CHAPTER 5 TRANSPORTATION

To proponents of smart growth, transportation is a cornerstone policy area, a framing element that contributes importantly to the overall success of any initiative. While most smart growth models focus on urban form—compact footprints, higher densities, mixed uses, redevelopment of existing urban centers, and preservation of farmlands and environmentally sensitive lands—many of these outcomes are possible only when a regional transportation system is in place. Indeed, Smart Growth America (n.d.), one of the most ardent proponents of this planning approach, considers the structure of the transportation network the backbone that supports smart growth.

While disagreement remains about the principles of the smart growth movement (Costa 2005; Ye, Mandpe, and Meyer 2005), there is general consensus that providing and encouraging transportation choices is among its primary goals. For example, of the ten organizations generally supporting some form of smart growth studied by Ye et al., nine specifically mention expanding choices in transportation modes, promoting transit usage, and/or incorporating pedestrian-friendly design into new development. While some interpret transportation choice more narrowly as increasing the use of public transit systems (Downs 2005), smart growth advocates generally support alternatives to single-occupancy vehicle (SOV) travel, including transit, carpooling, biking, and walking. By reducing the number of SOV trips, increased use of other modes can reduce traffic congestion levels, lower greenhouse gas emissions, and support a more compact, mixed-use, and dense urban form.

This chapter evaluates the evidence on the linkage between smart growth systems and desirable transportation outcomes. More specifically, the analysis looks at the relationship between state smart growth programs and the commute to work via transit and bicycling/walking, as well as changes in traffic congestion over time.

For most measures investigated here, the evidence that state smart growth policy has a positive impact on transportation outcomes is limited. Nevertheless, the analyses point to stronger growth in transit commute rates and more modest increases in congestion in states with smart growth programs. Commute rates for bicycling and walking, however, are no higher in cities in smart growth states than in the other selected states, with the notable exception of Portland, Oregon. Taken as a whole, these findings support the contention that smart growth programs can produce more desirable outcomes in the form of lower automotive travel and more moderate growth in traffic congestion. Even so, data limitations and a rather coarse level of analysis make it difficult to establish direct causality between specific smart growth policies and desirable transportation outcomes.

THE TRANSPORTATION–LAND USE CONNECTION

The idea that transportation and land use are linked has been the subject of research for decades. One of the earliest and most influential works is Mitchell and Rapkin's 1954 volume, *Urban Traffic: A Function of Land Use*. Although this connection is well understood intuitively, the precise nature of the relationship has generally eluded planners, public officials, and researchers. Fundamental to the literature are three conceptualizations of the transportation–land use connection (Handy 2005).

1. Transportation investments shape land development outcomes.
2. Land use mixes, densities, and intensities influence travel patterns and behaviors.
3. Travel patterns influence the choice of transportation investments.

Contributing to the debate concerning the strength and importance of the transportation–land use connection, Giuliano (1995) argues that the importance of this relationship is in decline for several reasons: the fact that large transportation systems are embedded in low density metropolitan areas (which flatten out travel costs); the reality that commute time is only one factor in household location decisions; and evidence that major transportation improvements (such as new highway links or transit lines) capture only a small share of regional trips. In a response to Giuliano's article, Cervero and Landis (1995) concede that the transportation–land use connection is not as strong as it was when regional highways and rail systems were being developed in the first half of the twentieth century. They do maintain, however, that transportation investments still influence land values and development patterns, making transportation an important element in a comprehensive regional land use strategy.

The three most detailed and comprehensive reviews of the evidence concerning the transportation–land use connection are found in Crane (2000), Ewing and Cervero (2001), and Handy (2005). In addition, the American Planning Association has published a planning advisory report providing a detailed discussion of the economic theory behind the transportation–land use connection, as well as an overview of the policy options available to local, regional, and state governments (Moore and Thornses 2007). Taken as a whole, research into the transportation–land use connection yields two clear conclusions.

1. *The nature of the connection between transportation and land use is much more complex than expected.* Factors such as household preferences, socio-demographic variables, and the geographic scale of policy prescriptions play roles in how this connection expresses itself.

2. *While urban form and urban design can influence transportation outcomes, these factors are usually secondary to personal preferences and socio-demographic characteristics.* Smart growth policies, such as increased density, mixed uses, transit-oriented design, and New Urbanist features, may play a role in transportation modes and miles traveled, but their effects appear to be modest at best.

The findings from the transportation–land use literature are important to the smart growth movement in at least two respects. First, many proponents of smart growth oversimplify the connection, assuming that greater densities, the mixing of uses, and the prevalence of other modes of travel will yield substantial gains in nonautomotive travel and declines in the number and distance of trips. Advocates often view this connection as a one-way relationship in which land use and land design determine transportation outcomes, a conceptualization that flies in the face of decades of research. Handy (2005, 163–164) effectively summarizes this complexity.

> Rather than a simple linear relationship between transportation investments, land development patterns, and travel patterns, we face a system of endogenous relationships between transportation and land use. . . In addition, countless exogenous factors also come into play: attitudes and sociodemographic characteristics influence travel patterns, land development patterns are influenced by land use policies, and transportation investments may reflect political forces.

Second, even the most successful smart growth initiatives are likely to have limited impacts on transportation outcomes. Empirical studies find that personal preferences influence travel modes and travel distances more than the best land use plans and quality urban design interventions (Crane 2000). This has led Giuliano (1995), Cervero (1989), and others to call for transportation pricing strategies in addition to land use strategies as a means to control development patterns. Indeed, Cervero goes so far as to label land use strategies the "second best" solution to addressing congestion and other transportation ills.

In summary, the contemporary view of the transportation–land use connection confirms that it is real, but complex and bidirectional. Empirical studies demonstrate that land use patterns can influence transportation choices and outcomes, but only after being filtered through personal attributes and preferences, and considering existing land use and transportation conditions. Similarly, transportation investments can and do influence land use patterns, but again only within the context of existing markets and transportation systems. Overall, then, this suggests that a land use approach to promote alternative travel modes, reduce commute times, and mitigate increases in congestion must be part of a broader strategy for achieving these goals.

DATA SOURCES

Transportation research benefits from a wealth of information. For example, the Federal Highway Administration (FHWA) collects a great deal of state-level data on road network system size, number of vehicles, and vehicle miles traveled (VMT). This information is collected annually from each state, providing a standardized, longitudinal dataset. In addition, the U.S. Census Bureau collects data on aspects of individual commute behavior, including travel mode and travel time to work. These data are readily available at the regional level and down to the census-tract level, although only for years ending in "0".

In the area of congestion, the Texas Transportation Institute (TTI) captures annual data for a subset of U.S. metropolitan areas. While generally recognized as the best available information on congestion, the TTI sample is limited. Some analysts have used data from surveys, travel diaries, and other proprietary sources—information that many researchers believe provides the most detailed and accurate picture of travel behavior and personal travel preferences.

For purposes of this study, the data had to meet several criteria: be available for all eight case study states; be reported at the county or metropolitan level; and allow testing of the core arguments of smart growth proponents. Given these parameters, the two datasets selected are from the Census Bureau on commute travel modes, and from the TTI on metropolitan congestion. These data speak directly to issues raised by smart growth advocates and are available at the substate level. The census data are available for all case study states, while the TTI data cover a sufficient number of metropolitan areas to allow comparison between states with and without smart growth programs.

