SPATIAL EVOLUTION OF THE US URBAN SYSTEM[1]

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Abstract

We test implications of economic geography models for location, size and growth of cities with US Census data for 1900 – 1990. Our tests involve non-parametric estimations of stochastic kernels for the distributions of city sizes and growth rates, conditional on various measures of market potential and on features of neighbors. We show that while these relationships change during the twentieth century, by 1990 they stabilize such that the size distribution of cities conditional on a range of spatial variables are all roughly independent of these conditioning variables. In contrast, similar results suggest that there is a spatial element to the city wage distribution.

Our parametric estimations for growth rates against market potential, entry of neighbors, and own lagged population imply a negative effect of market potential on growth rates, unless own lagged population is also included, in which case market potential has a positive effect and own lagged population a negative one. Cities grow faster when they are small relative to their market potential. In total, our results support some theoretical predictions, but also provide a number of interesting puzzles.

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1. Introduction

As a system of cities develops, existing cities grow and new metropolitan areas form and grow at varying rates. Questions pertaining to the location of economic activity, to the relative sizes of cities in different countries, and to changing roles for different geographical areas in the process of economic growth have attracted renewed interest recently. The theorists who have developed the so-called new economic geography, including Masahisa Fujita, Paul Krugman and Anthony Venables [Fujita, Krugman and Venables (1999)], have added important new spatial insights to the established literature on systems of cities, represented most notably by the work of J. Vernon Henderson [Henderson (1974; 1988)]. The system of cities approach featured powerful models of intrametropolitan spatial structure, but lacked an explicit model of intermetropolitan spatial structure. Subsequently, intermetropolitan spatial structure played a key role in the new economic geography literature, starting with the work of Paul Krugman [Krugman (1991)].[2]

While theoretical work on the spatial nature of the urban system has expanded rapidly in recent years, our knowledge about actual spatial features of the urban system pertains mostly to intra-metropolitan spatial structure. Our understanding of spatial features of inter-metropolitan relationships remains, at best, limited. The present paper seeks to address this imbalance, taking a broad view of temporal *cum* spatial interactions by estimating models of joint dynamic and spatial interdependence. Our results build directly on earlier empirical work by Dobkins and Ioannides (1998) and Black and Henderson (1999). However, in contrast to that earlier work, our focus is primarily on characterising the details of the spatial features of the urban system.

Theoretical reasoning has identified three fundamental features of any given location – the first, second and third "natures" – that determine the extent of development at that location. First nature features are those that are intrinsic to the site itself, independent of any development that may previously have occurred there. For example, locations on navigable rivers, with favourable climates have first nature features that might encourage development. The second nature features of a location are those that are dependent on the spatial structure of the economic system and not inherent to the location itself. For example, the benefits of good access to a large market would be classified as a second nature feature of a location. Finally, third nature features of a location are those that are dependent on previous development at that location. For example, the

[2] Tabuchi (1998) sets out to synthesise the older system of cities literature with the more recent economic geography based theories by incorporating intrametropolitan commuting costs as well as intermetropolitan transport costs.

availability of local specialist suppliers might encourage development of activity that uses those specialist suppliers.[3]

The evidence that we consider here predominantly relates to the importance of second and third nature features in understanding the evolution of the urban system. As we suggested earlier, this issue has received relatively little attention in the empirical literature, but it is fundamental to our understanding of the urban system.

Krugman-type economic geography models of urban development remain relatively unexplored empirically. Hanson (2000) and Thomas (1996) are arguably the only exceptions. Both use Krugman (1991) as a starting point, modifying it in order to incorporate diseconomies from congestion and to develop estimable models. Hanson (2000) estimates a new economic geography type model using data from US counties. The parameter estimates that he obtains are plausible, but as with all such calibration exercises, it is unclear to what extent this is actually a *test* of the underlying model.

Dobkins and Ioannides (1998) examine the basic dynamics of spatial interactions among US cities and its impact on their populations. They use some of the predictions offered by Fujita, Krugman and Venables (1999) and US Census data for metro areas, which span this century from 1900 to 1990, to look at patterns of city growth and the distribution of city sizes as new cities enter the distribution. They emphasise that entry of new cities along with spatial expansion are important characteristics of the United States system of cities. Key spatial characteristics they consider are the presence of neighboring cities, regional influence, and distance between a city and the nearest one in a higher tier. They find that among cities which enter the system, larger cities are more likely to locate near other cities. Moreover, older cities are more likely to have neighbors. Distance from the nearest higher-tier city is not always a significant determinant of size and growth. They find no evidence of persistent nonlinear effects on urban growth of either size or distance, although distance is important for city size for some years.

Black and Henderson (1999) consider the importance of both first and second nature geography in explaining the growth rates of cities. They find that both factors are important in explaining city growth. In contrast to their paper, we consider a much broader range of issues relating to second nature characteristics, and sidestep first nature characteristics.

The evidence that we consider falls in to two broad categories. The first relates to the location of

[3] The term first vs. second nature is due to Krugman (1993). A more standard classification might include these third nature features as second nature. We separate them here to aid the exposition that follows.

cities. The second to the size and growth of cities. The paper is structured as follows. In section 2 we introduce the key theoretical concepts relating to the evolution of city sizes, and provide notation with which to structure our empirical work. In section 3 we describe the data that we use. In section 4 we consider spatial features of the location of cities. Assuming that first nature characteristics are randomly distributed, allows us to test for the importance of second nature characteristics by considering the degree of randomness of the location of cities. We conduct nearest neighbor tests to see whether second nature characteristics are sufficient to distort city locations so as to be non-random. In section 5 we examine spatial elements of the city size distribution. We start by taking an alternative perspective on the relationship between first nature characteristics and city size. Rather than defining specific characteristics to capture good first nature locations, we argue that the best sites should be settled first. In this case, city size should be positively related to date of settlement. Next, we use a non-parametric approach to consider the relationship between city size and the spatial location of economic activity. We then use a parametric approach to consider the same relationship. This parametric approach also allows us to examine whether there is a second nature element to the entry of new cities. Finally, section 7 relates our findings to specific theoretical models and concludes.

2. Analytical Description and Notation

In this section, we briefly outline the theoretical issues underlying our empirical analysis. Let $\mathcal{I}$ denote a set of names of cities, i.e., $i = 1$, denotes Abilene TX, $i = 206$ denotes New York, NY, etc. Let $\mathcal{I}_t$ denote the set of cities *extant* at time t : $\mathcal{I}_t \subseteq \mathcal{I}$, Let $I_t = |\mathcal{I}_t|$. Let P_{it} denote the size, in terms of population (or employment), of city i at time t, $i \in \mathcal{I}_t$, $1 \leq i \leq I_t$, and time periods $t = 1, \ldots T$. Let P_t denote the vector of sizes of the I_t cities in existence in the economy at time t, $P_t \in R_+^{I_t}$, and $\bar{P}_t$ total population in the economy.

Next we introduce geography. Let ς denote the set of geographical *sites*, $\varsigma = \{1, \ldots, s, \ldots, S\}$, defined within a particular geography, such as the real line (or an interval thereof), a circle, a one-dimensional or a two-dimensional lattice, or simply the North American landscape. This description allows us to refer to distances between two cities i and j, which for simplicity we take to be the geodesic distances, D_{ij}. We assume that not all potential urban sites need be occupied at any time t, and that there is plenty of space for new urban development: $\max_t : I_t < |\varsigma|$. A particular attribute of geography that we use in this paper is the notion of a city's nearest neighbor, $\nu(i)$, which is defined in terms of geodesic distance as follows: $d_{it} = \min\{D_{ij} : i, j \in \mathcal{I}_t, i \neq j\}$ is the distance to the nearest neighbor, and $\nu(i) = \{j : D_{ij} \leq D_{ik}, j, k \neq i\}$, the nearest neighbor. We note that because of the evolution of urban system, both these concepts are time-varying.

We define a *settlement mapping,* $g_t : \varsigma \to \{0, \mathcal{I}_t\}$, where $g_t(s) = 0$, denotes that site s, $s \in \varsigma$, is not settled at time t, and $g_t(s)$, if site s is settled, $g_t(s) \neq 0$, denotes the site occupied by city $g_t(s) \in \mathcal{I}_t$. We keep track of the evolution of settlement sites by means of the vector $G_t = (g_t(1), \ldots, g_t(s), \ldots, g_t(S))$. Once settled and for as long as it remains settled, a site is indistinguishable from the city which occupies it. We refer to the time that site s of city $i = g_t(s)$ was first settled, t_i^s, as the settlement date.[4] A city may disappear, that is, ghost-towns are possible, though relatively rare in the United States during the twentieth century, and not a feature of our data, due to the size cutoff.

We define a system of cities in a dynamic setting. We first take the set and location of cities in each period as given, $(\mathcal{I}_t, g_t)$, and postpone until later the issue of entry of new cities.[5] The richness and complexity of theories of urban growth, whether they are of the system-of-cities genre [Henderson (1974)], or of the new economic geography variety [Fujita *et al.* (1999)], make it hard to obtain specific predictions that are testable by means of our data on emergence of new cities and their sites, populations and wages, and a number of additional characteristics on which we elaborate further below. However, new economic geography models, with their emphasis on national space, as opposed to the intrametropolitan one of the earlier theories, lend themselves better to overall descriptions of the spatial evolution of the urban system as a whole, and it is for this reason that we appeal to the simplified version of the general theory in Fujita, Krugman and Venables regarding, in particular, the emergence of new cities. That is, working from their Chapter 8 rather than Chapters 9–10, we can see that an existing city's new neighbors must have size exceeding a critical value, if they are to grow. The critical value depends in a highly nonlinear fashion on the existing city's population and on the various parameters, including in particular the size of the existing city's hinterland. We note that all this applies just as well to the case where an existing city that already has neighbors acquires a *new* neighbor. Fujita *et al.* also predict that the distance between two

[4] The settlement date may be different from the time a city enters the data, e_i, because of our definition of a city is predicated on a settlement's surpassing the population threshold of 50,000. See Section 3 for the definition of settlement dates.

[5] In our parametric analysis below, we consider the impact upon a city's growth from the entry of neighboring cities. In contrast, Dobkins and Ioannides (1998) examine the geographic patterns of new entrants and the impact of neighbors on city growth, where neighbors are construed in the sense of adjacency.

cities in a linear geography tends to a constant as the number of identical cities grows. However, different spatial patterns are likely to emerge when cities are different and form a hierarchy [*ibid.,* Ch. 11]. Furthermore, discontinuities in the landscape strengthen the role of cities' agglomeration shadows, as discussed in [*ibid.,* Ch. 13]. Finally, the nonlinearity of the dynamics of the setting makes it likely that the urban system exhibits asymmetric behavior when new cities emerge. The impact of changes in the system upon an individual city is different before and after the emergence of neighbors and/or other dramatic changes in the urban landscape.[6] Therefore, emergence of a city depends on national geography and the structure of transport costs, and is triggered by exogenous events, such as population growth, or by labor-saving technological change.

Once a particular site is settled, its presence may skew further development in its vicinity in its favor, via its "agglomeration shadow" [Krugman (1996)]. Therefore, the availability of data on the time of settlement may help anchor the original location of economic activity in an otherwise homogeneous setting. Of course, the fact that a particular site has already been settled may itself imply that the site is particularly advantageous in a first-nature sense. Subsequent shocks may cause reallocations of economic activity, that is to say second-nature changes, which may bring into the picture the full force of the asymmetric nature of nonlinear dynamics. The agglomeration shadow of existing cities implies that the earlier a site has been settled, the more likely a city is to grow, regardless of the specific reasons for which a site has been settled in the first place.

