PUBLIC POLICY IMPACTS OF

JURISDICTIONAL FRAGMENTATION

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ABSTRACT OF THE DISSERTATION

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For decades, there has been substantial debate regarding whether it is preferable for a metropolitan area to be governed by a single local government, or by some number of smaller municipalities. Advocates of the latter, informed by Tiebout (1956) and public choice theory, argue that competitive markets in public goods can and should exist, while those in the former camp believe economies of scale and ability to plan cohesively at the regional level make unitary systems preferable. The literature on this topic, reviewed extensively here, has focused disproportionately on matters of public finance while venturing into other fields of public policy inquiry far less often. Does jurisdictional fragmentation have broader implications? This work will use regression analysis to test whether the structure of local governance affects a variety of outcomes, including ethnic and racial segregation, land use patterns, economic performance and inequality, educational achievement, and housing costs. Overall, results are mixed, though they suggest a future course of research: investigating whether fragmentation has worsened spatial mismatch in the labor market among African-Americans.

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INTRODUCTION

Last October, the two major party nominees for President of the United States, Democrat Hillary Clinton and Republican Donald Trump, met in St. Louis, Missouri, at an event the Commission on Presidential Debates (2016) described as a "town meeting" and widely labeled by the media as a "town hall." A group of undecided voters was convened on stage; some had the chance to ask questions of the candidates directly. These labels were applied to the event despite the proceedings being held in a large urban area and viewed by tens of millions of people across the country, the vast majority of whom could not directly participate.

Earlier in the year, two unsuccessful candidates for the Republican nomination, Governors John Kasich and Chris Christie, traded claims about who had held more "town hall meetings" in New Hampshire in advance of the state's primary (Ward, 2016). One can infer that this was not an argument about which campaign had superior event planners, but rather took place because candidates wished to point to the number of such events as a proxy for engagement with the electorate, regardless of whether they led a candidate to adapt his or her policies or messaging.

This terminology is derived from the New England town meeting, where citizens convene to serve as a legislative body (Crawford, 2013; Mabry, 2016). The town meeting is only viable as a system of governance in communities small enough for all interested residents to meet and exists only in some localities in six of 50 states, but the idea behind it has been adapted beyond its original context. This is presumably because politicians and television networks find value in the format and its symbolism: that even someone who will govern 325 million people and command the most powerful military in human history is still, at least in theory, directly accountable to the people. In short, there is a clear positive connotation in the phrase “town hall.”

“City hall,” on the other hand, has a very different connotation. The ubiquitous saying that one “can’t fight city hall” conjures the plight of an aggrieved citizen, unable to receive redress from an anonymous, implacable bureaucracy. Articles with titles like “Can an Activist Crack L.A. City Hall’s Machine?” (Mandell, 2009) speak to a “David-and-Goliath battle” and an effort by “community members … trying to beat back heavily funded, government-friendly candidates who hope to waltz into the powerful $178,798-per-year City Council slot, which comes with 20 personal staffers and eight taxpayer-provided cars.” Rather than being a participatory system, the democratic process is an elitist force to be overcome and defeated.

This distinction can even find itself represented in physical space. While town halls are stereotypically portrayed as simple, unassuming structures at human scale (e.g., Crawford, 2013), city halls can appear to be distant and imperious, lording over the populace. Boston City Hall, built in 1968, was described less than generously by the *Boston Globe* as “cold and dark, imposing and uninspiring, technically and emotionally brutal,” placed on a list of civic embarrassments alongside the Salem Witch Trials and the city’s 86-year World Series title drought (Brodeur, 2016). Both Los Angeles and Philadelphia enforced regulations or agreements for decades ensuring their respective municipal buildings would be the tallest structures in the city (Grad, 2015; Finkel, 2013).

Two phrases, both of which refer to seats of municipal government, differing meaningfully only in the population and land area of the municipality being governed, have come to be represented very differently in the public eye. One can submit that Americans' feelings about local governance depend strongly on its scale, generally preferring that localities be small and highly responsive to their individual concerns.

Notably, this is not some sort of universal human impulse. The United States governs itself differently from other developed nations in this respect; the degree of autonomy accorded local governments with respect to fiscal authority, policymaking, and governance structure is well above global peers (Sellers, 2003). This can be attributed in some measure to the circumstances under which the nation was founded; the Constitution established a central authority constrained by checks and balances, with the Ninth and Tenth Amendments enshrining the idea that powers not explicitly granted to that authority belong to the states and the people, respectively.

As it happens, this is a rather consequential amount of power. Chait (2014) articulates just how much local government can do and how little attention some of its powers receive. Municipalities typically operate police departments and jails, which can establish policies that can deprive individuals of money, freedom, or even life itself. Cities have almost unchecked authority over zoning and land use policy, dictating what can be built where and what rights property owners have. Local authorities can enact licensing rules and other regulations that restrict one's options for earning a living. However, since local officials are often little known, Chait (2014) argues, their electoral fates are often bound up in national political winds, compromising their accountability.

The type and size of local government, then, should have some impact on the living conditions of those under their authority. This dissertation will argue the effects of local government structure are indeed quite extensive; it will also evaluate the influence of those structures on areas of public policy Chait (2014) identifies and others. However, it is hypothesized here that “town halls” are indeed the inferior form of governance for our nation’s metropolitan areas, that there are virtues in large, bureaucratic “city halls” that are underappreciated. There exist both evidence and theory positing that regions with more fragmented governance structures — where most people live in jurisdictions with small populations — are worse off.

Note that this argument does not speak to the character of communities as such. Unified local governance does not require, for instance, that everyone live in 50-story apartment buildings just because all inhabitants are residents of “the city.” Many core municipalities include peripheral suburban areas, and though the American small town is often an independent entity, there is no legal requirement or immutable historic precedent for this. In short, fragmentation is not about how people live, but simply where lines between governments are drawn and how many such boundaries there are.

A great deal of ink has been spilled on this topic from empirical and theoretical perspectives alike, and this paper does not claim to in any way settle the debate, but it brings several new data sources and approaches to the existing literature. It will be argued herein that the phenomenon of jurisdictional fragmentation, where hundreds of local public authorities collectively govern a region, can and does impose unnecessary costs on their residents and the nation at large.

CHAPTER I: FRAGMENTATION AND ITS DISCONTENTS

The role jurisdictional fragmentation plays in regional social welfare has been actively considered at least since the work of Tiebout (1956). He objected to the prevailing opinion among contemporary public economists that there was no market solution to the collection of taxes and allocation of public goods at the local level. In the alternative, Tiebout (1956) sketched out a conceptual model where individuals and/or households "vote with their feet." In it, households locate themselves in the community that offers the best possible bundle of public goods, given their consumer preferences and the prices of those goods (i.e., taxes and fees). Each municipality provides a unique bundle of goods at well-defined prices in a way that optimally satisfies individuals' economic and political preferences. In short, there is no coordination of fiscal policies among localities, and a market for public goods develops.

For Tiebout's (1956) model to hold, however, there must be enough jurisdictions for such a market to develop, just as perfect competition in economics requires numerous firms. Similarly, moves between communities must be relatively costless. Under low levels of fragmentation, "consumer-voters" would be much less likely to find baskets of public goods that match their preferences nearby. Long-distance moves cannot be made without incurring substantial transportation and information costs, employment disruptions, and moving expenses. Further, individuals are often loath to move long distances for cultural, familial, and other non-economic reasons. Together, these factors place geographic constraints on the size of the public service market, suggesting a metropolitan level of analysis.

Tiebout's (1956) analysis, then, implies metropolitan jurisdictional fragmentation is a positive, even necessary condition for maximizing welfare: Regions should have many municipalities to facilitate optimal allocation of public goods, given the temporal, spatial, and financial constraints on mobility of economic agents, a thesis first advanced by Ellickson (1971). Regional integration within a metropolitan area would hence dissociate local service and taxation levels from resident preferences, homogenizing regional fiscal policy and thereby reducing welfare. Tiebout (1956) concludes that advocates of governmental consolidation, given an unknown social welfare function, "cannot prove their case on purely economic grounds" (423).

Tiebout's theories were further articulated in a paper he co-authored (Ostrom, Tiebout, & Warren, 1961). After an introduction that outlines opposing arguments made by Wood (1958) and others, wherein "the multiplicity of political units in a metropolitan area is essentially a pathological phenomenon," the authors push back against the idea that such a system must lead to chaos. More precisely, they argue, interaction between localities can be "coherent … consistent and predictable" (831).

Ostrom, Tiebout, & Warren (1961) argue that "small-box" solutions will, in fact, often be required for the delivery of public services. Their most illustrative example considers a region and its demand for fire protection, which naturally will vary based on the magnitude of localized risk. Imposing a single level of capital expenses and human resources dedicated to fire-fighting across the metropolitan area would necessarily lead to some residents paying more than their local risk would justify, while others pay less, since tax rates must be uniform throughout a single governmental unit. The authors argue the alleged necessity of multi-purpose regional governance can be invalidated by decoupling the production and provision of public services; in short, there can still be economies of scale without the forfeiture of local control through the buying and selling of services among localities and private firms.

The next section of Ostrom, Tiebout, & Warren (1961) focuses on the potential pitfalls of unitary regional government. While a regionally consolidated entity is clearly appropriate for some capital-intensive public tasks, they argue, such a system will lead to the nightmarish “city hall” alluded earlier, with a system “apt to become a victim of the complexity of its own hierarchical or bureaucratic structure” (837), lacking the dexterity to effectively serve the public. Hence, Ostrom, Tiebout, & Warren (1961) posit, the civic health of the region would suffer, with the public feeling disconnected from their distant, unresponsive government, disengaging from civic discussions. Eventually, they suggest such large-scale inefficacy could lead to “the eclipse of the public” (837).

Ultimately, Ostrom, Tiebout, & Warren (1961) assert that there is no need for a metropolitan government to be established, that bottom-up cooperation on matters of regional import is no more difficult than specializing at the neighborhood level within an overarching authority, though this is claimed without evidence. The authors point to contracting arrangements between cities in Los Angeles County as an example of market principles at work. Ostrom, Tiebout, & Warren (1961) argue a fragmented metropolis can both capture economies of scale from public good production and maintain the responsiveness of the local “town halls.”

Ostrom, Tiebout, & Warren (1961) acknowledge significant caveats, however. "No community, on its own initiative, has much incentive to assume the full costs of controlling adverse consequences … shared by a wider public" (840). They suggest problems affecting the entire region equally, such as air pollution, can be resolved with relative ease by sharing the cost of solutions via informal institutions. When impacts are unevenly distributed, the authors present an argument that echoes Coase (1960) in proposing that councils of governments or similar entities can mitigate bargaining costs to the point where bargaining can achieve a solution that is both efficient and equitable. Creation of regional governance, Ostrom, Tiebout, & Warren (1961) argue, would hinder this process. They suggest localities have an incentive to negotiate among themselves to preserve autonomy and that more attention needs to be paid to civic institutions.

As noted earlier, the Tiebout hypothesis was very much a minority opinion among scholars at the time, though it found currency in emerging public choice theory (e.g., Buchanan & Tullock, 1962) and has since pervaded many areas of scholarly inquiry, many of which will be discussed in this work. The opposing contemporary view, voiced by Wood (1958), saw inherent danger in fragmentation. He argued that emerging development trends post-World War II threatened to fray America's metropolitan areas; hence, reform was necessary. "If such reorganization is not forthcoming," Wood (1958) wrote, "these areas face governmental crisis of substantial proportions. To drift with the tide is to court political, financial, and administrative disaster for urban government in the United States" (111-112) by 1975 — the same year, coincidentally, that New York City came to the precipice of bankruptcy (Nussbaum, 2015).

Why were the stakes so high? Wood (1958) outlined the crisis he saw in the structure of America's local governments. First, as the share of people living in one city and working in another grew throughout the 20th century, employment centers were forced to accommodate large daytime population growth, while suburbs lack scale to provide services effectively. This, he says, has two knock-on effects: disenfranchisement, as decisions in the urban core are made without the consent of a large share of its workforce, and polarization, with the urban fringe becoming staunchly Republican and the urban core becoming increasingly Democratic. On the latter point, Wood (1958) argues, "Metropolitan areas are likely to be split into two warring camps … the situation becomes cast in a rigid mold, and the opportunity for responsible consideration of regional problems diminishes" (110). Indeed, recent literature points to increasing polarization not just generally, but specifically in the way he describes (Nall, 2015).

Meanwhile, Wood (1958) notes, businesses had begun following residents to the suburbs as well, further depleting urban core tax bases that were also strained due to the disproportionate presence of tax-exempt universities and cultural institutions in such areas. Wood (1958) argues this shift exacerbates social costs and increases distress in urban neighborhoods, while also radically increasing such expenses, particularly for public schools, in suburbs that see extreme growth. Finally, Wood (1958) states, there are deleterious social effects, too, as social connections become more geographically scattered and "a regional consciousness is lost … only the ties of kinship and the stultifying communications of mass-media remain" (111) — words that fall comfortably within contemporary social capital literature (e.g., Putnam, 2001).

Wood’s (1958) solution, then, is metropolitan government. This is held up as a superior alternative, one more consistent with American democracy and liberalism than either top-down planning — referred to, in terms no doubt inflected by the Cold War, as “twentieth century socialism, American municipal style” (120) — or decision-making undertaken by small towns. In short, Wood (1958) argues, “Garden city planners may place too much reliance on the social nature of man, but grassroots advocates reach toward the opposite extreme of unfettered individualism” (121).

Speaking to the Tiebout model, though not citing it by name, Wood (1958) offers a robust critique. The sorting mechanism ignores broader consequences, he writes, namely segregation and stratification by income and their impact on social equity and humanitarian concerns. From a sociological standpoint, Wood (1958) argues parochial governance will encourage and amplify militant conformity. Hence, preferences for public goods will be correlated with preferences for other community characteristics, generating local jurisdictions with highly similar opinions on political and cultural issues. These views, then, rather than being debated in the public sphere, may well be enforced through social pressure, potentially to the detriment of democracy itself.

The development of unitary regional governance is Wood’s (1958) salvation from either extreme. Control over planning and development of the metropolis will be held by the regional populace, rather than being driven by elites, with a differentiated polity that tolerates many cultures and ideologies, bound together by a unifying purpose. It is not hyperbole to suggest Tiebout and Wood held fundamentally different viewpoints on the role of local governance in society.

In the intervening decades, the scholarly case for regionalism has perhaps been advanced most comprehensively by Briffault (1996, 2000). These works explicitly seek to establish that objectives putatively served by parochial governance would in fact be met more effectively within a regional structure. At its core, Briffault's argument relies on the presence of externalities generated by municipal boundaries crosscutting densely inhabited areas. In the 19th century, core municipalities held authority over nearly all densely populated communities; often, when this ceased to be the case, outlying areas were merged with the central community (Hamilton, 2014). As municipal fragmentation increased throughout the 20th century, the likelihood that decisions made by one city would influence residents of another grew dramatically. This compromises the ability for Tiebout's model to hold, since household-voters are unable to fully assess public goods if they are influenced by the decisions of adjacent municipalities.

In large measure, Briffault (1996, 2000) is a rejoinder to the arguments advanced by Ford (1994) and Frug (1993). While those pieces acknowledged such externalities, they argued that other considerations were more crucial, namely local autonomy and political participation that would be lost by the elevation of neighborhood concerns to a regional authority. Briffault claims that, rather than reifying values of the American federalist system, parochial government instead limits these virtues. While much of this argument falls outside the frame of this dissertation, it is important to note that the regionalist argument does not reject goals advanced by the advocates of decentralized government, but instead suggests they are poor means for achieving said objectives.

The key results of this fragmented governance structure, Briffault (1996) argues, are exclusionary zoning (which generates artificially inflated housing costs), “leapfrog” development, excess infrastructure spending, and increased interlocal competition, which leads to fiscal disparities among municipalities and concentrates those requiring high levels of social service expenditures in distressed cities. Ultimately, this adversely affects even affluent communities; while costs are avoided in the short run, there is no assurance that such pathologies will remain forever contained in the urban core. Further, not all expenditures are contained at the local level, as increased spending on federal and state social services will be paid by affluent areas as well.

Briffault (1996) then clarifies that a solution to this conundrum cannot come from a Tiebout-inspired model alone. In reference to of public choice models that draw upon Tiebout (e.g., Lyons & Lowery, 1989), he notes that fiscally distressed cities would not be able to respond in a market-driven way to inequities or other challenges. Briffault (1996) argues that localities are constrained by legal requirements and macroeconomic and social conditions; it is unclear whether a city with an undesirable bundle of taxes and public services could change them enough to mitigate the situation.

More broadly, Briffault (1996) pushes back against the proposals advanced by Ostrom, Tiebout, & Warren (1961) and refined by Ford (1994) and Frug (1993) for mitigating public policy challenges that crosscut municipalities, such as collaborative regional activity facilitated by constrained regional entities or permeable jurisdictional boundaries for purposes of voting on certain issues. The former of these is critiqued as lacking sufficient capacity to enforce compliance with interlocal agreements. The latter, Briffault (1996) argues, “might actually produce the worst of both worlds: the loss of the local autonomy that is the justification for decentralization, without the creation of … regional consciousness that would facilitate the adoption and implementation of policies serving the interests of the metropolitan area as whole” (1162).

A full account of Briffault’s arguments would require an extensive paper in and of itself, but he highlights adverse impacts with respect to both efficiency and equity in the now-widespread model of decentralized governance and flaws in the theoretical means for mitigating them. Ultimately, he argues that there must be a metropolitan level of governance with formal authority and fiscal capacity to make policy on issues of regional concern and mitigate adverse consequences of fragmentation.

Meanwhile, Rusk (1993, 2013) and Orfield (1997) advanced similar arguments from professional rather than academic perspectives. Rusk (2013) develops the concept of urban elasticity — the ability of a central city to expand into outlying suburban areas, hence growing and diversifying the property tax base of the core municipality. Through a series of bivariate correlations (i.e., lacking statistical controls), he concludes that central cities whose geographic footprints have not expanded geographically since 1950 performed far worse than high-elasticity central cities on a wide array of socioeconomic measures, with metropolitan areas centered on these generally older, more industrial cities perform worse than newer counterparts. Summarizing his findings, Rusk (2013) asserts that inelastic cities, unable to grow their tax base, become dependent on intergovernmental aid, destitute and segregated from the metropolitan area, with regional institutions less responsive to economic challenges.

Two fundamental rifts between Rusk (2013) and the academic literature become immediately clear. First, he presents a vision where the urban core municipality is paramount, a jurisdiction whose vitality dictates that of the surrounding region. Second, as opposed to the welfare of autonomous "consumer-voters" or that of the community, Rusk (2013) finds the fiscal viability of local government to be a primary determinant of residents' socioeconomic standing. Intermunicipal competition is viewed by Rusk (2013) not as an economically efficient market clearing mechanism, but as an obstacle to metropolitan unity. Maximization of household utility, in his view, is achieved through ensuring that government has the resources to provide it either directly (public services) or indirectly (economic development) rather than through personal economic choices made in the free market of a "perfectly" fragmented metropolis.

Given his observations about elasticity and the role of government, it is not surprising that Rusk (2013) has a far-reaching program for declining metropolitan areas. Foremost, it is desirable to make a central city more elastic via consolidation with surrounding jurisdictions or annexation of adjoining unincorporated areas. When such aggregation is politically and/or legally impossible, the recommended solution is to enact a set of regional policies that he calls "elasticity mimics" that, when implemented simultaneously, result in an inelastic, fragmented region acting as if it were unified. These include inclusionary zoning, regional land use and transportation planning, and tax base sharing. Combined, they mitigate the negative consequences of inelasticity identified by Rusk (2013).

This general line of argument is expounded upon by Orfield (1997). While both authors ascribe to the need to integrate the city and its suburbs to stabilize the urban core and, by extension, the region, this work takes a different approach. Rather than focus on elasticity and government structure, Orfield (1997) emphasizes the need for coalition building in achieving regional objectives as the end goal — as opposed to being an imitation of the ideal. In this sense, he is more politically oriented in his approach, speaking more in the context of policy function and process rather than institutional form or structure — though the focus in both models is governing at the regional level.

Orfield's (1997) buzzword is "polarization." Much like "elasticity" for Rusk (2013), it is the precept that informs his argument. His frame comes from neighborhood life-cycle theory, which implies decline of the inner city and older suburbs at the expense of those on the periphery (see Metzger, 2000, for a full treatment). In short, polarization is the condition of economic inequality within a metropolitan area, typified by the transfer of the tax base from poorer communities to richer ones. Orfield (1997) points to the real estate concept of the "favored quarter" as the impetus for polarization. The term refers to an empirical phenomenon where a region's wealthiest residents are often located disproportionately in a wedge-shaped cluster that includes about a quarter of regional land area. This cluster dominates regional economic growth and new infrastructure provision; cities therein "have mastered the art of skimming the cream from metropolitan growth while accepting as few metropolitan responsibilities as possible" (Orfield, 1997, 5-6). This process, unless abated, is self-perpetuating, starving the rest of the metropolitan area of development and inflicting ever-larger impacts on the region.

Unsurprisingly, Orfield's (1997) proposed policies are much like Rusk's (2013): comprehensive metropolitan planning and revenue sharing are essential to ensure consistent provision of physical and financial capital across all parts of the region and ensure businesses and their labor force are co-located. Central to these reforms is the creation of a political coalition that adapts progressive community development policies to operate within a conservative political climate that has strong attachments to heterogeneous local identity and home rule, uniting most of the region against the interests of the favored quarter. In the end, both Rusk (2003) and Orfield (1997) argue for comprehensive regional solutions to the myriad ills of the modern metropolis, though the latter is less exorcised about government boundaries than the former.

In short, this chapter offers two seemingly mutually exclusive approaches to metropolitan social welfare — one of unity and one of competition. To reduce this debate to such an assessment, however, would ignore the substantial caveats present in the arguments for fragmentation. As Ostrom, Tiebout, & Warren (1961) note, there are obvious instances where some goods and services must be provided on a regional scale; for example, having every municipality operate its own international airport is absurd on its face. That said, in their view, where does regionalism end and localism begin?

Broadly speaking, Ostrom, Tiebout, & Warren (1961) define four metrics upon which to measure the efficacy of public service delivery: control, efficiency, political representation, and local self-determination. The first requires that the public entity has the agency to enact policies over the geographic area affected. The second mandates cost-minimizing economies of scale. The third insists that all groups affected by a policy are represented. Finally, the fourth is a subjective criterion stipulated not by any theory, but by the American political culture of home rule; it suggests that cities should have sole authority over public policy in the absence of externalities.

While the competitive model would reject revenue sharing as a distortion of the market mechanism, their opinion on the other components of the regionalist agenda are less clear. Consider the decision of whether to build a new retail development in a rural township just beyond a city's boundaries. At what level of governance should this land use decision be made? If either entity made the decision alone, it would seem none of Ostrom, Tiebout, & Warren's (1961) criteria for optimal service delivery would be fully satisfied. Perhaps they would endorse tools such as joint development districts on an *ad hoc* basis for such instances.

Notably, this chapter has spoken of, but not yet defined, social welfare. This is not only because none of the treatises discussed here do so explicitly, but also because implicit definitions are radically different. As noted before, Tiebout (1956) is clearly focused on market-clearing efficiency as the goal, marginalizing concerns of equitable distribution of the benefits derived from such a system. Notably, the benefits Orfield (1997) seeks clearly exclude the "favored quarter." Regionalism is therefore not Pareto optimal in the short run; while he argues that benefits accrue to all in the long run, there is no clear evidence that this is the case. Definitively determining the "better" approach would require that there be a single, mutually agreed upon social welfare function, something that Arrow (1950) and others would appear to render impossible.

It is also worth noting a deceptively obvious observation by Ostrom, Tiebout, & Warren (1961): “No *a priori* judgment can be made about the adequacy of a polycentric system of government as against the single jurisdiction.” Its performance, they note, “can only be understood and evaluated by reference to the patterns of cooperation, competition and conflict that may exist among its various units” (838). In other words, as important as theoretical considerations are, results matter more. Works such as Reese (2004) and Thurmaier & Wood (2002) highlight the relevance of “unwritten rules” in local governance and illustrate the perils of merely examining institutions while ignoring the role of human actors and social capital. These strands of literature make it worth considering whether this topic is overhyped as a subject of inquiry.

The full scope of arguments between those supporting and opposing regional government to increasing social welfare is laid bare in Kim & Jurey (2013). The authors divide the literature into four distinct fields of inquiry. The first is, unsurprisingly, fiscal outcomes; this is the ground covered by Tiebout (1956), arguing against the premise that centralization is fiscally optimal. Instead, he advances his thesis that optimal outcomes are achieved by creating an efficient market for public goods.

The second field is regional economic policy. In many ways, there is an overlap here with the first field, but rather than applying simply to public budgets, similar logic applies to job and income growth. Acolytes of decentralization argue that competition between municipalities and other governments is beneficial, driving ever-improving public policy for businesses and households (Kim & Jurey, 2013). Economic development incentives can therefore be seen viewed as the cost of attracting productive firms, rather than a drain on public resources, as suggested by Rubin (1988) and others. Conversely, regionalists find that fragmentation compromises regional economic growth "due to administrative inefficiency, the lack of regulatory consistency, and difficulties in achieving strategic cooperation" (Kim & Jurey, 2013, 112).

The third field is social equity. Orfield (1997) clearly suggests fragmentation is associated with unequal development in metropolitan areas, arguing that some form of regional collaboration and/or consolidation is necessary to combat it. Chapter IV herein details how Weiher (1991) argues that fragmentation is not just correlated with, but leads directly to, increased levels of residential segregation. Kim & Jurey (2013), notably, do not identify a corresponding theoretical argument that decentralization facilitates social equity. The authors point to Aurand (2007), for one, who showed econometrically that jurisdictional fragmentation increased the quantity of affordable housing available to low-income households, but the lack of a full-throated counterpoint is of interest. "Tiebout sorting" literature often suggests that fragmentation does yield demographic, economic, and ethnoracial differences between municipalities, though the literature on the topic typically fails to fully address the implications of this finding. A brief review of this material is provided in Chapter II.

The fourth field is environmental consequences. Decentralization advocates argue that the flexibility gained through local sovereignty leads to better-tailored solutions to challenges faced by localized issues, as argued by Ostrom, Tiebout, & Warren (1961) in their discussion of fire protection. That said, this is generally extended to matters of pollution without conceptually establishing that it still holds. Conversely, Kim & Jurey (2013) point to evidence that this does not appear to be the case; for one, Bluestone (2008) finds that, *ceteris paribus*, more decentralized regions were less likely to attain compliance with federal ozone regulations than those with lower levels of fragmentation. Later, Chapter V will consider pro-regionalist literature investigating connections between fragmentation and land use.

Overall, then, we find an array of empirical and theoretical findings, but one that tends to consider individual elements of social welfare in isolation. This work will offer a modest push toward a more connected understanding of metropolitan fragmentation as a phenomenon; something adequately comprehensive, however, is beyond the scope of a single work by a single researcher. Ultimately, the question is whether the arguments of the decentralization camp, which may well have relevance within the narrow issue of fiscal matters, can be shown to hold beyond them. The three fields identified by Kim & Jurey (2013) will each be tested herein.

Finally, before concluding, it needs to be noted that the patterns of regional fragmentation do not occur in a vacuum; they are the result of an array of historical and legal choices made by various states. Measures like those of Miller (2002) and Rusk (2013) demonstrate that regions with the highest levels of fragmentation are largely situated the Midwest and Northeast, particularly older areas with an industrial history, while metro areas in other portions of the country are generally more unified. It is necessary to briefly review why this is, as well as to discuss the potential implications of this circumstance.

During much of the 19th century, appropriation of neighboring territory by a central city was a common process across the country. During the transportation and industrial revolutions, large cities regularly annexed surrounding communities. Many of the reasons are not unfamiliar to us today; civic leaders sought to raise their city's profile by becoming more populous and larger cities could provide public services more cheaply than surrounding areas, incorporated or otherwise, due to economies of scale. In the latter half of the century, many cities grew geographically; some areas were annexed willingly, but most were absorbed into the central city either without a vote or with the state legislature ignoring the results of local referenda. Detroit, Pittsburgh, Boston, St. Louis, and New Orleans all saw such annexations (Hamilton, 2014).

In an ironic reversal, the cities that pioneered wholesale annexation have become incapable of pursuing such policies, while others are now employing the same means in hopes of ensuring fiscal stability. In the late 19th century, industrialized states issued new laws that made municipal incorporation markedly easier, no longer requiring a specific enabling statute to be passed by the legislature (Hamilton, 2014). For instance, in New Jersey, the late 19th century was punctuated by "boroughitis," wherein state laws made incorporation so easy and financially beneficial that dozens of municipalities were created on even the flimsiest of pretenses, such as disputes over street lighting (Wright, n.d.). Other states passed similar legislation.

In many cases, it was at this point that urban areas stopped growing as incorporated suburbs surrounded inner cities, closing off the potential of annexation. For example, Cleveland had 915,000 people in 1930, making it the fifth most populated city in the United States; at the time, its geographic size was 71 square miles. Since then, it has added only seven square miles, mostly for the construction and expansion of Cleveland Hopkins International Airport, and its population has been more than halved (Davis & Smith, 2002). These measures lead Rusk (2013) to categorize Cleveland as a “zero elasticity” city.

Meanwhile, many southern cities can and do add surrounding land. Texas and North Carolina, among others, have very liberal annexation laws, allowing major cities in those states to add land area without approval of those annexed. Most other cities that actively annexed in the late 20th century are located in the Sun Belt (e.g., Phoenix and Oklahoma City) (Hamilton, 2014). An exception to this pattern is Columbus, Ohio, where the city only granted outlying areas access to municipal water supplies if they agreed to be annexed. This strategy has resulted in a far-reaching city that stretches into three counties and 16 school districts, taking control of surrounding tracts of land to facilitate suburban development. This approach means that there are “so many unincorporated areas — township fragments yet to be annexed — that a city map resembles a slice of Swiss cheese” (Davis & Smith, 2002). Columbus, then, is rated as being far more elastic by Rusk (2013) than any other city in Ohio, though this *ad hoc* approach to expanding municipal boundaries may well have its own adverse consequences.

Similarly, some governments have undergone city-county consolidation, wherein the core municipality becomes coterminous with its county and the governments of the two entities merge. Indianapolis, the other major Midwestern city that has undergone substantial geographic expansion, did so because of such a merger imposed by the state government in 1969, though such mergers have typically required a referendum of the city and county to endorse the move for decades. Again, like annexation, this tool was used to expand industrial cities like Philadelphia and New York in the 19th century (Hamilton, 2014). Modern consolidations, though, are largely concentrated in the Ohio Valley region and a handful of other states. The prevalence of merger efforts in Alaska, Georgia, and Virginia are attributable to unique size and form of county governments in those states; elsewhere, several cities in the upper South apparently emulated the example of Nashville and Davidson County in 1962. As with annexation, the existence of incorporated cities and townships make mergers less practical (Carr & Feiock, 2004).

The fact that certain governmental structures exist primarily in particular parts of the country, of course, makes an analysis challenging; fragmentation is an endogenous, rather than exogenous, phenomenon, the product of historical political events both intentional and accidental. Ultimately, this cannot be accounted for fully within the econometric models presented herein, though Chapter VII will consider the impact of fragmentation both in the present and the past. A further discussion of the composition of the models is confined to later in the paper.

The remainder of this work will be presented as follows. Chapter II will delve into the theoretical underpinnings of the efficiency and equity of local governance, focusing on the tension between advocates and detractors of Tiebout's (1956) model and its successors. Chapter III will present the data sources and methods that will be used to evaluate the impacts in question. Chapters IV through VI examine the effect of fragmentation with respect to prevalence of residential segregation on the basis of race and ethnicity, inefficiencies in land use patterns, and household income, respectively, through OLS regression analysis; these will be conducted across metropolitan areas nationally. Chapter VII will model education and housing outcomes for Ohio public school districts. Last, conclusions and discussion will be covered in Chapter VIII.

CHAPTER II: LITERATURE REVIEW

As noted in the previous chapter, Tiebout (1956) objected to the concept that there was no market solution to the collection of taxes and allocation of public goods at the local level, echoed by “good government” advocates through the early 20th century. In the alternative, he sketched out his model wherein individuals “vote with their feet.” Consumer-voters locate themselves in the community that offers the best possible bundle of public goods, given their preferences and the price of those goods (i.e., taxes). Each municipality provides a unique tax-service bundle in a way that optimally satisfies individuals’ economic and political preferences; hence, government services are “sold” in a pseudo-free market that maximizes social welfare.

Naturally, to reach this conclusion, Tiebout (1956) must define the environment in which he constructs his model. Three constraints are standard assumptions from classical economics: costless residential mobility, complete and symmetric information, and numerous “firms” (i.e., municipalities) that provide public goods as in perfect competition. Further, Tiebout assumes that income is exogenous of employment, there are no externalities, and — for a given bundle of taxes and services — there is an optimal city size. This ideal number of households will minimize average costs and, hence, the population level all cities will look to achieve.

Many of these postulates are clearly not reflective of reality or, at a minimum, can be challenged; a complete accounting is beyond the scope of this work. The primary concern is whether the central finding of the model is correct. Specifically, if households "vote with their feet" and choose their residence by examining tax-service bundles, then municipalities should be homogeneous in economic and socio-demographic dimensions; households with similar resource endowments and utility functions should locate in the same communities.

Alternatively, other works assess whether two corollaries of the model can be demonstrated empirically. First, it is presupposed that housing prices, *ceteris paribus*, will be higher in municipalities with lower property taxes and/or higher levels of public service delivery; in public finance parlance, the fiscal benefit is capitalized into the cost of the house. This is because a given locality's attractive property tax-public service bundle will increase demand for housing within its boundaries; if the municipality is "built out" and its housing supply is therefore relatively inelastic, the price of residential real estate will increase. Oates (1969) launched this line of inquiry.

The other corollary considers what happens when two model assumptions that are particularly unrealistic — perfect mobility and an absent labor market — are relaxed. Suppose transportation costs are proportionate to distance and that households do indeed earn their income through employment rather than capital; further, households are risk-averse, implying there is significant utility in retaining current employment. These essentially constitute barriers to exit from the metropolitan area in which the household currently resides. Hence, for Tiebout's model to hold, there must be many government jurisdictions within each region from which consumer-voters can choose. The nexus of "fiscal federalism" and the spatial distribution of households per their public good preferences can lead to substantial implications.

From here, a synopsis of several 20th century papers will be presented, a small sample of the papers in the Tiebout literature discussed above. Then, more recent works that extend these approaches will be compared with the prior articles to develop stylized facts and conclusions, both in theory and policy. What methods seem to yield convincing results? How might seemingly contradictory findings agree?

Some works in this first review are non-empirical; they construct a system of equations to assert mathematical relationships or pose questions in theoretical style, like that of the original Tiebout treatise. These include Ellickson (1971), Hamilton (1975), and Wheaton (1993). On the other hand, empirical works in this field, comprising much of this review, test whether results expected by the Tiebout model, i.e., demographic homogeneity within municipalities. These are Ebberts & Gronberg (1981); Grubb (1982); Hamilton, Mills, & Puryear (1975); Heikkila (1996); Munley (1982); Ottensmann (1982); Pack & Pack (1977); and Stein (1987).

This review begins with Ellickson (1971), who attempts to unite land use and location theory (i.e., Alonso, 1960, and its antecedents) with the Tiebout model to develop a unified conceptualization of urban political economy, seeking to explain the constancy of local government boundaries. He notes that existing models fail to recognize a fundamental general equilibrium: “The nature of local government in an urban environment is the product of the simultaneous interaction of residential location decisions and the local political process,” which “raises serious problems for the empirical study of residential location patterns or local governmental decision-making in a metropolitan context” (335).

Ellickson's (1971) households maximize their utility with respect to housing prices and public-service quality while municipalities maximize tax revenues through their local budgetary and land use authority. After a complex proof of income stratification among cities, he determines that any shift in local government boundaries within a metropolitan area will necessarily experience opposition, as it alters population density, one of the model's central parameters. In short, Ellickson (1971) bolsters the argument laid out by Ostrom, Tiebout, & Warren (1961), namely that the aggregation of jurisdictions is likely to have adverse consequences.

It is notable, however, that Ellickson's (1971) argument seems to rely on Pareto optimality, at least at the municipal level, as a basis for evaluation; a policy is bad if it makes one jurisdiction worse off. Regionalism advocates like Orfield (1997) explicitly disagree with this assertion, as his collaborative approach to regional governance relies on dispersion of short-run gains that would otherwise accrue to the "favored quarter." This question of analytic scale – municipal versus regional – is a common subtext.

Hamilton (1975) sought to expand the theoretical construct. "I believe that the major weakness of the Tiebout mechanism is that, whereas he has specified a device (namely migration), whereby consumers 'shop' for local public services, he has failed to endow his mechanism with a system of prices" (205). In other words, while Tiebout indicates that there would be an optimal municipal size, this would not be achieved automatically, but would need to be enforced via land use regulation. He also points out that some amenities, such as beachfront, are inherently limited in quantity and cannot simply be created, regardless of demand.

Hamilton (1975) then suggests this omission would imply an inefficient provision of goods and a game of "musical suburbs, with the poor following the rich in a never-ending quest for a tax base" (205). This, however, may not be a ridiculous premise. Gordon (2014) describes such a process in St. Louis County, Missouri, throughout the late 20th century, wherein African-Americans seeking suburban amenities would move into cities populated by wealthy whites, who would then decamp to areas further from the urban core, establish new municipalities, and leave concentric rings of older suburbs to a fate of decline. This is, indeed, consistent with principles of neighborhood life-cycle theory noted in Chapter I.

Regardless, Hamilton (1975) sketches a model where households derive utility from land and public services, with the costs of these goods being paid via property tax. Several potentially dubious assumptions, such as constant returns to scale in service delivery — an assertion explicitly rejected by Ostrom, Tiebout, & Warren (1961) — are introduced to the model. The surprising result is that, in this Pareto-optimal Tiebout environment, tax-and-service bundles play no role in housing markets. This finding stems from the observation that, assuming property and public goods markets in equilibrium, any such capitalization would be bid down through a form of arbitrage. This, Hamilton (1975) states, means housing in urbanized areas would be homogeneous if not for the pure acres-versus-commute trade-off of Alonso (1960). The author acknowledges that this, of course, does not match reality. In addition to the scale economies issue, he acknowledges that "interjurisdictional migration is a very expensive means of clearing a market" (Hamilton, 1975, 211), introducing inherent inefficiencies.

Wheaton (1993) builds a model with distinct and separate markets for improved and unimproved residential real property (i.e., housing and land), subject to zoning restrictions, and presupposes a single utility function, but different budget constraints, for all households. He finds that income sorting necessarily occurs both in the most *laissez-faire* context, an absence of zoning rules and public services paid via user fees, and the most heavily regulated, where minimum lot sizes are specified and revenues are collected through a property tax, as is true in most American contexts.

Wheaton (1993) outlines the mechanism at work, noting that zoning statutes mandating a certain level of land consumption eliminate the ability for households with lower levels of demand for public goods (or, alternatively, those with less ability to pay) from being able to buy into wealthier, high-demand jurisdictions, necessarily stratifying cities by income. Finally, in a concluding aside, Wheaton (1993) notes demand for land and housing are less elastic with respect to income than demand for public services, based on extant literature, meaning stratification should develop in any context because of the comparative statics outlined in the model.

Empirical works in this review vary substantially. While the subject matter is similar — tests of homogeneity with respect to a socioeconomic characteristic — scales of inquiry and methodologies vary quite substantially. Grubb (1982), Heikkila (1996), Munley (1982), and Ottensmann (1982) each focus on a single county or region and perform a cross-sectional analysis to determine the level of homogeneity in static terms. Ebberts & Gronberg (1981); Hamilton, Mills, & Puryear (1975); Pack & Pack (1977); and Stein (1987) perform similar analyses across multiple areas.

Grubb (1982) collected 1960 and 1970 Census data on resident age and income in 76 eastern Massachusetts municipalities to assess Tiebout sorting in a longitudinal context. The proportions of 1970 residents in each town that are aged 17 or younger, aged 65 or older, and in the top and bottom income quintiles nationally, were each regressed against corresponding 1960 data and a host of control variables. While town demographics were influenced by amenities, the population distribution did not appear to be in a Tieboutian equilibrium, as there was no convergence toward a steady state.

Munley (1982) focuses on one public good, primary and secondary education, and considers education spending to be the central Tiebout sorting mechanism among residents in 58 school districts across Long Island. (Given Census of Governments data on the primacy of education spending among local government expenditures, this is not an unwarranted assumption.) Creatively, the author examines tax referendum voting patterns to estimate variance in household preference for public spending to evaluate the degree of Tiebout sorting; if there were perfect intra-municipal homogeneity, voter preference would be unanimous, so deviation from that result represents heterogeneity.

Rudimentary regression analysis by Munley (1982) finds that homogeneity is indeed higher in political environments with smaller, more numerous local jurisdictions, even after controlling for the populations of the school districts themselves, though the results are weakly significant. The conclusion, then, is that there is ostensible evidence of a Tiebout sorting effect in public education spending, and that this explains the apparent efficacy of the median voter theorem in explaining such spending in the prior literature with respect to that location.

Ottensmann (1982) eschews the municipality as the scale of analysis, choosing to analyze the determinants of homogeneity in neighborhoods (i.e., census tracts) in the Indianapolis metropolitan area. As will be discussed in Chapter IV, this is a notable shift, not only because the Tiebout hypothesis speaks to public services that are provided by governments whose boundaries may have no relation to tract boundaries, but also because empirical data suggest tract-level and municipal-level sorting have played out very differently over time. Regardless, based on the literature, there is reason to think similar dynamics that dictate municipality choice would influence neighborhood choice.

Ottensmann (1982) evaluates income, housing cost, and educational attainment as dimensions of heterogeneity among tract residents, calculating standard deviations and coefficients of variance for each characteristic. These measures were regressed against racial composition, population density, and several variables pertaining to housing characteristics, which were largely found to be correlated with heterogeneity, particularly with respect to educational attainment.

The last work in this quartet, Heikkila (1996), uses 1990 decennial census data for cities and census tracts in Los Angeles County to evaluate the descriptive conclusions of Miller (1981) — that municipalities are Tieboutian clubs. Via factor analysis, the author selects 16 metrics of socioeconomic status, then conducts an analysis of variance on each to determine that there is sorting at the municipal level. He then employs a cluster analysis at the census tract level, which generally verifies that local incorporations are in fact the level at which sorting occurs.

Heikkila (1996) finds that municipality of residence is a significant determinant of population density, race and ethnicity, household composition, and income, and that variation at the tract level is dictated by variation at the municipal level. He notes that boundaries between municipalities are far less subject to change than the populations within them, which leads to an interesting analogy: Heikkila (1996) compared cities and regions to commercial tenants and malls, respectively: “The outside walls and internal dividers are relatively durable, but … turnover from year to year reflects changes in demographics and tastes” (223): in other words, the “musical suburbs” noted earlier.

Hamilton, Mills, & Puryear (1975) open their cross-regional analysis of tracts in 19 metropolitan areas by noting one of the previously discussed objections to the Tiebout model — that the “vote with your feet” mechanism is a “cumbersome” means of achieving a market-clearing equilibrium. More specifically, households are relatively unlikely to respond to fiscal incentives, given preferences for private amenities and, notably, the fact that local taxes can be deducted from itemized federal income taxes, introducing a moderating factor in fiscal differences among municipalities.

Hamilton, Mills, & Puryear (1975) calculate Gini coefficients (i.e., measures of income inequality, see Chapter III for explanation) for each census tract to measure heterogeneity and regress these against the number of school districts within the county, level of intergovernmental aid, and several demographic controls. The authors find an interaction: Compensatory aid mitigates Tiebout sorting, as one would expect, given that there is a sufficient quantity of jurisdictions that sorting would be possible in the first place. Essentially, the Tiebout hypothesis is verified, though weakly.

Pack & Pack (1977) in part responded to the prior article, noting the importance of validating homogeneity to evaluate normative implications of Tiebout. The authors devised metrics of homogeneity normalized to a zero-to-one scale, with any reading over 0.5 counting as a homogeneous jurisdiction, for 212 municipalities in Pennsylvania metropolitan areas across five metrics (education, occupation, household type, income, and age). Coefficient of variation was used for measures that could be measured continuous, while a Gini-like index was used for discrete variables.

On average, Pack & Pack (1977) found that most municipalities did not meet the threshold to be considered homogeneous in any of the five categories; none did so across all five categories. “The extent to which metropolitan fragmentation has resulted in socio-economically homogeneous suburban towns appears to be more limited than is generally believed, although there is substantial variation across metro areas” (Pack & Pack, 1977, 198). This was, in fact, especially true regarding income — perhaps the most crucial to the public finance-oriented Tiebout hypothesis.

Ebberts & Gronberg (1981) sought to evaluate the “efficiency” of Tiebout sorting by using Theil entropy measures to assess income dissimilarity by decomposing into within- and between-jurisdiction differences in mean earnings. The study examines school districts in 33 metropolitan areas nationally and establishes a two-stage least squares model to estimate the causes of heterogeneity within a district, using a series of state-level dummy variables as an instrument for government density. The results indicated that, *ceteris paribus*, there are greater levels of heterogeneity in larger jurisdictions, though providing little as to how much heterogeneity exists.

