PART I

GENERAL TOPICS

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David Darmofal
Excerpt
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The Social Sciences and Spatial Analysis

> "[F]ull information should be given as to the degree in which the customs of the tribes and races which are compared together are independent. It might be, that some of the tribes had derived them from a common source, so that they were duplicate copies of the same original. ...It would give a useful idea of the distribution of the several customs and of their relative prevalence in the world, if a map were so marked by shadings and colour as to present a picture of their geographical ranges."
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> Sir Francis Galton at The Royal Anthropological Institute, 1888
> *The Journal of the Anthropological Institute of Great Britain and Ireland* 18: 270.

1.1 INTRODUCTION

Concepts of space and geography play prominent roles in many social science theories. In fields as diverse as anthropology, criminology, demography, political science, sociology, and public health, our theories predict that spatially proximate units are more likely to behave similarly than spatially distant units. These theories, in short, predict positive spatial autocorrelation or spatial dependence, the spatial clustering of similar behaviors, processes, and events among neighboring observations. This common interest in geography across the social sciences is not surprising. The social sciences are defined by their focus on phenomena that are inherently social and interdependent. Shared concerns combine with spatial proximity to promote familiarity. This familiarity in turn breeds both contempt and conflict and interaction and interdependence.

Until recently our ability to incorporate the spatial dimension of our theories in our models was quite limited, relying primarily on dummy variables to capture differences in behavior across geographically disparate units. Such an approach is suboptimal, as it is unable to address some of the central issues posed by spatially dependent data. Consider, for example, Sir Francis Galton's comment in the epigraph to this chapter. Sir Galton's comment in response to Edward Tylor's presentation at the Royal Anthropological Institute in November 1888 clearly ranks among the most influential comments expressed at an academic presentation, remembered as it is more than a century later. Sir Galton's critique, which has since come to be known as Galton's problem, focuses on the critical substantive distinction between two alternative explanations for spatially dependent behavior.

On the one hand, spatial dependence may be produced by the diffusion of behavior between neighboring units. If so, the behavior is likely to be highly social in nature, and understanding the interactions between interdependent units is critical to understanding the behavior in question. For example, citizens may discuss politics across adjoining neighborhoods such that an increase in support for a candidate in one neighborhood directly leads to an increase in support for the candidate in adjoining neighborhoods.

Alternatively, neighboring units may independently adopt similar behaviors simply because the units share characteristics that promote the behavior in question. If so, the spatial dependence observed in our data does not reflect a truly spatial process, but merely the geographic clustering of the sources of the behavior of interest. For example, citizens in adjoining neighborhoods may favor the same candidate not because they talk to their neighbors, but because citizens with similar incomes tend to cluster geographically, and income also predicts vote choice. Such spatial dependence can be termed attributional dependence, as neighboring units have shared attributes that produce the clustering of behaviors. Clearly, determining which process is producing spatial dependence is critical to our understanding the behavior of interest. As a consequence, we need a way to determine which of the two forms of spatial dependence is at work in our data and model the particular form of spatial dependence.

Often our model specifications in the social sciences do not take space seriously. We may include regional, country, or state nominal variables that capture the uniqueness of particular geographic units. But rarely do we think of these dummy variables as spatial variables. Moreover, this standard dummy variable approach is unable to distinguish between the two quite different explanations for spatial dependence. As proxies for our ignorance of the sources of spatial autocorrelation, statistically significant parameters on dummy variables for geographic areas merely tell us that behaviors differ for units in these particular areas in contrast to the reference category. Such an approach cannot tell us whether the spatial dependence is consistent with diffusion or with the spatial clustering of the behaviors' sources.

Recent advances in spatial analysis, however, now allow us to address Galton's problem econometrically and model the alternative sources of spatial dependence. Although spatial econometric models come in a variety of forms, at their most basic level they share a common feature that distinguishes them from standard econometric models: they explicitly model spatial autocorrelation.