Exposition in the remainder of the paper is facilitated by means of a concise description of the spatial evolution of the urban system as follows. Let Ψ_t be a random function, defined in the space of Borel-measurable functions $\mathcal{B}$, and let $\mathcal{T}_t$ be a sequence of mappings, defined as follows: $\mathcal{T}_t : \mathcal{I} \times \{0, \mathcal{I}\} \times R^I_+ \times R^I_+ \times \mathcal{B} \longrightarrow \mathcal{I} \times \{0, \mathcal{I}\} \times R^I_+ \times R^I_+$

$$(\mathcal{I}_t, G_t; P_t, W_t) = \mathcal{T}_t(\mathcal{I}_{t-1}, G_{t-1}; P_{t-1}, W_{t-1}; \Psi_t). \tag{1}$$

This system of equations describes the co-evolution of new and existing cities, $\mathcal{I}_t$, the determination of the sites they occupy, G_t, and their populations and wages (P_t, W_t). It is, of course, highly nonlinear and expresses bifurcations, as when new cities emerge. Unfortunately, as all of the principal contributors in this area acknowledge, it is not possible to derive explicit analytical results, even in the case of a constant number of cities [*c.f.,* Krugman (1992); Fujita *et al., op. cit.*]. Whereas many of those analysts have resorted to simulations to obtain accurate but numerical

[6] This is due to the fact that the *sustain point* and the *break point* differ [*ibid.,* Ch. 3], a critical implication of nonlinearity of at least third-degree.

descriptions of results, we take some of those ideas to empirical work. Equations (1) form the basis for descriptions of the spatial evolution of the urban system outlined below.

The highly non-linear nature of the evolution of the urban system, as captured in equation 1, justifies the main empirical approach that we adopt below. In such a system, no city is truly representative of the entire distribution of cities. Standard parametric tools rely on the assumption that there is some average (representative) unit whose outcomes can be modelled in a concise way as the function of a limited number of variables and unknown parameters. According to equation 1 such an assumption may not be valid when explaining both the location and size of cities. Our empirical work on the location of cities, and the approach that we use to characterise the evolution of the city size distribution do not rely on this representative agent assumption. Instead, we use non-parametric tools that specifically allow for non-linearities in the evolution of the urban system.

3. Data

There are a variety of ways to define cities empirically. In this paper we use contemporaneous Census Bureau definitions of metropolitan areas, whenever possible. From 1900 to 1950, we use metropolitan areas as they were defined by the 1950 census. For years before 1950, we use Bogue's reconstructions of what each metro area's population would have been with the metropolitan areas defined as they were in 1950 [Bogue (1953)]. From 1950 to 1980, we use the metropolitan area definitions that were in effect for those years. However, between 1980 and 1990, the Census Bureau redefined metropolitan areas. The effect of the redefinitions were that the largest U.S. cities took a huge jump in size, and several major cities were split into separate metro areas. While this might be appropriate for some uses of the data, it would introduce "artificial" differences in growth patterns for the 1980–1990 period. Therefore, we reconstructed the metro areas for 1990, based on the 1980 definitions, much as Bogue did earlier. We believe that this gives us the most consistent definitions of US cities (metropolitan areas) that we are likely to find.

The method raises a question as to which cities, as defined or reconstructed, should be included. In the years from 1950 to 1980, we use the Census Bureau's listing of metropolitan areas. Although the wording of the definitions of metropolitan areas has changed slightly over the years, the number 50,000 is minimum requirement for a core area within the metropolitan area. Therefore, we used 50,000 as the cutoff for including metropolitan areas as defined by Bogue prior to 1950. Consequently we have a changing number of cities over time, from 112 in 1900 to 334 in 1990. While it is often difficult to deal with an increasing number of cities econometrically, we think that this is a key aspect of the US system of cities.

Data on earnings in all cities in the sample for all years are drawn from Census reports. Regional location is according to the Census Bureau division of the country into nine regions. Kim (1997) argues that the census regions are likely to serve well as economic regions, at least over the first half of the century.[7] Finally, we use the date of settlement for each city, as obtained by Dobkins and Ioannides, *op. cit.*. At first glance, one would suppose that the east to west settlement of the country would determine settlement dates, but we find early settlement dates in the west and late ones along the east coast. Settlement here refers to historical references to settlement in a location, and our variable is compiled by sifting through historical texts.[8]

4. The Number and Location of Cities

This section deals with issues pertaining to the number and location of cities. First, we consider the 'spacing' of cities by examining the evolution of average bilateral distances between cities relative to the average distance among nearest neighbors. Referring to Table 3, as the former rises from 802.5 miles 1900 to 1005 miles in 1990, (not surprisingly as the US urban system expanded over the North American land mass) by nearly 25%, the latter falls by 35%. The dispersion of the former declines while that of the latter slightly grows, as evidenced by the coefficient of variation and nonparametric densities that we have estimated but do not report here. Both those distributions become more symmetric, as evidenced by the ratio of medians to means and the nonparametric densities. The US urban system both expands and thickens during the twentieth century. The frequency distribution of bilateral distances is unimodal, although with a considerable upper tail.

Next, we consider whether the urban system has evolved such that the location of cities is non-random. When considering the location of cities, we need only consider the importance of first and second nature features of potential city sites. Third nature forces only arise *after* the city is established. If we assume that the distribution of first nature features is essentially random, in the

[7] Kim (1997), p. 7–9, discusses the original intention of the definition of U.S. regions as delineating areas of homogeneous topography, climate, rainfall and soil, but subject to requirement that they not break up states. By design, the definitions were particularly suitable for agriculture and resource-based economies. The role of those industries as inputs to manufacturing would make them likely to serve well as economic regions.

[8] In a number of cases, the dates are references to military forts. We use those dates because often the site of the fort determined the site of the city that grew up nearby. The earliest date is that of Jacksonville, Florida, in 1564, and the latest is Richland, Washington, originally the site of a nuclear facility settled in 1944. It is an interesting statistic in and of itself to see how age of settlement correlates with city size.

sense that there are a large number of potentially good sites, then we can test for the importance of second nature in determining city location by considering whether the distribution of cities is random[9]. In terms of equation 1, under the null hypothesis of randomness, we can separate out for the function determining the set of occupied sites. That is:

$$H_0 : (G_t) = \mathcal{T}_t^1(\Psi_t) \quad \text{independent of} \quad (\mathcal{I}_t, P_t, W_t, \mathcal{I}_{t-1}, G_{t-1}P_{t-1}, W_{t-1}). \tag{2}$$

There are many senses in which the location of cities can be non-random. In this section, we consider a sufficient test for non-randomness first proposed by Clark and Evans (1954). The basic idea is to assume that some underlying spatial probability process determines the distribution of cities and then to compare the distance between cities to the distance that we would expect, if cities were located randomly according to this distribution. Although a full matrix of intercity distances is available[10], Clark and Evans (1954) show that a "sufficient" test of non-randomness can be based on the distance to nearest neighbor city[11]. However, even if location of cities is non-random, we may fail to reject the null-hypothesis of randomness. Non-randomness might be manifested in higher dimensions than the distance to nearest neighbor.[12]

Define d_A as the actual mean nearest neighbor distance, $d_A = \bar{d_i}$; $d_E = \mathcal{E}[\bar{d_i}]$ as the expected mean nearest neighbor distance; $\sigma^2(d_E)$ as the expected variance of mean nearest neighbor distance; ρ as the density of cities; and I as the number of cities. Then the Clark-Evans test for non-randomness is based on the simple test statistic $CE = (d_A - d_E)/\sigma(d_E)$ which is distributed asymptotically $N(0, 1)$. To calculate the statistic, we need to make a specific assumption on the spatial probability

[9] This test on the randomness of the location of cities as complementary to that of Ellison and Glaeser (1997) on whether or not the location of industrial plants is random, *conditional* on the distribution of population across cities.

[10] These are calculated on the basis of great circle distances. For any two locations A and B, we can calculate the angle formed by a ray joining the two points A and B and a ray joining A to the centre of the earth as follows:

$$\text{angle} = (\sin(\text{latA}) \times \sin(\text{latB})) + (\cos(\text{latA}) \times \cos(\text{latB}) \times \cos(\text{longA} - \text{longB}))\,,$$

where latA and longA are the latitude and longitude of location A measured in radians. Similarly for latB and longB. For cities, they are the latitudes and longitudes given in the *1999 Times World Atlas.* For counties they are the latitudes and longitudes of the largest human settlement.

The distance is then

$$\text{distance} = 3954 \times \text{acos(angle)}.$$

acos(angle) gives us the approximate distance if the two points were located on a circle of radius one. We then need to multiply by the radius of (a circular) earth (3954 miles) to get an estimate of the distance. The assumption of a spherical earth leads to an error of approx 0.2% on an area the size of the US.

[11] Sufficient in the sense that our statistical test is asymptotically valid for a large number of underlying spatial probability processes obeying a number of standard assumptions. See also Ripley (1979)

[12] Indeed, the test we conduct here only considers departures from randomness at the smallest spatial scale. A large number of additional test statistics, including extensions to k-nearest neighbor methods, have been developed since the original Clark and Evans test used here. See, for example, Diggle (1983) for a description of these methods. We return to this possibility below.

process that governs the random location of cities. We assume that cities are randomly distributed according to a spatial Poisson process where the probability of a city locating in any given area is proportional to that area[13]. For a spatial Poisson distribution the expected mean nearest neighbor distance, $d_E = 1/2\sqrt{\rho}$ and the variance is $\sigma(d_E) = 0.26136/(\sqrt{I\rho})$.

Table 4 shows the results for the US as a whole for each of the census years. The final column reports $R = d_A/d_E$, the ratio of actual to expected distance. A number less than one indicates that cities are closer together than would be expected if they were randomly located. Conversely, a number greater than one indicates that cities are further apart than would be expected if they were randomly located. The $N(0,1)$ column then tells us whether this departure from randomness is significant. From the table, we see that US cities are spaced closer than we would expect if they were randomly located, but that this non-randomness is only significant at the beginning of the century. We find this result surprising given that casual observation suggests that cities are very clustered in certain parts of the country.

Table 5 shows the same statistic calculated for census regions. This shows that this non-randomness is not always reflected at the regional level. In particular, the South and West show strong evidence of non-randomness. Cities in the South are too far apart, cities in the West are too close together.

As suggested earlier, the location of cities may not necessarily be random, even if we cannot reject randomness on the basis of nearest neighbor distance tests. We examine such questions by using tools developed by Danny Quah [Quah(1993; 1996a,b; 1997; 1999)] to estimate stochastic kernels. The stochastic kernel shows the distribution of some variable y (distance to nearest neighbor) conditional on the distribution of another variable x (population). To estimate that stochastic kernel, we first derive a non–parametric estimate of the joint distribution $f(x, y)$. We then numerically integrate under this joint distribution with respect to y to get $f(x)$. [14] Next we estimate the distribution of y conditional on x by dividing through $f(x, y)$ by $f(x)$. Thus we estimate $f(y|x)$ by $\hat{f}(y|x) = \frac{\hat{f}(x,y)}{\hat{f}(x)}$. Under regularity conditions, this gives us a consistent estimator for the conditional distribution for any value x. The stochastic kernels plot this conditional distribution for all values of x.

Figure 1 shows a stochastic kernel mapping the distribution of population to the distribution of

[13] This formulation treats cities as points, and ignores their own area. For details see Cliff and Ord (1975) and Ripley (1979).

[14] We could also estimate the marginal distribution $f(x)$ using a univariate kernel estimate. The asymptotic statistical properties of both estimators are identical, and in practice tend to produce very similar estimates.

distance to nearest neighbors, $\hat{f}(d_i|P_i)$. The figure suggests that there are important non-random elements to the location of cities. The figure for 1910 shows that smaller cities tended to locate far away from their neighbors. By 1990 the relationship had begun to change. Smaller cities still tend to be further from their nearest neighbor, but the relationship is not as stark as in 1910. These higher dimension considerations suggest that there are important non-random elements to city location that are not yet fully captured by existing models.

5. Spatial Features of the US Urban System

5.1 First nature and city size

We now turn from the issue of city location, to consider the related issue of city size and growth. Both first nature and second nature characteristics of city locations are presumably important for understanding the relative sizes of cities. As we mentioned above, first nature characteristics are those that are intrinsic to a site. For example, good climate, good access to raw materials and a natural harbour are all first nature characteristics. Second nature characteristics are a result of the spatial structure of the economic system. For example, the distribution of market potential, the distribution of wages and the positioning of neighbors are all second nature characteristics. Our main interest is in the importance of second nature variables. However, it is important to understand and possibly control for the impact of first nature effects.

