The American Way of Land Use: A Spatial Hazard Analysis of Changes Through Time

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Abstract. This paper examines the ability of proportional hazard models to evaluate changes in land use through time. There are three specific objectives: (*i*) to review previous research on the complexity of urbanization and explain how the spatial hazard framework accommodates that complexity; (*ii*); to estimate a series of spatial hazard models characterizing land use in the 25 highest-growth core based statistical areas of the United States areas in 1990, 2000, and 2006; and (*iii*) to use the estimation results to track land use change region-by-region over the 16-year timeframe. Overall, the analysis reveals that the spatial hazard framework offers a highly effective means of describing land use change. Along the way, it also illustrates that the classic (Alonso 1964; Muth 1969; Mills 1972) model of urbanization continues to hold in an evermore-complex world — albeit, in an explicitly uncertain and inherently probabilistic manner. *Key Words: Land use, urbanization, sprawl, spatial hazard models, point pattern analysis; JEL classification:* C21; C41; R12; R14

1. Introduction

In their classic paper *The Urban Field,* Friedmann and Miller (1965, page 314) suggested that the city should no longer be viewed as a "physical entity," but, instead, as "a pattern of point locations and connecting flows of people, information, money, and commodities." The work was prescient because it had identified a fundamental break in the American way of land use — a break brought on by the outright disintegration of clear demographic, socioeconomic, and spatial boundaries between urban, suburban, exurban, and rural settings.[1] Over the nearly 50 years since, land use patterns have continued to evolve along this trajectory and essentially all urbanization, no matter how far-flung, is now anchored, one way or another, to one or more of the country's 967 core based statistical areas (CBSAs). As shown in Figure 1, the contemporary urban field — defined, following Friedmann and Miller (1965), as the area located within about a one-hour drive, or a 100-kilometer radius, of a CBSA — covers most of the continental United States. Not only is the nation personally urbanized, with around 83% and 10% of its population living in metropolitan and micropolitan areas, respectively, it is spatially urbanized, with most of its territory located within the sphere of one class of CBSA or the other.

Because of its geographic scope, this still-emerging reality poses daunting problems for the study of land use and, even more, land use change. In particular, urbanization is exceptionally diverse and so too are the people and activities it accommodates, plus the various landscapes that it is situated on. Consider, for instance, the vast differences between the Northeast Corridor and Southern California conurbations, or between the environments of the Atlantic Southeast and the Pacific Northwest — they confound both the simplifying assumptions of theoretical models of land use and the practical limits of empirical methods of describing it: to wit, flat, featureless plains and perfectly smooth, negative exponential density gradients can be hard to justify theoretically (Brueckner 1982, 1987) and even harder to locate empirically (Kau and Lee 1976a, 1976b, 1977; Johnson and Kau 1980; Kau et al 1983). As a consequence, researchers have struggled through the years to characterize urbanization in a way that enables scientific analysis of similarities and dissimilarities from place-to-place and time period-to-time period. But, in spite of this effort, a definitive approach has yet to be discovered. As soon as one group (Burchfield et al 2006, most recently) seems to have come up with one, another (Irwin and Bockstael 2007, in that case) delivers evidence to the contrary. In short, generalizing about the way of land use across a nation as large and variegated as the United States remains problematic. The challenge must be overcome, though, because social scientists and policymakers alike require the ability to compare and

[1] Others noticed this break, too, but interpreted it differently. For example, in another classic analysis, Vining and Strauss (1977) argued that the ongoing process of population deconcentration was a complete reversal of past patterns of urbanization and that it would eventually result in the population being more-or-less evenly distributed across the national landscape.

contrast outcomes around the country in order to address them on evidentiary — and not strictly interpretive — grounds (Batty 2007).

Toward that end, this paper examines the ability of proportional hazard models — a class of duration, or failure time, models originally developed for analyzing lifecycles (Heckman and Singer 1984; Kiefer 1988; Odland and Ellis 1992; Lawless 2002; Waldorf 2003; Cleves et al 2004; Selvin 2008) — to evaluate changes in land use through time. It builds directly off a previous analysis (Carruthers et al 2010) that establishes hazard models as a viable tool for studying spatial point patterns generated by urbanization. The present objectives are three: (*i*) to review previous research on the complexity of urbanization and explain how the spatial hazard framework accommodates that complexity; (*ii*); to estimate a series of spatial hazard models characterizing land use in the 25 highest-growth core based statistical areas of the United States areas in 1990, 2000, and 2006; and (*iii*) to use the estimation results to track land use change region-by-region over the 16-year timeframe. Overall, the analysis reveals that the spatial hazard framework offers an effective means of describing land use change and comparing diverse outcomes through time. Along the way, it also illustrates that the classic (Alonso 1964; Muth 1969; Mills 1972) model of urbanization continues to hold in an evermore-complex world — albeit, in an explicitly uncertain and inherently chaotic manner.

2. Background Discussion

2.1 Complexity, Land Use, and the Urban Field

Land use patterns are inherently complex: urbanization is, after all, composed of physical development — buildings, infrastructure, and other engineering — that has been shaped, large and small, by a literally countless number of individual actions taken by its builders, inhabitants, and planners (Jacobs 1961; Batty 2007). Plus, different regions have different cultures, functions, geographic constraints, and natural resources and have likewise (and consequently) experienced different cycles of growth and decline through time (Perloff et al 1960). Even in a nation as young as the United States, land use has evolved over the course of hundreds of years and it has done so under continually shifting economic, environmental, demographic, social, and technological circumstances. As an outcome, urbanization is a veritable mash-up of different modes of land use with an internal structure that varies significantly from spot-to-spot and era-to-era — no two regions are the same, and individual regions exhibit a diverse patchwork of development.

Adding to this complexity, the sphere of most regions has expanded so greatly over the past half-century that long-standing distinctions between urban, suburban, exurban, and rural settings have lost much of their meaning (Frey 2004; Clark et al 2009). Friedmann and Miller (1965) recognized this early on and responded by suggesting that urbanization should be reframed as a field — rather than material — concept, wherein the regional center exerts both centripetal and centrifugal forces. Specifically, they: (*i*) acknowledged that the net flow of migration from rural to urban parts of the country was unlikely to change; but (*ii*) at the same time, suggested that development patterns were taking on a new, far more expansive and elaborately structured, character.[2] Only a few years later, this view was vindicated by the Census Bureau's *Current Population Reports*, which revealed that, beginning in the late 1960s, internal migration had favored nonmetropolitan areas over metropolitan areas — in a dramatic turnaround, the former grew at the expense of the latter as households and, eventually, firms began relocating to outlying centers (Beale 1975; Gordon et al 1998). Though this trend, along with various explanations for it, has waxed and waned through the intervening years (see Frey 1993; Fuguitt and Beale 1996), it now seems clear that Friedmann and Miller's (1965) field concept is of enduring value. The nonmetropolitan turnaround may not have been the "clean break" that some analysts (Vining and Strauss 1977) initially interpreted it to be, but its decisive transformation of land use patterns is indisputable (Gordon 1979). Most regions still retain a dominant center of gravity, but their development is more complex than ever before — partly because of the nature of urbanization itself, and partly because of how the urban field holds its far-flung, polycentric anatomy together.

Yet, in spite of all this, the classic (Alonso 1964; Muth 1969; Mills 1972) economic model of urbanization continues to explain the general tendencies of land use, even within very large regions having an extended spatial hierarchy (Glaeser and Kahn 2004; Bogart 2006). In its simplest form, the model describes a perfectly smooth, monotonic rent gradient that declines with distance from its peak at the central business district of a circular region situated on a flat, featureless plane. At equilibrium, all households, which are assumed to be identical, attain the same level of utility — and, so, the rent gradient reflects the tradeoff between location and the cost of travel to and from downtown. A corresponding and equally smooth density gradient emerges as a result of households consuming progressively greater amounts of land, a normal good, toward the urban fringe where land is less expensive. The density gradient and, with it, urbanization come to an end once the rent gradient (minus the cost of construction) reaches zero and the highest and best use of land is no longer for development but, instead, for some natural resource oriented activity.[3] In practice, the pattern is rarely, if ever, monocentric, but the same story readily generalizes to polycentric settings. The reason for this is that, under the conditions just described, firms, which are also assumed to be identical — similar to households, all firms attain the same level of profits (zero) — have an incentive to decentralize: since a household's net income is its wage less the cost of commuting, a decentralizing firm can offer lower wages and still attract the labor that it

[2] See Lang (2003) for a recent exploration.
[3] In more realistic vintage models of urbanization, the density gradient is jagged, not smooth, because of structures are torn down and rebuilt over time according to their age and prevailing market conditions (Brueckner 2000).

requires (DiPasquale and Wheaton 1996). As shown in Figure 2, the result is a polycentric bid rent gradient, $r(d)$, that first falls with distance, d, from the central business district, then climbs as it approaches the outlying sub-center and, finally, falls again until it reaches the baseline rent, $r(n)$, which reflects the value of land as a natural resource (for empirical examples, see Heikkila et al 1989; Richardson et al 1990). This kind of rent gradient emerges organically when the marginal costs of production and/or transportation are large relative to the population and physical size of the region in question (Odland 1978; Scott 1988).

A more formal description of household behavior within this framework is as follows (see Fujita 1987 for a complete exposition). Households have a common utility function, $U(z,s)$, which contains a composite good, z, and urban space, or land, s. A household's budgetary constraint is determined by its income, y, less the cost of travel, k, between its place of work and its location at radial distance d from its place of work:

$$y - k(d) = z + r(d)s, \tag{1}$$

where $k(d)$ increases continuously with d and $r(d)$ is the rent per unit of land at d. The budgetary constraint, which sets limits on the consumption of land and all else, is equal to household income minus the cost of commuting. Given their particular — spatially explicit — budgetary constraint, households are faced with a utility maximization problem that involves choosing some combination of the composite good and land:

$$\max_{d,z,s} U(z,s) \;\Big|\; z + r(d)s = y - k(d). \tag{2}$$

The product of this decision is a household's bid rent, $\rho(d, u)$, which expresses the maximum price they are able per unit of land at distance d from their workplace while still maintaining a fixed level of utility, u:

$$\rho(d,\, u) = \max_{z,s} \left\{ \frac{y - k(d) - z}{s} \;\Big|\; U(z,s) = u \right\}. \tag{3}$$

Note that the reason bid rent decreases with d, as shown in Figure 2, is that location is exactly what determines net income: households are unwilling to pay the same price for an inferior spot located far from work as for a superior spot located close to work. In addition to land prices, bid rent yields a household's optimal quantity of land consumption, or lot size, $\varsigma(d, u)$, which is what ultimately determines the character of land use.

Figure 3 illustrates the connection between bid rent and optimal lot size. It displays the marginal rate of substitution, described by an indifference curve (the arc) for a fixed level of utility, u, between the composite good, z, and land, s, plus the budget constraints (the dashed lines) and corresponding consumption bundles (the dotted lines) for two households located at distances d_1 and d_2 from a common place of work, where $d_1 < d_2$. Because the cost of travel to and from work, $k(d)$, is lower at d_1 than it is at d_2, the net income of the household located at d_1 is greater than the net income of the household at d_2, or $y - k(d_1) > y - k(d_2)$. The two budget constraints, which must be tangent to the indifference curve in order for each of their respective households to achieve utility level u, show that: (*i*) the bid rent, which is equivalent to the slope of the budget constraint, for the household located at d_1 is greater than the bid rent for the household located at d_2, or $\rho(d_1, u) > \rho(d_2, u)$; and (*ii*) the optimal lot size for the household located at d_1 is less than the optimal lot size for the household located at d_2, or $\varsigma(d_1, u) > \varsigma(d_2, u)$. In short, all else being equal, households located closer to their workplace pay a higher price per unit of land and, so, consume less of it — but still manage to attain the same level of utility, by substituting more of the composite good.

The strength of this framework lies in its ability to distill the complexity of urbanization into a few simple relationships that explain the general tendencies of land use. In doing so, it also illuminates the explosion of the urban field that occurred in the wake of the nonmetropolitan turnaround: household income and commuting costs have, respectively, grown and declined dramatically in the years since World War II, and their combined impact first began materializing in the late 1960s (see Mieszkowski and Mills 1993). All else being equal, an increase in income, or, equivalently, a decrease in the cost of commuting, shifts the budget constraint shown in Figure 3 outward from the origin, enabling households to reach a higher level of utility through more land and/or other forms of consumption.[4] Households continue to face the same tradeoffs as always but they increasingly have more income to allot and less aversion to commuting and, so, adjust their land consumption accordingly. But the weakness of this framework — for all its explanatory power — is that it is baldly deterministic, when actual land use patterns are not. Urbanization rarely unfolds monotonically, much less smoothly, but, instead, for all the reasons given above and more, appears to be a discontinuous patchwork that becomes progressively more complex as the scale of perspective expands. Even though land use does normally grow less dense with distance from various centers of gravity, it typically does so in a disjointed and seemingly chaotic manner. The problem with modeling land use patterns anymore, then, rests not so much with theoretically explaining *why* they are as they are, but with empirically characterizing *how* they are — while certain potentials prevail throughout the urban field, actual material conditions do not necessarily (Stewart 1947; Stewart and Warntz 1958) meaning that it is one thing to predict general tendencies and another to model specific outcomes.

