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URBAN ROADWAY IN AMERICA:
THE AMOUNT, EXTENT, AND VALUE

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ABSTRACT

We predict the amount, share, and value of land dedicated to roadways within and across 316 US Primary Metropolitan Statistical Areas. Despite the amount and value of land dedicated to roadway, our study provides the first such estimate across a broad range of metropolitan areas. Our basic approach is to estimate roadway widths using a 10% sample of widths provided by the Highway Performance and Monitoring System and apply our estimates to the rest of the roadway system. Multiplying estimated widths by segment length and netting out double counting at intersections provide estimates of land area. We also match roadway segments and areas to existing land value estimates and satellite-based measures of urbanized land. We find that a little under a quarter of urbanized land—roughly the size of West Virginia—is dedicated to roadway. This land was worth around $4.1 trillion dollars in 2016 and had an annualized value that was higher than the total variable costs of the trucking sector and the total annual federal, state, and local expenditures on roadway. Conducting a back-of-the-envelope cost-benefit analysis, we found that the country likely has too much land dedicated to urban roads.

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A data visualization tool is available at https://usroadway.github.io/

1 Introduction

Academics, policymakers, and practitioners do not agree on whether the US has too much or too little roadway infrastructure.[1] Nevertheless, federal, state, and local governments spend hundreds of billions of dollars annually building, expanding, rebuilding, and maintaining roads (Federal Highway Administration, 2020; U.S. Census Bureau, n.d.-a, n.d.-b). Beyond disagreement on costs and benefits, researchers and policymakers do not even know how much land is dedicated to roadways, where it is located, or how much it is worth. Without a better accounting, it is difficult to assess whether there is too much or too little roadway or even whether outcomes, such as commute times, wealth, health, or employment, vary with the amount of roadway. For all the benefits to motorists, roadway takes land that could otherwise be used for homes, businesses, shops, and open spaces.[2] Better understanding roadway space and value is essential to assessing state and federal transportation policy, conducting cost-benefit analyses, and helping local officials understand how their cities, towns, and metropolitan areas compare to others.

Some systematic records do exist. For example, the federal government and states keep records on the total length of national and state roadway by roadway type (Federal Highway Administration, 2020; U.S. Department of Transportation, 2019). The number of lanes and width of these lanes, however, vary substantially. A centrally located arterial in an old Midwestern downtown likely occupies less space than a suburban arterial in a fast-growing sunbelt city. Spatial databases provide additional information, sometimes including total lane numbers and

[1] The federal government's model of highway investments finds a healthy average return on investment (U.S. Department of Transportation, 2019, Chapter 10). The model reports that benefits are at least equal to costs, even for the worst performing individual investments and investment scenarios. Academic estimates are less rosy. Studies present a wide range of effects on output, productivity, and income (Bhatta & Drennan, 2003; Boarnet, 1997).

[2] Major roads are also arguably a negative local amenity which bisect neighborhoods and bring accidents, noise, and pollution (Brinkman & Lin, 2022). Baum-Snow (2007), for example, estimates that each additional urban highway reduced central cities population by 18% on average.

approximate width, but only for a sample of roadways and disproportionately from highways and major arterials (U.S. Census Bureau, n.d.-c; U.S. Department of Transportation, n.d.).

Even in large cities with relatively good spatial databases, academics and practitioners know surprisingly little about how much space is dedicated to roadway and where this roadway is located. Manville and Shoup (2005; 1997) trace a widely reported statistic that two-thirds of Los Angeles' land area is dedicated to roadway and parking back to an uncited reference from 20 years earlier. An even earlier congressional report on the interstate program made a similar, uncited claim (The Special Assistant for Public Works Planning, 1960, p. 35), as did Lewis Mumford (1961, p. 510). A 1924 plan, by contrast, faulted Los Angeles for dedicating far less space to downtown roads than peer cities (Olmsted et al., 1924, tbl. I). As part of a project to help the World Bank develop its urban transportation investment strategy, Gwilliam (2002, 2003) argues that the 10–12% of land area dedicated to roadway in Asian cities is insufficient and well below a 20%-30% of space in US cities. No methods or citations support these assertions.

Scholars have provided more systematic estimates in a handful of US cities and counties. Using parcel data, Millard-Ball (2022) estimates that 17% to 21% of land area is dedicated to streets in 20 urban counties, predominantly from California and Texas, with adequate parcel-level data. This estimate is generally consistent with 13%-30% estimates collected from city officials and summarized in Meyer and Gómez-Ibáñez (1981) and estimates based on satellite imagery for the *Atlas of Urban Expansion* (Angel et al., 2016).

In this paper, we present a novel methodology for combining publicly available datasets to generate predictions of roadway widths and areas by roadway class across US metropolitan areas. We match these predictions to estimated land values (Davis et al., 2021) and aggregate data by metropolitan subarea, core city, and downtown for 316 Primary Metropolitan Statistical Areas (PMSA) where approximately 80% of the US population resides. We also provide three-dimensional visualization for our data and our results at https://usroadway.github.io/.

Roadway accounts for a fifth to a quarter of all urbanized land in US PMSAs—the equivalent of the total land area of West Virginia. This roadway is worth approximately $4.1 trillion dollars, with large, wealthy PMSAs like New York, Los Angeles, and Chicago representing a substantial share of this value. Within PMSAs, suburban neighborhoods generally dedicate more but less valuable land to roadways.

Demonstrating an application of our publicly available data set, we conduct a back-of-the-envelope cost-benefit analysis of US roadway investments. Land is an important component of the cost of providing roadway and is worth more per year than governments spend building and maintaining the roadway system. We find that dedicating more land to roadways would likely lead to net losses in social welfare even without accounting for external costs of driving, such as pollution and congestion. Even ignoring externalities and allowing for generous assumptions, we find that the costs of widening roadways exceed the benefits to drivers and truckers by a factor of three on average after accounting for the value of land. Expanding roadway systems is unlikely to have anything close to the economic benefits that state and federal policymakers hope. Removing and narrowing roadway, by contrast, may have the potential to generate substantial benefits.

The remainder of this paper is organized as follows. First, we summarize existing knowledge about the amount and location of roadway in US cities. Second, we present an overview of how we estimate the amount and value of land used for roadway by block group, city, and metropolitan area. A technical appendix provides additional details on the data, data-processing decisions, and modeling procedures. Next, we provide summary details of our findings about roadway amount and values across and within US metropolitan areas. We then discuss several ways that planners and researchers can use these data, including for benchmarking and cost-benefit analysis. Last, we conclude with a summary of our main findings and planning implications.

2 Existing estimates of road space

The existing literature relies on three main approaches to examining the amount of roadway in countries, cities, and neighborhoods.

2.1 Road network databases

The first and most common approach uses existing databases of road networks, such as the US Highway Performance Monitoring System (U.S. Department of Transportation, n.d.), the Topologically Integrated Geographic Encoding and Referencing (TIGER) system (U.S. Census Bureau, n.d.-c), OpenStreetMap (*OpenStreetMap Wiki*, n.d.), and the Global Roads Inventory Project (World Bank, n.d.). These databases typically contain information on the length, type, and other features of roadway in a geography. Most of these databases also contain geographic shape files, indicating the location of roadway networks. For example, the Highway Performance Monitoring System (HPMS) has provided data on US roadway since 1978 and currently contains spatial information on the extent and type of public roadways throughout the country. A 10% sample of roadways provides additional information, such as road widths and median widths.

Researchers have used these databases to generate measures of roadway supply to examine a wide of research topics, such as road provision and vehicle ownership (Ingram & Liu, 1999), vehicle travel (Duranton & Turner, 2018; Ewing & Cervero, 2010; Stevens, 2017), mode choice (Ewing & Cervero, 2010; Guerra & Li, 2021), city structure (Boeing, 2021), congestion (Couture et al., 2018; Ewing & Cervero, 2010; Stevens, 2017), and traffic safety (Dumbaugh & Rae, 2009; Merlin et al., 2020). Manville and Shoup (2005) use HPMS data reported for 85 urbanized areas in the Texas Transportation Institute's Urban Mobility Report (Schrank & Lomax, 2004) to estimate the lane miles per capita and per square mile of Census land area in 20 large metropolitan areas. The authors report a range of 0.8 lane miles per capita in New York to 1.7 lane miles per capita in Dallas. The authors also find that denser areas across and within metropolitan areas tend to have fewer lane-miles per capita but more lane-miles per acre. No information is provided about widths or land areas.

Our general research approach relies on the HPMS. Our contribution is to combine the HPMS with additional publicly available datasets to develop a predictive model of roadway widths, multiply roadway lengths by predicted widths, and assign these estimates to block groups, counties, and PMSAs for all US metropolitan areas.

2.2 Remote sensing

Researchers have frequently estimated features of roadways using high-resolution satellite imagery and other forms of remotely sensed data.[3] In early examples, Mena and Malpica (2005) and Mokhtarzade and Zoej (2007) use artificial neural networks to categorize high-resolution satellite images with limited distortion from shadows, trees, or other features into binary categories of roadway and not roadway. Processing large amounts of high-resolution satellite imagery across multiple cities, however, introduces substantial computational challenges. Most published work has thus focused on predicting roadways using small samples of imagery or

[3] The Multi-Resolution Land Characteristics Consortium (n.d.), a partnership of US federal agencies, provides 30m grid cell data that classify impervious surfaces, including roadway surfaces, across the US. The pixel resolution, however, is wider than most roadways. As a result, the impervious surfaces data assigns substantially more land areas to roadways than what can be seen from a satellite image.

existing datasets of imagery. While the general technique could be extended to estimate road widths (Guan et al., 2010; Manandhar et al., 2020; Zhang & Couloigner, 2007), estimating road areas introduces additional challenges, and most work focuses on classifying roads (Chaudhuri et al., 2012; Fakhri & Shah-Hosseini, 2022; Ghandorh et al., 2022). In one particularly relevant example, Engstrom, Hersh, and Newhouse (2017) use satellite imagery from Sri Lanka to estimate various urban features, such as the number of buildings and the length and density of roadways. The authors find that features extracted from satellite imagery explain around 60% of the variance in poverty rates across 1,291 administrative units using ordinary least squares regression. Chao et al. (2021) extend this work and apply estimated road widths by road classification in Accra (Ghana) and parts of Belize and Sri Lanka to generate estimates of total road area.

Due to the challenges of automatically extracting road area, researchers have also employed a hybrid approach. For example, Angel et al. (2016) hand-measure roadways and other urban features from randomly sampled 3-kilometer grid cells stratified by time periods of urban growth. Combined with road widths and features from existing road network files, such as OpenStreetMap, the authors also assign roads to different categories, such as local and major arterial. These hand calculations are then extrapolated to provide metropolitan estimates of the amount and share of land area dedicated to roadway by type for 200 out of 4,231 cities and metropolitan areas with 100,000 or more residents in 2010. Across the sample, roadways take up about one fifth of the total built-up land area. The sample includes fourteen US cities. New York has the least space dedicated to roadway at 13% of the built-up metropolitan area. Modesto, CA, has the most at 39%.

Researchers at UN Habitat apply a similar methodology to a selection of 30 global cities and find a similar average of 20% but a much more substantial range of values (UN Habitat, 2013). Instead of drawing all road area by hand, they apply average widths from a sample of roadways to all roadways of the same type in the sampled cities. Bangui (CAR) and Yerevan (Armenia) have just 6% of city area dedicated to roadway compared to 36% in Manhattan, 34% in Hong Kong, and 33% in Barcelona.