As part of recent decennial censuses, the long-form questionnaire incorporates questions on the travel behavior of respondents in their commutes to work.[1] Included are questions regarding the mode of travel and the time it takes to get to work. These data provide snapshots of commute modes in the eight case study states in 1990 and 2000, the decade during which smart growth policies gained mainstream appeal. The data allow a test of claims that cities or counties in smart growth states experience stronger growth (or smaller declines) in the shares of commute trips via transit and bicycling/walking than those in the other selected states.

The analysis is based on a subset of cities and counties in each state with gross densities of 50 or more people per square mile.[2] Focusing on urban and suburban areas enables the tracking of changes in counties where transit and bike/walk commutes are a reasonable option and where traffic congestion is likely to be an issue. Counties are categorized as very high density (more than 500 people per square mile), high density (100–500 people per square mile), and medium density (50–100 or more people per square mile). Of the 692 counties and cities in the sample, 82 are very high density, 118 high density, 127 medium density, 118 low density, and 247 very low density. While gross density is a coarse measure, these groupings allow comparison of counties with roughly the same level of urbanization.

SMART GROWTH AND TRAVEL MODES

Smart growth advocates call for transportation choices, and they promote investments in transportation systems—especially public transit, along with connected bicycling and pedestrian networks—that encourage travel by modes other than the personal automobile. In addition to those supply-side changes, smart growth proponents support policies that influence the demand for other travel modes. For example, transit-oriented developments (TODs), gridded street networks, and New Urbanist design features are hallmarks of the smart growth agenda.

Proponents of smart growth argue that when travelers have the opportunity to use alternative modes and live in a built environment that rewards these choices (with higher density, mixed uses, and an interesting and safe urban setting), the share of trips by these other modes will increase, bringing a myriad of environmental, health, and quality-of-life improvements to travelers and nontravelers alike. It stands to reason, then, that states with smart growth policies should see a greater share of trips via transit and biking/walking than those without such policies.

COMMUTES BY PUBLIC TRANSIT

Table 5.1 presents the share of commute trips by public transportation for the counties in the sample states, as well as for the United States as a whole, sorted by density. Florida, for example, has seven counties with more than 500 persons per square mile. Within this set, the share of work commute trips by public transit fell from 2.42 percent in 1990 to 2.35 percent in 2000, a decline of 3.06 percent over the decade. In contrast, New Jersey's 13 very high density counties saw an increase of more than 12 percent in the share of commutes by public transportation, growing from just under 9 percent to just over 10 percent.

Not surprisingly, the percentage of commute trips by public transit for the United States as a whole fell in all county categories. A second unsurprising finding is that transit use was generally higher for counties with higher gross densities. Averaging across the very high density counties, the share of commute trips by transit in 2000 was roughly 6.0 percent, compared with 1.0 percent in high density and 0.5 percent in medium density counties.

In terms of change in transit mode share, the smart growth states outperformed the U.S. average in each density category. For example, high density counties saw an average decline in public transit mode share of 2.61 percent, while counties in this category in all four smart growth states saw average increases ranging from about 7 percent to 46 percent. The findings for other density categories are similar, with those in smart growth states generally outperforming the U.S. average. Among the other selected states, only Colorado consistently outperformed the U.S. average on this measure.

Notably, counties in smart growth states saw larger increases (or smaller declines) in transit mode share than counties in the other selected states. New Jersey and Oregon experienced the largest gains over the decade, adding to their already sizable shares in 1990. While Florida and Maryland do not show the transit share increases of the other smart growth states, they still outperformed three of the four other selected states.

Table 5.1 also reveals that commute shares for public transit in general were falling in the other selected states.

Table 5.1 **Average Share of Commute Trips by Public Transportation by County Type, 1990 and 2000**

(A) VERY HIGH DENSITY COUNTIES (More Than 500 People Per Square Mile)

	Number of Counties	1990 (%)	2000 (%)	Average Percent Change
SMART GROWTH STATES				
Florida	7	2.42	2.35	-3.06
Maryland	6	9.44	9.13	-3.30
New Jersey	13	8.99	10.09	12.27
Oregon	1	9.97	11.63	16.66
OTHER SELECTED STATES				
Colorado	2	5.71	6.12	7.12
Indiana	4	2.54	2.02	-20.37
Texas	7	3.22	2.76	-14.06
Virginia	42	3.70	3.37	-8.90
ALL U.S.	197	6.38	6.15	-3.59

(B) HIGH DENSITY COUNTIES (101–500 People Per Square Mile)

	Number of Counties	1990 (%)	2000 (%)	Average Percent Change
SMART GROWTH STATES				
Florida	23	0.65	0.71	9.05
Maryland	11	1.00	1.29	29.24
New Jersey	8	2.44	2.60	6.82
Oregon	4	2.27	3.30	45.76
OTHER SELECTED STATES				
Colorado	4	2.76	3.49	26.44
Indiana	26	0.72	0.59	-17.53
Texas	25	0.71	0.63	-10.70
Virginia	17	1.19	1.10	-7.10
ALL U.S.	539	1.02	0.99	-2.61

(C) MEDIUM DENSITY COUNTIES (50–100 People Per Square Mile)

	Number of Counties	1990 (%)	2000 (%)	Average Percent Change
SMART GROWTH STATES				
Florida	12	0.65	0.72	10.65
Maryland	6	0.87	0.87	-0.50
New Jersey	0	N/A	N/A	N/A
Oregon	5	0.88	1.14	29.57
OTHER SELECTED STATES				
Colorado	3	1.08	1.09	1.43
Indiana	42	0.29	0.29	0.14
Texas	24	0.31	0.22	-26.77
Virginia	35	0.83	0.67	-19.04
ALL U.S.	564	0.56	0.52	-5.87

Source: U.S. Census Bureau (1990e; 2000f).

Indeed, even the densest counties in Indiana, Texas, and Virginia saw sizable transit share declines in the 1990s. Only Colorado showed improvements in public transportation mode share because the Denver metropolitan region embraced many tenets of smart growth during the 1990s, including an informal urban growth boundary and major investments in a rail system.

Overall, the evidence suggests a positive relationship between having a state smart growth mandate and an increase in public transit mode share. Nevertheless, even within the most successful smart growth states, only a small percentage of commuters use public transportation. Of the 692 counties and cities in the sample, only 12 had public transportation mode shares of more than 10 percent in 2000, and 5 of those counties are located in the suburban Washington, DC, area.

COMMUTES BY BICYCLING AND WALKING

Opportunities for individuals to bicycle and walk to work can be achieved through infrastructure (bike lanes, sidewalks, pathway networks), as well as design features that support these travel modes, such as smaller blocks, gridded networks, and interesting mixed-use environments (Dill and Carr 2003). If smart growth policies are successful, states should expect to see increases (or smaller declines) in bike/walk mode shares.

Florida's seven very high density counties saw a 33 percent decline in bike/walk trips, from 3.26 percent in 1990 to 2.18 percent in 2000 (table 5.2). Unlike mode share for public transit, bike/walk mode shares are not correlated with gross density because biking and walking trips can occur in places with either very low or very high densities. Bike/walk mode shares in the sample states in 2000 generally ranged between 2 percent and 6 percent, even in the lower density counties.