[4] This is why sprawl, often a pejorative term, does not bother many economists (see, for example, Gordon and Richardson 1997).

2.2 Modeling Land Use — and its Complexity

Efforts to scientifically evaluate changes in land use date at least to Clark's (1951) discovery of the negative exponential density gradient:

$$\delta(d_i) = \delta_0 \cdot e^{-\gamma \cdot d_i} + \upsilon_i, \qquad (4)$$

where $\delta(d_i)$ is the density of development at radial distance d_i from a regional center or sub-center; δ_0 is the population density there, where $d = 0$; $-\gamma$ is the density gradient, which registers the rate of decrease in density per unit of distance; and υ_i is a random error term. After taking the natural log of both sides, equation (4) can easily be estimated via ordinary least squares and then used to trace out the overall pattern of urbanization. Clark (1951) did just that for more than 20 major metropolitan areas around the world, including seven in the United States,[5] and compared results over time. The analysis revealed that, in most cases, both the peak and the slope of the regional density gradients had declined between intervening years — a finding that was ingeniously (especially for the time) attributed to falling commuting costs. As Batty and Kim (1992, page 1045) put it, "Clark's (1951) paper was wide-ranging, idiosyncratic, and brilliant."

Ever since, the density gradient has been the workhorse of land use analysis: it is straightforward to implement and very flexible — it can be estimated in virtually any functional form, and expanded to include any number of explanatory variables besides distance (McDonald 1988). Plus, it engages naturally with economic models of land use, which, as shown in Figure 2, normally portray development in a one-dimensional setting. Just like the theory outlined above, the strength of the density gradient lies in both its simplicity and its ability to representatively describe the general tendencies of land use worldwide (Anas et al 1998). But, likewise, the weakness of the density gradient lies in the fact that it, too, is restrictively deterministic and glosses over the inherent complexity of urbanization. Indeed, studies have shown that the negative exponential density gradient in particular rests upon unrealistically strong assumptions (Brueckner 1982, 1987) and may grossly mischaracterize underlying development (Kau and Lee 1976a, 1976b, 1977; Johnson and Kau 1980; Kau et al 1983). As always, generality comes at a loss of specificity, so it's only fair to ask: what is the alternative? Although faulting the density gradient is easy, modeling land use in a way that better reflects its complexity is not. Nevertheless, the fact is that contemporary urban centers project a far-reaching field that encompasses and influences — even organizes — various permutations of clustered, non-clustered, contiguous, non-contiguous, and linear development patterns (Clark et al 2009). A single transect may look more like Tobler's (1969) spectrum of Interstate 40 than a well-behaved distance gradient, monotonic or not. And, even in the most general of

[5] These were: (*i*) Boston, MA; (*ii*) Chicago, IL; (*iii*) Cleveland, OH; (*iv*) Los Angeles, CA; (*v*) New York, NY; (*vi*) Philadelphia, PA; and (*vii*) St. Louis, MO.

terms, it is a rare case that exhibits anything like a uniform pattern all 360º around the regional center of gravity. What's required, are empirical models of land use that somehow accommodate the gnawing uncertainty that attends complexity — and, more, that make that uncertainty a main aspect of the analytical framework (Batty 2007).

One such approach is the "fractal geometry" method pioneered by Batty and Longley (1987, 1994) and Frankhauser (1994). Fractals are chaotic shapes having, in the context of geographic phenomena, a dimension of between one and two — somewhere between a one-dimensional line and a two-dimensional polygon (Miller 2009) — that is a measure of space filling: the greater the fractal dimension, the greater the space filling, and the more compact the development pattern (see Peitgen et al 2004). For example, Batty (2007) reports the following fractal dimensions for six regions: (*i*) 1.539 for Albany, NY; (*ii*) 1.793 for Buffalo, NY; (*iii*) 1.760 for Cleveland, OH; (*iv*) 1.670 for Columbus, OH; (*v*) 1.673 for Pittsburgh, PA; and (*vi*) 1.370 for Syracuse, NY. By these measures, Buffalo is the most compact of the six and Syracuse is the least. The fractal dimension of urbanization (or any other object) is measured by estimating the power law:

$$size \propto scale^{\psi}, \tag{5}$$

where *size* is the size of the area in question; *scale* is the measurement scale; and ψ is the fractal dimension. Although the relationship looks simple enough, estimating it is difficult because there are multiple definitions of the fractal dimension, not all of which agree, and multiple ways of calculating it. Fractals are especially useful for modeling urbanization because of their characteristic "self-similarity," which arises in the form of repeated structures (Song and Knaap 2007 detail a number of these) across multiple spatial scales. Land use is generally shaped at a very local level but the regional outcome of individual actions, large and small, nonetheless ends up generating the same material pattern/s over-and-over again — as in the event of sub-center formation (Batty 2001). In this way, the apparently chaotic behavior of the system as a whole gives rise to an organized, hierarchical structure. Fotheringham et al (1989) and Longley and Mesev (1997, 2000, 2002) explore the relationship between the fractal dimension and density of development and Torrens (2007, 2008) illustrates how the approach may be used to measure and track sprawl.[6]

Another approach to modeling land use that places uncertainty at the center of the analytical framework is the "spatial hazard" method (Carruthers et al 2010). This turn on traditional (Boots and Getis 1988; Fotheringham et al 2000; Diggle 2003; Anselin and Rey 2010) point pattern analysis[7] —

[6] One important insight of the material on fractal geometry with respect to land use change — and this squares with directly with the vintage models of urban form (Brueckner 2000) invoked in the rational for using spatial hazard models to examine urbanization in the first place (Carruthers et al 2010) — is that the built environment is durable, so very little change may happen at the interior of regions after space filling norms have been achieved (Fotheringham et al 1989).

[7] See Getis (1964, 1983) for land use applications.

developed by Odland and Ellis (1992) and formalized by Waldorf (2003) — involves adapting proportional hazard models, also called accelerated failure time models, to spatial settings. Hazard models are longitudinal models designed to estimate the conditional probability of a timeframe ending (Heckman and Singer 1984; Kiefer 1988; Lawless 2002; Cleves et al 2004; Selvin 2008). They come out of engineering, but have been applied to a variety of issues in regional science and other fields — for example, Irwin and Bockstael (2002) and An and Brown (2008) use them to study the timing of land use change. Like time, distance, D, is a nonnegative random variable that terminates at a particular point, d, conditional on the probability of having made it to that point in the first place. This characteristic results in there being a hazard function that describes the baseline rate at which distances separating spatial points terminate:

$$h(d) = \lim_{\Delta d \to 0} \frac{\Pr(D \in [d, d + \Delta d] \mid D \geq d)}{\Delta d} \in (0, \infty). \tag{6}$$

A proportional hazard model is one that expands the hazard function so that the baseline hazard is scaled by a vector, X, of relevant exogenous factors:

$$h(d \mid X) = h_0(d) \cdot f(X). \tag{7}$$

This function can be parametric or not, but, either way, it gives the conditional probability that distances end at d, where the baseline probability, $h_0(d)$, is multiplied by some function of X that is constant over all d. Finally, a behavioral model of any given point generating process is achieved by choosing an appropriate statistical distribution for the baseline hazard — like the Weibull distribution, which is the distribution that is used here[8] — plus a set of exogenous factors that influence the rate at which distances between points terminate:

$$h(d \mid X) = h_0(d) \cdot \exp(X \cdot \Phi). \tag{8}$$

In this model, which must be estimated via maximum likelihood, the hazard function consists of two parts: (*i*) a Weibull-distributed baseline hazard, $h_0(d) = \lambda \cdot d^{\lambda-1}$, wherein λ, a shape parameter derived from the data, expresses the rate at which the distances between spatial points terminate when $X = 0$; and (*ii*) an exponential scale parameter, Φ , which either accelerates or decelerates the baseline hazard, depending on how the various factors contained in the vector X combine to influence the termination rate. With this probabilistic worldview, spatial hazard models directly address the uncertainty of chaotically evolved patterns of land use. Variations on the spatial hazard approach have been applied to a number of geographic phenomena, including: the spacing of settlements (Odland and Ellis 1992); the separation between parents and their adult children (Rogerson et al 1993); the reach of market areas (Esparza and Krmenec 1994, 1996); the adoption of agricultural technology (Pellegrini and Reader 1996); and the

[8] The Weibull distribution is the most widely used distribution in survival analysis and it is well suited for examining distance relationships, which typically decay rapidly across geographic space. Other commonly used distributions include the exponential, log-logistic, and Gamma (Lawless 2002); for discussions of distance decay, see Tobler 1970 and Longley et al 2005.

spread of disease (Reader 2000). And, Kuethe et al (2009) have just recently pushed the approach further still by using copula functions to model urban form.

In sum, the fractal geometry and spatial hazard approaches are complementary alternatives to analyzing land use via density gradients: both address the inherent complexity of development but, whereas fractals characterize its material condition, hazard functions characterize its field of potentials. The fractal method is an excellent means of evaluating land use change, but the hazard method — which holds great potential because it, like the density gradient, may be used to operationalize the very powerful behavioral theory outlined in the first half of this discussion — remains unproven. Is the approach viable? The following section tends to this question by estimating a series of spatial hazard models of urbanization and evaluating their ability to describe how the American way of land use has changed over the past two decades.

3. Empirical Analysis

3.1 Data and Econometric Specification

The empirical analysis is focused on the 25 highest-growth — between 1990 and 2000 — core-based statistical areas (CBSAs) of the United States in 1990, 2000, and 2006. The regions are listed from largest to smallest in Table 1. In the eight cases that are composed of two or more divisions, the divisions themselves are used, so, counting all of these, the actual number of settings is 36.[9] The units of analysis are census tracts, defined by their 2000 boundaries, and the data comes from four sources: (*i*) a nationwide count of housing units at the census block level in 2006;[10] (*ii*) a *Geolytics* product that allocates select Census Summary File 1 (SF-1) variables from 1990 census block group boundaries to 2000 boundaries; (*iii*) a second *Geolytics* product that allocates Census Summary File 3 (SF-3) from 1990 tract boundaries to 2000 boundaries; and (*iv*) SF-3, from the 2000 census. Comparing localized census data through time is hard because block group and tract boundaries are regularly redrawn to accommodate changes in the geography of the population — but the two *Geolytics* products were used to overcome this problem by reconciling population estimates from 1990 into 2000 block group boundaries and, then, by reconciling other (SF-3) data from 1990 into 2000 tract boundaries. Finally, block group level housing unit counts from 2006 were multiplied by 2000 estimates of average household size to develop 2006

[9] Edison, NY, part of the New York, NY-NJ-PA CBSA is omitted.
[10] Provided to the Department of Housing and Urban Development by the Census Bureau. The count represents the universe for the American Community Survey, an annual survey of about three million households that is set to replace the so-called "long form" of the decennial census, which will eventually yield census tract level data on an annual basis.

population estimates that could be compared to the 1990 and 2000 estimates.[11] Though intensive, these machinations were necessary in order to unify the geometry of the data across all three years.

