Chapter 10
Regional Structure and Economic Development:
Growth Empirics for U.S. Metropolitan Areas

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ABSTRACT

This chapter investigates several aspects of how local economic development and growth are shaped by regional differences in industrial structure on the one hand and interregional linkages on the other hand. The author begins by proposing an alternative regional classification of regions for U.S. Metropolitan Statistical Areas (MSAs) on the basis of clusters that were formed by principal component analysis from economic variables that are relevant for regional growth. These variables include labor productivity growth, measures of local industry mix, human capital, entrepreneurship, and innovation. He then uses these growth-based regional clusters to control the presence of cluster-specific fixed-effects when explaining the spatial characteristics of urban specialization and concentration in the United States. The empirical validity of these new economic regions are evaluated against alternative established classifications such as the BEA Regions, Crone's (2005) Economic Regions, the Census Regions, and the Federal Reserve Districts. Looking specifically at the empirics of regional growth both in a traditional β-convergence setting as well as a dynamic panel setting, the author examines the explanatory power of regional differences in economic structure such as industry concentration, employment specialization, and sectoral diversity.

1. INTRODUCTION

The complex causes of urban growth and its associated spatial patterns of industrial structure and economic development are at the heart of regional science inquiry. Unlocking the black box that contains the mechanisms responsible for economic growth and regional development has long been a coveted prize in theoretical and applied regional science. Even a partial identification of the determinants of growth would improve policy design, promising greater potential for improving

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local economic conditions and attenuating regional business cycle fluctuations. While the impetus for examining regional growth is clear, firm agreement on what constitutes a region remains elusive. In the United States, the Bureau of Economic Analysis (BEA) has grouped the states into eight regions based primarily on cross-sectional similarities in the socioeconomic characteristics in the 1950s. Recognizing the limitations of this regional classification scheme, several recent studies have looked to further the understanding of regional composition.

Crone (2005) and Crone and Clayton-Matthews (2005) group states into regions based on the similarities in their business cycles. They apply *k*-means cluster analysis to the cyclical components of Stock-Watson-type indices estimated at the state level to group the 48 contiguous states into eight regions with similar cycles. In related work, Ó hUallacháin (2008) uses principal components and cluster analyses as a framework for the identification of regions based on state-level growth measures in the US. More recently, Owyang, Rapach, and Wall (2009) model the US business cycle using a dynamic factor model that identifies common factors underlying fluctuations in state-level income and employment growth. In a similar vein, Kim and Rous' (2012) panel study on U.S. house price convergence utilizes a clustering algorithm to operationalize regions as convergence clubs where the cross-sectional dispersion of house prices of the club members decreases over time. While they find little evidence of overall convergence, their results strongly support the presence of multiple, regional convergence clubs.

A significant drawback of this literature is that it remains fairly agnostic about the micro-foundations that influence the differences in trajectories of the economic development across regions. Indeed, it has long been recognized that the sectoral composition of urban economies is a key determinant of their economic performance. Chinitz (1961) famously observed that larger cities are more diversified than smaller ones, putting "the whys and wherefores of urban diversification" at the center of inquiry right at the outset of the rapid regional transformation of the post-war U.S. economy. Despite ample evidence of how industrial bases vary across cities and how they vary by city size, our understanding to what extent the structure of cities and the activities its firms and households change over time remains limited.

How does the sectoral composition of cities influence their evolution? Henderson's (1974) canonical model of urban size has recently been extended by Duranton and Puga (2001) and Duranton (2007) to provide the micro-foundations of sectoral urban diversity. Although this work offers new insights by showing how innovation shapes the corresponding growth dynamics of urban rise and decline more formally, detailed empirical evidence of how the growth of one industry in an area affects the suitability of this area as a location for another industry is still sparse. One of the most promising recent approaches to tackle this issue is to relate urban growth directly to the economic geography of production (Storper and Scott, 2009). The recent work of Drucker and Feser (2012) on how concentrated regional industrial structure might limit agglomeration economies is an important contribution in this regard. They find a consistently negative and substantial direct productivity effect associated with regional industrial structure concentration and only mixed and relatively weak evidence that agglomeration economies are a mediating factor in that effect.

The aim of this chapter is to further explore the role of regional economic structure and economic development along two interrelated strands. The first aspect of this work attempts to further narrow the definition of a region by using indicators of economic growth, population, and social capital at the level of the Metropolitan Statistical Area (MSA), specifically taking advantage of the BEA's MSA-level GDP data.[1] In the second aspect of this work, we explore the relationship between differences in specialization and sectoral concentration and contrasts in agglomeration among US metro-

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