Last, Stein (1987) drew upon a substantially larger sample — 216 metropolitan areas nationwide. Using 1982 Census of Governments data and 1980 municipal-level decennial census data, six dimensions of residential segregation are identified and operationalized through coefficients of variance. These dependent variables are regressed against "index of functional performance" that measures how much policy responsibility is devolved to localities. Education was the only metric where substantial homogeneity existed; regardless, pursuing the OLS estimation found that the *a priori* conclusions were verified econometrically — i.e., variance in public services is positively correlated with homogeneity — but that these findings were far weaker than other determinants of between-jurisdiction demographic disparities. Ultimately, Stein (1987) finds some empirical support for the Tiebout hypothesis, but as with many of the studies reviewed here, it is very weak, and pales in comparison to other potential causes of disparities among geographic units.

In short, the first three works generally attempt to improve upon the Tiebout model by merging an inherently location-dependent model with location-based, explicitly market-clearing models of real estate and metropolitan political economy in hopes of bringing its results into closer accord with reality. Wheaton (1993) extended this into the context of exclusionary zoning and other more modern land use contexts beyond the rudiments of Alonso (1960).

The three oldest single-region empirical works diverge substantially in methods, though all find at least partial confirmation of the sorting hypothesis: Grubb (1982) through the conventional "demographics by municipality" approach, Munley (1982) by employing voters' revealed preferences at the school district level, and Ottensmann (1982) via delving into the sub-municipal scale of analysis. This argument was made more sophisticated by Heikkila (1996), who used spatial econometric analysis to classify municipalities as "Tieboutian clubs."

The four multi-region papers generate results that are less consistent. Hamilton, Mills, & Puryear (1975) find only indirect evidence of a sorting mechanism, namely that the level of state aid to municipalities is directly proportional to the intra-municipality level of diversity across socioeconomic dimensions. Pack & Pack (1977) develop complex indices to assess homogeneity, but the results defy intuitive interpretation. The same goes for Ebberts and Gronberg (1981); that larger jurisdictions have more dissimilarity in their population can hardly be considered a groundbreaking result. Stein's (1987) results are more robust, but mixed; homogeneity in municipal populations is generally low and, while Tiebout sorting is proven to exist, its effects are relatively minor.

Overall, to this point, the literature left a great deal to be desired. Theoretic work made incremental progress, but ultimately the lack of econometric sophistication made it unclear as to whether the Tiebout hypothesis had an empirical basis. From here, the review turns to more contemporary articles, starting with Alesina, Baqir, & Hoxby (2004) and Rhode & Strumpf (2003), who draw on both theory and econometrics that develop more compelling conclusions. These are followed by Bickers & Engstrom (2006), Lutz (2009), and Bayer & McMillan (2010), who advance the literature strains noted in earlier works. Finally, the review finishes with Hanushek & Yilmaz (2007), who attempt to collapse the Tiebout and Alonso models into a single unified theory.

Alesina, Baqir, & Hoxby (2004) consists of two arguments, one theoretical and one empirical. The authors' initial conceptual work evaluates whether economies of scale and heterogeneity explain the density and distribution of local governments and school attendance areas. They find "people are willing to give up economies of scale in order to avoid being in a jurisdiction with significant racial or income heterogeneity" (Alesina, Baqir, & Hoxby, 2004, 349-350). In other words, people are willing to pay more in taxes or have less effective public services to live around people like them. Their work also makes the relevant point that the necessity for the quantity of local jurisdictions to be a natural number introduces a degree of stickiness to the model — one that would be augmented by the political process.

Subsequently, Alesina, Baqir, & Hoxby (2004) use 1990 Census data for every county nationwide to determine the magnitude of these effects. When heterogeneity in race or income (as measured by a Gini coefficient) increases by two standard deviations in a county, the number of school districts in that county increases by 8-10%, all else being equal. Panel regressions hinted at causality, finding positive correlations between the number of school districts and the magnitude of African-American population inflows during the Great Migration of the early 20th century, which are taken to be exogenous. Overall, their conclusions are provocative:

> Heterogeneity of preferences [for public goods between municipalities] and avoidance of interaction [with other races] receive very little attention from analysts of local public goods. Indeed, most models of local jurisdictions assume that households care exclusively about the income of other residents in their jurisdiction. Our work suggests that diverse preferences and avoidance of interaction play at least as important a role as income, perhaps even a more important role. Moreover, our results suggest race and ethnicity are important determinants of these preferences (Alesina, Baqir, & Hoxby, 2004, 395).

Rhode & Strumpf (2003) conducted panel analyses of municipalities in eastern Massachusetts, a sample of cities nationally, and all counties nationally. The authors observe, as noted earlier herein, that the Tiebout hypothesis requires costless mobility; one can infer that, as transportation costs have declined throughout the 20th century (Glaeser & Kohlkase, 2004), localities should be experiencing increasing homogeneity. Instead of assessing the sorting mechanism by looking within jurisdictions, the authors examine whether heterogeneity *between* jurisdictions is increasing (i.e., whether stratification develops), which would be expected if the Tiebout hypothesis is accurate. This does not appear to comport with reality, however; coefficients of variance and dissimilarity indices among minor civil divisions (MCDs) declined through the lengthy panel period (1870 through 1990) across multiple demographic dimensions, though it is unclear how much of this result stems from local policymaking decisions.

Ultimately, regardless of how Rhode & Strumpf (2003) parse the data, there is rarely any compelling evidence in favor of Tiebout. Using Theil entropy measures to parse variation into within- and between-MCD sources in the Boston area divines no clear pattern in the distribution of dissimilarity over time. The authors find that over 80% of income heterogeneity is situated within MCDs. As a replacement for the Tiebout hypothesis, which they contend bears little relation to reality, the authors propose alternatives, wherein municipalities' average wage are a variable in household utility maximization and/or a second scale of sorting at the metropolitan area level, wherein differences between MCDs in a single region are not increasing because inter-regional disparities are increasing.

Bickers & Engstrom (2006) take an entirely different approach to the question of whether sorting takes place. Instead of empirically evaluating the level of heterogeneity and deciding whether it is “too high” to be random, the authors run 500 Monte Carlo simulations that randomly assign 1990 Census tracts in two MSAs (Atlanta and Houston) to hypothetical municipalities that are similar in gross population to actual ones. Indices of dissimilarity *à la* Stein (1987) based on ethnoracial data are calculated for these 500 sets of alternate-world suburbs, distributions are calculated, and results are compared to their real-world counterparts to determine whether municipal-level homogeneity is greater in the latter case than the former — in short, whether Tiebout sorting exists.

Of 86 municipalities, Bickers & Engstrom (2006) assert, only four were found to have racial composition that is statistically significantly different from random. Further, there was no correlation between the probability of non-randomness and the size of the municipality. More compelling is the finding that jurisdictions in the Houston MSA — a relatively consolidated region, as measured by the percentage of population residing within the central city, though a fragmented one with respect to special districts — were more likely to be non-randomly ethnoracially homogeneous than those in the extremely fragmented Atlanta MSA. These findings by Bickers & Engstrom (2006) suggest that not only does Tiebout sorting not appear to be occurring, but if any correlation is to be inferred, it is that smaller towns are less able to practice residential segregation than larger ones. That said, this study involves only two regions; a more comprehensive analysis would clearly be warranted.

Further work on property value capitalization by Lutz (2009) examines parcel assessments in New Hampshire. The notable characteristic of that state is that a shock to local fiscal conditions took place when state-imposed school funding reform took effect starting in 1999; further, county authority in New England is particularly weak (Hamilton, 2014). Lutz's (2009) theme is the primacy of elasticity of housing supply in the validity of the Tiebout model. His hypothesis, and later his econometric findings, suggests that the capitalization of public goods — as measured by public school quality per dollar expended — occurs only in the southern portion of the state. These areas are almost entirely built out due to exurban development encroaching north from Boston, meaning housing supply is largely inelastic. Meanwhile, in the northern part of the state, development is largely rural, meaning the increased desirability of a Tiebout bundle in a community would lead to increases in both the price and quantity of housing.

The significance of this work is complex. First, the approach taken by Lutz (2009) exposes the implicit bias in the Tiebout literature toward developed areas — cities and their established, incorporated suburbs. The original model ignores demographic and spatial growth that occurs on the exurban fringe, among numerous other complications, by sketching a result in which a final equilibrium is achieved. Further, most works considered herein focus largely on urban areas. While an overwhelming share of households are situated in developed areas, drawing a set of conclusions on the mechanics of the real estate market as they pertain to public goods without considering what occurs in the hinterlands — or merely assuming those areas away — can lead to incomplete theories.

Meanwhile, in a section dedicated to policy implications, Lutz (2009) observes that migration of responsibility in public education financing away from the local level "distort[s] the geographic location of housing capital" (28) by decoupling costs and benefits of local governance. In short, property taxes no longer exclusively serve as a funding mechanism for public goods, becoming — at least in part — a tax levied on capital. Lutz (2009) suggests that such impacts must be included in cost-benefit analyses of changes to federal architectures of public finance. While the author is far less vocal on the normative impacts of such market distortions than works like Ostrom, Tiebout, & Warren (1961), the descriptive conclusions are similar.

One could argue Lutz (2009) presents a more authoritative conclusion in favor of the Tiebout capitalization hypothesis than any other work herein. This is because there is an identifiable, exogenous event that clearly alters fiscal conditions of New Hampshire school districts and, therefore, the tax-benefit bundle they offer. Further, the study is longitudinal, allowing evidence of causality to be posited. That said, the degree of elasticity in housing supply is not merely a function of population density, but also local land use policy, especially as it pertains to exclusionary zoning, which is in and of itself a public "good." Ultimately, then, Lutz (2009) hints at a unified theory of "capitalization" that embodies both financial and spatial benefits, wherein the former becomes how favorable Tiebout bundles are reflected in the real estate market when the latter becomes impractical. Such a hypothesis would clearly require further study, but as the author suggests in his conclusions, prior findings that disputed the premise of capitalization may have relied on an incomplete definition of the term.

Much like Lutz (2009), Bayer & McMillan (2010) advances the state of research, this time with respect to sorting, by testing the degree to which bending assumptions of the Tiebout hypothesis alters the degree to which sorting occurs. This is done in reverse; statistical modeling removes real-world complications, such as financial and temporal disutilities of commuting, from the household decision model and estimates the degree to which sorting is affected. Specifically, their work takes a comparative statics approach that employs decennial census microdata to analyze both actual and counterfactual segregation in many of the dimensions noted earlier in this review. As the authors state in their introduction, the paper is an effort to explain heterogeneity in neighborhoods, particularly urban ones, *within* the context of the Tiebout model, rather than simply attributing such “imperfect” sorting to exogenous non-public good characteristics as many previous works have done.

A notable characteristic of Bayer & McMillan (2010) is that it took account of public schooling not merely as a fiscal entity but a geographic one. Among respondents to the 1990 Census long form in the San Francisco Bay Area, special interest was paid to a subpopulation that included only households located in blocks within one-fifth mile and one-tenth mile of a public school attendance boundary, but not close to another variety of jurisdictional boundary or major physical feature. This was designed to further eliminate confounding factors and focus on the dynamics of the Tiebout sort exclusively. Such approaches are natural extensions of extant literature that have become possible with the exponential growth in computing power that can be employed by statistical and mapping software.

Bayer & McMillan's (2010) analysis suggests that household preferences change greatly when commuting patterns are removed from the model; stratification along income and education dimensions increase substantially. This is to be expected, as the relative utility of segregation in the model increases as the number of utility function components falls. This also occurs because geographic preferences among households become identical once commuting disutility is removed; everyone wants to reside in the best school attendance area in the best school district available and is willing to commute, literally, an infinite distance to their place of employment to facilitate this. Such a result implies that, as polycentricism within a metropolitan area increases, the "effectiveness" of the Tiebout sorting declines; the commute distance variable would vary substantially by household within a neighborhood, depending on household workplaces. That said, not even total elimination of this term substantially removes neighborhood heterogeneity.

Another model examines preferences for housing quality in Tiebout sorting. When utility derived from housing size and quality is removed, segregation by income declines, as this effectively compresses the distribution of income. Segregation by education level increases, however, as one would expect from the reasoning presented in prior rounds of analysis. As Bayer & McMillan (2010) state, however, this is a partial equilibrium; siting of firms and supply of housing are taken as exogenous. While some research has been conducted in these fields, this counterfactual analysis is exceptional. As modeling power continues to increase, however, it appears the emergence of such models is merely a matter of time.

The question of how models that explain location choice in a metropolitan area — Tiebout (1956) and Alonso (1960) — interrelate both on a theoretical level and as they pertain to contemporary debate on school finance was taken up by Hanushek & Yilmaz (2007). As the article's title suggests, the authors believe there is a "complementarity" between the two theories and set out to devise a mathematical construct that incorporates underpinnings of both into a unified model.

The authors start by building a basic political-economic environment. Hanushek & Yilmaz (2007) posit the existence of a region, split between two school districts, with a single central business district. Income and household preferences are dichotomous; families are either high- or low-income, and make location decisions based primarily on either housing consumption or school quality. Fiscal policy is decided by majority vote, with mobility assumed to be costless.

Clearly, there are identifiable elements of the Tiebout and Alonso models contained in the assumptions Hanushek & Yilmaz (2007) make. Given these stipulations, the standard labor-leisure decision model, and a featureless Cartesian plane with the central business district at the origin and a school district boundary along the y-axis, Hanushek & Yilmaz (2007) painstakingly outline the mechanics of their simplified model. Among many conclusions, the authors find that, given the addition of a non-residential land use (agriculture) to the model, it is impossible to achieve an equilibrium condition with complete income stratification by public school district, as would be predicted by a pure Tiebout model. The introduction of a labor market that has a geographic dimension leads to a breakdown in the sorting mechanism.

Following the theoretical derivation, the parameters of the model are then calibrated to reflect what Hanushek & Yilmaz (2007) compute, based on data from the 1998 Statistical Abstract of the United States, to be reflective of a "typical" metro area. Plugging empirical numbers into the model generates results that would theoretically match actual settlement patterns in the hypothetical metropolitan area, were a cross-section of Americans exogenously moved to it. Results suggest that the presence of an Alonso land market weakens the strength of the Tiebout sorting mechanism.

In the end, 83% of households with "high valuation," i.e., a larger portion of their utility dependent on quality of public education, locate themselves in the school district with 33% "better" schools, while only 56% of skilled labor households chose to do so. Clearly, this indicates that sorting takes place less based on observable characteristics than personal preferences. Overall, only 52% of all households settled in the higher-quality district, even as superior public schools were valued positively by everyone — likely because rents were roughly 10% higher and property taxes were nearly 28% higher in the district with superior schools. (This, of course, provides evidence in favor of the capitalization hypothesis.) Hanushek & Yilmaz (2007) conclude that there is little sorting taking place, with both types of households in both jurisdictions in nearly equal proportions. Given this, they consider what would take place if the two districts merged, as happened nationwide after World War II as America's modern education system materialized, often took place with the consent of the electorate. As the gains from sorting appear minimal, it would seemingly be the case that mergers would increase the welfare of most households.

The model sketched by Hanushek & Yilmaz (2007), however, indicates otherwise. When the boundary between school districts is erased, tax rates and per-pupil spending fall to the level of the lower-quality district before the merger. This is because 55% of households are “low valuation” and, hence, outvote “high valuation” households when tax-benefit bundle choices are put to a vote. High valuation households are hence made worse off, as they are forced to consume suboptimal levels of education. Meanwhile, low valuation households residing in what was the lower-quality district (of which the clear majority do) also become worse off, as the disparity in rent disappears; once the merger takes place, households located in the “better” district for its superior schools move out, bidding up rents until they are equivalent. As Tiebout (1956) would predict, the new general equilibrium reduces utility for nearly all residents.

It is worth noting that the 55% parameter noted above is arbitrary. Were high valuation households the majority, the level of education would increase, now leading to an oversupply of public goods to the low valuation minority. Rents would still equalize as the education disparity drops out of the model. Seemingly, this would only generate negative impacts for a minority of the metropolitan population. Given this fragility in its outcomes, further analysis and critique of Hanushek & Yilmaz’s (2006) model may therefore be warranted.

Indeed, the Tiebout literature is rife with articles and theses that appear to be incomplete. The crucial problem is a reliance on operationalization that has been, and continues to be, inherently imperfect. This is best illustrated by Dawkins (2005); starting in his abstract, and throughout his paper, “Tiebout choice” is used interchangeably with jurisdictional fragmentation, measured using a Herfindahl index of population shares. Setting aside the array of methods for measuring the degree of general purpose political centralization at the metropolitan level, to conflate that concept with variation in public good provision ignores nuances in the America's federalist political structure; state laws dictate fiscal and policy authority held by various levels of government. A full discussion of this point, however, is beyond the scope of this paper.

Just as there are substantial challenges in operationalizing the independent variable in the Tiebout hypothesis, the same is true of the dependent variable. While there is agreement that homogeneity by race, income bracket, or another categorical variable is to be computed through an index of dissimilarity or comparable statistic, what such a number means is murky. Pack & Pack (1977) simply pick the midpoint of their scale as the limit where heterogeneity gives way to homogeneity; while arbitrary, theirs is the only work to make a decisive normative stand. Presumably, the Tiebout hypothesis is so studied because researchers are concerned about adverse political and sociological impacts borne of jurisdictions that exhibit a high degree of sameness in their population; without such a context, their work would be merely a matter of intellectual curiosity. The level of homogeneity at which such consequences would come into play is essentially ignored in this literature, an omission that leads to unanswered questions.

The papers in this review touch on numerous means of testing the Tiebout hypothesis. Overall, as one would expect from works with a wide array of methods and core assumptions, the findings are mixed. Theoretical writings can extend the premise laid out in Tiebout (1956), but only Wheaton (1993) provides another corollary to be empirically tested — that income sorting occurs when there are both lot size regulations and property tax-based revenues (i.e., no user fees), or neither, but not necessarily when only one is present. Similarly, Rhode & Strumpf (2003) sought to reconcile the Tiebout hypothesis with empirical analysis that found it to be incomplete, suggesting that adding models of human capital and the labor market could bring the theory into closer accord with reality. Analyses of such theories, however, do not appear to have been performed in the literature. This is regrettable, as it would push the empirical debate over Tiebout sorting beyond the oft-rehashed premises that have populated the literature since at least Oates (1969).

That said, there have been welcome advancements in the empirical literature. Heikkila's (1996) application of cluster analysis provides an innovative technique for divining homogeneity in an explicitly spatial way. It becomes clear from such analysis that Los Angeles County is socioeconomically fragmented, though the analysis stops at that point; the author largely brushes aside any need to consider the basis of the Tiebout hypothesis — public good production — on the grounds of difficulty in data collection and that "club theory has progressed beyond" the issue (210). It is unclear, then, why Heikkila (1996) dubs his clubs "Tieboutian" if there is no evidence that Tiebout sorting is the cause, with the link left only to be inferred. Indeed, this is reflected in much of the literature; great consideration is given to determining whether the projected effect is in evidence, but comparatively little to whether the hypothesized cause is responsible.

Ultimately, the empirical literature has been headed in the direction of using dynamic models and simulations to assess the validity of the Tiebout hypothesis. Alesina, Baqir, & Hoxby (2004) employed a realistic approach to modeling endogenous local government boundary change as well as households “voting with their feet,” followed by a substantive empirical analysis that develops compelling causal evidence. Bickers & Engstrom (2006), meanwhile, took a radically nontraditional approach with their Monte Carlo simulation method that, in large part, resembles Heikkila (1996). Applying this approach nationally would likely be instructive, though again, it is entirely descriptive in that it fails to definitively relate their results to the source of the Tiebout hypothesis. That said, however, as the authors find sorting to not be empirically observable, the point is somewhat moot.

These discussions lead us to the final paper, Hanushek & Yilmaz (2007). It is rather surprising that so many prior works in this review failed to comment on either an accord or tension between the Tiebout hypothesis and Alonso (1960), given the latter’s influence in the field of urban economics. Though the authors’ model has several parameters that are exogenously determined, such as the number of jurisdictions and the levels of labor skill and “valuation” (two each), there is clearly a great deal here to build upon, especially when combined with the work in Alesina, Baqir, & Hoxby (2004). The authors develop a compelling mathematical explanation as to why, even in a uni-polar region, Tiebout sorting will not fully materialize, given even modest differences among households. Crucially, the authors directly acknowledge that not all households place the same utility on various aspects of the taxation-public good bundle.

Ultimately, by dedicating so much effort to whether sorting is taking place, it is often ignored that a finding of non-homogeneity at the municipal level does not mean that the dynamics of the Tiebout model do not still apply to household decision-making. They may simply be confounded by household preferences (Hanushek & Yilmaz, 2007), or the nature of the labor market (Rhode & Strumpf, 2003), or the presence of local zoning regulations and taxation authority (Wheaton, 1993). As it would be impossible to conduct a natural experiment to ascertain whether municipal homogeneity based on public good provision would occur *ceteris paribus*, the data collection and statistical analysis required to econometrically decompose household location choices — to see if the Tiebout hypothesis has empirical bases — may simply be too daunting.

At least one work mentioned here regards this entire topic as something of a tempest in a teapot. Bickers & Engstrom (2006) write, “What do our results say about the debate between the two camps — advocates of decentralization and advocates of consolidation? Essentially, we conclude that both sides have been beating a dead horse” (1196). Realistically, this is not unfounded. Were there clear evidence that pernicious segregation was occurring on a great scale because of Tiebout sorting, alarm might be well founded, but there are greater inequities produced by other elements of America’s economic and political systems. That said, however, Chapter IV will review the argument advanced by Weiher (1991) and interrogate this question using methods borrowed from other academic fields, while the remainder of the empirical work will look at impacts beyond segregation.

CHAPTER III: DATA AND METHODS

This work includes four newly developed econometric analyses that will assess effects of jurisdictional fragmentation, often also referred to as “fiscal federalism” or “governmental density” (especially in favorable treatments of the phenomenon). Throughout, this work will be done using Stata econometrics software (StataCorp, 2011; StataCorp, 2013). Fragmentation will, except by necessity in Chapter VII, be evaluated within metropolitan statistical areas (MSAs). A metropolitan region in the United States, unlike other spatial scales at which public policy can be analyzed, is not merely a product of bureaucratic paperwork or historical accident, but is instead a reflection of the land area in which individuals choose to associate with one another.

Specifically, the federal Office of Management and Budget (OMB) defines the boundaries of MSAs based on regional commuting patterns; outlying areas are included if at least one-quarter of their workforce commutes to the central county of the MSA (Federal Register, 2010). This fact makes these regions an “organic” scale of analysis; they are the areas in which individuals elect to sell their time and skill via employment. Hence, for many socioeconomic issues, the metropolitan area is the proper scale of policy intervention — and evaluation of the outcomes of those activities. OMB considers any region containing an urban core of 50,000 residents an MSA, of which there are currently 388 nationwide. (In this work, however, to ensure continuity across data sources, pre-Census 2010 MSAs will be used; 361 were designated as of 2007.)

Governmental authority, however, is rarely scaled to the metropolitan region; indeed, many include hundreds of distinct municipalities. This is particularly true in the Midwest and Northeast, where state laws noted earlier have made annexation difficult and incorporation of new municipalities rather easy. This led older industrial cities to become “boxed in” by their suburbs early in the 20th century (Rusk, 2013). Therefore, authority over land use and zoning has become fragmented. Collectively, the equity and efficiency of local government can have major impacts on welfare within a region.

The first three models should be considered collectively and focus on three potential adverse impacts of provincial governance hypothesized in prior literature: residential segregation, inefficient land use, and economic distress. They are estimated based on national data and isolate key relationships *ceteris paribus* without connection to a broader socioeconomic model. Dependent variables are measured as close to the present as possible, while independent variables are lagged; this lends a temporal dimension to the analysis that would bolster potential claims of causality. Alongside this main policy variable, a handful of statistical controls are introduced to describe the demographic and economic characteristics of each metropolitan area. The nature and source of each is noted here.

Naturally, the variable of interest is the degree of fragmentation itself. In 2012, there were 90,056 separate units of local government in the United States; this included 3,031 counties, 19,519 cities or villages, 16,360 towns or townships, 12,880 independent school districts, and 38,266 other special districts, which includes entities like park districts or port authorities. These data come from the Census of Governments, which is published once every five years by the U.S. Census Bureau. Further, these local entities employed nearly 12 million people nationally (full-time equivalent), paying them more than $50 billion in March 2012 alone.

Fragmentation is operationalized in three ways herein. The most rudimentary approach is to compute the number of governments per capita for a MSA. Descriptive statistics for governments per million inhabitants, per an analysis of data from the 2007 Census of Governments (Briem, 2011), are included below.

Mean — 284.23	Standard Deviation — 241.60
Minimum — 5.52	(Honolulu, HI MSA)
1st Quartile — 122.59	(Auburn-Opelika, AL MSA)
Median — 222.61	(Dayton, OH MSA)
3rd Quartile — 366.93	(Appleton, WI MSA)
Maximum — 1729.94	(Grand Forks, ND-MN MSA)

A second measure is that advanced by Rusk (2013). This work seeks to show that metropolitan areas whose central cities are more “elastic” experience more positive socioeconomic outcomes. To wit, he establishes a measure of elasticity for 137 cities. (Of those, only 125 are the primary city in a metropolitan area, since the computation was also made for localities such as Newark and Oakland.) He computes the population density of the center city in 1950 and the percent of central city land area in 2010 annexed since 1950. These values are sorted into deciles; the elasticity index developed by Rusk (2013) is the density decile plus three times the annexation decile. Low values indicate central cities that have not expanded and added lower-density areas to its boundaries, while cities with higher values did so over the six decades in question. Rusk’s (2013) index as computed, therefore, ranges from four to 40.

This is not an intuitive measure, however; the Rusk index will be modified to fall between one and ten, with higher numbers representing less elasticity and more fragmentation. This aligns elasticity with other measures of fragmentation used herein, with lower numbers signifying more unified regions. The transformation is below.

$$R_{modified} = \frac{44 - R_{original}}{4}$$

The descriptive statistics of the new index for the 125 MSAs are included here:

Mean — 5.42	Standard Deviation — 2.37
Minimum — 1	(Anchorage)
1st Quartile — 3.5	(Boise)
Median — 4.625	(seven cities, Sacramento the largest)
3rd Quartile — 7.5	(Flint)
Maximum — 10	(Detroit, New York, and Washington)

While this measure and central city population or land shares have much utility, they ignore the distribution of suburban governments, which can compete with the central city for economic influence in a polycentric metropolis. Elasticity quantifies how much control that single municipality can exert within a region, particularly over zoning and other land use powers. The opposite approach is to use the Metropolitan Power Diffusion Index (MPDI), developed at the University of Pittsburgh (Mitchell-Weaver, Miller, & Deal, 2000; Miller, 2012). A region's MPDI is the sum of the square root of the fractional share of local government spending by each jurisdiction in the metro area. This amplifies the impact of smaller entities on the statistic, whereas governmental density is a simple ratio and elasticity examines only the actions of the central city. Computationally, if a region has N governments and the *i*th entity spends E_i in a year:

$$MPDI = \sum_{i=1}^{N} \sqrt{\frac{E_i}{\sum_{i=1}^{N} E_i}}$$

A region's MPDI is one when it is governed by a single entity; this number will increase as additional cities divided a region's population and its tax base. While less intuitive than prior measures, the square root function means small governments are given outsized quantitative significance when computing MPDI. Descriptive statistics for the 361 MSAs in 2007 (Miller, 2012) are displayed below.

Mean — 4.53	Standard Deviation — 2.44
Minimum — 1.19	(Honolulu, HI MSA)
1st Quartile — 3.00	(Redding, CA MSA)
Median — 3.91	(San Luis Obispo, CA MSA)
3rd Quartile — 5.22	(Niles-Benton Harbor, MI MSA)
Maximum — 17.97	(Chicago-Naperville-Joliet, IL-IN-WI MSA)

In a sense, these two measures evaluate fragmentation from opposite sides of the same coin. MPDI places emphasis on the role of small suburbs and rural towns in contributing to regional disunity, while the Rusk measure considers only what has happened to the central city over time. In other words, these various measures of fragmentation provide statistical data that overweight, underweight, and evenly weight jurisdictions with respect to their population, land area, or fiscal authority. They will be used in parallel to highlight the different dimensions that relationships between fragmentation and policy outcomes discussed here have.

First, residential segregation with respect to race will be modeled using a dissimilarity index. This index, used by Pack & Pack (1977) and lauded by Weiher (1991), is mathematically complex but relatively intuitive; it computes the distribution of a minority group by geographic unit to return a figure that reflects the percentage of households that would need to relocate for all portions of a region to be equally heterogeneous. As an example, an index measuring black-white dissimilarity would be computed as below, where the region has B black residents and W white residents and the *i*th subunit of the metropolitan area (Census tracts are used herein) has b_i black residents and w_i white residents:

$$D = \frac{1}{2}\sum_{i=1}^{N}\left|\frac{b_i}{B} - \frac{w_i}{W}\right|$$

D ranges from zero (perfect integration) to one (complete segregation). Conceptually, this represents the fractional share of minority residents that would need to relocate to another neighborhood to ensure that the same proportion of minorities would be present in each area. When reported, the value is multiplied by 100 to convert it to a percentage scale. Indices were computed by the University of Michigan Population Studies Center from 2010 Census data for three minorities groups. Beyond the different histories and cultures reflected in different races and ethnicities, works like Rusk (2013) suggest governance structures have disparate impacts on the residential development and settlement patterns of various communities. Descriptive statistics for these and other dependent variables will be discussed in their respective chapters.

The difficulty of identifying and defining sprawl is notorious. Many authors rely on vague descriptions, while others have given up being able to define it, resorting to an axiom describing its futility — as Supreme Court Justice Potter Stewart famously said of pornography, “I know it when I see it” (Ewing & Hamidi, 2014). Unlike other variables to be assessed herein, sprawl is a more nebulous and, to an extent, a qualitative concept.

Therefore, there is a need to parse what is meant by sprawl and why this dissertation chooses to assess land use as it does.

Urban sprawl is a modern phenomenon that did not become economically and technologically viable at a large scale until after World War II. Beginning in earnest with the creation of Levittown, New York, in 1947, the layout of cities changed dramatically throughout much of America (Kelly, 1993). Residential and commercial development became more dispersed in response to the newfound primacy of personal vehicles for transportation and demand for housing on the urban fringe. As Rusk (2013) argues,

> Washington, Wall Street, Detroit, Hollywood and Madison Avenue made middle-class families an offer they could not refuse: The American Dream. Sustained economic growth, cheap home mortgages, affordable private cars, and federally subsidized highways … made that dream house with its own yard, quiet neighborhood, local school, and nearby shopping possible for millions of families. Urban America became Suburban America (7-8).

Very early on, there was pushback from some urban planners on this trend, viewing the new American pattern of development as inferior to the contemporary "new towns" in Britain (e.g., Windels, 1948; Blumenfeld, 1949). An early treatment of this new pattern (Woodbury, 1955) attempted to operationalize the phenomenon, drawing a subtle distinction between sprawl *per se* and a pattern of building that would be labeled leapfrog development today:

> Poor location is hard to measure accurately or to generalize about. Roughly speaking, however, it is of two kinds. The first is what the British call "urban sprawl" — the planless extension of urban building on and on into the countryside with … inadequate attention to community facilities and services, topography, future transit and transport problems, etc. The other is a similarly planless scattering of individual houses or small groups whenever pieces of land can be bought quickly and cheaply (6).

Subsequently, Woodbury (1960) cataloged adverse fiscal and spatial consequences of suburban development, notably identified jurisdictional fragmentation as a likely cause, and stated with some foreboding that “in too many parts of suburban and fringe areas, we are building some of the blighted and slum areas of the future” (360).

Later, McKee & Smith (1972) offered a better definition of sprawl, even as they acknowledged the difficulty of doing so. Specifically, they wrote that sprawl had four components: very low residential density, strip mall-style construction along highways, leapfrog development, and a mixture of developed and vacant land at the urban fringe. As Ewing (1997) noted, one or more of these characteristics emerged repeatedly in the literature to indicate sprawl. Burchell et al. (1998) expanded this working definition, concluding that sprawl is also typified by spatial segregation of land uses. Ultimately, they conclude, “sprawl development can be characterized with some certainty as low-density residential and nonresidential intrusions into rural and undeveloped areas, and with less certainty as leapfrog, segregated, and land-consuming in its typical form” (8) — and that measuring some of these elements is “virtually impossible” (7).

Clearly, the literature submits that sprawl is a multi-dimensional phenomenon, defined by several disparate spatial development patterns. Further, these characteristics of sprawl, while distinct, are clearly coincident; it is hard to imagine how low residential density does not imply segregated land uses in the American context. Given that sprawl is defined in a variety of ways, with no universally accepted conceptualization (let alone measurement) thereof, it is far beyond the scope of this work to attempt to decisively settle such disputes. It would be preferable, then, to have some means to assess alleged components of sprawl both separately and jointly, measured at the proper geography (i.e., MSAs) for analysis herein. As it happens, such data do exist. Though their methods are by no means immune to critique (e.g., Hasse, 2002), this work will use the sprawl metrics developed by Ewing & Hamidi (2014).

In explaining the development of their sprawl indices, Ewing & Hamidi (2014) refer to Ewing's (1997) literature review. That work found sprawl is fundamentally a matter of poor accessibility, both for residences and destinations, which generates inefficient household travel patterns. This view is echoed both in Burchell et al. (1998) and more recent work (e.g., Crane, 2008). Ewing & Hamidi (2014) identify 21 measures of sprawl, which were condensed into four categories using factor analysis: low-density development, segregated land uses, lack of significant centers, and poor street connectivity. (A complete list of measures is included in Table 5-8.)

It is not a reach to explain the connection between the root idea of accessibility and these four "types" of sprawl. Low density, by definition, indicates a relatively high distance between any two properties; segregation of land uses, all else being equal, increases the average distance between any two properties of a different type. A lack of centeredness indicates consistent density throughout the region, whereas increasing the disconnectedness of streets increases the distance and time of travel for any two given points. (Centeredness is particularly interesting here; a region with low density overall but high centeredness would imply that a large percentage of residences and businesses would be in proximity to one another despite the overall regional trend.)

The resulting indices from each category are normalized to a national mean of 100 and a standard deviation of 25, with higher numbers representing regions with the lowest levels of sprawl. From these elements, a composite index is then computed with the same mean and variance. Each of these five indices will be used separately to evaluate fragmentation's role in creating sprawl.

Last, economic distress will be measured using four variables that address multiple dimensions of conditions experienced by the residents of the region. Each of these assesses the change in one variable between 2007 and 2013. Two pertain to the amount of economic activity: percent change in median household income and gross metropolitan product (i.e., gross regional product); these were derived from American Community Survey (ACS) and Bureau of Economic Analysis (BEA) data, respectively. The first of these quantifies the material well-being of a typical household, while the second speaks to the raw economic output of the region.

The latter two speak to the distribution of income, both of which also come from ACS estimates. The first is simply the change by percentage points in the poverty rate, which measures proportion of households with incomes below a federally defined level (adjusted for household size). The second is change in the Gini coefficient, a measure of income inequality, which ranges from 0 to 100. The minimum value indicates that every individual earns an identical income, while the maximum value means that one person earned all the income in a jurisdiction. Graphically, this is the proportion of the income distribution that lies below a 45-degree diagonal line representing perfect equality but above a "Lorenz curve," which charts percentile of the population on the x-axis and percentile of total income earned on the y-axis, making Gini more conceptually clear than other similar statistics. In this model, it speaks to whether income became more concentrated during the study period. (Bellù & Liberati, 2006, provide a detailed but accessible summary of conceptual and computational background; also, alternative approaches are briefly discussed in Chapter VI.)

Control variables will be included that describe demographic and socioeconomic conditions of the region. As argued by Stansel (2005), there is clear value in parsimony in such models, so the OLS regressions will include just ten controls, all of which are based on ACS data. A list of the variables is provided below, some of which are drawn from Stansel (2005) and, in turn, Glaeser, Scheinkman, & Shliefer (1995):

- MSA population (in thousands)
- Percent change in MSA population since the 2000 Census
- Housing units per square mile
- Employment-population ratio
- Percent of workers employed in the manufacturing sector
- Four-year college graduation rate among those 25 or older
- Percent of housing units built before 1940
- Housing vacancy rate
- Homeownership rate
- Median single family home value in thousands

The inclusion of population should be clear. As noted earlier, an intent of this work is to isolate the effect of average government size from that of population size, even though these are naturally correlated (hence why governments per capita, and not simply the raw count of governments, is one of the key independent variables). Further, agglomeration theory points to economic activity per capita being positively correlated with population size (Glaeser, 2010), necessitating its inclusion in the Chapter VI models and suggesting effects for the others as well; as will be discussed later, there is an inherent connection between housing decisions and economic conditions. The inclusion of population change in the model adds a longitudinal dimension to this otherwise cross-sectional analysis.

Housing density is clearly a relevant variable to include in these models. Consider two regions, one dominated by traditional urban development with a relatively high level of density and another consisting almost entirely of contemporary suburban development mandating large lot sizes and automobile dependence. The latter will clearly have a higher level of sprawl, given earlier discussion. It is also likely to be more segregated, as minority groups are less likely to be able to access such housing due to economic limitations; lots become expensive, and automobile dependency increases.

Housing density should also be included here for conceptual reasons; all else being equal, regions with lower levels of density ought to be more fragmented, particularly in states with town or township forms of government that were often established based on geography rather than population. For one, the Land Ordinance of 1785 divided the Northwest Territory into townships six miles square (The Library of Congress, n.d.), boundaries that still exist today in much of the Midwest. Further, though annexation is — as discussed earlier — a process that varies appreciably from state to state, one would expect the frictions of political contestation to limit the geographic size of a core municipality to some degree and, therefore, its Rusk elasticity.

The employment-population ratio represents the percentage of individuals that are eligible to work (i.e., 16 years of age or older) that have at least one job. At its root, this is a measure of labor utilization, which establishes a constraint on the economic capacity of the region. It also approximates the proportion of individuals who commute, and provides a metric analogous to a dependency ratio, reflecting the share of residents who must be financially supported by others. In these senses, the ratio influences residential choice and transportation demand.

Meanwhile, the share of employment in the manufacturing sector (specifically, employers with a North American Industry Classification System industry code starting with a 3) effectively serves as a regional proxy, with MSAs in the so-called Rust Belt having the highest proportions of such jobs. This measure also controls for the fact that urban areas with higher manufacturing employment have had slower economic growth since the 1960s (Glaeser, Scheinkman, & Shliefer, 1995).

Last among these economic variables is the four-year college graduation rate. This measures the level of human capital, which also influences economic capacity. Further, college graduation rates serve as a proxy here for income, with which it is highly correlated. It is also possible that more highly educated populations are more likely to support anti-segregation and smart growth policies, though the capacity to assess this directly is well outside the scope of this dissertation. Some support for this hypothesis comes from the literature (e.g., O'Connell, 2008).

The final four control variables assess housing characteristics. These diverge from the Stansel (2005) framework, but contribute substantially to the dependent variables being assessed. Some connections are immediately clear. Because, as noted earlier, the American urban form changed dramatically after World War II, it is natural to expect that the proportion of homes built before that point would greatly affect the level of sprawl and where households situated themselves in the built environment. Similarly, there is reason to expect that housing vacancy, tenure, and value would be correlated with both land use and segregation, with such connections being identified in prior works (e.g., Cunningham & Droesch, 2005; Glaeser, 2011; Resnik, 2010).

Meanwhile, though the Great Recession of 2007-09 clearly showed that housing is connected to the broader economy, much of the literature from before that point did not focus on housing markets and stock as a correlate of regional outcomes. A growing awareness of these connections is now emerging, however. In the wake of that crisis, $7.6 billion was allocated from the Troubled Asset Relief Program to capitalize the Hardest Hit Fund (HHF), established to mitigate high foreclosure rates in the 18 states, plus the District of Columbia, most affected by the recession (U.S. Department of the Treasury, 2016). While this program originally consisted of direct assistance to homeowners having difficulty paying their mortgage, federal authorities allowed funds to be used for the demolition of blighted, vacant homes once evidence was established (e.g., Griswold & Norris, 2007) that such activities stabilized the equity positions of nearby homeowners. This, in turn, should lead to changes in consumption patterns generated by wealth effects on those whose equity increased; though this claim is contentious, there is much support in the literature for such an effect (Case, Quigley, & Schiller, 2005; Carroll, Otsuka, & Slacalek, 2011; Calomiris, Longhofer, & Miles, 2012). Indeed, a more comprehensive evaluation of HHF in this policy context is forthcoming (Holtzen, Moulton, Russell, Richter, Ratcliffe, & Quercia).

Given the hypothesized direction of causation — i.e., that fragmentation induces policy impacts — independent variables will be lagged; specifically, relevant data will be drawn from 2007 Census of Governments and, for the control variables, the 2007 ACS. This technique is designed to establish "Granger causality" (Granger, 1969). This is a well-worn approach in the literature for such relationships, though typically for longitudinal rather than cross-sectional analysis. The data needed for such an effort do not yet exist, however, given that the Census of Governments is pentennial, and ACS has only been conducted since 2005. What is done here is, admittedly, a weak substitute. Coincidentally, this aligns with the beginning of the previous economic downturn, which means that these models will serve as an evaluation of the role that fragmentation played in these three policy outcomes during a time of substantial economic distress.

Following these simpler approaches is a three-stage least squares (3SLS) model (Zellner & Theil, 1962) in Chapter VII that estimates effects of fragmentation on median gross housing costs and educational quality in Ohio public school districts, as well as the interaction between the two. While previous models cover the entire nation, it is necessary to limit this evaluation to a single state to ensure that consistent data on educational quality exist. Fragmentation is measured within the 3SLS model by the number of school districts per 10,000 residents within a county, computed based on the 1957 and 2012 Census of Governments. For districts that cross one or more county boundaries, the county reported by the Ohio Department of Education (ODE) is used. This divergence from earlier models is necessary, given that Ohio contained all or part of 15 MSAs in 2007, sharply limiting the range of any metropolitan-level metric.

Just as it is hypothesized that fragmented regions produce more economic and spatial inefficiency than do integrated ones, this work posits, *ceteris paribus*, that larger school districts produce better educational outcomes than smaller ones, owing to increased economies of scale and reduced administrative overhead. Works like Alesina, Baqir, & Hoxby (2004) and Hanushek & Yilmaz (2007) hint at the plausibility of this correlation. In turn, educational quality, as measured by standardized test scores, should be positively correlated with median housing costs, given the centrality of schools in location decisions of families with school-aged children; increased demand for housing, and hence increased costs, should be stimulated by higher-quality districts.

Though this may be relatively clear on a conceptual level, it is worth spending some time on the mechanics and context of the 3SLS approach. The purpose of this model is to produce efficient econometric estimates from a system of equations that both exhibits endogeneity and cross-equation covariance, i.e., at least one variable is dependent in one equation and independent in another, and there is reason to suspect that the error terms in one equation are not independent of the error terms in another. In short, it combines the instrumentation of two-stage least squares (2SLS) with the correlation correction of seemingly unrelated regressions (Zellner, 1962). Given that the model in Chapter VII has three dependent variables—median housing cost, test scores, and median household income—that should, *prima facie*, exhibit interdependence, there are merits to using this model rather than the available alternatives. Though rare in the literature, relatively speaking, 3SLS is employed in some contemporary contexts, such as development and transportation economics, where it is essential to disentangle complex and interrelated hypothesized relationships (e.g., Pitfield, Caves, & Quddus, 2012; Campbell & Agbiokoro, 2014).

That said, 3SLS comes with substantial constraints. As noted by Godwin (1985), because this approach involves maximum likelihood estimation to correct for cross-equation correlation, 3SLS is more susceptible to specification error. This means, in turn, that a model may exhibit signs of overidentification, potentially making parameter estimates unreliable. While more basic ways of identifying overidentification exist, Sargan (1958) and Hansen (1982) co-developed the eponymous Sargan-Hansen test to evaluate the residuals of a multi-equation model, testing the null hypothesis that the overidentifying restrictions are valid. This is operationalized within Stata using the “overid” command (Baum, Schaffer, Stillman, & Wiggins, 2006), which is freely available through the Statistical Software Components (SSC) archive.

While there are now 613 school districts in Ohio, there were 614 prior to 2014. Of these, data were collected for 609; five were excluded due to incomplete data from the Ohio Department of Education (ODE): North Bass Local, Middle Bass Local, Put-In-Bay Local, Kelley’s Island Local, and College Corner Local. (The first four districts are on the Lake Erie Islands, which have few year-round residents; the fifth straddles a state boundary and is administered by Indiana authorities.) ACS data used in prior models (here, 2005-2009 averages) were obtained by school district. Other variables affecting school performance include fiscal variables, such as property tax millage (equalized by state law, setting assessed value at 35% of market value), school income tax rates, and property value per pupil. The model is described in further detail in Chapter VII.