To that end, Figure 2 shows the mapping from the distribution of US-relative city sizes to the distribution of date-relative city sizes [*c.f.,* Quah (1999)]. The first of these, is constructed by taking the (log of the) ratio of city size to the US average city size. The second of these, same-date relative city size takes the (log of the) ratio of city size to the mean city size for cities that were settled at a similar period. Settlement dates are constructed as outlined in section 3 and grouped in to similar settlement dates using twenty year bands. If better first-nature sites are settled earlier – arguably, a rather simplistic view of history – then early settlement would confer a permanent advantage in terms of city size[15]. How would this be reflected in the stochastic kernel? Cities that were large relative to the US average, would be better first-nature sites, settled earlier. Thus, although they are large relative to the US, we would expect them to be a similar size to sites that were settled at the same time. Likewise, smaller cities would be located on poorer sites with respect

[15] In terms of equation (1), $(P_t) = \mathcal{T}_t(t_i^s; \Psi_t)$.

to first nature characteristics. However, although they are small relative to the US, we would expect them to be a similar size to sites that were settled at similar late dates. That is, if first nature characteristics matter most, then the stochastic kernel should map cities to approximately zero in the same-date relative distribution. Cities settled at similar dates should be of similar sizes.

Two things stand out from the stochastic kernels. First, the nature of the relationship changes somewhat over time. Second, first nature characteristics do seem to impart a benefit for cities at the beginning of the period (large cities have similar settlement dates), but that advantage has largely disappeared by the end of the century. These results are consistent with Dobkins and Ioannides *op. cit.,* finding that "initial benefit conferred an advantage that only began to wane at the end of the century."

5.2 Second nature and city size

In this section, we examine spatial characteristics of the evolution of the US urban system. We again use tools developed by Danny Quah [Quah (1993; 1996; 1997)] to characterise some key aspects of that evolution. We start by considering whether second nature features determine the distribution of city sizes. To clarify the issues, consider again equation (1). If second nature is irrelevant for understanding city size, then we can write:

$$(P_t, W_t) = \mathcal{T}_t^2(P_{t-1}, W_{t-1}; \Psi_t). \tag{3}$$

Note, city sizes and wages are still interdependent - in a sense cities "compete" for population (both with respect to other cities and with respect to some outside rural option). However, information on these two distributions is now sufficient - we do not need separate information on the set of settled sites G to understand the evolution of either distribution. This is because, in equilibrium, the population and wage of a city are sufficient statistics for the first nature characteristics of that city. In contrast, if second nature matters then

$$(G_t, P_t, W_t) = \mathcal{T}_t^2(G_{t-1}, P_{t-1}, W_{t-1}; \Psi_t). \tag{4}$$

That is, we need specific information on the location of cities, to understand the evolution of both populations and wages.

Traditionally, models of the urban system have captured the spatial interaction between city sizes and wages using the concept of market potential. Market potential measures whether a location has good access to markets. Thus, it is supposed to capture the importance of demand from other cities or regions while allowing for the “friction of distance”. The models suggest that market potential should be a function of city incomes, distances between cities and the city price indices for manufactured goods. Theoretical reasoning suggested that cities should be large and pay high wages if their location has high market potential [See for example Harris (1954)]. New economic geography models have formalised this reasoning, but suggest that the effect of high market potential at a location might not be unambiguously positive.

We adopt a similar approach for our initial analysis of the spatial evolution of the urban system. That is, initially, we will restrict the form of spatial (second nature) interactions between cities and assume that these can be captured through a market potential type concept. Thus, in terms of equation (1) we estimate a reduced form like:

$$(P_t, W_t) = \mathcal{T}_t^3(MP_t; \Psi_t), \tag{5}$$

where MP_t is the distribution of market potentials across all sites occupied in period t.

Before turning to details on the construction of the market potential, we consider empirical implementation of equation 5. In what follows, we examine the relationship between city sizes and market potential using a series of stochastic kernels. The distinct advantage of our non-parametric approach is that we do not need to impose any additional restrictions on the mapping $\mathcal{T}_t^3$. In particular, we do not have to impose any form of linearity, nor do we have to restrict the mapping to be stationary over time. As we show below, neither feature is present in the data, a fact that would be completely obscured were we to adopt a more standard approach.

Data availability limits the types of market potential that we are able to construct. In particular, we have no information on sectoral composition and no accurate information on the network distances between cities. We comment on some of these issues below. Given the available data we can construct three different definitions of market potential for city i at time t based on the following formula:

$$mp_{it} = \sum_{j \neq i} \frac{P_{jt}}{D_{ij}}. \tag{6}$$

The first two measures differ depending on whether the summation is across all cities or all counties in the US. In words, city i’s market potential is the sum over all other cities (counties) j of population in city (county) j $[P_{jt}]$, weighted by the inverse of geodesic distance between i and j $[D_{ij}]$.[16]

[16] One may view this as an approximation of the of the market potential as obtained by new economic geography theorists. See Krugman (1992).

When the summation is across all cities, we will refer to this as city based market potential, and when it is across counties as county based market potential[17]. Taking different definitions is interesting for two reasons. First, it allows us to see whether spatial interactions between cities differs from general spatial interactions between cities and other (non–city) locations in the US. Second, we have wage data for cities back till 1900, and do not have similar information for counties.

These data allow us to construct a third measure of market potential, where cities are weighted by average wages as well as distance: $mp_{it}^{W} = \sum_{j \neq i} W_{jt} \frac{P_{jt}}{D_{ij}}$. This measure may better capture the importance of demand from other cities and regions than the measures that only consider population, and is thus closer to the Krugman version of the market potential model.

We report results based on a somewhat arbitrary choice on the importance of distance. That is, whether distance should enter linearly or non-linearly. Results do not appear to be too sensitive to these assumptions. For example, the GMM results that we report in Section 6 below are not markedly different if we weight by the square root of distance – although the degree of variation in market potential is substantially reduced and we tend to see higher standard errors. It would also be possible to allow for the effect of distance to decrease through time. However, the changing composition of consumption from manufacturing to services, means that, at an aggregate level, it is not clear whether general transport costs have risen or fallen over time. Thus, Hanson (2000) finds that the estimated effects of distance increase between 1970 and 1980, which he interprets as a net increase in effective transport costs.

Without accounting for actual transport costs and changes in sectoral composition of output, we have chosen to take the "neutral" viewpoint that general transport costs are unchanged over the sample period. Further, in common with many authors, we assume that transport costs are directly related to the distance between cities without any consideration of actual transport networks and costs. Again, without any further information on transport costs over the period, it is unclear what alternative assumption would be better.

All variables are relative. That is, they are normalised by contemporaneous sample means as follows:

$$RPOP_{i,t} = pop_{i,t}/\overline{pop}_t,$$

$$RMP_{i,t} = mp_{i,t}/\overline{mp}_t;$$

[17] For the county based market potential measure, note that the sum is over all counties that are not part of that metropolitan area in 1990.

where $\overline{pop}_t$ is the mean population in time t, and $\overline{mp}_t$ is the mean market potential in time t.[18]

Relative city sizes vary dramatically across the US. At points in the sample period, New York is up to 25 times the mean city size (1930). Including these very large cities is conceptually simple, but technically problematic. Very large outliers automatically drive up the optimal bandwidth that we use to nonparametrically calculate the stochastic kernels.[19] When this happens, the detail in the lower end of the distribution (comprising the main body of cities) is obscured, as the estimates are over–smoothed. We have tried two different solutions to this problem. One is to restrict the sample according to size, the second according to a functional urban hierarchy classification. We used such a classification in Overman and Ioannides (1999) and showed that there were some differences in intra–distribution mobility across different tiers in the urban system. In fact, it turns out that the two methods deliver very similar results. Here we report results restricting the sample range to the bottom 95% of all cities in any single year.

Both population and market potential are normalized by subtracting the mean and dividing by the standard deviation, so that each univariate distribution has a variance of 1 and a mean of 0. Thus, the way to interpret this stochastic kernel is as follows. Take a point on the relative market potential axis, say 1.0, which corresponds to a city with log market potential that is one standard deviation above the log mean. Cutting across the stochastic kernel parallel to the relative city size axis, gives the conditional distribution of relative city sizes for cities with market potential one standard deviation above the mean. The stochastic kernel plots these conditional distributions for all values of market potential.[20]

5.3 Stochastic Kernels for City Sizes

Our estimation of stochastic kernels is intended to provide an accurate description of the data and no causal interpretation is made of conditional distribution functions that we estimate and discuss in this section. We report results for several stochastic kernels in the form of three-dimensional figures

[18] We also normalise the wage weighted market potential variable.

[19] The optimal bandwidth is based on Silverman (1986) and is a function of the range or the variance whichever is the larger.

[20] These kernels are closely related to the parametric spatial autoregressions suggested by Anselin [Anselin (1988)] and others. In fact, the calculation of market potential uses a spatial weighting matrix with each element (w_{ij}) equal to the inverse of the distance D_{ij} between cities i and j. However, our nonparametric approach does not impose a uniform coefficient on the spatial AR term thus constructed; and does not require the mapping from the spatial AR term to be one-to-one.

and contours.[21] Figure 3 reports stochastic kernels $\hat{f}(P_i|mp_i)$, for city size distributions conditional on city-market potential and Figure 4 on county-based market potential. Figure 5 reports stochastic kernels for city size distributions conditional on wage-weighted city-based market potential, and Figure 6 for wage distributions conditional on wage-weighted city-based market potential. Figure 7 reports stochastic kernels for the distribution of city size conditional on nearest neighbor market potential and conditional on nearest neighbor size.[22]

From Figures 3, a and b, and 4, a and b, we see that the 1910 kernels are somewhat skewed towards the diagonal. In the beginning of the period, the smallest cities tend to have smaller market potentials and larger relative city size is associated with larger relative market potential. To see this, observe that for 1910, there are peaks in both city- and county-based stochastic kernels, centred in the lower southwest corner, which contains most of the mass for the smaller cities. In contrast, the conditional distribution for the largest cities is relatively flat. The entire series of snapshots, not reported here, show the stochastic kernels for the each decennial year 1900 − 1990, respectively, slowly twisting back until they appear, by 1990, to have become virtually independent of the relative market potential. The peaks become less and less pronounced, as the distribution of city sizes conditional on low market potential shows greater variance. By 1990, Figures 3, c and d, and 4, c and d, suggest that the conditional distributions of relative city sizes are almost identical across all values of relative market potential. Only for the very largest cities is city size positively related to market potential.

We underscore the importance of this finding. It suggests, at least from a non-parametric vantage point, that the distribution of city sizes conditional on market potential is nearly independent of relative market potential: $\hat{f}(P_i|mp_i) \approx \hat{f}(P_i)$. The panels of Figure 3 show that for 1990 the conditional distribution of city size is virtually independent of relative market potential. Again, the only exception is for the very largest cities, where market potential is positively related to relative city size.

Figure 5 considers the co-evolution of wage weighted market potential and the distribution of city sizes. The stochastic kernels for city size distributions conditional on wage-weighted city-based market potential, for 1910 and 1990, accord with those in Figures 3 and 4. The kernel slowly twists back until it appears, by 1990, to have become virtually independent of the relative market

[21] The contours work exactly like the more standard contours on a map. Any one contour connects all the points on the stochastic kernel at a certain height.

[22] We define nearest neighbor market potential below.

potential, thus providing additional support for for our earlier comments.

Before proceeding, we summarise what our results so far tell us about the spatial interactions between cities. First, they tell us that this relationship is non-linear - at least to the extent that there may be differences between small and large cities. Second, the nature of the interaction evolves over time. That is, the mapping $\mathcal{T}_t^3$ is not stationary. Third, if, as theory suggests, we can capture the second nature features of the system through a reduced-form market potential variable, then the spatial relationship between cities has weakened over time.

We can also use our approach to analyse the evolution of the wage distribution, W_t. Again, we capture spatial interactions between cities in the determination of the wage distribution through the use of our market potential measures. In general, we would expect cities with high relative market potential to have high relative wages. This prediction is not confirmed by the 1910 data, reported in Figure 6 a and b. Wages are relatively high for cities with low market potential. As the urban system develops the relationship changes. According to Figure 6, c and d, 1990, the stochastic kernel is slowly twisted towards the diagonal with higher wages associated with larger market potential. This finding agrees with a backward linkages interpretation of the Krugman model, namely that the value of labor is higher in locations which are "closer" in terms of transport costs to areas with high consumer demand. We note, however, that the weakly positive relationship implied by our finding is actually consistent with the broad implications of what Krugman calls the "no black-hole" condition: increasing returns, which are responsible for the backward linkages effect, must not be too strong, or else all economic activity would concentrate in one location [Fujita *et al.* (1999), p. 58].