After laying this groundwork, a database of spatial point patterns and relevant attributes was assembled in a geographic information system (GIS) via a process detailed in Renner et al (2009). In a nutshell, the process involved five steps. In the first step, a base-map consisting of all census block groups in the continental United States — there are 208,643 — was created and their population estimates used to generate a population weighted center for each of the 66,157 tracts that make up the country in 1990, 2000, and 2006. As opposed to the geometric center, this so-called "mean center" (see, for example, Barber 1988) is a point that marks where people were concentrated within the tracts, which can be quite expansive, at the three points in time. In the second step, similar routines were run to generate population weighted centers the 939 CBSAs and for each county subdivision in 2006. Here again, the points produced by this process mark the mean center of the regions and their various sub-centers; they were held constant (arbitrarily, at their 2006 position) in order to facilitate consistent analysis through time.[12] In the third step, each tract-level point was assigned to a CBSA-level point, whether it "officially" belongs there or not, and to a sub-center-level point via a nearest neighbor routine. In the fourth step, the GIS was used to generate three sets of rays measuring the distances separating tract-level points from: (*i*) their regional center; (*ii*) their nearest sub-center; and (*iii*) their nearest neighbor. Finally, in the fifth step, relevant data (identified below) from SF-3 was assigned to the tract-level points; since 2006 is between census years, those points had to be matched with data from 2000. This attribute data was then stacked, forming an $n \times t$ panel for each CBSA involved in the analysis, where n refers to the number of tracts and t refers to the three years of observation. The results of this data assembly process are illustrated in Figure 4, which contains maps of spatial point patterns in the four regions — Las Vegas, NV, Austin, TX, Raleigh, NC, and Phoenix, AZ — that experienced the highest rates of growth between 1990 and 2000. The rays visible in the maps connect nearest neighbor tracts to one another and measure the distances that are the object of this analysis.

Returning to the modeling framework that was outlined above, economic theory yields the following two core premises: (*i*) the baseline hazard function for distance separating the spatial points that make up an overall pattern of urbanization is bound to exhibit positive spatial dependence; and (*ii*) the baseline hazard decelerates with distance from regional centers of gravity. In other words, the probability of the distance between tract-level points terminating increases with the distance that separates them and

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[11] Housing unit counts from 2000 and 2006 were available for 2000 block groups, but not from 1990; population estimates from 1990 and 2000 were available for 2000 block groups, but not from 2006. So, the data was reconciled by converting 2006 housing unit counts into population estimates — alternatively, 1990 population estimates could have been converted to (estimated) housing unit counts.

[12] As will become more apparent below, it is the movement of the tract-level points relative to other points is what is of interest.

decreases with the distance that separates them from their regional center and their nearest sub-center (see Carruthers et al 2010). A Weibull distributed spatial hazard model of urbanization based on these expectations is as follows:

$$h(d_{ij} \mid X_{ik}) = h_0(d_{ij}) \cdot \exp(\tau_{2000,\,2006} + \phi_{i \Rightarrow center} \cdot x_{i \Rightarrow center} + \phi_{i \Rightarrow sub\text{-}center} \cdot x_{i \Rightarrow sub\text{-}center} + X_{ik} \cdot \Phi_k). \tag{9}$$

Here, $h(d_{ij} \mid X_{ik})$ indicates that the baseline hazard, $h_0(d) = \lambda \cdot d^{\lambda-1}$, for distance between nearest neighbor tracts i and j is scaled by, τ, a temporal fixed effect for 2000 and 2006, and by X_{ik}, a vector of k independent variables, that includes $x_{i \Rightarrow center}$, the distance from i to the regional center of gravity and $x_{i \Rightarrow sub\text{-}center}$, the distance from i to the nearest sub-center. The parameter Φ_k (including $\phi_{i \Rightarrow center}$ and $\phi_{i \Rightarrow sub\text{-}center}$) registers the influence the vector of independent variables has on the rate at which distance between nearest neighbors terminates. The model itself, which is estimated as a panel region-by-region, or a total of 36 times, is probabilistic in nature so it is highly flexible and there is no requirement that transitions in land use play out smoothly, or even that they proceed consistently around the circumference of the region in question.

The other explanatory variables (besides the two distance measures) contained in the vector X_{ik} also flow directly from theory. Specifically, the economic model of urbanization points to three main variables: (*i*) land is a normal good, so household income, including wages and all other sources, positively affects the optimal lot size — meaning that income is expected to decelerate the hazard of the distance between points terminating; (*ii*) commuting costs are what determine the budgetary constraint, so time spent traveling to work is expected to either accelerate or decelerate the hazard of the distance between points terminating, depending on region-specific conditions; and (*iii*) as footnoted above, due to vintage effects, aged development, which is often of a different density than contemporary market conditions call for, is expected to influence the hazard of the distance between points terminating. In addition these three factors, population is included in order to control for the fact that, other things being equal, larger tracts will encompass a larger area. This variable is expected to decelerate the hazard of the distance between points terminating. Table 1 gives the specific definition and source of each variable; descriptive statistics are available upon request.

3.2 Estimation Results

The maximum likelihood estimates of the 36 individual spatial hazard models, which were generated CBSA-by-CBSA using the `streg` command in *Stata*, are listed in alphabetical order in Table 2. Note that none of the parameter estimates carry a negative sign, because they are "hazard ratios" that scale the baseline hazard — values less than one decelerate the baseline hazard and values greater than one accelerate it. The estimates are for the most part consistent with the estimates of previous research (Carruthers et al 2010), which: (*i*) focused on a somewhat different set of regions; (*ii*) dealt only with the

2006 time period; (*iii*) did not address sub-centers; and (*iv*) used block groups, not tracts, as the unit of analysis. As a precursor to evaluating the models' ability to describe changes through time, the following paragraphs summarize the estimates.

First, every region's shape parameter, λ, is positive and statistically significant at well over a 99% confidence level, confirming the expectation that the probability of the distance between points terminating increases with the distance that separates them. Once again, a general finding is that, as a set, the shape parameters indicate that urbanization — however chaotically evolved and uncertain it may be — exhibits genuine, probabilistic order. Second, the parameter estimates on the two temporal fixed effects are almost all statistically significant and all positive, signaling that, if all else remained equal through time (which it did not) every region would have grown more compact. This aspect of the analysis is dealt with in detail below. Third, moving under the Φ heading, the parameter on distance from the regional center is negative and highly significant in every case, indicating that, as also expected, the probability of the distance between points terminating decreases with the distance that separates them from their regional center. Fourth, the parameter on distance from the nearest sub-center is nearly always negative and statistically significant, meaning that the probability of the distance between points terminating decreases with the distance that separates them from their nearest sub-center. The exceptions, where the opposite effect is registered, are very large, dense regions like New York City and Chicago. Fifth, the parameter on household income is almost uniformly negative and statistically significant — land is a normal good so, other things being equal, income decelerates the spatial hazard function. Sixth, as in previous research, the parameter on travel cost has a somewhat mixed effect: in those regions registering a positive sign, as most all do, it is associated with a more compact pattern of urbanization whereas, in those regions having a negative sign — New York City and Newark — it is associated with more sprawl. Seventh, the parameter on the age of housing units varies across regions: in about two-thirds of the cases where the variable is statistically significant, the influence is positive, suggesting that older development is generally denser than newer development. This finding is different from before, but it seems plausible that adding distance to the nearest sub-center to the mix alters the effect of the variable. Finally, the parameter on population, a control for the shear size of census tracts, is nearly always statistically significant and negative.

Moving on to aggregate patterns of land use, spatial hazard models, as explained above, portray urbanization not as a material condition but, instead, as a field of potentials. To illustrate this, the estimation results just summarized are evaluated by tracing out survival functions — which are simply the opposite, and more intuitive, way of expressing hazard functions[13] — at relevant values of explanatory variables. Following Carruthers et al (2010), this is done by varying $x_{i\Rightarrow center}$, distance from the regional center, and, on top of that, the two temporal fixed effects while holding the remainder of X_{ik} constant at the mean $\overline{X}_{ik}$. To do this, radial distances, $\xi_{i\Rightarrow center}$, capturing ~5%, ~15%, ~25%, ~35%, ~45%, ~55%, ~65%, ~75%, ~85%, and ~95% of each region's total population were calculated year-by-year, and these specific values were used as values of $x_{i\Rightarrow center}$. They were applied to the models by substituting relevant values into equation (10):

$$h(d_{ij} \,|\, X_{ik}) = \hat{h}_0(d_{ij}) \cdot \exp(\hat{\tau}_{2000,\,2006} + \hat{\phi}_{i\Rightarrow center} \cdot \xi_{i\Rightarrow center} + \hat{\phi}_{i\Rightarrow sub\text{-}center} \cdot \overline{x}_{i\Rightarrow sub\text{-}center} + \overline{X}_{ik} \cdot \hat{\Phi}_k). \quad (11)$$

Here, the hats denote estimated parameters; the bars denote mean values of the vector X, including distance from the nearest sub-center; and $\xi_{i\Rightarrow center}$ is $\in$ [$d_{i\Rightarrow center}$ ~5%, …, ~95%], where the percentages refer to the distance from the CBSA's population weighted center to capture approximately that proportion of the regions total population. To be clear, $\xi_{i\Rightarrow center}$ was calculated for each year of the analysis, so the distances for the same region vary between years. Last, in the exercise, $\hat{\tau}$ was set to each of the three years being examined: (*i*) 2000 = 0 and 2006 = 0, indicating 1990; (*ii*) 2000 = 1 and 2006 = 0; and (*iii*) 2000 = 0 and 2006 = 1.

The resulting survival curves, which were generated using the `stcurve` command in *Stata*, are shown region-by-region in alphabetical order in the left hand panes of the panels contained in Figure 5. These survival curves, which are cumulative probability functions, describe the conditional probability of the distance between nearest neighbor tracts extending past a particular distance at relevant locations within the regions. In the graphs, the *x*-axis, which registers distance between nearest neighbors, ranges from zero to 5,000 meters, and the *y*-axis, which registers the probability that d_{ij} extends, ranges from zero to one. Going from left to right, the 10 separate curves shown in each of the graphs correspond to the distance from the CBSA center, $\xi_{i\Rightarrow center}$, that captures ~5%, …, ~95% of the region's population; the graphs are all consistent and, so, are directly comparable to one another. As a set, they show that (subjectively, at least) each of the 36 regions falls into one of four basic typologies (Carruthers et al 2010): (*i*) high-density, compact — Chicago, IL, Los Angeles, CA, Nassau, NY, New York, NY and San Francisco, CA; (*ii*) low-density sprawl — Atlanta, GA, Austin, TX, Bethesda-Frederick, MD, Charlotte, NC, Ft. Worth, TX, Gary, IN, Nashville, TN, Orlando, FL, Phoenix, AZ, Raleigh, NC, Riverside, CA, and San Antonio, TX; (*iii*) high-density core, with sprawling outer areas — Dallas, TX, Denver, CO, Houston, TX, Las Vegas, NV, Miami, FL, Minneapolis-St. Paul, MN, Newark, NJ, Portland, OR, Sacramento, CA, and San Diego, CA; (*iv*) nearly spatially invariant, at various densities — Ft.

[13] The hazard function is expressed as $H(d_{ij}) = \Pr(D < d_{ij})$ and the survival function is $S(d_{ij}) = 1 - H(d_{ij}) = \Pr(D \geq d_{ij})$. From these identities, it is easy to see that whereas the hazard function, $H(d_{ij})$, expresses the conditional probability of distance terminating, the survival function, $S(d_{ij})$, expresses the conditional probability of distance extending.

Lauderdale, FL, Lake-Kenosha, IL-WI, and Oakland, CA. Whatever the particular case, the graphs displayed in Figure 5 reveal how land use unfolds outward from the regional center of gravity and, because they express only probabilities, they portray urbanization not as a material condition but, rather, as a spectral field of potentials.

3.3 Changes

When the three sets of survival functions shown in the left-hand panes of the panels in Figure 5 were generated in *Stata*, the `outfile` option was used to capture the numeric data that describes them. This operation produced a total of 108 (36 × 3) new "`.dta`" files, containing 10 columns apiece, or one column for every curve shown in the graphs. Additional graphs registering changes from year-to-year were then generated by using the numeric data to difference the various survival functions for each region, and the results are shown in the right-hand panes of the panels in Figure 5: (*i*) 1990 – 2000; (*ii*) 2000 – 2006; and 1990 – 2006. For example, the 1990 numeric data was subtracted from the 2000 numeric data to obtain the 1990 – 2000 graphs. This procedure is an effective means of evaluating land use change within individual regions because the proportional hazard models were estimated as panels with temporal fixed effects and, so, the functions for individual regions have a single underlying shape parameter — what's being compared, is how the estimated baseline hazard, $\hat{h}_0(d_{ij})$, is affected by: (*i*) the fixed effects, $\hat{\tau}_{2000,\,2006}$; (*ii*) the explanatory variables, *X*, which vary by year; and (*iii*) the corresponding scale parameter, $\hat{\Phi}_k$, which is constant across all years. The confluence of these three factors is what accounts for the differences — some are easily visible and some are not — between the year-specific survival functions.