The evidence in table 5.2 lends little support to the idea that state smart growth programs promote biking and walking to work, with one notable exception. Bike/walk commute shares declined in every density category in every state except for Oregon's one very high density county, Multnomah, which lies at the center of the Portland metropolitan area. Furthermore, the rates of decline are similar across all states, regardless of their smart growth orientation. Overall, 600 of the 692 jurisdictions

Table 5.2 **Average Share of Commute Trips by Biking/Walking by County Type, 1990 and 2000**

(A) VERY HIGH DENSITY COUNTIES (More Than 500 People Per Square Mile)

	Number of Counties	1990 (%)	2000 (%)	Average Percent Change
SMART GROWTH STATES				
Florida	7	3.26	2.18	-33.02
Maryland	6	3.62	3.07	-15.21
New Jersey	13	4.34	3.52	-18.88
Oregon	1	5.74	6.33	10.21
OTHER SELECTED STATES				
Colorado	2	4.28	3.55	-17.03
Indiana	4	3.53	2.87	-18.60
Texas	7	3.20	2.41	-24.58
Virginia	42	6.23	5.12	-17.68
ALL U.S.	197	4.56	3.79	-16.94

(B) HIGH DENSITY COUNTIES (101–500 People Per Square Mile)

	Number of Counties	1990 (%)	2000 (%)	Average Percent Change
SMART GROWTH STATES				
Florida	23	3.15	2.35	-25.52
Maryland	11	3.43	2.27	-33.85
New Jersey	8	4.12	2.88	-30.00
Oregon	4	6.29	5.54	-11.92
OTHER SELECTED STATES				
Colorado	4	5.25	3.80	-27.69
Indiana	26	3.54	2.75	-22.16
Texas	25	2.94	2.16	-26.58
Virginia	17	2.81	2.27	-18.94
ALL U.S.	539	4.04	2.96	-26.91

(C) MEDIUM DENSITY COUNTIES (50–100 People Per Square Mile)

	Number of Counties	1990 (%)	2000 (%)	Average Percent Change
SMART GROWTH STATES				
Florida	12	3.74	2.70	-27.59
Maryland	6	4.83	3.83	-20.80
New Jersey	0	N/A	N/A	N/A
Oregon	5	6.17	5.05	-18.26
OTHER SELECTED STATES				
Colorado	3	3.64	2.93	-19.69
Indiana	42	3.69	2.57	-30.53
Texas	24	3.62	2.37	-34.50
Virginia	35	2.77	2.05	-25.86
ALL U.S.	564	4.07	2.85	-29.82

Source: U.S. Census Bureau (1990e; 2000f).

showed decreases in this mode of travel between 1990 and 2000, with most of these losses in small cities and counties with low bike/walk shares.

Only eight places with populations above 50,000 in 2000 saw increases in bike/walk mode share: the counties of Clark (Indiana), Escambia (Florida), Grant (Indiana), Multnomah (Oregon), San Patricio (Texas), Spotsylvania (Virginia), Wichita (Texas), and the City of Norfolk (Virginia). By far the largest of these locations is Multnomah County, where the increase in mode share over the decade was more than 10 percent. While this finding cannot be directly attributed to the region's smart growth program, some analysts argue that Portland's success can be tied to Oregon's Transportation Planning Rule, requiring local governments to produce bike and pedestrian plans as well as policies that support public transit (Adler and Dill 2004).

SMART GROWTH PROGRAMS AND CONGESTION

At least 16 states passed some form of smart growth legislation through the year 2000.[3] While the rationales for these legislative acts are many and varied, the laws were passed largely in response to growing concern over two sprawl-related issues—rising automobile congestion and ongoing environmental degradation.

The relationship between sprawl and congestion is the subject of considerable debate. One side takes the position that more compact urban forms will reduce traffic congestion by increasing public transit use, reducing travel distances, and providing a closer mix of commercial and residential uses (Ewing 1997; Downs 2004; 2005). Those on the other side argue that more dispersed metropolitan areas allow residents to avoid suburbs-to-center-city commuting. That is, as people move to the suburbs, jobs follow, and work trips become shorter in time and distance (Gordon and Richardson 1997).

Few studies relate automobile congestion to urban form, and none links state smart growth legislation to automobile congestion. There is, however, a literature that has investigated the relationship between commuting times and distances and suburbanization. Gordon and Richardson (1997) and Ewing (1997) review these studies and reach different conclusions regarding the relationship between sprawl and commutes.

The only report to investigate the relationship between urban form and congestion is by the U.S. Environmental Protection Agency (2004), which divides data from 13 MSAs into 5 matched sets based on population size. Within each set, one city is identified as having a more "19th-century urban design" with a relatively dense and well-connected network of streets, shorter block sizes, and extensive transit service. The measure of automobile congestion, which comes from the Texas Transportation Institute's *Mobility Monitoring Program* (n.d.), is the annual delay per peak-period traveler.

Because these data are only available for the nation's largest 85 cities, the EPA could make congestion comparisons within just three of their five sets. In each group, the cities considered most traditional in design—Philadelphia, Pittsburgh, and New Orleans—had the least delay per traveler. Other variables related to congestion (obtained from local metropolitan planning organizations) could be compared within all five EPA groups. These results show that vehicle miles of road travel per capita per day were lower, and weekly transit trips per capita were higher, in the traditional cities. However, the unsophisticated nature of EPA's methodology—particularly the choice of MSAs forming the matched sets and the absence of control variables—has come under serious attack (Cox and Utt 2004).

The following section uses panel data estimation techniques to investigate the impact of state smart growth programs on automobile congestion. Of the 16 states that have passed some form of legislation calling for a state role in managing growth, 13 have adopted comprehensive planning with sufficient emphasis on implementation to be considered by some observers to be termed a smart growth state: California, Colorado, Florida, Georgia, Hawaii, Maine, Maryland, New Jersey, Oregon, Rhode Island, Tennessee, Vermont, and Washington.[4]

Isolating the effect of state smart growth programs involves controlling for a whole host of current and historical factors that affect congestion levels in particular metropolitan areas. Many of these factors (e.g., the spatial arrangement of land uses or the amount of state and local expenditures on transportation infrastructure) are complex and difficult to measure. The advantage of using panel data is that including fixed effects in both the level of and change in automobile congestion captures many of these factors. Fixed effects control for unobservable heterogeneity across areas. Aggregate time effects that have a uniform impact on congestion across cities also can be included. With these three-way fixed effects models, it is possible to estimate with reliability the effect of state smart growth programs on congestion with parsimoniously specified models. Using two alternative TTI measures, the results strongly suggest that state smart growth programs reduce growth in automobile congestion.

Other three-way fixed effects models were estimated where the dependent variable alternatively equals the annual change in per capita daily VMT, in population density, and in per capita transit use. These models attempt to uncover how state smart growth programs are able to slow the growth in automobile congestion. The causal pathway that relates a state smart growth program to congestion may involve an intermediate link through one or more of the above three variables. For example, it may be that the primary avenue by which a state smart growth program affects congestion is by first causing an increase in transit ridership. Program-induced changes in these intermediate output variables are found to explain less than 20 percent of the total impact that a smart growth program has on congestion. These results suggest that specific anti-congestion policies inspired by a state smart growth program may largely account for the impact that such programs have on congestion.