We wish to underscore that our results for early twentieth century suggest that there is no simple relationship governing the spatial interaction of cities. Indeed, in this section, we have shown that the co–evolution of the city size distribution and market potential may actually conflict with traditional views on the forces driving the evolution of the city size distribution. Further, we have shown that this relationship changes over time urging caution be used in working with data from all available years. The reader should bear this in mind with respect to the parametric results that we present later.

Our results suggest that the nature of spatial interactions between cities weakens over time. Here, we consider some further spatial features of the urban system concerning the relationships between neighboring cities. In particular, we concentrate on the relationship between cities and their nearest neighbors. Table 3 reports simple correlation coefficients between sizes of cities that are nearest neighbors. From negative and small, these coefficients become positive and somewhat larger by 1990. In contrast, simple correlations between population growth rates of cities and of their nearest neighbors, also reported on Table 3 remain fairly high for most of the century, ranging from a minimum of .126 to a maximum of .674. Next, we decompose the impact of the urban system on each city in terms of the market potential of the nearest neighbor city and of the remainder of the urban system. Figure 7, a and b, reports stochastic kernels for city size distributions conditional on city-based market potential excluding the market potential from the nearest neighbor, for 1910 and 1990. Figure 7, c and d, reports stochastic kernels city size distributions conditional on city size of nearest neighbor, for 1910 and 1990, respectively. In terms of equation (1) excluding market potential of the nearest neighbor is a restriction of the set of G_t that are relevant for any particular city. The motivation for so doing comes from the insight from new economic geography that large cities might cast an agglomeration shadow that affects the growth of their immediate neighbors. We can see from Figure 7, a and b, that such considerations do not change our overall conclusions with respect to the spatial interactions between cities. Figure 7, c and d, also correspond to a particular restriction on equation (1) such that $(P_t) = \mathcal{T}_t^4(V_t; \Psi_t)$, where V_t identifies the nearest neighbor for all cities $i = 1, ..., I_t$. We see, again, that by the end of the century, the distribution of city sizes is independent of the nearest-neighbor size. This finding reinforces our conjecture of weakening spatial interactions between cities over time.

6. Growth and the Spatial Structure of the Urban System.

In terms of equation (1) our nonparametric results in section 5 were based on a restriction of that general system such that the mappings that we estimated empirically were given by equation (5). In this section, we turn to the growth of cities. That is, we want to allow for the past history of the system to matter in determining the current city sizes and locations. However, in line with section 5 we still assume that we can capture spatial interactions through the use of a market potential concept. In addition, once we allow for a dynamic setting, we explicitly need to deal with first nature effects that might permanently alter city growth processes. Thus, in this section, we consider the following restriction of equation (1):

$$(P_t, W_t) = \mathcal{T}_t^5(G_t, MP_{t-1}, P_{t-1}, W_{t-1}; \Psi_t), \tag{7}$$

where we now assume that G_t provides information on the first nature characteristics of each site.

The discussion above suggested that we want to condition out first nature variables that may make some cities grow faster than others independent of second nature geography. To do this, we consider the difference between this period's relative growth rates and the (time) average of growth rates for that city. We also do the same for relative market potential. Figure 8 shows stochastic kernels for the distribution of relative growth rates conditional on the distribution of relative market potentials. They show clearly, once again, that the relationship changes slowly during the century to show, by 1990, that higher market potential implies higher growth.

These plots suggest that there is no simple stable relationship between the distribution of relative growth rates and the distribution of relative market potentials. This suggests why the results that follow tend to be fragile. In the parametric specifications that follow, market potential tends to have a weak impact on relative growth rates. This is, perhaps, unsurprising when we observe the degree of instability in the relationship over time.

Given these results on the evolution of the distribution of city sizes, we next take a parametric look at the relationship between city growth rates and the spatial structure of the urban system. The basic economic geography story suggests that cities with the highest market potential should grow fastest. Newer versions of this story suggest that the effects of high market potential on city growth are not necessarily monotonic. A city that is very close to a big city will have high market potential, but may fall within the agglomeration shadow of the bigger city [Fujita, Krugman, and Venables (1999)]. Thus, a–priori we cannot say whether higher market potential is good or bad for growth[23].

We use the fact that we have a panel of cities and absorb all first nature variables in the fixed effect for any given city. Thus, we are assuming that the effect of a favourable site on growth rates is constant over the entire time period. After absorbing first nature factors into the fixed effects, we are left with a group of time–varying second nature variables that we think may influence the growth rate of cities.

The first type of variables are the different normalized market potential measures. Again, as in section 5, we may want to consider market potential calculated on the basis of either cities or

[23] We have not yet found a satisfactory solution to this problem. Black and Henderson (1999) using a quadratic form in a similar specification find that there appears to be a negative relationship between growth and market potential at the very top of the market potential distribution. This result is suggestive, but does not get around the problem that trade models predict that the coefficient on market potential will vary as a function of the distance from the cities casting agglomeration shadows. Thus high and low growth rates are consistent with high market potential.

counties, with or without weighting by wages.

The second type of variable is a dummy variable for entry of a neighboring city. As the urban system grows, new cities reach the threshold size of 50000 which is necessary for inclusion in our sample. Thus, our sample is characterized by "entry" of new cities. So, for example, in 1900 we have 112 cities, and by 1990 there are 337 cities. City entry occurs in all census years although, more cities enter towards the end of the period. This is hardly surprising for two reasons. First, is our choice of an absolute cut–off point for city definitions. In a sense, this is a "higher" hurdle at the beginning of the period. Second, is that we would expect the growing rate of urbanization towards the end of the sample to result in a faster rate of city creation. It is interesting to examine the effect of city entry on the growth rates of the surrounding cities. We discussed earlier how new economic geography models predict bifurcation of the city system as the system grows [See Fujita and Mori (1996; 1997), and Fujita, Krugman and Mori (1999)]. When a new city enters, these models predict that the population size of its nearest neighbor will decline. As absolute population declines are rare in the data we do not test for this strict result. Instead, we consider a "growth equivalent". It may be possible that when a city enters close to an existing city, that the existing city does not grow as fast as we would predict given the levels of the other explanatory variables. The entry dummy tries to capture this effect. It is defined as follows:

$\text{Entry}_{it} = 1,$ if city i is the nearest neighbor to a newly entering city at time t;

$\text{Entry}_{it} = 0,$ otherwise.

The third type of variable that we consider is the lagged population size of a city. Again, a–priori it is hard to predict the impact of lagged population size on city growth. Convergence type reasoning would suggest that lagged population size should be negatively related to growth. However, if we think of own city size as a proxy for "self–potential", then we would expect lagged population size to be non–negatively related to growth. This would then take account of the fact that the size of the home market is excluded from our calculation of market potential.

Finally, we consider the interaction between own city size and market potential. Some new economic geography models suggest that it is actually the ratio of city size to market potential that is important for city growth. Cities enter the urban system at sites where market potential reaches some threshold. That threshold is established relative to the high market potential of existing cities. Thus when cities enter, they will be small relative to the high value market potential at the site where they enter. When cities are small relative to the market potential of their site, they grow quickly. In the theory this fast growth takes the form of a bifurcation of the urban system. Small cities grow very (infinitely) fast at the cost of larger cities that loose population. We discussed this above with reference to the entry variable. Pushing this theoretical proposition somewhat, we would expect to see fast city growth when market potential is large relative to current city size.

Our parametric results allow for a more general system of interactions, and a more formal treatment of first nature effects. In terms of equation (1) we now restrict the system such that:

$$(P_t, W_t) = \mathcal{T}^6(G_t, MP_t, V_t, V_{t-1}, P_{t-1}, W_{t-1}; \Psi_t) \tag{8}$$

where, as before, G_t provides information on a (complete) set of first nature characteristics, and V_t and V_{t-1} provide information on nearest neighbors, which allows us to examine the effect of entry. However, the parametric formulation is much more restrictive along two dimensions – the mapping $\mathcal{T}^6$ is assumed to be both linear, and stationary over time. Theoretical reasoning, and our previous results, suggest that this is a very strong assumption when we are dealing with the spatial evolution of the urban system.

Before turning to the results, we briefly summarise our discussion above:

- City growth should be a function of market potential. Traditionally, models predicted that market potential should have an unambiguous, positive, effect on growth. New economic geography models suggest that large cities may cast agglomeration shadows, which make the effects of market potential on growth ambiguous.

- City growth should be affected by the entry of other cities. In traditional models, city entry should have a positive effect on growth, working through increases in market potential for the existing city. New economic geography models suggest that entry should have a negative effect on the growth rate of nearby cities. Strictly, city entry represents a bifurcation of the urban system and should lead to absolute population decline in nearby cities.

- Own lagged city size has an ambiguous effect on growth. Models that predict convergence of city size predict a negative impact of own lagged city size on growth [as do some new economic geography models]. Models that emphasise intra- as well as inter-metropolitan distance also may predict a negative effect of own lagged city size on growth. This reflects congestion forces internal to the city that may reduce growth rates. Finally, some models predict a positive impact of lagged city size on own growth. This positive impact may reflect the fact that own lagged city size is a measure of self–potential and thus should have a positive impact on growth.

- New economic geography models that consider the spatial evolution of the urban system allowing for endogenous entry make clearer predictions about the ratio of own city size and market potential, than they do about the effect of either variable separately. A city should grow fast when it is small relative to its market potential.

6.1 Parametric results

The general equation that we estimate is:

$$\gamma_{it} = a_i + a_t + b \cdot mp_{it} + c \cdot \ell n P_{it-1} + d \cdot \text{Entry}_{it} + \varepsilon_{it}, \tag{9}$$

where γ_{it} is the growth rate of city i between time period t and $t+1$. We begin with the relationship between market potential and city growth.

Table 6 (column 1) gives results for fixed effects (FE) estimates on the unbalanced panel for the time period 1900 to 1990. For consistency with later results, the time period is restricted to 1930 to 1990. Only cities that have entered the urban system by 1950 are included in the sample. However, the whole urban system is used when calculating the value of market potential.

The fact that market potential is a function of the whole urban system introduces a significant complication. Standard fixed effects estimates assume strict exogeneity, but market potential is endogenous to the system. A high value of the error for city i this period, drives up the growth rate of city i. But higher growth rate of city i changes the market potential, and hence growth rates, of all the other cities in the system. This, in turn, feeds back in to future values of market potential for city i. To allow for this we switch to a GMM formulation. We first difference Equation (9) to eliminate the fixed effects. As instruments, we use predetermined values of market potential and lagged values of the city size. For efficient estimation, we allow the number of instruments exploited to vary across time periods[24]. For year t, time varying instruments are thus market potential and lagged city size for time period $t - s$ where $s > 2$. After differencing operations and construction of instruments, we are left with an unbalanced panel with seven years of data. Results for GMM estimation of Equation (9) are reported in column 2 of Table 6[25].

[24] For details see, for example, Arellano and Bond (1991).

[25] For both fixed effects and GMM we report one–step estimates with robust standard errors. See Arellano and Bond (1991) for why this is preferable to either non–robust errors or two–step estimators with robust standard errors.

The results reinforce our earlier results from the stochastic kernel showing the mapping from population to market potential. City growth and market potential tend to be negatively related. This is true even when we allow for the growth of the south–west (pulled out by the fixed effects) which we know could not be driven by market potential.

Next we consider the importance of neighboring city entry for growth. The fixed effects results show that both market potential and entry are negatively related to growth. The coefficient on market potential is lower, suggesting that some of the negative result may be due to the fact that cities with high market potential tend to see neighboring (competing?) cities enter. The results are reported in column 3 of Table 6. The GMM results are somewhat disappointing. Allowing for entry of a neighbor has a negative effect on growth rates, but the coefficient is (just) insignificant at the 10% level if we allow for heteroscedasticity. The results are reported in column 4. We suspect that this lack of significance reflects the lack of good instruments for the entry variable. We have to instrument entry, because entry may not be exogenous with respect to neighbor size. However, lagged city size and market potential may not be good instruments for the entry of a neighboring city. We experienced similar problems with other specifications.

Next, we allow for the introduction of lagged own city size. The results here are somewhat surprising. If we account for lagged own city size, the effect of the market potential variable becomes insignificant with fixed effects, but significantly *positive* in the GMM specification. The effect of entry is now insignificant in both specifications. Lagged own city size has a large negative effect on growth rates. See columns 5 and 6.