Proprietary estimates of roadways based on other types of remotely sensed data also exist. For example, major phone and map producing companies, such as Google and Apple, have sufficient data from cell phone traces to develop detailed models of roadway systems. Vehicle-mounted LiDAR and cameras also provide inputs to develop models of roadway networks that are almost certainly being applied in the development of automated vehicles. Ravi et al. (2020), for example, use LiDAR data to estimate road widths around work zones.

2.3 Parcel data

The third general approach to estimating land areas relies on detailed parcel-level data. Millard-Ball (2022) collects spatial parcel data from 20 urban counties and uses parcel areas to net out the amount of space dedicated to streets (including sidewalks) and match these to street line data from OpenStreetMap. Across counties, Millard-Ball (2022) reports a consistent range of 7% to 20% of land area dedicated to local streets, and 14% to 30% dedicated to all streets. Matching localized land value data (Davis et al., 2021) to roadway area estimates results in a total estimated $1.8 trillion dollars of land value in the 20 counties. This approach provides fine-grained and accurate estimates of road widths but requires detailed geospatial parcel-level data, which are not consistently publicly available, particularly for smaller counties and towns.

2.4 Research design

Our general approach to estimating road widths is to develop predictive models using the 10% sample of HPMS roadway segments by roadway class that have data on lane numbers, lane widths, shoulder lanes, and medians and apply this model to predict road widths for the remaining 90% of HPMS roadways and a sample of TIGER roadways to account for the significant number of missing local roadways in the HPMS data (58% of the total length of local roads in our final dataset). We then net out overlapping intersection widths, sum the product of estimated widths and segment lengths by geography, and match these estimates to existing data on land values, populations, and other physical features. This section summarizes our key data transformation choices and predictive modeling approach. A technical Appendix provides additional details.

2.5 Road network data

The HPMS provides geographic data on the location and characteristics of seven classes of roadway in the US, ranging from Interstate Highways to local roadways. The 10% sample provides additional data, including the number of through lanes, width of through lanes (excluding parking lanes), width of left and right shoulder lanes, and width of the median lane. Since the HPMS excludes many local and service roads, we supplement the dataset with TIGER shapefiles. This requires a combination of spatial joins, matching segments, cutting segments, and removing overlapping roadway segments and intersections from the dataset. We also test for selection bias in the HPMS' sample and find evidence of small but statistically significant selection bias based on observable attributes. Appendix A provides additional details on the HPMS data, spatial matching procedures, and tests for selection bias. The final dataset (Guerra et al., n.d.) uses the 2016 HPMS, 2016 TIGER, and 2016 5-year ACS data.

2.6 Predictions

We predict road segment features (number of through lanes, width of through lanes, width of left and right shoulder lanes, and width of the median lane) as a function of their distance to the metropolitan center, county-level indicators, and surrounding block groups' 2016 5-year ACS socioeconomic indicators, such as income, population density, and ethnic compositions. We also try segment length as a predictor but drop this due to limited predictive power and inconsistencies across the HPMS and TIGER segment lengths. Our final road-width estimates rely on random forest models predicting each of the five road-width features for each of the seven roadway classes (35 sets of models) on an 80% training set using the default model parameters from Python's scikit-learn library. We use the 20% remainder of the sample for testing model performance at the end. Appendix B provides additional details on our model selection, model fits, and overall model performance.

2.7 Estimating road area

Next, we assign roadway segments geographically to Census block groups. In instances where segments cross multiple block groups, we assign a fraction of the roadway to each block group. In the case where a road segment is the boundary line of two census block groups, we divide the fraction evenly between two census block groups. When aggregating road quantity to Census block groups, we use these fractions as weights. At intersections, we estimate the area of the intersection using road widths estimates and drop overlapping areas based on the number of road segments passing through the intersection. Appendix C provides additional details on the process of estimating and assigning land areas to block groups.

2.8 Land value and land cover data

We supplement our road width predictions with estimated land values (Davis et al., 2021) and the Multi-Resolution Land Characteristics Consortium's 2019 Urban Imperviousness descriptor land cover raster data from Landsat (Dewitz & U.S. Geological Survey, 2021). For maximum coverage, we use Davis's pooled cross-section estimates of "Land Value (Per Acre, As-Is)" from 2012 to 2019 (2015 dollars) and assigned Census tract values to constituent block groups or the next best geographic equivalent area (Appendix C).

We use the impervious Landsat data to provide better estimates of urbanized land than the Census block group estimates, which often include deserts, mountains, farmland, national parks, and other types of non-urbanized land. For 30-meter grid cells throughout the US, the land cover dataset provides estimates of different impervious surface classes. These classes vary substantially from what most planners would classify as impervious land and include yards, parks, and other urban features associated with urbanized land. For context, roughly 85% of New York's Central Park is classified as impervious. The Central Park Reservoir accounts for most of the land identified as non-impervious.

We also estimate land areas using only the Census-designated land areas of urban blocks within PMSAs (Appendix C). Our publicly available datasets (Guerra et al., n.d.) include land area measurements from the Landsat, Census block groups, and urban Census blocks. We focus our discussion of the share of land dedicated to roadway on the Landsat data because it best represents the urbanized land within entire PMSAs (Appendix C).

2.9 Geographic aggregation

Finally, we aggregate block-group estimates to three geographic units: PMSA, the primary city within each PMSA, and the downtown as defined by all Census block groups within 3-miles of the PMSA center. We define PMSA centers using coordinates returned by Google Map when using the PMSA name as the search query.

2.10 Data limitations and robustness check

Our estimates of the land area used for roadway include several limitations related to our reliance on the HPMS data. All data are self-reported by state DOTs and may contain systematic differences in reporting within and across metropolitan areas. Of note, estimates do not include parking lanes, whose existence is also poorly reported throughout the HPMS sample and universe. Different considerations of bike lanes, shoulders, and average lane widths may also have affected data consistency.

As a robustness check, we compare our block group estimates to Millard-Ball's (n.d., 2022) estimates after assigning the latter to the block group level. The two measures of land area occupied by roadway have Pearson's correlations of 0.88 at the block group level and 0.98 at the county level (Appendix D). Regressing the estimates on one another, we find our estimates to be 81% to 86% of Millard-Ball's estimates on average. The exclusion of parking lanes and sidewalks from our estimates likely contributes to this difference.

Our land value estimates are also generally consistent with Millard-Ball (2022) and Albouy et al.'s (2018, tbl. 2) estimates. For example, Albouy et al. (2018) estimate the New York PMSA's land to be worth roughly $14.4 million per hectare compared to our estimate of $12.7 million despite substantial methodological and moderate spatial differences. Our estimated street values per capita also tend to fall within Millard-Ball's (2022) estimated range of $20,000 to $275,000 per household.

3 Findings

3.1 How much and what share?

In total, we estimate that there are 58,000 square kilometers (22,000sq miles) of roadway—roughly the total land area of West Virginia—in the US's 316 PMSAs. This corresponds to 0.06 hectares per household (around three times more than a new US single-family house's average size and a little under half its average lot size), 3.2% of all PMSA Census land area, and 21.7% of urbanized land estimated from the Landsat data.

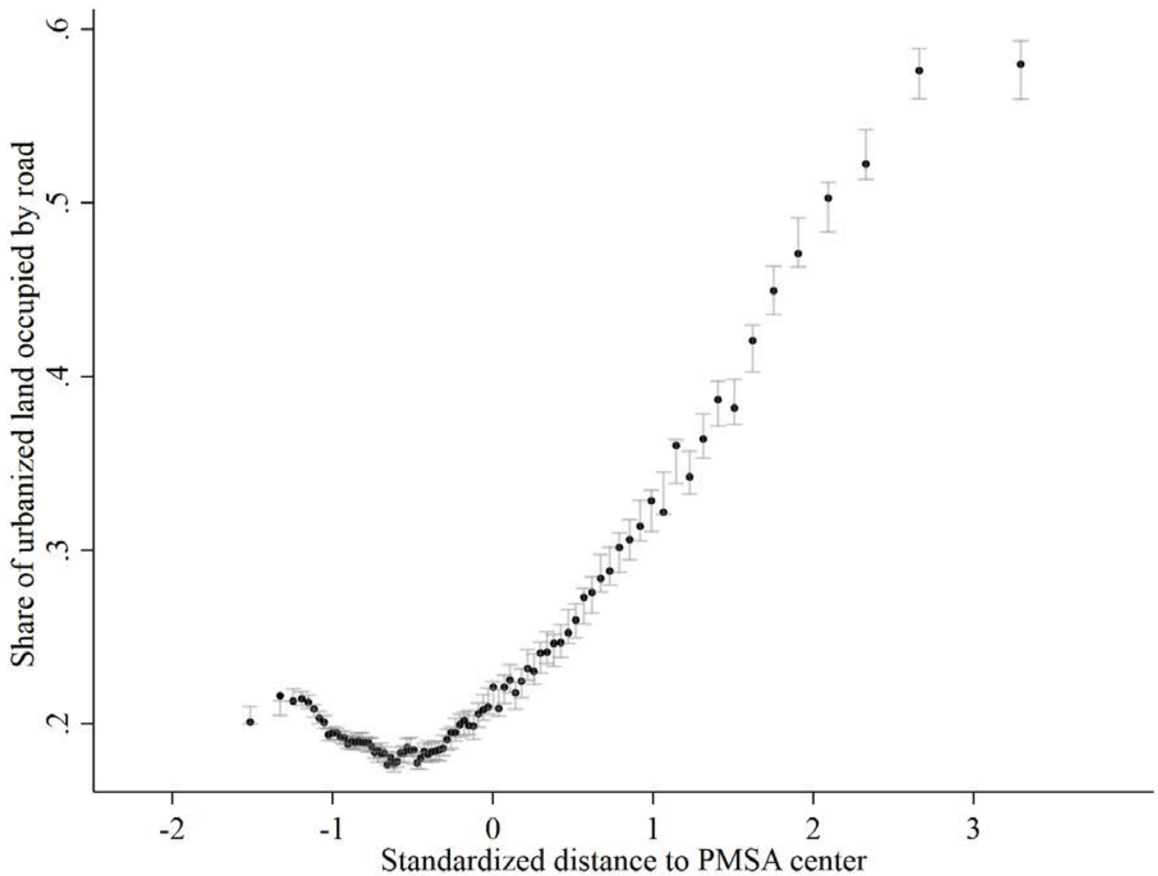
More dispersed settlement patterns generally require more roadway (Table 1). On average, city cores and central cities have less than half as much roadway per capita and per household as entire metropolitan areas (Table 1). Suburban and rural areas also tend to dedicate more urbanized land to roadways than central cities and city cores on average. Cities and city cores use an average of 17% of urbanized land compared to 24% for PMSAs. The relationship is also non-linear. Within PMSAs, the share of urbanized land covered by roadway tends to decrease from around 23% close to the CBD until about 18% at an average distance from the downtown and then increase substantially in block groups that are one to three standard deviations away from the average distance (Figure 1). Roadway occupies a big share of land in urban centers—likely to allow for traffic volumes— and on the outskirts of cities—likely to provide access to low-density parcels.