TTI TRAFFIC DATA

The Texas Transportation Institute provided 22 years of mobility data (1982–2003) for each of the 85 urbanized areas (UAs) that it tracks.[5] These data contain two measures of automobile congestion: annual delay per peak traveler; and a travel time index. The first measure is an estimate of the extra travel time beyond what would occur at free-flow speeds, divided by the number of travelers who begin a trip during peak periods (6:00–9:00 a.m. and 4:00–7:00 p.m.).[6] For example, this measure equaled 51 for the Miami, Florida UA in 2003, meaning that the average peak period traveler experienced 51 hours of delay during that year. The second measure is the ratio of travel time in the peak period to the travel time at free-flow conditions. In this case, a value of 1.35

Table 5.3 **Mean Annual Delay per Peak-Period Traveler in Large Cities (Hours)**

	SMART GROWTH STATES			OTHER SELECTED STATES			
Year	Florida	Maryland	Oregon	Colorado	Indiana	Texas	Virginia
1982	15	9	7	16	4	7	12
1983	15	12	5	16	4	12	12
1984	20	13	7	30	6	10	13
1985	22	13	7	19	5	16	16
1986	21	17	10	20	5	19	16
1987	24	19	12	21	5	14	18
1988	26	21	14	20	5	11	22
1989	26	31	17	22	6	12	19
1990	28	35	19	26	8	13	20
1991	36	34	21	28	11	13	18
1992	38	29	27	32	15	14	19
1993	41	30	33	38	28	12	18
1994	45	34	33	38	36	11	22
1995	44	36	36	45	40	20	23
1996	45	37	41	51	45	28	25
1997	46	39	42	45	48	21	24
1998	48	35	42	58	38	27	27
1999	47	35	43	57	36	37	28
2000	48	36	41	60	38	40	20
2001	51	40	42	60	40	35	20
2002	49	47	44	52	37	36	23
2003	51	50	39	51	38	33	27
Rank in 2003	1	3	4	1	5	6	7
Gross Change in Delay 1982–2003	36	41	32	35	34	26	15
Rank by Gross Change in Delay	2	1	5	3	4	6	7

Source: Authors' calculations based on automobile congestion data provided by the Texas Transportation Institute.

Table 5.4 **Yearly Changes in Mean Annual Delay per Peak-Period Traveler in Large Cities (Hours)**

	SMART GROWTH STATES			OTHER SELECTED STATES			
Year	Florida	Maryland	Oregon	Colorado	Indiana	Texas	Virginia
1983	0	3	-2	0	0	5	0
1984	5	1	2	14	2	-2	1
1985	2	0	0	-11	-1	6	3
1986	-1	4	3	1	0	3	0
1987	3	2	2	1	0	-5	2
1988	2	2	2	-1	0	-3	4
1989	0	10	3	2	1	1	-3
1990	2	4	2	4	2	1	1
1991	8	-1	2	2	3	0	-2
1992	2	-5	6	4	4	1	1
1993	3	1	6	6	13	-2	-1
1994	4	4	0	0	8	-1	4
1995	-1	2	3	7	4	9	1
1996	1	1	5	6	5	8	2
1997	1	2	1	-6	3	-7	-1
1998	2	-4	0	13	-10	6	3
1999	-1	0	1	-1	-2	10	1
2000	1	1	-2	3	2	3	-8
2001	3	4	1	0	2	-5	0
2002	-2	7	2	-8	-3	1	3
2003	2	3	-5	-1	1	-3	4
Average Change 1983–2003	1.71	1.95	1.52	1.67	1.62	1.24	0.71
Rank of Average Changes	2	1	5	3	4	6	7
Average Change Before Smart Growth Program	2.33	2.00		2.44			
Average Change After Smart Growth Program	1.61	1.91		-3.00			

Source: Authors' calculations based on automobile congestion data provided by the Texas Transportation Institute.

indicates that a 20-minute free-flow trip takes 27 minutes during the peak.

In addition to the congestion measures, the TTI data include estimates of daily vehicle miles of travel; annual unlinked passenger trips on public transit; population; population density (persons/square mile); and lane miles of freeway and principal arterial streets.[7] All of these variables are used in estimating the three-way fixed effects models. The panel also includes the annual real per capita income of the UA's MSA as reported by the Bureau of Economic Analysis.

The analyses focus on two groups of states: (1) seven of the eight case study states (TTI does not provide data for New Jersey); and (2) seven other states that both adopted a smart growth program between 1982 and 2003, and included at least one UA for which the TTI provides congestion measures. Colorado, Florida, and Maryland are in both groups. The data for the second group, which also includes Georgia, Rhode Island, Tennessee, and Washington, allow estimation of regression models to investigate the effect of smart growth programs on the change in congestion.[8]

COMPARISON OF CASE STUDY STATES

TTI divides the urban areas for which it reports congestion measures into four groups according to population: small (less than 500,000); medium (more than 500,000 and less than 1 million), large (more than 1 million and less than 3 million); and very large (more than 3 million). More meaningful comparisons across the seven case study states were obtained by focusing on just their large urbanized areas. Using one of TTI's most popular congestion measures—annual delay per peak-period traveler—table 5.3 shows the mean for large cities in each of the seven case study states for which data are available.

Focusing first on interstate differences in congestion levels in 2003, three states without smart growth programs had the least congestion: Virginia (27 hours of delay), followed by Texas (33 hours of delay), and Indiana (38 hours of delay). Moreover, with the exception of Oregon, these three states had the smallest increases in delay over the 1982–2003 period. These results suggest that either smart growth programs worsen congestion, or states with higher congestion are more likely to adopt such programs. The direction of causality cannot be determined from table 5.3.

Table 5.4 reports the intrastate yearly changes in the mean annual delay per peak-period traveler. Focusing on these means of first differences nets out systematic variation in intrastate congestion due to history or scale effects. The average of the changes in delay computed over the length of the panel for each state appears at the bottom of the table. As in table 5.3, the results show a systematic difference between states with and without smart growth programs, with the smart growth states evidencing the highest average change in mean annual delay.

Colorado, Florida, and Maryland adopted smart growth programs after 1982, the first year of the panel. For these states, the post-adoption average changes in delay are smaller than the pre-adoption averages, again indicating a possible link between smart growth programs and automobile congestion. The estimates in table 5.4 suggest that state smart growth programs are associated with slower growth in congestion. The difference between tables 5.3 and 5.4 is that limiting the comparisons to intrastate changes in congestion before and after adoption of a smart growth program partially controls for confounding factors (namely those that vary across areas but do not vary over time), thereby providing a more reliable assessment of whether a true relationship exists. Hence, the results in table 5.4 can be viewed with greater confidence.

Although table 5.4 provides some evidence that state smart growth programs may reduce the growth in automobile congestion, it should be noted that only three of the case study states adopted such a program over the course of the panel. In addition, it would be useful to control for other factors in isolating the effect of state smart growth programs on automobile congestion. The before-and-after approach is taken to the next level in the following section by reporting the results from estimating three-way fixed effects models, so named because they include level, change, and time fixed effects.

MODELING CONGESTION EFFECTS

Using panel data makes it possible to measure the change in, rather than the level of, the dependent variable in the models. This approach has two attractive features.[9] First, the use of change variables eliminates systematic differences across urbanized areas that are due to history or scale effects. Second, level variables are highly persistent over time and may therefore result in spurious regression results.[10]

The econometric approach used here also involves UA dummy variables in the estimated models. This allows dependent variables to increase at different rates across areas, capturing fixed effects in changes in congestion. This further controls for unobservable heterogeneity, which may include factors that have an independent effect on the change in the dependent variable and may be correlated with whether the state has a smart growth program or not. Without these controls, omitted variable bias would result. Also included are year dummy variables measuring aggregate time effects, which capture factors that vary over time and uniformly affect all UAs.