Spatial econometric models allow us to address Galton's problem because each of the two alternative sources of spatial dependence posed by Galton presents its own distinct spatial econometric specification.

1.2 Spatial Lag and Spatial Error Models

Spatial diffusion occurs because units' behavior is directly influenced by the behavior of "neighboring units." (The definition of neighbors is generalizable and need not imply a geographic relationship. Spatial models, as a consequence, are quite flexible for a variety of modeling situations involving dependent data). This diffusion effect corresponds to a positive and significant parameter on a spatially lagged dependent variable capturing the direct influence between neighbors.

Conversely, the geographic clustering of the sources of the behavior implies an alternative specification. Assuming that we are unable to model fully the sources of spatial dependence in the data generating process (DGP), these sources will produce spatial dependence in the error terms between neighboring locations. This spatial error dependence can be modeled via a spatially lagged error term. Spatial error dependence is also consistent with spatial clustering in measurement errors.

The substantive implications of properly modeling spatial dependence are intimately linked with methodological implications. Ignoring either form of spatial dependence in our models poses its own distinct implications for inference. For example, estimating an ordinary least squares (OLS) model that ignores a diffusion effect in the DGP can produce biased and inconsistent parameter estimates. Estimating an OLS model that ignores spatial clustering in the sources of the behavior can produce inefficient parameter estimates, standard error estimates that are biased downward, and type I errors.

Many social scientists are familiar with problems that dependent data pose for inference in time series analysis. And the two alternative sources of spatial dependence bear a surface similarity with lagged dependent variables and lagged error terms in time series analysis. However, time series methods for modeling temporal dependence cannot simply be applied to the case of spatial dependence because spatial dependence is not simply the cross-sectional analogue of serial dependence. In the time series context, influence flows in one direction, from the past to the present. In contrast, spatial dependence is simultaneous: in the diffusion case, neighbors influence the behavior of their neighbors and vice versa. In the case of attributional dependence, errors for neighboring observations exhibit simultaneous dependence. As a consequence of this multidimensional, simultaneous spatial autocorrelation, OLS cannot be used to estimate a model with spatially lagged dependent variables, and simple iterative estimators for unidimensional dependence such as the Cochrane–Orcutt estimator cannot be used to estimate a model with spatially lagged errors. Instead, either maximum likelihood or instrumental variables approaches must be employed to estimate spatial models.

Happily, the diagnosis and modeling of spatial dependence is a straightforward process that can be adapted easily by applied researchers in the social sciences. First, global and local measures of spatial autocorrelation are estimated to determine whether the data exhibit spatial autocorrelation. If the data do exhibit spatial autocorrelation, the researcher simply applies diagnostics to an OLS specification to determine whether the variables in the model sufficiently capture this spatial dependence. If the variables do not fully model the dependence, the diagnostics indicate whether the researcher should estimate a model with a spatially lagged dependent variable or a spatially lagged error term.

This book examines how social scientists can diagnose and model the spatial dependence that is predicted by our theories. It is designed to provide a comprehensive, up-to-date introduction to spatial analysis for applied researchers in the social sciences. As such, examples are employed throughout the book to demonstrate how spatial analysis can be applied to research questions in the social sciences. The book assumes little in the way of prerequisites, although training in linear regression and maximum likelihood estimation will prove helpful.

1.3 Outline of the Book

The book is structured as follows. Chapter 2 examines a critical but often underexplored question in spatial analysis: Which units are to be considered "neighbors of each other"? Neighbors are defined via a spatial weights matrix. This is a critical step in any spatial analysis, as it limits the spatial dependence that can be diagnosed and modeled in one's data. As a consequence, the definition of neighbors in the spatial weights matrix should in most cases be guided by substantive theory.