Table 1. Average land area consumed by roadway in US urban areas

	PMSA	City	Core
Roadway (m2) per capita	391.2	147.3	129.8
	(382.5)	(71.8)	(60.2)
Roadway (m2) per household	1031.0	380.7	328.5
	(1019.1)	(203.0)	(146.0)
Share of Census land area	0.036	0.101	0.143
	(0.09)	(0.05)	(0.05)
Share of Landsat-estimated urban land area	0.242	0.169	0.175
	(0.08)	(0.04)	(0.04)

Notes: Standard deviations in parentheses

Figure 1. Roadways as a share of urbanized land (as estimated from Landsat) against standardized distance from the center



Notes: Standardized distance is calculated by subtracting from a block group's distance to the PMSA center the average distance for all block groups in the same PMSA. This result is then divided by the standard deviation of distances to PMSA center for all block groups in the same PMSA. The black dot shows the average share of urbanized land used for roadway by distance with the 95% confidence interval of the mean in brackets.

The relationship between geography and the share of land dedicated to roadway, however, depends heavily on the denominator used. The average PMSA dedicates 24% of Landsat-estimated urban land to roadways, with 95% of PMSAs dedicating 11.8% to 45.0%. The average PMSA, by contrast, has 3.6% of Census land area covered by roadway, with 95% of PMSAs having 1.2% to 7.8% of land area covered by roadway. Moreover, metropolitan areas with a lower share of Census land area dedicated to roadway tend to have a higher share of Landsat-estimated urban land dedicated to roadway (Pearson's of -0.27). This inverse relationship has two primary explanations. First, metropolitan areas with the largest amounts of land area in Census block groups tend to include the most rural and uninhabited land. For example, just 2.4% of the Las Vegas PMSA's 102 thousand square kilometers of Census land area is urbanized, as measured from the Landsat data. Most of the Census land area is desert and includes multiple national parks and mountain ranges. Like in Las Vegas, desert, parkland, and mountains dominate the landscape in many PMSAs. Second, more dispersed settlement patterns tend to include more rural and uninhabited land, with development occurring in spread out patterns along roadway.

The measures of roadway consumption also vary substantially across the 20 most populous PMSAs (Appendix D). Large metropolitan areas have an average of 19% of urbanized land to roadway. Los Angeles is no outlier and dedicates less land area to roadways than New York, Chicago, Boston, and other large cities. If anything, large dense cities tend to dedicate a higher share of land to roadway than smaller or more sprawling ones. Contrary to the rest of the sample but consistent with earlier findings (Manville & Shoup, 2005; Meyer & Gómez-Ibáñez, 1981), the largest metropolitan areas tend to have more or equivalent urbanized land dedicated to roadway in the core and central cities than the rest of the metropolitan area. There is also substantial variation in the share of the PMSA population that lives in the primary city or within three miles of the PMSA center. For example, 86% of the New York PMSA residents live in New York City, compared to just 8% of the Riverside PMSA (Orange County) living in Riverside.

The mix of roadway types also varies by geography. On average, highways account for 7% of the land area consumed by roadways in metropolitan areas; arterial for 27%; and local roads for the remaining two-thirds (Table 2). Primary cities and city cores tend to have a higher share of highways and arterials than suburban areas. This distribution is consistent with early national efforts to locate highways in central locations where they would generate the most traffic, thereby raising the most fuel tax revenue to build new highways (Lewis, 2013; Rose & Mohl, 2012; Taylor et al., 2023).

Table 2. Average share of roadway area by roadway type

	PMSA	**City**	**Core**
Share highway	0.067	0.086	0.084
	(0.037)	(0.055)	(0.059)
Share arterial	0.268	0.318	0.338
	(0.107)	(0.107)	(0.115)
Share local road	0.665	0.596	0.578
	(0.126)	(0.124)	(0.122)

Notes: Standard deviations in parentheses

3.2 What was it worth?

We estimate that the land area dedicated to roads in US metropolitan areas is worth \$4.1 trillion, 22% of the national gross domestic product, in 2016. Based on the share and value of land dedicated to roadway, this figure is generally consistent with Albouy et al.'s (2018) inflation-adjusted estimate of urban land being worth \$30 trillion. The total value translates to \$43,000 per PMSA household, \$16,000 per person, and \$710,000 per hectare (\$287,000 per acre) in 2016.

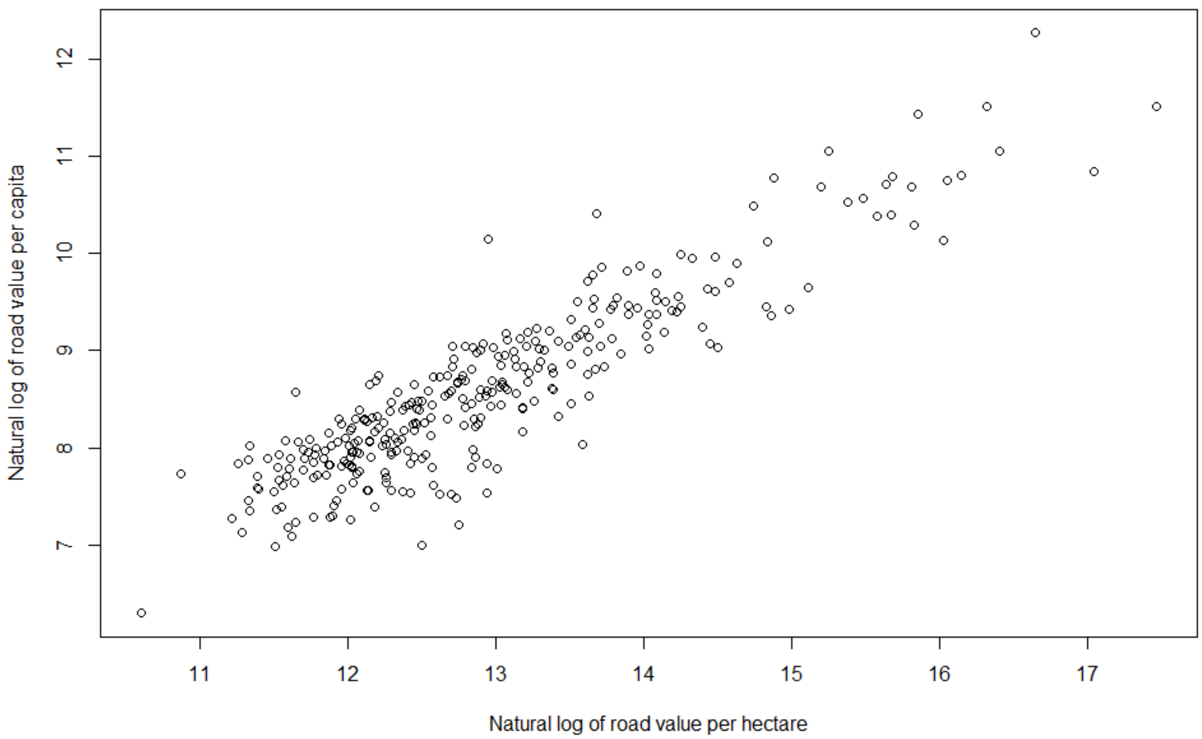
Even more than with the share of land dedicated to roadway, there is substantial variation in the value of road area within and across metropolitan areas. On average, the land value of roadway per hectare in central cities and city cores is double or more the value of roadway in suburban areas (Table 3). Since these more central locations are denser, however, the value per capita and per household is lower. Despite some extremely high land values, such as the core of New York City at $114 million per hectare, land values fall between $66,000 and $3.1 million per hectare in 95% of PMSAs. Despite the greater variance in land values per hectare than land values per capita, the two are strongly correlated (with a correlation of 0.77 to 0.93 across the three different geographies when taking the variables in log). Figure 2 plots the relationship for central cities. Across the sample, cities with 10% more valuable roadway per hectare have 6% more valuable roadway per capita.

Table 3. Roadway land value across metropolitan areas

	PMSA	**City**	**Core**
Road value per capita	$12,124	$9,518	$9,768
	($15,730)	($17,582)	($15,235)
Road value per household	$32,994	$24,125	$24,089
	($44,884)	($39,170)	($34,936)
Road value per hectare	$571,342	$1,124,133	$1,601,520
	($1,479,616)	($3,205,545)	($7,307,983)

Notes: Standard deviations in parentheses. Dollar values in 2016 USD

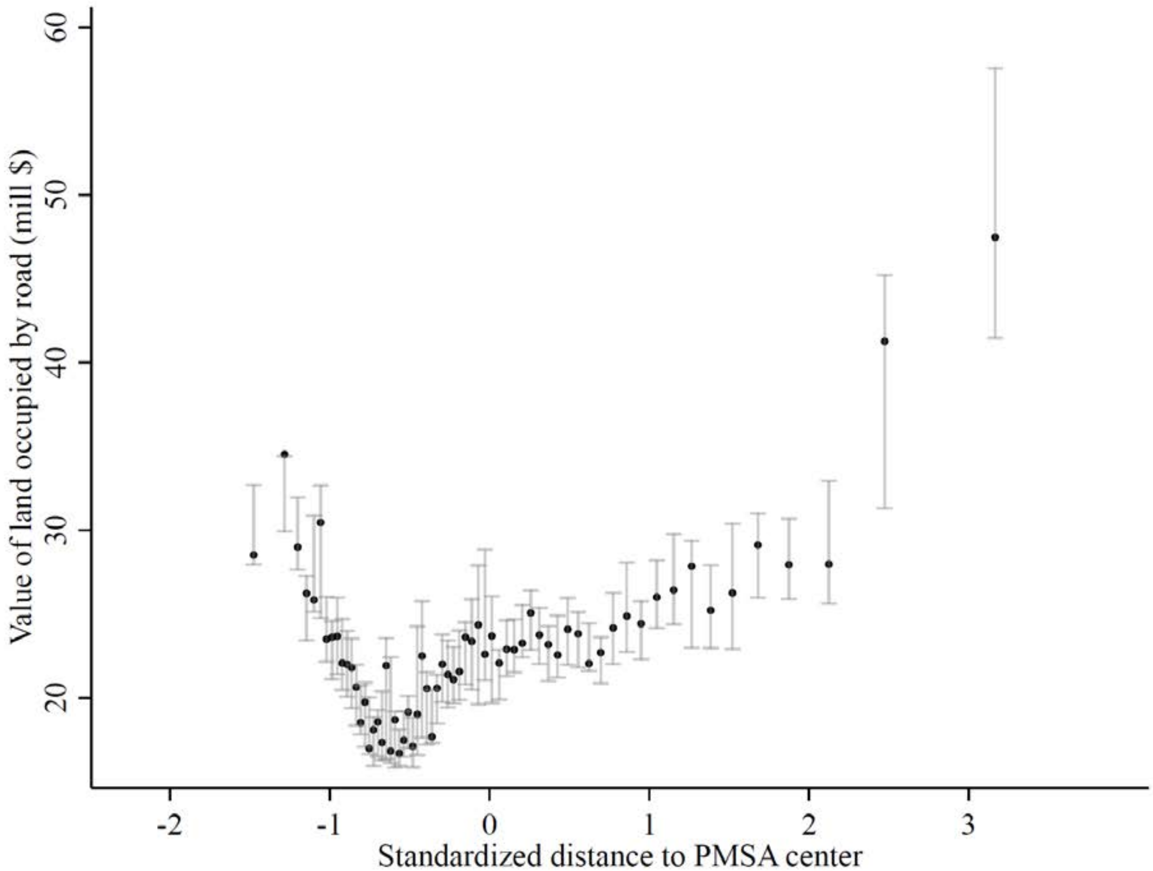
Figure 2. Relationship between land value per hectare and land value per capita across central cities



Within PMSAs, the total value of land dedicated to roadway is high close to the center and decreases before rising again into the suburbs (Figure 3). Despite lower land values per hectare, suburban areas tend to occupy substantially more land, with more of that land dedicated to roadways.