To see just how and why this works, consider a simpler model than the one in equation (10) wherein the baseline hazard is influenced by a single generic fixed effect, θ:

$$h(d \mid X) = h_0(d) \cdot \exp(\theta). \tag{12}$$

When $\theta = 0$ the model collapses to the baseline hazard function, $h_0(d) = \lambda \cdot d^{\lambda-1}$, but when $\theta = 1$ the baseline hazard is accelerated or decelerated, as the case may be, by the fixed effect, which is constant across all *d*. As long as the shape parameter, λ, is the same for both groups ($\theta = 0$ and $\theta = 1$) there is a strictly proportional relationship between the two circumstances, and the hypothesis test associated with the fixed effect is analogous to the classic difference in means *t*-test (Selvin 2008). The situation here is more complicated because both the fixed effects and explanatory variables, though not their estimated influence, $\hat{\Phi}_k$, are in play — but that does not change the fact that the requirement of a single shape parameter for each region is met.

Back to the matter at hand, the graphs in the right-hand panes of Figure 5 illustrate how land use has changed in the 36 regions engaged in the analysis over the past two decades. As before, the *x*-axis, which ranges from zero to 5,000 meters, registers distance between nearest neighbors — but the *y*-axis, which ranges from –0.4 to 0.2, now registers the change in the probability that distance extends. Note that the changes need not be homogeneous across the 10 survival functions, and, indeed, as the background discussion suggests, it is reasonable to expect upfront that, in many cases, they are quite heterogeneous. Most urbanization is a mash-up of different eras and modes of development, so the patterns of change registered by the functions necessarily depend on the within-region location (i.e.: core *vs*. periphery) and nature (i.e.: compact *vs*. sprawl) of growth. Plus, as footnoted above, some locations may exhibit little or no change at all, if the have been build out according to space filling norms (see Fotheringham et al 1989). When the change curves are positive, they imply a sprawling effect and, when they are negative, they imply a compacting effect — positive (negative) changes correspond to an increased (decreased) survival rate, or, stated the other way around, positive (negative) changes correspond to a decreased (increased) hazard rate. So, using the four regions displayed in Figure 4 as examples: (*i*) Austin, TX grew uniformly more dense between 1990 and 2000 and experienced little or no change between 2000 and 2006, for a net effect consistent with what took place in the 1990s; (*ii*) parts of Las Vegas, NV grew more dense between 1990 and 2000 and other parts grew less dense between 2000 and 2006, for a net effect of some increased density and some increased sprawl — but in different parts of the region; (*iii*) Phoenix, AZ grew consistently more dense between 1990 and 2000 and consistently less dense, but not by quite as much, between 2000 and 2006, for a net effect of a moderate increase in density that may be eroded with the passage of additional time if the more recent trend persists; and (*iv*) and Raleigh, NC grew a lot more dense between 1990 and 2000 and a bit less dense between 2000 and 2006, for a net effect of increased density. Similar stories can be told about each of the 32 other regions in the figure.[14]

Table 3 provides a more detailed taxonomy of the net (1990 – 2006) changes just described by listing some of the numeric data that went into generating them. Specifically, the table gives the changes in the probability of distance between nearest neighbor census tracts extending that were obtained by differencing each of the 10 survival curves. In order to conserve space and facilitate readability, the rows correspond to just a few of the distances separating tract mean centers — 500 meters, 1,000 meters, 2,000 meters, 3,000 meters, 4,000 meters, and 5,000 meters between nearest neighbors — but the functions themselves are continuous, so they are based on much greater detail: the spreadsheets the data was taken from have about 100 rows corresponding to distances of zero to 5,000 meters in 50 meter increments. The

[14] Note that the exact scale over which changes in density are observed (or not) varies from region-to-region, according to idiosyncratic differences in spatial patterns of development. The units of analysis are census tracts, which hold between 2,000 and 8,000 people (the average in 2000 was about 4,000 people), so, by definition, the area of the units is quite different both within and among the regions considered in the analysis.

table shows that the differenced survival functions yield two lines of insight into how patterns of urbanization have changed through time: (*i*) by reading across through the columns, the table reveals where within the regions land use has changed; and (*ii*) by reading down through the rows, the table reveals at what spatial scales.

Specific insights related to the four example regions are as follows. First, Austin experienced a sharp compacting effect staggered by distance from the regional center of gravity, where the probability of distance between nearest neighbors extending beyond certain lengths declined by about a third. The probability of extending beyond 1,000 meters fell at distances from the regional center of gravity capturing between ~5% and ~45% of the population; beyond 2,000 meters, at distances capturing between ~25% and ~75%; beyond 3,000 meters, at distances capturing between ~55% and ~85%; beyond 4,000 meters, at distances capturing between ~65% and ~85%; and beyond 5,000 meters, at a distance capturing ~95%. (This pattern of infill is compelling because it seems consistent with some of the density changes reported by Torrens [2008, Figure 12] but it is worth pointing out that that analysis also found that Austin's fractal dimension dropped slightly — from 1.230 to 1.213 — between 1990 and 2000, which is an indication of greater sprawl. It may therefore be a matter of where, in terms of center versus fringe, the development contributing to the change actually occurs — especially in growing regions, like Austin that are experiencing both space filling at the interior and expansion at the fringe.) Second, Las Vegas experienced an interesting mix of two different effects. The probability of distance between nearest neighbors extending beyond 1,000 meters fell by a small amount at the very center of the region (~5% of the population) but the probability of distance between nearest neighbors extending beyond 1,000 and 2,000 meters grew by roughly 25% midway (~55% of the population) to its periphery. Third, Phoenix grew marginally denser from the center to middle (~5% – ~65% of the population) of the region; marginally less dense close to periphery (~75% – ~85% of the population); and less dense at the periphery, where the probability of distance between nearest neighbor tracts extending beyond 3,000, 4,000, and 5,000 meters increased by about 10%. And, as pointed out, the 2000 – 2006 trend, which covers the duration of the recent housing boom in the United States, points decisively in the direction of more sprawl in Phoenix — whether or not the trend will continue now that the market and construction activity have wound down is an open question that is worth pursuing. Finally, Raleigh experienced a spatially staggered compacting effect very similar to what took place in Austin. The probability of the distance between nearest neighbor tracts extending beyond 1,000 and 2,000 meters fell by about a third at the region's interior (~5% and ~45% of the population) and the same happened for probability of extending beyond 3,000 and 4,000 meters at its exterior (~55% and ~95% of the population). The table yields other insights too — but these are the main trends in land use change in the four regions.

4. Summary and Conclusion

The three central objectives of this paper, now met, were: (*i*) to review previous research on the complexity of urbanization and explain how the spatial hazard framework accommodates that complexity; (*ii*) to estimate a series of spatial hazard models characterizing land use in the 25 highest-growth core based statistical areas of the United States areas in 1990, 2000, and 2006; and (*iii*) to use the estimation results to track land use change region-by-region over the 16-year timeframe. All that remains are a few closing comments and directions for future research.

To begin, the evidence presented in the empirical analysis of this paper squares nicely with the both the classic (Alonso 1964; Muth 1969; Mills 1972) theoretical model of urbanization and newer empirical approaches that place uncertainty at the center of the analytical framework (Batty 2007; Torrens 2007, 2008; Carruthers et al 2010). As Friedmann and Miller (1965) noticed some time ago, the American way of land use changed dramatically over the course the 20th century and it continues to change no less dramatically in the 21st century. And, as people continue to grow wealthier and transport costs continue to fall, especially in the post-industrial economy, the evolutionary process that took hold with the nonmetropolitan turnaround (Beale 1975) is only going to accelerate. Contemporary urbanization is composed of layer-upon-layer of development, varies greatly by regional culture and circumstance, has a far-flung, polycentric anatomy, and is the outcome of a chaotic system of innumerable actions taken by its denizens. Yet, in spite of all of this, all of the regions addressed by the analysis, seen through the lens of spatial hazard models, exhibit striking order and a consistent overall pattern of development, no matter their own peculiarities. Thinking of urbanization as a field, rather than material, concept and treating it that way empirically is helpful because it allows for the fact that, while certain potentials prevail throughout the field, actual material conditions do not necessarily. This view also enables traditional theory to hold in an evermore-complex world, but in an explicitly uncertain and chaotic — though definitely not random — manner.

The spatial hazard approach addresses all of this and is a means of scientifically analyzing the similarities and dissimilarities of development from place-to-place and time period-to-time period. In particular, the models are a highly flexible means of: (*i*) operationalizing a traditional method of spatial analysis with a long and distinguished history — namely, point pattern analysis (Boots and Getis 1988; Diggle 2003) — via very powerful behavioral models of urbanization; (*ii*) generalizing about the way of land use across a diversity of settings; and (*iii*) standardizing development patterns in the face of their inherent complexity. As such, the approach is viable for comparing and contrasting dynamic outcomes across very elaborate urban systems.

Future research should focus on several key areas. First, both this and previous research (Carruthers et al 2010) have applied spatial hazard models to very large metropolitan settimgs — so it would be interesting to apply the approach to smaller, micropolitan and rural settings. In principle, these places should exhibit the same general tendencies of land use but they merit investigation, particularly given the extreme growth (and decline) pressures that many face. Second, while spatial hazard models clearly line up well with traditional theories of land use, other, less tested, frameworks addressing the spatial distribution of activity may also be worth evaluating via the approach. For example, the "new economic geography" (see Fujita et al 1999) has gained great currency in economics, geography, regional science, and elsewhere — but has so far been subjected to only a limited amount of empirical evaluation (Head and Mayer 2004). Whether or not spatial hazard models have anything to contribute on this front is unclear at the present, but they very well may. Third, the approach has so far been applied region-by-region and not to any greater system of urbanization, like the Northeast Corridor and/or Southern California conurbations, but there is, in principle, no reason that it could not. In fact, the success realized here in comparing changes through time suggests that, if estimated as part of an urban system, land use patterns of the system's various components could be compared in a very direct way. Last, most progress in applying spatial hazard models to urbanization thus far has been made by using census block groups or census tracts as the units of analysis. While these are typically small, neighborhood-sized units it would be even better to get down to the level of individual structures, as Kuethe et al 2009 do in their analysis of housing sales, including both residential and commercial buildings. Just as attributes from the census are used to explain the process generating neighborhood level points, micro attribute data, if available, could be used to explore the very fabric of development. Each of these directions and more would be an excellent extension of research involving spatial hazard models.

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Table 1. 25 Highest Growth CBSAs, 1990 – 2000