The basic model can be expressed as:

$$Y\Delta_{i,t} = \alpha_i + \gamma_t T_t + SGMP_{i,t} + u_{i,t},$$

where:

- $Y\Delta_{i,t}$ is the annual change in one of the five dependent variables (delay per traveler, travel time index, per capita daily vehicle miles of road travel, per capita annual publi-transit trips, and population density) measured for the UA;
- α_i is the urbanized area-specific effect;
- T_t are year dummy variables; and
- $SGMP_{i,t} = 1$ if the UA is located in a state that has a smart growth program in year t.

Including fixed effects in levels and changes, along with the aggregate time effects, mitigates the need for additional control variables. Bias will result only if excluded variables simultaneously satisfy three conditions: they commonly vary within areas; are commonly correlated with the date that a smart growth program was adopted within areas; and have a common effect on dependent variables across areas. Although these conditions are unlikely to be satisfied, all of the models were run with and without the following control variables: freeway lane miles divided by the size of the urban area in square miles; arterial lane miles divided by the size of the urban area in square miles; population; and real per capita income.

The panel includes 22 years of data for 17 UAs located in 7 states that initiated a smart growth program after 1982. After first differencing the data (i.e., subtracting the previous year's value from the current year's value, $Y_{i,t} - Y_{i,t-1}$), there are 374 observations.

PANEL ESTIMATION RESULTS

While three-way fixed effects models have several desirable features, they also have the drawback that they assume smart growth programs have a similar effect on automobile congestion across states. If this assumption is violated (i.e., if there is at least one outlier), the estimated effects of a smart growth program on the change in congestion may be badly biased.

The first step in the analysis was therefore to estimate separate models for each state to determine whether any of them were outliers and should not be pooled with the other states. Separate state models have their own limitations, however. First, there is an increased likelihood that the estimated effect does not arise from a state smart growth program, but rather from some event correlated in time with the program's adoption. Second, the number of observations is much smaller in comparison with the pooled sample, especially for states with only a single urban area for which congestion data are available. Small sample sizes can result in imprecise estimates.

Table 5.5 reports the results from estimating separate state models for the seven states in our second group (see note 8). The change in annual delay per traveler is regressed on the smart growth program dummy variable and alternative sets of control variables. Note that for those states with a single UA (Georgia, Maryland, and Rhode Island), aggregate time effects and UA fixed effects cannot be included.

In five of these seven states, smart growth programs appear to reduce the increase in automobile congestion in one or more of the model specifications. The exceptions are Florida and Rhode Island, where the smart growth program coefficient is positive across all available specifications. Rhode Island has only one UA (Providence) and therefore contains only 21 observations. In addition, only two of the four alternative specifications can be estimated for this state. The results make it impossible to determine with confidence whether Rhode Island is an outlier. In the case of Florida, however, there are seven UAs (147 observations) and the estimated smart growth program coefficient is positive in all four models. Here the evidence is sufficiently strong to conclude that Florida's smart growth program did not reduce the growth in automobile congestion. The state is therefore treated as an outlier and excluded from the pooled sample.

The results from estimating the three-way fixed effects model for the first automobile congestion measure (the change in annual delay per peak-period traveler) appear in table 5.6.[11]

Table 5.5 **Change in Annual Delay per Peak-Period Traveler with Models Estimated for Each State in Second Group**

STATE	NUMBER OF OBSERVATIONS	CONTROL VARIABLES: None	Area Descriptors[a]	Year and Area[b]	All[c]
Colorado	63	-1.622~ (.949)[d]	-2.095~ (1.129)	-.333 (.848)	6.451 (4.614)
Florida	147	.094 (.466)	.484 (.505)	.143 (.977)	.364 (.894)
Georgia	21	2.067 (1.844)	16.649** (3.080)		
Maryland	21	-1.444 (1.428)	4.628 (14.046)		
Rhode Island	21	.962 (.664)	.108 (1.892)		
Tennessee	42	-8.333* (.914)	-4.393** (1.234)	2.000 (1.208)	-34.399 (17.626)
Washington	42	-2.607* (1.061)	.649 (1.614)	-3.000** (.753)	-.523 (9.891)

[a] See table 5.6 for list of area descriptors.
[b] Includes only aggregate time effects and urbanized area fixed effects.
[c] Includes both the area descriptors and the time and urbanized area fixed effects.
[d] Standard errors robust to arbitrary heteroskedasticity are in parentheses.
~ = p<.10
* = p<.05
** = p<.01
*** = p<.001

With no control variables except for the fixed effects, the estimated impact of having a state smart growth program is -2.200, which is statistically significant at the 5 percent level. This indicates that the annual increase in delay is 2.2 hours less for any year that a smart growth program is in place. Adding the control variables has little impact, reducing the estimate to -2.076.[12] These results suggest that a smart growth program has a nontrivial effect on the growth in automobile congestion. To illustrate, if Maryland had not adopted its program in 1992, Baltimore's delay for peak-period travelers would have been 72 hours in 2003 rather than the 50 hours it actually experienced.

Switching to the other TTI congestion measure (change in the travel time index) yields the same conclusion: the estimated effect of a state smart growth program on congestion growth is negative and nontrivial in magnitude. As table 5.7 shows, the estimated effects with and without the control variables are virtually identical, and each is statistically significant.

The robust results obtained from estimating the fixed effects models are consistent with the simple tabular comparisons of congestion growth before and after adoption of a state smart growth program, as reported in table 5.4. In combination, these findings provide strong evidence that states with smart growth programs have been able to slow growth in automobile-based traffic congestion.

THREE-WAY FIXED EFFECTS MODELS

There are several pathways by which state smart growth programs may reduce congestion: (1) alter the growth in population density, which in turn may affect the growth in automobile congestion; (2) increase the growth in public transit ridership, which may decrease the growth in congestion; and (3) create a closer mix of residential and commercial land uses, reducing the growth in VMT and thereby the growth in congestion.

The results reported here were obtained from estimating three-way fixed effects models that employ a different dependent variable: change in population density; change in the number of transit trips per capita; and change in per capita vehicle miles traveled. These are "intermediate output variables" because it is hypothesized that state smart growth programs work through them to achieve their ultimate impact on congestion. While these variables are obviously interrelated, each has unique aspects. Moreover, apart from the linkages they may form to the growth in automobile congestion, it is also of interest how smart growth programs affect these particular dependent variables.