The distribution of land values varies substantially by geography. In some places, such as Boston, New York, Washington DC, and Chicago, central land values are substantially higher than in suburban areas (Appendix E). In others, such as Los Angeles, Irvine, and Detroit, land values are substantially flatter. In the case of Irvine, land values are relatively high throughout Orange County at around $8 million per hectare. In the case of Detroit, average land values are similarly low throughout the metropolitan area. In total, the 20 most populous PMSAs account for 50% of the total land value dedicated to roadways in the sample. New York, Los Angeles, and Chicago alone account for 22% of the total value.

Figure 3. Total land value of roadway against standardized distance from the center



Notes: Standardized distance is calculated by subtracting from a block group's distance to the PMSA center the average distance for all block groups in the same PMSA. This result is then divided by the standard deviation of distances to PMSA center for all block groups in the same PMSA. The black dot shows the average value of land used for roadway by distance with the 95% confidence interval of the mean in brackets.

4 Road area, road value, and the cost-benefit of roadway expansion

Knowing the amount and value of land used for roadway has intrinsic value for planning. Other than residential land—and possibly parking (Chester et al., 2010) —no other land use consistently uses as much urban land as roadway. Given that few houses or apartments cover all or even most of their lots, roadway likely does more to contribute to impervious surfaces than any other land use. Table 4 provides comparative data on some of the costs and benefits of the transportation network to help put the $4.1 trillion dollar value of the 58,000 square kilometers of urban roadway in perspective. Annualized at 5% to 9% of total land value—a range between a common figure for public funds and an estimate provided by the Managing Director of Morgan Stanley Infrastructure Partners (J. F. Pfeiffer, personal communication, August 1, 2023)—urban roadway is worth more than either government spending on roadway (Federal Highway Administration, 2020; U.S. Census Bureau, n.d.-a, n.d.-b) or the total variable costs of the freight trucking sector (American Transportation Research Institute, 2020; US Department of Transportation, 2019).

The value is also a bit less than the inflation-adjusted estimates of the total external costs of travel (including greenhouse gas emissions, local pollution, oil dependency, congestion, and traffic collisions) estimated using figures from the Federal Highway Administration (n.d.) and Parry, Walls, and Harrington (2007). Using more recent and less conservative estimates of the external costs of greenhouse gas emissions (Tol, 2023) could put the carbon costs of driving at $500 to $6,500 per household, 5 to 80 times higher than Parry, Walls, and Harrington's (2007) carbon cost estimates.[4] Of note, consumer money and time spent on car travel—estimated as the total time spent traveling by car times half the wage rate using a common transportation heuristic—are much higher than any of the other measures of the costs of travel (US Bureau of Labor Statistics, 2016, 2017; U.S. Department of Transportation, 2017).

[4] Authors' calculations based on total emissions from surface transportation and total vehicle miles of travel.

Table 4. Summary of annual roadway transportation costs and benefits in 2016

	Per household	**Total (billions)**	**Calculation Sources**
Government spending on roads	$1,590	$200	Federal Highway Administration (2020) US Census Bureau (n.d.-a, n.d.-b)
Consumer spending on vehicle purchases	$3,634	$471	US Bureau of Labor Statistics (2016, 2017)
Consumer spending on motor fuel	$1,909	$247	Ibid
Consumer spending on other vehicle expenses	$2,884	$374	Ibid
Time costs (urban households)	$11,026	$1,075	US Bureau of Labor Statistics (2016, 2017) US Department of Transportation (2017)
Variable costs of urban freight trucking	$2,521	$246	American Transportation Research Institute (2020) US Department of Transportation (2019)
Land value of urban roads	$2164-$3895	$206-$370	Authors' calculations
External costs of urban VMT	$3,020	$295	Federal Highway Administration (n.d.) Parry, Walls, and Harrington (2007)

In addition to illuminating the quantity and value of land used for roadway, our findings and database have specific and general applications for planning and public policy. Below we discuss uses in benchmarking and cost-benefit analysis before outlining several other ways that public planners and researchers might use our database.

4.1 Benchmarking

Planners and policymakers use comparative benchmarking to help set public policy. For example, City of Philadelphia transportation staff have frequently presented comparisons of peer cities' congestion measures and traffic fatality rates to support arguments that public policy and planning should emphasize traffic safety more broadly than congestion mitigation (City of Philadelphia, 2022). Benchmarking has also been used more generally to encourage reduced energy consumption (Hsu et al., 2019; Meng et al., 2017), compare water and sanitation systems (Carolini & Raman, 2021), develop airport plans (Suh & Ryerson, 2017), support environmental justice planning (Brinkley & Wagner, 2024), compare the relative sustainability of buildings (Retzlaff, 2008), and set public policy and planning goals more generally.

Our data provide opportunities for public planners to compare their jurisdictions to others for benchmarking purposes (Appendix E). Los Angeles, for example, tended to have less roadway area per urbanized area, household, and person than most other large cities (Appendix E). Whatever planning critiques may hold in Los Angeles (Ewing, 1997; Manville & Shoup, 2005), the city does not appear to allocate a disproportionate amount of space to roadway. This is not to say that Los Angeles should widen roads. Manville (2017) found that a Los Angeles law requiring developers to add roadway capacity to mitigate traffic from new developments does not improve congestion and likely reduces housing production. There may also be challenges related to roadway type. Arterials consumed a higher share of roadway area in Los Angeles than in any other large city.

On the other side of the country in Philadelphia, planners and policymakers have often asserted that the narrowness of roads makes it difficult to develop complete streets with adequate space for pedestrians, buses, cars, and cyclists. With 19% of road area dedicated to streets, however, Philadelphia had about the same amount of space dedicated to roadway on average as other large cities (Appendix E). With its urban blocks about half as wide as San Francisco's, Philadelphia planners may do well to consider pairs of streets rather than individual streets in isolation when planning for bicycle and bus facilities.

As with other metrics defining cities and towns, no single measure of roadway area captures all aspects of cities' road networks. Values per acre and per capita are highly dependent on land values and the distribution of land values within PMSAs. Other measures are highly associated with population density. Nevertheless, road area per household appears to be a particularly effective comparative metric. More compact cities tend to dedicate a higher share of urban land to roadway, but notably less roadway per capita. The largest metropolitan areas dedicate around 200-800 square meters to roadway per household in the PMSA; 50-300 square meters in the primary city; and 25-300 square meters in the central core (Appendix E).

4.2 Cost-benefit analysis

Given the substantial amount and value of land dedicated to urban roadway, we investigate whether the value exceeds the costs on average and what role land values play in those estimates. Our basic approach is to compare the expected value of time savings to truckers and car drivers from a 10% increase in roadway supply to the costs of government spending, the value of the land used, and the expected external costs associated with increased driving from the road investments. We assume that the increase would come primarily from widening highways and converting local roads and arterials to highways. We chose a 10% increase because it is enough to see impacts that could be achieved through plausible and common lane widening and new road investments. Similarly, a 10% increase or reduction in roadway capacity is a small enough figure that it might be achieved without major impacts on the access or amenity values of surrounding parcels. From a theoretical perspective, a city with no roads and a city comprised only of roadway would have close to no value.

In general, we choose conservative estimates, such as the lowest annualized land values, more generous expectations of how much time new infrastructure would save drivers, and lower estimates of how much traffic new roadway investments would generate. We assume that the 10% increase in urban roadway would have resulted in a 1% increase in speed and travel times savings. This is on the high end of existing estimates (Akbar et al., 2023) and doubles our own estimates when matching our road supply database to speed data using similar approaches. Other important assumptions include the assumption that a 10% increase in roadway would have proportionately increased the amount of land consumed and the public sector costs of building and maintaining roadway. We estimate the value of travel time savings by multiplying half of the wage rate by the estimated reductions in travel times based on increased speeds. We reduce the variable costs of the trucking sector using a similar approach. Finally, we assume that a 10% increase in roadway supply corresponds to a 7% increase in vehicle travel—on the lower end of existing estimates (Cervero & Hansen, 2002; Downs, 2004; Duranton & Turner, 2011)—and associated externalities using Parry, Walls, and Harrington's (2007) estimates per mile of vehicle travel. Due to data limitations, we exclude investment costs borne by private developers, benefits to bus users, and external costs other than greenhouse gas emissions, local pollution, oil dependency, congestion, and traffic collisions.

Despite conservative assumptions, we find that the estimated costs of increased road investments substantially outweigh the estimated benefits on average, especially when accounting for land values (Table 5). Ignoring externalities and land values entirely, the costs of expanding urban roadways exceed the benefits by a somewhat modest 17%. The external costs of new traffic and especially the opportunity costs of lost urban land, however, are the largest costs of adding road supply. Including the land value, costs outweigh benefits by a factor of nearly three. Including externalities resulted in costs that are four to five times higher than benefits.

Table 5. Estimated costs and benefits per urban household of a 10% increase in urban roadway capacity

Benefits	
Time savings	$110.26
Freight trucking	$25.21
Costs	
Government spending	$158.96
Land value	$216.42
Externalities	$211.39
Benefit-cost ratios	
without land or externalities	0.85
without land	0.36
Total	**0.23**

The poor economic performance of US roadway investments on average is robust to major changes in assumptions about the value of time, external costs of travel, or the value of trucking. Beyond the high costs, the main assumption that drives the results is the increases in speeds associated with road investments. Including land values but ignoring externalities, speeds would have to have increased by 3% for a 10% increase in urban roadway investments to have economic benefits that exceeded costs. Including externalities, the increased speeds would need to have been closer to 50%.

These results are consistent with findings that the construction costs of urban Interstate highways are twice the benefits on average (Duranton & Turner, 2011) and that new highways have produced little in the way of economic development for quite some time (Boarnet, 1997). The main issue is that widening roadways does not produce benefits to drivers or truckers that are as high as the already high and increasing costs of construction (Brooks & Liscow, 2023). Our main contribution is to show that the opportunity costs of using land for other productive uses are also substantial and should be incorporated along with construction costs and the social and environmental costs of the increased driving caused by new roadway capacity. This is not, of course, to say that all roadway construction projects are bad construction projects. Given the increasing costs and decreasing benefits of highway construction over time, however, most new road widenings are unlikely to produce benefits that outweigh costs at the margin. Moreover, the places where new road investments are likely to produce the highest benefits are also likely the places where the construction and land costs are highest.

Dedicating more land for housing, offices, and other land uses instead of roadway would likely increase net social benefits on average. Following our calculations, a 10% reduction in urban roadway from removing, narrowing, or downgrading roadway results in an estimated net benefit of $27.8 billion per year. At some point, reductions in roadway would result in economic harm, but across US urban areas today, reducing the amount of space dedicated to urban roadways appears to have the potential to generate substantial gains.