As outlined above, new economic geography models actually suggest that what matters for city growth is the size of the city relative to its market potential. New cities should enter when market potential at a site is above the market potential of existing cities. Thus cities will grow fastest when they are small relative to the market potential at the site. This suggests that we should actually enter population and market potential in ratio form. The results for entering them individually are consistent with this – we cannot reject the hypothesis that the coefficients are equal but opposite in size. Columns 7 and 8 show that when we enter the variable in ratio form, the effect is significant and negative.

As for the stochastic kernel specifications, we have recalculated market potential weighting each city by wage. The results in terms of parameter signs and significance are identical using this alternative market potential variable. Results are reported in Table 7.

The results that we have reported so far use city based market potential (with and without weighting by wage). Table 8 shows that these results are not robust to the use of county based versus city based market potential. The major difference between these sets of results is that market potential is insignificant when entered market potential and lagged own city size are entered separately in levels. However, the results for population relative to market potential are the same for all three types of market potential.[26]

To summarize:

- Market potential has a negative effect on growth rates if we do not take in to account own lagged city size. This result is robust to the use of the three different definitions of market potential.
- Entry has a weak negative impact on the growth rates of neighboring cities. This result is not very robust. However, this may reflect the lack of good instruments for the entry variable.
- Own lagged city size has a robust negative effect on growth rates. When both own lagged city size and market potential are entered in levels, market potential has a positive effect on city growth. The results are not very robust to the definition of market potential.
- The ratio of own lagged city size to market potential has a robust negative impact on city growth. Cities grow fastest when they are small relative to their market potential.

7. Conclusions

This paper has used a number of different approaches to analyse the spatial evolution of the US urban system over the period 1900 to 1990. The results confirm some theoretical insights, but also throw up a number of puzzles.

The first group of findings concern the spatial pattern of the location of cities in the US. Cities appear to be closer together than what one would expect if cities were randomly distributed only

[26] How do we reconcile these results with those of Black and Henderson (1999)? The stochastic kernels in Figure 8 suggest one possible solution. As discussed above our definition of cities uses an absolute cut–off point of 50000, whereas Black and Henderson use a relative cut–off point. One of the implications of this choice of cut–off is that cities enter the sample later in our data set. However, Figure 8 shows that the positive relationship between city growth rates and market potential is stronger at the start of the century. Thus, one explanation of the difference between our results is that our estimations place *less* weight on the period when the positive relationship between growth rates and market potential is strongest. This factor is reinforced by the fact that Black and Henderson use a balanced panel of cities that existed in 1930, whereas we use an unbalanced panel which allows for entry.

at the beginning of the twentieth century. However, regional patterns show stronger evidence of nonrandomness.

The second group of findings concern the nature of the spatial relationship between cities. Our results in section 5 suggest that there is no simple positive relationship between the distribution of city sizes and the distribution of market potentials, in the beginning of the century. Indeed this relationship appears to change substantially over time. There is some evidence of a positive relationship between city sizes and market potential at the start of the century. That relationship is much weaker at the end of the century, apparently only holding for the largest cities. In fact, an important finding stands out very clearly – by the end of the century the distribution of city sizes conditional on market potential is nearly independent of relative market potential. Similar results hold for the distribution of city sizes conditional on city-based market potential, and on nearest neighbor city-based market potential. All these findings suggest that spatial interactions between cities have weakened over the time period that we study. The evolution of the city size distribution during the century raises questions about the validity of procedures that assume stationary dynamics. This is arguably one of the most useful results of our analysis.

Our third group of findings concern the evolution of the city wage distribution. When we condition on city-based market potential we see that the spatial nature of the wage distribution has changed over time. Initially, high market potential cities had lower wages (contrary to our expectation); by the end of the period, high market potential cities pay higher wages. Taken together our results on wages and populations provide an interesting, but puzzling picture. Spatial relationships between cities with respect to the distribution of population have weakened over time in a way that is not always consistent with theory. However, in contrast, the wage distribution has evolved such that spatial features of the wage distribution are now more consistent with theory. These findings on the spatial features of the wage distribution would appear to be consistent with Hanson's (2000) results.

Our fourth group of findings concern the relationship between city growth rates and market potential. Again, our non–parametric results show that this is a complex relationship which appears to have evolved over time. Parametric specifications appear to be quite fragile, presumably as a result of this evolution in the relationship over time. Initial parametric results suggest that there is a negative relationship between city size and market potential if we do not take in to account own lagged city size. Once we allow for own lagged city size, there is a positive relationship between market potential and city growth. Own lagged city size has a negative effect. These results are not robust to the definition of market potential.

By far the most robust parametric result relates to the ratio of lagged own city size to market potential. When cities are small relative to their market potential they grow faster. This result is consistent with theoretical models advanced as part of the new economic geography. However, if the results are driven by the own lagged city size variable, then these results may also be consistent with theoretical models that emphasise congestion effects within cities. Separating out these two hypotheses is left to further work.

8. References

Arellano, M. , and Steven Bond (1991), “Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations,” *Review of Economic Studies*, 58, 277-297

Black, Duncan, and J. Vernon Henderson (1999), “Spatial Evolution in the USA,” working paper, LSE and Brown University.

Bogue, Donald (1953), *Population Growth in Standard Metropolitan Areas 1900 – 1950,* Oxford, Ohio: Scripps Foundation in Research in Population Problems.

Clark, Philip J., and Francis C. Evans (1954), “Distance to Nearest Neighbor as a Measure of Spatial Relationships in Populations,” *Ecology,* 35, 4, 445–453.

Cliff, A. D., and J. K. Ord (1975), “Model Building and the Analysis of Spatial Pattern in Human Geography,” *Journal of the Royal Statistical Society,* B, 39, 297–348.

Diggle, Peter J. (1983), *Statistical Analysis of Spatial Point Patterns*, Academic Press, London.

Dobkins, Linda Harris , and Yannis M. Ioannides (1998), “Spatial Interactions among U.S. Cities,” presented at the 1998 North American Meeting of the Econometric Society, Chicago, January, working paper, Tufts University.

Ellison, Glenn, and Edward E. Glaeser (1997), “Geographic Concentration in U.S. Manufacturing Industries: A Dartboard Approach,” *Journal of Political Economy,* 105, 889–927.

Fujita, Masahisa, Paul Krugman, and Tomoya Mori (1999), “On The Evolution of Hierarchical Urban Systems,” *European Economic Review,* 43(2), 209–51

Fujita, Masahisa, Paul Krugman, and Anthony Venables (1999), *The Spatial Economy,* MIT Press, Cambridge, MA.

Fujita, Masahisa, and Tomoya Mori (1996), ”The Role of Ports in the Making of Major Cities: Self-agglomeration and Hub-effect,” *Journal of Development Economics,* 49(1), 93 –120.

Fujita, Masahisa, and Tomoya Mori (1997), “Structural Stability and Evolution of Urban Systems,” *Regional Science and Urban Economics* 27(4-5), 399–442.

Gabaix, Xavier (1999), "Zipf's Law for Cities: An Explanation," *Quarterly Journal of Economics,* CXIV, August, 739 – 767.

Hanson, Gordon (2000), "Market Potential, Increasing Returns and Geographic Concentration," University of Michigan, working paper, *Economic Geography*, forthcoming.

Harris, C. D. (1954), "The Market as a Factor in the Localization of Industry in the United States," *Annals of the Association of American Geographers,* 44, 315–348.

Henderson, J. Vernon (1974), "The Types and Size of Cities," *American Economic Review*, 64, 640-656.

Henderson, J. Vernon (1988), *Urban Development: Theory, Fact and Illusion,* Oxford University Press, Oxford.

Ioannides, Yannis M., and Henry G. Overman (2000), "Zipf's Law for Cities: An Empirical Examination," working paper, Tufts University and London School of Economics, May.

Kim, Sukkoo (1997), "Economic Integration and Convergence: U.S. Regions, 1840-1987," *Journal of Economic History,* 58(3), 659–683.

Krugman, Paul (1991), "Increasing Returns and Economic Geography," *Journal of Political Economy,* 99, 483–499.

Krugman, Paul (1992), "A Dynamic Spatial Model," NBER Working Paper No. 4219, November.

Krugman, Paul (1993), "First Nature, Second Nature and Metropolitan Location," *Journal of Regional Science,* 33, 129–144.

Krugman, Paul (1996), "Confronting The Mystery of Urban Hierarchy," *Journal of The Japanese and International Economies,* 10(4), 399–418.

Pred, Allan R. (1966), *The Spatial Dynamics of U.S. Urban-Industrial Growth, 1800-1914: Interpretive and Theoretical Essays,* MIT Press, Cambridge, MA.

Overman, Henry G., and Yannis M. Ioannides (1999), "Cross-Sectional Evolution of the US City Size Distribution," working paper, LSE and Tufts University, October.

Quah, Danny T. (1993), " Empirical Cross-Section Dynamics and Economic Growth," *European Economic Review,* 37, 2/3, 426–434.

Quah, Danny T. (1996a), "Empirics for Economic Growth and Convergence" *European Economic Review,* Vol 40, no.6 pp 1353-1375.

Quah, Danny T. (1996b), "Regional Convergence Clusters across Europe," *European Economic Review,* 40, 951–958.

Quah, Danny T. (1997), "Empirics for Growth and Distribution: Stratification, Polarization and Convergence Clubs, " *Journal of Economic Growth,* 2, 1, 27–59.

Quah, Danny T. (1999), "Regional Convergence from Local Isolated Actions: II Conditioning". Published in Spanish as "Cohesion Regional Mediante Actuaciones Locales Aisladas: Condiciones," in *Dimensiones de la Desigualdad, III Simposio Sobre Igualdad y Distribucion de la Renta y la Riqueza,* Volumen I.

Ripley, B. D. (1979), "Tests of 'Randomness' for Spatial Point Patterns," *Journal of Royal Statistical Society,* B, 41, 3, 368–374.

Silverman, Bernard W. (1986), *Density Estimation for Statistics and Data Analysis,* Chapman and Hall, New York.

Tabuchi, Takatoshi (1998), "Urban Agglomeration and Dispersion: A Synthesis of Alonso and Krugman," *Journal of Urban Economics,* 44, 333–351.

Thomas, Alun (1996), "Increasing Returns, Congestion Costs, and The Geographic Concentration of Firms," I.M.F., March, mimeo.

1	2	3	4	5	6	7
Year	U.S. Pop. (000)	U.S.Pop.: Urban (000)	Number of cities	Mean Size	Median Size	GNP billion $
1900	75,995	29,215	112	259952	121830	71.2 2
1910	91,972	39,944	139	286861	121900	107.5
1920	105,711	50,444	149	338954	144130	135.9
1930	122,775	64,586	157	411641	167140	184.8
1940	131,669	70,149	160	432911	181490	229.2
1950	150,697	85,572	162	526422	234720	354.9
1960	179,323	112,593	210	534936	238340	497.0
1970	203,302	139,419	243	574628	259919	747.6
1980	226,542	169,429	322	526997	232000	963.0
1990	248,710	192,512	334	577359	243000	1277.8

All figures are taken from *Historical Statistics of the United States from Colonial Times to 1970*, Volumes 1 and 2, and *Statistical Abstract of the United States, 1993.* Column 7: GNP adjusted by the implicit price deflator, constructed from sources above; 1958=100.

Table 1. Descriptive statistics: decennial data, 1900 - 1990

Variable	Mean	Std. Dev.	Skewness	Kurtosis	Min	Max
Population (000)	479.5	1001.5	6.6	58.8	50.7	9,372.0
Log(Population)	12.4028	0.9895	1.0	4.1	10.8343	16.374
Growth Rate (%)	10.62	41.98	-1.1	5.8	-.999	1.8752
New England	.0879	.2833	2.9	9.5	0.00	1.00
Mid Atlantic	0.1276	0.3338	2.2	6.0	0.00	1.00
South Atlantic	0.1673	0.3734	1.8	4.2	0.00	1.00
East North Central	0.2030	0.4023	1.5	3.2	0.00	1.00
East South Central	0.0663	0.2489	3.5	13.1	0.00	1.00
West North Central	0.0910	0.2876	2.8	9.1	0.00	1.00
West South Central	0.1221	0.3275	2.3	6.3	0.00	1.00
Mountain	0.0462	0.2100	4.3	19.7	0.00	1.00
Pacific	0.0884	0.2840	2.9	9.4	0.00	1.00
Education (%)	57.1085	20.9284	-0.4	1.8	11.80	92.73
Real Wage ($)	3197.92	1132.37	0.2	2.3	1020.00	7311.00

1990 Observations. Data on education and real wage are taken from *Historical Statistics of the United States from Colonial Times to 1970, Vol. 1 and 2, and* Statistical Abstract of the United States, 1993. Educational percentage refers to the mean percent of 15 to 20 age cohort in school. Mean real annual earnings, by city proper or metro area, are in dollars, deflated by the Consumer Price Index, 1967 = 100.