Population Density. Controversy surrounds both the effect of smart growth programs on population density and the effect of population density on automobile congestion. The results from prior studies are mixed. Carruthers (2002) estimates the effect of state smart growth programs on the size of the developed area of

Table 5.6 **Estimated Effects of Smart Growth Programs on Change in Annual Delay per Peak-Period Traveler**

	(1)[a]	(2)
Smart Growth Program	-2.200*	-2.076*
	(8.98)[b]	(.945)
Freeway Lane Miles		1.817
		(2.250)
Arterial Lane Miles		.093
		(.885)
Population		-.004*
		(.002)
Real Per Capita Income		-.004
		(.039)
Observations	210	210
R^2	.162	.189

[a] Includes aggregate time effects and urbanized area fixed effects.
[b] Standard errors robust to arbitrary heteroskedasticity are in parentheses.
~ = p<.10
* = p<.05
** = p<.01
*** = p<.001

Table 5.7 **Estimated Effects of Smart Growth Programs on Change in the Travel Time Index**

	(1)[a]	(2)
Smart Growth Program	-1.142**	-1.135*
	(.435)[b]	(.464)
Freeway Lane Miles		.995
		(1.096)
Arterial Lane Miles		-.263
		(.462)
Population		.000
		(.001)
Real Per Capita Income		-.011
		(.024)
Observations	210	210
R^2	.203	.208

[a] Includes aggregate time effects and urbanized area fixed effects.
[b] Standard errors robust to arbitrary heteroskedasticity are in parentheses.
~ = p<.10
* = p<.05
** = p<.01
*** = p<.001

counties (in acres), while Wassmer (2006) estimates their effect on the size of urbanized areas (in square miles). Because both studies include population as a control variable, the estimated effect of a smart growth program registers as a change in population density.

Carruthers uses a panel of counties to separately estimate the effects of smart growth programs in five states (California, Georgia, Florida, Oregon, and Washington). Only Florida's program exerted a significant nonzero effect, which was to increase the size of developed areas (and thereby reduce population density). Carruthers hypothesizes that Florida's concurrency policy—requiring that infrastructure to support new development be in place before the development is allowed to proceed—explains these results. Because existing infrastructure is less likely to be at capacity on the urban fringe, developers can build there without waiting for additional infrastructure to be added (Chapin 2007). Concurrency is therefore hypothesized to contribute to, rather than constrain, urban sprawl.

Wassmer focuses on a cross-section of urbanized areas in 2000. He finds that a UA located in a smart growth state is smaller in size, *ceteris paribus*. This implies that a state smart growth program increases population density. When he replaces his dummy variable registering the existence of a state smart growth program with the number of years a state has had a program, however, the results are insignificant.

The two most recent studies examining the effect of state smart growth programs on population density are Yin and Sun (2007) and Howell-Moroney (2007). Using MSAs as the units of observation, Yin and Sun regress the percentage change in density from 1990 to 2000 on a dummy variable indicating whether the MSA is located in a state with a smart growth program, along with a set of control variables. As an alternative to using a dummy variable indicating the existence of a state smart growth program, they also use the length of time that the MSA's state has had a program. Analogous to the findings of Wassmer, Yin and Sun conclude that the existence of a state smart growth program, but not its duration, increases the percentage change in population density.

None of the studies reviewed thus far controls for unobserved heterogeneity at the unit of observation level. Only the Carruthers study includes fixed effects, which are defined at the state rather than the county level. In the population density models described below, the estimated effect of having a state smart growth program is positive and statistically significant if area fixed effects are excluded from the model. Adding the area fixed effects causes a reversal in sign, with the effect statistically significant. These results therefore cast suspicion on the findings of Wassmer as well as Yin and Sun, who find a positive connection between smart growth programs and population density.

Unlike previous studies, Howell-Moroney includes fixed effects at the unit of observation level, which is the state. He divides nine states that have adopted comprehensive smart growth legislation into three groups based on the intensity of the state's effort. Intensity is considered strong if the state mandates comprehensive planning at the local level and has an auxiliary policy aimed at growth control, such as urban growth boundaries or infrastructure concurrency. Oregon, Florida, and Washington are the three states in this category.

Howell-Moroney's panel includes eight years of data (spanning 1964 to 1997 at five-year intervals) for each of the nine states. He uses two alternative dependent variables: the amount of urban land within the state (in square kilometers), and the state's urban population density (urban population/ urban land). Included in the model are dummy variables registering for each year and state whether the state's smart growth program was in effect and, if so, whether its intensity was strong, moderate, or weak. Following previous studies, he also uses a variable that counts the years a state has had a smart growth program. All models include state fixed effects to capture unobserved heterogeneity across states. Howell-Moroney concludes that only strong smart growth programs affect a state's urban land and population density. His findings suggest that adoption of such a program reduces the amount of urban land and raises the level of urban population density.

While improving upon prior studies by including fixed effects at the unit of observation level, Howell-Moroney uses level-dependent variables that make the results difficult to interpret. For example, how is it possible for the amount of urban land in the state to shrink in response to the adoption of a smart growth program? In addition, his use of level variables, combined with the omission of time effects, suggests that spurious correlation may bias the results.

No prior studies link population density and automobile congestion. *A priori*, the direction of the relationship is unclear. On the one hand, lower growth in density may hinder increases in walking and transit commutes. In addition, if lower density growth is tied to an increase in the number of center city workers who relocate from inside to outside the UA, work trips may lengthen, resulting in more congestion. On the other hand, lower density growth may result in less growth in vehicle trips simply because there is less growth in population. In addition, congestion is in part a function of overall development density; as densities increase, congestion also increases (Taylor 2002).

All other things being equal, traffic congestion will increase less if fewer homes, businesses, and other facilities are developed per acre. Moreover, lower density growth may result in longer origin-destination distances, which increase the average cost per trip. More expensive trips mean fewer vehicle trips and therefore less growth in congestion. These linkages—some working to create a positive relationship between growth in population density and growth in congestion, others working in the opposite direction—make it impossible to predict the actual relationship between the two variables.

Transit Ridership. Another possible pathway whereby state smart growth programs may reduce the growth in congestion is to increase the growth in transit ridership. A common feature of these programs is that they promote policies that favor public transportation, such as transit-oriented development, park-and-ride facilities, and paratransit. No evidence, however, directly links state smart growth programs to public transit use. Even if a positive relationship did exist, reductions in the growth in automobile congestion would likely be small given that the share of commuters using public transit is also relatively small. As a result, even substantial growth in public transit use may not significantly slow the growth in congestion.

Land Use Mix. The third pathway investigated here is that state smart growth programs may alter the mix of land uses within cities such that they reduce the need for automobile travel. For example, the prototypical smart growth development is a self-contained community that offers work, religious, entertainment, and shopping opportunities in close proximity. Smart growth communities are expected to capture more automobile trips within the local traffic network, minimizing trips on the regional transportation system and thereby reducing impacts on congestion levels. These communities also promote alternative transportation modes, especially bicycling and walking. If state smart growth programs create a more spatially concentrated mix of land uses, the expectation is that the growth in per capita VMT will decline, which may in turn reduce the growth in automobile congestion. Like the other two causal pathways explored here, there is no prior evidence on how smart growth programs affect vehicle miles traveled.

EMPIRICAL EVIDENCE ON THE PATHWAYS

The results obtained from estimating the three-way fixed effects model for the change in population density are reported in table 5.8. Regardless of whether the control variables are included in the model, the estimated state smart growth program effect is negative and statistically significant. These findings suggest that the growth in population density is lower in UAs located in states with smart growth programs.

These results are inconsistent with those of Wassmer (2006) and Yin and Sun (2007), who find that smart growth programs increase population density. As noted above, an important difference is that this study includes UA fixed effects, which control for unobservable heterogeneity in density growth across UAs. Excluding these effects from the model reproduces the findings reported in the above two studies. The results are also inconsistent with those of Howell-Moroney but, as noted above, his models are misspecified in certain ways.