		Abbreviation	Pop. 1990	Pop. 2000	Δ	% Δ	Lat.	Long
1.	New York-Northern New Jersey-Long Island, NY-NJ-PA							
	Nassau-Suffolk, NY	Nassau, NY	2,609,212	2,753,913	144,701	5.5	40.78	–73.31
	New York-Wayne-White Plains, NY-NJ	New York, NY	10,378,385	11,296,377	917,992	8.8	40.79	–73.94
	Newark-Union, NJ-PA	Newark, NJ	1,960,063	2,098,843	138,780	7.1	40.80	–74.40
2.	Los Angeles-Long Beach-Santa Ana, CA							
	Los Angeles-Long Beach-Glendale, CA	Los Angeles, CA	8,863,164	9,519,338	656,174	7.4	34.06	–118.26
	Santa Ana-Anaheim-Irvine, CA	Santa Ana, CA	2,410,556	2,846,289	435,733	18.1	33.73	–117.86
3.	Chicago-Naperville-Joliet, IL-IN-WI							
	Chicago-Naperville-Joliet, IL	Chicago, IL	6,894,440	7,628,412	733,972	10.6	41.86	–87.87
	Gary, IN	Gary, IN	643,037	675,971	32,934	5.1	41.50	–87.33
	Lake County-Kenosha County, IL-WI	Lake-Kenosha, IL-WI	644,599	793,933	149,334	23.2	42.37	–87.96
4.	Dallas-Fort Worth-Arlington, TX							
	Dallas-Plano-Irving, TX	Dallas, TX	2,622,562	3,451,226	828,664	31.6	32.89	–96.77
	Fort Worth-Arlington, TX	Ft. Worth, TX	1,366,732	1,710,318	343,586	25.1	32.75	–97.28
5.	Miami-Fort Lauderdale-Pompano Beach, FL							
	Fort Lauderdale-Pompano Beach-Deerfield Beach, FL	Ft. Lauderdale, FL	1,255,488	1,623,018	367,530	29.3	26.14	–80.21
	Miami-Miami Beach-Kendall, FL	Miami, FL	1,937,094	2,253,362	316,268	16.3	25.79	–80.28
	West Palm Beach-Boca Raton-Boynton Beach, FL	West Palm Beach, FL	863,518	1,131,184	267,666	31.0	26.60	–80.13
6.	Washington-Arlington-Alexandria, DC-VA-MD-WV							
	Bethesda-Frederick-Gaithersburg, MD	Bethesda-Frederick, MD	907,235	1,068,618	161,383	17.8	39.14	–77.17
	Washington-Arlington-Alexandria, DC-VA-MD-WV	Washington, DC	3,215,679	3,727,565	511,886	15.9	38.83	–77.16
7.	Houston-Baytown-Sugar Land, TX	Houston, TX	3,767,335	4,715,407	948,072	25.2	29.77	–95.39
8.	Atlanta-Sandy Springs-Marietta, GA	Atlanta, GA	3,069,425	4,247,981	1,178,556	38.4	33.81	–84.36
9.	San Francisco-Oakland-Fremont, CA							
	Oakland-Fremont-Hayward, CA	Oakland, CA	2,082,914	2,392,557	309,643	14.9	37.80	–122.09
	San Francisco-San Mateo-Redwood City, CA	San Francisco, CA	1,603,678	1,731,183	127,505	8.0	37.72	–122.42
10.	Riverside-San Bernardino-Ontario, CA	Riverside, CA	2,588,793	3,254,821	666,028	25.7	34.01	–117.14
11.	Phoenix-Mesa-Scottsdale, AZ	Phoenix, AZ	2,238,480	3,251,876	1,013,396	45.3	33.48	–111.98
12.	Seattle-Tacoma-Bellevue, WA							
	Seattle-Bellevue-Everett, WA	Seattle, WA	1,972,961	2,343,058	370,097	18.8	47.65	–122.23
	Tacoma, WA	Tacoma, WA	586,203	700,820	114,617	19.6	47.19	–122.42
13.	Minneapolis-St Paul-Bloomington, MN-WI	Minneapolis-St. Paul, MN	2,538,834	2,968,806	429,972	16.9	44.99	–93.25
14.	San Diego-Carlsbad-San Marcos, CA	San Diego, CA	2,498,016	2,813,833	315,817	12.6	32.88	–117.12
15.	Tampa-St Petersburg-Clearwater, FL	Tampa, FL	2,067,959	2,395,997	328,038	15.9	28.02	–82.57
16.	Denver-Aurora, CO	Denver, CO	1,666,883	2,179,240	512,357	30.7	39.70	–104.98
17.	Portland-Vancouver-Beaverton, OR-WA	Portland, OR	1,523,741	1,927,881	404,140	26.5	45.51	–122.67
18.	Sacramento--Arden-Arcade--Roseville, CA	Sacramento, CA	1,481,102	1,796,857	315,755	21.3	38.65	–121.28
19.	San Antonio, TX	San Antonio, TX	1,407,745	1,711,703	303,958	21.6	29.49	–98.49
20.	Orlando, FL	Orlando, FL	1,224,852	1,644,561	419,709	34.3	28.58	–81.43
21.	Las Vegas-Paradise, NV	Las Vegas, NV	741,459	1,375,765	634,306	85.5	36.14	–115.14
22.	Charlotte-Gastonia-Concord, NC-SC	Charlotte, NC	1,024,643	1,330,448	305,805	29.8	35.19	–80.84
23.	Nashville-Davidson-Murfreesboro, TN	Nashville, TN	1,048,216	1,311,789	263,573	25.1	36.14	–86.68
24.	Austin-Round Rock, TX	Austin, TX	846,227	1,249,763	403,536	47.7	30.31	–97.74
25.	Raleigh-Cary, NC	Raleigh, NC	541,100	797,071	255,971	47.3	35.78	–78.60

Table 2. Data Definitions and Sources

	Definition	Source
Distance from Nearest Neighbor	Distance from population weighted center to the population weighted center of the nearest tract, 1990, 2000, 2006	Authors' calculations, U.S. Census and *Geolytics*
Distance from CBSA	Distance from population weighted center to the population weighted center of the nearest CBSA, 1990, 2000, 2006	Authors' calculations, U.S. Census and *Geolytics*
Distance from Sub-Center	Distance from population weighted center to the population weighted center of the nearest county subdivision, 1990, 2000, 2006	Authors' calculations, U.S. Census and *Geolytics*
Household Income	Median household income, 1989, 1999	U.S. Census Bureau, and *Geolytics* — SF-3, Table P68
Travel Cost	Average duration of journey to work, 1990, 2000	Author's calculations, from U.S. Census Bureau and *Geolytics* — SF-3, Tables P31 and P33
Age of Housing Units	Median age of housing units, 1990, 2000	U.S. Census Bureau and *Geolytics* — SF-3, Table H35
Population	Estimated population, 1990, 2000, 2006	U.S. Census Bureau and *Geolytics*

Note: All data is at the level of census tracts.

Table 3. Estimated Spatial Hazard Functions — Distance from Nearest Neighbor

	λ	τ 2000	τ 2006	ϕ Dist. from CBSA Center	ϕ Dist. from Sub-center	ϕ Household Income	ϕ Travel Cost	ϕ Age of Housing Units	ϕ Population	LL	$n \times t$
	Est.	Est.	Est.	Est.	Est.	Est.	Est.	Est.	Est.		
1. Atlanta, GA	3.26 ★★★	1.25 ★★★	1.31 ★★★	0.999900 ★★★	0.999882 ★★★	0.999992 ★★★	0.67 n/s	5.63 ★★★	0.999915 ★★★	–548.51	1,684
	(67.80)	(3.33)	(4.03)	(33.51)	(8.35)	(5.40)	(1.57)	(6.86)	(8.45)		
2. Austin, TX	2.19 ★★★	2.11 ★★★	2.37 ★★★	0.999932 ★★★	0.999867 ★★★	0.999982 ★★★	37.33 ★★★	0.04 ★★★	0.999902 n/s	–612.67	809
	(51.98)	(3.94)	(3.60)	(22.26)	(10.90)	(8.62)	(8.05)	(3.21)	(1.60)		
3. Bethesda-Frederick, MD	2.09 ★★★	1.87 ★★★	2.05 ★★★	0.999958 ★★★	0.999844 ★★★	0.999978 ★★★	10.97 ★★★	0.0008 ★★★	0.999848 ★★★	–600.95	750
	(26.53)	(6.34)	(7.12)	(9.88)	(4.29)	(11.82)	(5.08)	(10.89)	(8.39)		
4. Charlotte, NC	3.25 ★★★	1.26 ★	1.54 ★★★	0.999818 ★★★	1.000089 ★★★	0.999999 n/s	0.23 ★★★	9.37 ★★★	0.999876 ★★★	–188.81	518
	(35.24)	(1.91)	(3.35)	(14.81)	(3.41)	(0.40)	(3.01)	(3.73)	(6.21)		
5. Chicago, IL	2.74 ★★★	1.57 ★★★	1.66 ★★★	0.999933 ★★★	1.000201 ★★★	0.999977 ★★★	0.95 n/s	5.97 ★★★	0.999865 ★★★	–2115.31	4,462
	(98.10)	(11.35)	(12.59)	(39.19)	(26.24)	(21.10)	(0.38)	(24.21)	(19.38)		
6. Dallas, TX	2.63 ★★★	1.26 ★★★	1.29 ★★★	0.999887 ★★★	0.999981 n/s	0.999988 ★★★	1.13 n/s	2.58 ★★★	0.999967 ★★★	–948.33	1,822
	(58.62)	(3.76)	(4.02)	(30.87)	(1.47)	(10.28)	(0.50)	(3.45)	(3.30)		
7. Denver, CO	2.60 ★★★	1.14 ★	1.11 n/s	0.999861 ★★★	0.999929 ★★★	0.999996 ★★★	3.19 ★★★	0.30 ★★★	1.000028 ★	–791.19	1,484
	(52.20)	(1.84)	(1.39)	(28.59)	(4.82)	(3.22)	(4.89)	(6.59)	(1.91)		
8. Ft. Lauderdale, FL	4.06 ★★★	1.48 ★★★	1.51 ★★★	0.999984 ★★★	0.999814 ★★★	0.999984 ★★★	14.12 ★★★	104.05 ★★★	0.999950 ★★★	–110.79	936
	(58.70)	(4.37)	(4.44)	(2.76)	(5.66)	(8.61)	(9.44)	(3.26)	(3.66)		
9. Ft. Worth, TX	2.62 ★★★	1.10 n/s	1.10 n/s	0.999899 ★★★	0.999980 n/s	1.000002 n/s	43.32 ★★★	0.33 ★★★	0.999989 n/s	–595.17	1,080
	(43.63)	(1.18)	(1.14)	(20.93)	(1.28)	(0.89)	(10.54)	(2.93)	(0.66)		
10. Gary, IN	1.57 ★★★	1.54 n/s	1.57 ★★★	0.999966 ★★★	0.999868 ★★★	0.999974 ★★★	4.21 ★★★	3.54 ★★★	0.999959 ★★	–740.26	726
	(17.36)	(4.30)	(4.54)	(7.92)	(4.82)	(7.16)	(3.64)	(3.75)	(2.02)		
11. Houston, TX	2.41 ★★★	1.15 ★★★	1.17 ★★★	0.999930 ★★★	0.999961 ★★★	0.999997 ★★★	7.05 ★★★	0.73 n/s	0.999968 ★★★	–1607.37	2,468
	(58.64)	(2.73)	(2.92)	(35.78)	(4.75)	(2.79)	(11.52)	(1.25)	(4.48)		
12. Lake-Kenosha, IL-WI	2.26 ★★★	1.09 n/s	1.09 n/s	0.999982 ★★★	0.999796 ★★★	0.999998 n/s	11.50 ★★★	0.40 ★	1.000002 n/s	–476.83	704
	(30.38)	(0.80)	(0.78)	(4.38)	(4.13)	(0.97)	(5.60)	(1.95)	(0.09)		

Notes: LL is the log-likelihood; $n \times t$ is the number of observations in the panel; in the event that an observation/s was dropped in the estimation process, $n \times t$ is not symmetric; values in () are z-statistics; all hypothesis tests are two-tailed; ★★★ denotes significant at 99%; ★★ denotes significant at 95%; ★ denotes significant at 90%; and n/s denotes not significant.

Table 3. Estimated Spatial Hazard Functions — Distance from Nearest Neighbor (cont…)

	λ	τ 2000	τ 2006	ϕ Dist. from CBSA Center	ϕ Dist. from Sub-center	ϕ Household Income	ϕ Travel Cost	ϕ Age of Housing Units	ϕ Population	LL	$n\times t$
	Est.	Est.	Est.	Est.	Est.	Est.	Est.	Est.	Est.		
13. Las Vegas, NV	2.35 ***	1.00 n/s	1.01 n/s	0.999862 ***	0.999931 ***	1.000003 n/s	1.12 n/s	0.0001 ***	0.999956 ***	–633.61	1,005
	(38.13)	(0.02)	(0.11)	(20.25)	(5.16)	(1.54)	(0.57)	(3.14)	(3.70)		
14. Los Angeles, CA	2.79 ***	1.23 ***	1.25 ***	0.999927 ***	0.999951 ***	0.999979 ***	4.62 ***	0.25 ***	0.999993 n/s	–2529.32	5,497
	(107.44)	(6.15)	(6.59)	(48.73)	(9.70)	(28.11)	(11.83)	(12.04)	(1.04)		
15. Miami, FL	2.57 ***	1.15 n/s	1.10 n/s	0.999909 ***	0.999743 ***	0.999986 ***	1.72 ***	13.75 ***	1.000043 ***	–558.18	1,041
	(43.06)	(1.74) n/s	(1.19)	(22.24)	(8.90)	(7.71)	(2.36)	(5.12)	(4.52)		
16. Minneapolis-St. Paul, MN	2.99 ***	1.54 ***	1.56 ***	0.999896 ***	1.000035 **	0.999983 ***	6.97 ***	2.29 ***	0.999908 ***	–856.01	2,096
	(69.90)	(7.24)	(7.40)	(37.04)	(2.00)	(11.82)	(8.64)	(7.36)	(6.58)		
17. Nashville, TN	2.80 ***	1.84 ***	1.84 ***	0.999915 ***	0.999970 **	0.999974 ***	163.95 ***	1.79 n/s	0.999973 n/s	–333.81	667
	(35.81)	(5.96)	(5.90)	(16.83)	(2.16)	(9.49)	(13.10)	(1.26)	(1.28)		
18. Nassau, NY	2.79 ***	1.32 ***	1.30 ***	0.999944 ***	0.999644 ***	0.999990 ***	7.08 ***	2.30 ***	0.999976 n/s	–673.78	1,374
	(51.98)	(3.94)	(3.60)	(22.26)	(10.90)	(8.62)	(8.05)	(3.21)	(1.60)		
	(50.27)	(7.95)	(7.93)	(25.34)	(0.20)	(12.59)	(7.96)	(1.35)	(0.63)		
19. New York, NY	2.21 ***	1.23 ***	1.22 ***	0.999916 ***	1.000031 ***	0.999992 ***	0.35 ***	6.67 ***	0.999991 **	–5578.95	8,745
	(114.69)	(7.40)	(7.30)	(48.90)	(5.49)	(16.37)	(14.55)	(36.25)	(2.21)		
20. Newark, NJ	2.33 ***	2.34 ***	2.45 ***	0.999921 ***	0.999994 n/s	0.999962 ***	0.54 ***	8.35 ***	0.999900 ***	–1103.58	1,732
	(50.79)	(13.39)	(13.98)	(26.83)	(0.31)	(30.00)	(2.74)	(13.16)	(7.51)		
21. Oakland, CA	3.14 ***	2.50 ***	2.58 ***	0.999975 ***	0.999759 ***	0.999965 ***	0.68 n/s	14.69 ***	0.999916 ***	–417.02	1,194
	(55.72)	(11.77)	(12.03)	(6.29)	(9.65)	(23.19)	(1.20)	(15.67)	(6.73)		
22. Orlando, FL	2.50 ***	1.34 ***	1.38 ***	0.999889 ***	0.999915 ***	0.999990 ***	3.78 ***	10.42 ***	0.999943 ***	–538.66	909
	(37.69)	(3.30)	(3.39)	(21.27)	(3.47)	(4.46)	(4.43)	(3.61)	(4.69)		
23. Phoenix, AZ	2.11 ***	1.10 n/s	1.17 ***	0.999923 ***	0.999960 ***	0.999996 ***	0.87 n/s	1.66 n/s	0.999969 ***	–1464.69	2,061
	(50.18)	(1.63)	(2.63)	(34.94)	(5.62)	(4.90)	(0.91)	(1.17)	(4.33)		
24. Portland, OR	2.77 ***	1.96 ***	1.98 ***	0.999863 ***	0.999997 n/s	0.999971 ***	19.47 ***	0.79 n/s	1.000010 n/s	–564.54	1,192
	(50.27)	(7.95)	(7.93)	(25.34)	(0.20)	(12.59)	(7.96)	(1.35)	(0.63)		