Table 2. Descriptive statistics for all cities, pooled 1900 – 1990

	Bilateral distances			Nearest neighbor distances			Nearest neighbor correlations	
	mean	median	variance	mean	median	variance	sizes	growth rates
1900	802.5	642.5	594.8	70.9	55.7	61.8	-.073	.557
1910	863.8	686.5	623.2	68.3	54.6	58.3	-.059	.256
1920	864.0	697.9	609.6	66.2	51.8	54.5	-.058	.528
1930	876.9	720.1	600.2	64.8	51.8	50.0	-.065	.457
1940	884.9	734.9	596.7	64.4	53.4	46.1	-.062	.674
1950	890.8	745.7	594.0	65.3	53.4	46.6	-.062	.436
1960	940.4	813.8	603.0	56.9	46.3	52.5	.027	.126
1970	981.3	841.3	631.3	52.5	42.0	41.2	.091	.394
1980	998.7	856.9	639.6	45.9	36.9	33.2	.138	.467
1990	1005	868.5	637.1	45.5	37.0	32.3	.172	

First three columns provide summary statistics for matrix of bilateral distances to all cities at time t. Last three columns provide summary statistics for distance from nearest neighbor. Distances are calculated as great circle distances based on latitudes and longitudes from the Times Atlas 1997 edition. Calculations exclude Honolulu and Anchorage.

Table 3. Distances and Nearest neighbor Correlations

Year	Area	Number of cities	Actual distance	Density	Expected distance	Variance	N(0,1)	R
1900	2969834	112	70.9	3.77E-05	81.41	4.02	-2.61	0.87
1910	2969565	139	68.3	4.68E-05	73.08	3.24	-1.47	0.93
1920	2969451	149	66.2	5.01E-05	70.58	3.02	-1.45	0.93
1930	2977128	157	64.8	5.27E-05	68.85	2.87	-1.41	0.94
1940	2977128	160	64.4	5.37E-05	68.20	2.81	-1.34	0.94
1950	2974726	162	65.3	5.44E-05	67.75	2.78	-0.88	0.96
1960	2968054	209	56.9	7.04E-05	59.58	2.15	-1.24	0.95
1970	2967166	242	52.5	8.15E-05	55.36	1.86	-1.53	0.94
1980	2966432	320	45.9	11.0E-05	48.14	1.40	-1.59	0.95
1990	2963421	332	45.5	11.2E-05	47.23	1.35	-1.28	0.96

Table 4. Clark Evans Test - US

Year	Mid West	North East	South	West
1900	1.14	1.11	0.89	0.93
1910	1.15**	1.1	1.13*	0.68**
1920	1.13*	1.1	1.08	0.8
1930	1.12	1.1	1.17**	0.64**
1940	1.12	1.1	1.12*	0.72**
1950	1.12	1.1	1.17**	0.72**
1960	1.04	0.93	1.16**	0.84
1970	1.03	0.92	1.14**	0.83**
1980	1.03	1.08	1.08**	0.83**
1990	1.03	1.08	1.11**	0.83**

** indicates significant at the 5% level, * indicates significant at the 10% level. Mid-West comprises East North Central and East South Central; North-East comprises Mid-Atlantic and North East; South comprises South Atlantic; West North Central and West South Central; West comprises Mountain and Pacific (excluding Hawaii and Alaska)

Table 5. Clark Evans Test - Regions

	FE	GMM	FE	GMM	FE	GMM	FE	GMM
	1	2	3	4	5	6	7	8
ℓn market potential	-0.137** (.052)	-0.082** (0.042)	-0.104** (0.046)	-0.082* (0.048)	-0.09 (0.06)	0.200** (0.101)		
entry			-0.036* (0.021)	-0.032 (0.021)	-0.02 (0.019)	-0.021 (0.020)		
ℓn pop					-0.126** (0.02)	-0.174** (0.05)		
ℓn (pop/market potential)							-0.146** (0.020)	-0.127** (0.035)

* Significant at 10% level.
** Significant at 5% level.

Table 6. City growth rates – city based market potential

	FE	GMM	FE	GMM	FE	GMM	FE	GMM
	1	2	3	4	5	6	7	8
ℓn market potential	-0.064** (0.030)	-0.110** (0.040)	-0.065** (0.030)	-0.112 ** (0.043)	-0.03 (0.03)	0.08* (0.04)		
entry			-0.030* (0.02)	-0.034 (0.021)	-0.029 (0.020)	-0.020 (0.020)		
ℓn population					-0.116** (0.019)	-0.100** (0.03)		
ℓn (pop/market potential)							-0.113** (0.017)	-0.091** (0.031)

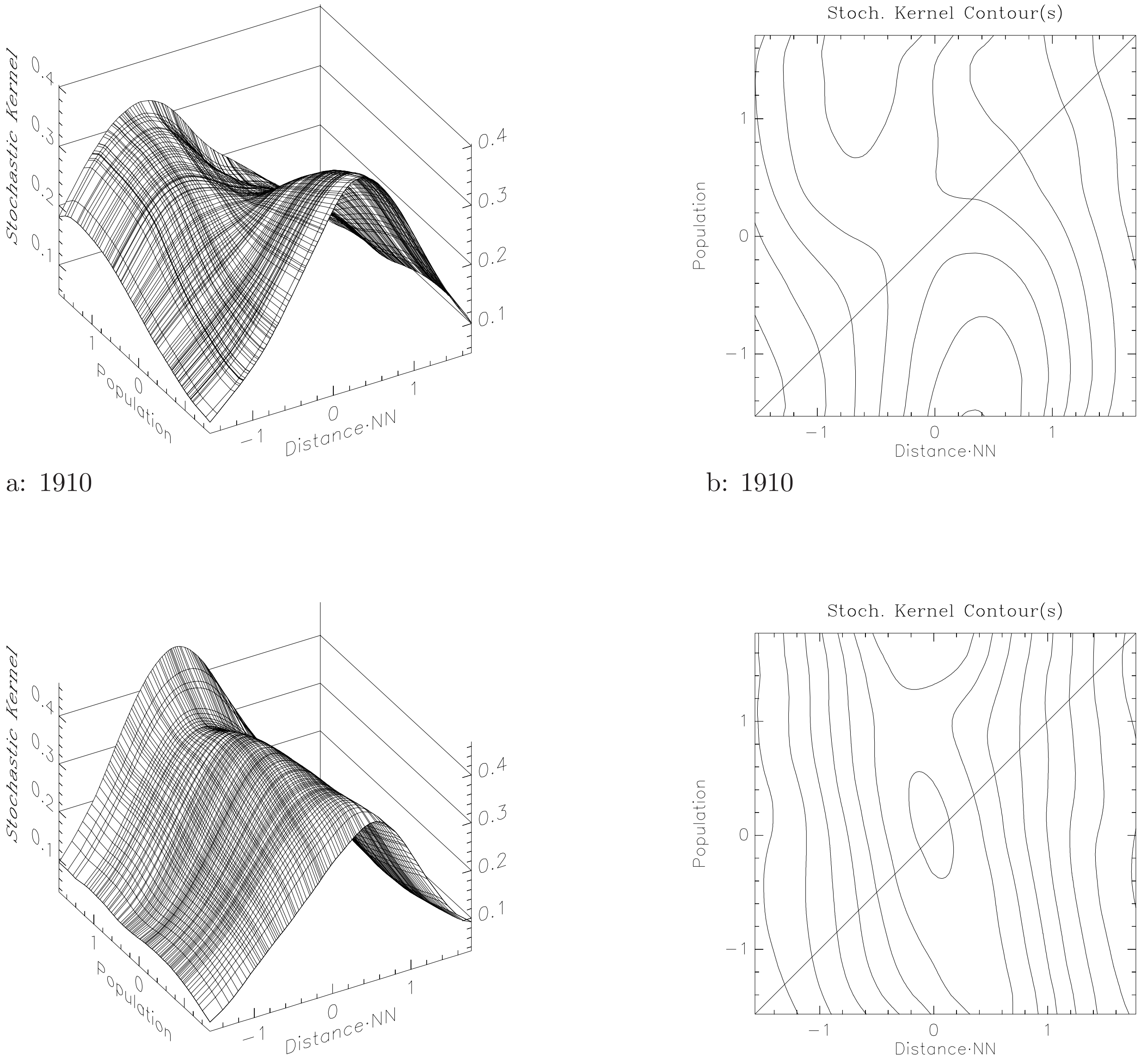
* Significant at 10% level.
** Significant at 5% level.

Table 7. City growth rates – wage weighted market potential

	FE	GMM	FE	GMM	FE	GMM	FE	GMM
	1	2	3	4	5	6	7	8
ℓn market potential	-0.181** (0.065)	-0.178* (0.094)	-0.175** (0.065)	0.182** (0.083)	0.055 (0.109)	0.216 (0.162)		
entry			-0.034 (0.021)	0.036 (0.038)	-0.030 (0.019)	0.048 (0.045)		
ℓn population					-0.111** (0.020)	-0.140** (0.045)		
ℓn (pop/market potential)							-0.124** (0.018)	-0.086** (0.029)

* Significant at 10% level.
** Significant at 5% level.

Table 8. City growth rates – county based market potential



a: 1910

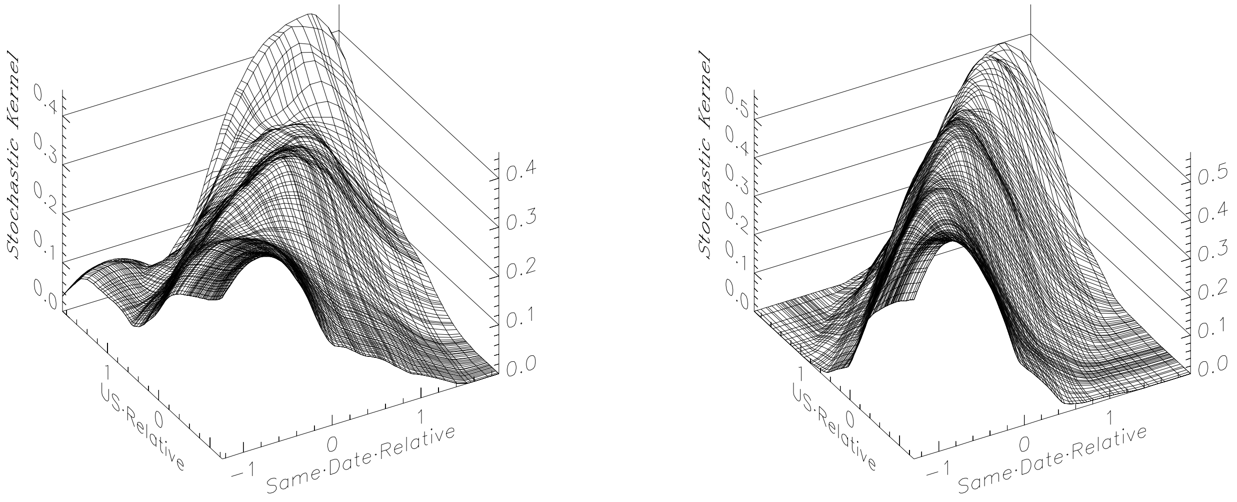
b: 1910

c: 1990

d: 1990

All calculations done using Danny Quah's tSrF econometric shell.
Stochastic kernel from (normalised) population at time t to (normalised) distance to nearest neighbor at time t.