Due to its configuration, this model can do more than evaluate whether local governance structure has an impact on the efficacy of schooling. It will also test the legitimacy of the Tiebout (1956) hypothesis described in the previous chapters by determining, indirectly, whether the value of educational excellence with respect to expenditures is capitalized in the cost of housing, as would be predicted by Oates (1969) and Wheaton (1993). Given efficient markets, it should be impossible to relocate to a higher-performing or lower-cost school district without paying more for housing, all else being equal. If there are statistically significant disparities, this suggests opportunities for households of limited means to secure housing and improve their fiscal condition and/or children's educational performance.

CHAPTER IV: RESIDENTIAL SEGREGATION

While *de jure* housing discrimination on the basis of race or ethnicity has been illegal throughout the United States since passage of the Fair Housing Act of 1968 (U.S. Department of Justice, 2015), that legislation and others passed during the civil rights movement did not eliminate segregation. Indeed, the Obama Administration has developed new regulations to ensure that local jurisdictions meet the federal mandate to “affirmatively further” fair housing, particularly for persons of color (U.S. Department of Housing and Urban Development, 2015). Further, works like Rusk (2013) build a *prima facie* case that there is appreciable discrimination on the base of race and ethnicity, and that local governments may influence the level of that discrimination, given their extensive authority over land use planning and permitting. While Boustan (2013) notes that white-black residential segregation (measured by a dissimilarity index) fell 32% nationwide between 1960 and 2000, this was driven by a 60% decline in segregation between neighborhoods within jurisdictions. Therefore, segregation across city boundaries, i.e., of the sort implied by a Tiebout sorting model, increased appreciably in that time. This chapter seeks to investigate whether this finding holds with data that are more recent and whether it can be explained by other factors.

Before proceeding with this analysis, however, it is worth putting forward the argument that explains why segregation is thought to derive from the geographic density of local government. That case was made by Weiher’s (1991) *The Fractured Metropolis*, which goes as far as to term the process of municipal boundary creation and change “anti-government.” This may not be nearly as hyperbolic as it first appears. Weiher (1991) begins by establishing the uniqueness of America’s system of local governance. In Europe, he observes, the creation of a new municipality can only take place with the approval of a national authority that judges the request based on national interest rather than local preference. Instead, geographic locations can acquire meaning that has the power to exclude and recruit potential inhabitants, far beyond what a mere neighborhood or district would be able to accomplish. Combined with the rampant suburbanization that occurred following World War II, the stage was set for the emergence of “eccentricity” among cities and towns located on the metropolitan periphery — which most often appears by race. In his words,

> All that is necessary to the argument that eccentricity will occur in jurisdictions is faith in probability…. It is much easier for the distribution of some characteristic over a small population to become skewed with respect to the overall distribution of that characteristic…. When eccentricity has emerged, a spatial unit, or jurisdiction, is transformed into a place by the interaction of geography, sociology, demography, and the economy (Weiher, 1991, 55-56).

What does Weiher mean by “anti-government”? It is clear from the description above that the process of local government creation is not accidental, and once a municipality is carved into the political map, its identity is perpetually reinforced — both actively by community elites and passively through social processes. Such a condition, Weiher (1991) argues, is not a benign accident, but the result of private interests extracting rents from the public, i.e., the reverse of how the public sector typically functions. Therefore, government becomes anti-government. To elaborate further on this co-option, he writes:

> Its intent is to protect parochial interests from interference by overarching units of government representing the interests of a more heterogeneous sample of the public. The result of anti-government is to produce 'theme-park' suburbs on one hand and slums and ghettoes on the other. The politics of boundary creation in the United States permits some to enjoy pleasant lifestyles, while costs of urbanization are concentrated and imposed on others (Weiher, 1991, 166).

In short, the goal of *The Fractured Metropolis* is to illustrate that political boundaries are themselves politically determined, not an exogenous obstacle to be overcome. Furthermore, they have a "pernicious effect," building fences that defend and separate space; at their worst, they allocate "social pathologies" to those least equipped to handle them (Weiher, 1991, 192). The root message to planners comes in the final sentence of the book: "Policy initiatives intended to produce a more integrated and tolerant society cannot be entirely successful while metropolitan areas remain spatially fractured and politically fragmented" (Weiher, 1991, 194).

Beyond practical public policy considerations, there is an even more profound yet less easily perceptible issue at play. Weiher (1991) argues that "urban political boundary systems have a cognitive impact" (190) and there is a purposive and malicious dimension to fragmentation that has been ignored:

> There is nothing 'given' about sorting or a system of boundaries that supports it. It is not dictated by the workings of markets because markets can be readily manipulated toward certain ends. Nor can it be considered immune against human ingenuity on any other grounds because it is produced by a very human activity — politics. Settlers eventually arrive in certain locations in part because of conscious decisions made by specific individuals within political systems…. Boundaries wed a political unit to a geographic area. They are a way of "organizing political space." Quite frequently, they also are social boundaries, separating socioeconomic and ethnic groups from one another. This is not accidental (Weiher, 1991, 191-192).

Ultimately, Weiher (1991) believes in the centrality of local governance scale in the advancement of social justice:

> Considerable energies have been expended since World War II to create an integrated and fair society. There are a number of indications that as a people we perceive that the American model of democracy requires a citizenry in which social groups are not radically isolated from one another. I have argued that one of the instruments of group isolation has been the system of urban jurisdictional boundaries. Policy initiatives intended to produce a more integrated and tolerant society cannot be entirely successful while metropolitan areas remain spatially fractured and politically fragmented (195).

There is no need to rehash prior discussion of Tiebout (1956) sorting, which covers a wide body of work with contradictory opinions. Most of the literature found that there is little evidence of municipal-level homogeneity (e.g., Pack & Pack, 1977; Rhode & Strumpf, 2003), though many authors dissent (e.g., Heikkila, 1996; Alesina, Baqir, & Hoxby, 2004; Bischoff, 2008). Notably, however, dissimilarity is computed at the Census tract level, a geographic scale more analogous to a neighborhood, so this may not be as instructive as might be expected.

Alongside such partial equilibrium approaches are dynamic “tipping” models (e.g., Schelling, 1971), which show how segregation can develop over time through individual choice. As Greene (2008) notes, extant literature suggests these effects are more substantive than those derived from Tieboutian preferences and must, like the Alonso (1960) land use model, be integrated into models of location choice. Recent efforts like Hanushek & Yilmaz (2007) are steps in this direction. That said, these works are outside the scope of this limited exploratory analysis.

Beyond those already discussed, two works explicitly and empirically touch on the question of segregation and local government fragmentation. Clotfelder (1999) developed an econometric model to evaluate the level of racial isolation, as represented by a Gini coefficient, in public school districts for all MSAs nationwide (331 at the time). *Ceteris paribus*, segregation was higher in regions that were more populated regions, had more school districts, had higher percentages of minorities, and were in the Northeast or Midwest.

Similarly, Dawkins (2005) found that, "Following a 10% increase in Tiebout choice … total segregation across neighborhoods would increase by no more than 1%, while segregation across jurisdictions would increase by between 4% and 7%" (753). Dawkins (2005) suggests this is a distortion that may limit benefits hypothesized by Tiebout (1956) by diverting minority households to communities such that they fail to maximize their household utility.

Two further papers are worth noting here, as they touch explicitly on the relationship between local governance structures and the welfare of racial minorities. DeHoog, Lowery, & Lyons (1991) compared the satisfaction of whites and blacks in Kentucky's two most populated counties: Jefferson and Fayette. The former, home to Louisville, then had over 90 municipalities within its borders and large areas of unincorporated territory, while Fayette County had consolidated with the city of Lexington in the 1970s. (Louisville and Jefferson County since consolidated in 2003, bringing unincorporated areas under its jurisdiction and establishing a county council.)

Surveys were conducted in ten neighborhoods, five in each county, which were then paired by socioeconomic characteristics. Satisfaction with government was found to be higher in Fayette for two pairs and higher in Jefferson for one pair. When the survey samples were split by race, however, whites were equally satisfied in both counties, but blacks had a much more negative view of local government in Jefferson County. Hence, DeHoog, Lowery, & Lyons (1991) find evidence that fragmented regions produce disproportionately negative outcomes for African-Americans and other minorities, as argued by those arguing for regional consolidation and cooperation.

Hart, Kunitz, Sell, & Mukamel (1998) hypothesized that central city elasticity, as defined by Rusk (2013), and the health outcomes of blacks in large MSAs were correlated, noting that the highest rates of mortality among African-Americans are in Northeastern and Midwestern populous urban areas. These regions are the areas that are found to be the most fragmented and inelastic, as well as the most segregated, which naturally led to competing hypotheses. Indeed, there is a strong correlation coefficient between Rusk's index and a measure of racial segregation (r=-0.58), a finding verified in a simple OLS regression controlling for alternative causes of segregation. Further modeling found that, when specified in separate OLS models, Rusk elasticity and segregation were both positively correlated with African-American mortality rates.

However, when both variables are included in the same model, the impact of governance structure is insignificant — the result is entirely attributable to segregation. This work, however, offered a call for other researchers to further interrogate the potential connections between health, housing, and governance. "Our study suggests the importance of studying macro-level policies to improve the health of urban populations. Changes … in areas that are not traditionally thought of as 'health policy' areas, may lead to improvements where attempts at the individual level have failed" (Hart, Kunitz, Sell, & Mukamel, 1998, 437).

Based on this literature and the available data noted in Chapter III, **it is hypothesized that the level of jurisdictional fragmentation within a metropolitan area will be positively correlated, controlling via regression for demographic and economic characteristics, with residential segregation by race or ethnicity.**

Some clarity in terminology is necessary here. The residential patterns of three minority groups will be considered in this analysis. These groups are labeled based on self-identification volunteered on decennial Census forms (U.S. Census Bureau, 2008). Two questions on that form are relevant: Question 5 ("Is this person Spanish/Hispanic/ Latino?") and Question 6 ("What is this person's race?")

The dispersion of three minority groups will be assessed: (a) Individuals who marked only one or more Asian nationalities (Asian Indian, Chinese, Filipino, Japanese, Korean, Vietnamese, or "Other Asian") on question 6 and marked "No" on question 5; (b) individuals who marked only "Black, African American, or Negro" on question 6 and marked "No" on question 5; and (c) individuals who marked one or more "Yes" boxes on question 5, regardless of how s/he answered question 6. The majority group consists of individuals who marked only "White" on question 6 and "No" on question 5. For clarity, these groups will be termed "Asian," "Black," "Hispanic," and "White," respectively, though these may not perfectly reflect every respondent's racial or ethnic identities.

Descriptive statistics of the dissimilarity indices and population shares for Asians, Blacks, and Hispanics based on Census 2000 and Census 2010 data are in Table 4-1. The University of Michigan computed these values for the largest 102 MSAs (i.e., having over 500,000 residents). Note that these figures reflect the percentage of the minority group that would have to move to be evenly distributed within the white majority.

Table 4-1: Descriptive Statistics of Dissimilarity Indices and Population Shares (n=102)

Variable	Mean	Std. Dev.	Minimum	1st Quartile	Median	3rd Quartile	Maximum
Asian Index, 2000	39.8	7.5	21.0	35.4	40.5	45.2	54.3
Asian Index, 2010	39.7	7.5	20.5	35.4	40.9	44.9	54.4
Black Index, 2000	58.4	12.4	26.8	49.9	59.2	67.9	85.7
Black Index, 2010	55.0	11.7	21.9	47.7	55.6	64.3	81.5
Hispanic Index, 2000	43.9	10.8	22.6	35.2	44.3	52.2	65.6
Hispanic Index, 2010	43.5	9.2	23.8	36.9	43.1	49.6	63.4
Asian Share, 2010	4.4	5.8	0.6	1.8	2.8	4.5	43.0
Black Share, 2010	12.6	10.1	0.4	5.4	9.9	16.8	47.5
Hispanic Share, 2010	15.8	9.5	1.3	5.1	9.5	20.2	90.6

Residential segregation is more pronounced among Blacks, but this is also the group that also experienced the greatest decrease in segregation during the prior decade. Overall, segregation is generally highest in northern industrial areas and lowest in Florida and the Southwest, though this is less true for Hispanics. With respect to 2010 population shares, distributions for all three groups are skewed, with averages well above medians. This is particularly true for Hispanics; while neither Asians nor Blacks constitute a majority of any MSA, four are majority-Hispanic.

A brief review of descriptive statistics for control variables in this model, drawn from the 2007 ACS, is given in Table 4-2. Notably, these same terms will be employed in the OLS models specified in the subsequent chapters as well. Statistics are provided here for the full range of 361 MSAs, though only the 102 most populated are included in this model. All MSAs will be included in later specifications, however.

Table 4-2: Descriptive Statistics of Control Variables (n=361)

Variable	Mean	Std. Dev.	Minimum	1st Quartile	Median	3rd Quartile	Maximum
MSA population in thousands, 2007	697.4	1,573.9	71.8	142.8	242.2	546.6	18,816.0
Population change in percent, 2000-2007	8.0	9.2	-21.7	2.1	6.6	11.6	77.4
Housing units per square mile, 2007	121.4	130.8	3.2	49.6	84.3	147.6	1,103.3
Employment-population ratio, 2007	59.5	5.2	36.3	56.0	59.6	63.1	73.5
Jobs in manufacturing sector (%), 2007	12.1	6.2	1.5	7.7	10.7	15.9	44.5
Four-year college graduation rate, 2007	25.0	7.9	10.6	19.0	24.2	29.3	54.5
Percent of units built before 1940, 2007	12.8	9.7	0.2	5.2	9.9	19.4	43.1
Housing vacancy rate in percent, 2007	11.6	5.2	4.0	8.5	10.7	13.0	53.8
Owner-occupancy rate in percent, 2007	68.1	5.5	49.2	65.1	69.0	71.8	82.5
Median SF home value in thousands, 2007	187.2	115.4	69.5	116.1	147.4	218.4	756.8

Given three dissimilarity indices and three distinct measures of fragmentation, nine regression results will be presented. As noted previously, controls are based on Stansel (2005) — income is excluded due to collinearity with educational attainment — and an additional panel designed to account for differences in regional housing markets. (Appendix B includes bivariate correlation tables, while Appendix C includes alternate specifications that include census region dummy variables. In no instance did the significance of fragmentation at the 90% level change in a specification where the three dummy variables were found to be jointly significant.)

Table 4-3: 2010 Asian-White Dissimilarity Index Regression Coefficients (t-statistics)

Governments per million residents, 2007	-0.009 (1.22)		
Metropolitan Power Diffusion Index, 2007		0.390 (1.15)	
Modified Rusk elasticity index, 2010			0.536 (1.12)
Asian population (percent), 2010	0.618 (3.47)	0.553 (3.09)	1.047 (4.05)
MSA population in thousands, 2007	0.001 (3.83)	0.001 (1.89)	0.001 (2.47)
Population change in percent, 2000-2007	-0.170 (1.75)	-0.166 (1.71)	-0.116 (1.15)
Housing units per square mile, 2007	-0.015 (2.37)	-0.104 (1.67)	-0.006 (1.00)
Employment-population ratio, 2007	0.085 (0.30)	-0.149 (0.05)	-0.117 (0.44)
Jobs in manufacturing sector (%), 2007	0.333 (1.82)	0.316 (1.72)	0.215 (1.10)
Four-year college graduation rate, 2007	0.062 (0.37)	0.095 (0.58)	0.061 (0.39)
Percent of units built before 1940, 2007	0.209 (2.15)	0.086 (0.85)	0.045 (0.46)
Housing vacancy rate in percent, 2007	0.194 (0.85)	0.137 (0.61)	0.283 (0.88)
Owner-occupancy rate in percent, 2007	-0.369 (2.00)	-0.482 (2.49)	-0.159 (0.78)
Median SF home value in thousands, 2007	-0.027 (3.45)	-0.025 (3.24)	-0.034 (3.84)
Number of observations/R-squared	102/0.4414	102/0.4404	90/0.4371

Table 4-4: 2010 Black-White Dissimilarity Index Regression Coefficients (t)

Governments per million residents, 2007	0.024 (2.79)		
Metropolitan Power Diffusion Index, 2007		1.243 (3.25)	
Modified Rusk elasticity index, 2010			0.715 (1.15)
Black population (percent), 2010	0.366 (4.07)	0.321 (3.78)	0.166 (1.75)
MSA population in thousands, 2007	0.001 (1.82)	-0.000 (0.55)	0.001 (1.26)
Population change in percent, 2000-2007	-0.323 (2.59)	-0.373 (3.10)	-0.475 (3.47)
Housing units per square mile, 2007	0.023 (3.19)	0.022 (3.16)	0.021 (2.72)
Employment-population ratio, 2007	0.492 (1.53)	0.602 (1.94)	0.724 (2.09)
Jobs in manufacturing sector (%), 2007	0.288 (1.37)	0.245 (1.18)	0.188 (0.79)
Four-year college graduation rate, 2007	-0.083 (0.43)	-0.183 (0.98)	-0.248 (1.22)
Percent of units built before 1940, 2007	0.219 (1.92)	0.149 (1.25)	0.076 (0.52)
Housing vacancy rate in percent, 2007	0.791 (3.02)	0.865 (3.39)	0.629 (1.50)
Owner-occupancy rate in percent, 2007	-0.155 (0.79)	-0.300 (1.48)	-0.149 (0.61)
Median SF home value in thousands, 2007	-0.011 (1.29)	-0.105 (1.30)	-0.020 (2.23)
Number of observations/R-squared	102/0.6956	102/0.7042	90/0.6966

Table 4-5: 2010 Hispanic-White Dissimilarity Index Regression Coefficients (t)

Governments per million residents, 2007	-0.005 (0.56)		
Metropolitan Power Diffusion Index, 2007		-0.187 (0.44)	
Modified Rusk elasticity index, 2010			-0.625 (0.97)
Hispanic population (percent), 2010	0.219 (3.32)	0.218 (3.31)	0.364 (4.02)
MSA population in thousands, 2007	0.000 (0.94)	0.001 (0.96)	0.000 (0.34)
Population change in percent, 2000-2007	-0.034 (0.26)	-0.029 (0.23)	-0.163 (1.15)
Housing units per square mile, 2007	0.009 (1.11)	0.009 (1.23)	0.015 (1.81)
Employment-population ratio, 2007	0.515 (1.42)	0.488 (1.37)	0.612 (1.68)
Jobs in manufacturing sector (%), 2007	0.143 (0.61)	0.147 (0.63)	-0.048 (0.19)
Four-year college graduation rate, 2007	0.056 (0.27)	0.080 (0.38)	-0.100 (0.46)
Percent of units built before 1940, 2007	0.334 (2.81)	0.332 (2.68)	0.410 (3.06)
Housing vacancy rate in percent, 2007	0.016 (0.05)	-0.000 (0.00)	0.162 (0.37)
Owner-occupancy rate in percent, 2007	-0.202 (0.92)	-0.185 (0.80)	0.070 (0.27)
Median SF home value in thousands, 2007	-0.004 (0.47)	-0.004 (0.51)	-0.005 (0.51)
Number of observations/R-squared	102/0.4054	102/0.4046	90/0.4604

Table 4-3 shows fragmentation does not appear to be a statistically significant determinant of segregation experienced by Asians. Segregation is higher in MSAs where the Asian population is a larger share of the population, a larger overall population exists regardless of race, and single-family home values are lower, all else being equal. There is a clearer relationship here in Table 4-4; fragmentation and segregation among Blacks are positively correlated in two of the three specifications. Again, here, higher concentrations of the minority group are correlated with higher dissimilarity indices.

Segregation is higher in denser MSAs with shrinking populations and higher rates of housing vacancy — a description that tends to align with so-called “Rust Belt” cities. Last, in Table 4-5, residential segregation for Hispanics is not correlated with fragmentation within this model. The main drivers of dissimilarity here are the share of the population in the relevant minority group, as in both prior cases, and the share of housing built before 1940, which was not significant in either prior case. Areas with older housing stock have higher levels of residential segregation for Hispanics.

The hypothesis that local governance structure is correlated with the geographic concentration of minority groups held only for Blacks, and even then, only for two of the three statistics used. The direction of the relationship was as expected, in that higher levels of fragmentation led to more segregation. Further, based on R^2 values, this model is far more predictive of segregation levels for Blacks than either Asians or Hispanics. Beyond the core of the analysis, in all nine specifications, the minority group’s share of the population was positively correlated with segregation, suggesting that — whether by voluntary or involuntary means — minority groups are more highly concentrated in higher numbers. Housing variables seemed to matter, though not in a consistent way across minority groups.

That results differed for Blacks vis-à-vis other ethnicities is not a startling finding. While other immigrant groups have also experienced extreme bias, it has been far more persistent, long lasting, and destructive with respect to blacks. Beyond the obvious destructive influences of slavery and Jim Crow, policies such as redlining that persisted in law into the 1960s (and often, illegally, thereafter) were directed explicitly at restricting geographic mobility of Blacks; even more crucially to this topic, municipal boundaries were often explicitly drawn to exclude African-Americans from residency (Gordon, 2014). Meanwhile, Asians are on average wealthier than whites and constitute a smaller share of the population, so their settlement patterns are likely not to be driven by the mechanics outlined by Weiher (1991). Hispanics, while earning less income than whites, were until the latter half of the 20th century a small, regional group, and their mobility can be a function of matters such as language and, for some, legal status.

Regression coefficient outputs can be somewhat esoteric, so it may be useful to put the scope of this finding in context. Consider that increasing fragmentation by one standard deviation (2.44 MPDI units or 241.60 governments per million) would cause the white/black index of dissimilarity to go up by between 3.0 and 5.8; in other words, between one in 17 and one in 33 Black households that would otherwise be living in integrated neighborhoods instead find themselves "ghettoized." This should not be a startling realization; land use policy is the nearly exclusive province of local government in the United States. Hence, municipalities can act as agents of displacement, controlling zoning standards and their enforcement.

An obvious critique to these findings, however, is that racial segregation could well be an artifact of economic segregation, given that households headed by African-Americans have lower household incomes on average than those headed by whites, rather than an independent phenomenon. To assess this possibility, data used in Florida & Mellander (2015) to evaluate economic segregation were obtained; their analysis generated a dissimilarity index based on 2010 Census data where households living below the federal poverty line comprise the “minority” group. First, to determine whether there is, in fact, statistically significant segregation because of income, poverty dissimilarity will be the dependent variable in the same specifications as were used for racial dissimilarity. Second, poverty dissimilarity will be included as a control variable in each specification from Table 4-4; if fragmentation is significant in the first regression but insignificant in the second, the correlation between local government structure and African-American residential segregation may be spurious.

Table 4-6: Poverty Dissimilarity Index Regression Coefficients (t)

Governments per million residents, 2007	-0.003 (1.91)		
Metropolitan Power Diffusion Index, 2007		0.477 (2.85)	
Modified Rusk elasticity index, 2010			0.593 (1.98)
Poverty rate (official federal line), 2007	0.202 (2.20)	0.221 (2.41)	0.596 (2.94)
MSA population in thousands, 2007	-0.000 (0.33)	-0.001 (1.97)	-0.000 (1.17)
Population change in percent, 2000-2007	-0.007 (0.20)	-0.005 (0.15)	0.099 (1.68)
Housing units per square mile, 2007	0.013 (3.67)	0.016 (4.72)	0.009 (2.55)
Employment-population ratio, 2007	0.163 (2.02)	0.131 (1.64)	0.408 (2.51)
Jobs in manufacturing sector (%), 2007	0.017 (0.31)	0.036 (0.67)	0.105 (1.03)
Four-year college graduation rate, 2007	0.341 (6.81)	0.332 (6.68)	0.214 (2.65)
Percent of units built before 1940, 2007	0.160 (4.01)	0.083 (2.09)	0.091 (1.36)
Housing vacancy rate in percent, 2007	-0.158 (2.49)	-0.164 (2.61)	-0.014 (0.09)
Owner-occupancy rate in percent, 2007	-0.041 (0.60)	-0.060 (0.88)	0.189 (1.44)
Median SF home value in thousands, 2007	-0.009 (2.63)	-0.008 (2.35)	-0.003 (0.58)
Number of observations/R-squared	357/0.4447	357/0.4517	125/0.5215

The interpretation of the first step (see Table 4-6) suggests a positive correlation between jurisdictional fragmentation and poverty dissimilarity, i.e., that decentralized local governance increases segregation among the poor, though the negative sign on the government density coefficient (despite being narrowly statistically insignificant at the 95% threshold) is at odds with this.

Table 4-7: Revised Black-White Dissimilarity Index Regression Coefficients (t)

Governments per million residents, 2007	0.023 (2.85)		
Metropolitan Power Diffusion Index, 2007		1.180 (3.21)	
Modified Rusk elasticity index, 2010			0.444 (0.72)
Poverty dissimilarity index, 2010	0.599 (3.13)	0.564 (2.97)	0.528 (2.48)
Black population (percent), 2010	0.330 (3.76)	0.290 (3.48)	0.159 (1.73)
MSA population in thousands, 2007	0.001 (2.12)	-0.000 (0.30)	0.001 (1.59)
Population change in percent, 2000-2007	-0.338 (2.83)	-0.388 (3.35)	-0.494 (3.72)
Housing units per square mile, 2007	0.018 (2.55)	0.017 (2.50)	0.017 (2.14)
Employment-population ratio, 2007	0.462 (1.44)	0.597 (1.93)	0.656 (1.95)
Jobs in manufacturing sector (%), 2007	0.272 (1.34)	0.227 (1.14)	0.139 (0.60)
Four-year college graduation rate, 2007	-0.203 (1.06)	-0.307 (1.64)	-0.326 (1.64)
Percent of units built before 1940, 2007	0.135 (1.19)	0.078 (0.67)	0.056 (0.39)
Housing vacancy rate in percent, 2007	0.943 (3.60)	0.993 (3.87)	0.758 (1.85)
Owner-occupancy rate in percent, 2007	-0.175 (0.92)	-0.319 (1.61)	-0.111 (0.46)
Median SF home value in thousands, 2007	-0.007 (0.86)	-0.007 (0.91)	-0.015 (1.58)
Number of observations/R-squared	101/0.7276	101/0.7338	90/0.7194

Poverty dissimilarity is in fact a statistically significant explanatory variable for the Black-White index, showing a strong positive association (see Table 4-7). While the value of coefficients for governmental density and MPDI declined slightly, they retained their statistical significance. This suggests racial segregation is not primarily economic in nature, though a more elaborate model would need to be constructed to fully quantify the interrelations between varieties of residential segregation, including across criteria such as occupation and education level (also computed by Florida & Mellander (2015)).

There are limitations to this finding, however. The dissimilarity index (hereafter referred to as D), while used widely in Tiebout sorting literature (see Chapter II) and elsewhere as a metric of segregation, have been critiqued for decades as being incomplete or insufficient as a measure of residential displacement. Many articles in the literature outline the problems with the metric — while implicitly clarifying why using another statistic would also have its challenges.

Massey & Denton (1988) submit that residential segregation has five dimensions, each of which must be studied and assessed as distinct phenomena. D only addresses the first of these, evenness, which measures the degree to which the proportion of a minority deviates from overall share in the region being studied. The other dimensions are exposure of minority populations to the majority group, spatial concentration and centralization of the minority population, and geographic clustering; a less spatially agnostic approach must be used to evaluate them (e.g., Reardon & O'Sullivan, 2004). Putting this aside, however, Massey & Denton (1988) note that there are problems with the index just as a measure of evenness:

> Among its properties, the dissimilarity index is strongly affected by random departures from evenness when the number of minority members is small compared to the number of areal units and it is insensitive to the redistribution of minority members among areal units with minority proportions above or below the city's minority proportion. Only transfers of minority members from areas where they are overrepresented (above the city's minority proportion) to areas where they are underrepresented (below the minority proportion) affect segregation as measured by the dissimilarity index. The index thus fails what is known as the "transfers principle" (284).

Massey & Denton (1988) go on to review a series of alternatives, settling on the Atkinson index as a preferred choice to resolve the mathematical issues noted above. They note, though, that adopting a new standard of measurement would erode the utility of past literature that employed dissimilarity indices; further, computation of the Atkinson index relies on a parameter specified by the researcher, meaning another layer of consensus would need to be reached on an arguably subjective matter. Ultimately, prominence of the dissimilarity index in the literature is a matter of path dependency.

Meanwhile, Galster (1988) takes issue with D and similar computations from a broader, more theoretical perspective. In short, he argues that such approaches take the segregation as an exogenous outcome, rather than a result of complex, interrelated phenomena in both the public and private sectors. In reviewing extant literature, Galster (1988) highlights four distinct causes of segregation: economic status, location of employment, neighborhood or housing preferences, and discrimination, with the last of these having the clearest impact.

Because these phenomena are interrelated, Galster (1988) charts 14 distinct and interconnected causal relationships between segregation and job location choices, racial economic differences, social preferences, and housing market discrimination; it is argued implicitly that any quantitative assessment of segregation must consider said relationships. It is unclear how such a thing would be operationalized, though, or how it could be distilled into a single number with the utility of D. Any single quantitative measure inherently omits detail, though attempting to resolve this with a thicket of measures reduces the utility of measurement.

Another pair of articles, Gorard & Taylor (2002) and Allen & Vignoles (2007), touch upon the history of quantitative assessment of segregation and more fine-grain issues with D. Gorard & Taylor (2002) note that competing papers on this topic date back to at least Wright (1937) before the landmark paper by Duncan & Duncan (1955) that led to D becoming the eminent metric used. Their work argues that D lacks what the authors term “strong compositional invariance,” meaning that D varies when the quantity of either group changes — even if the distribution of the minority group is unchanged. Hence, Gorard & Taylor (2002) develop their own metric like D, but works around this issue, which they claim generates false positives with respect to changes in segregation levels.

Allen & Vignoles (2007), however, establish that this computation merely yields a statistic that is equal to D times the proportion of the majority group in the population. Further, they note that the measure developed by Gorard & Taylor (2002) loses some desirable properties of D, such as its zero-to-one range and "symmetry" (meaning that swapping majority and minority groups does not change the value). Having defended D, however, Allen & Vignoles (2007) argue for a measure based on generalized entropy (see Theil, 1972) that resolves the transfer principle issue but can also be adapted to determine the "skew" of segregation, i.e., Lorenz, curves.

It is also worth noting that dissimilarity indices, as discussed here, are computed by census tract. Therefore, this measure essentially measures segregation at the level of urban neighborhoods or suburban subdivisions, not local government boundaries, and it would be unsound to assume the two are identical. Developing D based on local government boundaries would be logistically challenging, given the complexity and inconsistency of how county subdivisions are treated from state to state in federal data (U.S. Census Bureau, n.d.2). Attempting to resolve this issue would require an extensive data collection effort beyond the scope of this work.

Regardless, there is a firm correlation between government density and some element of racial segregation experienced by African-Americans that must be further interrogated. Weiher (1991) sets forth a compelling argument. The analysis herein does nothing to discredit his central thesis and may in fact provide some support for it and, by extension, advocates of regionalism like Rusk (2013). As noted earlier, metropolitan areas reflect the land area in which individuals choose to associate with one another, the scale that best matches human behavior — and alteration of said behavior by government. It is reasonable to suggest that unifying such regions would eliminate cleavages that allow segregation to persist.

CHAPTER V: LAND USE INEFFICIENCY

Many volumes and authors have devoted countless pages to documenting and understanding the phenomenon of "sprawl," which has been likened to cancer metastasis in its form and impact on the landscape (Ryan, Dows, Kirk, Chen, Eastman, Dyer, & Kier, 2010). The land use patterns known as sprawl that have predominated in the last fifty years have been blamed for myriad ills. Burchell et al. (1998) identify income segregation, excessive travel, and, particularly, excessive public expenditures. Their study examines the "never-ending upward spiral of costs" generated by sprawl. This was quantified recently by Litman (2015), who determined that automobile-centric land development patterns in the United States imposed an annual cost of over $1 trillion nationally, or more than 5% of gross domestic product.

The costs of decreased density and increased dispersion of activities identified by Litman (2015) are wide-ranging. Many stem from elevated use of private vehicles, which increases travel time, costs of vehicle operation, environmental disamenities, quantity of land devoted to parking, and the number of deaths and injuries due to crashes. Economic knock-on effects identified by Litman (2015) included negative impacts on physical health, reduced job opportunities for non-drivers, increased costs of maintaining infrastructure, and reduced agricultural activity, among others. Notably, nearly 40% of these costs are borne by the nation generally, regardless of whether where they live is sprawling or dense.

Additionally, sprawl is implicated in exacerbating carbon emissions by driving growth in vehicle miles traveled (VMT), bringing about more intense climate change. Vehicles are the second most significant sector of greenhouse gases worldwide and projected to grow the fastest of all contributing sectors. Per the Environmental Protection Agency (EPA), carbon dioxide emissions resulting from vehicles increased by 33% nationwide between 1985 and 2000 (Davis & Diegel, 2000). Sprawl unequivocally bears a share of the blame.

It is clear, at least, that the nation's cities have been declining in density for the past 50 years. Average developed land per capita increased from 0.32 acres in 1982 to 0.38 acres in 2002 (Ingram, Carbonell, Hong, & Flint, 2009). Alternatives to sprawl have arisen in recent decades, variously termed "smart growth," "compact development," or "transit-oriented development." These initiatives seek to direct development toward existing cities and/or design such development in such a way to make walking, biking, and transit accessible. Researchers (e.g., Burchell et al., 1998) have found significant potential for smart growth to ameliorate the adverse consequences of sprawl. That said, in the aggregate, such efforts have not made an impact; the percentage of Americans workers for whom commuting is done alone in a private vehicle has never been higher, reaching 76.6% in 2010 (Polzin & Pisarski, 2013).

Jurisdictional fragmentation is often identified as a consequence, or at least a neutral accompaniment, of sprawl, given that — if boundaries are considered fixed — development across a larger land area will necessarily include more local governments. Fragmentation has more rarely been examined as itself a cause of sprawl. Yet, there is significant evidence that the fractionalized nature of land use decision making is exacerbating the prevalence of sprawl. Carruthers (2002) writes, "Metropolitan areas continue to spread outward, spurred forward by the autonomy of local governments and their land use regulations…. In this way, sprawl has evolved into one of the most vexing problems encountered by contemporary urban and regional policy" (1960).

Carruthers & Ulfarsson (2002) first studied the relationship between the two in a comprehensive way and found a significant correlation. The authors specified a three-stage least squares (3SLS) regression to determine effects of fragmentation on variables related to sprawl and municipal fiscal impacts within a system of equations that controls for endogeneity. Inquiries into this topic have primarily stemmed from the premise that county-level variables, their model used municipalities and special districts per capita, plus dummy variables for consolidation and central city status as independent variables, with controls for racial and economic composition in place. The four dependent variables were population density, urban land area, property value, and infrastructure spending. Their findings indicated that fragmentation was associated with increased sprawl but improved fiscal stability. This work was followed up by Ulfarsson & Carruthers (2006) (see Chapter VII).

Another approach was developed by Razin & Rosentraub (2000), who also examined the nexus of sprawl and fragmentation in Canadian and U.S. metropolitan areas with over 500,000 people. They concluded that governments per capita and residential density are linked, but that one is not an inherent attribute of the other. More interestingly, they suggested that low levels of fragmentation do not guarantee compact development, but noted that the combination of high levels of fragmentation and low levels of sprawl is rare. Low-fragmentation, high-sprawl regions are often unitary cities resulting from city-county consolidation or aggressive annexation. In sum, "a lack of excessive fragmentation seems … a pre-condition for compact development in North America, [but] not a sufficient condition" (Razin & Rosentraub, 2000, 835).

The explanation for prior findings is clear. The size of a municipality, both with respect to population and land area, affects the decision making of zoning authorities. Their incentives, *ceteris paribus*, are to maximize tax revenues from commercial and industrial land uses and minimize service provision by limiting residential density — without regard to nearby jurisdictions. This can lead to highly adverse consequences; division of the New Jersey Meadowlands among over a dozen municipalities incentivized development of heavy industry and landfills in an ecologically sensitive area, leading to the regionalization of zoning in the area under pressure from federal authorities (Goldman, 1975). Further, proliferation of single-family home development maintains social homogeneity, a veiled but implicit goal of zoning policy (Burchell et al., 1998). While regional zoning is no panacea for eliminating perverse incentives, as Goldman's account highlights, it can mitigate the most destructive parochial impulses.

On the other hand, large city governments are less likely to be captured by the interests of neighborhood residents. These jurisdictions are more likely to have low-income and minority residents within their boundaries who do not have the same exclusionary priorities as wealthy, largely white landowners and must account for a greater share of the externalities generated by adverse development. When local constituencies' desires clash with the broader interests of the city, politicians can "weather" local opposition, particularly if the policy is broadly beneficial. Large cities are also more likely to seek the revenues from commercial and high-density development, as they are better placed to meet the need for infrastructure and public sector capacity.

Pioneering work in exclusion of density was done by Levine (2005), who found:

> Zoning and other municipal interventions lead both to development that is lower in density and to communities that are more exclusive than would arise in the absence of such regulation…. [The] American way of zoning makes the suburbs [and cities] of U.S. metropolitan areas more spread out that they might otherwise be.… [Private sector-based alternatives to sprawl are] impeded by municipal regulations that lower development densities, separate land uses, specify wide roadways, and mandate large parking areas (3).

Duany & Brain (2005) commented on difficulties encountered in permitting projects with high levels of density. "In spite of significant efforts among national environmental organizations … to mobilize anti-sprawl initiatives, urban projects that recognize the link between urbanity and land conservation often run up against ... opposition at the local and regional level" (296). Zoning, therefore, is the prerogative of the local community, and local communities tend to see their interest as separate and exclusive from that of the region, or even the community next door. Frug (1999) expanded on this point:

> Localities … decide their zoning policies in the interests of their own residents with little regard to their effect on outsiders…. Residents who desire to make their suburb into what Gregory Weiher has called a 'theme park' … are entitled to do so as long as they do not intentionally discriminate on the basis of race.… It has fostered not only the suburbs ability to exclude potential residents but also their ability to recruit them (77).

What Rusk (2013) calls "elastic cities" make decisions that are more regional in scope and less exclusionary in their focus. Throughout fragmented suburbs, there is little incentive for local officials and employees to consider policy implications beyond the parochial interests of one's geographically concentrated constituents. Indeed, officials are incentivized to place aesthetically and environmentally undesirable uses (e.g., industry and retail) on the fringes of the city, deflecting much of the impacts outside one's borders, and compete with neighboring communities to increase property values and, hence, tax bases. In other words, to borrow from Weiher (1991), when each small jurisdiction plans only for itself, do we get "anti-planning"?

It is hypothesized that this is exactly what happens, that fragmentation and sprawl are positively correlated. Specifically, each measure of fragmentation specified in Chapter IV should be, all else being equal, associated with higher levels of sprawl. There are many ways to operationalize the measurement of land use. As noted in Chapter III, Ewing & Hamidi (2014) developed four indices of sprawl. These indices quantify low-density development, segregation of land uses, lack of significant centers, and poor street accessibility. These measures are computed at the census tract level, then averaged across the metropolitan statistical area (MSAs). These indices are significantly but generally not strongly correlated with one another (see Appendix B).

Each of the four indices computed by Ewing & Hamidi (2014) is normalized to a national mean of 100 and a standard deviation of 25, with higher values representing regions with the lowest levels of sprawl. (This, effectively, makes the measures better described as anti-sprawl indices.) A fifth composite index, which averages the four component measures, has the same characteristics. The New York MSA, unsurprisingly, was the least sprawling according to this measure (with a density rating twice that of any other region), while Hickory, North Carolina, was the least dense metropolitan area. The descriptive statistics of these measures are provided below in Table 5-1.

Table 5-1: Descriptive Statistics of Ewing & Hamidi (2014) Sprawl Indices (n=206)

Variable	Mean	Std. Dev.	Minimum	1st Quartile	Median	3rd Quartile	Maximum
Density Index	98.87	25.05	78.64	89.16	94.54	101.58	384.29
Mixed Use Index	98.24	24.60	39.67	81.12	99.66	116.00	167.17
Centeredness Index	101.46	25.11	51.43	86.07	97.55	112.77	230.92
Streets Index	97.81	23.73	53.34	81.25	94.39	111.76	193.80
Composite Index	99.54	25.34	24.86	79.92	102.79	115.68	203.36

This was computed across all MSAs and metropolitan divisions with more than 200,000 residents. In the case of metropolitan divisions, given that all other data in these OLS regressions are at the MSA scale, the index value for the division containing the core municipality was used. If this imperfect solution introduces some form of bias to the results, these areas are accounted for with a dummy variable. Otherwise, the regression specification is as in Chapter IV, absent the racial controls. Model outputs are provided on the next two pages. Again, bivariate correlation tables and alternate specifications with census region dummies are included in the appendices; once again, introduction of these variables did not alter the statistical significance of the fragmentation measure in question. Regression model outputs assessing correlates of each of the five sprawl indices are provided on the next two pages.

Table 5-2: Ewing & Hamidi (2014) Density Index Regression Coefficients (t)

Governments per million residents, 2007	0.003 (0.63)		
Metropolitan Power Diffusion Index, 2007		-2.409 (5.01)	
Modified Rusk elasticity index, 2010			-1.876 (1.57)
Metropolitan division dummy	0.097 (0.02)	-1.092 (0.21)	2.414 (0.35)
MSA population in thousands, 2007	0.008 (10.62)	0.011 (12.09)	0.008 (8.40)
Population change in percent, 2000-2007	0.066 (0.50)	0.073 (0.59)	-0.019 (0.08)
Housing units per square mile, 2007	0.034 (3.43)	0.022 (2.42)	0.024 (1.68)
Employment-population ratio, 2007	-0.019 (0.07)	0.102 (0.37)	-0.534 (0.92)
Jobs in manufacturing sector (%), 2007	-0.265 (1.29)	-0.242 (1.24)	-0.349 (0.85)
Four-year college graduation rate, 2007	-0.016 (0.09)	0.045 (0.27)	0.208 (0.65)
Percent of units built before 1940, 2007	0.213 (1.45)	0.595 (4.21)	0.721 (2.64)
Housing vacancy rate in percent, 2007	-0.228 (0.92)	-0.179 (0.76)	-0.296 (0.49)
Owner-occupancy rate in percent, 2007	-0.724 (3.52)	-0.515 (2.60)	-0.663 (1.52)
Median SF home value in thousands, 2007	0.019 (2.40)	0.018 (2.38)	0.034 (2.47)
Number of observations/R-squared	206/0.7916	206/0.8153	121/0.8042

Table 5-3: Ewing & Hamidi (2014) Mixed Use Index Regression Coefficients (t)

Governments per million residents, 2007	0.015 (2.12)		
Metropolitan Power Diffusion Index, 2007		1.637 (2.39)	
Modified Rusk elasticity index, 2010			0.944 (0.76)
Metropolitan division dummy	6.947 (0.94)	7.329 (0.99)	8.529 (1.18)
MSA population in thousands, 2007	-0.000 (0.15)	-0.002 (1.43)	0.001 (0.73)
Population change in percent, 2000-2007	-0.109 (0.62)	-0.107 (0.60)	0.031 (0.13)
Housing units per square mile, 2007	0.044 (3.29)	0.041 (3.20)	0.011 (0.72)
Employment-population ratio, 2007	1.054 (2.68)	1.045 (2.67)	0.522 (0.87)
Jobs in manufacturing sector (%), 2007	-0.653 (2.36)	-0.674 (2.44)	-0.046 (0.11)
Four-year college graduation rate, 2007	-0.448 (1.92)	-0.473 (2.03)	-0.675 (2.05)
Percent of units built before 1940, 2007	0.516 (2.61)	0.471 (2.34)	0.711 (2.52)
Housing vacancy rate in percent, 2007	-1.207 (3.60)	-1.200 (3.60)	-1.393 (2.22)
Owner-occupancy rate in percent, 2007	-0.736 (2.66)	-0.947 (3.36)	-0.300 (0.66)
Median SF home value in thousands, 2007	0.072 (6.62)	0.071 (6.57)	0.084 (5.83)
Number of observations/R-squared	206/0.6095	206/0.6119	121/0.6209

Table 5-4: Ewing & Hamidi (2014) Centering Index Regression Coefficients (t)

Governments per million residents, 2007	0.008 (0.82)		
Metropolitan Power Diffusion Index, 2007		-1.428 (1.57)	
Modified Rusk elasticity index, 2010			1.622 (1.05)
Metropolitan division dummy	8.086 (0.82)	7.237 (0.74)	5.850 (0.65)
MSA population in thousands, 2007	0.001 (0.64)	0.002 (1.50)	0.001 (0.45)
Population change in percent, 2000-2007	-0.216 (0.91)	-0.208 (0.88)	0.028 (0.09)
Housing units per square mile, 2007	0.024 (1.35)	0.013 (0.76)	0.030 (1.60)
Employment-population ratio, 2007	0.739 (1.41)	0.835 (1.60)	1.027 (1.37)
Jobs in manufacturing sector (%), 2007	-0.899 (2.43)	-0.886 (2.41)	-0.186 (0.35)
Four-year college graduation rate, 2007	0.381 (1.22)	0.422 (1.36)	0.849 (2.06)
Percent of units built before 1940, 2007	0.750 (2.85)	1.048 (3.91)	0.413 (1.17)
Housing vacancy rate in percent, 2007	-0.134 (0.30)	-0.092 (0.21)	0.440 (0.56)
Owner-occupancy rate in percent, 2007	-0.550 (1.49)	-0.449 (1.20)	-1.641 (2.90)
Median SF home value in thousands, 2007	0.001 (0.06)	-0.001 (0.03)	-0.014 (0.78)
Number of observations/R-squared	206/0.3323	206/0.3383	121/0.4708

Table 5-5: Ewing & Hamidi (2014) Streets Index Regression Coefficients (t)

Governments per million residents, 2007	-0.000 (0.03)		
Metropolitan Power Diffusion Index, 2007		2.054 (2.85)	
Modified Rusk elasticity index, 2010			-0.187 (1.12)
Metropolitan division dummy	10.87 (1.43)	11.83 (1.52)	13.15 (1.49)
MSA population in thousands, 2007	0.001 (1.40)	-0.001 (0.55)	0.002 (1.59)
Population change in percent, 2000-2007	-0.351 (1.84)	-0.356 (1.90)	-0.361 (1.22)
Housing units per square mile, 2007	0.083 (5.81)	0.092 (6.81)	0.062 (3.39)
Employment-population ratio, 2007	0.305 (0.72)	0.212 (0.51)	0.503 (0.69)
Jobs in manufacturing sector (%), 2007	-0.997 (3.35)	-1.018 (3.49)	-0.793 (1.53)
Four-year college graduation rate, 2007	-0.276 (1.10)	-0.325 (1.32)	-0.588 (1.46)
Percent of units built before 1940, 2007	-0.372 (1.76)	-0.666 (3.14)	-0.110 (1.32)
Housing vacancy rate in percent, 2007	-0.190 (1.53)	-0.226 (0.64)	0.118 (0.15)
Owner-occupancy rate in percent, 2007	0.360 (1.21)	0.170 (0.57)	0.736 (1.34)
Median SF home value in thousands, 2007	0.020 (1.75)	0.021 (1.87)	0.039 (2.23)
Number of observations/R-squared	206/0.5171	206/0.5366	121/0.5245

Table 5-6: Ewing & Hamidi (2014) Composite Index Regression Coefficients (t)

Governments per million residents, 2007	0.028 (3.23)		
Metropolitan Power Diffusion Index, 2007		-2.107 (2.55)	
Modified Rusk elasticity index, 2010			0.311 (0.20)
Metropolitan division dummy	16.74 (1.90)	15.10 (1.69)	16.97 (1.88)
MSA population in thousands, 2007	-0.004 (3.11)	-0.001 (0.79)	-0.002 (1.65)
Population change in percent, 2000-2007	-0.320 (1.51)	-0.303 (1.49)	-0.172 (0.57)
Housing units per square mile, 2007	0.074 (4.66)	0.047 (3.07)	0.048 (2.54)
Employment-population ratio, 2007	0.696 (1.48)	0.907 (1.91)	0.271 (0.36)
Jobs in manufacturing sector (%), 2007	-1.196 (3.62)	-1.181 (3.54)	-0.170 (0.32)
Four-year college graduation rate, 2007	-0.257 (0.92)	-0.179 (0.64)	-0.158 (0.38)
Percent of units built before 1940, 2007	0.402 (1.71)	1.038 (4.27)	0.711 (2.01)
Housing vacancy rate in percent, 2007	-0.726 (1.82)	-0.627 (1.56)	-0.694 (0.88)
Owner-occupancy rate in percent, 2007	-0.856 (2.59)	-0.769 (2.26)	-1.013 (1.79)
Median SF home value in thousands, 2007	0.048 (3.70)	0.044 (3.40)	0.056 (3.07)
Number of observations/R-squared	206/0.4764	206/0.4661	121/0.5075

Table 5-7: Summary of OLS Regression Model Correlations

Sprawl Index	Gov’ts per capita	Power diffusion	Rusk elasticity
Density	None	Negative	None
Mixed-Use	Positive	Positive	None
Centering	None	None	None
Streets	None	Positive	None
Composite	Positive	Negative	None

Results throughout are substantially divergent. Governments per capita were positively correlated with the composite index, meaning that this measure is positively correlated with inefficiency of land use; MPDI was negatively correlated with the composite index, however, while no correlation with the Rusk index was identified. This stark divergence did not appear in any of the other four specifications. Further analysis is warranted to determine the potential causes for this disparity.