4.3 Uses of the dataset

There are many other ways that researchers and policymakers might use our publicly available dataset beyond demonstrating the high land costs of urban roadway, benchmarking against other cities, and articulating the high costs and relatively low average benefits of using more urban land for roads. Examples include: (1) examining whether shorter, more walkable blocks tend to dedicate more land to roadway than larger, wider blocks; (2) including the amount of roadway in local and metropolitan studies of the effects of the built environment on travel behavior, traffic safety, or other outcomes; and (3) examining whether there are equity issues related to the distribution of roadway within and across metropolitan areas.

In addition to the limitations described in our research design section, we also emphasize that these data are best used over large geographies and more aggregated scales. If a researcher or policymaker would like to know the amount of roadway in a specific geography or the width of a specific roadway, we recommend measuring them directly. As with any statistical predictions and extrapolations, ours contain both measurement and prediction error.

5 Conclusion

In this paper, we develop predictive models to estimate the amount and share of land covered by roadway in US metropolitan areas. We then match these predictions to estimates of land value to generate estimates of the value of land dedicated to roadway across metropolitan areas, cities, and central cores. Finally, after showing how much the land used for roadways was worth, we discuss potential uses of the data for planning, including for benchmarking and a back-of-the-envelope cost-benefit analysis that incorporates the value of urban land. Two key findings emerge.

First, the amount and value of urban land dedicated to roadway is substantial at over $4 trillion on the land area of West Virginia. Roadway in suburban areas tends to consume both a high share and high total amount of land and land value. Downtown roads generally use the most expensive land but tend to have higher densities and thus lower land consumption per capita. Contrary to previous assertions, Los Angeles is no outlier in its share of land dedicated to roadway. If anything, the city has less land dedicated to roadways than the average city (Appendix E).

Second, even with generally optimistic assumptions, the costs of adding urban road capacity substantially outweigh the benefits, especially when incorporating the land costs of roadway. This result is unsurprising given the US history of building roadway to meet peak demand decades out into the future. Although numerous policy reforms have called for an emphasis on economic competitiveness, conservative roadway networks, and environmental protection, government agencies have continued to direct billions of dollars into expanding, rebuilding, and maintaining roadway networks each year. Future research could shed light onto why government agencies tend to assume these investments will generate net economic benefits. The likely answer is that they assume both much higher increases in travel speeds from new investments and much higher congestion benefits for existing roadway users, despite decades of empirical evidence to the contrary.

Finally, we have made our data publicly available at the county, block group, and segment-level in addition to the three summary geographies used in this paper (Guerra et al., n.d.) and provide interactive web maps at the county and block group levels (*US Roadway Project*, n.d.). We hope that other researchers and policymakers find these useful in generating their own estimates and analyses of the state of US urban roadway.

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Appendix A. Road network data and data processing

HPMS Road width data

The Highway Performance Monitoring System Field Manual (HPMS) provides detailed guidance on how state departments of transportation should measure the number of lanes and the estimated widths of lanes, shoulders, and medians for the dataset's 10% data sample (Office of Highway Policy Information, 2016). According to the documentation, ***lane widths*** should be measured to the nearest foot and reported as the average width for through lanes. Where marking does not delineate between shoulders and lanes, the document instructs evaluators to make reasonable measurements based on roadway use. Of note, the documentation instructs evaluators to net out parking lanes based on statewide parking standards and provides a graphical description of how to net out parking spaces. The document also requests that evaluators indicate whether parking exists on one or both sides of the roadway. Reporting, however, was too sparse to include parking in our estimates.

Median widths should be measured as the predominant width of the roadway segment to the nearest foot. Widths of 100 feet or greater should be recorded as 99. Raised medians and ditches should not be recorded. Left shoulders should be included in estimates of median widths.

Right and left shoulders should also be measured to the nearest foot. Bicycle lanes should be excluded from shoulder estimates when clearly delineated but otherwise included. Left shoulders should only be estimated for divided highways and otherwise included in median width estimates.

To verify HPMS-reported data, we spot-check roadway sections using Google Street View. We also examine the distribution of measured widths by state and metropolitan area. Based on these checks, we made several adjustments to the number and width of reported lanes:

- In MA, NE, and IA, we recode 18’ or greater lane widths as 12’.
- In IN, we recode highways recorded as having a single lane to having 4 lanes and arterial roadways as having two lanes.
- In WI, we divide lane widths of greater than 18’ by 2 and multiply the number of lanes by two.

Table A1 provides the mean, standard deviation, and number of observations of shoulder widths, lanes, land widths, and median widths in the HPMS sample data by Functional System. We provide width estimates in the original unit (feet).

Table A1. HPMS sample measurements in feet by Functional System

	Functional System						
	1	**2**	**3**	**4**	**5**	**6**	**7**
Left Shoulder Width	6.7	6.1	5.6	4.9	3.7	3.3	3.9
Std. Dev.	3.6	3.3	3.2	2.8	2.2	1.7	1.7
Observations	213811	99704	141785	94601	92926	30686	171960
Right Shoulder Width	10.3	9.6	6.8	5.1	4.0	3.7	3.8
Std. Dev.	3.2	3.4	3.7	3.1	2.5	2.6	1.8
Observations	215209	97135	230164	208446	200870	53379	196160
Number of through lanes	4.7	4.3	3.4	2.5	2.1	2.1	2.0
Std. Dev.	2.2	1.9	1.3	1.0	0.5	0.4	0.2
Observations	442014	223988	1066017	909776	879958	158483	2273089
Lane Width	12.3	12.3	12.1	11.9	11.4	10.8	9.5
Std. Dev.	1.8	1.7	1.8	2.1	2.0	1.9	2.2
Observations	197329	102418	291827	260968	225152	37510	147680
Median width	52.5	42.5	30.6	20.1	19.3	17.2	18.3
Std. Dev.	29.7	26.5	23.1	17.2	15.4	11.3	15.5
Observations	213957	103086	147620	46229	12320	1676	3647

Functional System: (1) Interstate; (2) Principal Arterial – Other Freeways and Expressways; (3) Principal Arterial – Other; (4) Minor Arterial; (5) Major Collector; (6) Minor Collector; (7) Local

Matching TIGER files to HPMS data

To supplement the low coverage of local roads by the HPMS, we spatially match the Topologically Integrated Geographic Encoding and Referencing (TIGER) and HPMS roadways, remove matched segments, and add unmatched TIGER roadways to the sample. We assign TIGER's code S1400 (Local Neighborhood Road, Rural Road, City Street) to HPMS' Local roads (Functional System 7) classification and S1640 (Service Drive, usually along a limited access highway) to HPMS' Minor Arterial (Functional System 4) classification. In total, TIGER accounts for 61.2% of local roads by segment length and 4.6% of minor arterials in our final dataset. Within PMSAs, approximately half of the TIGER local neighborhood roads (S1400) and half of the service roads (S1640) do not match to HPMS segments and are thus included in our final dataset.

Our first step to matching TIGER roads is to draw an iterative buffer (.5 to 5m) in half meter increments around each TIGER roadway segment and match it to HPMS segments within those distances. This leaves any TIGER segments not within a 5m distance of an HPMS segment unmatched. Since TIGER segments are generally longer, we then compute an overlap function for each segment of the HPMS and only consider roadway for inclusion if they have less than 50% overlap for each segment under 5km and 20% or less for segments greater than 5km. We then compute a ratio of the length of matched segments HPMS segments to TIGER segments and sum all matched segments to ensure that matches sum to 1. Finally, we map local roadways with a spatial offset so that any overlap would be visible as a parallel roadway to check our work. Unmatched TIGER segments are then added to the final dataset of roadways.

HPMS selection bias

The 10% HPMS sample includes a higher share of higher-capacity roadways, such as highways and arterials (Table A1). As shown above, the universe of HPMS roadways also excludes a substantial number of local roadways. The HPMS potentially over samples from wider roadways within roadway classes as well. We thus test for selection bias based on the observable categories in our dataset by running regressions predicting whether a roadway segment is in the sample dataset as a function of observable categories in our dataset, such as surrounding Census attributes, distance for the downtown, segment length, and metropolitan area.

In general, road segments are more likely to be in the sample group in denser, wealthier, and older neighborhoods that are closer to the downtown. Longer segments are also likelier to be selected. Although most of the observable characteristics of the roads or block groups have a statistically significant relationship with whether the road segment is in the sample (likely due to the large sample size), the effect sizes are small. For example, a doubling of population density moves the probability of being in the sample by just a small fraction of a percentage point. Limited selection bias based on observables suggests that selection on unobservable attributes is also unlikely. Moreover, bias from selecting from more substantial roadways may be offset by other differences in the data, such as the exclusion of on-street parking. We find around 15% to 20% less space dedicated to roadways across block groups and counties on average than Millard-Ball (2022) (see Appendix D.)

Appendix B. Model selection and performance

We estimate random forest models to predict each of the five road-width features for each of the seven roadway classes (35 sets of models) on an 80% training set using Python's scikit-learn library. We used the RandomForestClassifier's default model parameters of one hundred trees in the random forest and Gini purity as the splitting measure. We use the 20% remainder of the sample for testing model performance at the end. We also test multinomial and ordered logit models, but these do not predict the data as accurately. Moreover, the multinomial logit models often fail to converge, and the ordered logit models generally just predict the most common width across roadway class. Table B1 provides a summary of the roadway predictions from our 35 sets of models that are used to estimate the amount of space used for roadways outside of those provided in the HPMS sample.

Table B1. Predicted road width measurements by Functional System

	Functional System						
	1	**2**	**3**	**4**	**5**	**6**	**7**
Left Shoulder Width	1.9	1.7	1.3	1.2	1.0	1.1	1.0
Std. Dev.	1.0	0.9	0.8	0.8	0.5	0.4	0.3
Observations	233201	138361	925811	850973	787500	149661	7635914
Right Shoulder Width	3.0	3.0	1.9	1.2	0.9	1.0	1.0
Std. Dev.	0.7	0.8	1.1	0.8	0.6	0.6	0.4
Observations	231803	140930	837432	737128	679556	126968	7611714
Number of through lanes	4.7	4.8	3.7	2.2	2.0	2.0	1.9
Std. Dev.	1.4	1.9	0.7	0.6	0.0	0.0	0.3
Observations	4998	14077	1579	35798	468	21864	5534785
Lane Width	3.7	3.7	3.6	3.6	3.6	3.3	2.5
Std. Dev.	0.1	0.1	0.1	0.1	0.2	0.5	0.2
Observations	249683	135647	775769	684606	655274	142837	7660194
Median width	15.5	12.4	6.3	4.4	3.9	3.6	3.9
Std. Dev.	9.5	8.1	5.7	4.4	3.3	1.8	2.5
Observations	233055	134979	919976	899345	868106	178671	7804227

Functional System: (1) Interstate; (2) Principal Arterial – Other Freeways and Expressways; (3) Principal Arterial – Other; (4) Minor Arterial; (5) Major Collector; (6) Minor Collector; (7) Local

Model fits

Since road-width features are ordinal, a wrong road width prediction that is closer to the true value should incur a smaller error than one further from the true value. Therefore, we use mean absolute error (MAE) as our metric to evaluate the model performances. MAE is calculated as the average of absolute differences between the true width and the predicted width for all roads in the test sample. To compare performance across different road-width features, we further divide the MAE by the average value of the true width. The standardized MAE can be interpreted as the average percentage difference between the predicted width and the true width.