Notes: LL is the log-likelihood; $n\times t$ is the number of observations in the panel; in the event that an observation/s was dropped in the estimation process, $n\times t$ is not symmetric; values in () are z-statistics; all hypothesis tests are two-tailed; *** denotes significant at 99%; ** denotes significant at 95%; * denotes significant at 90%; and n/s denotes not significant.

Table 3. Estimated Spatial Hazard Functions — Distance from Nearest Neighbor

		τ		ϕ							
	λ	2000	2006	Dist. from CBSA Center	Dist. from Sub-center	Household Income	Travel Cost	Age of Housing Units	Population		
	Est.	Est.	Est.	Est.	Est.	Est.	Est.	Est.	Est.	LL	$n \times t$
25. Raleigh, NC	3.30 ***	2.22 ***	2.60 ***	0.999888 ***	0.999750 ***	1.000007 ***	880.66 ***	0.84 n/s	0.999872 ***	–112.77	333
	(29.24)	(4.95)	(5.81)	(9.44)	(4.99)	(2.01)	(10.65)	(0.28)	(6.17)		
26. Riverside, CA	1.65 ***	1.20 ***	1.33 ***	0.999978 ***	0.999842 ***	0.999995 ***	3.66 ***	0.06 ***	0.999920 ***	–1382.17	1,467
	(29.12)	(2.77)	(4.15)	(16.77)	(12.37)	(2.41)	(6.64)	(5.28)	(8.65)		
27. Sacramento, CA	2.02 ***	1.48 ***	1.40 ***	0.999950 ***	0.999839 ***	0.999981 ***	56.72 ***	0.32 ***	0.999997 n/s	–881.43	1,109
	(33.12)	(4.95)	(4.26)	(16.87)	(8.46)	(9.09)	(14.18)	(3.29)	(0.17)		
28. San Antonio, TX	2.53 ***	1.43 ***	1.39 ***	0.999897 ***	0.999971 **	0.999980 ***	14.04 ***	0.63 n/s	0.999984 n/s	–585.08	1,001
	(40.65)	(4.27)	(3.90)	(26.10)	(2.21)	(8.31)	(9.69)	(1.57)	(1.22)		
29. San Diego, CA	1.81 ***	1.34 ***	1.36 ***	0.999931 ***	0.999922 ***	0.999983 ***	1.68 ***	2.44 ***	0.999980 **	–1576.51	1,815
	(37.09)	(4.81)	(5.03)	(30.29)	(7.87)	(13.27)	(3.00)	(4.04)	(2.14)		
30. San Francisco, CA	2.07 ***	1.48 ***	1.49 ***	0.999919 ***	0.999960 **	0.999990 ***	4.14 ***	5.04 ***	1.000024 n/s	–820.77	1,165
	(37.91)	(4.78)	(4.84)	(19.94)	(2.05)	(6.46)	(5.90)	(12.04)	(1.63)		
31. Santa Ana, CA	2.63 ***	1.28 ***	1.20 ***	0.999951 ***	0.999809 ***	0.999989 ***	0.81 n/s	0.04 ***	1.000016 *	–1268.49	2,507
	(69.88)	(4.64)	(3.40)	(23.88)	(13.26)	(12.94)	(1.67)	(11.02)	(1.94)		
32. Seattle, WA	2.76 ***	1.93 ***	1.92 ***	0.999913 ***	0.999887 ***	0.999973 ***	16.56 ***	3.33 ***	1.000000 n/s	–597.71	1,209
	(48.66)	(8.07)	(7.71)	(19.42)	(7.54)	(12.94)	(8.57)	(6.31)	(0.02)		
33. Tacoma, WA	2.29 ***	1.08 n/s	1.12 n/s	0.999914 ***	0.999867 ***	1.000000 n/s	2.98 ***	0.58 n/s	0.999961 *	–443.79	654
	(29.05)	(0.73)	(1.01)	(14.65)	(4.74)	(0.08)	(3.17)	(1.41)	(1.91)		
34. Tampa, FL	2.97 ***	1.41 ***	1.40 ***	0.999942 ***	0.999792 ***	0.999984 ***	64.03 ***	34.89 ***	1.000002 n/s	–611.83	1,482
	(58.91)	(4.88)	(4.65)	(20.53)	(14.64)	(6.61)	(17.07)	(12.08)	(0.17)		
35. Washington, DC	2.20 ***	1.62 ***	1.65 ***	0.999916 ***	0.999921 ***	0.999981 ***	0.86 n/s	15.78 ***	0.999953 ***	–1386.89	2,048
	(52.22)	(8.31)	(8.62)	(30.54)	(4.39)	(19.27)	(0.78)	(20.47)	(4.90)		
36. West Palm Beach, FL	3.51 ***	1.73 ***	1.75 ***	0.999963 ***	0.999669 ***	0.999986 ***	30.48 ***	20.37 ***	0.999933 ***	–160.11	679
	(46.89)	(5.21)	(5.02)	(7.71)	(13.11)	(7.08)	(9.15)	(5.13)	(3.52)		

Notes: LL is the log-likelihood; $n \times t$ is the number of observations in the panel; in the event that an observation/s was dropped in the estimation process, $n \times t$ is not symmetric; values in () are z-statistics; all hypothesis tests are two-tailed; *** denotes significant at 99%; ** denotes significant at 95%; * denotes significant at 90%; and n/s denotes not significant.

Table 4. Taxonomy of Land Use Change

Austin, TX

Dist. from Near. Neigh.	At a Distance from the Regional Center of Gravity Capturing % of Population									
	~5%	~15%	~25%	~35%	~45%	~55%	~65%	~75%	~85%	~95%
500	–0.13	–0.10	–0.10	–0.10	–0.09	–0.04	–0.02	–0.02	–0.01	-
1,000	–0.35	–0.31	–0.32	–0.31	–0.29	–0.16	–0.10	–0.08	–0.04	–0.01
2,000	–0.20	–0.22	–0.28	–0.28	–0.31	–0.38	–0.30	–0.26	–0.17	–0.04
3,000	–0.02	–0.03	–0.06	–0.06	–0.08	–0.30	–0.39	–0.39	–0.31	–0.08
4,000		-	-	-	–0.01	–0.12	–0.30	–0.37	–0.38	–0.15
5,000		-	-	-	-	–0.03	–0.16	–0.25	–0.36	–0.21

Las Vegas, NV

Dist. from Near. Neigh.	At a Distance from the Regional Center of Gravity Capturing % of Population									
	~5%	~15%	~25%	~35%	~45%	~55%	~65%	~75%	~85%	~95%
500	–0.10	-	0.05	-	-	0.07	-	-	-	-
1,000	–0.11	–0.01	0.09	-	-	0.25	-	-	-	-
2,000	-	-	-	-	-	0.24	-	-	-	-
3,000	-	-	-	-	-	0.03	-	-	-	-
4,000	-	-	-	-	-	-	-	-	0.01	-
5,000	-	-	-	-	-	-	-	-	0.01	-

Phoenix, AZ

Dist. from Near. Neigh.	At a Distance from the Regional Center of Gravity Capturing % of Population									
	~5%	~15%	~25%	~35%	~45%	~55%	~65%	~75%	~85%	~95%
500	–0.03	–0.02	–0.02	–0.01	–0.01	–0.01	-	-	-	-
1,000	–0.06	–0.05	–0.04	–0.03	–0.03	–0.02	-	0.01	0.01	0.01
2,000	–0.01	–0.02	–0.03	–0.03	–0.03	–0.03	–0.01	0.02	0.02	0.05
3,000	-	-	-	–0.01	–0.01	–0.01	-	0.01	0.02	0.08
4,000	-	-	-	-	-	-	-	0.01	0.02	0.10
5,000	-	-	-	-	-	-	-	-	0.01	0.10

Raleigh, NC

Dist. from Near. Neigh.	At a Distance from the Regional Center of Gravity Capturing % of Population									
	~5%	~15%	~25%	~35%	~45%	~55%	~65%	~75%	~85%	~95%
500	–0.11	–0.09	–0.08	–0.06	–0.05	–0.04	–0.04	–0.03	–0.03	–0.03
1,000	–0.32	–0.29	–0.25	–0.22	–0.19	–0.15	–0.14	–0.13	–0.12	–0.12
2,000	–0.20	–0.27	–0.28	–0.30	–0.30	–0.29	–0.29	–0.32	–0.31	–0.35
3,000	–0.02	–0.06	–0.07	–0.10	–0.12	–0.15	–0.19	–0.25	–0.29	–0.44
4,000	-	-	–0.01	–0.01	–0.02	–0.03	–0.06	–0.10	–0.14	–0.33
5,000	-	-	-	-	-	-	–0.01	–0.02	–0.05	–0.18

Note: Values are the change in the conditional probability of distance extending; - denotes zero or negligible.