With the importance of a theoretically based weights matrix in hand, Chapter 3 returns to Galton's problem introduced in this chapter. The discussion in Chapter 3 focuses on the two alternative explanations for spatial dependence and the corresponding spatial lag and spatial error models. The distinction between multidimensional spatial dependence and unidimensional temporal dependence is expanded on and the performance of OLS for multidimensional spatial models is contrasted against the performance of OLS for unidimensional time series models. Chapter 3 also examines the performance of OLS when a spatially lagged dependent variable or spatially lagged errors are inappropriately omitted from the model specification. The analytical and empirical results of these analyses argue for the use of explicitly spatial methods for modeling spatial data.

Chapter 4 begins the discussion of the sequential process of diagnosing and modeling spatial autocorrelation. The chapter focuses on the initial step: the diagnosis of univariate spatial autocorrelation in the absence of covariates. The discussion builds on the previous chapters, examining how theoretically based weights matrices and measures of spatial autocorrelation are employed to diagnose univariate spatial autocorrelation in the absence of covariates. A variety of global and local measures of spatial autocorrelation are examined. The chapter also examines how spatial autocorrelation measures can be used as an initial diagnostic for possible spatial heterogeneity in the effects of substantive covariates in one's model.

Chapter 5 examines how the spatial dependence diagnosed via the methods presented in Chapter 4 can be modeled. OLS models with which social scientists are most familiar will perform well if attributional dependence, and not diffusion, is responsible for the spatial autocorrelation that has been diagnosed, and if these common causal factors can be modeled fully with covariates. As a consequence, the next step in treating spatial dependence in models for continuous dependent variables is to estimate an OLS model and apply diagnostics to determine whether the covariates fully model the spatial autocorrelation. The chapter considers several spatial autocorrelation diagnostics for OLS models and demonstrates how they can be employed in social science applications.

Chapter 6 turns to maximum likelihood, instrumental variables, and generalized method of moments (GMM) approaches for modeling spatial lag dependence and maximum likelihood and GMM estimation of models for spatial error dependence. The chapter presents applied examples of the estimation of both spatial lag and spatial error models. The chapter also discusses estimation approaches for large sample sizes, the interpretation of substantive effects, and goodness of fit statistics for spatial models.

Chapter 7 returns to the topic of spatial heterogeneity first introduced in Chapter 4. Because spatial dependence can be produced by differing effects of substantive covariates across geographic areas, it is important to examine whether such spatial heterogeneity exists in one's data. This chapter examines models for spatial heterogeneity such as spatial random coefficients models, spatial switching regressions, spatial expansion models, and geographically weighted regressions.

Having focused on cross-sectional analyses in the preceding chapters, Chapter 8 examines the modeling of spatial dependence in time-series cross-sectional (TSCS) and panel data. The space–time model with a spatially lagged dependent variable is examined, as is the space–time model with spatially lagged errors. Both fixed effects and random effects models are considered, as is the TSCS spatial lag model with a temporal lag. A spatial Hausman testing framework is discussed next, followed by nonparametric covariance matrix estimation for space–time models. The chapter also discusses recently developed Lagrange multiplier tests for space–time models.

Chapter 9 examines the modeling of spatial dependence in specialized models. Three broad classes of models are examined. Spatial models for limited and categorical dependent variables are discussed by examining recent innovations in spatial logit and probit models as well as spatial multinomial models. Next, spatial event count models are examined. Finally, spatial survival models are discussed in which spatial dependence in risk propensity is incorporated in the survival model specifications.

Chapter 10 summarizes and reviews how social scientists can employ spatial models in their research. The chapter also examines emerging research frontiers in spatial analysis. The book concludes with three appendices and a glossary. The first appendix presents a brief introduction to getting one's data ready for a spatial analysis, an important issue in that social science datasets do not come with geometry included for the areal units such as countries, states, cities, and census tracts whose behavior social scientists seek to explain. The second appendix examines routines for spatial analysis in both standard statistical packages and in dedicated spatial software. The third appendix examines Web resources for spatial analysis. The glossary provides definitions of many of the central concepts in spatial analysis that are discussed in the book.