The findings of Carruthers (2002) may help explain the results reported in table 5.8. Recall that he found that Florida's smart growth program reduced the population density of developed areas. He attributed this result to developers building on the urban fringe where Florida's concurrency policy is less likely to limit development or increase its cost. In addition to concurrency, other land use regulations may be tied to smart growth programs that raise the cost of closer-in versus further-out development. The population density results are consistent with those of Cheung, Ihlanfeldt, and Mayock (2008), who find that metropolitan area housing starts decline after a state adopts a smart growth program. One possible explanation is that these programs may cause center cities to raise their development standards relative to those in suburban or rural areas.

The results obtained from estimating the model using the change in annual per capita public transit trips and the change in per capita vehicle miles of road traveled as the dependent variables are reported in tables 5.9 and 5.10. While the estimated effect of a state smart growth program on the growth in

Table 5.8 **Estimated Effects of Smart Growth Programs on the Change in Population Density**

	(1)[a]	(2)
Smart Growth Program	-33.955*	-35.032*
	(17.263)[b]	(15.884)
Freeway Lane Miles		53.536
		(97.133)
Arterial Lane Miles		-18.911
		(22.524)
Population		.010
		(.028)
Real Per Capita Income		2.212*
		(.949)
Observations	210	210
R^2	.246	.281

[a] Includes aggregate time effects and urbanized area fixed effects.
[b] Standard errors robust to arbitrary heteroskedasticity and serial correlation are in parentheses.
~ = p<.10
* = p<.05
** = p<.01
*** = p<.001

transit trips is positive both with and without control variables, neither estimate is statistically significant. Similarly, the smart growth program effects in the VMT models are statistically insignificant, but both estimates have a negative sign as expected.

As an aside, it is interesting to examine the effect of a change in population density on the change in VMT. Adding the change in density as a variable explaining the change in VMT (column 3 of table 5.10), the estimated effect is negative and statistically significant. The estimated smart growth program effect on VMT remains negative (with some increase in magnitude) and insignificant.

The final question is what proportion of the effect of state smart growth programs on the growth in automobile congestion can be attributed to changes in each of the three intermediate outcome variables. There are two approaches to examining this issue. In the first, the change in congestion models can be estimated including the intermediate variables, along with the smart growth program variable. If the programs work primarily through one or more of the pathways, adding the intermediate variables will result in a nontrivial reduction in the absolute magnitude of the estimated smart growth program coefficient.

Table 5.9 **Estimated Effects of Smart Growth Programs on the Change in Annual Per Capita Public Transit Trips**

	(1)[a]	(2)
Smart Growth Program	.0003	.0007
	(.0008)[b]	(.0008)
Freeway Lane Miles		.0001
		(.0027)
Arterial Lane Miles		-.0004
		(.0010)
Population		.000
		(.000)
Real Per Capita Income		.000
		(.001)
Observations	210	210
R2	.166	.200

[a] Includes aggregate time effects and UA fixed effects.
[b] Standard errors robust to arbitrary heteroskedasticity are in parentheses.
~ = p<.10
* = p<.05
** = p<.01
*** = p<.001

Table 5.10 **Estimated Effects of Smart Growth Programs on the Change in Per Capita Daily Vehicle Miles Traveled**

	(1)[a]	(2)	(3)
Smart Growth Program	-.286	-.264	-.369
	(.278)[b]	-(.366)	(.302)
Freeway Lane Miles		-1.172	
		(.933)	
Arterial Lane Miles		.586	
		(.712)	
Population		-.002*	
		(.001)	
Real Per Capita Income		.016	
		(.022)	
Density Change			-.022~
			(.001)
Observations	210	210	210
R^2	.117	.181	.133

[a] Includes aggregate time effects and urbanized area fixed effects.
[b] Standard errors robust to both arbitrary heteroskedasticity and serial correlation are in parentheses.
~ = p<.10
* = p<.05
** = p<.01
*** = p<.001

The results from implementing this approach are presented in table 5.11. Including the change in population density, per capita transit trips, or per capita VMT separately in the model has little impact on the estimated smart growth program effect regardless of the congestion measure used. Including all three variables reduces the smart growth program effect on the change in delay from -2.200 (table 5.6) to -1.889 (top panel of table 5.11). This represents a 14 percent reduction in absolute magnitude. The corresponding reduction in the change in the travel time index model is from -1.142 (table 5.7) to -0.975 (bottom panel of table 5.11), or a 15 percent decline in absolute magnitude.

Under the second approach, the estimated effect of a state smart growth program on an intermediate variable can be multiplied by the estimated effect of the intermediate variable on congestion growth. The ratio of this product to the original estimated smart growth effects (reported in tables 5.6 and 5.7) provides an estimate of the importance of the pathway.[13] This approach yields percentages similar to those above: the three

Table 5.11 **Sensitivity of Estimated Smart Growth Program Effects to Inclusion of Covariates**

	CHANGE IN ANNUAL DELAY PER PEAK-PERIOD TRAVELER			
	(1)[a]	(2)	(3)	(4)
Smart Growth Program	-2.058*	-2.173*	-2.112*	-1.889*
	(.914)[b]	(.906)	(.872)	(.892)
Change in Population Density	.004			.005~
	(.003)			(.003)
Change in Per Capita Transit Trips		-83.864		-97.260
		(77.728)		(77.370)
Change in Per Capita VMT			.308	.365~
			(.208)	(.225)
R2	.170	.168	.175	.194
Observations	210	210	210	210

	CHANGE IN TRAVEL TIME INDEX			
	(1)[a]	(2)	(3)	(4)
Smart Growth Program	-1.027*	-1.122*	-1.130**	-.975*
	(.443)	(.438)	(.433)	(.442)
Change in Population Density	.003*			.004*
	(.001)			(.001)
Change in Per Capita Transit Trips		-60.318~		-64.343~
		(34.299)		(34.231)
Change in Per Capita VMT			.041	.080
			(.074)	(.080)
R^2	.222	.215	.204	.238
Observations	210	210	210	210

[a] Includes aggregate time effects and urbanized area fixed effects.
[b] Standard errors robust to arbitrary heteroskedasticity are in parentheses.
~ = p<.10
* = p<.05
** = p<.01
*** = p<.001

intermediate output variables together account for 14 percent and 16 percent of the estimated smart growth program's effect on the change in delay and the change in the travel time index.

The estimated effects of the intermediate output variables on the congestion measures are worth noting. Greater growth in population density increases the growth in both the annual delay per traveler and the travel time index. An increase in the growth in the number of transit trips per capita reduces the growth in both congestion measures, but only the effect on the travel time index model is statistically significant. Finally, higher growth in VMT increases the growth in both congestion measures, but here the effect is significant only in the annual travel delay model.

In summary, the results suggest that smart growth-induced changes in the three intermediate outcome variables (population density, public transit use, and vehicle miles traveled) explain no more than a fifth of the effect that state programs have on the growth in automobile congestion. State smart growth programs typically encourage local governments to adopt specific policies designed to reduce automobile congestion. These policies are well known and include such strategies as high-occupancy vehicle lanes, ramp metering, reversible lanes, and traffic management systems.

The relatively small role played by changes in the intermediate variables suggests that specific anti-congestion policies may account for the effect that smart growth programs are found to have on congestion growth. Further research using more detailed data is needed to explore the pathways underlying the smart growth program effects.