Table 5-7 summarizes correlations found between fragmentation metrics and the five sprawl indices. Recall that a higher "sprawl index" reading indicates lower levels of sprawl. The clearest result is that the Rusk index is not correlated with these land use phenomena, just as it failed to be correlated with racial segregation. This is particularly notable, however, given the central theme in Rusk (2013) of a central city needing to extend into suburban areas in mediating sprawl. Perhaps the basic method used to compute Rusk's index does not fully capture his conceptualization of elasticity, or impacts do not manifest themselves in these metrics. It may also be that not having indices for all central cities led to skewed results.

The correlation with the highest level of statistical significance ($p<0.001$) was that of a negative relationship between MPDI and the density index. This was, in fact, the only finding among the four elements of the composite sprawl index to align with the relationship hypothesized earlier — and work in extant literature (e.g., Levine, 2005) discussed previously. The coefficient estimated by the OLS model indicates that an increase of one standard deviation in MPDI is associated with a roughly one-half of a standard deviation decrease in the density index.

On the other hand, the prevalence of mixed-use development was substantially greater in more fragmented regions, even after controlling for MSA characteristics. Relative impacts are smaller than that of MPDI on density, however; an increase of one standard deviation in fragmentation correlates with an increase of about one-sixth of a standard deviation in the mixed-use index. Deeper analysis is necessary to determine where such development occurs within the region to determine its impact on the area.

It is also worth assessing the explanatory power of the models. Independent variables did the best job explaining variation in Ewing & Hamidi's (2014) density index, with R^2 values around 0.8; this is no doubt because total population and gross housing density are baked into the model. The second-strongest models set of estimate the mixed-use index, driven by a very strong positive correlation with median single-family home value. Meanwhile, the weakest specifications are those modeling centeredness. Not only were none of the fragmentation variables significantly associated with this variable, but few control variables were either.

A potential explanation of this comes from Laidley (2016), who offers a lengthy critique of Ewing & Hamidi (2014) and similar measures of sprawl. He argues centrality may not be a valid measure of land use efficiency: "The general balance between housing and jobs in a given subarea is a more important influence on transportation behavior than proximity to a given [central business district]" (Laidley, 2016, 69). Further, concentration of development may be environmentally harmful, as a region with development concentrated on a single site can generate greater negative externalities, such as automobile emissions. Further, he raises concerns over the use of the coefficient of variation of density as a measure of centeredness, noting that it treats the notoriously sprawling Atlanta MSA as more centered than that of Los Angeles simply because the latter is more consistently dense throughout the region.

A second explanation comes from the construction by Ewing & Hamidi (2014) of the four sprawl indices themselves, which were developed via factor analysis. As noted in Chapter III, the four indices are not direct measures themselves, but instead the result of factor loadings based on 21 underlying variables. Of these, the centeredness factor explains the lowest percentage of total variance (37.89%), raising the question from another perspective of whether the centering index is a valid measure of sprawl.

More broadly, when considering variables that are the product of a factor analysis, nothing is directly measured, but instead a composite (and, because the four indices were summed and reweighted to generate the overall index, a composite of a composite). Ewing & Hamidi's (2014) measures were built using on a variety of sources; most were developed by the federal government, but others are from private entities, such as Walk Scores and GPS map data. Each of these will have their own independent data quality issues. (See Table 5-8.)

This brings up another element of Laidley's (2016) critique pertaining to geographic scale. The variables feeding into the Ewing & Hamidi (2014) analysis are measured at several levels, including tract, block groups, and blocks, depending on the data point. As Laidley (2016) notes, using Dallas density data as an example, scale and cut points can dramatically influence evaluation of sprawl. Mixing and matching scales of analysis, even if justified by data availability, could bias results.

Table 5-8: Ewing & Hamidi (2014) Factor Loadings for MSA Sprawl Analysis

Variable Name and Description		Data Source	Factor Loadings
Density Factor			
popden	gross population density	Census 2010	0.900
empden	gross employment density	LEHD 2010	0.898
lt1500	percent of the population living at low suburban densities	Census 2010	-0.597
gt12500	percentage of the population living at medium to high urban densities	Census 2010	0.879
urbden	net population density of urban lands	National Land Cover Database	0.925
dgcent	estimated density at the center of the metro area derived from a negative exponential density function	Census 2010, Tiger 2010	0.948
popdcen	weighted mean population density of centers	Census 2010	0.810
empdcen	weighted mean employment density of centers	LEHD 2010	0.817
Eigenvalue			**5.82**
Explained variance			**72.80%**
Mixed Use Factor			
jobpop	job-population balance	LEHD 2010	0.834
jobmix	degree of job mixing (entropy)	LEHD 2010	0.921
walkscore	weighted average Walk Score	Walk Score Inc.	0.870
Eigenvalue			**2.30**
Explained variance			**76.72%**
Centeredness Factor			
varpop	coefficient of variation in census block group population densities	Census 2010	0.495
varemp	coefficient of variation in census block group employment densities	LEHD 2010	0.313
dgrad	density gradient moving outward from the CBD	Census 2010, Tiger 2010	-0.375
popcen	percent of population in CBD or sub-centers	Census 2010	0.833
empcen	percent of employment in CBD or sub-centers	LEHD 2010	0.847
Eigenvalue			**1.90**
Explained variance			**37.89%**
Streets Factor			
smlblk	percentage of small urban blocks	Census 2010	0.871
avgblksze	average block size	Census 2010	-0.804
avgblklng	average block length	NAVTEQ 2012	-0.649
intden	intersection density	TomTom 2007	0.729
4way	percent of four-or-more-way intersections	TomTom 2007	0.380
Eigenvalue			**2.51**
Explained variance			**50.03%**

Note: Adapted from Ewing & Hamidi (2014), page 29

Finally, there is the question of how data should be presented. Ewing & Hamidi (2014) computed sprawl indices at four geographic scales. The one presented here was developed for metropolitan areas, but separate indices were developed for counties, urban areas (described later), and census tracts. Notably, these were all developed using distinct methodologies due to variable data availability, meaning that indices cannot be directly compared across geographic scales; this leaves no clear indication of what might be the “best” measure.

Beyond the question of what measure to use, there are conceptual issues stemming from scale as well. Ewing & Hamidi (2014) themselves note that while the District of Columbia has an extremely low composite sprawl measure among counties (sixth out of 969), the Washington MSA comes in 91st out of 221, since the metropolitan area covers a large swathe of exurban Virginia. Is the nation’s capital among our most compact places or merely a bit above average? While MSAs are used as the scale of analysis herein, given the theoretical preferences established earlier, it is worth asking whether sprawl would be better measured at smaller geographic scales instead.

However, if one was to adopt a sprawl index — either from Ewing & Hamidi (2014) or another source — that is based on a sub-metropolitan scale, this would raise questions of how to evaluate fragmentation within such areas. County-level data on government density are available, but not power diffusion. It is worth noting, however, that the structure and size of county governments can vary wildly between states (Hamilton, 2014), losing the appeal of reasonably standardized MSAs.

An alternative, then, might be to assess urban areas, which are developed following each decennial census using established procedures by the U.S. Census Bureau (Federal Register, 2011). Individual blocks with a population density of 1,000 people per square mile or more — 500 under some circumstances — are identified and aggregated; if the resulting cluster has a population of over 50,000, it is designated an urban area. Using this as a geographic scale, however, would make evaluating fragmentation even more complicated. Since urban areas cut across all boundaries except blocks, what share of a jurisdiction would need to be within the urban area to qualify? Alternatively, evaluating the degree of sprawl within an urban area with respect to the level of fragmentation of a metropolitan area raises questions as to the relationship between development patterns in urban and non-urban areas within a metro area. Would a specification that ignores this question by mixing and matching scales be valid? There is no clear answer, either intuitively or in the literature.

Leaving these concerns aside for the moment, however, it is worth considering other ways to evaluate sprawl. Indeed, if one only wishes to evaluate land use based on residential density, there do appear to be superior measures available. The most basic metric relies on these urban areas. If the geographic footprint of an urban area grows at a faster rate between decennial censuses than its population, meaning that acreage per resident is increasing, it can be said, *ceteris paribus*, that the level of sprawl in that area is increasing. Analysis of this relationship has long been in the literature (e.g., Brueckner & Fansler, 1983).

Similarly, more sophisticated extensions of this idea have employed GIS software and aerial photos to attempt to evaluate the level of sprawl by examining the nature of development on the fringe of urbanized areas (e.g., Hasse, 2002; Burchfield, Overman, Puga, & Turner, 2006). However, this sort of analysis only indicates whether an area's density has reached a minimum threshold and essentially ignores changes in density of the urban core.

The use of Longitudinal Employer-Household Dynamics (LEHD) data in the factor analysis by Ewing & Hamidi (2014) may hold promise; as the name implies, it provides information regarding the location and characteristics of all workers and workplaces. Data for many states now covers 13 years (2002 to 2014), allowing for more compelling comparisons over time. Rudimentary assessments of sprawl using LEHD have been developed (Hertz, 2016); further research should attempt to determine whether these data can more effectively define and assess the phenomenon of inefficient land use.

Overall, the relationship between fragmentation and sprawl appears to be much more muddled than that with residential segregation experienced by African-Americans assessed in Chapter IV. It is unclear whether a more refined statistical model would identify a correlation, or whether these patterns are driven by more localized development patterns that are not picked up in this OLS specification. The focus in Chapter VI will pivot toward the implications of local governance on metrics of economic well-being. A more complete discussion of these findings and others is included in Chapter VIII.

CHAPTER VI: ECONOMIC DISTRESS

In Chapter III, this work cited Stansel (2005) as a basis for the control variables in the OLS models developed herein. That paper was a key work in a rich and ongoing literature that seeks to determine what relationship, if any, exists between jurisdictional fragmentation and economic outcomes like income. Leland & Thurmaier (2004), among others, highlight the import of economic development messaging in local campaigns to consolidate jurisdictions, so the natural question is whether claims of government mergers leading to positive economic effects have a clear basis. Are regions that are more integrated better at creating prosperity for their residents? The answers have been decidedly mixed.

A key work in this literature is Nelson & Foster (1999), who sought to develop a model that would evaluate the impact of several measures of fragmentation on the change in per capita income between 1976 and 1996 for the 287 largest metropolitan areas in the United States. Data for independent variables were drawn from as near the start of that period as possible, Nelson & Foster (1999) note, such that "the model is designed to indicate causality" (317). Governmental density (defined as the number of jurisdictions per million residents in 1977) was included, as was a measure like the Rusk index and four other variables built to assess fragmentation. Last, four dummy variables were included to denote the presence of various categories of regional governance structures. Twenty-eight control variables were added to the specification to account for a variety of socioeconomic and locational factors.

The results were inconclusive. Neither density nor elasticity was found to have an impact on income growth. Only two policy variables were statistically significant ($p<0.05$): the percentage of the MSA population located within the central city and the presence of a two-tier federated county (e.g., Miami-Dade County, Florida), which were both negatively correlated with income growth. Reducing the significance threshold to $p<0.10$, however, makes the average population of a metro area's incorporated suburbs positively correlated with income growth.

There were fundamental issues with the approach implemented by Nelson & Foster (1999), however. Chief among these was the fragmentation and government structure variables being specified concurrently in a single model, despite obvious reasons to suspect collinearity among them (e.g., as a central city's population share increases, *ceteris paribus*, mean population of suburban municipalities must decrease). Inclusion of collinear variables increases standard errors in a regression model, leading to depressed t-statistics and potential false rejection of null hypotheses.

Indeed, there is evidence to suggest that this is, in fact, what happened. Of the 41 independent variables specified by Nelson & Foster (1999), 23 were not statistically significant, despite the model being a very good fit for the data (adjusted $R^2 = 0.76$). Indeed, all seven variables assessing sectoral composition of the regional economy, which seemingly should affect income growth, were not significant. Though the authors assert "there is no evidence of problematic multicollinearity among the variables" (317), they did not indicate how this conclusion was reached. Given these questions, it was unsurprising that there was interest in attempting to replicate the findings.

Stansel (2005) was, in many ways, a rejoinder to Nelson & Foster (1999), providing substantial commentary on their econometric methods. He wrote that his predecessors' work "seems to suffer from overspecification" and that "the inclusion of numerous conceivably irrelevant variables could explain their large number of insignificant coefficients" (58). For that reason, the narrower range of demographic and econometric variables was adopted. Further, he suggested government density and central city population share are "intended to measure the same thing" (Stansel, 2005, 61), and placed them in separate specifications to both mitigate collinearity and assess two different measurements of similar phenomena. Finally, he also noted that Nelson & Foster (1999) used dollar change in per capita income as the dependent variable, rather than a percent change, and that the decision to omit the smallest metropolitan areas was made without explanation.

Stansel (2005) measured governmental density (county, municipal, township, and special districts per 100,000 residents, as of 1962) and 1960 central city population share as his two gauges of fragmentation; his dependent variable was the percent change in real per capita personal income from 1959 to 1989 for the 314 metropolitan areas for which data were available. Six control variables were included. The results of the model provide clearer evidence bolstering the Tiebout hypothesis, with the densities of county and municipal governments positively correlated with real income growth. While perhaps on more methodologically sound footing, these results cover a period more than a quarter century in the past, suggesting that an update might be in order.

Outside of this narrow dispute between two similar papers, other works touch on the issue of fragmentation's role in economic outcomes, often with divergent results. For one, Carr & Feiock (1999) employ time-series econometrics to evaluate employment levels in the manufacturing and service sectors from 1950 to 1993 in nine counties that had undergone city-county consolidation between 1967 and 1984. In seven of 18 cases, employment was found to have increased. However, once statewide economic trends were factored in, the authors determined that consolidation did not have a statistically significant impact on employment levels in any of the metropolitan areas studied. Despite the rather limited sample size, this result suggests that state economies might have more influence on regional outcomes than local governmental conditions.

Indeed, there have been several works seeking to interrogate this relationship. Post & Stein (2000) sought to quantify impacts of jurisdictional fragmentation in relation to inequality between central city and suburban per capita income growth, as well as the role of statewide economic policy in altering that relationship, across the 150 largest metropolitan areas. The dependent variable is 1985-1989 income growth, controlling for growth in the urban core and the state as a whole; fragmentation is measured in parallel specifications as the number of cities per 10,000 residents and number of cities per square mile (much rarer measures of fragmentation in the literature). Unsurprisingly, there were strong correlations between state and regional economic growth, but the governance variables turned out not to be statistically significant; Post & Stein (2000) conclude regional inequality has other causes.

Rather than focusing on income, Ardashev (2005) used gross metropolitan product (GMP) as the dependent variable. His model seeks to assess covariates of GMP, focusing on four variables: fragmentation (i.e., MPDI), sprawl, educational attainment, and tax effort, with state economic performance as a control variable. Ardashev's (2005) measure of sprawl comes from Lopez & Hynes (2003), which compares the percentage of population in a metro area residing in census tracts on either side of a 3,500 people per square mile threshold; higher proportions of individuals in lower-density tracts indicate higher levels of sprawl. Ardashev (2005) finds that MPDI is positively correlated with GMP ($p<0.01$), aligning with the Tiebout position, but state economic performance is again a more consistent explanatory factor. High levels of sprawl, as measured by Lopez & Hynes (2003), were found to adversely affect economic performance, but only in metropolitan areas with a population between 250,000 and 1,000,000.

Lobao, Jeanty, Partridge, & Kraybill (2012) focused on poverty, as measured by the Census Bureau's Small Area Income and Poverty Estimates (SAIPE) and survey data on local economic development activities as their dependent variables. Employment growth was negatively correlated with government density in an OLS model, while it was not correlated with income, poverty, or child poverty in 2SLS models with spatial autocorrelation corrections. The relative amount of intergovernmental aid, however, was positively correlated with both poverty measures and negatively correlated with employment. Together, findings suggest that less fragmented and more autonomous regions have better outcomes, implying that state economic performance as well as budgetary and regulatory context may play a key role.

Paytas (2003) took a different approach, using shift-share analysis to develop a measure of metropolitan economic flexibility and competitiveness over the years 1973 to 1997. This was regressed against MPDI, as well as an index evaluating the level of fiscal and statutory authority states had over their localities, plus a handful of control variables. Fragmentation was found to be a drag on metropolitan adaptability, as was state centralization. Therefore, Paytas (2003) concludes, it is optimal for a region to be both internally unified and externally autonomous — a challenging imperative.

Further studies represent variations on these themes while pivoting away from the question of state governmental role. Hammond & Tosun (2011) evaluated growth in county-level population, employment, and real household income from 1970 to 2000, finding that number of special districts per square mile were positively correlated with growth among metropolitan counties, while general purpose governments per capita were negatively correlated in non-metro counties ($p<0.01$). Further, the share of local government revenue collected by counties was negatively associated with real income growth over the same period, suggesting areas where counties are the primary form of local government performed worse, *ceteris paribus*, than those where cities and special districts predominate. There was also some evidence that general purpose government density had an adverse effect on non-metro employment and population growth. Problematically, however, Hammond & Tosun (2011) specify models similarly to Nelson & Foster (1999), as the various measures of "fiscal decentralization" were specified concurrently, not separately, and appear to suffer from the same "kitchen sink" issue with control variables.

Grassmueck & Shields (2010) also employed MPDI in a multivariate context. Their work modeled three equations simultaneously, modeling changes in employment, income, and population at once, as outlined in prior literature (Carlino & Mills, 1987; Deller, Tsai, Marcoullier, & English, 2001). Grassmueck & Shields (2010) determined that fragmentation is positively correlated with all three variables. Notably, MPDI was computed only across general purpose governments, leaving aside the potential impact of special districts and other authorities.

Benner & Pastor (2014) assessed economic growth not as an ongoing process, but as discrete events, evaluating the length of regional "growth spells" to determine metropolitan resilience in the face of broader economic headwinds. The hazard model found that fragmentation (MPDI) and inequality (Gini), as well as the ratio between principal city and suburban poverty rates, were the three most significant contributing factors to the beginning of a regional recession. Metropolitan areas, then, are more economically resilient when politically integrated and less economically unequal.

Even further afield was Brueckner (2005), who developed two theoretical models of economies in a steady state condition (i.e., equilibrium that, unless affected exogenously, will persist in perpetuity), one governed by a unitary state and one with a federal system of government. Mathematically, Brueckner (2005) found economic gains from a more decentralized structure; namely, a federal system with variegated levels of taxation and public goods generates a higher level of saving among younger workers than a unitary one, which — per the work of Solow (1956) and others — leads to greater capital accumulation and, ultimately, high levels of economic growth.

Similarly, Hatfield (2015) developed a model finding that unified governments produce suboptimal tax policies and, by extension, suboptimal levels of social welfare. This occurs because government will, responding to the median voter, select a level of capital taxation that compromises economic growth. However, "Under a decentralized government, in every equilibrium at least one district will choose the growth-maximizing tax policy … and all capital will be invested in districts with this tax policy" (120). The degree to which these models reflect economic reality, however, is indeterminate.

Last, two recent papers have interrogated connections between fragmentation and adverse outcomes in the housing market. Newman, Gu, Kim, Bowman, & Li (2016) evaluated whether central city land area growth per capita (a measure, they note, explicitly inspired by Rusk elasticity) was correlated with vacancy rates measured by the U.S. Postal Service. While there was a strong bivariate correlation, wherein elasticity was found to be positively correlated with vacancies, there was only a weak finding ($p<0.10$) of correlation with residential vacancy rates once controls were added. Newman et al. (2016) had hypothesized a stronger finding, suggesting that spatial expansion of central cities into the exurban fringe would exacerbate the abandonment and blighting of urban properties; it is not explained why this authors suspected that phenomenon would be dependent on spatial expansion of the central city, as opposed to that of suburban municipalities. It is also worth noting that the study does not evaluate a large sample; only the 20 most and least elastic cities are examined in six consecutive years (2008 to 2013), and the statistical significance of annual fixed effects appear to eclipse the rest of the model.

Meanwhile, Acevedo-Garcia et al. (2016) include MPDI in a broader multilevel model seeking to identify correlates of the Location Affordability Index (LAI), a federal statistic that evaluates combined burden of housing and transportation costs for a given geography. Notably, residential segregation (as measured by Black-white and Hispanic-white dissimilarity) and sprawl (i.e., the Ewing & Hamidi (2014) composite index) are introduced as other policy variables of interest, as is a child opportunity index that measures educational, environmental, and socioeconomic conditions. LAI was found to be negatively correlated with sprawl, but positively correlated (in other specifications) with fragmentation and both segregation measures, contrary to their hypotheses. In the words of Acevedo-Garcia et al. (2016), “A possible explanation is that the neighborhood opportunity structure already reflects metro-area patterns of fragmentation and segregation” (627); in other words, it may be challenging to disentangle the effects of fragmentation itself from the socioeconomic impacts it has generated. This chicken-and-egg matter clouds the meaning of both the presence and absence of statistically significant findings in the prior chapters; this will be expounded upon later.

As noted previously, the four dependent variables of interest for this analysis are the percent change in household income, gross metropolitan product, poverty rate, and Gini coefficient between 2007 and 2013. Descriptive statistics for these variables are summarized in Table 6-1. The first two measures are available for 353 of 361 MSAs in the data set; eight regions were demoted from metropolitan status or absorbed into other MSAs in 2013, meaning comparable statistics are no longer collected. Suppressed data eliminated seven additional MSAs from the poverty and Gini computations.

Table 6-1: Descriptive Statistics of Dependent and New Control Variables (n=346-361)

Variable	Mean	Std. Dev.	Minimum	1st Quartile	Median	3rd Quartile	Maximum
HH income change	+4.48	7.95	-16.38	-0.84	+3.78	+8.85	+39.54
GMP ($M) change	+15.71	11.54	-10.08	+9.47	+14.94	+21.00	+119.01
Poverty change	+2.83	2.44	-6.1	+1.4	+2.7	+4.4	+10.2
Gini coef. change	+1.16	1.95	-7.38	+0.10	+1.27	+2.20	+8.20
Median HHI, 2007	47,630	8,340	29,347	42,079	45,903	52,406	83,798
GMP ($B), 2007	36.75	100.08	2.39	5.08	9.53	24.31	1,278.23
Poverty (%), 2007	13.8	4.3	4.7	10.9	13.4	16.1	34.7
Gini coef., 2007	44.4	2.7	37.0	42.6	44.5	46.1	53.4

Notably, GMP has increased substantially more over the period in question than median household income, suggesting returns to capital were substantially higher than returns to labor during and after the 2007-2009 recession. Positive outliers can generally be attributed to region booms in energy production; the four metro areas with GMP growth of over 50% were in North Dakota or west Texas.

As before, **it is hypothesized that more fragmented areas** (i.e., those with higher levels of government density, power diffusion, and Rusk elasticity index) **will, all else being equal, experience worse economic outcomes, namely lower rates of growth in income and economic activity** (as measured by GMP) **and higher rates of poverty and inequality** (as measured by Gini coefficient).

Tables 6-2 through 6-5 show the OLS regression results when these variables are regressed against the policy and control variables from Chapters IV and V, with the additional control to account for the initial level of the dependent variable in 2007. Overall, predictive ability, as measured by R^2, was substantially lower for these models than those specified previously, with one model (Rusk-GMP) narrowly failing to attain overall statistical significance using an F-test (p=0.0538).

Table 6-2: Percent Change in Nominal Household Income Regression Coefficients (t)

Governments per million residents, 2007	0.006 (3.11)		
Metropolitan Power Diffusion Index, 2007		0.138 (0.54)	
Modified Rusk elasticity index, 2010			-0.690 (1.70)
Median household income in thousands, 2007	-0.317 (3.19)	-0.363 (3.61)	-0.002 (0.01)
MSA population in thousands, 2007	-0.000 (0.03)	-0.000 (0.17)	0.001 (1.67)
Population change in percent, 2000-2007	-0.140 (2.27)	-0.160 (2.56)	-0.218 (2.72)
Housing units per square mile, 2007	0.002 (0.32)	-0.003 (0.55)	-0.006 (1.26)
Employment-population ratio, 2007	0.186 (1.49)	0.262 (2.11)	-0.070 (0.34)
Jobs in manufacturing sector (%), 2007	-0.293 (3.62)	-0.324 (3.99)	-0.279 (1.98)
Four-year college graduation rate, 2007	0.139 (1.84)	0.121 (1.58)	0.239 (2.02)
Percent of units built before 1940, 2007	-0.045 (0.76)	0.015 (0.24)	-0.119 (1.35)
Housing vacancy rate in percent, 2007	-0.297 (3.13)	-0.283 (2.95)	-0.420 (1.98)
Owner-occupancy rate in percent, 2007	0.076 (0.78)	0.079 (0.79)	0.039 (0.23)
Median SF home value in thousands, 2007	0.003 (0.42)	0.004 (0.72)	-0.012 (1.54)
Number of observations/R-squared	353/0.1788	353/0.1561	125/0.2145

Table 6-3: Percent Change in Gross Metropolitan Product Regression Coefficients (t)

Governments per million residents, 2007	0.002 (0.64)		
Metropolitan Power Diffusion Index, 2007		0.320 (0.86)	
Modified Rusk elasticity index, 2010			-0.697 (1.16)
Gross metropolitan product in billions, 2007	0.075 (2.05)	0.087 (2.28)	0.057 (1.83)
MSA population in thousands, 2007	-0.005 (2.00)	-0.006 (2.22)	-0.003 (1.51)
Population change in percent, 2000-2007	-0.106 (1.20)	-0.110 (1.25)	-0.037 (0.31)
Housing units per square mile, 2007	-0.002 (0.34)	-0.004 (0.51)	-0.009 (1.25)
Employment-population ratio, 2007	0.568 (3.49)	0.573 (3.55)	-0.013 (0.05)
Jobs in manufacturing sector (%), 2007	-0.292 (2.57)	-0.298 (2.64)	-0.144 (0.72)
Four-year college graduation rate, 2007	-0.106 (1.01)	-0.124 (1.18)	0.141 (0.86)
Percent of units built before 1940, 2007	-0.136 (1.61)	-0.147 (1.70)	0.063 (0.49)
Housing vacancy rate in percent, 2007	-0.415 (3.12)	-0.410 (3.10)	-0.464 (1.49)
Owner-occupancy rate in percent, 2007	-0.454 (3.56)	-0.472 (3.66)	-0.142 (0.63)
Median SF home value in thousands, 2007	-0.027 (4.49)	-0.026 (4.48)	-0.014 (1.94)
Number of observations/R-squared	353/0.2197	353/0.2204	125/0.1629*

Table 6-4: Change in Poverty Rate Regression Coefficients (t)

Governments per million residents, 2007	-0.001 (0.98)		
Metropolitan Power Diffusion Index, 2007		-0.010 (0.13)	
Modified Rusk elasticity index, 2010			0.304 (2.34)
Federally defined poverty rate, 2007	-0.245 (5.90)	-0.245 (5.87)	-0.106 (1.20)
MSA population in thousands, 2007	-0.000 (0.53)	-0.000 (0.40)	-0.000 (0.84)
Population change in percent, 2000-2007	0.070 (3.69)	0.072 (3.80)	0.102 (3.95)
Housing units per square mile, 2007	-0.000 (0.15)	0.000 (0.18)	-0.001 (0.84)
Employment-population ratio, 2007	-0.110 (2.94)	-0.115 (3.10)	-0.077 (1.09)
Jobs in manufacturing sector (%), 2007	0.054 (2.21)	0.057 (2.33)	0.102 (2.27)
Four-year college graduation rate, 2007	-0.011 (0.49)	-0.008 (0.38)	-0.089 (2.51)
Percent of units built before 1940, 2007	0.009 (0.46)	0.003 (0.14)	-0.025 (0.84)
Housing vacancy rate in percent, 2007	0.059 (2.06)	0.057 (1.99)	0.058 (0.85)
Owner-occupancy rate in percent, 2007	-0.105 (3.33)	-0.104 (3.27)	-0.071 (1.24)
Median SF home value in thousands, 2007	0.000 (0.25)	0.000 (0.26)	0.004 (1.85)
Number of observations/R-squared	346/0.2009	346/0.1987	124/0.3104

Table 6-5: Change in Gini Coefficient Regression Coefficients (t)

Governments per million residents, 2007	-0.001 (1.38)		
Metropolitan Power Diffusion Index, 2007		0.063 (1.08)	
Modified Rusk elasticity index, 2010			0.074 (0.82)
Gini coefficient (0 to 100 scale), 2007	-0.444 (11.17)	-0.440 (11.09)	-0.241 (4.19)
MSA population in thousands, 2007	0.000 (0.70)	-0.000 (0.11)	-0.000 (0.03)
Population change in percent, 2000-2007	-0.011 (0.76)	-0.009 (0.63)	-0.006 (0.32)
Housing units per square mile, 2007	0.002 (1.58)	0.003 (2.16)	0.001 (0.89)
Employment-population ratio, 2007	-0.044 (1.66)	-0.052 (1.96)	-0.014 (0.33)
Jobs in manufacturing sector (%), 2007	-0.013 (0.70)	-0.009 (0.50)	0.059 (1.90)
Four-year college graduation rate, 2007	0.052 (2.89)	0.052 (2.89)	0.016 (0.63)
Percent of units built before 1940, 2007	-0.007 (0.50)	-0.020 (1.44)	-0.023 (1.15)
Housing vacancy rate in percent, 2007	0.039 (1.80)	0.037 (1.70)	0.034 (0.69)
Owner-occupancy rate in percent, 2007	-0.026 (1.23)	-0.029 (1.33)	0.004 (0.12)
Median SF home value in thousands, 2007	-0.001 (1.28)	-0.001 (1.17)	0.002 (1.65)
Number of observations/R-squared	346/0.2922	346/0.2906	124/0.2480

Only two specifications had a significant policy variable at the 95% level, namely positive correlations between increased poverty rates and the modified Rusk index and governmental density is positively associated with income growth. Both findings are in the opposite direction hypothesized, i.e., more fragmented regions performed better in both instances. None of the three fragmentation measures were correlated with change in GMP or Gini.

The overarching takeaway — given that few policy variables were significant and overall goodness of fit was substantially lower than models from Chapters IV and V — may be that local government structure may have less impact on economic outcomes than sociospatial ones. This is particularly notable given that campaigns for city-county consolidation and other forms of government reorganization are most often successful when appealing to concerns about economic development (Leland & Thurmaier, 2004). These findings, however, are based on limited data, so it would be ill-advised to place too much weight on them; perhaps the results would have been different if changes in economic variables during more conventional times were examined.

While all outcomes estimated in this chapter are established economic metrics, they are not without their caveats. Critiques of gross domestic product as a measure of economic activity are longstanding and diverse, as the measure does not consider factors such as household labor and environmental degradation, as well as other elements of social welfare beyond financial transactions (Stiglitz, Sen, & Fitoussi, 2010). Even putting aside these definitional concerns, there are challenges in accurately measuring GDP, which are numerous ("The Trouble with GDP," 2016).

The federal poverty line, and the rate calculated therefrom, has also often been pilloried in the literature. The modern threshold has its origins in the 1963 work of economist Mollie Orshansky, which was set at three times the cost of a subsistence diet from U.S. Department of Agriculture estimates; the measure was never intended to be a blanket measure of poverty, but was adopted by the Johnson Administration as such. This measure has essentially been maintained, adjusted for inflation since (Fisher, 1997). While other measures of poverty exist, including the supplemental poverty measure produced by the U.S. Census Bureau (2015) and others (e.g., Kutty, 2005), that are more complex and consider a more multifaceted approach to household welfare, research is again limited by the availability of data. The ubiquity of the poverty line and the degree to which it is used in instruments such as the ACS inhibits the adoption of alternatives.

Last, the Gini coefficient is far from the only measure of economic inequality. Much like the dissimilarity index in Chapter IV, it is largely the second most utilized of a set of imperfect alternatives. (The idea of income ratios by percentile clearly supersedes more sophisticated metrics in public consciousness, given recent political phenomena such as the Occupy Movement and the presidential campaign of Sen. Bernie Sanders.) Other measures such as the Theil index, Atkinson's index, and the Hoover index all have their advantages and disadvantages, but the challenge of computing such figures over the hundreds of geographies reviewed herein, let alone others, is prohibitive without an extensive staff. Research of this sort does exist at the state level, however (Frank, 2014).

This work will now pivot to a new methodological approach with a pair of new policy outcomes, namely median housing costs and the quality and cost of public education within public school districts. This constitutes part of a broader, more holistic effort at measuring the impacts of fragmentation and the validity of the Tiebout (1956) and Alonso (1960) theories with respect to the economics of real estate.

CHAPTER VII: HOUSING COSTS AND EDUCATION IN OHIO

Alesina, Baqir, & Hoxby (2004) and Hanushek & Yilmaz (2007), as noted earlier in the literature review, have suggested that there may be a relationship between the density of school districts within a region and the efficacy of the educational systems operated therein. By now, the theoretical question should be clear. Tiebout (1956) argues that public goods are provided more efficiently by many small governments, each calibrating their bundles of taxes and services to attract residents; having more choices leads to households being able to select a municipality that more closely meets their preferences. This thesis is offered as a critique of the alternative premise that larger entities operating at the regional level can provide services in a more cost-effective manner due to economies of scale, improving social welfare by reducing the level of taxation required to achieve a certain level of service provision. Controlling for other factors, are locations with larger or smaller school districts generating higher student performance?

Meanwhile, seminal works in urban economics noted earlier (Alonso, 1960; Oates, 1969) submit that the value of public education will be capitalized in residential property values and, hence, the cost of housing. In other words, because education is a public good with a clear *prima facie* economic value to households, particularly those with school-aged children, houses and apartments in higher-performing school districts should be more expensive than those located in lower-performing ones are, all else being equal. While it seems clear that schools in distressed urban and rural communities perform worse than those located in wealthy suburbs, the direction of causality in this relationship is less clear, especially as there are often vast economic and demographic disparities between such areas. Are schools better where housing costs more, or does housing cost more where schools are better? Alternatively, what conflating factors might explain this relationship instead? Might both housing costs and educational achievement be separately driven by entirely different characteristics? These are the questions will be assessed in this chapter.

The connection between government fragmentation and local housing policy is one that has been underappreciated in the literature, but has been noted at times. Basolo (1999) shows that, among other findings, local governments are significantly less likely to expend funds on affordable housing when facing higher levels of intercity competition, i.e., a more fragmented metropolitan area. Basolo (2000) then explicitly contrasts this relationship with local economic development spending, showing that the ratio of expenditures in the latter relative to the former is positively correlated with the level of fragmentation. "[I]nter-city competition limits policy choices by local decision makers. In an effort to maintain fiscal health, policy makers will favor developmental policies such as economic development programs and avoid redistributive policies such as affordable housing programs" (329), she notes, highlighting that this aligns with expectations in public choice theory.

This is made even clearer by Basolo and Hastings (2003), where it is demonstrated that "fair share" housing policies are almost universally a function of contested state-level policy (e.g., New Jersey's *Mount Laurel* decision; see Massey, Albright, Casciano, Derickson, & Kinsey, 2013) rather than local initiative. Notably, even in metropolitan areas with the strongest histories of collaboration among localities and political climates favoring social equity (Minneapolis-St. Paul and Portland, Oregon), regional action toward affordable housing is compromised by weak enforcement mechanisms and anti-development biases.

Dawkins (2009) examines how the built environment can affect first-time homeownership rates, assessing three elements: density, fragmentation, and the presence of an urban growth boundary, or UGB. The analysis uses Panel Study of Income Dynamics (PSID) data, which provide a sample of renters who formed an independent household between 1978 and 1987. Dawkins (2009) summarizes:

> For the average renter in the sample, first-time homeownership occurs sooner in areas with lower urban densities, increased local government fragmentation, and the presence of a regional UGB. The effects of UGB presence and local government fragmentation are largest among suburban low-income households (84).

The author notes later, however, that the finding for density is not statistically significant when controlling for median home value. This result presents some interesting implications, as it suggests that the goals of homeownership and cohesive regional governance are at odds; Dawkins (2009) submits that this is a finding consistent with the Tiebout (1956) hypothesis. More perplexing is the finding regarding urban growth boundaries, as one would expect UGBs to restrict housing choice. It is possible that a UGB makes home rental relatively more expensive vis-à-vis homeownership, prompting younger adults to buy real estate. Dawkins (2009) notes, however, that UGBs often exist in states where fair-share housing statutes or other comprehensive planning measures exist to enhance affordable housing availability.

Approaching the topic from another angle, Katz & Turner (2001) discuss the difficulties in administering the Section 8 voucher program (now known as the Housing Choice Voucher program) that stem from jurisdictional fragmentation. “The current balkanized system undermines the potential of the program to promote mixed-income communities and the deconcentration of poverty” (239), Katz & Turner (2001) argue, noting that public housing authorities (PHAs) typically have jurisdiction over individual cities or counties. Exclusionary zoning limits the amount of rental housing in suburban jurisdictions, concentrating rental properties that could be obtained with vouchers in central cities. Property owners in wealthier locales may refuse to accept vouchers, whether for purely economic or discriminatory reasons. In short, “By fragmenting the metropolitan rental market, the current system makes it difficult for low-income families, particularly minority families living in central cities, to know about and act on the full range of housing options” (Katz & Turner 2001, 241).

Katz & Turner (2001) argue that public housing authorities should conform to the boundaries of metropolitan areas, a practice that only existed then in Portland, Oregon, and Jacksonville, Florida. This, they argue is essential to ensure not only that voucher holders have housing choice, but also to ensure they can live near potential sources of employment. Echoing arguments outside the public housing arena, they conclude:

> If HUD were developing a housing voucher program from scratch … it seems unlikely that local PHAs would be the first choice as administrators for sprawling metropolitan areas. Instead, it would make more sense to foster the development of regional entities capable of administering the program across the housing market as a whole (Katz & Turner, 2001, 259).

Though much of the research asserts affordable housing policy is compromised by fragmented local government, there is a substantial community of researchers arguing that the opposite is true. While there are lengthy treatises in defense of the Tiebout hypothesis that address affordable housing in passing (e.g., Fischel, 2001), an econometric argument is made by Aurand (2007) that consolidation would constrict the supply of affordable housing.

The work presents two hypotheses. The first is that affordable rental housing will be more segregated in metropolitan areas with higher levels of fragmentation. The second is that the share of affordable rental units available will be negatively correlated with fragmentation. Aurand's (2007) hypotheses are consistent with the Tiebout model, as well as broader public choice theory, as they suggest municipalities will become more homogeneous through sorting and that competition for property tax revenue among numerous jurisdictions will make dedicating resources toward affordable housing provision a relatively costlier proposition.

Aurand (2007) finds, through OLS regressions, that there is no clear statistical relationship between fragmentation and affordable housing segregation (as measured by a dissimilarity index). Meanwhile, there was a clear positive correlation between fragmentation (as defined by both MPDI and governments per capita) and the supply of affordable housing. Aurand (2007) suggests this could be due to either a "monopolistic zoning power," leading to a dominant municipality driving high property values, or anti-development impulses overriding "rational" economic decision-making.

In an extension of this analysis, Aurand (2013) considers the relationship between sprawl and affordable housing provision. The author considers arguments that more spatially inefficient land use patterns facilitate filtering in the real estate market, thereby making more housing available to low-income households. To test this thesis, Aurand (2013) presents the change in quantity of affordable housing over time as a function of changes in sprawl, housing input costs, and demographic factors that influence housing demand. The econometric analysis does not indicate a statistically significant relationship between sprawl and affordable housing supply in either direction, a finding he suggests is consistent with existing literature.

To conduct an analysis of the sort proposed here, it is necessary to collect a large quantity of data across public school districts. Given the American political context, where the federal role in education is rather limited, particularly after passage of the 2015 Every Student Succeeds Act (U.S. Department of Education, n.d.), developing a consistent measure of educational achievement across districts in multiple states would be extremely challenging. Therefore, unlike other work conducted herein, it is necessary to limit analysis to a single state. In this case, that state is Ohio.

Based on data from the U.S. Census of Governments (Briem, 2011; Miller, 2012), Ohio has a particularly high level of fragmentation. With respect to school districts, however, the degree of fragmentation ranges widely within the state; the number of districts per 100,000 county residents ranges from 1.32 (Franklin) to 25.94 (Putnam), averaging 5.27 for the statewide (i.e., 614 districts serving 11.6 million people), per the 2012 Census of Governments. This means there is a wide dispersion of political configurations even within a single state with one set of laws regarding incorporation and disincorporation of local governments. Beyond this, there is reason to think that these divides have implications, not only as discussed earlier, but specifically with respect to Ohio. Specifically, Katz & Turner (2001) state, "Central business districts in Ohio's seven major cities [Akron, Canton, Cincinnati, Cleveland, Columbus, Dayton, and Toledo] experienced a net increase of only 636 jobs [between 1994 and 1997]. Their suburbs, by contrast, gained 186,410 new jobs" (243).