1.4 FOR FURTHER READING

Researchers interested in exploring the roles of space and geography in social science theories will find examples in a variety of disciplines. These include fields as diverse as anthropology, criminology, demography, political science, sociology, and public health. The following list of publications is by no means exhaustive, but instead provides some examples of research in these and other disciplines. In anthropology, examples include White, Burton, and Dow's (1981) network autocorrelation analysis of the sexual division of labor in agriculture in Africa. In sociology, Baller and Richardson (2002) examine geographic patterns in suicide and Farley and Frey (1994) examine residential segregation (see also Gieryn's [2000] review essay on the role of place in sociology). In demography there is Loftin and Ward's (1983) work on the effects of population density on fertility; Logan, Zhang, and Alba's (2002) study of immigrant enclaves and ethnic communities; and Yang, Shoff, and Matthews' (2013) study of the relationship between the second demographic transition and infant mortality. In migration studies, Johnson et al. (2005) examined age-specific migration in the United States and Hunter (2000) explored immigrant residential concentration and environmental hazards.

In criminology, Land, McCall, and Cohen (1990) studied the structural covariates of homicide rates, and Sampson and Raudenbusch (1999) studied public disorder and crime in urban neighborhoods. In the field of communication, Øyen and De Fleur (1953) studied the effects of dropping leaflets on the spatial diffusion of information. In political science, there is Most and Starr's (1980) work on spatial proximity and international conflict and Gleditsch and Ward's (2006) work on democratization. In public health, there is Snow's (1855) pioneering work on the London cholera epidemic. These are, of course, only a small subset of the examples of work on spatial theory in the social sciences. Many additional examples can be found in these and other social science disciplines.

The renewed interest in spatial concerns in the social sciences is also reflected in a variety of special issues on spatial topics in social science journals. Readers interested in this spatial turn in the social sciences may be interested in reading further in the following special issues: *Social Science History* 24(3), 2000; *Agricultural Economics* 27(3), 2002; *Political Analysis* 10(3), 2002; *Political Geography* 21(2), 2002; *Journal of Economic Geography* 5(1), 2005; *American Journal of Preventive Medicine* 30(2), 2006; *Proceedings of the National Academy of Sciences* 102(43), 2005; *Population Research and Policy Review* 26(5-6), 2007 and 27(1), 2008; *Environmetrics* 19(7), 2008; *Children and Youth Services Review* 31(3), 2009; and *Historical Social Research* 39(2), 2014.

2

Defining Neighbors via a Spatial Weights Matrix

2.1 The Importance of Space in the Social Sciences

All social science data are spatial data. The behaviors, processes, and events we seek to explain occur at specific geographic locations. As discussed in Chapter 1, these geographic locations are often central to our understanding of these phenomena. Consider, for example, research on behavioral interactions between units in shared networks (see, e.g., Huckfeldt and Sprague 1987, 1988). Research has shown that spatial proximity affects the nature of interactions between actors in these networks (Baybeck and Huckfeldt 2002). This mirrors a long line of research in international relations that has found that spatial proximity between countries promotes interactions between countries (Most and Starr 1980; Starr 2002). This spatial proximity in turn affects a variety of behaviors and processes of interest to scholars and observers alike, including democratization (Gleditsch and Ward 2006), civil wars (Salehyan and Gleditsch 2006; Gleditsch 2007), and war (Gleditsch and Ward 2000).

Similarly, consider the interest of both observers and scholars in the causes and consequences of poverty (see, e.g., Wilson 1987). Here, both researchers and pundits have recognized that geographic locations marked by deep poverty are increasingly segregated from economic opportunity and the opportunity for the residents in these locations to participate fully in American society. Inherent here again is the recognition that geography matters and that understanding the factors that produce poverty at the local level is a critical first step in producing policy options that can alleviate this poverty and produce positive outcomes for both the residents of these locations and for society as a whole.

These are but two of many prominent examples that reflect a growing interest in spatial concerns within the social sciences. It's easy to think of a myriad of additional examples that highlight how we are increasingly becoming attuned to the importance of geography in our lives. From capital tax competition (Franzese and Hays 2008) to crime (Getis 2010) to legislative