Figure 1. Population to distance to nearest neighbor

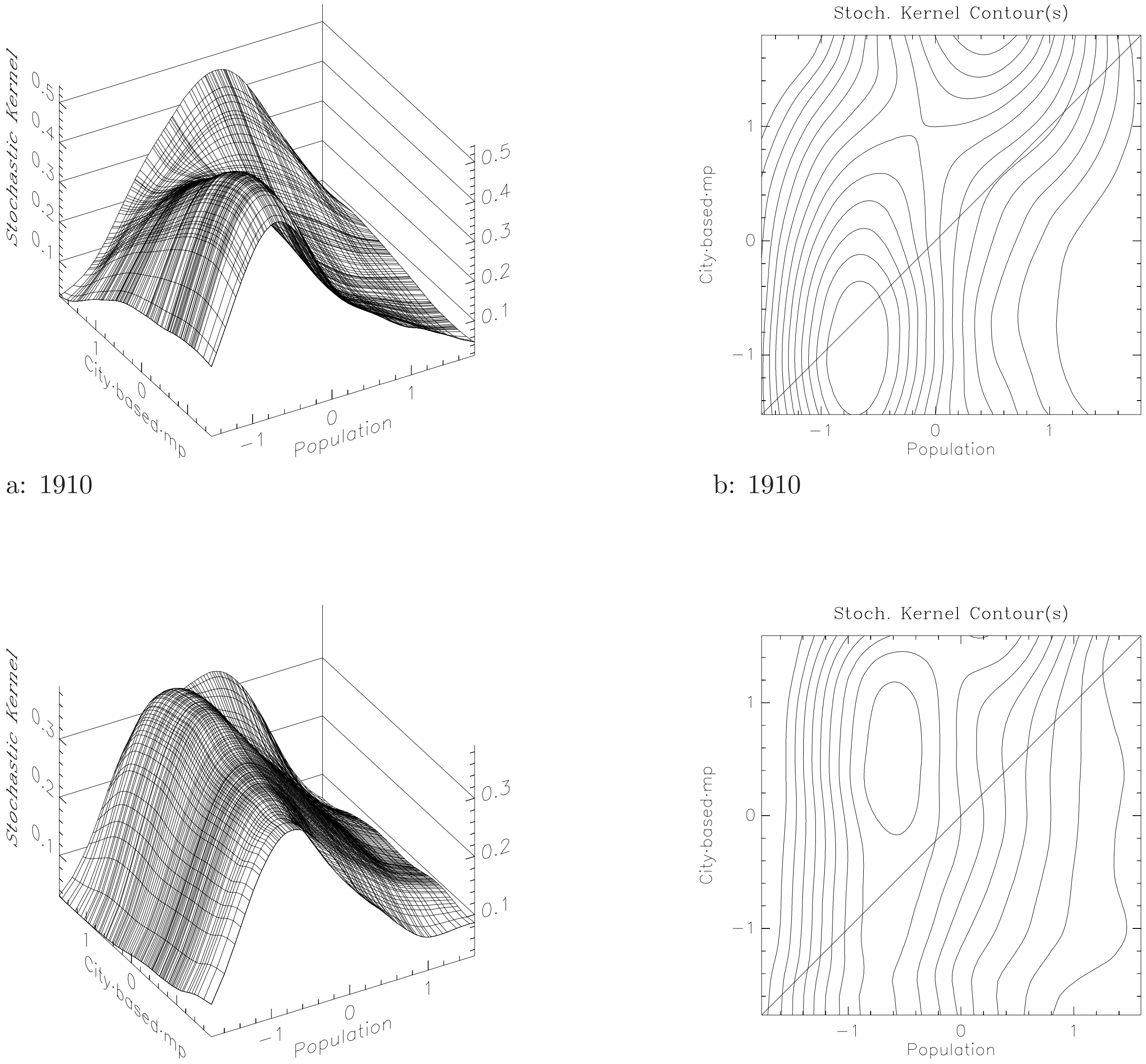


a: 1910

b: 1990

All calculations done using Danny Quah's tSrF econometric shell.
Stochastic kernel from (normalised) population at time t to (normalised) date conditioned population at time t.

Figure 2. Date Conditioning



a: 1910

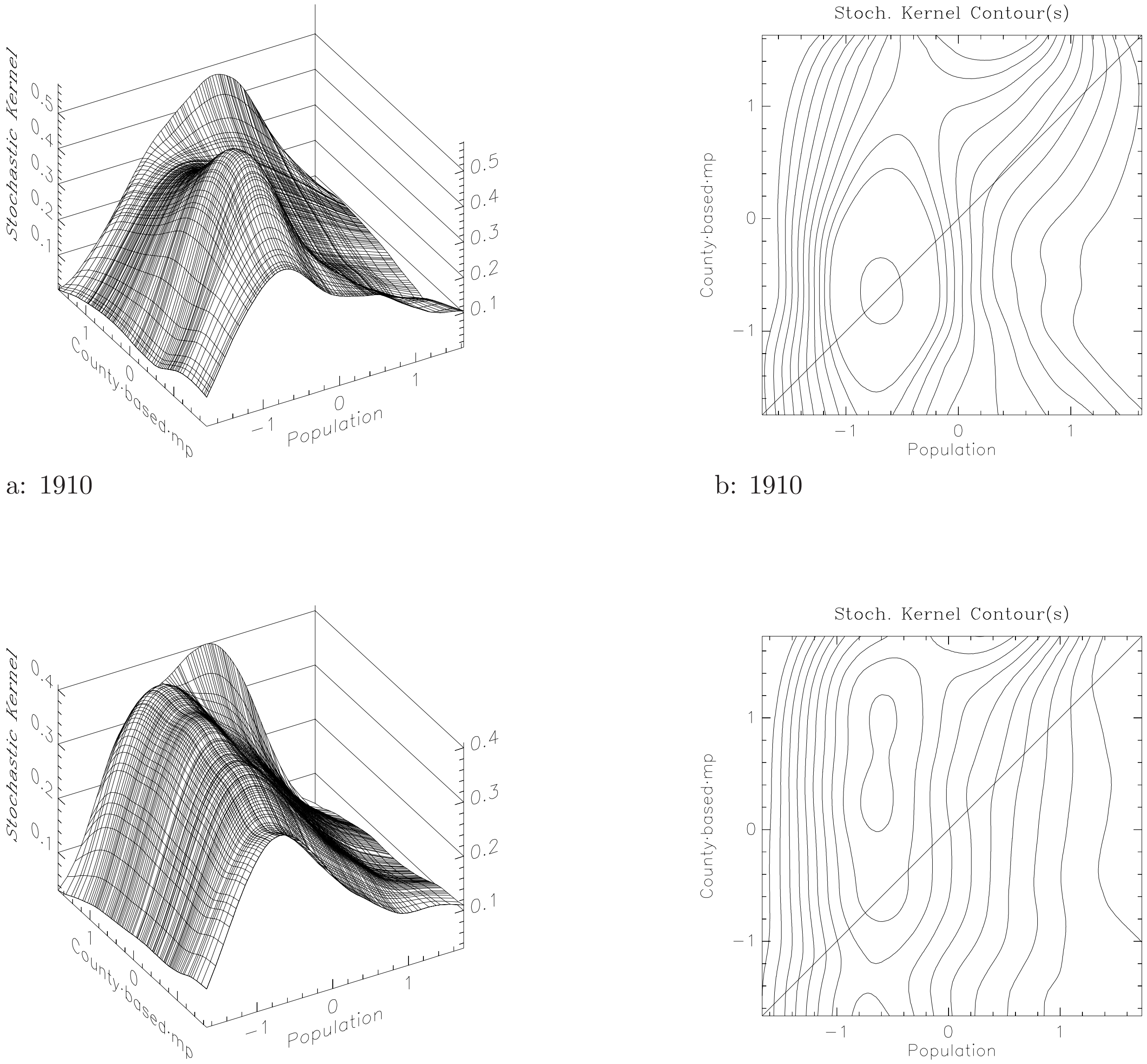
b: 1910

c: 1990

d: 1990

All calculations done using Danny Quah's tSrF econometric shell.
Stochastic kernel from (normalised) city based market potential at time t to (normalised) population at time t.

Figure 3. Market potential to population



a: 1910

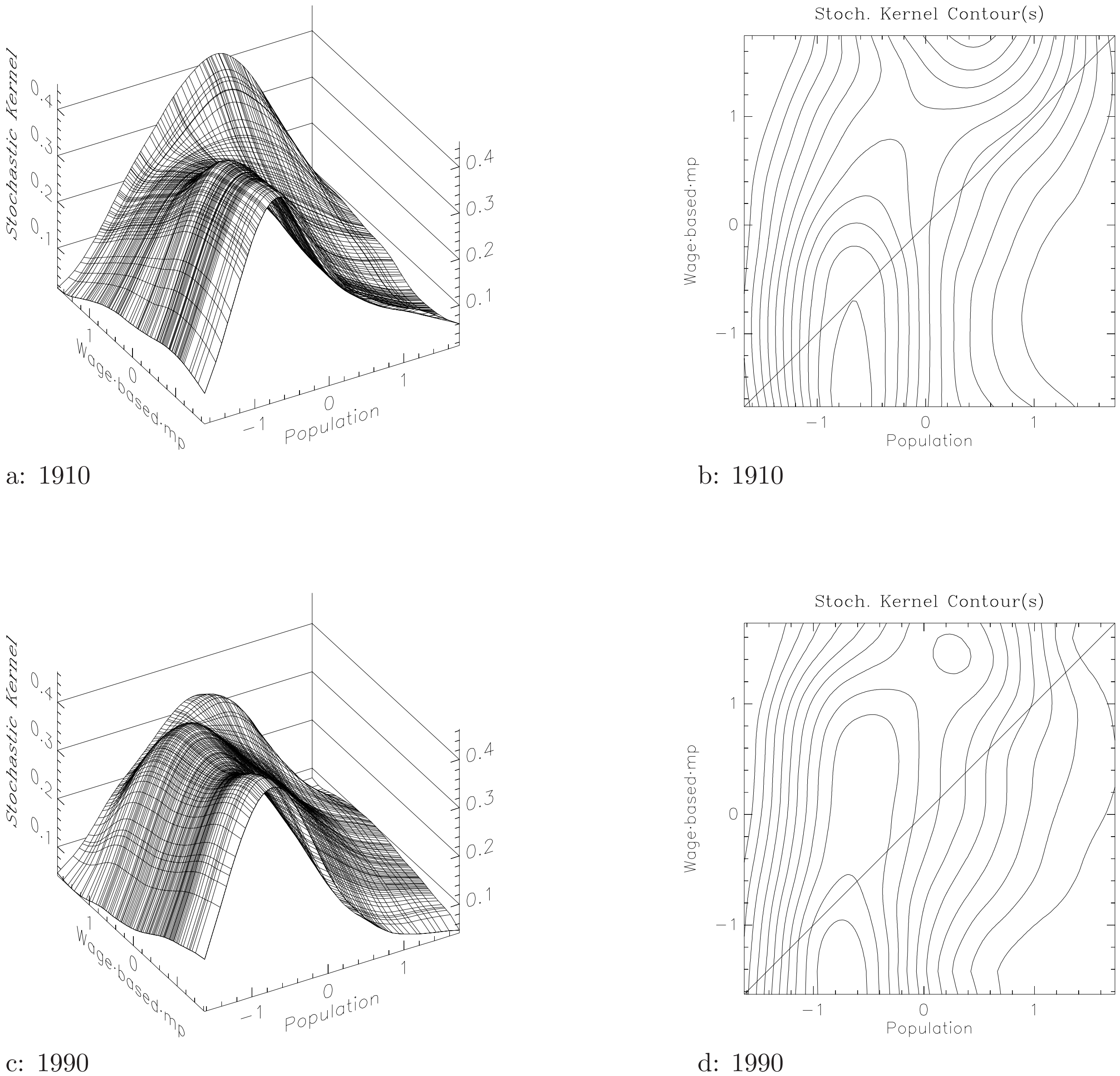
b: 1910

c: 1990

d: 1990

All calculations done using Danny Quah's tSrF econometric shell.
Stochastic kernel from (normalised) county based market potential at time t to (normalised) population at time t.