There are similar variations in the other variables of interest. Monthly median housing costs by district (including utilities), as reported by 2010-2014 ACS Five-Year Estimates, ranged from $411 (Frontier Local School District, Washington County) to $1869 (Indian Hill Exempted Village School District, Hamilton County). Last, educational attainment is measured using Performance Index Percentage, which aggregates scores from standardized tests administered in grades 3 to 8, as well as the Ohio Graduation Test (first administered in grade 10). These figures are then calibrated to a 100-point scale and assigned corresponding letter grades; scores for the 2013-14 academic year ranged from a mid-A of 94.2 (Wyoming City, Hamilton County) to a low D of 60.0 (Warrensville Heights City, Cuyahoga County) (Ohio Department of Education, 2016a).

Keating (1994) profiles the history of racial residential segregation in Cuyahoga County, Ohio, during the late 20th century. This area, which includes Cleveland and many of its suburbs, fell from being an industrial powerhouse and home to one of the ten largest cities in America to a Rust Belt also-ran within this time frame. The book opens by noting multiple studies that found the Cleveland metropolitan area to be the second most segregated for racial minorities in the country, with only Chicago rating worse. Keating (1994) articulates the negative consequences of isolation for African-Americans and the need for integration, relying heavily on prior work by Downs (1973), as a fundamental crisis for urban and suburban communities.

While this can in large measure be attributed to federal policies like redlining that established racial boundaries as the city reached maturity, which Keating (1994) addresses at length, substantial attention is paid to the structure of local government. He notes that efforts to bring about fair-share housing in Cuyahoga County — like what New Jersey implemented due to the *Mount Laurel* decisions — were stymied by the obstinacy of most suburban governments; a lawsuit filed by tenant groups to compel compliance was rejected by the federal courts, largely based home rule authority held by municipalities.

Keating (1994) notes that efforts to develop metropolitan governance began in Cuyahoga County in 1927; in 1935, a county charter was approved by voters, but was invalidated by the Ohio Supreme Court (*State ex rel. Howland v. Krause et al.,* 1936). Four later efforts would be made to reform county government, but all were rejected. Cuyahoga County would eventually adopt a charter in 2009, though the primary change that took place was the replacement of a three-member county commission with an executive and 11-member council; no authority was transferred from municipalities to the county government (Naymik, 2009).

One area in Ohio made a serious effort to implement fair-share housing. In 1970, the Miami Valley Regional Planning Commission (MVRPC) enacted such a plan for the Dayton area. While MVRPC overwhelmingly represented suburban municipal interests, Keating (1994) notes, elected officials and school districts in those communities turned against the proposal. While the effort had strong federal support at the outset, notably from HUD Secretary George Romney, President Nixon essentially ensured that federal authorities would not go about enforcing any such policy.

Keating (1994) contrasts the fates of various inner-ring suburbs. Shaker Heights and Cleveland Heights racially integrated while retaining economic prosperity; this is partially attributed to a commitment by municipal authorities to financially support fair housing efforts. East Cleveland, through what Keating (1994) suggests was a mix of ineffective leadership and race-neutral policies, is today almost exclusively African-American and deeply financially distressed, to the point where a merger with Cleveland is under consideration (Atassi, 2016). On the west side, Parma remains overwhelmingly white despite federal court remedies in response to fair housing lawsuits that proved overt racial bias and intimidation toward African-Americans living in the community.

This work is not the first occasion where fragmentation, housing, and education were jointly assessed quantitatively in Ohio. Margulis (2001) modeled the probability of property resale by municipality in four Cleveland-area counties. An OLS regression model found that city size and housing stock characteristics did not have statistically significant coefficients in either Cuyahoga County or its suburban neighbors, suggesting to the author that a Tiebout-style model would better explain market dynamics.

Therefore, Margulis (2001) added per capita expenditures and a handful of school district quality measures. City size was negatively correlated with property turnover, and was in fact the only statistically significant variable in Cuyahoga County. In the suburban counties, general government expenditures per capita were also negatively correlated with turnover, while amenity expenditures per capita and a composite education measure were positively correlated with the dependent variable.

It is unclear, though, whether this dependent variable truly registers preferences of consumer-voter households. Margulis (2001) states, “A high number of moves … indicates that the municipality possesses characteristics that appear to meet household expectations; a low number of moves … indicates that households are not attracted to the municipality because it does not possess conditions conducive to high in-migration” (662). Of course, it is necessary for each buyer to be matched with a seller, as this data set does not include new housing construction, so it is unclear why a high resale probability would necessarily indicate desirability.

Nationally, the interconnected nature of relationships among land economics, education, and local governance investigated here were explicated by Ulfarsson & Carruthers (2006), who assessed longitudinal data on 777 counties in 309 metropolitan areas using a two-stage generalized least squares fixed effects model. As hypothesized, municipal fragmentation is bi-directionally correlated with lower levels of density and urbanization and higher property values. Fragmentation is also far more likely to be present in locations with larger populations and older housing stock.

Notably, regarding state-level locational effects in Ulfarsson & Carruthers (2006), Ohio was found to have higher than expected government density relative to the nation at large, given the model design, but less urbanized land and lower property values. Fragmentation levels, however, were not found to be significantly divergent from the national mean. While works such as Miller (2002) show that Ohio's metropolitan areas are among the most fragmented in the country, this model indicates that this is simply a function of the variables that Ulfarsson & Carruthers (2006) indicate are determinants of that structure. Therefore, there is apparent value in evaluating fragmentation's role in housing and education policy outcomes through a more nuanced model.

As noted earlier, this work employs a three-stage least squares (3SLS) model, developed by Zellner & Theil (1962), where median gross housing cost (2010-2014 ACS) and aggregate standardized test scores (2014 ODE data), measured by school district, are both dependent variables, with each as an independent variable for the other. Instead of running separate OLS specifications, however, the 3SLS model evaluates the equations jointly as a system, accounting for simultaneous, bidirectional causality and correlated error terms across equations to maximize model efficiency.

Jurisdictional fragmentation is the central independent variable of interest, as in previous chapters, though it is measured here at the county level due to a change in geography. School districts per 10,000 residents were computed based on population and Census of Governments data for 1957 and 2012, with both included as independent variables in each equation. Also, median household income and population density (2005-2009 ACS) are independent variables in both equations specified.

Other controls in the model are dictated by the dependent variable employed. The housing cost equation is supplemented simply by two measures used earlier from the 2005-2009 ACS that describe local housing market: the percentages of housing units that (a) were built before 1940 and (b) are owner-occupied. There is a clear *prima facie* case for presuming that age and tenure are relevant to the price of housing.

In the test score equation, again, two 2005-2009 ACS variables from the earlier OLS models are used: percent of residents who are white non-Hispanic and the percent of adults aged 25 or older with a four-year college degree. Intergenerational persistence of educational attainment has been well documented in relevant literature (e.g., Huang, 2013), while whiteness of the district serves as a proxy for explicit and implicit racial biases in education (e.g., Rudd, 2014; Gershenson, 2015; White, 2015).

Beyond these, as briefly discussed in Chapter III, three fiscal variables are included as potential correlates of test scores. The first of these is equalized property valuation per pupil, computed by ODE in 2014, which indicates the tax base (commercial as well as residential) from which a school district can raise revenue; one would expect districts with fewer physical assets would have lower standardized test performance.

The second variable is property tax millage, i.e., the levy charged per $1,000 of valuation. This was reported by the Ohio Department of Taxation in 2014. Controlling for the tax base noted above and all other variables, one would expect districts with higher tax rates to have better test scores, as they would have more financial resources available to allocate toward instruction. Notably, school districts in Ohio must assess properties at a minimum of 20 mills to be eligible for state aid, though many districts charge themselves a much higher rate; importantly, however, Ohio counties assess properties at 35% of market value, so reported millage is nearly three times higher than the "real" millage, if assessed and market valuations are equal (Sullivan & Sobul, 2010).

Notably, Ohio is rare among states in that they allow school districts to levy income taxes directly upon residents of the district and/or employees of firms within its boundaries, subject to referendum (Ross, 2012). These are assessed as a fixed share of total income, i.e., a flat tax. That rate, which ranges from 0% (if no tax is assessed) to a maximum of 2%, is included as the third variable. Again, *ceteris paribus*, one would expect academic achievement to be positively correlated with this variable.

This bifurcation of local revenue sources for K-12 education allows for the testing of whether the relationships between educational outcomes and revenue are the same across sources of incidence. It is, of course, worth emphasizing the word local here; federal and state funds for education are not measured in this model, which does make the revenue picture incomplete, but local funds are a plurality of revenues for school districts in Ohio (Cornman, 2015), and it may be worth ignoring intergovernmental aid within the context of evaluating the Tiebout hypothesis.

On the advice of reviewers, two changes were made to this initial construction. First, median household income was added as a third dependent variable. Given the nature of the other controls and their correlation with income, particularly educational attainment, there is ample reason to suggest that this should be considered endogenous to the system of equations being modeled, rather than simply a parameter. That third component includes the same independent variables as the test score equation.

Second, the model did not account for housing quality, potentially introducing latent bias. Unfortunately, the avenues for doing so are quite limited by data availability. The only variables in the 2005-2009 ACS that directly address housing quality are those reporting whether a unit has incomplete kitchen or plumbing facilities; only 2-3% of homes fall in each category, however, so they are only relevant at the very lowest strata of housing stock. The only viable alternative within the ACS was to account for the physical size of a housing unit, as assessed by including the percentage of homes in a school district with four or more bedrooms in the median gross housing cost equation. While this is admittedly an imperfect control, its inclusion in the model is warranted. Ideally, there would be better metrics of housing quality, but its subjective nature and inconsistent condition and valuation measures among counties make this challenging.

Overall, then, the model developed here offers a rudimentary yet generally comprehensive model of the mechanisms that, theoretically, should inform the housing, educational, and economic conditions of local jurisdictions. Before proceeding, though, a brief review of the control variables is warranted. Table 7-1 provides summary statistics for these elements of the model. Even within a single state, there are radical differences across school districts; the median household in the wealthiest district earns more than seven times more than the median household in the poorest district does. Notably, many distributions are radically skewed; the median district is more than 95% white non-Hispanic, despite the state being much more racially and ethnically diverse. Most districts elect not to impose income tax; those that do are concentrated in the northwest part of the state.

Notably, fragmentation levels were higher in 1957 than 2012; there were 1,168 districts in 1957, nearly twice the number today, despite having a smaller population. Through the mid-20th century, there was a concerted effort to merge districts in rural areas, one that — given two recent mergers and support from state government — may yet re-emerge ("Merging Schools," 2014). A full set of bivariate correlations is included in Appendix D, but notably, there was essentially no relationship between school district performance and jurisdictional fragmentation (r=0.02), while there was a strong positive correlation between performance index and housing costs (r=0.50).

Table 7-1: Descriptive Statistics of Ohio School District Variables (n=609)

Variable	Mean	Std. Dev.	Minimum	Median	Maximum
Median monthly gross housing cost, 2010-2014	$853	$241	$390	$798	$1922
Performance index percentage, 2013-14	82.6	5.3	60.0	83.0	94.2
Median nominal household income, 2005-2009	$51,345	$14,345	$16,384	$49,386	$118,324
School districts per 100,000 county residents, 2012	7.9	4.6	1.3	7.3	25.9
School districts per 100,000 county residents, 1957	21.0	16.8	1.9	17.2	109.3
Total population per square mile (density), 2007	750.5	1,181.6	25.0	203.3	9,284.2
Percent of housing units built pre-1940, 2005-2009	22.1	12.8	1.0	21.3	73.9
Percent of housing units owner-occupied, 2005-2009	77.0	10.2	37.1	78.9	96.3
Percent of housing units w/4+ bedrooms, 2005-2009	20.7	8.6	6.0	18.8	69.2
Percent of population white non-Hispanic, 2005-2009	91.6	11.1	5.3	95.2	99.9
Percent of adults 25+ with college degree, 2005-2009	19.4	12.9	2.6	15.1	74.4
Property market valuation per pupil, 2014	$141,282	$64,199	$45,379	$129,954	$757,881
School district property tax millage, 2014	52.5	20.7	20.1	48.9	186.8
School district income tax rate (%), 2014	0.35	0.55	0.00	0.00	2.00

Results of the 3SLS model (see Table 7-2) were appreciably different, however. Including both past and present fragmentation lead to mixed results across all three dependent variables. The highest t-statistics align with expectations (i.e., that richer communities would have higher housing costs, that whiter districts would have higher test scores, etc.). Coefficients for race and education in the income equation have an unexpected sign; this can be accounted for by inclusion of test scores. A Sargan-Hansen test indicated that the model was not overidentified (p=0.9841).

Table 7-2: Ohio School District Three-Stage Least Squares Model Results (t) (n=609)

↓ Independent Variable \ Dependent Variable →	Housing Cost	Test Scores	Income
Median monthly gross housing cost, 2010-2014		0.000 (0.20)	
Performance index percentage, 2013-14 school year	-4.239 (2.30)		6511 (9.03)
Median nominal household income, 2005-2009	0.018 (15.23)	0.000 (4.92)	
School districts per 100,000 county residents, 2012	-7.410 (5.86)	0.170 (3.46)	-1090 (4.27)
School districts per 100,000 county residents, 1957	0.486 (1.53)	-0.035 (3.43)	227.5 (3.38)
Total population per square mile (density), 2007	0.005 (1.09)	-0.000 (2.32)	2.665 (2.25)
Percent of housing units built pre-1940, 2005-2009	-0.784 (2.22)		
Percent of housing units owner-occupied, 2005-2009	-3.679 (5.95)		
Percent of housing units w/4+ bedrooms, 2005-2009	-1.369 (1.29)		
Percent of population white non-Hispanic, 2005-2009		0.237 (16.33)	-1539 (7.74)
Percent of adults 25+ with college degree, 2005-2009		0.094 (3.98)	-628.3 (3.47)
Property market valuation per pupil, 2014		0.004 (1.85)	-28.94 (1.90)
School district property tax millage, 2014		0.015 (1.49)	-101.0 (1.55)
School district income tax rate, 2014		0.142 (0.56)	-624.3 (0.40)

This model generates one finding drastically at odds with longstanding theory, however; an increase in performance index is associated with a drop in median gross housing cost. Why are these variables inversely correlated? Why does this model argue against the hypothesis laid out by Oates (1969) that has attracted widespread and decades of empirical and theoretical support? The intuitive explanation — given that the other coefficients in the model conform to expectations, and there is no reason to suspect parents do not consider their children's education to be a valuable public good — is that excess assumptions are being made.

For an economic agent to behave in a way that follows the Tiebout (1956) hypothesis and its theoretic extensions, that individual or household must have complete knowledge of taxes paid and public goods provided. Further, this knowledge must play an appreciable role in household decision-making. In the former case, there is reason to think this may be close to reality, considering income taxes must be filed annually and homeowners regularly receive statements apprising them of their property tax bills, even if they are paid in escrow. In the latter case, is there similar evidence?

Does the typical household have a complete, or even working, grasp of the quality and quantity of public goods they receive with which to vote with one's feet? Do parents review and understand, for instance, performance index data cited here when they are looking for a community for their family to call home? If so, do these data drive households to locate in a way consistent with the "vote with your feet" model?

A comprehensive evaluation is beyond the scope of this work, but recent literature suggests the theoretical underpinnings necessary to justify the framework articulated by Oates (1969) may not hold. For one, Rhodes & DeLuca (2014) examine the decision-making processes of low-income households with respect to school enrollment in Mobile, Alabama, through in-depth interviews. While parents clearly express a preference for their children to go to quality schools, other concerns matter more: "Poor families do not make residential decisions based on school considerations; rather, they emphasize factors such as safety concerns, proximity needs for child care or transportation, and housing amenities" (Rhodes & DeLuca, 2014, 159). Further, when educational concerns are relevant, they are expressed in subjective observation rather than quantifiable data. "Notably missing from discussions about school choice and what makes a 'good school' are policy-focused measures of academic school quality; families rarely talk about test scores, teacher qualifications, or classroom size" (155-156).

This apparent disconnect does not apply only to those in economic distress, however. Lareau (2014) conducted another set of interviews with parents from a variety of different class and race backgrounds in the Philadelphia suburbs. In general, her work concluded that locational choice is entirely unquantified. Households with the time and resources to assess publicized information about schools generally did not do so, relying instead on consensus among friends about what constitutes a "good" school district. Research, if done, was often conducted after the fact and subject to confirmation bias. Parents had little knowledge of schools that were not nearby and, if confronted with the possibility they may have made a suboptimal choice, "downplayed the significance of the school choice in a life trajectory" (Lareau, 2014, 194). Ultimately, parents are simply not able or willing to evaluate educational quality effectively, relying on word of mouth and the desire for a vague sense of belonging. Notably, this contrasts with a strong level of reported involvement in their children's education evidenced in volunteer activities, encouraging extracurricular activities, and the like.

How does this help to explain the unexpected results of the model? Not only do parents not behave in a way consistent with education being evaluated as a public economic good, but they also appear to assume school quality is a function of more easily observed neighborhood factors. Lareau (2014) cites a Gallup poll finding that 19% of parents give the U.S. education system a grade of A or B, while 77% do so for their eldest child's school; parents appear to believe the problem of low-quality schools is a concern for others, not themselves. Controlling for demographic and socioeconomic factors, as this model does, may eliminate the intangible "belonging" element. Might it be the case, then, that more distressed districts, far from being a waste of state and federal resources, over-perform relative to expectations based on exogenous factors? Such a hypothesis clearly merits further study.

Finally, there are limitations in the measurement of education data elided here. As noted, given the sharply limited role of the federal government in developing education policy, there is no national measure of student assessment. In Ohio, there are two primary means of evaluation. The first is the performance index, which assigns a point value to various thresholds on standardized tests in both reading and math for students in grades 3 to 8 and on the Ohio Graduation Test. A further calculation places this index on a 0-to-100 scale to create the performance index percentage.

There are potential issues with this index. First, PI is computed asymmetrically to ensure that students who do not register as “proficient” have a larger impact on scoring than those who far exceed that level. A proficient student receives one point; two levels of achievement below proficient receive 0.3 and 0.6 points, while the three tiers above proficient receive only 1.1, 1.2, and 1.3 points. This approach may understate the degree to which high-performing districts exceed state benchmarks or, alternatively, overstate the deficiencies of low-performing ones. It would be necessary to obtain raw student achievement data to determine the impact of this asymmetry.

Second, it is unclear that the thresholds are meaningful. There is not a consistent number that correlates with a certain assessment rating across tests; a “proficient” score corresponds to a different number of correct answers on different tests; performance index thresholds also vary, not only in raw score but also scaled scores (Ohio Department of Education, 2014). Hence, equivalent results on different tests may yield different results. It would be preferable to have an index accounting for every student’s score as a continuous variable, but no such measure does so with raw scores.

Third, the performance index automatically assigns a score of zero to students who do not take the standardized tests. As Common Core educational standards have become a topic of heated political debate, an increasing number of parents have decided to opt out of testing. Further, these children and their families are not necessarily representative, potentially skewing results (Strauss, 2016).

Given these caveats, then, one might wonder if there is an alternative measure that could be used instead of the performance index. As it turns out, there is, though it also has a great number of methodological challenges as well. “Value added,” which is also based on state standardized test results, seeks to measure educational growth rather than raw achievement, controlling for district, school, and teacher factors, as well as the student’s own past scores. In recent years, Ohio has begun reporting value added scores by grade, subject, and various special populations, such as gifted students and English language learners (Ohio Department of Education, 2016b).

There are methodological concerns with value added, chief among them the fact that the model is a proprietary computation (Battelle for Kids, 2015). Fundamentally, however, the problem with a more complex measure is that it fails to comport with parental behavior. At its core, given that education is being evaluated in the Chapter VII model as a function of housing costs, what is most important is not the degree to which children are learning, but the collective perception thereof, as this drives willingness to pay of economic agents in the real estate market. This would be a highly challenging thing to measure, however, so actual achievement is used as a proxy.

Prima facie, it can be argued that parents, to the extent that they observe educational data, would be more likely to care about a single number that measures how “good” a district does on standardized tests, rather than a complicated calculation with readings that could be at odds with one another. However, as Lareau (2014) and Rhodes & DeLuca (2014) suggest, even this may be invalid, as parents in a variety of economic strata rely largely on the opinions of friends and acquaintances, which are described as far from rigorous.

Regardless, there needs to be a much greater breadth and depth of research into describing and quantifying the decision-making process when it comes to selecting a school for one’s children. Given the paramount role that schools play in the location decisions of many households, it is an under-analyzed element. Furthermore, there is a role for better measuring actual achievement and disseminating that information in a clear and intelligible way to parents weighing locational decisions.

CHAPTER VIII: CONCLUSIONS AND DISCUSSION

Throughout this work, econometric analysis has sought to determine whether local government structure is relevant to public policy outcomes, and if so, in what way. Perhaps the two clearest findings herein were that jurisdictional fragmentation, as measured by the Metropolitan Power Diffusion Index (MPDI), was correlated with both residential segregation experienced by African-Americans (Chapter IV) and low levels of residential density (Chapter V).

While each is interesting alone, these findings together suggest a hypothesis. If, as a function of local government structure, African-Americans are residing in more isolated enclaves with depressed levels of density (which implies more spatially distant non-residential land uses, namely employment opportunities), the elements are in place for a vicious cycle that deprives black neighborhoods of their economic potential.

There is much assessment in the literature of the “social mismatch hypothesis.” In short, starting with Kain (1968), many works have discussed the role that geographic concentration of poor working age adults, particularly African-Americans, in severely distressed neighborhoods has on the labor market (Ihlanfeldt, 2006). Suburbanization in new automobile-centric communities following World War II was largely a whites-only phenomenon, as the Federal Housing Administration, banks, and real estate agents implemented segregationist policies (Jackson, 1987). Later, as workplaces followed suburban residents out of the central city, impoverished African-Americans found themselves stranded,

> forced to choose between buying a private automobile and thus spending a disproportionate share of their low incomes on transportation, making a very long and circuitous trip by public transit (if any service is available at all), or foregoing the job altogether. Where the job in question is a marginal one, their choice may frequently be the latter. More often they will not even seek out the job in the first instance because of the difficulties of reaching it from possible residence locations (Kain 1968, 181).

Gobillon, Selod, & Zenous (2007) sought to clarify the nature of spatial mismatch. They identified seven potential sources of the spatial mismatch effect within extant literature, four that apply to job seekers (particularly African-Americans, but other groups as well) and three that apply to employers, each of which would require a different policy solution. The first, however — increased housing costs — has received the most attention in the literature, perhaps because it is easiest to test empirically.

As the development of modern econometrics software made large-scale testing of the spatial mismatch hypothesis easier, empirical evidence has begun to mount. Raphael (1998) found differences in job accessibility contributed strongly to disparities in neighborhood-level youth unemployment rates in San Francisco. Ong & Miller (2005) established a significant correlation between high levels of households without a vehicle and employment outcomes in Los Angeles, even when controlling for other factors. Li, Campbell, & Fernandez (2013) found the share of black households without a car within a metro area was negatively correlated with personal per capita income growth in central cities, claiming that “affluent residents, voting with their feet, actually produce a negative externality that impedes the growth of metropolitan areas” (14).

Andersson, Haltiwanger, Kutzbach, Pollakowski, & Weinberg (2014) employed LEHD data to identify lower-income workers searching for a new job post-termination. Across nine large MSAs near the Great Lakes, the researchers computed a metric of job accessibility (which is, in turn, a function of the number of job opportunities, number of competing searchers, and the geographic proximity of both to the worker's residence) for every individual in the sample. The accessibility measure was negatively correlated, *ceteris paribus*, with job search duration in both the population at large and a variety of subgroups, suggesting that spatial mismatch does impair the labor market.

In short, spatial mismatch represents a potentially major impediment for marginalized groups, particularly African-Americans, to integrate fully into social and economic structures. Given this nexus of findings, future research should work to quantify spatial mismatch and investigate whether fragmentation is in fact more tightly associated with this phenomenon. Should it be found that such a correlation does exist, this could represent a new front for researchers and advocates alike with respect to the challenges faced by post-industrial urban areas.

Indeed, just as spatial mismatch needs to be measured better, so too does the measure of the core policy variable: jurisdictional fragmentation. Many of the papers cited herein dedicate a passing word to this issue, but a fuller treatment is warranted. As noted in Chapter III, each of the measures used here — governmental density, power diffusion, and the Rusk index — as well as others like the share of population or land area share contained within the MSA central city (Post & Stein, 2000), fails to capture the dynamics of local government relations. MPDI is the most complete, considering the relative size of budgets as well as the number and size of governments, but it is a measure that lacks an intuitive interpretation and fails to incorporate the dynamics over time captured by Rusk's (2013) elasticity measure.

Realistically, case studies are required to determine the degree to which the quantitative measures align with networks of public sector decision-making. Centers of authority can often be individuals or institutions that have gained power or credibility in ways not codified in law or embodied in government boundaries; such arrangements can be opaque and particularly informal and *ad hoc*, making analysis difficult (Thurmaier & Wood, 2002). There have been many case studies of government merger efforts (e.g., Leland & Thurmaier, 2004) that could be instructive in this area.

Another set of issues exists regarding the geographic scale of analysis used in Chapters IV through VI — the metropolitan statistical area (MSA). This analysis elided the changes in MSAs that take place over time, mostly following decennial censuses. Notably, all variables used herein are based on 2010 MSAs; data from ACS and the BEA had to be recalculated to reflect additions and subtractions of counties made by OMB in February 2013. MSA boundaries, procedures for delineation, and even terminology and categorization of areas have varied over time.

Further, other data sources prefer to use other scales of analysis. It was noted in Chapter V that large regions are divided into metropolitan divisions. Sprawl indices were computed at this geography, but the MPDI (for one) was not; generating diffusion variables for a new scale would have entailed a massive undertaking. (The magnitude of this makes the yeoman's work done by the Graduate School of Public and International

Affairs at the University of Pittsburgh to produce MPDI values a deeply appreciated addition to this field of research.) This distinction was simply elided by adding a binary variable to denote regions for which the MSA-level independent variables did not coincide with the division-level sprawl measures. Other analysis in this field uses consolidated statistical areas as their scale, a higher level of geography that combines MSAs with each other or adjacent micropolitan statistical areas to create larger regions.

This brings to the fore two angles for future research. First, there should be more effort to generate policy outcome variables and measures of fragmentation at all conceivable scales of geographic analysis, ensuring that there is always data available for a given project. Second, it is worth assessing what boundaries, if any, are most economically and sociologically meaningful. Ultimately, no matter the scale chosen, there will always be some artificiality (i.e., following county lines, which are historical artifacts that vary widely in geographic scale from state to state) and/or impracticality (e.g., employing urban areas as a scale of analysis, which cross-cut all geographies except census blocks).

More broadly, there are variations in the types and powers of local governments across states. One of the biggest differences is the treatment and supremacy of county governments within a state’s federalist framework. In the south and west, counties are often the primary form of local government, particularly outside the few incorporated cities that exist; in the north, land not within a city is often part of a town or township, which often holds much authority. Compiling these individual quirks of states requires an entire supplement to the Census of Governments (U.S. Census Bureau, 2013).

While MPDI seeks to assess this by using the size of each public entity's budget in the computation of the index, such a framework implicitly assumes that budgetary and policymaking authorities are coterminous. Given the variety of formal and informal means through which the public sector affects change, it is unclear that eliminating such an abstraction is possible. Walker's (1987) identification and stratification of 17 types of regional collaboration could form the basis of an ordinal measure of fragmentation that better reflects these realities.

Finally, there are two broader concerns regarding these analyses pertaining not to the specific variables studied, but to overall methodology. First, throughout large portions of this work, demographic and economic data have come from the American Community Survey. In the past, detailed data were collected through the "long form," which was randomly sent to a large proportion of households nationwide as part of the decennial Census; every sixth household received the "long form" in 2000. While ACS allows for data to be collected annually, the sample size is appreciably smaller; in 2014, about 2.3 million households, plus another 165,000 persons living in group quarters, were interviewed (U.S. Census Bureau, n.d.1).

While this figure is clearly enough to get reliable estimates of the nation, a state, or a large region, margins of error increase substantially for smaller geographic scales. Even with the Census Bureau only reporting five-year averages for areas with fewer than 65,000 residents, confidence intervals can become incredibly wide. Naturally, then, this comes into play most in the multi-level model in Chapter VII. For example, the median monthly housing cost for 2010-2014 in Independence Local, a school district just outside

Cleveland, is reported as “$1,167 +/- $233.” This means it can only be said — with just 90% certainty — that the actual figure is somewhere within a range 40% as large as the reported value. While this is not representative, several sparsely populated districts have margins of error over $100, though the largest districts have enough observations to be confident within $10 or less.

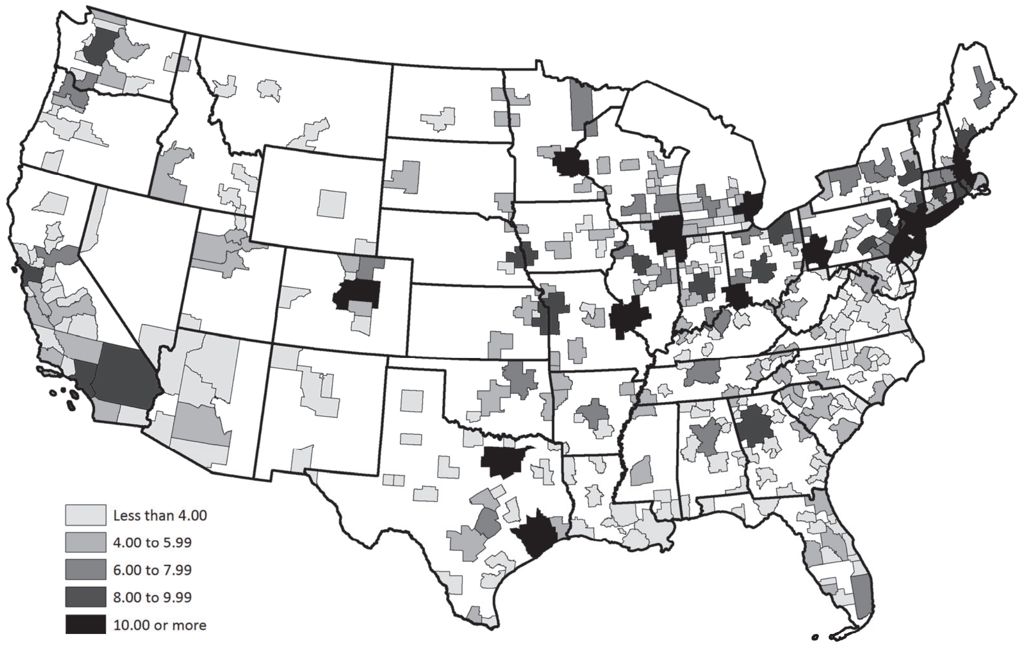
These margins were stripped from the data for the sake of simplicity, as is typical in the literature, but it would be valuable to the body of knowledge on this topic, as well as any other research that relies on government survey data, to conduct “stress tests” on the results. In short, it would be determined whether statistical significance held under circumstances where data points for a certain variable were assumed to be at the ends of a confidence interval rather than its midpoint. While such research might be less than scintillating, they would endeavor to determine whether bold-faced results are more mathematical coincidence than overarching truth.

Ultimately, to generate a convincing and meaningful model of fragmentation as a phenomenon with multi-faceted and interlocking policy impacts, not only must all the issues noted in this chapter be addressed, but would require a general equilibrium approach. While the work in Chapter VII and more complex modeling like Ulfarsson & Carruthers (2006) seek to integrate disparate socioeconomic processes within a single system of equations, any such statistical work is inherently incomplete without placing fragmentation in a context that explicitly includes all variables necessary for a complete empirical model of household choice, its causes, and its effects.

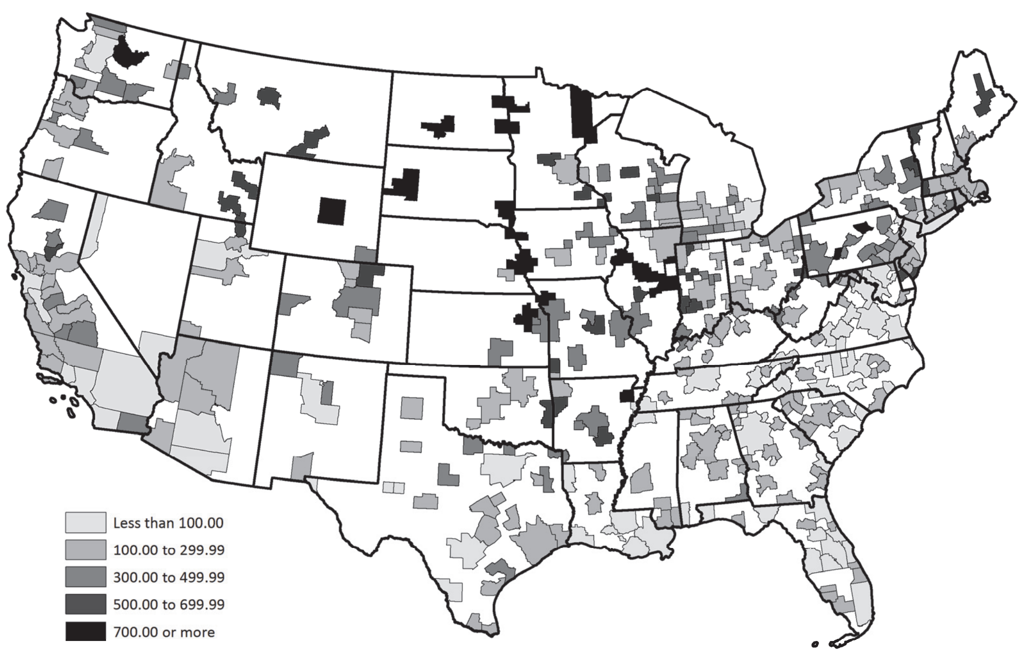
Whether such a reckoning is feasible with current data and resources is unclear. There has been a great deal of progress in what is ultimately a short time in the scope of social change, however, with just six decades from the identification of a question of interest by Tiebout (1956) to the wide-ranging empirical and theoretical work that extends that hypothesis to innumerable political and policy contexts. Though results are often muddled, even contradictory, the work toward a body of knowledge accessible and applicable to policymakers and citizens striving to make their communities and regions a better place to live continues.

APPENDIX A: SPATIAL DISTRIBUTION OF KEY VARIABLES

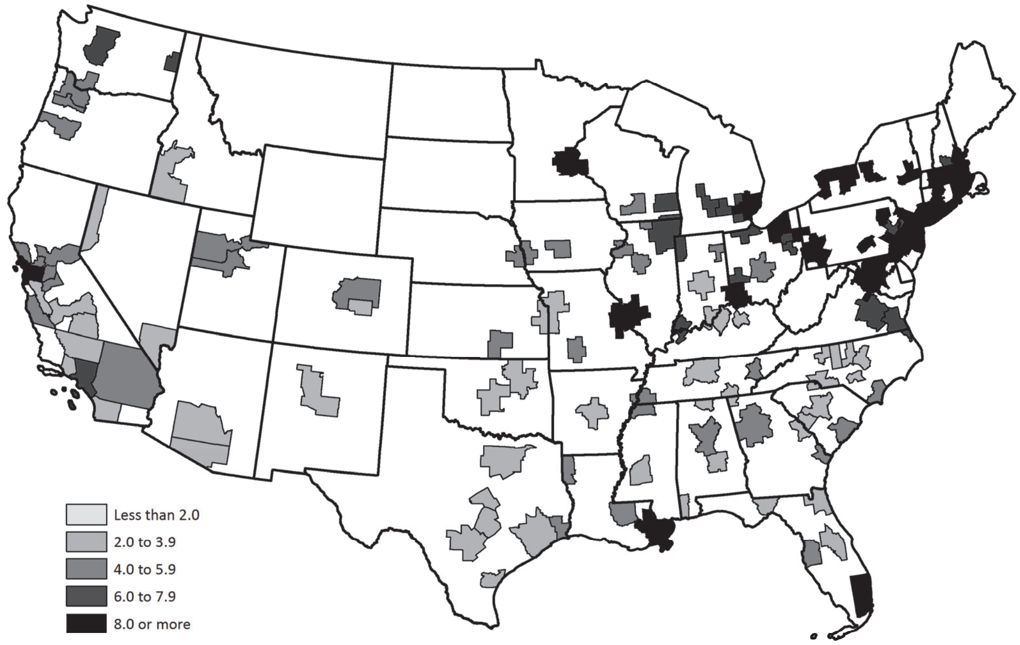
Metropolitan Power Diffusion Index by Metropolitan Statistical Area, 2007



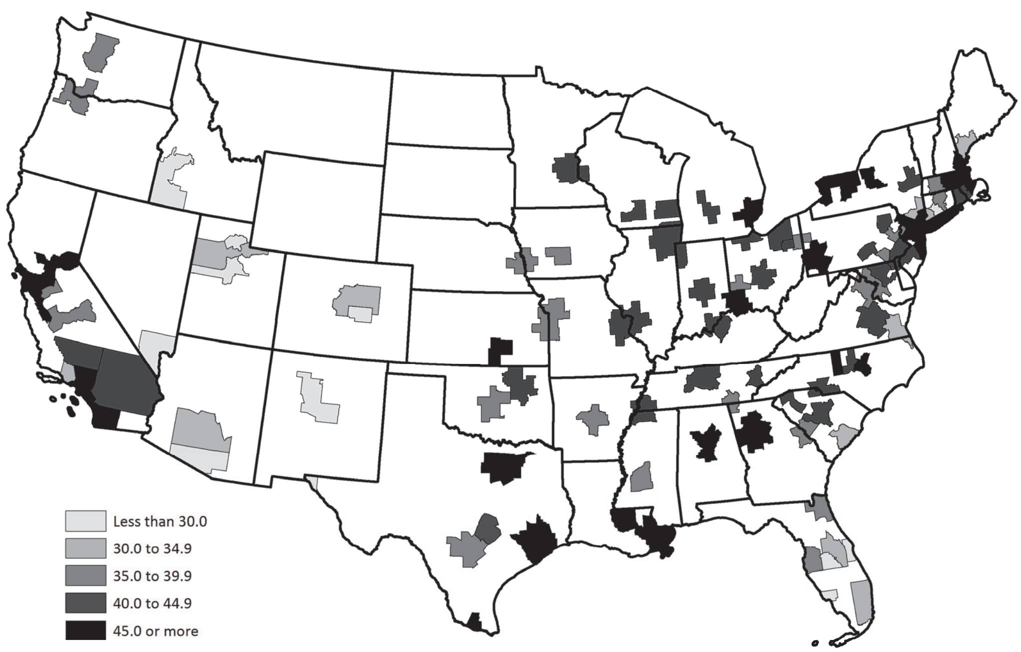
Governments per Million Residents by Metropolitan Statistical Area, 2007



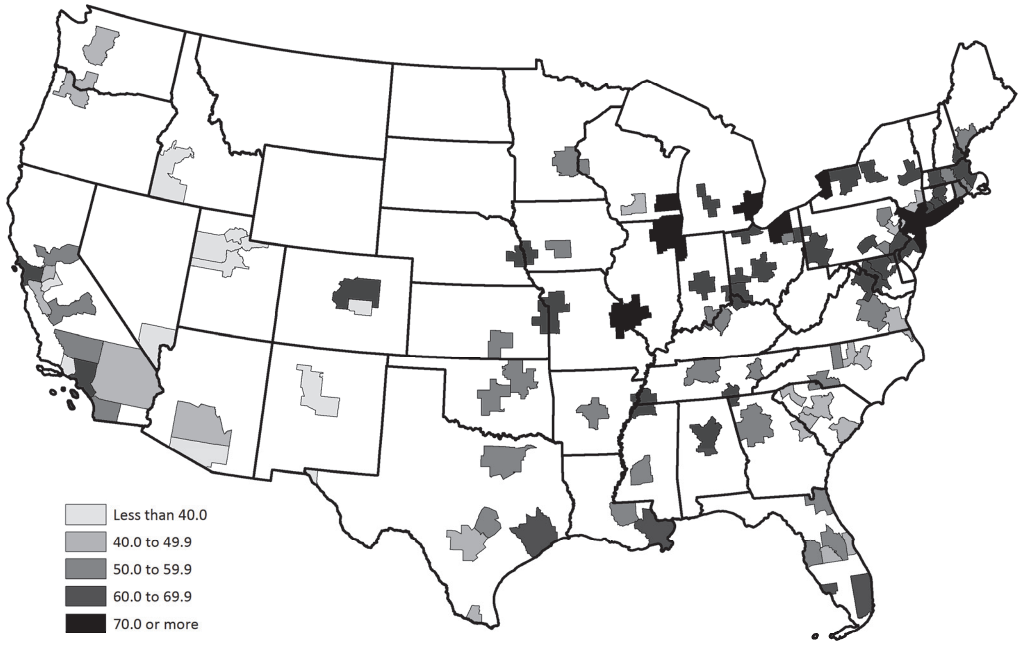
Modified Rusk Index for Primary City in Metropolitan Statistical Area, 2010



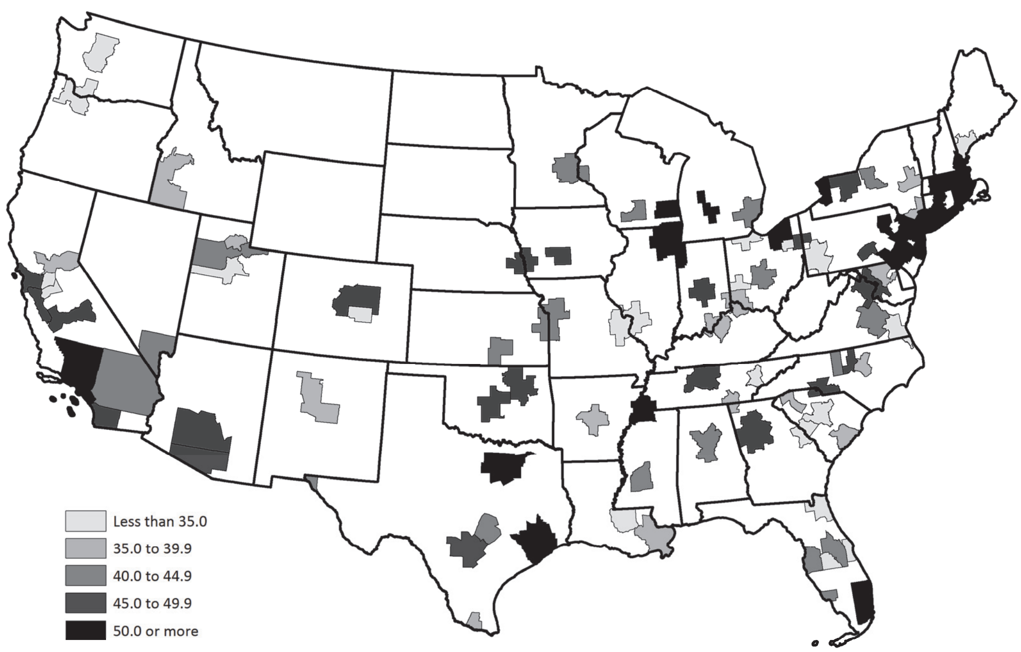
Asian-White Dissimilarity Index by Metropolitan Statistical Area, 2010



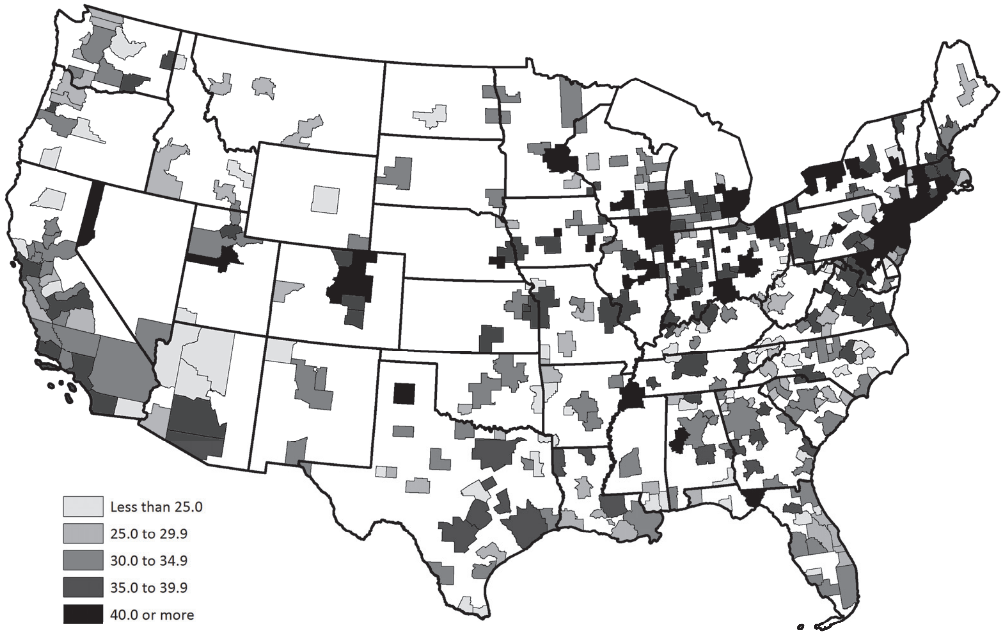
Black-White Dissimilarity Index by Metropolitan Statistical Area, 2010