CONCLUSIONS

Taken as a whole, the analyses presented here support the contention that state smart growth programs can yield desirable transportation outcomes. The results indicate that these programs have a positive impact on two key transportation indicators: public transit commute shares, and changes in congestion levels as measured by growth in the delay per peak-period traveler and in a travel time index.

Even so, the news for smart growth advocates is not all good. Commutes by bicycling/walking show no correlation with smart growth programs, with the notable exception of Portland, Oregon. That city's aggressive and comprehensive approach to planning for bicyclists and pedestrians demonstrates the capacity to encourage large shares of commuters to travel by non-automotive modes. Elsewhere, bike/walk commutes remain in sharp decline in all the states studied.

The results for transit ridership are somewhat mixed. While census data indicate that counties in smart growth states fare better than those in the other selected states, the regression analyses do not find a statistically significant relationship between smart growth programs and changes in per capita transit ridership. Each of the analyses, however, uses a different dependent variable and measures change over a different time interval, which may account for these seemingly incongruous findings. It is possible that transit commute *shares* may be maintained in smart growth states, even in the face of declining *per capita trips*. For example, an increasing number of people may work from home and therefore do not commute to work. Under this scenario, the per capita number of transit trips may fall, but the share of commute trips by transit may remain nearly flat.

The results also reveal notable variations across smart growth states. Oregon and the Portland metropolitan area, widely known for their aggressive smart growth programs, fare very well on most measures. Similarly, New Jersey performed well on the public transit commute share analysis. In contrast, Florida—one of the nation's most comprehensively planned states—performs poorly on almost all measures. These findings support a major conclusion of this volume: that the form and content of each state's smart growth system significantly affects the direction and magnitude of its impacts.

The other selected states performed generally as expected, with the exception of Colorado. That state did well on most measures, with notable increases in transit commute shares and lower growth in delays per peak-period traveler (table 5.5). These findings primarily reflect Denver's aggressive regional planning efforts and the state's substantial investments in public transportation systems. In addition, many local governments in Colorado have been committed to comprehensive planning and growth management for decades. As a result, while lacking a state-mandated smart growth system, Colorado does have transportation planning and growth management at both the regional and local levels.

The empirical work presented in this chapter supports the view that state smart growth programs can positively influence transportation outcomes. These mandates typically require local governments to perform rigorous planning analyses and consider a variety of transportation options. They also often bring a state commitment to invest in alternative travel modes. Moreover, state smart growth systems require better linkages between transportation and land use plans and objectives, which have the potential to yield more desirable transportation outcomes.

It is essential to note, however, that the evidence presented here mirrors the existing literature on the transportation–land use connection. The findings indicate that state smart growth programs work at the margin, successfully increasing transit commute shares and reducing the growth in commute times, but making only modest dents in the larger trend toward increased automotive travel. Given this, proponents of smart growth should neither expect nor promise major near-term changes in transportation behavior and outcomes when a state implements such a program.

Notes

1. In 2005 the Census Bureau replaced the long form with the American Community Survey. This annual survey of a sample of three million households is intended to provide more timely data on the range of topics included in the traditional long-form questionnaire, including commute characteristics (MacDonald 2006).

2. Both Virginia and Maryland have independent cities for which the Census Bureau reports data on commuting behavior. These cities look like counties in that data are reported separately for these places rather than folded into the estimates of the counties where they are located. For simplicity, the text refers to these places as counties.

3. These states (and the year of the initial legislation) are Arizona (1998), California (1965), Colorado (2000), Florida (1985), Georgia (1989), Hawaii (1961), Maine (1988), Maryland (1992), Minnesota (1994), New Jersey (1986), Oregon (1973), Rhode Island (1988), Tennessee (1998), Vermont (1988), Washington (1990), and Wisconsin (2000).

4. The list includes states that the Sierra Club and the American Planning Association identify as smart growth states on their Web sites. Upon investigation of the specifics of the legislation in each state, Colorado was included on the list because preliminary regression analysis suggests its year 2000 smart growth legislation has had an effect on congestion. Three other states—Arizona, Minnesota, and Wisconsin—

were excluded from the list because their growth management legislation only "encourages" comprehensive planning at the local level.

5. The U.S. Census Bureau defines an urbanized area as a densely settled territory that contains at least 50,000 people and consists of census blocks with a minimum of 1,000 people per square mile. The criteria for including a census block with a lower density as part of a UA depend on the block's proximity and relationship to the central place(s) in the UA. Conceptually, the UA can be thought of as the physical city—the center city plus adjacent areas with high population densities.

6. The procedures TTI uses to compute the congestion measures are complex and involve estimating a series of equations. The complete methodology is described at http://mobility.tamu.edu/ums/report/methodology_appB.pdf.

7. These variables are based on data TTI obtains from a variety of sources, including the U.S. Census Bureau, the Highway Performance Monitoring System, the American Public Transportation Association, and local area metropolitan planning organizations. Lane miles of freeway and principal arterial streets are normalized by dividing each by the size of the UA in square miles.

8. The year each of these seven states adopted its smart growth program is listed in parentheses, followed by the cities included in the panel: Colorado (2000: Boulder, Colorado Springs, Denver); Florida (1985: Cape Coral, Jacksonville, Miami, Orlando, Pensacola, Sarasota, Tampa); Georgia (1989: Atlanta); Maryland (1992: Baltimore); Rhode Island (1988: Providence); Tennessee (1998: Memphis, Nashville); and Washington (1990: Seattle, Spokane).

9. See Mark, McGuire, and Papke (2000) for an extensive discussion of the econometric advantages of analyzing the growth in a dependent variable rather than its level when panel data are available.

10. Spurious regression results exist when a regressor is statistically significant because it and the dependent variable, although unrelated, trend similarly over time.

11. Each model was checked for heteroskedasticity and serial correlation. The heteroskedasticity tests involved regressing the squared residuals on the predicted value of the dependent variable, the latter variable squared, and the time dummies. The overall F-statistic is significant in all of the regressions, indicating heteroskedasticity. The test for serial correlation follows the procedure suggested by Wooldridge (2002, 275). The residuals are regressed on their lagged values and a t-statistic robust to serial correlation is estimated on the lagged value. A statistically significant t-statistic indicates the presence of serial correlation. Where serial correlation exists, the tables report standard errors that are robust to both arbitrary heteroskedasticity and arbitrary serial correlation. Where serial correlation is not found, the tables report standard errors robust only to heteroskedasticity.

12. Lagged values of the smart growth program variable and the control variables were tried for each estimated model to investigate the possibility of an impact lag (i.e., some time may have to pass before the provisions of a legislative planning act start to have an effect). Results are somewhat weaker if lagged values are used. One explanation for this is that local government policies may change in anticipation of new state laws. However, the three-way fixed effects model compares the average annual change in the dependent variable before and after the adoption of a state smart growth program. Differences between the implementation (or impact) date and the adoption date are therefore less of a problem than if both the dependent and the independent variables are first differenced.

13. Mathematically, estimated effects are entered into the following equation: $dC/dSGMP = (dC/dPT)^* (dPT/dSGMP)+(dC/dD)^* (dD/dSGMP)+(dC/dVMT)^* (dVMT/dSGMP)$, where C is the congestion measure; PT equals public transit trips per capita, D equals population density, and VMT equals vehicle miles traveled per capita.