Assessing model performance at the road level, across road classes and road-width features (35 MAE scores), our model achieves an average MAE score of 0.11, with a standard deviation of 0.12 (Table B2). Therefore, our model predicts road width off by an average of 11 percent. Compared with other road classes, local roads have the smallest training sample and worst predictive power. We also test the performance of models with fewer predictor variables. So long as we include metropolitan indicators, distance to the metropolitan center, and at least one of the socioeconomic variables from the Census, predictions are stable and produce relatively similar predictive accuracy.

Table B2. Road-Level Model Performance

Width Measure	Road Class	True Mean	MAE	MAE Divided by True Mean
Number of Through Lanes	1	4.82	0.74	0.35
	2	4.30	0.57	0.27
	3	3.44	0.22	0.08
	4	2.52	0.20	0.07

	5	2.13	0.10	0.04
	6	2.06	0.03	0.01
	7	2.01	0.03	0.01
Through Lane Width (ft)	1	12.07	0.09	0.01
	2	12.03	0.07	0.01
	3	11.90	0.09	0.01
	4	11.68	0.16	0.01
	5	11.24	0.20	0.02
	6	10.80	0.18	0.02
	7	9.56	0.62	0.06
Median Lane Width (ft)	1	52.88	1.31	0.06
	2	42.84	1.42	0.08
	3	30.84	1.63	0.15
	4	20.33	1.77	0.17
	5	19.96	2.01	0.16
	6	17.80	0.99	0.07
	7	18.24	6.49	0.53
Left Shoulder Lane Width (ft)	1	6.69	0.15	0.04
	2	6.06	0.19	0.05
	3	5.58	0.22	0.06
	4	4.93	0.29	0.08
	5	3.74	0.40	0.15
	6	3.24	0.39	0.14
	7	3.91	0.88	0.31
Right Shoulder Lane Width (ft)	1	10.29	0.20	0.04
	2	9.63	0.27	0.05
	3	6.89	0.30	0.07
	4	5.20	0.37	0.10
	5	4.03	0.38	0.12
	6	3.72	0.31	0.10
	7	3.77	0.88	0.32

Functional System: (1) Interstate; (2) Principal Arterial – Other Freeways and Expressways; (3) Principal Arterial – Other; (4) Minor Arterial; (5) Major Collector; (6) Minor Collector; (7) Local

We further assess model performances at the metropolitan level. We first compute averages of predicted and true road-width feature at the PMSA level by aggregating the road-level data. Then we compute the MAE and standardized MAE scores at the PMSA level. The average standardized MAE across models is 0.036. Across the 35 models, 25 have a standardized MAE less than 0.05 (5 percentage difference between the true and the predicted).

Feature importance in random forest models

We compute two sets of metrics to understand the importance of each predictor variable in the random forest models. The first set of metrics is based on the extent to which a feature decreases the Gini impurity criterion used to measure the quality of a split in training the models. For each of the features, we first compute how it decreases the impurity of the split of a decision tree and then average the decreases over all trees in the random forest to measure the importance of the feature. For the vector of PMSA indicators, we add up the feature importance scores and used the sum to determine the predictive importance of knowing in which PMSA a road segment was located. The importance scores are further normalized to sum to one across all features in the model. The importance of a feature is thus between 0 and 1, with a higher value indicating that the feature, on average, decreases the impurity of the model more. The Gini impurity metric has the tendency to give higher weight to variables with higher magnitudes. In other words, it is not invariant to the scale in which a feature is measured. It also relies on the training data, rather than the test data, making it more subject to overfitting.

To complement the Gini impurity metric, we also compute a set of permutation-based metrics, which we estimate by randomly shuffling one feature's value across observations (while holding other features fixed) and computing the change in mean absolute error (the measure of model performance). For each of the numerical features (road segment's distance to PMSA center, block group population density, median household income at the block group level, etc.), we directly assign the observation's feature value to a random observation in the data. For the PMSA categorical variable, we shuffle by assigning a road segment to a random PMSA. For each of the features, we repeat the process 100 times and take the average change in mean absolute error. The average change in mean absolute error thus measures how much worse the model's predictive performance would be if a feature is removed. Unlike the Gini impurity-based metric, the permutation-based metric is computed on the test data and thus is less subject to overfitting. Additionally, since the importance measure is the change in performance (mean absolute error), the metric is less subject to different scales in which the features were measured.

The two distinct metrics provide complementary views on feature importance—the first based on model fit using in-sample data and the second based on model accuracy with out-of-sample data. Examining the two sets of metrics in conjunction provides a more comprehensive understanding of the importance of the features in the model.

Figure B1 presents feature importance scores using the Gini impurity-based metric, across all road classes and road width measures (all 35 models). A road segment's distance to PMSA city center is the most important factor. On average, 35% of the decrease in Gini impurity is attributed to this feature. The PMSA indicators collectively provide the second most important factor in explaining the decrease in Gini impurity. The rest of the demographic variables for the block group in which the road segment is located have similar strengths. We further present the feature importance for the models predicting the width of thoroughlanes for interstate highways and local roads using Gini impurity-based metric (Figures B2 and B3). For thorough lane width prediction for interstate highways, PMSA indicators are slightly more important than road segment's distance to PMSA center, both of which explain a 30% decrease in the Gini impurity measures. For through lane width prediction for local roads, road segment's distance to PMSA center is the most important factor.

Figure B1. Gini impurity importance (all width measures and road classes combined)

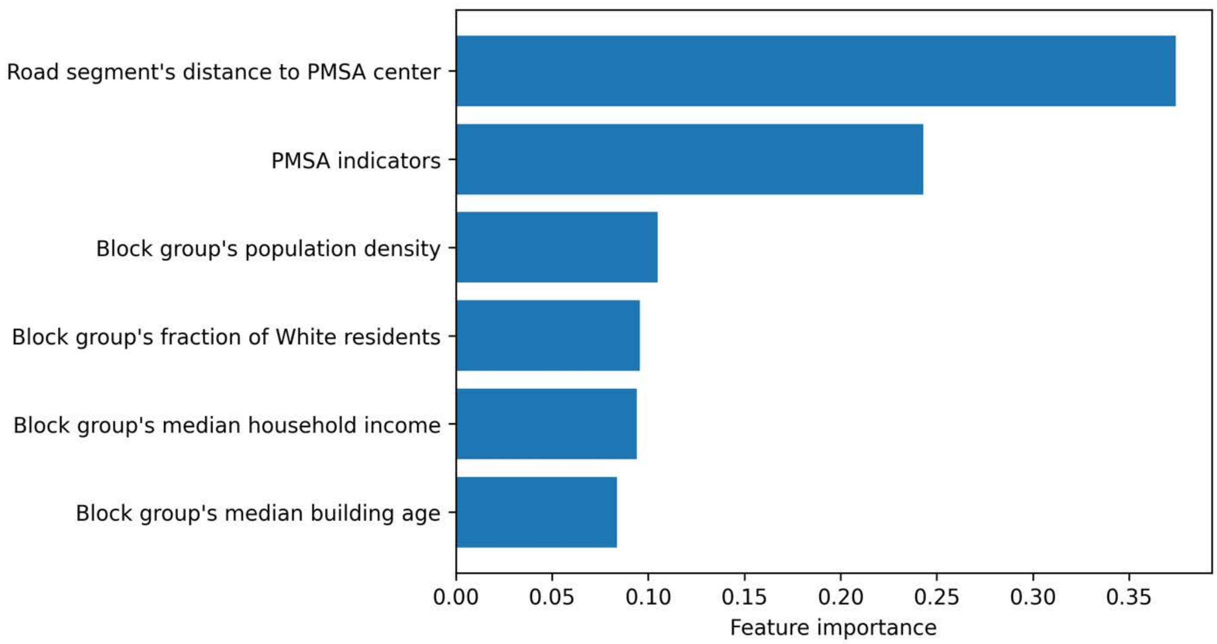


Figure B2. Gini impurity importance (Interstate through lane widths)

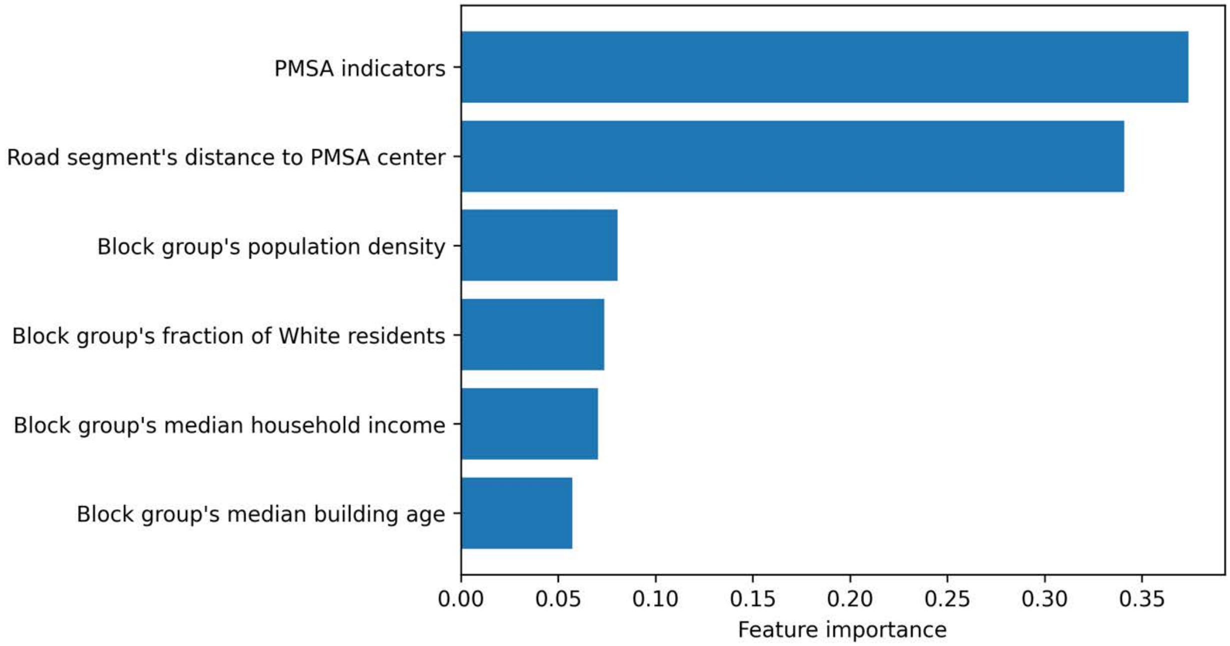


Figure B3. Gini impurity importance (local road through lane widths)