Figure 4. Market potential to population



a: 1910

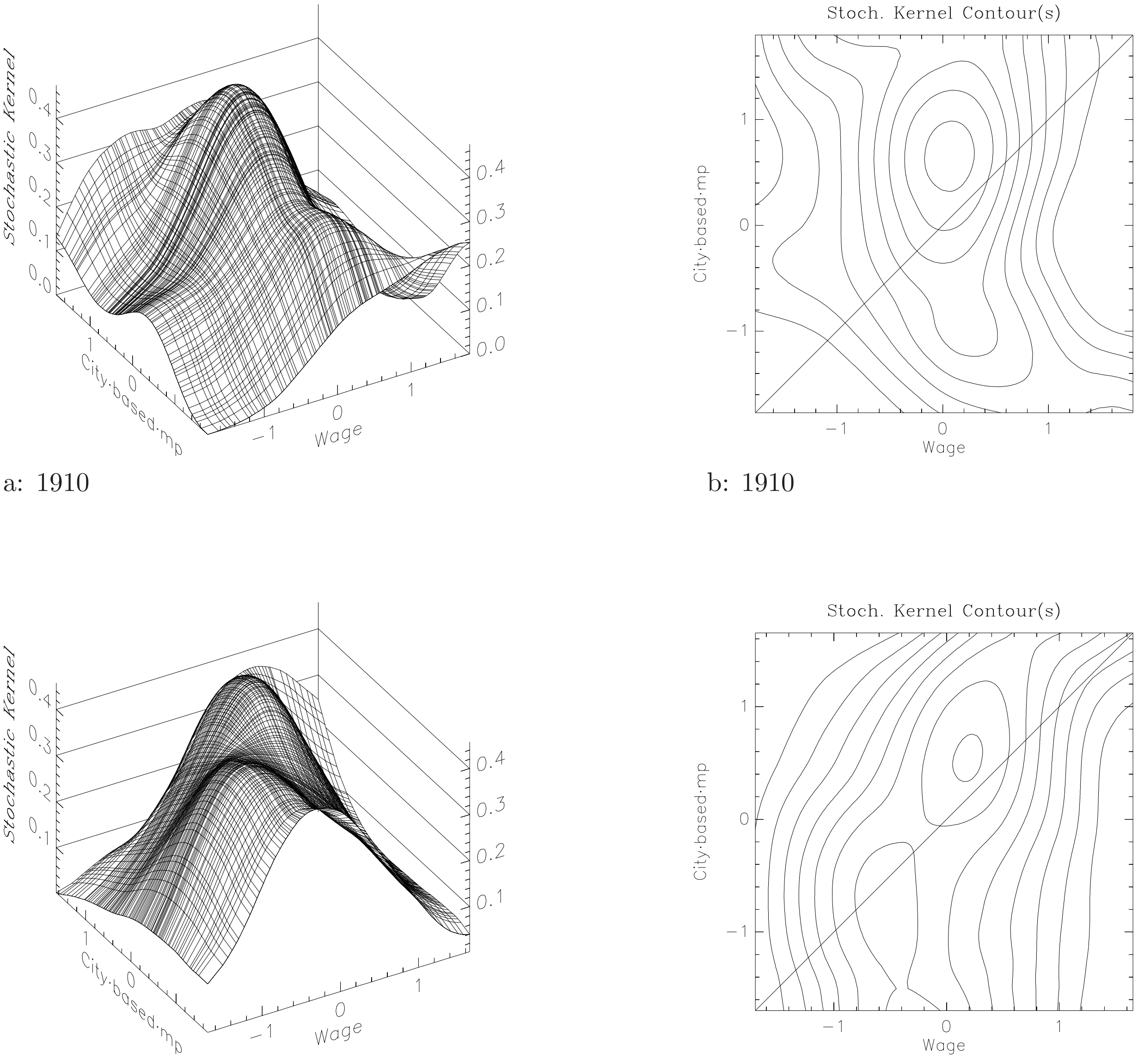
b: 1910

c: 1990

d: 1990

All calculations done using Danny Quah's tSrF econometric shell.
Stochastic kernel from (normalised) wage weighted city based market potential at time t to (normalised) population at time t.

Figure 5. Market potential to population



a: 1910

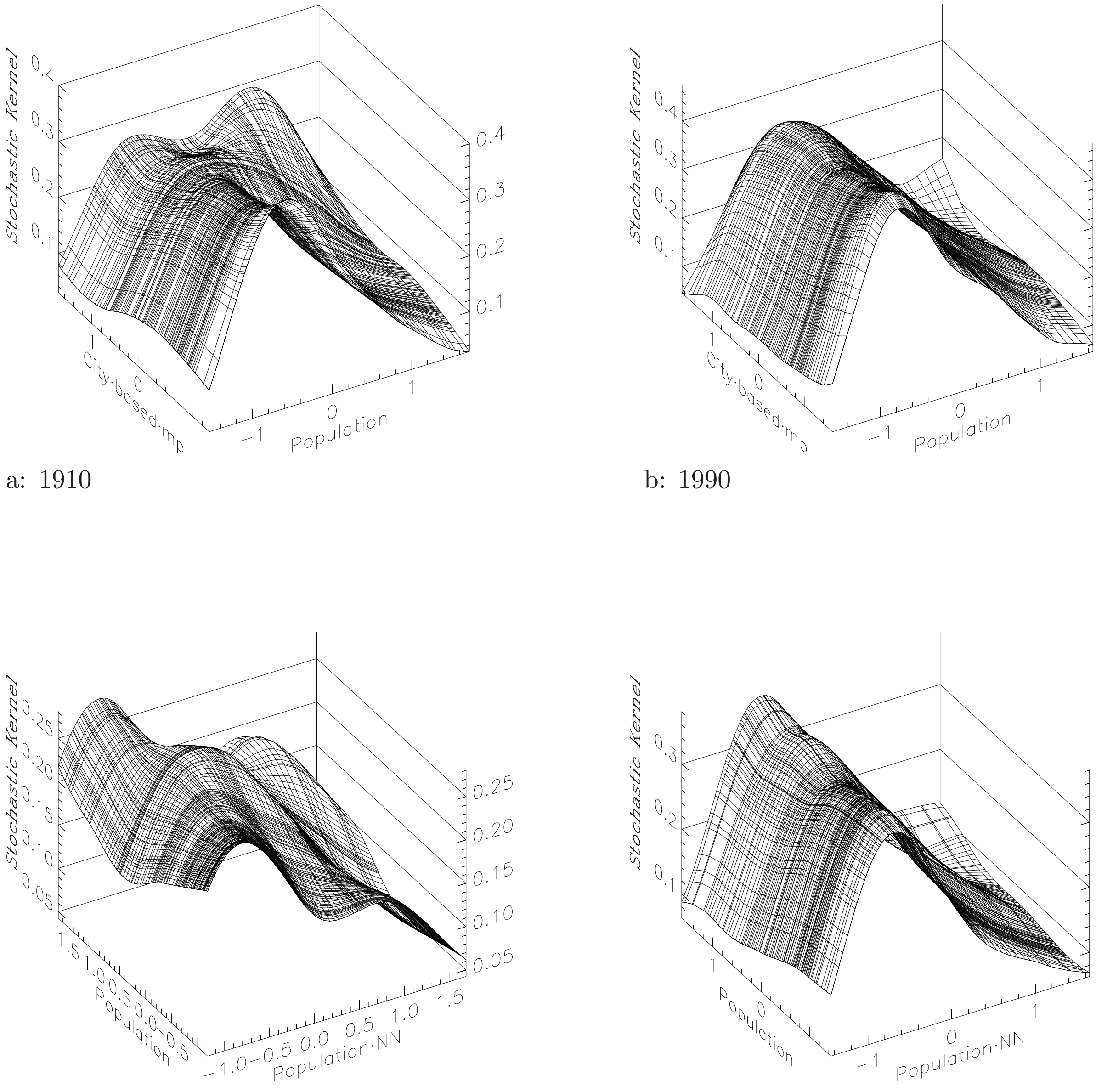
b: 1910

c: 1990

d: 1990

All calculations done using Danny Quah's tSrF econometric shell.
Stochastic kernel from (normalised) city based market potential at time *t* to (normalised) wage at time *t*.

Figure 6. Market potential to wage



a: 1910

b: 1990

a: 1910

b: 1990

All calculations done using Danny Quah's tsrf econometric shell.
a & b report stochastic kernels from (normalised) city based market potential excluding the market potential component from the nearest neighbor at time t to (normalised) population at time t.
c & d report stochastic kernels from (normalised) population at time t to (normalised) population of nearest neighbor at time t.

Figure 7. Nearest neighbor

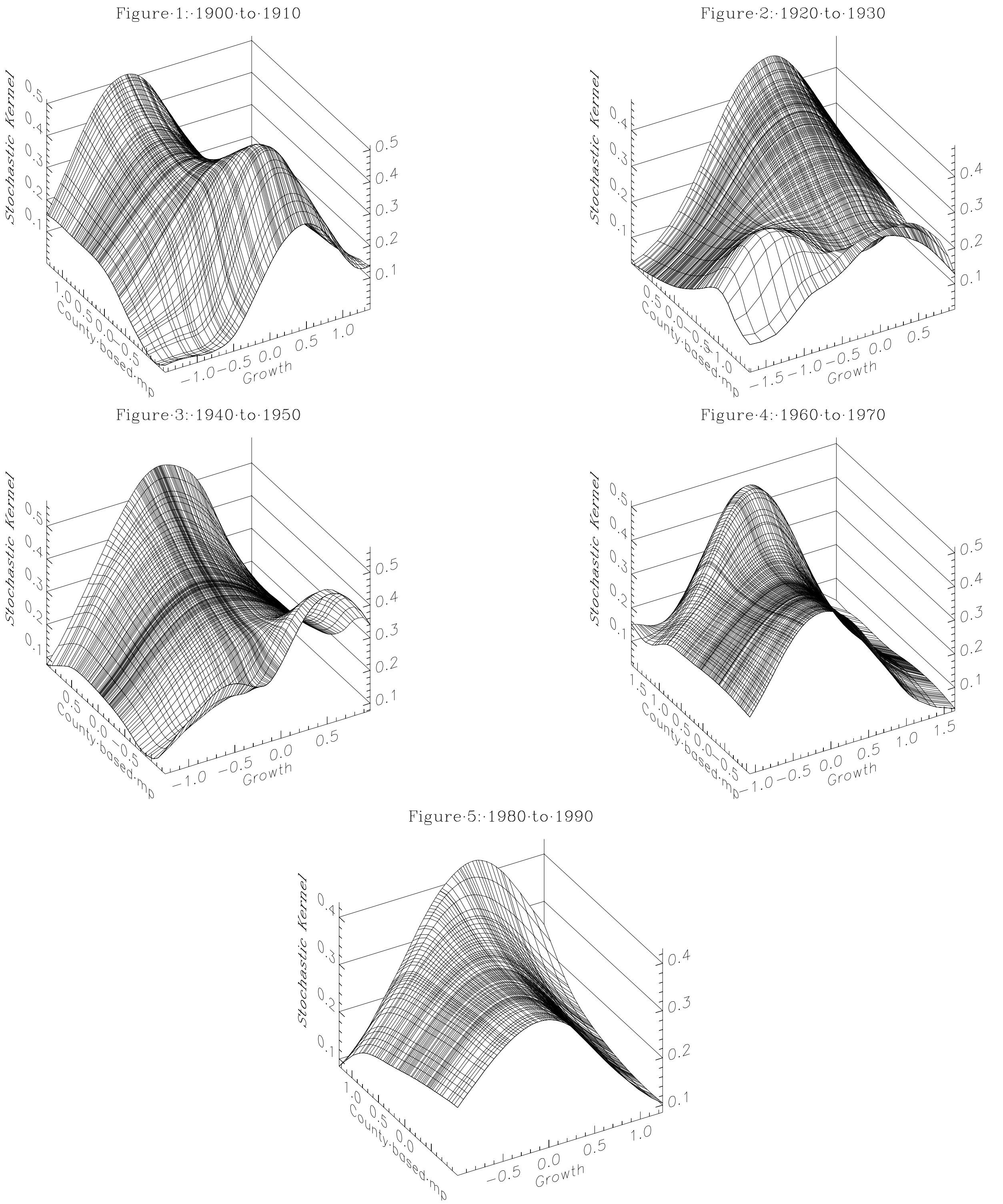


Figure 1: 1900 to 1910

Figure 2: 1920 to 1930

Figure 3: 1940 to 1950

Figure 4: 1960 to 1970

Figure 5: 1980 to 1990

All calculations done using Danny Quah's tsrf econometric shell.
Stochastic kernel from (normalised) county based market potential at time *t* to rate of city growth over the period *t* to *t+1*.

Figure 8. Market potential to growth rates