Figure 1. The Contemporary Urban Field

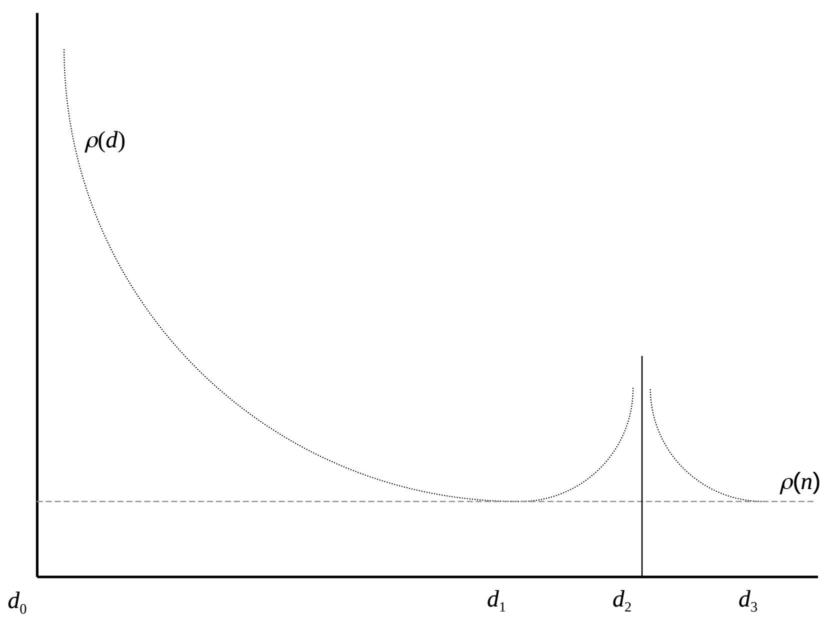

Figure 2. A Polycentric Rent Gradient

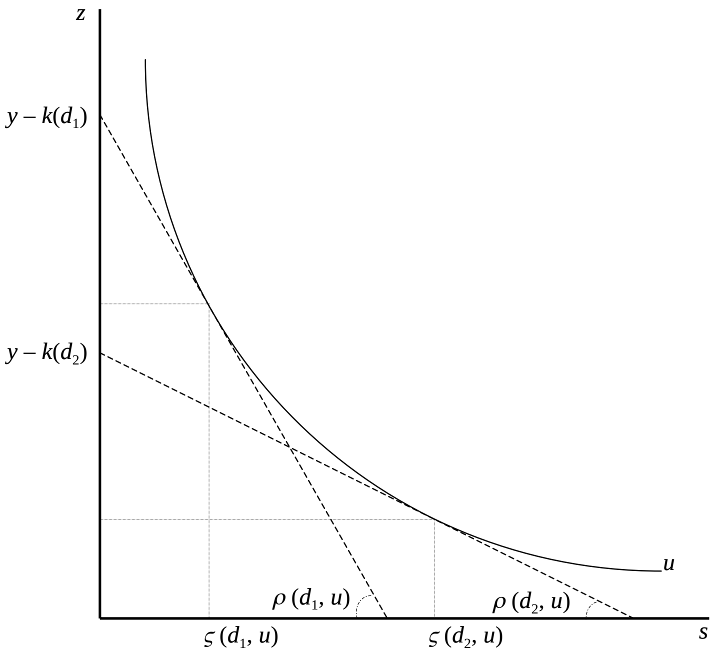

Figure 3. Bid Rent Process and Residential Land Use

Figure 4. Spatial Point Patterns in (clockwise from upper left) Austin, TX, Las Vegas, NV, Phoenix, AZ, and Raleigh, NC

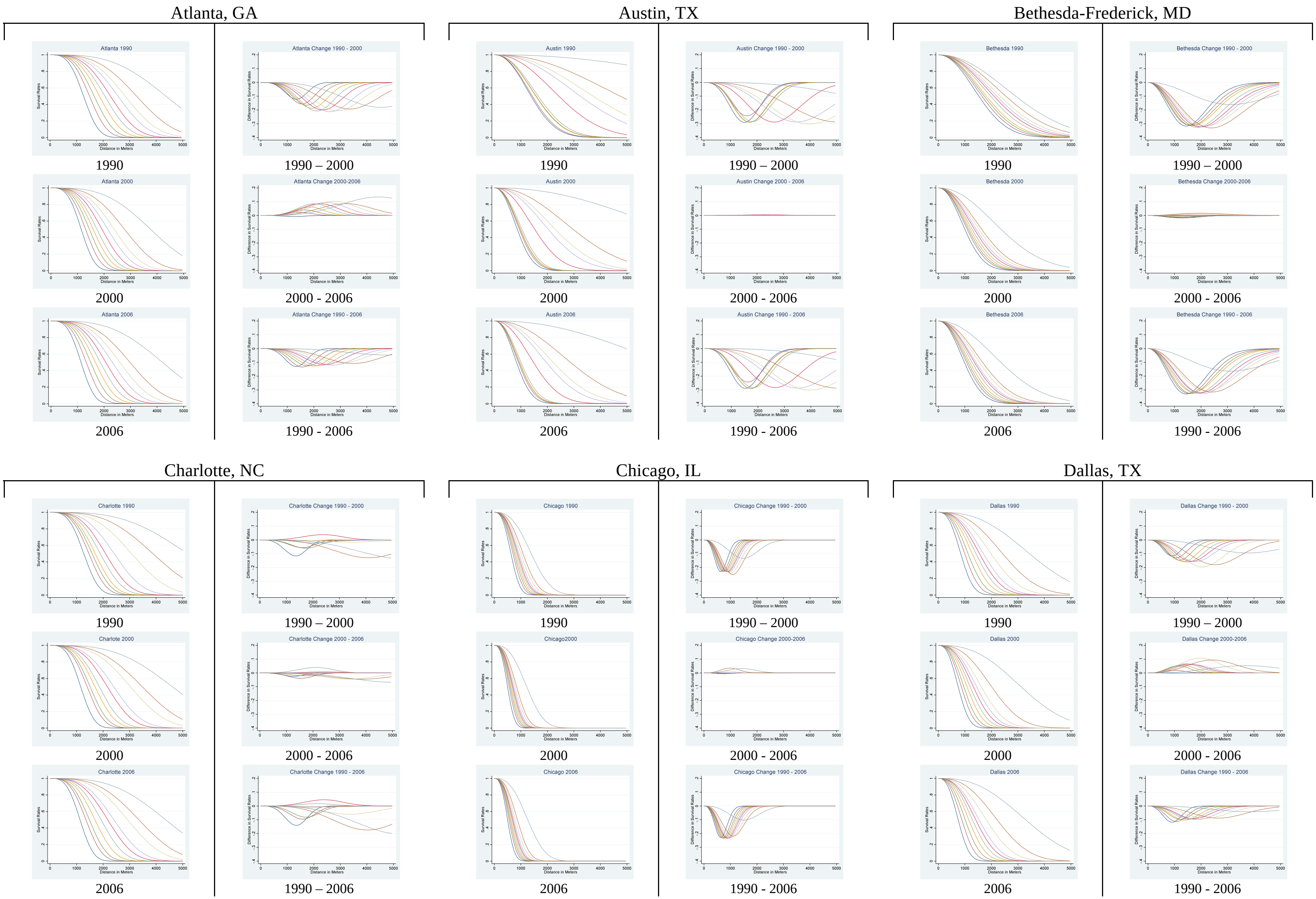

Figure 5. Estimated and Differenced Survival Functions

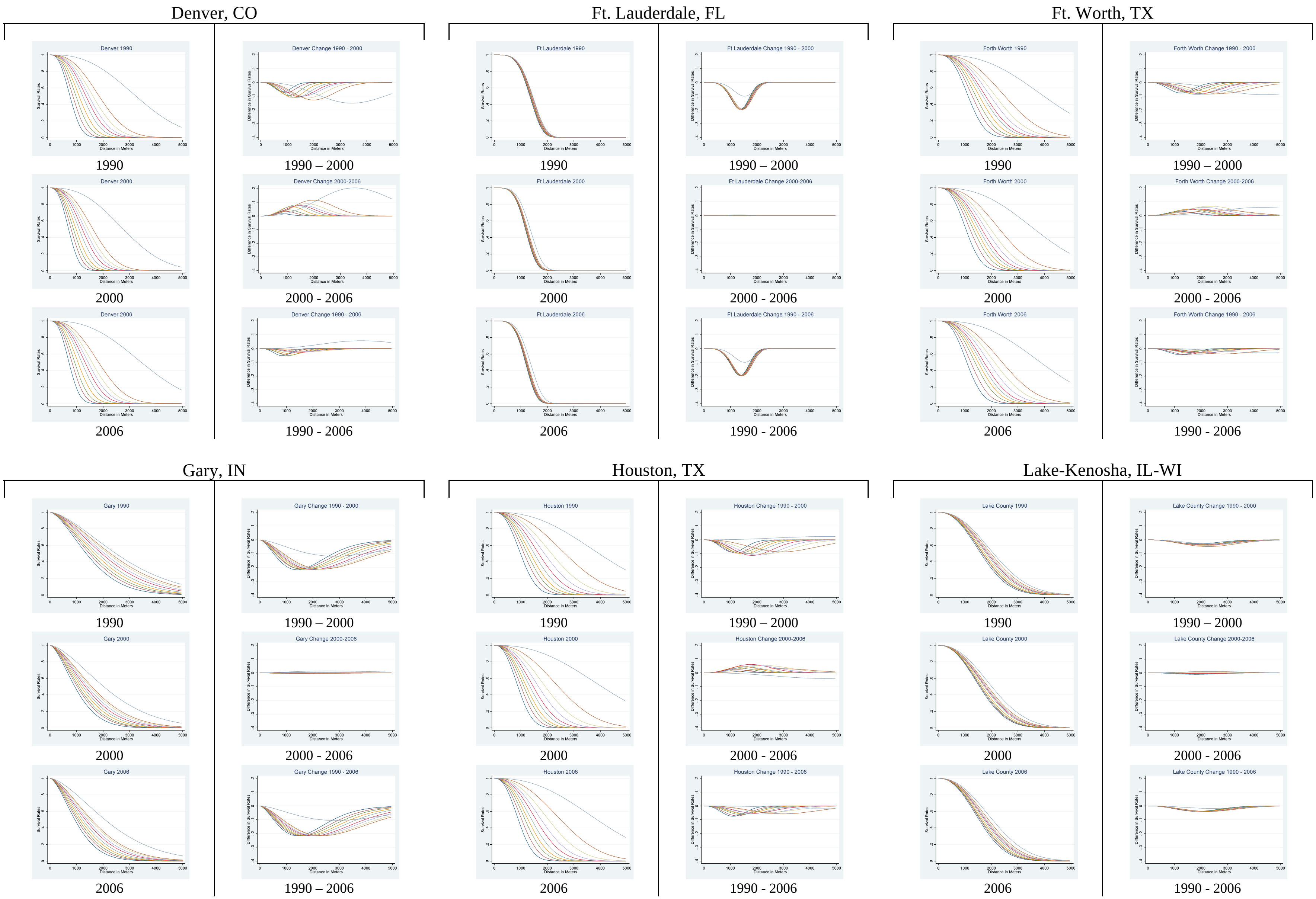

Figure 5. Estimated and Differenced Survival Functions (cont…)

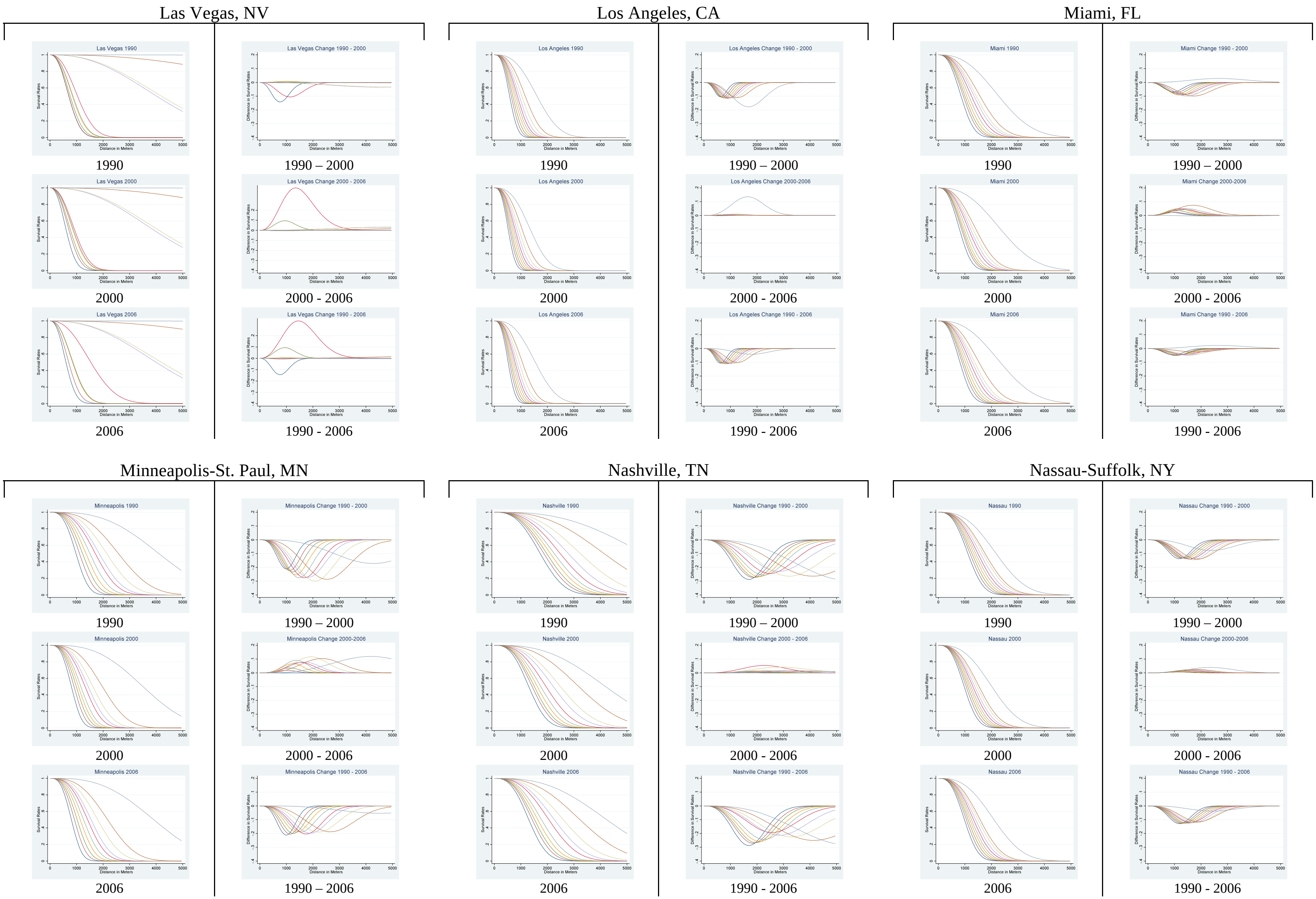

Figure 5. Estimated and Differenced Survival Functions (cont…)

