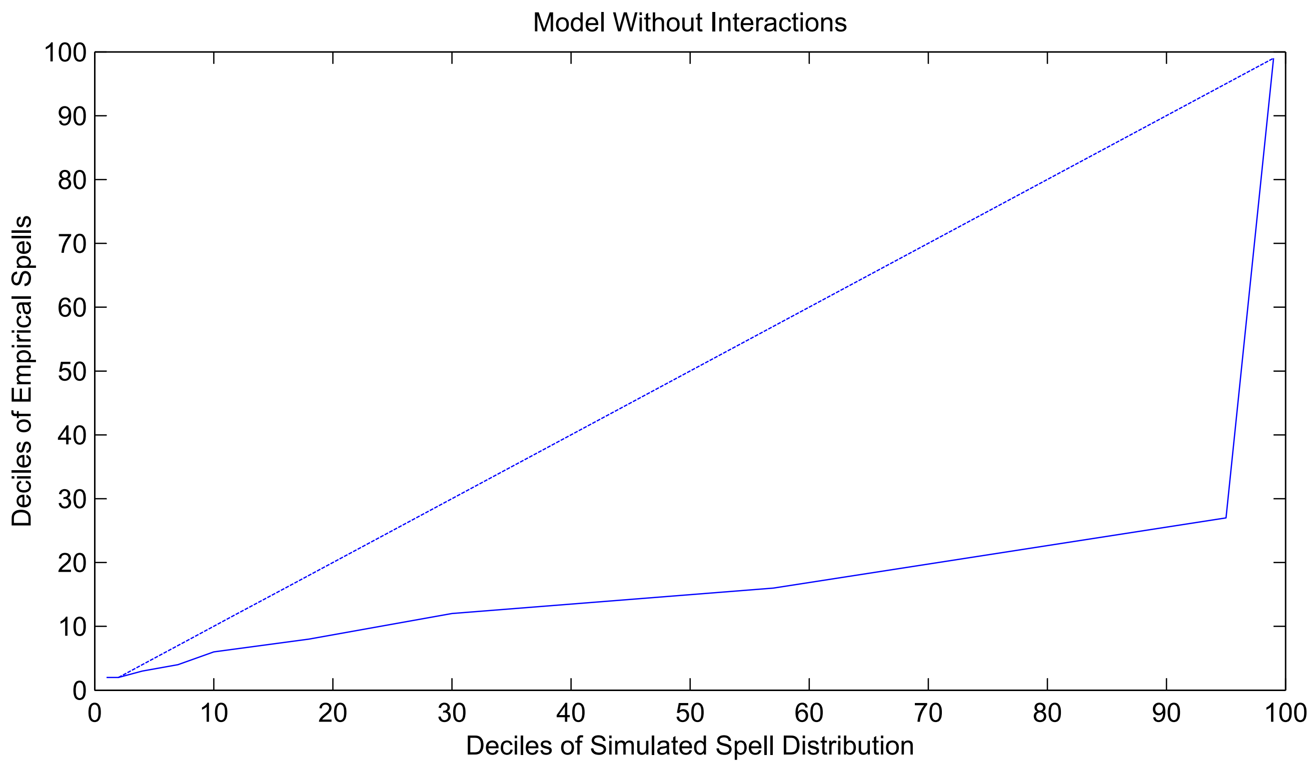


FIGURE 5: Spells, Model WITH Interactions



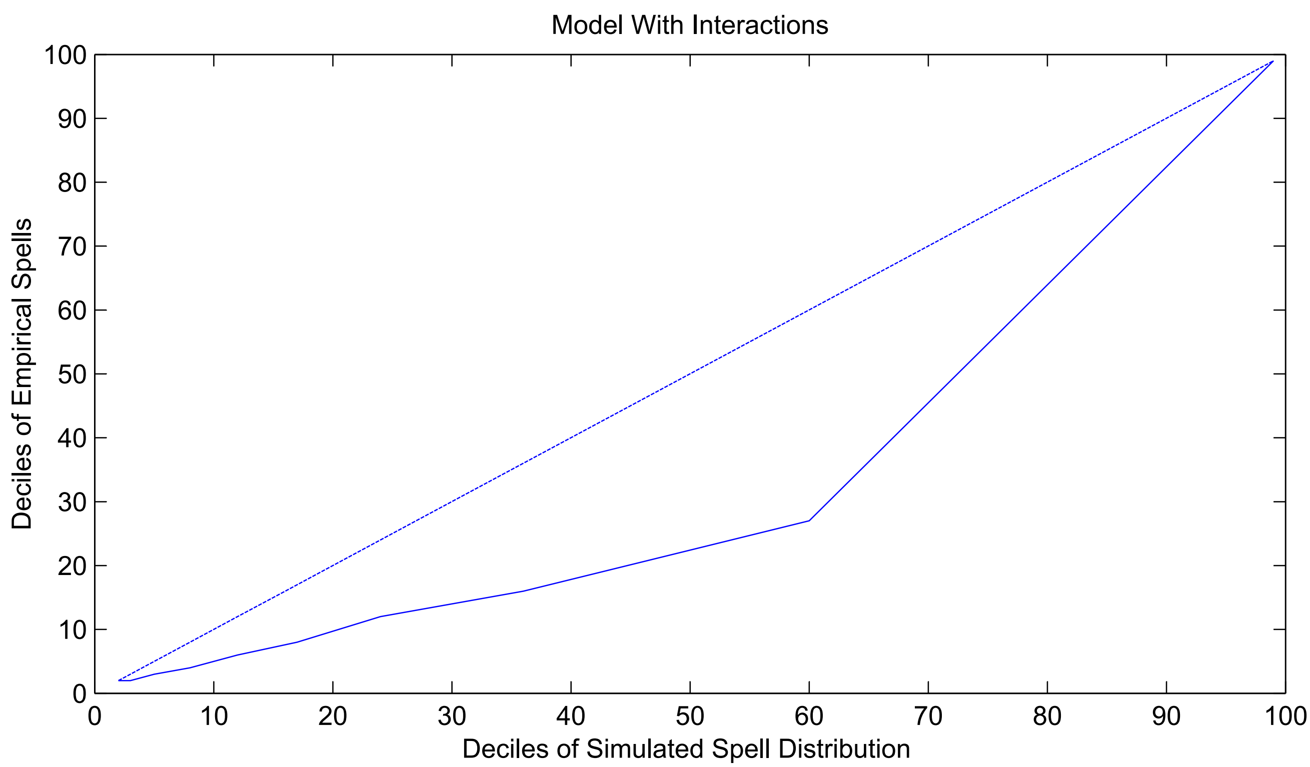


FIGURE 6: Empirical vs. Simulated Spells