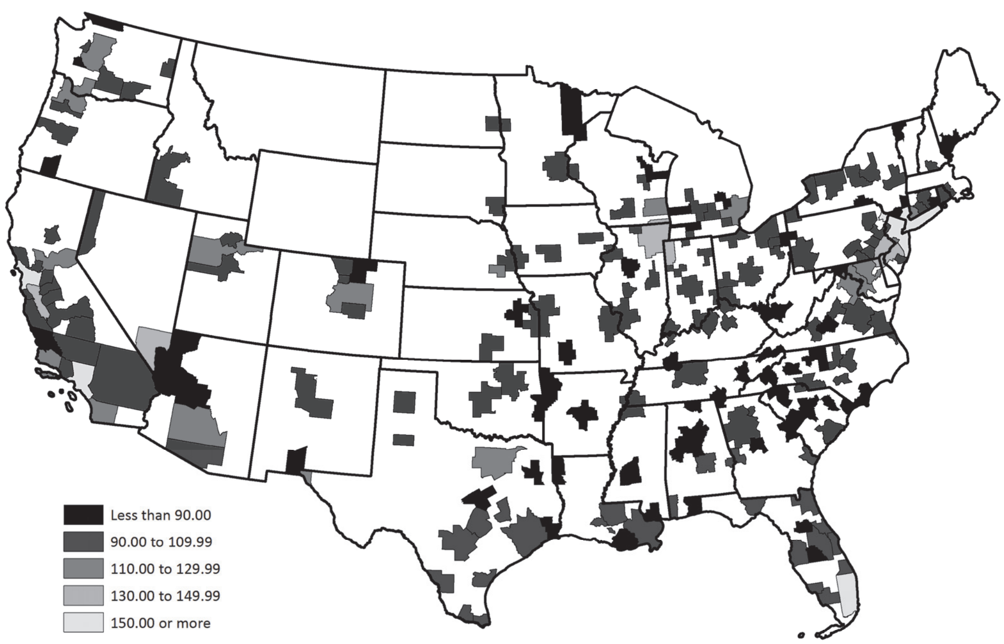
Hispanic-White Dissimilarity Index by Metropolitan Statistical Area, 2010



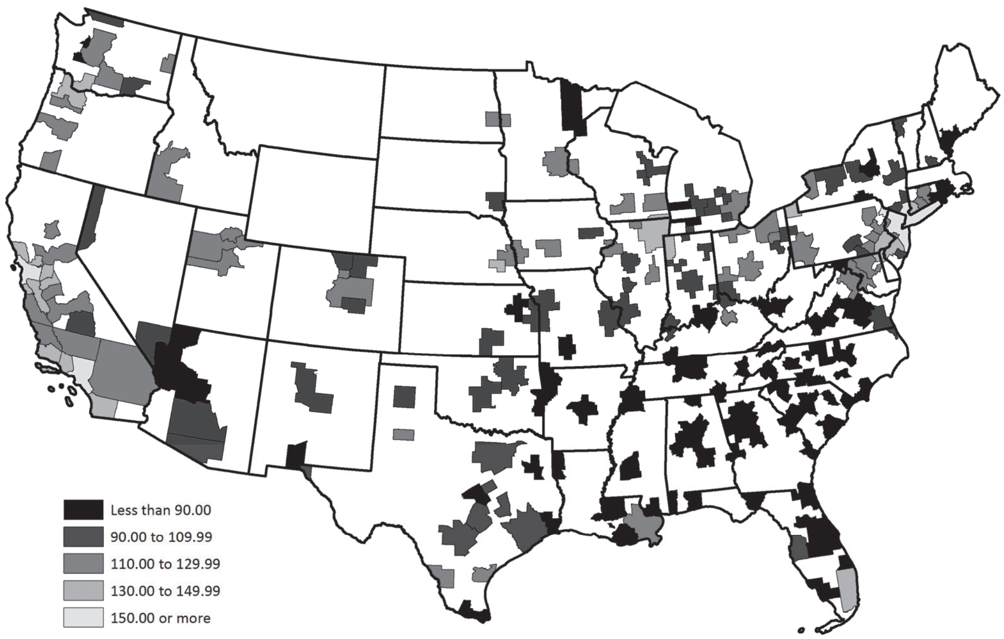
Poverty Dissimilarity Index by Metropolitan Statistical Area, 2010



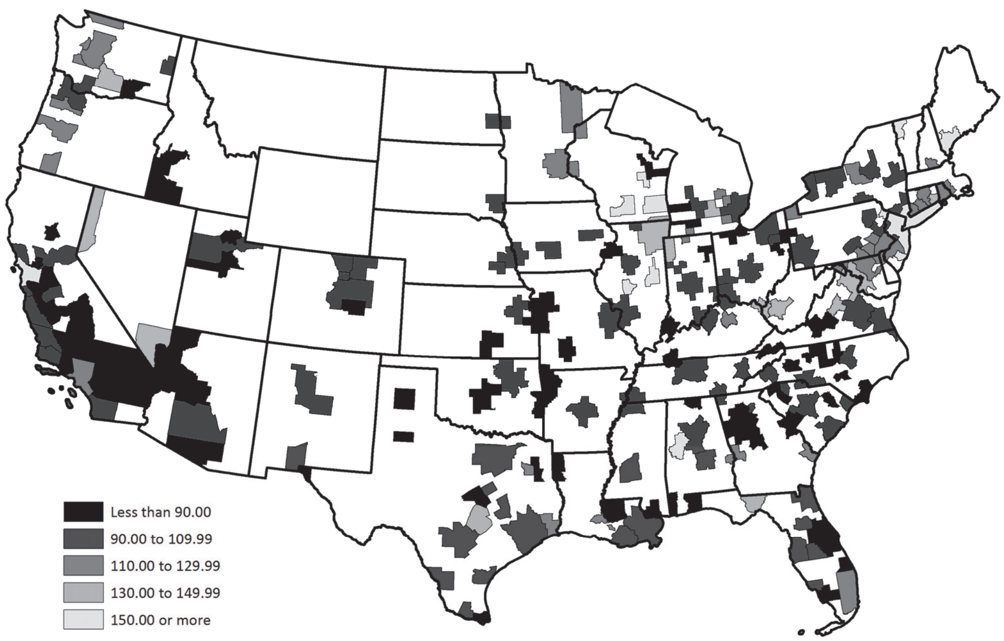
Ewing and Hamidi (2014) Density Index by Metropolitan Statistical Area, 2010



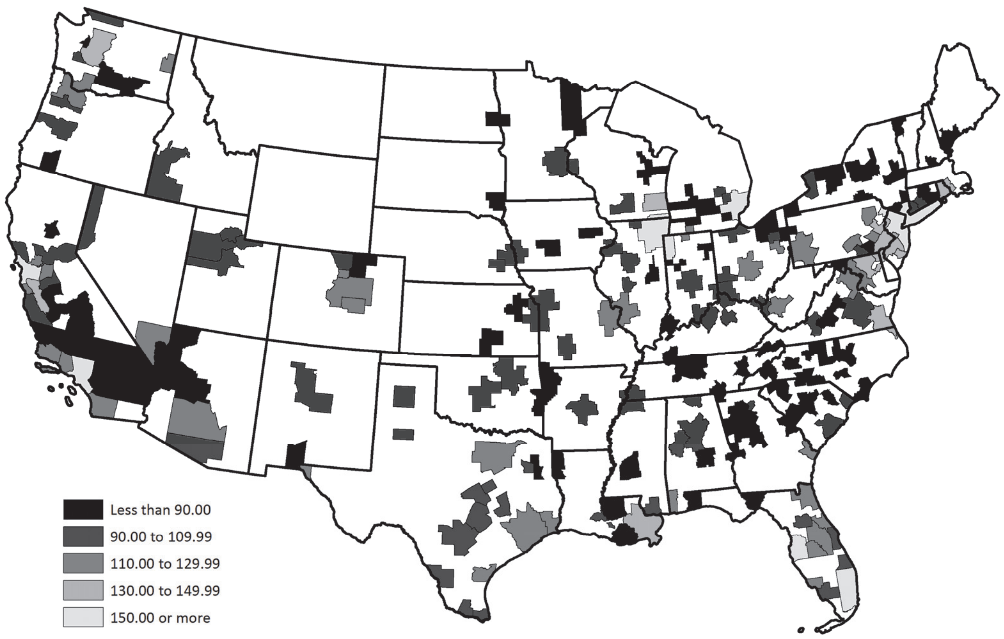
Ewing and Hamidi (2014) Mixed Use Index by Metropolitan Statistical Area, 2010



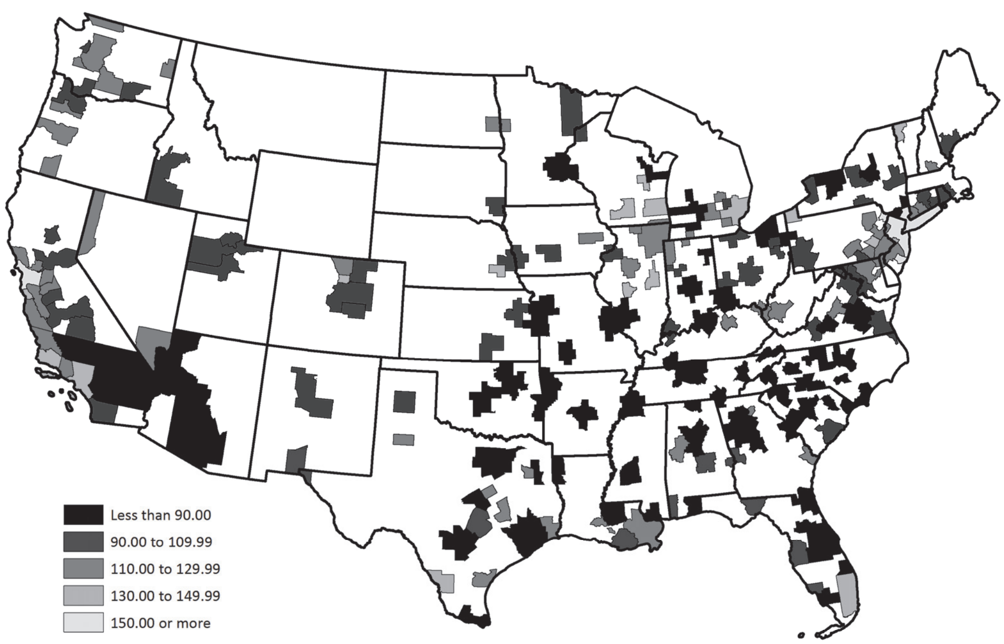
Ewing and Hamidi (2014) Centering Index by Metropolitan Statistical Area, 2010



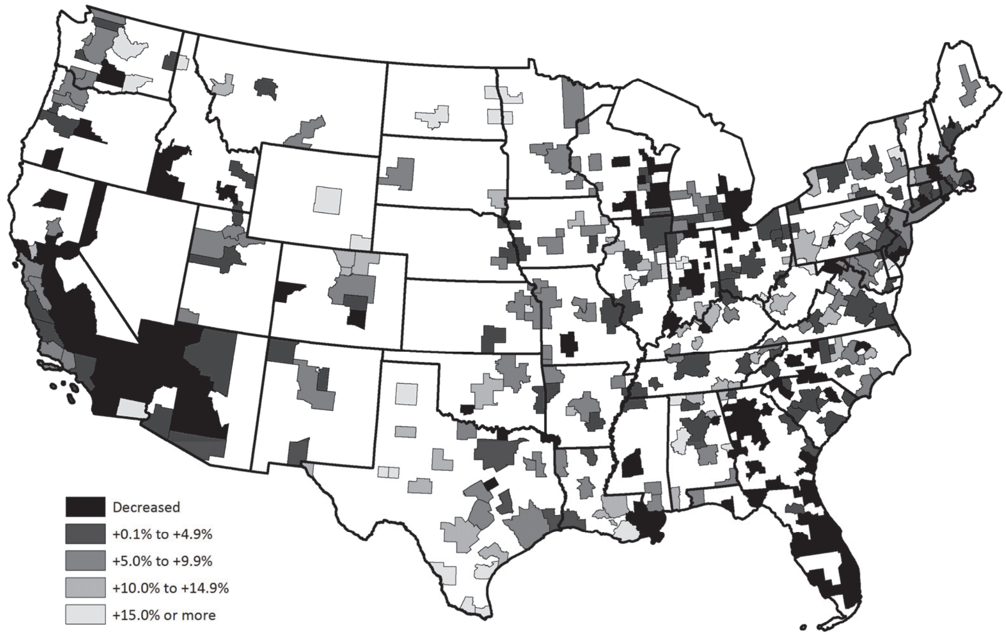
Ewing and Hamidi (2014) Streets Index by Metropolitan Statistical Area, 2010



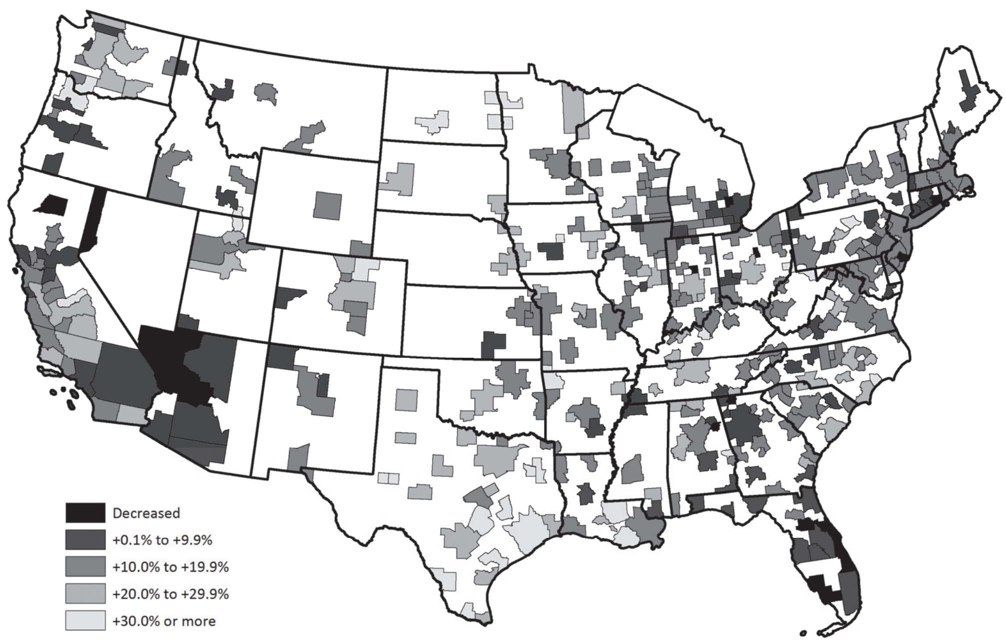
Ewing and Hamidi (2014) Composite Index by Metropolitan Statistical Area, 2010



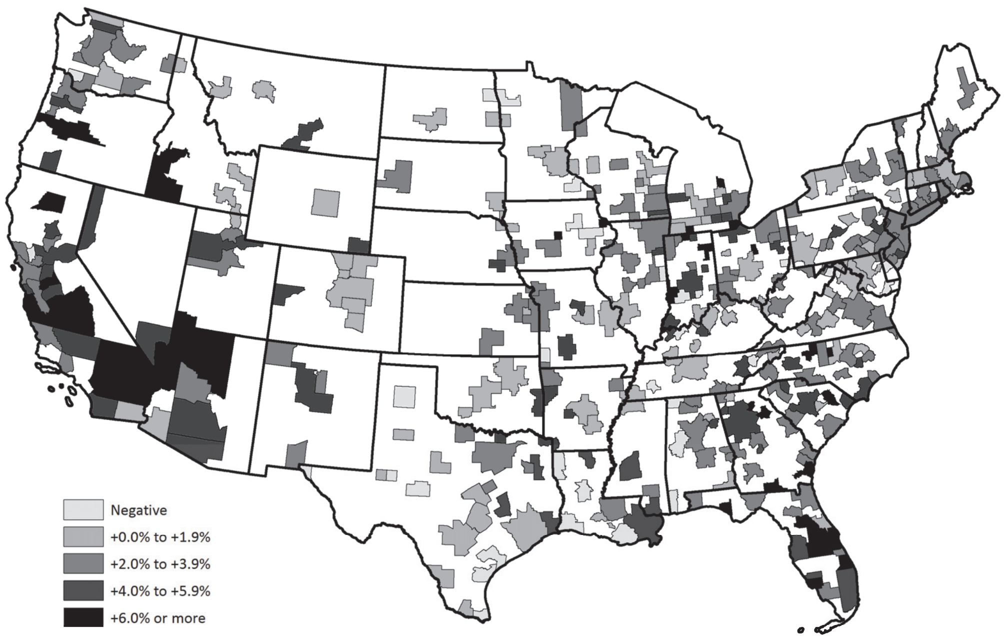
Change in Nominal Household Income by Metropolitan Statistical Area, 2007-13



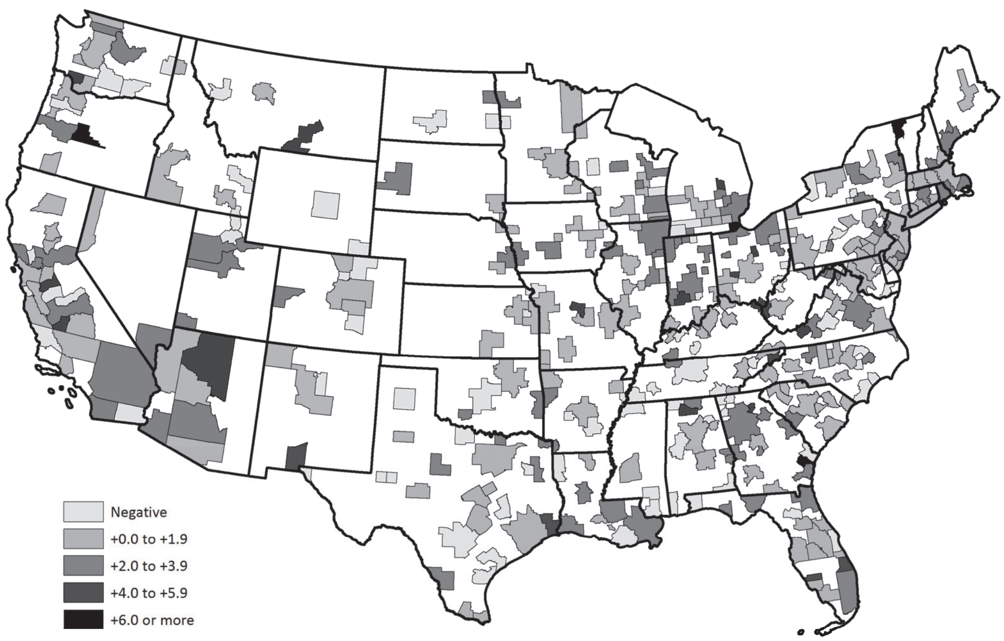
Change in Gross Metropolitan Product by Metropolitan Statistical Area, 2007-13



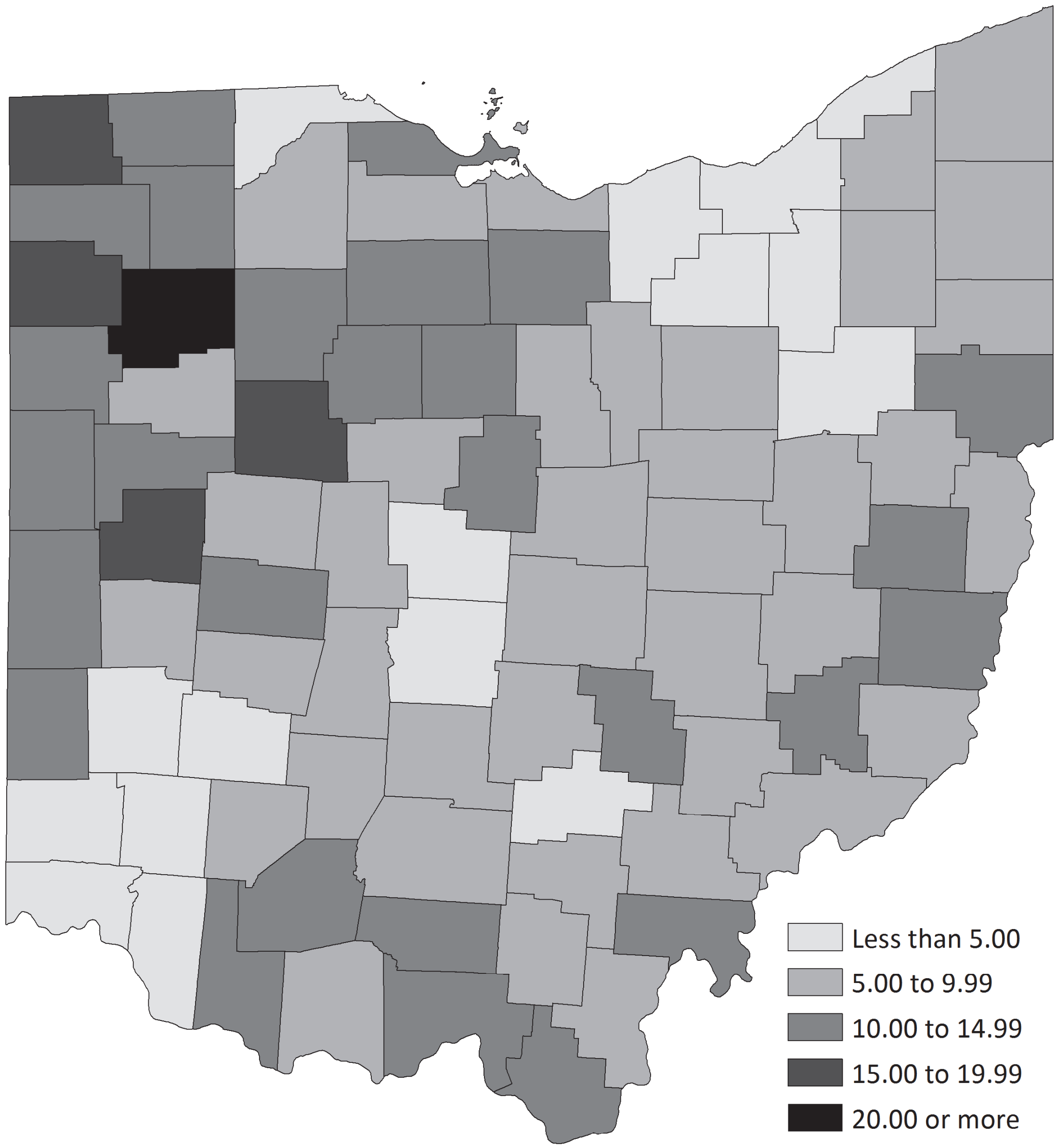
Change in Poverty Rate by Metropolitan Statistical Area, 2007-13



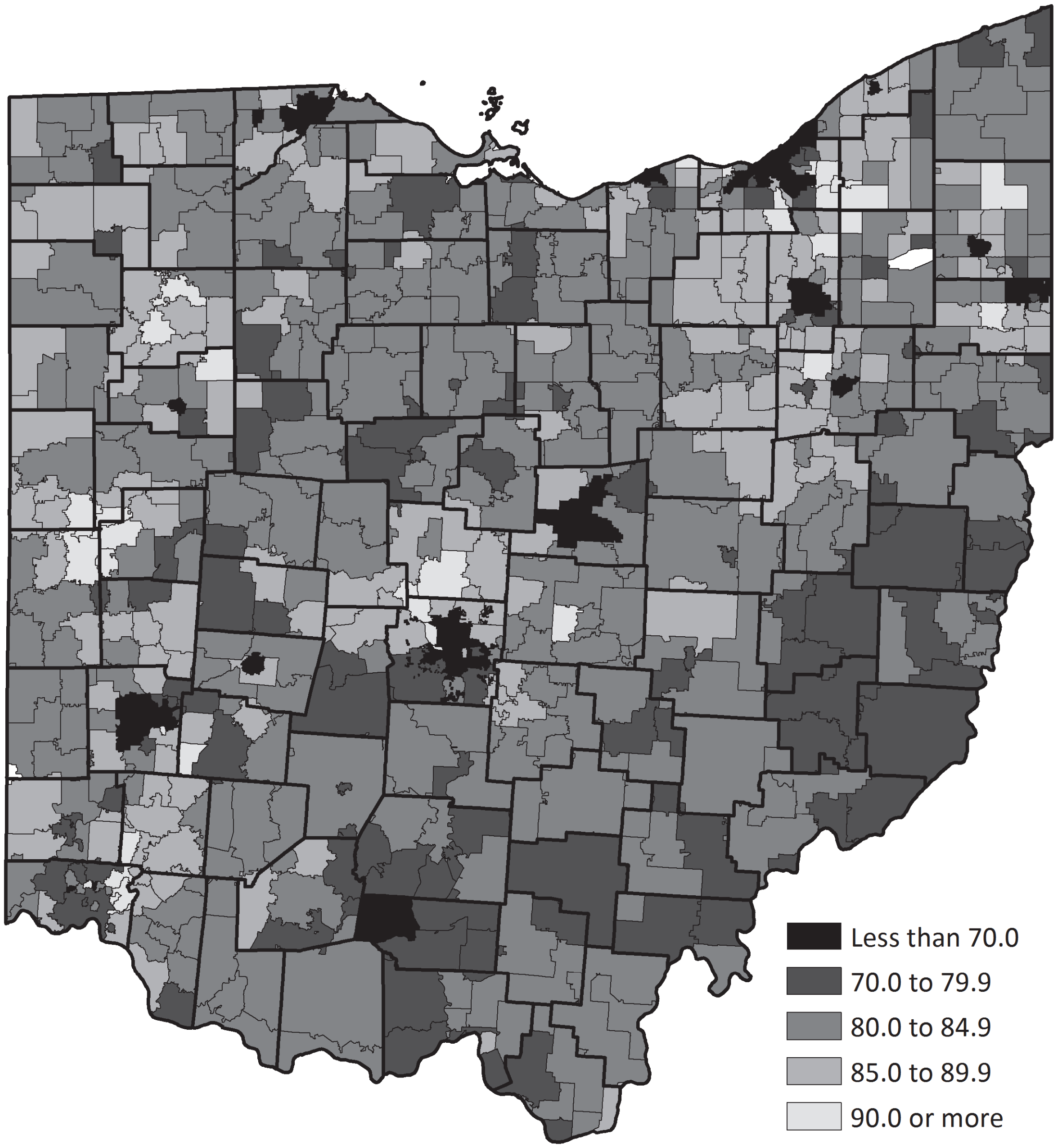
Change in Gini Coefficient by Metropolitan Statistical Area, 2007-13



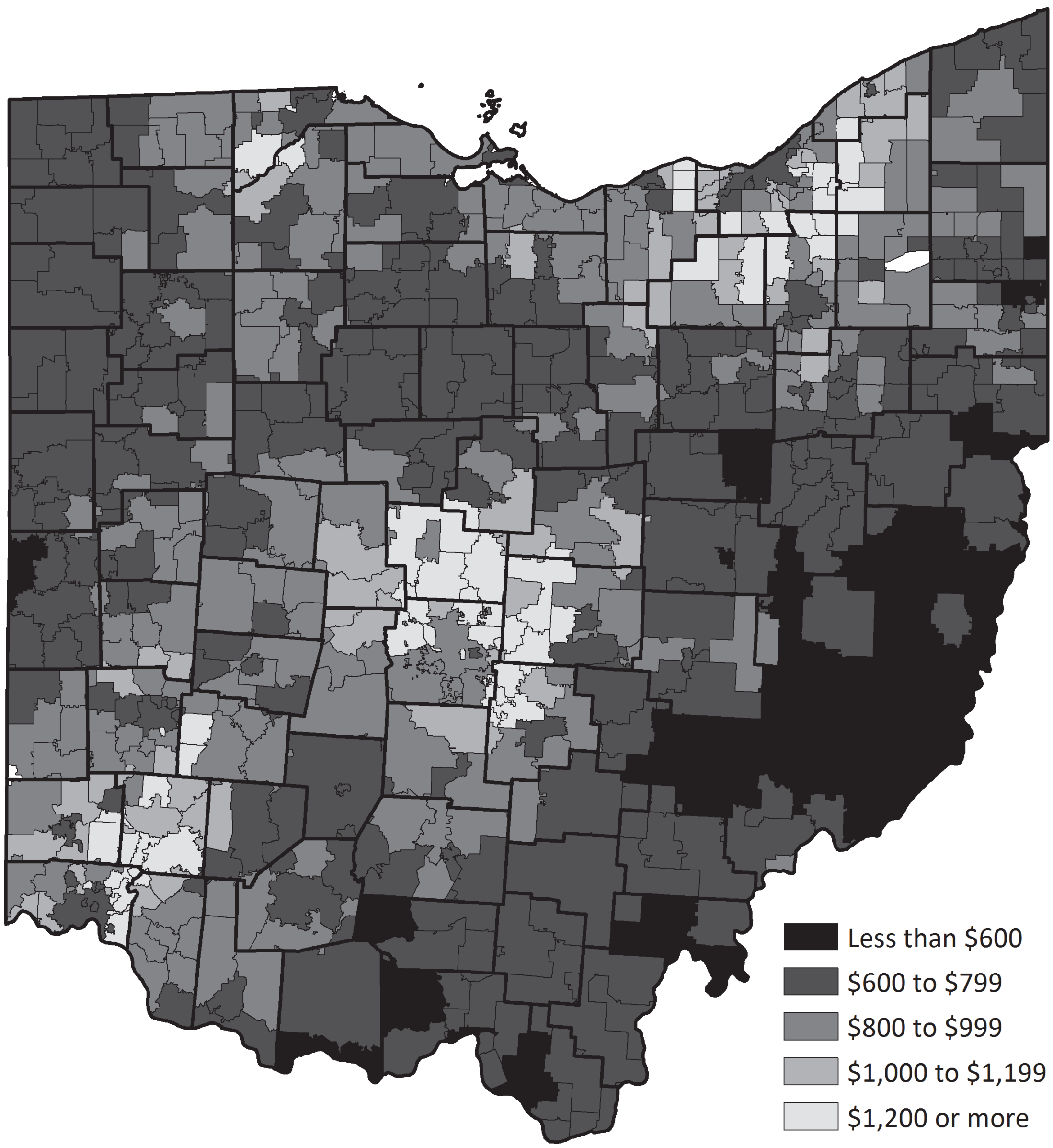
School Districts per 100,000 County Residents, Ohio, 2012



Performance Index Percentage by School District, Ohio, 2014



Median Monthly Housing Cost, Ohio, 2010-2014



APPENDIX B: CORRELATION TABLES FOR NATIONAL VARIABLES

Tables in this section provide the pairwise correlation coefficients (Pearson's r) for all bivariate relationships included in the OLS regression models (Chapters IV-VI) as computed by Stata.

Table B-1: Correlation Table for National Fragmentation Variables

	1	2	3
1. Governments per million residents, 2007	1.0000		
2. Metropolitan Power Diffusion Index, 2007	0.1199	1.0000	
3. Modified Rusk elasticity index, 2010	0.1540	0.5576	1.0000
MSA population in thousands, 2007	-0.2240	0.6276	0.2914
Population change in percent, 2000-2007	-0.2358	-0.1311	-0.5811
Housing units per square mile, 2007	-0.3171	0.4874	0.5674
Employment-population ratio, 2007	0.1260	0.2834	0.0599
Jobs in manufacturing sector (%), 2007	0.0911	0.0514	0.2420
Four-year college graduation rate, 2007	-0.0770	0.2705	0.2109
Percent of units built before 1940, 2007	0.4069	0.4317	0.7890
Housing vacancy rate in percent, 2007	-0.1120	-0.1744	-0.2385
Owner-occupancy rate in percent, 2007	0.0940	0.0696	0.2485
Median SF home value in thousands, 2007	-0.2276	0.1274	0.1130

Table B-2: Correlation Table for Dissimilarity Indices (Chapter IV)

	1	2	3	4	5	6
1. Asian-White dissimilarity index, 2010	1.0000					
2. Black-White dissimilarity index, 2010	0.5283	1.0000				
3. Hispanic-White dissimilarity index, 2010	0.2004	0.3896	1.0000			
4. Asian population (percent), 2010	0.2073	-0.1223	0.0699	1.0000		
5. Black population (percent), 2010	0.2891	0.3277	-0.0523	-0.1955	1.0000	
6. Hispanic population (percent), 2010	-0.1712	-0.3743	0.2006	0.1565	-0.3692	1.0000
MSA population in thousands, 2007	0.3188	0.3747	0.4173	0.2531	0.0856	0.1781
Population change in percent, 2000-2007	-0.3490	-0.5566	-0.1707	-0.0446	-0.1467	0.3745
Housing units per square mile, 2007	0.1836	0.4704	0.4245	0.3773	0.0204	0.0404
Employment-population ratio, 2007	0.0765	0.0302	0.1412	0.0116	-0.0328	-0.3355
Jobs in manufacturing sector (%), 2007	0.2383	0.2371	0.0470	-0.1346	-0.0650	-0.3350
Four-year college graduation rate, 2007	0.0797	0.1085	0.2008	0.3027	0.0339	-0.2894
Percent of units built before 1940, 2007	0.3101	0.5252	0.3472	-0.0936	-0.1907	-0.3757
Housing vacancy rate in percent, 2007	-0.2129	0.0767	-0.2627	-0.2638	0.1570	0.0131
Owner-occupancy rate in percent, 2007	-0.2979	0.0278	-0.3108	-0.5794	0.0530	-0.3922
Median SF home value in thousands, 2007	0.0013	-0.1132	0.2551	0.7612	-0.2665	0.2592

Table B-3: Correlation Table for Sprawl Variables (Chapter V)

	1	2	3	4	5
1. Density sprawl index, 2010	1.0000				
2. Mixed use sprawl index, 2010	0.5283	1.0000			
3. Centering sprawl index, 2010	0.2004	0.3896	1.0000		
4. Streets sprawl index, 2010	0.2073	-0.1223	0.0699	1.0000	
5. Composite sprawl index, 2010	0.2891	0.3277	-0.0523	-0.1955	1.0000
MSA population in thousands, 2007	0.3188	0.3747	0.4173	0.2531	0.0856
Population change in percent, 2000-2007	-0.3490	-0.5566	-0.1707	-0.0446	-0.1467
Housing units per square mile, 2007	0.1836	0.4704	0.4245	0.3773	0.0204
Employment-population ratio, 2007	0.0765	0.0302	0.1412	0.0116	-0.0328
Jobs in manufacturing sector (%), 2007	0.2383	0.2371	0.0470	-0.1346	-0.0650
Four-year college graduation rate, 2007	0.0797	0.1085	0.2008	0.3027	0.0339
Percent of units built before 1940, 2007	0.3101	0.5252	0.3472	-0.0936	-0.1907
Housing vacancy rate in percent, 2007	-0.2129	0.0767	-0.2627	-0.2638	0.1570
Owner-occupancy rate in percent, 2007	-0.2979	0.0278	-0.3108	-0.5794	0.0530
Median SF home value in thousands, 2007	0.0013	-0.1132	0.2551	0.7612	-0.2665

Table B-4: Correlation Table for Economic Variables (Chapter VI)

	1	2	3	4
1. Change in nominal household income, 2007-2013	1.0000			
2. Change in gross metropolitan product, 2007-2013	0.5228	1.0000		
3. Change in federal poverty rate, 2007-2013	-0.6016	-0.3586	1.0000	
4. Change in Gini coefficient, 2007-2013	-0.4011	-0.1944	0.3409	1.0000
MSA population in thousands, 2007	-0.0598	-0.0310	0.0181	0.0521
Population change in percent, 2000-2007	-0.1307	-0.0045	0.2164	0.0155
Housing units per square mile, 2007	-0.1254	-0.1572	0.0507	0.0987
Employment-population ratio, 2007	0.0888	0.2082	-0.0597	0.0192
Jobs in manufacturing sector (%), 2007	-0.1071	-0.0753	-0.0199	0.0027
Four-year college graduation rate, 2007	0.0864	0.0847	-0.0193	0.0269
Percent of units built before 1940, 2007	0.0877	-0.0373	-0.1044	0.0612
Housing vacancy rate in percent, 2007	-0.1599	-0.2632	0.1449	0.0460
Owner-occupancy rate in percent, 2007	-0.0818	-0.2157	-0.0180	0.0912
Median SF home value in thousands, 2007	-0.1286	-0.1502	0.1971	0.0727

Table B-5: Correlation Table for OLS Control Variables (Chapters IV-VI)

	1	2	3	4	5	6	7	8	9	10
1. MSA population in thousands, 2007	1.0000									
2. Population change in percent, 2000-2007	0.0441	1.0000								
3. Housing units per square mile, 2007	0.7137	-0.0921	1.0000							
4. Employment-population ratio, 2007	0.1514	0.1256	0.0857	1.0000						
5. Jobs in manufacturing sector (%), 2007	-0.1044	-0.2928	-0.0119	0.0524	1.0000					
6. Four-year college graduation rate, 2007	0.2511	0.1006	0.3042	0.5884	-0.2843	1.0000				
7. Percent of units built before 1940, 2007	0.0451	-0.5387	0.1876	0.1630	0.3530	0.0496	1.0000			
8. Housing vacancy rate in percent, 2007	-0.1015	0.1342	0.0294	-0.4109	-0.2599	-0.1788	-0.2518	1.0000		
9. Owner-occupancy rate in percent, 2007	-0.1894	-0.0171	-0.0263	0.0104	0.3235	-0.2609	0.2103	0.2141	1.0000	
10. Median SF home value in thousands, 2007	0.3365	0.1662	0.4143	0.1591	-0.2752	0.4071	-0.1131	-0.0309	-0.3206	1.0000

APPENDIX C: FULL OLS MODEL OUTPUT

As noted in the body of the report, the econometric analysis from Chapters IV through VI was repeated using dummy variables that represented the census region of the state in which the first principal city of the metropolitan area was situated. This was done on the hypothesis that there may be a latent quality based on geography that was not captured in the other control variables, e.g., that racial segregation experienced by African-Americans is distinct in the south, given that those states practiced slavery until the Civil War while others did not. The three variables were rdm, rds, and rdw, representing MSAs situated in the Midwest, South, and West Regions, respectively. (Northeast was omitted as the reference category.) Raw Stata output is provided beginning on the next page, beginning with specifications from models in Chapter IV. Equations and variables are presented in the same order as in the main document.