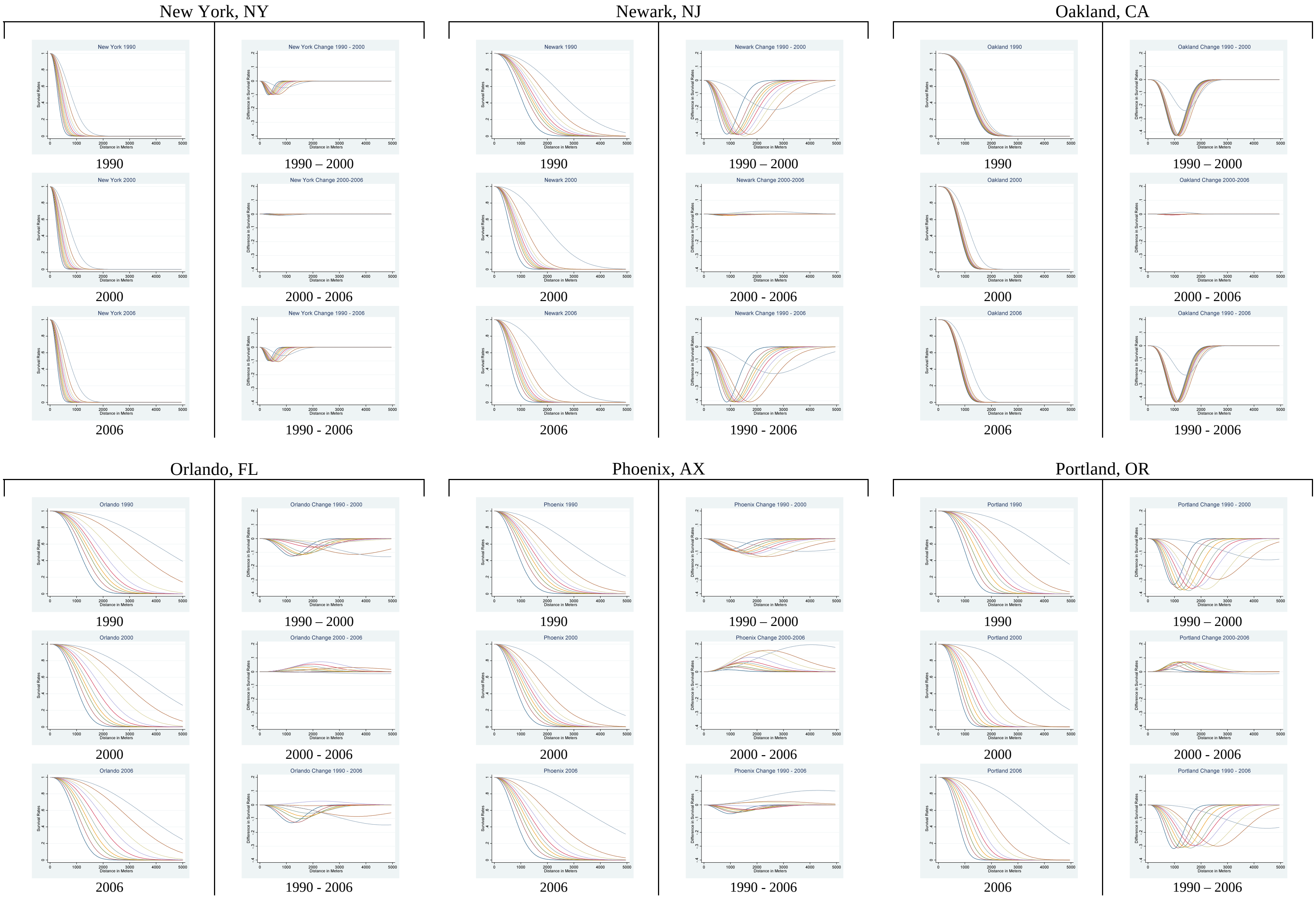

Figure 5. Estimated and Differenced Survival Functions (cont…)

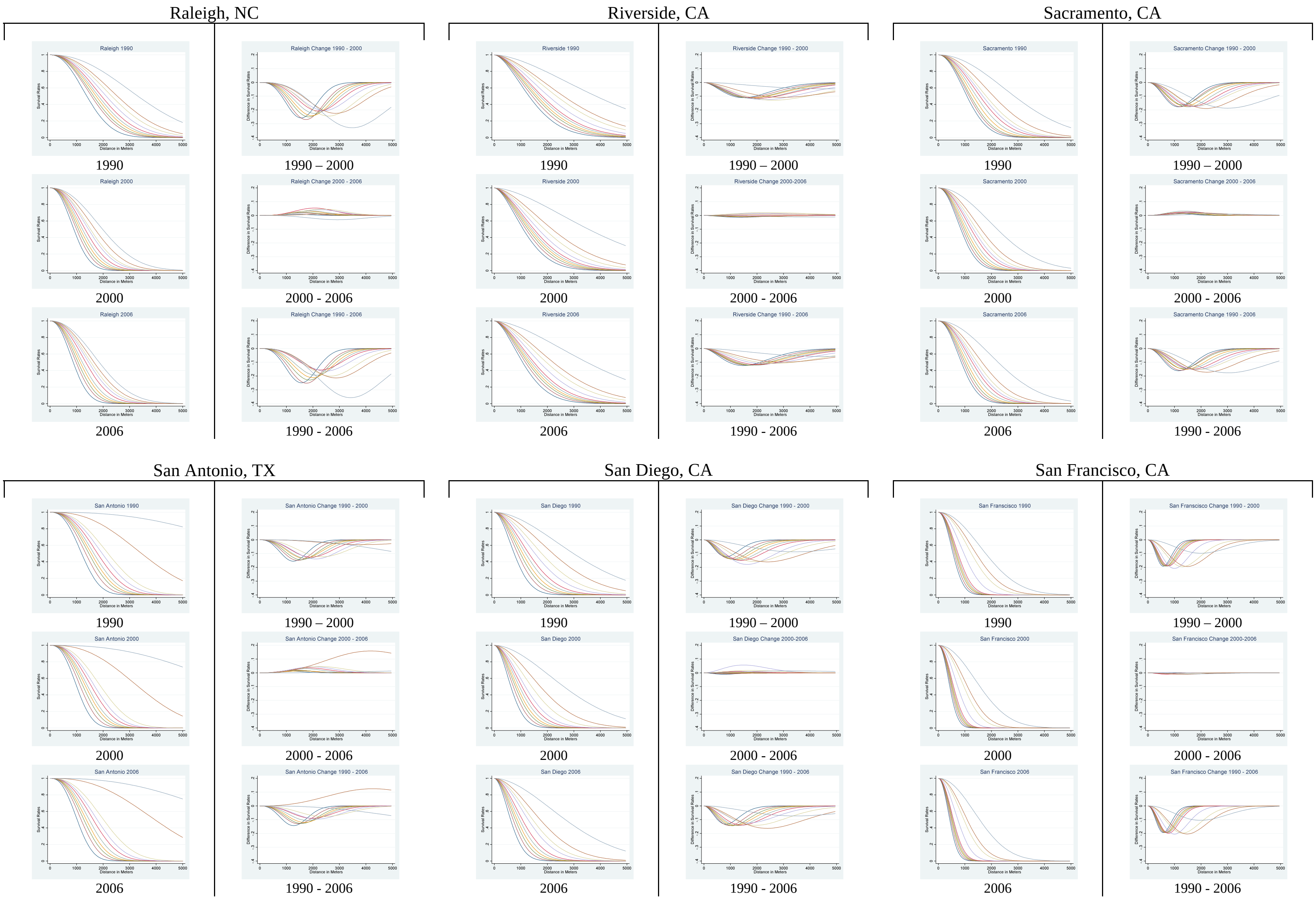

Figure 5. Estimated and Differenced Survival Functions (cont…)

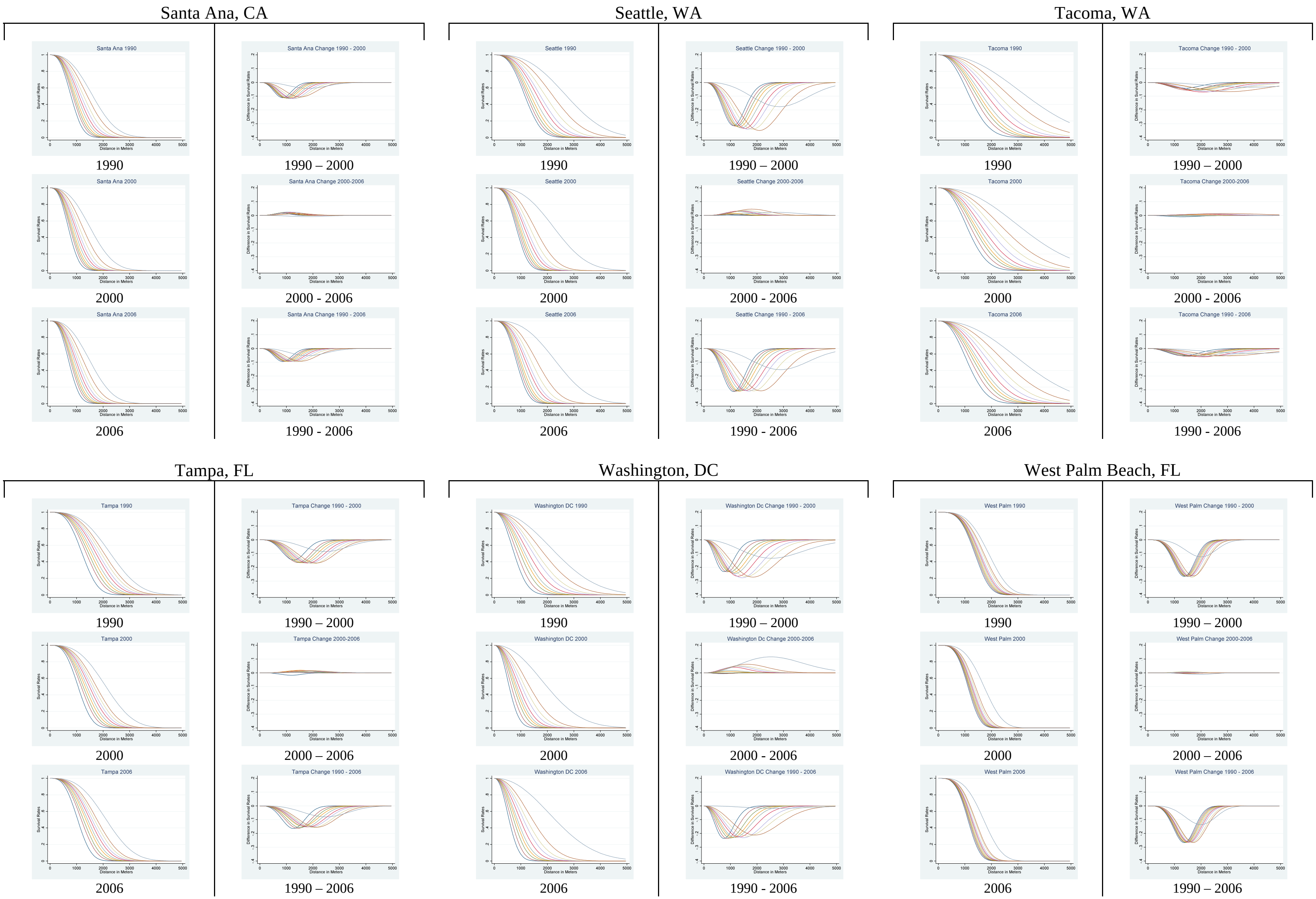

Figure 5. Estimated and Differenced Survival Functions (cont…)