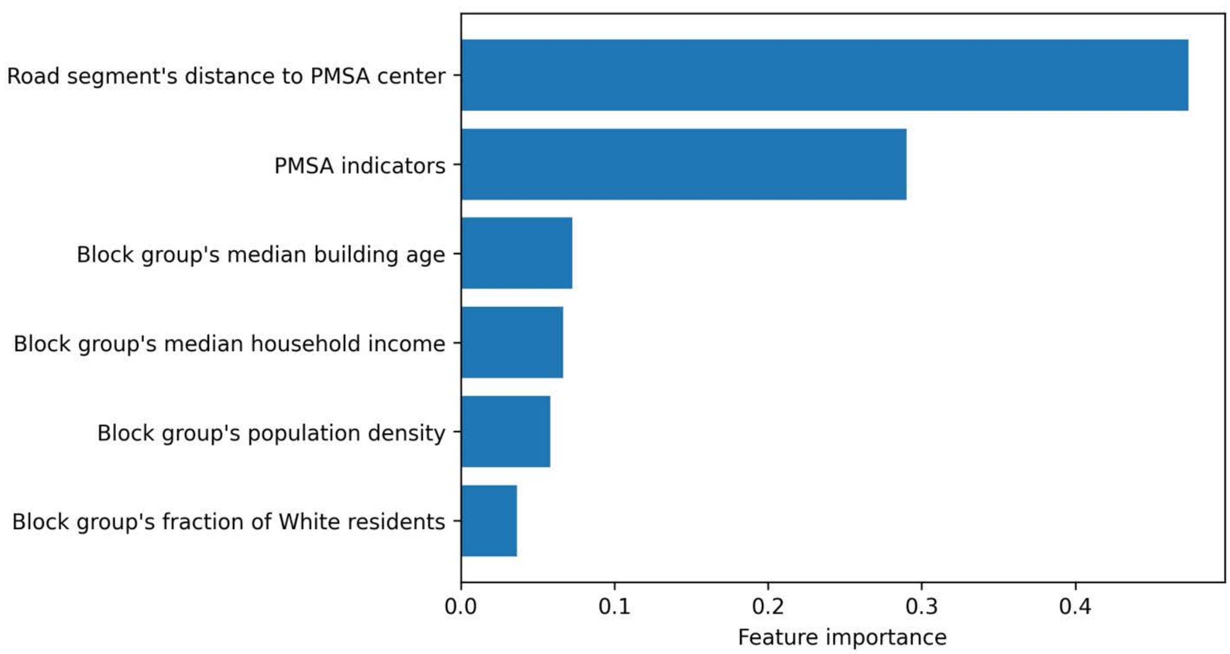


Figure B4 presents feature importance scores using the permutation-based metric across all 35 models. Under this metric, the PMSA indicators collectively are the most important features in determining model accuracy (mean absolute error). Removing this feature leads to a greater than 500% increase in mean absolute error. A road segment's distance to PMSA city center is the second most important factor. Surrounding population density is also important in model accuracy.

Figures B5 and B6 show analogous results for the through lane width prediction for interstate highway and local roads. In both cases, PMSA indicators are still the most important features in determining model accuracy, followed by a road segment's distance to PMSA center. However, the strength of PMSA indicators is weaker for interstate highway than for local roads (80% increase in mean absolute error vs 200% increase in mean absolute error).

Figure B4. Permutation importance (all width measures and road classes combined)

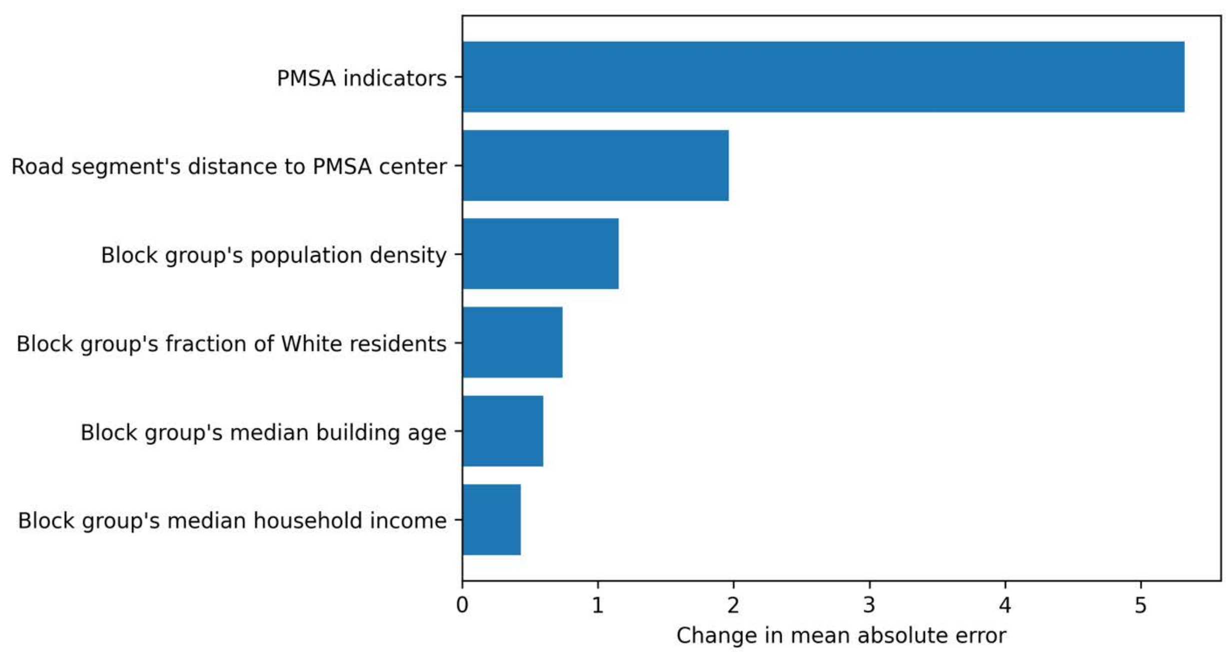


Figure B5. Permutation importance (Interstate through lane widths)

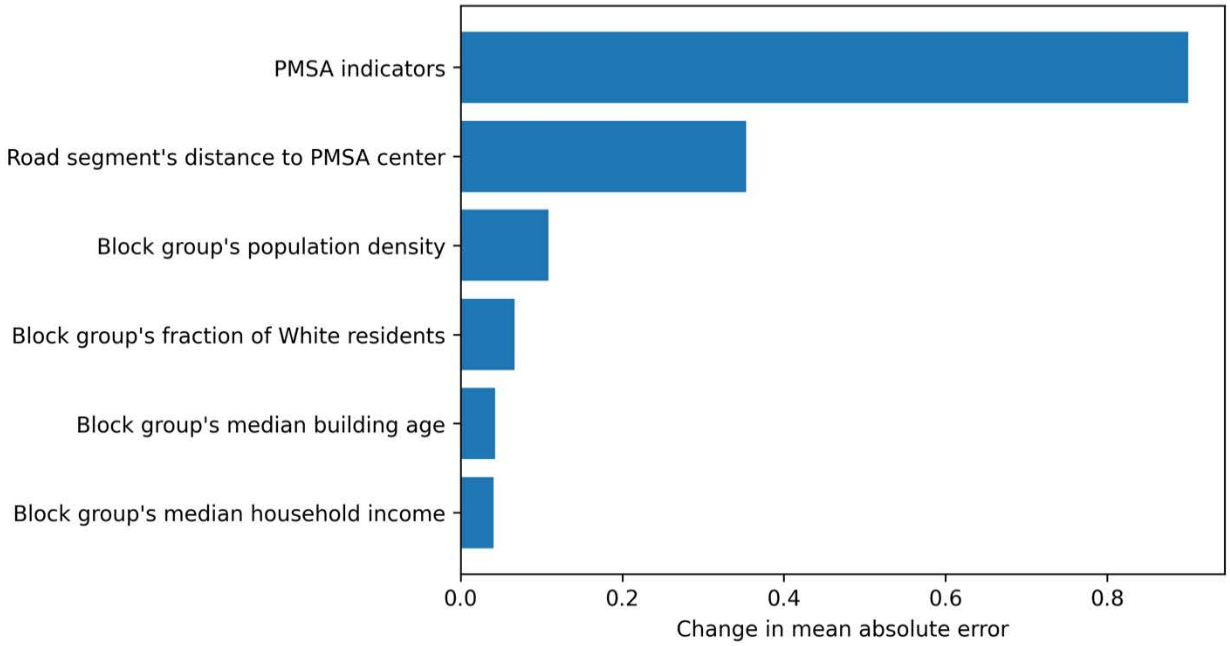
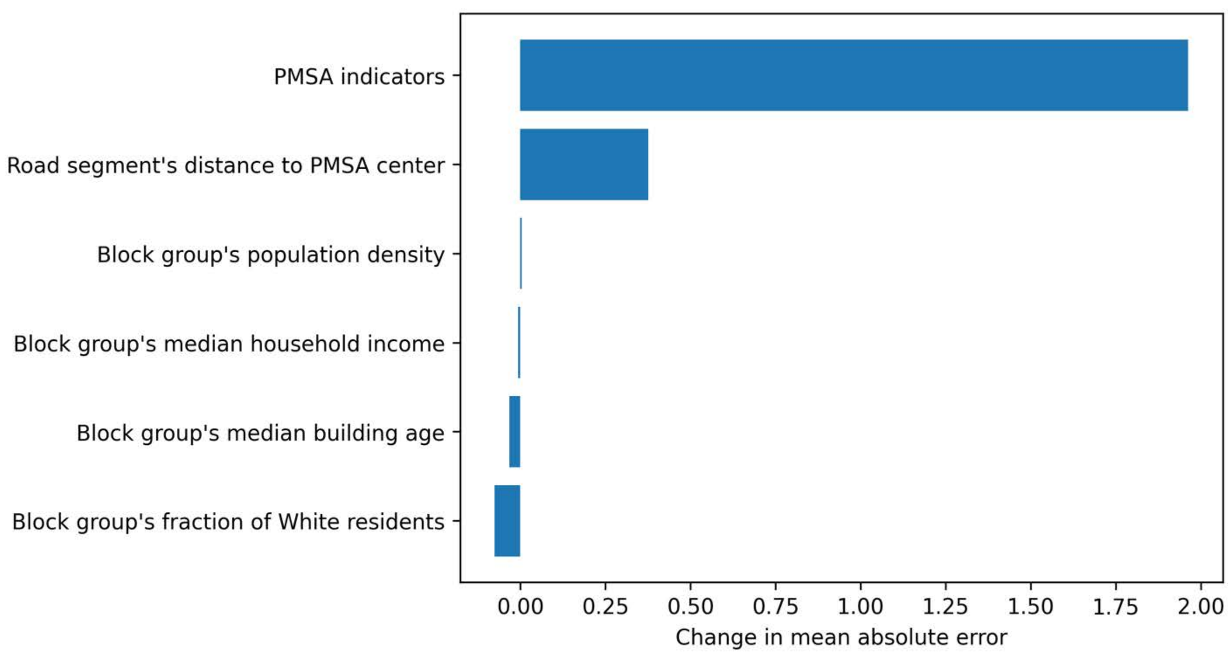


Figure B6. Permutation importance (Local road through lane widths)



Appendix C. Spatial data processing

Assigning road areas to block groups

Next, we multiply segment lengths by estimated widths to generate estimates of the total roadway area of each roadway segment. To account for the double counting of intersections, we remove overlapping areas of intersections using the following process within counties: We first convert road segments into polygons using 5-meter buffers. For each buffered road segment, we compute its intersection with all other buffered road segments. For each intersection, we record the centroid of the intersection, round it to the nearest meter, and assign a unique id. At each unique intersection, we net out the area estimated from the width of the widest segment times the width of each other segment intersection from the non-widest segment. For example, if a 10-meter roadway segment intersects a 5-meter roadway segment, we net out 50 square meters from the 5-meter roadway segment. For intersections with multiple widest segments, we assign one randomly to be the widest. Lastly, to account for segments compromised of multiple non-intersecting points due to geometry, we ignore segments whose length was less than the width.