Chapter IV Models

```
. regress wa10 GPM07 A10 pop07k popchg hdensity epr mfgind pctba pre1940 vacancy ownocc
medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     102
-------------+------------------------------           F( 15,    86) =    6.48
       Model |  3042.9423    15  202.86282           Prob > F      =  0.0000
    Residual |  2691.1676    86  31.2926465           R-squared     =  0.5307
-------------+------------------------------           Adj R-squared =  0.4488
       Total |  5734.1099   101  56.7733654           Root MSE      =   5.594

------------------------------------------------------------------------------
        wa10 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       GPM07 |  -.0043493   .0071975    -0.60   0.547    -.0186576    .0099589
         A10 |    .642898   .1671541     3.85   0.000     .3106066    .9751894
      pop07k |   .0015864   .0003561     4.45   0.000     .0008784    .0022944
      popchg |  -.0386088   .0976189    -0.40   0.693    -.2326687    .1554512
    hdensity |  -.0229126   .0064577    -3.55   0.001      -.03575   -.0100752
         epr |  -.0843843   .2708537    -0.31   0.756    -.6228238    .4540551
      mfgind |   .3283792   .1820822     1.80   0.075    -.0335883    .6903468
       pctba |  -.0291457   .1561859    -0.19   0.852     -.339633    .2813415
     pre1940 |    .351019   .1511219     2.32   0.023     .0505985    .6514394
     vacancy |  -.0574517   .2224208    -0.26   0.797    -.4996097    .3847064
      ownocc |  -.3864597   .1761914    -2.19   0.031    -.7367165   -.0362028
     medvalk |  -.0065851   .0089849    -0.73   0.466    -.0244465    .0112763
         rdm |   2.636091    2.56782     1.03   0.307    -2.468566    7.740747
         rds |   5.097767   3.610683     1.41   0.162    -2.080034    12.27557
         rdw |  -4.181645   3.811277    -1.10   0.276    -11.75821    3.394922
       _cons |   64.74535   18.63142     3.48   0.001     27.70732    101.7834
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

       F(  3,    86) =    5.45       Prob > F =    0.0018

. regress wa10 MPDI07 A10 pop07k popchg hdensity epr mfgind pctba pre1940 vacancy ownocc
medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     102
-------------+------------------------------           F( 15,    86) =    6.87
       Model | 3126.15966    15  208.410644           Prob > F      =  0.0000
    Residual | 2607.95025    86  30.3250029           R-squared     =  0.5452
-------------+------------------------------           Adj R-squared =  0.4659
       Total |  5734.1099   101  56.7733654           Root MSE      =  5.5068

------------------------------------------------------------------------------
        wa10 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      MPDI07 |   .5618798   .3180516     1.77   0.081    -.0703858    1.194145
         A10 |   .5909974   .1652897     3.58   0.001     .2624124    .9195824
      pop07k |   .0009805   .0004792     2.05   0.044     .0000279    .0019332
      popchg |  -.0353264   .0959392    -0.37   0.714    -.2260472    .1553945
    hdensity |  -.0188919   .0061754    -3.06   0.003    -.0311681   -.0066156
         epr |  -.1356874   .2643813    -0.51   0.609    -.6612599    .3898852
      mfgind |   .3316879   .1786175     1.86   0.067     -.023392    .6867677
       pctba |  -.0292557   .1524248    -0.19   0.848    -.3322662    .2737548
     pre1940 |   .2742458   .1505529     1.82   0.072    -.0250434    .5735351
     vacancy |  -.0969573   .2173096    -0.45   0.657    -.5289544    .3350398
      ownocc |  -.4971931    .181296    -2.74   0.007    -.8575976   -.1367887
     medvalk |  -.0043695   .0088924    -0.49   0.624    -.0220469     .013308
         rdm |   2.488801   2.513124     0.99   0.325    -2.507125    7.484726
         rds |   6.400397   3.535558     1.81   0.074    -.6280599    13.42885
         rdw |  -3.371025   3.752638    -0.90   0.372    -10.83102    4.088973
       _cons |   71.57931   18.57811     3.85   0.000     34.64725    108.5114
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

       F(  3,    86) =    6.61       Prob > F =    0.0005
```

```
. regress wa10 ruskmod A10 pop07k popchg hdensity epr mfgind pctba pre1940 vacancy ownocc
medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =      90
-------------+------------------------------           F( 15,    74) =    6.06
       Model |   2083.6344    15   138.90896           Prob > F      =  0.0000
    Residual |  1697.18382    74  22.9349165           R-squared     =  0.5511
-------------+------------------------------           Adj R-squared =  0.4601
       Total |  3780.81822    89  42.4811036           Root MSE      =   4.789

------------------------------------------------------------------------------
        wa10 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     ruskmod |    .616424   .4370665     1.41   0.163      -.25445    1.487298
         A10 |   .9754611   .2366727     4.12   0.000     .5038805    1.447042
      pop07k |   .0011152   .0003346     3.33   0.001     .0004484    .0017819
      popchg |   .0049294   .0992071     0.05   0.961    -.1927451    .2026039
    hdensity |  -.0163382   .0060631    -2.69   0.009    -.0284193   -.0042572
         epr |   -.274062   .2652871    -1.03   0.305    -.8026581     .254534
      mfgind |   .2859245   .1918953     1.49   0.140    -.0964351    .6682842
       pctba |  -.0309171   .1460087    -0.21   0.833    -.3218458    .2600116
     pre1940 |    .153765   .1410469     1.09   0.279    -.1272771    .4348072
     vacancy |   .0531452    .308284     0.17   0.864     -.561124    .6674145
      ownocc |  -.2259177   .1889737    -1.20   0.236    -.6024561    .1506207
     medvalk |  -.0134056   .0095438    -1.40   0.164    -.0324221    .0056109
         rdm |   .8550933   2.387289     0.36   0.721    -3.901684     5.61187
         rds |   3.468754   3.238484     1.07   0.288    -2.984066    9.921575
         rdw |  -5.529847   3.555095    -1.56   0.124    -12.61353    1.553835
       _cons |   64.68927   18.93876     3.42   0.001     26.95297    102.4256
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

       F(  3,    74) =    6.26            Prob > F =    0.0008

. regress wb10 GPM07 B10 pop07k popchg hdensity epr mfgind pctba pre1940 vacancy ownocc
medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     102
-------------+------------------------------           F( 15,    86) =   14.34
       Model |  9948.42644    15  663.228429           Prob > F      =  0.0000
    Residual |  3977.61209    86  46.2513034           R-squared     =  0.7144
-------------+------------------------------           Adj R-squared =  0.6646
       Total |  13926.0385   101   137.88157           Root MSE      =  6.8008

------------------------------------------------------------------------------
        wb10 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       GPM07 |   .0173437   .0089605     1.94   0.056    -.0004691    .0351565
         B10 |   .3441062   .0991857     3.47   0.001     .1469316    .5412808
      pop07k |   .0008315   .0004308     1.93   0.057    -.0000249    .0016879
      popchg |   -.270771   .1261585    -2.15   0.035    -.5215659   -.0199762
    hdensity |   .0175724   .0078255     2.25   0.027     .0020158     .033129
         epr |   .3041316   .3295048     0.92   0.359    -.3509024    .9591655
      mfgind |   .1163042    .222353     0.52   0.602    -.3257188    .5583273
       pctba |   -.085452   .1897989    -0.45   0.654    -.4627597    .2918557
     pre1940 |   .2079942   .1829146     1.14   0.259    -.1556281    .5716165
     vacancy |   .6668261   .2701529     2.47   0.016       .12978    1.203872
      ownocc |  -.1948346   .2006131    -0.97   0.334    -.5936401     .203971
     medvalk |   -.003655   .0098037    -0.37   0.710     -.023144    .0158341
         rdm |   4.441414   3.136049     1.42   0.160    -1.792846    10.67567
         rds |  -1.269515   4.477772    -0.28   0.777    -10.17103    7.632001
         rdw |  -3.595952   4.655845    -0.77   0.442    -12.85147    5.659562
       _cons |   32.27637   22.16953     1.46   0.149    -11.79519    76.34794
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

      F(  3,    86) =    1.88            Prob > F =    0.1390
```

```
. regress wb10 MPDI07 B10 pop07k popchg hdensity epr mfgind pctba pre1940 vacancy ownocc
medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     102
-------------+------------------------------           F( 15,    86) =   15.36
       Model |  10140.4371    15  676.029139           Prob > F      =  0.0000
    Residual |  3785.60144    86  44.0186214           R-squared     =  0.7282
-------------+------------------------------           Adj R-squared =  0.6808
       Total |  13926.0385   101   137.88157           Root MSE      =  6.6347

------------------------------------------------------------------------------
        wb10 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      MPDI07 |   1.094431   .3799163     2.88   0.005     .3391823    1.849679
         B10 |   .3131081    .094107     3.33   0.001     .1260295    .5001867
      pop07k |  -.0001609   .0005665    -0.28   0.777     -.001287    .0009652
      popchg |  -.2956354   .1218522    -2.43   0.017    -.5378695   -.0534013
    hdensity |   .0171861    .007352     2.34   0.022     .0025708    .0318014
         epr |   .3434348   .3185225     1.08   0.284    -.2897669    .9766365
      mfgind |   .0608324   .2157702     0.28   0.779    -.3681046    .4897694
       pctba |  -.1607773   .1841509    -0.87   0.385    -.5268573    .2053026
     pre1940 |   .1488034   .1806738     0.82   0.412    -.2103642    .5079711
     vacancy |   .6941368   .2619234     2.65   0.010     .1734502    1.214823
      ownocc |  -.3306109   .2032283    -1.63   0.107    -.7346153    .0733935
     medvalk |   -.002461     .00958    -0.26   0.798    -.0215054    .0165833
         rdm |   5.186464   3.028881     1.71   0.090    -.8347519    11.20768
         rds |  -.6989888   4.372393    -0.16   0.873    -9.391018     7.99304
         rdw |  -3.379764   4.534399    -0.75   0.458    -12.39385    5.634322
       _cons |   39.75802   21.84621     1.82   0.072    -3.670796    83.18685
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

       F(  3,    86) =    2.52            Prob > F =    0.0630

. regress wb10 ruskmod B10 pop07k popchg hdensity epr mfgind pctba pre1940 vacancy ownocc
medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =      90
-------------+------------------------------           F( 15,    74) =   13.39
       Model |  8551.75263    15  570.116842           Prob > F      =  0.0000
    Residual |  3150.92737    74  42.5800997           R-squared     =  0.7308
-------------+------------------------------           Adj R-squared =  0.6762
       Total |    11702.68    89  131.490787           Root MSE      =  6.5253

------------------------------------------------------------------------------
        wb10 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     ruskmod |   .6842937    .606135     1.13   0.263    -.5234565    1.892044
         B10 |   .1381926   .1079273     1.28   0.204    -.0768572    .3532423
      pop07k |      .0006    .000454     1.32   0.190    -.0003045    .0015045
      popchg |  -.3921058   .1369841    -2.86   0.005    -.6650526   -.1191591
    hdensity |   .0159873   .0081195     1.97   0.053    -.0001911    .0321657
         epr |   .3192223   .3652491     0.87   0.385    -.4085523    1.046997
      mfgind |   -.079584   .2498797    -0.32   0.751    -.5774802    .4183122
       pctba |  -.2340917   .1972328    -1.19   0.239    -.6270866    .1589032
     pre1940 |  -.0160002   .1966652    -0.08   0.935    -.4078642    .3758637
     vacancy |   .3024347   .4197132     0.72   0.473     -.533862    1.138731
      ownocc |  -.2680131   .2416185    -1.11   0.271    -.7494485    .2134224
     medvalk |  -.0097984   .0102494    -0.96   0.342    -.0302208     .010624
         rdm |   4.703287   3.259679     1.44   0.153    -1.791764    11.19834
         rds |  -2.233307   4.549014    -0.49   0.625    -11.29741    6.830801
         rdw |  -6.940708   4.866707    -1.43   0.158    -16.63783    2.756417
       _cons |   56.36972   26.00844     2.17   0.033     4.546774    108.1927
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

       F(  3,    74) =    3.13            Prob > F =    0.0308
```

```
. regress wh10 GPM07 H10 pop07k popchg hdensity epr mfgind pctba pre1940 vacancy ownocc
medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     102
-------------+------------------------------           F( 15,    86) =    4.66
       Model |  3823.09049    15  254.872699           Prob > F      =  0.0000
    Residual |  4700.19941    86  54.6534816           R-squared     =  0.4485
-------------+------------------------------           Adj R-squared =  0.3524
       Total |   8523.2899   101  84.3890089           Root MSE      =  7.3928

------------------------------------------------------------------------------
        wh10 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       GPM07 |   .0002734    .009459     0.03   0.977    -.0185305    .0190772
         H10 |   .2193278   .0655372     3.35   0.001     .0890442    .3496113
      pop07k |   .0005325   .0004625     1.15   0.253    -.0003869    .0014519
      popchg |  -.0176497   .1346975    -0.13   0.896    -.2854196    .2501201
    hdensity |   .0053048   .0084155     0.63   0.530    -.0114247    .0220342
         epr |   .5622957   .3711076     1.52   0.133    -.1754419    1.300033
      mfgind |   .2827154   .2454505     1.15   0.253     -.205224    .7706548
       pctba |  -.0210706   .2101223    -0.10   0.920      -.43878    .3966388
     pre1940 |   .1590494   .2002902     0.79   0.429    -.2391142    .5572131
     vacancy |  -.0505533   .3018135    -0.17   0.867    -.6505386     .549432
      ownocc |  -.2859702   .2227361    -1.28   0.203    -.7287549    .1568145
     medvalk |   .0072481   .0107158     0.68   0.501    -.0140542    .0285504
         rdm |  -5.267664   3.385064    -1.56   0.123    -11.99695     1.46162
         rds |  -3.564867    4.81893    -0.74   0.461    -13.14458    6.014848
         rdw |  -8.918973   5.070515    -1.76   0.082    -18.99882    1.160877
       _cons |   21.50088    27.1471     0.79   0.431    -32.46576    75.46752
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

       F(  3,    86) =    2.25            Prob > F =    0.0888

. regress wh10 MPDI07 H10 pop07k popchg hdensity epr mfgind pctba pre1940 vacancy ownocc
medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     102
-------------+------------------------------           F( 15,    86) =    4.67
       Model |  3825.30344    15   255.02023           Prob > F      =  0.0000
    Residual |  4697.98646    86  54.6277495           R-squared     =  0.4488
-------------+------------------------------           Adj R-squared =  0.3527
       Total |   8523.2899   101  84.3890089           Root MSE      =  7.3911

------------------------------------------------------------------------------
        wh10 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      MPDI07 |  -.0859999   .4229454    -0.20   0.839    -.9267877    .7547878
         H10 |   .2198694   .0655757     3.35   0.001     .0895092    .3502296
      pop07k |   .0006192   .0006236     0.99   0.324    -.0006205     .001859
      popchg |  -.0185375   .1344296    -0.14   0.891    -.2857747    .2486997
    hdensity |   .0048498    .008166     0.59   0.554    -.0113837    .0210832
         epr |   .5688301   .3683816     1.54   0.126    -.1634883    1.301149
      mfgind |   .2835685    .244665     1.16   0.250    -.2028095    .7699464
       pctba |  -.0192529   .2086222    -0.09   0.927    -.4339801    .3954743
     pre1940 |   .1689534   .2025299     0.83   0.406    -.2336627    .5715694
     vacancy |  -.0458877    .299828    -0.15   0.879    -.6419261    .5501507
      ownocc |  -.2722256   .2314066    -1.18   0.243    -.7322466    .1877954
     medvalk |   .0070945   .0107369     0.66   0.511    -.0142497    .0284387
         rdm |  -5.249926   3.361293    -1.56   0.122    -11.93196    1.432103
         rds |  -3.724399   4.788852    -0.78   0.439    -13.24432    5.795524
         rdw |  -9.015161   5.067655    -1.78   0.079    -19.08933    1.059003
       _cons |   20.60194   27.42354     0.75   0.455    -33.91425    75.11813
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

        F(  3,    86) =    2.30            Prob > F =    0.0831
```

```
. regress wh10 ruskmod H10 pop07k popchg hdensity epr mfgind pctba pre1940 vacancy ownocc
medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =      90
-------------+------------------------------           F( 15,    74) =    5.80
       Model |   3881.6638    15  258.777587           Prob > F      =  0.0000
    Residual |  3304.04776    74   44.649294           R-squared     =  0.5402
-------------+------------------------------           Adj R-squared =  0.4470
       Total |  7185.71156    89  80.7383321           Root MSE      =   6.682

------------------------------------------------------------------------------
        wh10 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     ruskmod |  -.5934262    .609444    -0.97   0.333     -1.80777    .6209175
         H10 |   .3856922   .0892252     4.32   0.000     .2079071    .5634772
      pop07k |   .0003646   .0004694     0.78   0.440    -.0005707    .0012999
      popchg |  -.1553668   .1416895    -1.10   0.276    -.4376894    .1269557
    hdensity |   .0065866   .0083302     0.79   0.432    -.0100116    .0231848
         epr |   .7562113   .3730201     2.03   0.046     .0129525     1.49947
      mfgind |   .1871622   .2576051     0.73   0.470    -.3261271    .7004515
       pctba |  -.0285948   .2067016    -0.14   0.890    -.4404566    .3832671
     pre1940 |   .2124332   .2018946     1.05   0.296    -.1898507    .6147171
     vacancy |   .1338891   .4297481     0.31   0.756    -.7224027    .9901809
      ownocc |   .0020474   .2566127     0.01   0.994    -.5092645    .5133593
     medvalk |   .0094389   .0108591     0.87   0.388    -.0121983    .0310762
         rdm |  -7.468996   3.341318    -2.24   0.028    -14.12672   -.8112747
         rds |  -5.670046   4.644659    -1.22   0.226    -14.92473     3.58464
         rdw |  -12.49373   4.994826    -2.50   0.015    -22.44614    -2.54132
       _cons |  -6.699808   28.42584    -0.24   0.814    -63.33952    49.93991
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

       F(  3,    74) =    4.28            Prob > F =    0.0076

. regress povsi GPM07 povrate pop07k popchg hdensity epr mfgind pctba pre1940 vacancy
ownocc medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     357
-------------+------------------------------           F( 15,   341) =   21.52
       Model |    .7395459    15   .04930306           Prob > F      =  0.0000
    Residual |  .781157835   341  .002290785           R-squared     =  0.4863
-------------+------------------------------           Adj R-squared =  0.4637
       Total |  1.52070373   356   .00427164           Root MSE      =  .04786

------------------------------------------------------------------------------
       povsi |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       GPM07 |  -.0000542   .0000143    -3.79   0.000    -.0000824   -.0000261
     povrate |   .0024156   .0008948     2.70   0.007     .0006556    .0041756
      pop07k |   3.46e-07   2.51e-06     0.14   0.890    -4.58e-06    5.27e-06
      popchg |  -.0001212   .0003625    -0.33   0.738    -.0008342    .0005918
    hdensity |   .0000955   .0000367     2.60   0.010     .0000234    .0001676
         epr |   .0011023   .0007903     1.39   0.164    -.0004521    .0026567
      mfgind |  -.0004436   .0005541    -0.80   0.424    -.0015334    .0006462
       pctba |   .0030324   .0004937     6.14   0.000     .0020614    .0040035
     pre1940 |   .0004128   .0005445     0.76   0.449    -.0006582    .0014839
     vacancy |  -.0016824   .0006357    -2.65   0.009    -.0029328    -.000432
      ownocc |  -.0005366   .0006631    -0.81   0.419     -.001841    .0007677
     medvalk |  -.0000676   .0000389    -1.73   0.084    -.0001441    9.03e-06
         rdm |   .0091365   .0109968     0.83   0.407    -.0124936    .0307667
         rds |  -.0445049   .0142291    -3.13   0.002    -.0724927    -.016517
         rdw |  -.0367423   .0152539    -2.41   0.017    -.0667459   -.0067386
       _cons |   .2461965   .0747449     3.29   0.001     .0991773    .3932156
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

       F(  3,   341) =    9.21            Prob > F =    0.0000
```

```
. regress povsi MPDI07 povrate pop07k popchg hdensity epr mfgind pctba pre1940 vacancy
ownocc medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     357
-------------+------------------------------           F( 15,   341) =   20.35
       Model |  .718319352    15  .047887957           Prob > F      =  0.0000
    Residual |  .802384383   341  .002353033           R-squared     =  0.4724
-------------+------------------------------           Adj R-squared =  0.4491
       Total |  1.52070373   356   .00427164           Root MSE      =  .04851

------------------------------------------------------------------------------
       povsi |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      MPDI07 |   .0037893   .0016986     2.23   0.026     .0004483    .0071303
     povrate |   .0024608   .0009075     2.71   0.007     .0006758    .0042458
      pop07k |  -4.35e-06   3.13e-06    -1.39   0.165    -.0000105    1.79e-06
      popchg |   -.000033   .0003665    -0.09   0.928    -.0007539    .0006879
    hdensity |   .0001458   .0000357     4.08   0.000     .0000754    .0002161
         epr |   .0008191   .0007988     1.03   0.306    -.0007521    .0023904
      mfgind |    .000012   .0005515     0.02   0.983    -.0010727    .0010968
       pctba |   .0031475    .000499     6.31   0.000     .0021661     .004129
     pre1940 |  -.0001087   .0005467    -0.20   0.843     -.001184    .0009667
     vacancy |  -.0018198   .0006427    -2.83   0.005    -.0030839   -.0005557
      ownocc |  -.0006071   .0006766    -0.90   0.370    -.0019379    .0007238
     medvalk |  -.0000585   .0000395    -1.48   0.139    -.0001361    .0000191
         rdm |    .005035   .0110751     0.45   0.650    -.0167492    .0268191
         rds |  -.0302118   .0147064    -2.05   0.041    -.0591384   -.0012851
         rdw |  -.0275176   .0158134    -1.74   0.083    -.0586217    .0035865
       _cons |   .2225246    .075596     2.94   0.003     .0738316    .3712177
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

       F(  3,   341) =    4.45            Prob > F =    0.0044

. regress povsi ruskmod povrate pop07k popchg hdensity epr mfgind pctba pre1940 vacancy
ownocc medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     125
-------------+------------------------------           F( 15,   109) =    9.81
       Model |  .184792801    15   .01231952           Prob > F      =  0.0000
    Residual |  .136923571   109   .00125618           R-squared     =  0.5744
-------------+------------------------------           Adj R-squared =  0.5158
       Total |  .321716371   124  .002594487           Root MSE      =  .03544

------------------------------------------------------------------------------
       povsi |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     ruskmod |   .0048997   .0028689     1.71   0.091    -.0007863    .0105857
     povrate |   .0066786   .0019548     3.42   0.001     .0028042    .0105529
      pop07k |  -2.43e-06   2.24e-06    -1.09   0.280    -6.86e-06    2.00e-06
      popchg |    .000591   .0006119     0.97   0.336    -.0006218    .0018038
    hdensity |    .000096    .000038     2.53   0.013     .0000207    .0001714
         epr |   .0044646   .0016413     2.72   0.008     .0012117    .0077175
      mfgind |   .0008687    .001078     0.81   0.422    -.0012678    .0030053
       pctba |   .0021684   .0007883     2.75   0.007      .000606    .0037308
     pre1940 |  -.0012898   .0009104    -1.42   0.159    -.0030942    .0005146
     vacancy |   .0002752   .0016201     0.17   0.865    -.0029358    .0034863
      ownocc |   .0016108    .001272     1.27   0.208    -.0009103    .0041318
     medvalk |  -.0000339   .0000515    -0.66   0.511    -.0001359    .0000681
         rdm |  -.0280466   .0151004    -1.86   0.066    -.0579751    .0018819
         rds |  -.0717577   .0208005    -3.45   0.001    -.1129836   -.0305318
         rdw |  -.0567912   .0224559    -2.53   0.013    -.1012982   -.0122843
       _cons |  -.1522139   .1573726    -0.97   0.336    -.4641214    .1596936
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

        F(  3,   109) =    4.52            Prob > F =    0.0050
```

```
. regress wb10 GPM07 povsi pop07k popchg hdensity epr mfgind pctba pre1940 vacancy ownocc
medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     101
-------------+------------------------------           F( 15,    85) =   14.33
       Model |  9979.51099    15  665.300733           Prob > F      =  0.0000
    Residual |  3946.49713    85   46.429378           R-squared     =  0.7166
-------------+------------------------------           Adj R-squared =  0.6666
       Total |  13926.0081   100  139.260081           Root MSE      =  6.8139

------------------------------------------------------------------------------
        wb10 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       GPM07 |   .0168884   .0089834     1.88   0.064     -.000973    .0347498
       povsi |   78.05005    21.9691     3.55   0.001     34.36959    121.7305
      pop07k |   .0012374   .0004233     2.92   0.004     .0003957    .0020791
      popchg |  -.3952564   .1194594    -3.31   0.001    -.6327736   -.1577392
    hdensity |   .0089634   .0078448     1.14   0.256    -.0066341     .024561
         epr |   .2965669   .3421049     0.87   0.388    -.3836293     .976763
      mfgind |   .1321536    .224108     0.59   0.557    -.3134331    .5777403
       pctba |  -.2058838   .1996967    -1.03   0.305    -.6029343    .1911666
     pre1940 |   .2222904   .1835946     1.21   0.229    -.1427448    .5873255
     vacancy |    .855981   .2815189     3.04   0.003      .296246    1.415716
      ownocc |  -.1670071   .2036457    -0.82   0.414    -.5719093    .2378951
     medvalk |   .0012008   .0100448     0.12   0.905    -.0187709    .0211724
         rdm |   5.519858   3.119672     1.77   0.080    -.6828869     11.7226
         rds |   7.436391   4.678998     1.59   0.116     -1.86671    16.73949
         rdw |   -.760526     4.8126    -0.16   0.875    -10.32926    8.808212
       _cons |    4.98583     24.074     0.21   0.836    -42.87973    52.85139
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

        F(  3,    85) =    3.33            Prob > F =    0.0232

. regress wb10 MPDI07 povsi pop07k popchg hdensity epr mfgind pctba pre1940 vacancy
ownocc medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     101
-------------+------------------------------           F( 15,    85) =   15.40
       Model |  10179.9247    15  678.661648           Prob > F      =  0.0000
    Residual |  3746.08339    85  44.0715693           R-squared     =  0.7310
-------------+------------------------------           Adj R-squared =  0.6835
       Total |  13926.0081   100  139.260081           Root MSE      =  6.6386

------------------------------------------------------------------------------
        wb10 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      MPDI07 |   1.093135    .380102     2.88   0.005     .3373901    1.848879
       povsi |   71.85299   20.89044     3.44   0.001      30.3172    113.3888
      pop07k |   .0002067   .0005591     0.37   0.713     -.000905    .0013183
      popchg |  -.4110117   .1159308    -3.55   0.001    -.6415131   -.1805103
    hdensity |   .0094671   .0075155     1.26   0.211    -.0054758      .02441
         epr |    .353788   .3289928     1.08   0.285    -.3003377    1.007914
      mfgind |   .0729845   .2169364     0.34   0.737    -.3583431    .5043121
       pctba |  -.2812764   .1939959    -1.45   0.151    -.6669923    .1044395
     pre1940 |   .1606686   .1811839     0.89   0.378    -.1995736    .5209107
     vacancy |   .8555586   .2740387     3.12   0.002     .3106963    1.400421
      ownocc |  -.3124279   .2061081    -1.52   0.133     -.722226    .0973703
     medvalk |   .0019183   .0097884     0.20   0.845    -.0175437    .0213802
         rdm |   6.134789   3.018656     2.03   0.045     .1328916    12.13669
         rds |    7.29794   4.477797     1.63   0.107     -1.60512      16.201
         rdw |  -.7483938    4.66347    -0.16   0.873    -10.02062    8.523833
       _cons |   14.40941   23.61716     0.61   0.543    -32.54783    61.36665
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

       F(  3,    85) =    3.61            Prob > F =    0.0166
```

```
. regress wb10 ruskmod povsi pop07k popchg hdensity epr mfgind pctba pre1940 vacancy
ownocc medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =      90
-------------+------------------------------           F( 15,    74) =   14.13
       Model |  8673.67746    15  578.245164           Prob > F      =  0.0000
    Residual |  3029.00254    74  40.9324667           R-squared     =  0.7412
-------------+------------------------------           Adj R-squared =  0.6887
       Total |    11702.68    89  131.490787           Root MSE      =  6.3978

------------------------------------------------------------------------------
        wb10 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     ruskmod |   .6135213   .5921148     1.04   0.304    -.5662931    1.793336
       povsi |    49.9399   23.07448     2.16   0.034     3.963002     95.9168
      pop07k |   .0007844   .0004507     1.74   0.086    -.0001137    .0016824
      popchg |  -.4236724   .1324024    -3.20   0.002      -.68749   -.1598548
    hdensity |    .011384   .0082346     1.38   0.171    -.0050237    .0277918
         epr |   .2296655   .3543908     0.65   0.519    -.4764737    .9358047
      mfgind |  -.0860088   .2446327    -0.35   0.726    -.5734501    .4014326
       pctba |  -.2899169     .19606    -1.48   0.143    -.6805749    .1007411
     pre1940 |   .0354876   .1945454     0.18   0.856    -.3521525    .4231278
     vacancy |    .465558   .4168231     1.12   0.268      -.36498    1.296096
      ownocc |  -.2074705    .239257    -0.87   0.389    -.6842005    .2692595
     medvalk |  -.0051193    .010374    -0.49   0.623    -.0257899    .0155513
         rdm |   5.701844   3.185971     1.79   0.078    -.6463415    12.05003
         rds |   2.897163   4.619575     0.63   0.532    -6.307541    12.10187
         rdw |  -4.446675   4.963508    -0.90   0.373    -14.33668     5.44333
       _cons |   38.20457   27.47946     1.39   0.169    -16.54946     92.9586
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

       F(  3,    74) =    3.13            Prob > F =    0.0307
```

Chapter V Specifications

```
. regress Density GPM07 MD pop07k popchg hdensity epr mfgind pctba pre1940 vacancy ownocc
medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     206
-------------+------------------------------           F( 15,   190) =   49.35
       Model |  102345.987    15  6823.06578           Prob > F      =  0.0000
    Residual |  26270.0033   190  138.263175           R-squared     =  0.7957
-------------+------------------------------           Adj R-squared =  0.7796
       Total |   128615.99   205  627.395073           Root MSE      =  11.759

------------------------------------------------------------------------------
     Density |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       GPM07 |   .0012765   .0059502     0.21   0.830    -.0104604    .0130134
          MD |   1.310331   5.528934     0.24   0.813    -9.595647    12.21631
      pop07k |   .0078147    .000751    10.41   0.000     .0063334    .0092961
      popchg |  -.0186636   .1430263    -0.13   0.896     -.300787    .2634599
    hdensity |   .0365618   .0105441     3.47   0.001     .0157633    .0573603
         epr |   .0341759   .3067089     0.11   0.911    -.5708161     .639168
      mfgind |  -.2620088   .2160216    -1.21   0.227    -.6881174    .1640998
       pctba |   .0002284   .1742647     0.00   0.999    -.3435137    .3439704
     pre1940 |   .0098311   .2202681     0.04   0.964    -.4246539    .4443161
     vacancy |  -.0930215   .2701797    -0.34   0.731    -.6259587    .4399157
      ownocc |  -.7485611   .2078884    -3.60   0.000    -1.158627   -.3384953
     medvalk |   .0086547   .0107239     0.81   0.421    -.0124984    .0298078
         rdm |  -2.026069   3.701367    -0.55   0.585     -9.32712    5.274981
         rds |  -6.263558   5.049411    -1.24   0.216    -16.22366    3.696546
         rdw |  -.7611356   5.400855    -0.14   0.888    -11.41447    9.892202
       _cons |   138.5401   22.58205     6.13   0.000     93.99635    183.0838
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

       F(  3,   190) =    1.27            Prob > F =    0.2851
```

```
. regress Density MPDI07 MD pop07k popchg hdensity epr mfgind pctba pre1940 vacancy
ownocc medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     206
-------------+------------------------------           F( 15,   190) =   59.34
       Model |  105989.942    15  7065.99615           Prob > F      =  0.0000
    Residual |  22626.0476   190  119.084461           R-squared     =  0.8241
-------------+------------------------------           Adj R-squared =  0.8102
       Total |   128615.99   205  627.395073           Root MSE      =  10.913

------------------------------------------------------------------------------
     Density |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      MPDI07 |  -2.658904   .4802472    -5.54   0.000    -3.606205   -1.711603
          MD |    .706485   5.131823     0.14   0.891     -9.41618    10.82915
      pop07k |   .0106682   .0008659    12.32   0.000     .0089602    .0123762
      popchg |   -.032136    .132636    -0.24   0.809    -.2937642    .2294922
    hdensity |   .0252043   .0094459     2.67   0.008      .006572    .0438366
         epr |   .1278651   .2851436     0.45   0.654    -.4345887    .6903189
      mfgind |  -.2573086   .1991055    -1.29   0.198    -.6500498    .1354325
       pctba |   .0626907   .1621123     0.39   0.699    -.2570803    .3824617
     pre1940 |   .2593235   .2048587     1.27   0.207    -.1447661    .6634131
     vacancy |  -.0323761   .2509595    -0.13   0.897    -.5274008    .4626486
      ownocc |  -.5249402   .1957576    -2.68   0.008    -.9110776   -.1388028
     medvalk |   .0054909   .0099625     0.55   0.582    -.0141603    .0251421
         rdm |   -2.61416   3.358978    -0.78   0.437    -9.239839    4.011519
         rds |  -10.08749   4.705566    -2.14   0.033    -19.36935   -.8056259
         rdw |  -3.060369    5.01909    -0.61   0.543    -12.96067    6.839928
       _cons |   128.5227   20.78146     6.18   0.000     87.53068    169.5147
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

       F(  3,   190) =    3.17            Prob > F =    0.0256

. regress Density ruskmod MD pop07k popchg hdensity epr mfgind pctba pre1940 vacancy
ownocc medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     121
-------------+------------------------------           F( 15,   105) =   30.04
       Model |  92741.0968    15  6182.73979           Prob > F      =  0.0000
    Residual |  21610.3889   105  205.813227           R-squared     =  0.8110
-------------+------------------------------           Adj R-squared =  0.7840
       Total |  114351.486   120  952.929047           Root MSE      =  14.346

------------------------------------------------------------------------------
     Density |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     ruskmod |  -2.189026   1.206715    -1.81   0.073    -4.581718    .2036659
          MD |    4.54021   7.055861     0.64   0.521    -9.450259    18.53068
      pop07k |   .0081489   .0010111     8.06   0.000     .0061442    .0101537
      popchg |  -.2097037   .2576902    -0.81   0.418    -.7206558    .3012484
    hdensity |   .0335355   .0158001     2.12   0.036     .0022069    .0648641
         epr |  -.2868546   .6110451    -0.47   0.640    -1.498444     .924735
      mfgind |   -.344029   .4473032    -0.77   0.444    -1.230949    .5428906
       pctba |   .2673546   .3230459     0.83   0.410    -.3731857    .9078949
     pre1940 |    .375958   .3858367     0.97   0.332    -.3890849    1.141001
     vacancy |    .080165   .6563122     0.12   0.903    -1.221181    1.381511
      ownocc |  -.6761929     .44332    -1.53   0.130    -1.555215    .2028287
     medvalk |   .0153974   .0184435     0.83   0.406    -.0211726    .0519674
         rdm |  -4.552725   6.127222    -0.74   0.459    -16.70187    7.596426
         rds |  -10.66655   8.579796    -1.24   0.217     -27.6787    6.345599
         rdw |  -.6937627   9.134163    -0.08   0.940    -18.80512     17.4176
       _cons |   153.7019   42.69622     3.60   0.000     69.04313    238.3606
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

       F(  3,   105) =    1.27            Prob > F =    0.2897
```

```
. regress Mixed GPM07 MD pop07k popchg hdensity epr mfgind pctba pre1940 vacancy ownocc
medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     206
-------------+------------------------------           F( 15,   190) =   29.23
       Model |  86572.7698    15  5771.51799           Prob > F      =  0.0000
    Residual |  37515.7543   190  197.451338           R-squared     =  0.6977
-------------+------------------------------           Adj R-squared =  0.6738
       Total |  124088.524   205  605.309874           Root MSE      =  14.052

------------------------------------------------------------------------------
       Mixed |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       GPM07 |   .0010797   .0071106     0.15   0.879    -.0129462    .0151056
          MD |   12.19577   6.607211     1.85   0.066    -.8371438    25.22868
      pop07k |  -.0009125   .0008975    -1.02   0.311    -.0026828    .0008578
      popchg |  -.3803856     .17092    -2.23   0.027      -.71753   -.0432411
    hdensity |   .0606542   .0126004     4.81   0.000     .0357995     .085509
         epr |   1.246169   .3665247     3.40   0.001     .5231883    1.969149
      mfgind |  -.8392413    .258151    -3.25   0.001    -1.348451   -.3300311
       pctba |  -.3873268   .2082506    -1.86   0.064    -.7981069    .0234533
     pre1940 |    .211482   .2632257     0.80   0.423    -.3077381    .7307021
     vacancy |  -.6162757   .3228714    -1.91   0.058    -1.253149    .0205972
      ownocc |  -.7751211   .2484318    -3.12   0.002     -1.26516   -.2850824
     medvalk |   .0256365   .0128153     2.00   0.047      .000358     .050915
         rdm |   7.880683   4.423224     1.78   0.076    -.8442502    16.60562
         rds |  -10.13776   6.034169    -1.68   0.095    -22.04033     1.76481
         rdw |   14.49317   6.454153     2.25   0.026     1.762172    27.22417
       _cons |   88.19359    26.9861     3.27   0.001     34.96275    141.4244
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

        F(  3,   190) =   18.47            Prob > F =    0.0000

. regress Mixed MPDI07 MD pop07k popchg hdensity epr mfgind pctba pre1940 vacancy ownocc
medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     206
-------------+------------------------------           F( 15,   190) =   29.87
       Model |  87134.3584    15  5808.95723           Prob > F      =  0.0000
    Residual |  36954.1656   190  194.495609           R-squared     =  0.7022
-------------+------------------------------           Adj R-squared =  0.6787
       Total |  124088.524   205  605.309874           Root MSE      =  13.946

------------------------------------------------------------------------------
       Mixed |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      MPDI07 |   1.047128    .613751     1.71   0.090    -.1635135    2.257769
          MD |   12.45543   6.558416     1.90   0.059     -.481236    25.39209
      pop07k |  -.0020293   .0011066    -1.83   0.068    -.0042121    .0001535
      popchg |  -.3734131   .1695074    -2.20   0.029    -.7077712    -.039055
    hdensity |   .0642114   .0120718     5.32   0.000     .0403995    .0880234
         epr |   1.208696   .3644106     3.32   0.001     .4898857    1.927506
      mfgind |  -.8478288   .2544547    -3.33   0.001    -1.349748   -.3459097
       pctba |  -.4115738   .2071778    -1.99   0.048    -.8202378   -.0029098
     pre1940 |     .12504   .2618073     0.48   0.633    -.3913823    .6414624
     vacancy |  -.6393362   .3207237    -1.99   0.048    -1.271973   -.0066997
      ownocc |  -.8703114   .2501762    -3.48   0.001    -1.363791   -.3768317
     medvalk |   .0267877   .0127319     2.10   0.037     .0016736    .0519018
         rdm |   8.322024    4.29274     1.94   0.054    -.1455255    16.78957
         rds |  -8.779422   6.013664    -1.46   0.146    -20.64154      3.0827
         rdw |   15.31087   6.414346     2.39   0.018     2.658389    27.96334
       _cons |   93.09512   26.55849     3.51   0.001     40.70776    145.4825
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

        F(  3,   190) =   19.19            Prob > F =    0.0000
```

```
. regress Mixed ruskmod MD pop07k popchg hdensity epr mfgind pctba pre1940 vacancy ownocc
medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     121
-------------+------------------------------           F( 15,   105) =   21.02
       Model |  47220.8705    15  3148.05803           Prob > F      =  0.0000
    Residual |  15728.3915   105  149.794205           R-squared     =  0.7501
-------------+------------------------------           Adj R-squared =  0.7144
       Total |   62949.262   120  524.577183           Root MSE      =  12.239

------------------------------------------------------------------------------
       Mixed |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     ruskmod |   .2154781   1.029474     0.21   0.835    -1.825779    2.256735
          MD |   13.72961   6.019506     2.28   0.025     1.794037    25.66518
      pop07k |  -.0003574   .0008626    -0.41   0.679    -.0020677    .0013529
      popchg |  -.3887175   .2198411    -1.77   0.080    -.8246217    .0471867
    hdensity |   .0483191   .0134794     3.58   0.001      .021592    .0750462
         epr |   .9850395   .5212957     1.89   0.062    -.0485936    2.018673
      mfgind |  -.4577627   .3816039    -1.20   0.233    -1.214413    .2988875
       pctba |  -.3862912   .2755974    -1.40   0.164    -.9327498    .1601675
     pre1940 |   .4762078   .3291656     1.45   0.151    -.1764667    1.128882
     vacancy |  -.3241692    .559914    -0.58   0.564    -1.434375    .7860369
      ownocc |  -.1338796   .3782058    -0.35   0.724    -.8837918    .6160326
     medvalk |     .02184   .0157345     1.39   0.168    -.0093587    .0530386
         rdm |   7.789312   5.227265     1.49   0.139    -2.575389    18.15401
         rds |  -6.417929   7.319608    -0.88   0.383    -20.93136    8.095501
         rdw |   25.67404   7.792551     3.29   0.001     10.22286    41.12523
       _cons |   49.42775   36.42506     1.36   0.178    -22.79642    121.6519
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

       F(  3,   105) =   18.10            Prob > F =    0.0000

. regress Center GPM07 MD pop07k popchg hdensity epr mfgind pctba pre1940 vacancy ownocc
medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     206
-------------+------------------------------           F( 15,   190) =    6.47
       Model |  43705.3953    15  2913.69302           Prob > F      =  0.0000
    Residual |  85501.1324   190   450.00596           R-squared     =  0.3383
-------------+------------------------------           Adj R-squared =  0.2860
       Total |  129206.528   205  630.275745           Root MSE      =  21.213

------------------------------------------------------------------------------
      Center |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       GPM07 |    .013135   .0107346     1.22   0.223    -.0080393    .0343093
          MD |   6.611084   9.974641     0.66   0.508    -13.06418    26.28634
      pop07k |   .0010188   .0013549     0.75   0.453    -.0016537    .0036913
      popchg |  -.1767797    .258031    -0.69   0.494    -.6857531    .3321936
    hdensity |   .0226223   .0190224     1.19   0.236    -.0148999    .0601445
         epr |   .7713917   .5533276     1.39   0.165    -.3200625    1.862846
      mfgind |  -.8085449   .3897202    -2.07   0.039    -1.577279   -.0398108
       pctba |   .3796364   .3143875     1.21   0.229    -.2405018    .9997747
     pre1940 |   .8813455   .3973813     2.22   0.028     .0974997    1.665191
     vacancy |  -.2090517    .487426    -0.43   0.668    -1.170513    .7524098
      ownocc |  -.5159563   .3750475    -1.38   0.171    -1.255748    .2238354
     medvalk |   .0081825   .0193467     0.42   0.673    -.0299794    .0463444
         rdm |  -2.621235   6.677563    -0.39   0.695    -15.79292    10.55045
         rds |   4.418869   9.109542     0.49   0.628    -13.54996     22.3877
         rdw |  -.3137716   9.743576    -0.03   0.974    -19.53325    18.90571
       _cons |   71.83219   40.73983     1.76   0.079    -8.528263    152.1926
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

       F(  3,   190) =    0.57            Prob > F =    0.6331
```

```
. regress Center MPDI07 MD pop07k popchg hdensity epr mfgind pctba pre1940 vacancy ownocc
medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     206
-------------+------------------------------           F( 15,   190) =    6.53
       Model |  43959.1172    15  2930.60781           Prob > F      =  0.0000
    Residual |  85247.4105   190  448.670582           R-squared     =  0.3402
-------------+------------------------------           Adj R-squared =  0.2881
       Total |  129206.528   205  630.275745           Root MSE      =  21.182

------------------------------------------------------------------------------
      Center |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      MPDI07 |  -1.340262   .9321828    -1.44   0.152    -3.179019    .4984946
          MD |   6.479214   9.961113     0.65   0.516    -13.16936    26.12779
      pop07k |   .0025119   .0016807     1.49   0.137    -.0008034    .0058272
      popchg |  -.1704129   .2574528    -0.66   0.509    -.6782457      .33742
    hdensity |   .0096695    .018335     0.53   0.599    -.0264967    .0458358
         epr |   .8140697   .5534774     1.47   0.143    -.2776801    1.905819
      mfgind |  -.8593547   .3864732    -2.22   0.027    -1.621684   -.0970254
       pctba |    .413899   .3146677     1.32   0.190    -.2067918     1.03459
     pre1940 |   1.100359   .3976406     2.77   0.006     .3160014    1.884716
     vacancy |  -.1719864   .4871244    -0.35   0.724    -1.132853    .7888802
      ownocc |  -.4594743   .3799749    -1.21   0.228    -1.208986    .2900368
     medvalk |   .0058396   .0193376     0.30   0.763    -.0323043    .0439836
         rdm |  -1.261968   6.519938    -0.19   0.847    -14.12273    11.59879
         rds |   1.326181   9.133728     0.15   0.885    -16.69036    19.34272
         rdw |  -2.165739   9.742295    -0.22   0.824    -21.38269    17.05121
       _cons |    74.3334    40.3378     1.84   0.067    -5.234052    153.9008
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

        F(  3,   190) =    0.18            Prob > F =    0.9097

. regress Center ruskmod MD pop07k popchg hdensity epr mfgind pctba pre1940 vacancy
ownocc medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     121
-------------+------------------------------           F( 15,   105) =    6.35
       Model |  33621.2741    15  2241.41827           Prob > F      =  0.0000
    Residual |  37079.6989   105  353.139989           R-squared     =  0.4755
-------------+------------------------------           Adj R-squared =  0.4006
       Total |  70700.9729   120  589.174775           Root MSE      =  18.792

------------------------------------------------------------------------------
      Center |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     ruskmod |   1.764749   1.580671     1.12   0.267    -1.369429    4.898927
          MD |   4.955611   9.242444     0.54   0.593    -13.37045    23.28167
      pop07k |   .0005211   .0013244     0.39   0.695     -.002105    .0031471
      popchg |   .1027238   .3375474     0.30   0.761    -.5665703    .7720179
    hdensity |   .0315302   .0206964     1.52   0.131     -.009507    .0725674
         epr |   .9250617   .8004055     1.16   0.250    -.6619946    2.512118
      mfgind |  -.2848527   .5859206    -0.49   0.628    -1.446625    .8769197
       pctba |    .876815   .4231565     2.07   0.041     .0377738    1.715856
     pre1940 |   .7464364    .505406     1.48   0.143    -.2556903    1.748563
     vacancy |   .3805735   .8597007     0.44   0.659    -1.324054    2.085201
      ownocc |  -1.563778   .5807031    -2.69   0.008    -2.715205   -.4123515
     medvalk |  -.0129973    .024159    -0.54   0.592    -.0609002    .0349056
         rdm |   7.013331   8.026024     0.87   0.384    -8.900792    22.92745
         rds |   10.53046   11.23864     0.94   0.351    -11.75369    32.81461
         rdw |    9.60661    11.9648     0.80   0.424    -14.11738    33.33061
       _cons |   92.77155   55.92761     1.66   0.100    -18.12257    203.6657
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

       F(  3,   105) =    0.32            Prob > F =    0.8124
```

```
. regress Streets GPM07 MD pop07k popchg hdensity epr mfgind pctba pre1940 vacancy ownocc
medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     206
-------------+------------------------------           F( 15,   190) =   15.00
       Model |  62567.0479    15  4171.13653           Prob > F      =  0.0000
    Residual |  52836.3157   190  278.085872           R-squared     =  0.5422
-------------+------------------------------           Adj R-squared =  0.5060
       Total |  115403.364   205  562.943237           Root MSE      =  16.676

------------------------------------------------------------------------------
     Streets |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       GPM07 |  -.0026508   .0084385    -0.31   0.754     -.019296    .0139945
          MD |   11.52624   7.841111     1.47   0.143    -3.940576    26.99305
      pop07k |   .0010086   .0010651     0.95   0.345    -.0010923    .0031095
      popchg |  -.4164229   .2028393    -2.05   0.041    -.8165293   -.0163166
    hdensity |    .097148   .0149536     6.50   0.000     .0676516    .1266443
         epr |   .5211132   .4349733     1.20   0.232     -.336884     1.37911
      mfgind |  -1.053403   .3063609    -3.44   0.001    -1.657708   -.4490974
       pctba |  -.2337174   .2471415    -0.95   0.346    -.7212109    .2537762
     pre1940 |   .0762698   .3123832     0.24   0.807    -.5399149    .6924545
     vacancy |   .1164792   .3831678     0.30   0.761    -.6393301    .8722884
      ownocc |   .4544732   .2948265     1.54   0.125    -.1270805    1.036027
     medvalk |   .0006174   .0152085     0.04   0.968    -.0293818    .0306167
         rdm |   10.70028   5.249263     2.04   0.043     .3459657     21.0546
         rds |    13.6389   7.161053     1.90   0.058    -.4864752    27.76428
         rdw |   22.73834    7.65947     2.97   0.003     7.629818    37.84686
       _cons |   25.89546   32.02576     0.81   0.420    -37.27627    89.06718
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

        F(  3,   190) =    3.47            Prob > F =    0.0172

. regress Streets MPDI07 MD pop07k popchg hdensity epr mfgind pctba pre1940 vacancy
ownocc medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     206
-------------+------------------------------           F( 15,   190) =   16.31
       Model |  64954.9456    15  4330.32971           Prob > F      =  0.0000
    Residual |   50448.418   190   265.51799           R-squared     =  0.5629
-------------+------------------------------           Adj R-squared =  0.5283
       Total |  115403.364   205  562.943237           Root MSE      =  16.295

------------------------------------------------------------------------------
     Streets |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      MPDI07 |   2.162849   .7171075     3.02   0.003     .7483345    3.577364
          MD |   11.99516   7.662863     1.57   0.119    -3.120055    27.11037
      pop07k |  -.0013196   .0012929    -1.02   0.309      -.00387    .0012308
      popchg |  -.4071624   .1980527    -2.06   0.041    -.7978269   -.0164979
    hdensity |   .1073195   .0141047     7.61   0.000     .0794976    .1351415
         epr |     .44549   .4257779     1.05   0.297    -.3943688    1.285349
      mfgind |  -1.050362   .2973053    -3.53   0.001    -1.636805   -.4639186
       pctba |   -.284885   .2420668    -1.18   0.241    -.7623686    .1925986
     pre1940 |  -.1387136   .3058961    -0.45   0.651    -.7421022     .464675
     vacancy |   .0663095    .374734     0.18   0.860    -.6728638    .8054828
      ownocc |    .279831   .2923062     0.96   0.340    -.2967513    .8564133
     medvalk |   .0032876    .014876     0.22   0.825    -.0260558    .0326309
         rdm |   10.96494   5.015643     2.19   0.030     1.071441    20.85844
         rds |   16.89983   7.026374     2.41   0.017     3.040108    30.75955
         rdw |   24.69807   7.494531     3.30   0.001     9.914899    39.48124
       _cons |   33.06931   31.03097     1.07   0.288    -28.14016    94.27878
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

       F(  3,   190) =    3.81            Prob > F =    0.0111
```

```
. regress Streets ruskmod MD pop07k popchg hdensity epr mfgind pctba pre1940 vacancy
ownocc medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     121
-------------+------------------------------           F( 15,   105) =    9.08
       Model |  42256.3514    15  2817.09009           Prob > F      =  0.0000
    Residual |  32588.3931   105  310.365649           R-squared     =  0.5646
-------------+------------------------------           Adj R-squared =  0.5024
       Total |  74844.7445   120  623.706204           Root MSE      =  17.617

------------------------------------------------------------------------------
     Streets |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     ruskmod |  -.2067247   1.481852    -0.14   0.889    -3.144963    2.731513
          MD |   13.49538   8.664634     1.56   0.122    -3.684991    30.67574
      pop07k |    .001471   .0012416     1.18   0.239    -.0009908    .0039329
      popchg |  -.5203672   .3164449    -1.64   0.103    -1.147819    .1070846
    hdensity |   .0839234   .0194026     4.33   0.000     .0454517    .1223951
         epr |   .8169049   .7503665     1.09   0.279    -.6709334    2.304743
      mfgind |  -.8703507   .5492906    -1.58   0.116    -1.959492    .2187911
       pctba |  -.3813674    .396702    -0.96   0.339    -1.167954    .4052193
     pre1940 |   .3732982   .4738095     0.79   0.433    -.5661785    1.312775
     vacancy |   .7782312   .8059548     0.97   0.336    -.8198282    2.376291
      ownocc |   1.007009   .5443992     1.85   0.067    -.0724338    2.086452
     medvalk |   .0033633   .0226487     0.15   0.882    -.0415449    .0482714
         rdm |   9.531818   7.524261     1.27   0.208    -5.387401    24.45104
         rds |   15.50334   10.53603     1.47   0.144    -5.387664    36.39435
         rdw |    31.8318    11.2168     2.84   0.005     9.590958    54.07264
       _cons |  -35.77989   52.43118    -0.68   0.496    -139.7412    68.18146
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

        F(  3,   105) =    3.22            Prob > F =    0.0257

. regress Total GPM07 MD pop07k popchg hdensity epr mfgind pctba pre1940 vacancy ownocc
medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     206
-------------+------------------------------           F( 15,   190) =   12.99
       Model |  66641.3224    15  4442.75483           Prob > F      =  0.0000
    Residual |  64988.1557   190  342.042925           R-squared     =  0.5063
-------------+------------------------------           Adj R-squared =  0.4673
       Total |  131629.478   205  642.095015           Root MSE      =  18.494

------------------------------------------------------------------------------
       Total |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       GPM07 |    .021871   .0093587     2.34   0.020     .0034106    .0403314
          MD |   19.54967   8.696179     2.25   0.026     2.396217    36.70313
      pop07k |   -.004207   .0011812    -3.56   0.000     -.006537   -.0018771
      popchg |  -.5159233   .2249588    -2.29   0.023    -.9596609   -.0721857
    hdensity |   .0875525   .0165843     5.28   0.000     .0548396    .1202654
         epr |   .9179461   .4824069     1.90   0.059     -.033615    1.869507
      mfgind |  -1.244826   .3397693    -3.66   0.000     -1.91503   -.5746214
       pctba |  -.2016977   .2740921    -0.74   0.463     -.742352    .3389567
     pre1940 |   .3063685   .3464484     0.88   0.378    -.3770107    .9897478
     vacancy |   -.284976    .424952    -0.67   0.503    -1.123206    .5532537
      ownocc |  -.8445315   .3269771    -2.58   0.011    -1.489503   -.1995599
     medvalk |   .0155097    .016867     0.92   0.359    -.0177609    .0487804
         rdm |   3.796539   5.821691     0.65   0.515    -7.686911    15.27999
         rds |  -3.132946   7.941961    -0.39   0.694    -18.79869     12.5328
         rdw |   13.06276   8.494729     1.54   0.126    -3.693329    29.81886
       _cons |   105.0109   35.51815     2.96   0.004     34.95038    175.0715
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

       F(  3,   190) =    3.83            Prob > F =    0.0107
```

```
. regress Total MPDI07 MD pop07k popchg hdensity epr mfgind pctba pre1940 vacancy ownocc
medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     206
-------------+------------------------------           F( 15,   190) =   13.65
       Model |  68262.5169    15  4550.83446           Prob > F      =  0.0000
    Residual |  63366.9612   190  333.510322           R-squared     =  0.5186
-------------+------------------------------           Adj R-squared =  0.4806
       Total |  131629.478   205  642.095015           Root MSE      =  18.262

------------------------------------------------------------------------------
       Total |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      MPDI07 |  -2.599572   .8036963    -3.23   0.001    -4.184885   -1.014258
          MD |   19.24411   8.588132     2.24   0.026     2.303775    36.18444
      pop07k |  -.0013268   .0014491    -0.92   0.361    -.0041851    .0015316
      popchg |  -.5073721    .221967    -2.29   0.023    -.9452082   -.0695359
    hdensity |   .0645156   .0158078     4.08   0.000     .0333343    .0956969
         epr |   1.002037   .4771893     2.10   0.037     .0607675    1.943306
      mfgind |  -1.328027    .333204    -3.99   0.000    -1.985281   -.6707725
       pctba |  -.1360437   .2712957    -0.50   0.617    -.6711822    .3990947
     pre1940 |   .7042498   .3428322     2.05   0.041     .0280037    1.380496
     vacancy |  -.2149593   .4199821    -0.51   0.609    -1.043386    .6134672
      ownocc |  -.7187467   .3276014    -2.19   0.029     -1.36495   -.0725437
     medvalk |   .0111814   .0166722     0.67   0.503     -.021705    .0440679
         rdm |   5.955067   5.621268     1.06   0.291    -5.133042    17.04318
         rds |  -8.795204   7.874789    -1.12   0.265    -24.32845     6.73804
         rdw |   9.670717   8.399474     1.15   0.251    -6.897482    26.23892
       _cons |   107.6828   34.77788     3.10   0.002     39.08251    176.2832
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

       F(  3,   190) =    6.91            Prob > F =    0.0002

. regress Total ruskmod MD pop07k popchg hdensity epr mfgind pctba pre1940 vacancy ownocc
medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     121
-------------+------------------------------           F( 15,   105) =    9.33
       Model |  43421.0224    15  2894.73482           Prob > F      =  0.0000
    Residual |  32586.8295   105  310.350757           R-squared     =  0.5713
-------------+------------------------------           Adj R-squared =  0.5100
       Total |  76007.8519   120  633.398765           Root MSE      =  17.617

------------------------------------------------------------------------------
       Total |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     ruskmod |  -.2609792   1.481816    -0.18   0.861    -3.199147    2.677189
          MD |    21.0405   8.664426     2.43   0.017      3.86054    38.22045
      pop07k |  -.0029859   .0012416    -2.40   0.018    -.0054477   -.0005241
      popchg |  -.5120235   .3164373    -1.62   0.109     -1.13946    .1154133
    hdensity |   .0768286   .0194021     3.96   0.000     .0383578    .1152994
         epr |    .660553   .7503485     0.88   0.381    -.8272495    2.148356
      mfgind |  -.4591495   .5492774    -0.84   0.405    -1.548265    .6299662
       pctba |    .065539   .3966925     0.17   0.869    -.7210289    .8521069
     pre1940 |   .5014397   .4737981     1.06   0.292    -.4380144    1.440894
     vacancy |   .1624346   .8059354     0.20   0.841    -1.435586    1.760456
      ownocc |  -.8858935   .5443862    -1.63   0.107    -1.965311    .1935237
     medvalk |   .0063994   .0226481     0.28   0.778    -.0385077    .0513065
         rdm |    4.95842    7.52408     0.66   0.511    -9.960441    19.87728
         rds |  -5.863569   10.53578    -0.56   0.579    -26.75408    15.02694
         rdw |   19.37743   11.21653     1.73   0.087     -2.86288    41.61773
       _cons |    103.179   52.42992     1.97   0.052    -.7798143    207.1379
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

       F(  3,   105) =    5.21            Prob > F =    0.0022
```

Chapter VI Specifications

```
. regress medhhipc GPM07 medhhik pop07k popchg hdensity epr mfgind pctba pre1940 vacancy
ownocc medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     353
-------------+------------------------------           F( 15,   337) =    5.74
       Model |  4525.1349    15  301.67566           Prob > F      =  0.0000
    Residual |  17722.4911   337  52.5889944           R-squared     =  0.2034
-------------+------------------------------           Adj R-squared =  0.1679
       Total |  22247.626   352  63.2034829           Root MSE      =  7.2518

------------------------------------------------------------------------------
    medhhipc |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       GPM07 |   .0089261   .0021924     4.07   0.000     .0046136    .0132386
     medhhik |  -.3181707   .1011225    -3.15   0.002    -.5170815     -.11926
      pop07k |   .0000367   .0003799     0.10   0.923    -.0007106     .000784
      popchg |  -.1368674   .0636476    -2.15   0.032    -.2620641   -.0116707
    hdensity |   .0008898   .0055789     0.16   0.873    -.0100841    .0118636
         epr |    .231093   .1247084     1.85   0.065    -.0142118    .4763979
      mfgind |   -.228605   .0848152    -2.70   0.007    -.3954389   -.0617712
       pctba |   .1473786   .0758784     1.94   0.053    -.0018764    .2966336
     pre1940 |  -.0596059   .0843414    -0.71   0.480    -.2255078     .106296
     vacancy |   -.333834   .0985062    -3.39   0.001    -.5275985   -.1400694
      ownocc |   .0945482   .0967389     0.98   0.329    -.0957399    .2848363
     medvalk |   .0048594   .0071954     0.68   0.500    -.0092941    .0190129
         rdm |   -3.94842   1.696912    -2.33   0.021    -7.286294   -.6105461
         rds |  -.4303126   2.204919    -0.20   0.845    -4.767451    3.906826
         rdw |  -2.191543   2.393625    -0.92   0.361    -6.899871    2.516785
       _cons |   2.197341   8.280549     0.27   0.791    -14.09073    18.48542
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

       F(  3,   337) =    3.47            Prob > F =    0.0164

. regress medhhipc MPDI07 medhhik pop07k popchg hdensity epr mfgind pctba pre1940 vacancy
ownocc medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     353
-------------+------------------------------           F( 15,   337) =    4.43
       Model |  3664.06955    15  244.271303           Prob > F      =  0.0000
    Residual |  18583.5564   337  55.1440844           R-squared     =  0.1647
-------------+------------------------------           Adj R-squared =  0.1275
       Total |  22247.626   352  63.2034829           Root MSE      =  7.4259

------------------------------------------------------------------------------
    medhhipc |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      MPDI07 |   .1149656   .2615077     0.44   0.660    -.3994273    .6293586
     medhhik |  -.3843694   .1025188    -3.75   0.000    -.5860269    -.182712
      pop07k |   .0000188   .0004786     0.04   0.969    -.0009227    .0009603
      popchg |  -.1639275   .0648385    -2.53   0.012    -.2914668   -.0363883
    hdensity |  -.0049907   .0055366    -0.90   0.368    -.0158814       .0059
         epr |   .2989502   .1265484     2.36   0.019     .0500258    .5478745
      mfgind |  -.2988463   .0850141    -3.52   0.000    -.4660713   -.1316212
       pctba |   .1193784   .0776493     1.54   0.125    -.0333601    .2721169
     pre1940 |  -.0128616   .0861954    -0.15   0.881    -.1824104    .1566872
     vacancy |  -.3110249   .1007476    -3.09   0.002    -.5091983   -.1128516
      ownocc |   .0955321   .0999479     0.96   0.340    -.1010682    .2921324
     medvalk |   .0068235   .0073687     0.93   0.355    -.0076711     .021318
         rdm |   -2.71002   1.727459    -1.57   0.118     -6.10798    .6879403
         rds |  -1.536959   2.282232    -0.67   0.501    -6.026174    2.952255
         rdw |  -2.475262   2.489861    -0.99   0.321     -7.37289    2.422365
       _cons |   4.737967   8.455239     0.56   0.576    -11.89373    21.36966
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

       F(  3,   337) =    1.16            Prob > F =    0.3268
```

```
. regress medhhipc ruskmod medhhik pop07k popchg hdensity epr mfgind pctba pre1940
vacancy ownocc medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     125
-------------+------------------------------           F( 15,   109) =    3.05
       Model |  1072.17099    15  71.4780662           Prob > F      =  0.0004
    Residual |   2556.9625   109  23.4583715           R-squared     =  0.2954
-------------+------------------------------           Adj R-squared =  0.1985
       Total |  3629.13349   124  29.2672056           Root MSE      =  4.8434

------------------------------------------------------------------------------
    medhhipc |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     ruskmod |  -.5826776   .3910196    -1.49   0.139    -1.357666    .1923105
     medhhik |   .0452669   .1343451     0.34   0.737    -.2210007    .3115345
      pop07k |    .000574   .0003055     1.88   0.063    -.0000314    .0011794
      popchg |  -.2105096   .0836083    -2.52   0.013    -.3762185   -.0448007
    hdensity |  -.0076439   .0051878    -1.47   0.144    -.0179259    .0026382
         epr |  -.0021209   .2090778    -0.01   0.992    -.4165063    .4122644
      mfgind |  -.1238732   .1484831    -0.83   0.406    -.4181618    .1704155
       pctba |   .2079217   .1151209     1.81   0.074    -.0202441    .4360876
     pre1940 |   .2809282   .1254101     2.24   0.027     .0323695    .5294869
     vacancy |  -.3961461   .2216471    -1.79   0.077    -.8354434    .0431512
      ownocc |   .0641423   .1621091     0.40   0.693    -.2571526    .3854373
     medvalk |  -.0134554   .0091435    -1.47   0.144    -.0315775    .0046667
         rdm |  -1.020896   2.097688    -0.49   0.627    -5.178445    3.136654
         rds |   5.292656   2.929137     1.81   0.074    -.5127984    11.09811
         rdw |   3.724338   3.209177     1.16   0.248    -2.636147    10.08482
       _cons |  -1.656758   14.22806    -0.12   0.908    -29.85632     26.5428
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

        F(  3,   109) =    4.17            Prob > F =    0.0077

. regress gdppctchg GPM07 gdp2007b pop07k popchg hdensity epr mfgind pctba pre1940
vacancy ownocc medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     353
-------------+------------------------------           F( 15,   337) =    7.16
       Model |  11329.9009    15   755.32673           Prob > F      =  0.0000
    Residual |  35549.1468   337  105.487083           R-squared     =  0.2417
-------------+------------------------------           Adj R-squared =  0.2079
       Total |  46879.0478   352  133.179113           Root MSE      =  10.271

------------------------------------------------------------------------------
   gdppctchg |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       GPM07 |   .0049939   .0031022     1.61   0.108    -.0011082    .0110961
    gdp2007b |   .0575229   .0367654     1.56   0.119    -.0147956    .1298415
      pop07k |  -.0035442    .002316    -1.53   0.127    -.0080999    .0010115
      popchg |  -.0529553   .0907374    -0.58   0.560    -.2314383    .1255277
    hdensity |  -.0051022   .0078778    -0.65   0.518    -.0205981    .0103937
         epr |   .5924271   .1648089     3.59   0.000     .2682434    .9166108
      mfgind |  -.2819392   .1195406    -2.36   0.019     -.517079   -.0467994
       pctba |  -.1090815   .1062955    -1.03   0.306    -.3181678    .1000047
     pre1940 |  -.0297115   .1188197    -0.25   0.803    -.2634332    .2040103
     vacancy |   -.487494   .1370892    -3.56   0.000    -.7571524   -.2178356
      ownocc |   -.440354   .1263408    -3.49   0.001    -.6888699   -.1918382
     medvalk |  -.0151955   .0078251    -1.94   0.053    -.0305877    .0001967
         rdm |  -.7049791   2.383639    -0.30   0.768    -5.393664    3.983705
         rds |   4.113065    3.06347     1.34   0.180    -1.912867      10.139
         rdw |  -1.532298   3.310125    -0.46   0.644    -8.043408    4.978811
       _cons |   24.12526   11.71563     2.06   0.040     1.080289    47.17022
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

       F(  3,   337) =    3.26            Prob > F =    0.0216
```

```
. regress gdppctchg MPDI07 gdp2007b pop07k popchg hdensity epr mfgind pctba pre1940
vacancy ownocc medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     353
-------------+------------------------------           F( 15,   337) =    7.02
       Model |  11164.8798    15  744.325318           Prob > F      =  0.0000
    Residual |   35714.168   337   105.97676           R-squared     =  0.2382
-------------+------------------------------           Adj R-squared =  0.2043
       Total |  46879.0478   352  133.179113           Root MSE      =  10.295

------------------------------------------------------------------------------
   gdppctchg |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      MPDI07 |   .3838558    .379637     1.01   0.313     -.362901    1.130613
    gdp2007b |   .0779875   .0382409     2.04   0.042     .0027665    .1532084
      pop07k |  -.0051571   .0025593    -2.02   0.045    -.0101914   -.0001228
      popchg |  -.0631204   .0906475    -0.70   0.487    -.2414265    .1151858
    hdensity |  -.0078914   .0076066    -1.04   0.300    -.0228538    .0070709
         epr |   .6027916   .1649925     3.65   0.000     .2782467    .9273364
      mfgind |   -.317061   .1174675    -2.70   0.007    -.5481229   -.0859991
       pctba |  -.1413954   .1064039    -1.33   0.185    -.3506949     .067904
     pre1940 |   -.017897    .119047    -0.15   0.881    -.2520658    .2162717
     vacancy |  -.4651481   .1369959    -3.40   0.001    -.7346229   -.1956733
      ownocc |  -.4676744   .1280948    -3.65   0.000    -.7196406   -.2157082
     medvalk |  -.0160143   .0078265    -2.05   0.042    -.0314093   -.0006194
         rdm |   .3651005   2.369444     0.15   0.878    -4.295663    5.025864
         rds |   4.122385   3.111601     1.32   0.186    -1.998222    10.24299
         rdw |  -.9638871   3.384987    -0.28   0.776    -7.622252    5.694477
       _cons |    26.4408   11.68538     2.26   0.024     3.455319    49.42628
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

       F(  3,   337) =    2.62            Prob > F =    0.0508

. regress gdppctchg ruskmod gdp2007b pop07k popchg hdensity epr mfgind pctba pre1940
vacancy ownocc medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     125
-------------+------------------------------           F( 15,   109) =    2.05
       Model |  1591.05015    15   106.07001           Prob > F      =  0.0180
    Residual |  5645.33821   109  51.7920937           R-squared     =  0.2199
-------------+------------------------------           Adj R-squared =  0.1125
       Total |  7236.38836   124  58.3579706           Root MSE      =  7.1967

------------------------------------------------------------------------------
   gdppctchg |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     ruskmod |  -.5822705   .5884542    -0.99   0.325    -1.748568    .5840267
    gdp2007b |   .0465159   .0306385     1.52   0.132    -.0142087    .1072405
      pop07k |  -.0022962   .0019459    -1.18   0.241    -.0061529    .0015604
      popchg |   .0274189   .1275173     0.22   0.830    -.2253162     .280154
    hdensity |   -.011832   .0077117    -1.53   0.128    -.0271162    .0034523
         epr |  -.0326388   .2991369    -0.11   0.913    -.6255185    .5602408
      mfgind |  -.0886527   .2175952    -0.41   0.684    -.5199193    .3426138
       pctba |    .119396   .1640459     0.73   0.468    -.2057376    .4445296
     pre1940 |    .353812   .1844827     1.92   0.058    -.0118268    .7194508
     vacancy |  -.6003966   .3295262    -1.82   0.071    -1.253507    .0527138
      ownocc |  -.0977408   .2224306    -0.44   0.661     -.538591    .3431094
     medvalk |   -.006946   .0090681    -0.77   0.445    -.0249186    .0110267
         rdm |   2.521858   3.047219     0.83   0.410    -3.517631    8.561348
         rds |    9.25994   4.199751     2.20   0.030     .9361702    17.58371
         rdw |   4.910712   4.549936     1.08   0.283    -4.107113    13.92854
       _cons |    23.8926   20.84575     1.15   0.254    -17.42301     65.2082
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

       F(  3,   109) =    2.66            Prob > F =    0.0521
```

```
. regress povallchg GPM07 pov07all pop07k popchg hdensity epr mfgind pctba pre1940
vacancy ownocc medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     346
-------------+------------------------------           F( 15,   330) =    6.48
       Model |  468.765835    15  31.2510557           Prob > F      =  0.0000
    Residual |  1592.09514   330  4.82453073           R-squared     =  0.2275
-------------+------------------------------           Adj R-squared =  0.1923
       Total |  2060.86097   345  5.97351007           Root MSE      =  2.1965

------------------------------------------------------------------------------
   povallchg |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       GPM07 |   -.001414   .0006633    -2.13   0.034    -.0027189   -.0001091
    pov07all |  -.2417421    .041287    -5.86   0.000    -.3229609   -.1605233
      pop07k |  -.0000823   .0001209    -0.68   0.496    -.0003201    .0001555
      popchg |   .0645723   .0194923     3.31   0.001     .0262274    .1029172
    hdensity |   .0003686   .0017709     0.21   0.835    -.0031152    .0038523
         epr |  -.1199298   .0375633    -3.19   0.002    -.1938236   -.0460361
      mfgind |   .0394442    .025773     1.53   0.127    -.0112559    .0901444
       pctba |  -.0121099   .0230627    -0.53   0.600    -.0574782    .0332585
     pre1940 |   .0055823   .0254474     0.22   0.827    -.0444773    .0556419
     vacancy |   .0738948   .0295371     2.50   0.013       .01579    .1319997
      ownocc |  -.1103164   .0311872    -3.54   0.000    -.1716672   -.0489656
     medvalk |  -.0010703     .00186    -0.58   0.565    -.0047293    .0025887
         rdm |   .9964015   .5130953     1.94   0.053    -.0129486    2.005752
         rds |  -.1467149   .6574816    -0.22   0.824    -1.440099    1.146669
         rdw |   .7323934   .7160465     1.02   0.307     -.676198    2.140985
       _cons |   19.50653   3.468138     5.62   0.000     12.68409    26.32898
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

       F(  3,   330) =    3.78            Prob > F =    0.0109

. regress povallchg MPDI07 pov07all pop07k popchg hdensity epr mfgind pctba pre1940
vacancy ownocc medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     346
-------------+------------------------------           F( 15,   330) =    6.09
       Model |  447.070397    15  29.8046932           Prob > F      =  0.0000
    Residual |  1613.79058   330  4.89027448           R-squared     =  0.2169
-------------+------------------------------           Adj R-squared =  0.1813
       Total |  2060.86097   345  5.97351007           Root MSE      =  2.2114

------------------------------------------------------------------------------
   povallchg |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      MPDI07 |  -.0172218   .0797143    -0.22   0.829    -.1740342    .1395905
    pov07all |  -.2422515   .0416068    -5.82   0.000    -.3240994   -.1604035
      pop07k |  -.0000766   .0001511    -0.51   0.613    -.0003739    .0002207
      popchg |    .068955   .0195156     3.53   0.000     .0305644    .1073456
    hdensity |   .0014585   .0017078     0.85   0.394     -.001901    .0048181
         epr |  -.1266741   .0376866    -3.36   0.001    -.2008104   -.0525378
      mfgind |   .0497471   .0254837     1.95   0.052    -.0003839    .0998781
       pctba |  -.0061084    .023121    -0.26   0.792    -.0515915    .0393746
     pre1940 |  -.0030284   .0254603    -0.12   0.905    -.0531135    .0470566
     vacancy |   .0682867   .0296486     2.30   0.022     .0099625    .1266108
      ownocc |  -.1072171   .0315791    -3.40   0.001    -.1693388   -.0450954
     medvalk |  -.0009299   .0018735    -0.50   0.620    -.0046154    .0027556
         rdm |   .7920484    .512606     1.55   0.123    -.2163393    1.800436
         rds |  -.0028249   .6718288    -0.00   0.997    -1.324432    1.318782
         rdw |   .7477079   .7319085     1.02   0.308    -.6920869    2.187503
       _cons |   19.07423    3.48664     5.47   0.000     12.21538    25.93307
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

       F(  3,   330) =    2.56            Prob > F =    0.0546
```

```
. regress povallchg ruskmod pov07all pop07k popchg hdensity epr mfgind pctba pre1940
vacancy ownocc medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     124
-------------+------------------------------           F( 15,   108) =    3.64
       Model |  140.451541    15  9.36343604           Prob > F      =  0.0000
    Residual |  277.776851   108  2.57200788           R-squared     =  0.3358
-------------+------------------------------           Adj R-squared =  0.2436
       Total |  418.228392   123  3.40023083           Root MSE      =  1.6037

------------------------------------------------------------------------------
   povallchg |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     ruskmod |   .2876967   .1299015     2.21   0.029     .0302094     .545184
    pov07all |  -.1035822   .0884758    -1.17   0.244    -.2789566    .0717922
      pop07k |  -.0001081   .0001025    -1.06   0.294    -.0003112     .000095
      popchg |   .0971987   .0278542     3.49   0.001     .0419868    .1524105
    hdensity |  -.0005401   .0017515    -0.31   0.758    -.0040118    .0029317
         epr |  -.0844128    .074632    -1.13   0.261    -.2323464    .0635207
      mfgind |   .0755919   .0490311     1.54   0.126    -.0215962      .17278
       pctba |  -.0793837     .03594    -2.21   0.029     -.150623   -.0081444
     pre1940 |  -.0334934   .0412103    -0.81   0.418    -.1151793    .0481925
     vacancy |   .0739825   .0735202     1.01   0.317    -.0717474    .2197123
      ownocc |  -.0717809   .0578932    -1.24   0.218    -.1865354    .0429735
     medvalk |   .0024966    .002331     1.07   0.287    -.0021239    .0071171
         rdm |   .5132415   .6834299     0.75   0.454    -.8414351    1.867918
         rds |  -.3327984   .9424897    -0.35   0.725    -2.200976     1.53538
         rdw |   .4010425   1.021718     0.39   0.695     -1.62418    2.426265
       _cons |   12.77651   7.121075     1.79   0.076      -1.3387    26.89171
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

       F(  3,   108) =    1.38            Prob > F =    0.2541

. regress ginichg GPM07 gini07 pop07k popchg hdensity epr mfgind pctba pre1940 vacancy
ownocc medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     346
-------------+------------------------------           F( 15,   330) =    9.52
       Model |  397.526307    15  26.5017538           Prob > F      =  0.0000
    Residual |  918.724188   330  2.78401269           R-squared     =  0.3020
-------------+------------------------------           Adj R-squared =  0.2703
       Total |   1316.2505   345  3.81521883           Root MSE      =  1.6685

------------------------------------------------------------------------------
     ginichg |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       GPM07 |  -.0007718    .000504    -1.53   0.127    -.0017632    .0002196
      gini07 |  -.4448363   .0411101   -10.82   0.000    -.5257072   -.3639654
      pop07k |   .0000782   .0000919     0.85   0.396    -.0001026     .000259
      popchg |   -.003859    .014868    -0.26   0.795     -.033107     .025389
    hdensity |   .0010574   .0013514     0.78   0.435     -.001601    .0037158
         epr |  -.0545856    .027162    -2.01   0.045    -.1080181   -.001153
      mfgind |  -.0240823   .0195701    -1.23   0.219    -.0625801    .0144156
       pctba |   .0455692   .0182242     2.50   0.013     .0097189    .0814194
     pre1940 |   -.010249   .0193158    -0.53   0.596    -.0482467    .0277487
     vacancy |   .0283833   .0225131     1.26   0.208     -.015904    .0726705
      ownocc |  -.0277139     .02158    -1.28   0.200    -.0701656    .0147379
     medvalk |   .0003563   .0013104     0.27   0.786    -.0022215    .0029341
         rdm |   .2247434   .3891924     0.58   0.564    -.5408675    .9903543
         rds |  -.1007071   .5046905    -0.20   0.842    -1.093523    .8921093
         rdw |  -.6826949   .5430049    -1.26   0.210    -1.750883    .3854928
       _cons |   25.16591   2.922955     8.61   0.000     19.41593    30.91588
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

       F(  3,   330) =    1.55            Prob > F =    0.2013
```

```
. regress ginichg MPDI07 gini07 pop07k popchg hdensity epr mfgind pctba pre1940 vacancy
ownocc medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     346
-------------+------------------------------           F( 15,   330) =    9.40
       Model |  394.067431    15  26.2711621           Prob > F      =  0.0000
    Residual |  922.183065   330  2.79449413           R-squared     =  0.2994
-------------+------------------------------           Adj R-squared =  0.2675
       Total |   1316.2505   345  3.81521883           Root MSE      =  1.6717

------------------------------------------------------------------------------
     ginichg |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      MPDI07 |   .0631958   .0602864     1.05   0.295    -.0553983    .1817898
      gini07 |  -.4482758   .0412384   -10.87   0.000    -.5293991   -.3671524
      pop07k |  -1.66e-07   .0001142    -0.00   0.999    -.0002249    .0002246
      popchg |  -.0016418    .014817    -0.11   0.912    -.0307896    .0275059
    hdensity |   .0017781   .0012971     1.37   0.171    -.0007736    .0043298
         epr |  -.0597388   .0271244    -2.20   0.028    -.1130973   -.0063802
      mfgind |  -.0178192   .0192578    -0.93   0.355    -.0557027    .0200644
       pctba |     .04783   .0181595     2.63   0.009     .0121071    .0835529
     pre1940 |  -.0180359   .0192356    -0.94   0.349    -.0558758     .019804
     vacancy |   .0264406   .0224944     1.18   0.241    -.0178099    .0706911
      ownocc |  -.0301816   .0218811    -1.38   0.169    -.0732256    .0128624
     medvalk |   .0004827   .0013123     0.37   0.713    -.0020989    .0030642
         rdm |   .1720801   .3870537     0.44   0.657    -.5893237    .9334839
         rds |   .1160218   .5143228     0.23   0.822    -.8957431    1.127787
         rdw |  -.5534193    .552961    -1.00   0.318    -1.641192    .5343538
       _cons |   25.09896   2.928169     8.57   0.000     19.33872    30.85919
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

       F(  3,   330) =    1.38            Prob > F =    0.2491

. regress ginichg ruskmod gini07 pop07k popchg hdensity epr mfgind pctba pre1940 vacancy
ownocc medvalk rdm rds rdw

      Source |       SS       df       MS              Number of obs =     124
-------------+------------------------------           F( 15,   108) =    2.59
       Model |  47.9233873    15  3.19489248           Prob > F      =  0.0024
    Residual |  133.328875   108  1.23452662           R-squared     =  0.2644
-------------+------------------------------           Adj R-squared =  0.1622
       Total |  181.252262   123  1.47359562           Root MSE      =  1.1111

------------------------------------------------------------------------------
     ginichg |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     ruskmod |   .0646876   .0900272     0.72   0.474    -.1137621    .2431372
      gini07 |  -.2218254   .0598865    -3.70   0.000    -.3405308   -.1031199
      pop07k |  -3.47e-06   .0000711    -0.05   0.961    -.0001443    .0001374
      popchg |  -.0138698   .0194533    -0.71   0.477    -.0524297      .02469
    hdensity |    .001216   .0012404     0.98   0.329    -.0012428    .0036747
         epr |  -.0045943   .0463607    -0.10   0.921    -.0964893    .0873007
      mfgind |   .0600232   .0338677     1.77   0.079    -.0071084    .1271548
       pctba |   .0174473   .0253345     0.69   0.493    -.0327701    .0676646
     pre1940 |  -.0486974   .0284068    -1.71   0.089    -.1050045    .0076098
     vacancy |   .0469927   .0518987     0.91   0.367    -.0558795     .149865
      ownocc |   .0023505   .0348443     0.07   0.946     -.066717     .071418
     medvalk |   .0010639   .0014077     0.76   0.451    -.0017264    .0038541
         rdm |   -.391689   .4707736    -0.83   0.407    -1.324844     .541466
         rds |  -.8556871   .6528635    -1.31   0.193    -2.149776    .4384017
         rdw |  -.3991275   .7063672    -0.57   0.573     -1.79927    1.001015
       _cons |   10.31041    4.40609     2.34   0.021     1.576774    19.04404
------------------------------------------------------------------------------

. test (rdm=0) (rds=0) (rdw=0)

       F(  3,   108) =    0.80            Prob > F =    0.4959
```

APPENDIX D: OUTPUT AND TABLE FOR 3SLS OHIO MODEL

Included below is the full Stata output for the three-stage least squares model specified in Chapter VII. The following page includes correlation coefficients for all pairs of variables included in the model.

```
. reg3 (All PIPct medhhi09 SDFrag Frag57 pd09 P40P09 oop09 pct4pbr) (PIPct All medhhi09
SDFrag Frag57 pd09 wnhpct09 c4_09 vpp14k Mills ITR) (medhhi09 PIPct SDFrag Frag57 pd09
wnhpct09 c4_09 vpp14k Mills ITR)

Three-stage least-squares regression
----------------------------------------------------------------------
Equation          Obs  Parms        RMSE    "R-sq"       chi2        P
----------------------------------------------------------------------
All               609      8    94.04124    0.8473    3177.25   0.0000
PIPct             609     10    2.804596    0.7180    1350.41   0.0000
medhhi09          609      9    18220.48   -0.6159     342.99   0.0000
----------------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
All          |
       PIPct |  -4.238672   1.839688    -2.30   0.021    -7.844393   -.6329502
    medhhi09 |   .0180486   .0011851    15.23   0.000     .0157258    .0203715
      SDFrag |  -7.410686   1.264017    -5.86   0.000    -9.888114   -4.933258
      Frag57 |   .4862381   .3176097     1.53   0.126    -.1362654    1.108742
        pd09 |   .0054388   .0049736     1.09   0.274    -.0043093    .0151869
      P40P09 |  -.7837949   .3528316    -2.22   0.026    -1.475332   -.0922577
       oop09 |  -3.678636   .6401075    -5.75   0.000    -4.933224   -2.424049
     pct4pbr |  -1.369123   1.058353    -1.29   0.196    -3.443457    .7052116
       _cons |   649.3976     130.05     4.99   0.000     394.5043    904.2909
-------------+----------------------------------------------------------------
PIPct        |
         All |   .0005146   .0026336     0.20   0.845    -.0046472    .0056764
    medhhi09 |    .000148   .0000301     4.92   0.000      .000089     .000207
      SDFrag |    .169587   .0490767     3.46   0.001     .0733984    .2657756
      Frag57 |   -.035125   .0102308    -3.43   0.001     -.055177    -.015073
        pd09 |  -.0003993   .0001718    -2.32   0.020    -.0007361   -.0000625
    wnhpct09 |   .2373952   .0145402    16.33   0.000     .2088969    .2658935
       c4_09 |   .0943862    .023688     3.98   0.000     .0479586    .1408139
      vpp14k |   .0043199   .0023317     1.85   0.064    -.0002501    .0088899
       Mills |   .0150414   .0101285     1.49   0.138    -.0048101    .0348929
         ITR |   .1419036   .2548054     0.56   0.578    -.3575058    .6413129
       _cons |   49.21327    1.87429    26.26   0.000     45.53973    52.88681
-------------+----------------------------------------------------------------
medhhi09     |
       PIPct |   6511.392   700.1765     9.30   0.000     5139.072    7883.713
      SDFrag |  -1089.865   255.4523    -4.27   0.000    -1590.543   -589.1881
      Frag57 |   227.5017   67.30117     3.38   0.001     95.59383    359.4096
        pd09 |   2.665049   1.183972     2.25   0.024     .3445074    4.985591
    wnhpct09 |  -1538.983   198.7636    -7.74   0.000    -1928.553   -1149.414
       c4_09 |  -628.3327   181.2842    -3.47   0.001    -983.6432   -273.0222
      vpp14k |  -28.93725   15.24144    -1.90   0.058    -58.80992     .935429
       Mills |  -100.9714   65.22659    -1.55   0.122    -228.8132    26.87039
         ITR |  -624.3333   1555.321    -0.40   0.688    -3672.707     2424.04
       _cons |  -321757.4   37863.92    -8.50   0.000    -395969.4   -247545.5
------------------------------------------------------------------------------
Endogenous variables:  All PIPct medhhi09
Exogenous variables:   SDFrag Frag57 pd09 P40P09 oop09 pct4pbr wnhpct09 c4_09
     vpp14k Mills ITR
------------------------------------------------------------------------------
```

Table D-1: Correlation Table for Ohio School District 3SLS Model

Variable	1	2	3	4	5
1. Median monthly gross housing cost, 2010-2014	1.0000				
2. Performance index percentage, 2013-14	0.5000	1.0000			
3. Median nominal household income, 2005-2009	0.8870	0.6680	1.0000		
4. School districts per 100,000 county residents, 2012	-0.4580	0.0189	-0.2646	1.0000	
5. School districts per 100,000 county residents, 1957	-0.3529	-0.0421	-0.2354	0.6533	1.0000
6. Total population per square mile (density), 2007	0.1729	-0.2773	-0.0074	-0.4782	-0.4800
7. Percent of housing units built pre-1940, 2005-2009	-0.4294	-0.2550	-0.3722	0.3880	0.3007
8. Percent of housing units owner-occupied, 2005-2009	0.3078	0.5358	0.5268	0.2090	0.1805
9. Percent of housing units w/4+ bedrooms, 2005-2009	0.7793	0.5757	0.8513	-0.2071	-0.1808
10. Percent of residents white non-Hispanic, 2005-2009	-0.0597	0.5531	0.1191	0.3213	0.3202
11. Percent of adults 25+ with college degree, 2005-2009	0.7936	0.4886	0.7505	-0.4472	-0.4023
12. Property market valuation per pupil, 2014	0.5003	0.4253	0.5195	-0.2492	-0.1499
13. School district property tax millage, 2014	0.5076	0.0867	0.3875	-0.5330	-0.4987
14. School district income tax rate (%), 2014	-0.0571	0.1153	0.0427	0.3927	0.2478

	6	7	8	9	10	11	12	13	14
6	1.0000								
7	0.0399	1.0000							
8	-0.5043	-0.1360	1.0000						
9	0.0121	-0.2616	0.4300	1.0000					
10	-0.5859	0.0421	0.5251	0.0634	1.0000				
11	0.3655	-0.3661	0.0366	0.7118	-0.1496	1.0000			
12	0.0016	-0.2908	0.2167	0.4860	0.0687	0.5420	1.0000		
13	0.6644	-0.1680	-0.2284	0.3577	-0.4411	0.6640	0.2280	1.0000	
14	-0.2862	0.3748	0.1970	0.0324	0.1948	-0.1799	-0.0956	-0.2940	1.0000

APPENDIX E: RESPONSE TO COMMITTEE FEEDBACK

As conditions of considering the dissertation defense successful, the committee requested two additional contributions. First, members noted that the OLS regression models were not estimated using heteroscedasticity-consistent (robust) standard errors, first developed by Eicker (1967) and Huber (1967). This econometric procedure corrects for potential violations of the OLS model assumption that variances in one variable are not correlated with the value of any other variable. Estimation of all equations from Chapters IV through VI were repeated using this method. The complete statistical output is omitted here, but nowhere did the significance of a coefficient at the 95% level change due to implementation of the robust standard error correction.

Second, it was suggested that the 3SLS model did not account for students residing in a district that may be attending schools other than those in the traditional public school system, i.e., charter and private schools. Data were obtained for 2014 that indicated shares of such students in charter schools, as well as those receiving vouchers to attend private schools (C.D. Grady, personal communication, December 23, 2016). There are no records of enrollment by district of origin for private school students not receiving state funds, but the sum of the two percentages available were added to the model as a control variable in the performance index equation. Assuming there is selection bias in parental decisions regarding whether to remove their children from traditional public schools, it would be expected that the share of such students would have some correlation with public school students' performance on standardized tests.

This would appear to be an instance of bidirectional causality, however, in that parents who live in low-performing school districts would be far more likely to remove their children from the traditional public school system than those in high-performing school districts. Indeed, Ohio Revised Code limits the ability of charter schools to be created outside of distressed districts (State of Ohio, 2016). Therefore, this measure was also included as a fourth dependent variable, specifying the same control variables as in the performance index equation.

The full model output is provided on the next page. The key finding (the first coefficient, representing the effect of standardized test scores on median housing cost) retained its negative sign and statistical significance at the 95% level from Chapter VII. Indeed, little has changed overall. Notably, the model finds that, with respect to the mutual causality between performance index percentage and proportion of charter and voucher students, the first effect described was not found to be statistically significant, while the second effect was.

```
. reg3 (All PIPct medhhi09 SDFrag Frag57 pd09 P40P09 oop09 pct4pbr) (PIPct All medhhi09
SDFrag Frag57 pd09 wnhpct09 c4_09 vpp14k Mills ITR combpct) (medhhi09 PIPct SDFrag Frag57
pd09 wnhpct09 c4_09 vpp14k Mills ITR) (combpct PIPct medhhi09 SDFrag Frag57 pd09 wnhpct09
c4_09 vpp14k Mills ITR)

Three-stage least-squares regression
----------------------------------------------------------------------
Equation          Obs  Parms        RMSE    "R-sq"       chi2        P
----------------------------------------------------------------------
All               608      8    94.11227    0.8471    3170.35   0.0000
PIPct             608     11    2.648119    0.7473     966.06   0.0000
medhhi09          608      9    18124.48   -0.5963     326.95   0.0000
combpct           608     10    4.619508    0.0564     713.86   0.0000
----------------------------------------------------------------------
------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
All          |
       PIPct |  -4.363801   1.866996    -2.34   0.019    -8.023046   -.7045557
    medhhi09 |   .0181752   .0012784    14.22   0.000     .0156697    .0206807
      SDFrag |  -7.305196   1.286052    -5.68   0.000    -9.825811   -4.784581
      Frag57 |   .4651225    .319431     1.46   0.145    -.1609508    1.091196
        pd09 |    .005358   .0050335     1.06   0.287    -.0045075    .0152234
      P40P09 |  -.7493403   .3719504    -2.01   0.044     -1.47835   -.0203308
       oop09 |  -3.647974   .6423589    -5.68   0.000    -4.906975   -2.388974
     pct4pbr |   -1.52209   1.301039    -1.17   0.242     -4.07208      1.0279
       _cons |   653.2046   130.5812     5.00   0.000     397.2702    909.1391
-------------+----------------------------------------------------------------
PIPct        |
         All |   .0010896   .0011323     0.96   0.336    -.0011296    .0033088
    medhhi09 |   .0001225   .0000265     4.62   0.000     .0000706    .0001745
      SDFrag |   .1481485     .09395     1.58   0.115    -.0359902    .3322872
      Frag57 |  -.0393925   .0126106    -3.12   0.002    -.0641088   -.0146761
        pd09 |  -.0002999   .0003298    -0.91   0.363    -.0009463    .0003465
    wnhpct09 |   .1480265   .1778309     0.83   0.405    -.2005157    .4965688
       c4_09 |   .0757016   .0480205     1.58   0.115    -.0184168      .16982
      vpp14k |   .0044074   .0028811     1.53   0.126    -.0012395    .0100543
       Mills |   .0128878   .0132081     0.98   0.329    -.0129995    .0387751
         ITR |   .1148324   .3019115     0.38   0.704    -.4769033    .7065681
     combpct |  -.3239985   .6305993    -0.51   0.607     -1.55995    .9119533
       _cons |   60.16772   21.84627     2.75   0.006     17.34982    102.9856
-------------+----------------------------------------------------------------
medhhi09     |
       PIPct |   6564.579   812.8739     8.08   0.000     4971.375    8157.782
      SDFrag |  -1140.541   262.3267    -4.35   0.000    -1654.692   -626.3896
      Frag57 |   238.8792   69.41763     3.44   0.001     102.8231    374.9353
        pd09 |   2.706222    1.24164     2.18   0.029     .2726531    5.139791
    wnhpct09 |  -1548.904   224.5474    -6.90   0.000    -1989.009   -1108.799
       c4_09 |  -641.0171   202.9408    -3.16   0.002    -1038.774   -243.2604
      vpp14k |  -29.76869   15.41557    -1.93   0.053    -59.98265    .4452736
       Mills |  -97.95972   65.45798    -1.50   0.135     -226.255    30.33556
         ITR |  -840.7128   1574.003    -0.53   0.593    -3925.702    2244.276
       _cons |  -324952.1   43666.87    -7.44   0.000    -410537.6   -239366.6
-------------+----------------------------------------------------------------
combpct      |
       PIPct |  -1.638454   .5457172    -3.00   0.003     -2.70804   -.5688681
    medhhi09 |   .0002011   .0000798     2.52   0.012     .0000446    .0003576
      SDFrag |   .1697496   .1033826     1.64   0.101    -.0328766    .3723759
      Frag57 |  -.0672611   .0230953    -2.91   0.004     -.112527   -.0219951
        pd09 |   -.000312   .0003175    -0.98   0.326    -.0009343    .0003103
    wnhpct09 |   .1099057   .1306248     0.84   0.400    -.1461141    .3659256
       c4_09 |   .1008015    .063781     1.58   0.114     -.024207      .22581
      vpp14k |   .0068558    .003742     1.83   0.067    -.0004783    .0141899
       Mills |   .0176363   .0145556     1.21   0.226    -.0108922    .0461647
         ITR |   .2294342   .3037027     0.76   0.450    -.3658121    .8246806
       _cons |   115.2496   27.20055     4.24   0.000      61.9375    168.5617
------------------------------------------------------------------------------
Endogenous variables:  All PIPct medhhi09 combpct
Exogenous variables:   SDFrag Frag57 pd09 P40P09 oop09 pct4pbr wnhpct09 c4_09
     vpp14k Mills ITR
------------------------------------------------------------------------------
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