We then match segments to Census block groups and sum the land area of roadway classes within block groups. Where roadways cross or divide block groups, we assign a proportional amount of a roadway area to the block group based on the share of the segment within and across block groups. Segments dividing block groups are equally assigned to those block groups for the share of the segment dividing them. To avoid double counting, we ensure that the fractions of each segment assigned to different block groups are summed to one.

Land value data

We match Davis's (2021) pooled cross-section estimates of "Land Value (Per Acre, As-Is)" from 2012 to 2019 to our data and assign Census tract values to constituent block groups. For missing values (38,054 out of 169,602 Census block groups), we first apply ZIP Code level data (31,746 matches). If no match was found, we use the average of five Census tracts within a kilometer (224 matches), followed by county-level (6,036 matches), and then PMSA data (48 matches). We then assign block group land values to estimated roadway area by block group. This process likely results in underestimates of land values in some core areas with major data gaps. For example, most Manhattan Census tracts are missing and thus generally assigned the value of New York County.

Land area data

We add three different measures of land area to our datasets of the estimated road area in US block groups. These include the total land area within Census block groups, the total land area within urban Census blocks in Census block groups, and the amount of land in block groups estimated from the Multi-Resolution Land Characteristics Consortium's 2019 Urban Imperviousness descriptor land cover raster data from Landsat (Dewitz & U.S. Geological Survey, 2021).

The Census block group land area measures correspond with the total populations reported by PMSA, as well as the most commonly used measurements of land area to estimate densities for cities, towns, and metropolitan areas. However, Census block group data often include deserts, mountains, farmland, national parks, and other types of non-urbanized land. For example, the land area measured from the Landsat data accounted for just 2.4% of the Las Vegas

PMSA’s 102 thousand square kilometers of Census land area. The land area in urban Census blocks accounted for even less at 1.5% of the total land area.

Table C1 provides summary statistics on the land area by PMSA, primary city, and city core using all three measures of land area. The measures are most similar in the more urbanized cities and city cores. The amount of land recorded diverges substantially in larger, more rural PMSAs.

When discussing the share of land dedicated to roadways, we prefer to focus our findings on the Landsat-based estimates of land area. These match spatially with the total population estimates within PMSAs and better represent development patterns along highways across a broad range of PMSAs. Smaller, more rural places in states, like Wyoming, Utah, and Montana are particularly affected by using only urbanized Census blocks. For example, our estimated road areas are larger than the urban Census land area in Bismark, ND, Casper, WY, Duluth, MN, Enid, OK, Fargo, MN, Flagstaff, AZ, Grand Forks, ND, and Great Falls, MT. For researchers interested in using urban Census blocks, we recommend using only the subset of block groups where the land area from urban blocks is equal to the land area from all block groups. More generally, we recommend caution when examining the share of land area used for roadway in small, rural PMSAs. Different measures of land area can have dramatic effects on share-of-roadway estimates.

Table C1. Total estimated square kilometers of land area using Landsat, Census block groups, and urban Census blocks

	Mean	Std. Dev	Min.	Max
PMSA				
Landsat	844	989	108	6617
Census	5802	8430	120	102006
Census urban	730	1011	62	7482
City				
Landsat	160	210	3	2171
Census	302	342	3	2752
Census urban	175	225	3	2345
Core				
Landsat	50	17	6	141
Census	61	13	20	108
Census urban	55	13	4	78

Appendix D. Out-of-sample validation tests

We compare our block group estimates to Millard-Ball's (2022) estimates and data from thirteen additional counties (Millard-Ball, n.d.) after assigning them to the block group level using the procedures described above. For consistency across the datasets, we only compare block groups comprised entirely of urban blocks (90% of matched block groups). Table D1 provides a summary of the relationship between the two measures of road area within block groups. A pure linear comparison shows that a one square kilometer increase in the parcel-based estimates of road area corresponds to a 0.812 increase in our HPMS-based estimates. Adding county-level indicator variables strengthens the relationship revealing some systematic differences across geographies. Log-transforming both measures of road area also increases the estimated strength of the relationship.

The validation is generally successful, and we obtain high correlations across metrics, although Millard-Ball (2022) tends to measure a bigger share of roadway. Methodological differences help explain these differences. Millard-Ball (2022) derive the roadway width estimates by differencing out land parcels instead, thus including parking lanes, sidewalks, and additional landscaping. Our approach, by contrast, builds estimates from recognized road segments and excludes sidewalks and parking lanes.

Table D1. Validation test comparing HPMS-based estimates to Millard-Ball's 2022 parcel-based estimates of road area by block group

	Dependent variable: Road area estimated from HPMS (standard errors in parentheses)			
	Linear estimate		Natural log against natural log	
	(1)	(2)	(3)	(4)
Millard-Ball estimates	0.812***	0.817***	0.921***	0.868***
	(0.002)	(0.002)	(0.002)	(0.003)
County fixed effects	No	Yes	No	Yes
Constant	0.009***	0.028***	-0.345***	-0.256***
	(0.000)	(0.001)	(0.007)	(0.010)
Observations	37,452	37,452	37,452	37,452
R^2	0.772	0.801	0.789	0.821
Adjusted R^2	0.772	0.8	0.789	0.821
Note:	*p**p***p<0.01			

Appendix E. Tables of road area and value for most populous PMSAs

Table E1. Land consumption of roadways by the twenty most populous PMSAs

	PMSA			City			Core		
Primary City	**Population**	**Share of urban land area**	**Share of Census land area**	**Share Population**	**Share of urban land area**	**Share of Census land area**	**Share Population**	**Share of urban land area**	**Share of Census land area**
Atlanta	5437374	0.16	0.06	0.09	0.15	0.12	0.03	0.19	0.19
Baltimore	2780873	0.22	0.07	0.22	0.24	0.22	0.10	0.27	0.27
Boston	6502249	0.25	0.08	0.10	0.27	0.25	0.06	0.32	0.32
Chicago	8656303	0.18	0.08	0.31	0.20	0.19	0.04	0.27	0.27
Dallas	4682683	0.18	0.05	0.30	0.15	0.11	0.03	0.21	0.19
Detroit	4260835	0.16	0.06	0.16	0.20	0.20	0.02	0.26	0.26
Houston	5800581	0.13	0.04	0.60	0.12	0.10	0.03	0.23	0.23
Los Angeles	10057155	0.17	0.06	0.39	0.15	0.13	0.04	0.18	0.17
Minneapolis	3420041	0.22	0.05	0.12	0.25	0.17	0.07	0.28	0.27
Nassau	2854931	0.19	0.12	0.02	0.24	0.24	0.08	0.22	0.22
New York	9853240	0.22	0.12	0.86	0.24	0.22	0.08	0.24	0.25
Orange County	3132211	0.15	0.09	0.08	0.15	0.08	0.07	0.16	0.15
Philadelphia	5393549	0.17	0.07	0.29	0.19	0.17	0.09	0.27	0.26
Phoenix	4486153	0.27	0.03	0.35	0.18	0.09	0.02	0.19	0.18
Riverside	4430646	0.23	0.01	0.08	0.12	0.09	0.03	0.13	0.11
San Francisco	3253356	0.14	0.03	0.44	0.13	0.07	0.06	0.15	0.14
Seattle	2918312	0.26	0.05	0.23	0.24	0.23	0.07	0.29	0.28
St. Louis	2759413	0.13	0.05	0.11	0.13	0.25	0.03	0.12	0.23
Tampa	2927714	0.15	0.06	0.13	0.15	0.12	0.04	0.20	0.20
Washington, DC	6139769	0.24	0.06	0.11	0.22	0.20	0.06	0.25	0.23
Average	4987369	0.19	0.06	0.25	0.19	0.16	0.05	0.22	0.22
Standard Deviation	2241449	0.04	0.03	0.20	0.05	0.06	0.02	0.05	0.05

Table E2. Land value of roadways by the twenty most populous PMSAs

	PMSA			City			Core		
Primary City	Road value per capita	Road value per household	Road value per hectare	Road value per capita	Road value per household	Road value per hectare	Road value per capita	Road value per household	Road value per hectare
Atlanta	$4,372	$12,310	$273,882	$11,796	$28,426	$1,251,084	$15,223	$37,047	$1,840,324
Baltimore	$15,237	$40,717	$954,567	$16,348	$41,879	$2,156,427	$26,976	$67,174	$4,175,355
Boston	$23,691	$62,715	$1,207,727	$49,151	$124,767	$10,284,478	$78,280	$189,779	$16,642,181
Chicago	$11,694	$32,260	$1,024,687	$15,531	$40,441	$3,665,886	$43,350	$84,933	$10,645,321
Dallas	$7,937	$22,457	$518,125	$9,122	$24,087	$971,844	$15,716	$34,287	$1,530,859
Detroit	$4,479	$11,490	$293,920	$2,718	$7,229	$255,825	$5,458	$11,140	$351,386
Houston	$8,008	$23,428	$698,742	$9,430	$26,693	$1,227,790	$42,447	$92,695	$4,349,036
Los Angeles	$31,175	$95,534	$5,199,647	$29,622	$85,611	$7,513,564	$18,261	$54,360	$6,609,972
Minneapolis	$11,403	$29,628	$499,511	$11,858	$28,371	$1,312,429	$9,583	$22,643	$1,201,416
Nassau	$25,070	$76,961	$1,900,594	$8,342	$29,222	$1,989,024	$24,385	$81,344	$3,396,021
New York	$46,628	$127,509	$12,745,484	$51,165	$138,402	$25,280,107	$131,821	$287,525	$114,091,285
Irvine	$48,619	$149,738	$8,390,058	$100,738	$275,545	$12,304,814	$35,830	$124,691	$7,319,016
Philadelphia	$8,700	$23,513	$726,010	$12,356	$33,084	$3,226,677	$26,213	$65,932	$6,992,892
Phoenix	$12,058	$33,880	$565,643	$8,065	$23,246	$825,727	$14,141	$37,894	$1,037,220
Riverside	$18,926	$63,302	$792,631	$8,220	$28,764	$1,251,375	$8,528	$29,368	$1,337,189
San Francisco	$26,087	$76,935	$2,929,169	$32,509	$91,943	$5,821,223	$45,689	$108,675	$9,252,839
Seattle	$31,021	$79,133	$1,591,417	$49,025	$107,867	$6,467,957	$61,484	$116,071	$7,925,208
St. Louis	$6,789	$17,188	$218,698	$6,847	$15,444	$537,233	$9,214	$21,199	$563,803
Tampa	$7,528	$18,969	$555,790	$12,535	$31,592	$1,152,660	$18,694	$44,205	$1,620,864
Washington, DC	$27,630	$77,001	$1,707,106	$63,637	$151,647	$13,424,159	$85,004	$183,561	$19,421,335
Average	$18,853	$53,733	$2,139,670	$25,451	$66,713	$5,046,014	$35,815	$84,726	$11,015,176
Standard Deviation	$12,932	$38,278	$3,101,383	$24,638	$64,401	$6,089,035	$31,272	$67,737	$24,200,396