Urban roadway in America: the amount, extent, and value

Problem, Research Strategy, and Findings

In this paper, we predict the amount, share, and value of land dedicated to roadways within and across 316 US Primary Metropolitan Statistical Areas. These urban areas account for 80% of the US population and an even larger share of Gross Domestic Product. 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 remaining 90% and additional local roads not covered by the Highway Performance and Monitoring System. Multiplying estimated widths by segment length provides 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 quarter of urbanized land—roughly the size of West Virginia—is dedicated to roadway. This land is worth around $5 trillion dollars and has an annualized value that is 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 find that the country likely has too much land dedicated to urban roads.

Takeaway for Practice

Federal, state, and local agencies dedicate substantial time, money, and resources to providing roadway. Even with relatively generous assumptions and no external costs from driving, however, the average cost of expanding roadways exceeds the benefits by a factor of three. Policymakers should question policies focused on roadway expansion and consider options to reduce the amount of space dedicated to roadway. In addition to our findings, we provide a novel

dataset that academics and policymakers can use to draw their own conclusions about the state of America’s urban roadways.

Keywords: Roadway, land value, transportation policy, land use, streets

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Introduction

US federal, state, and local governments spend about 200 billion dollars annually building, expanding, and maintaining roads (Federal Highway Administration, 2020; U.S. Census Bureau, n.d.-a, n.d.-b).[1] Yet there is little consensus on the returns to these investments or whether the space devoted to roadway is really at its highest and best use.[2] 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). Spatial databases provide additional information, sometimes including total lane numbers and approximate width (U.S. Census Bureau, n.d.-c; U.S. Department of Transportation, n.d.). The total amount of land dedicated to roadways, where it is located, and how much it is worth, however, remain poorly understood.

Even in large cities with relatively good spatial databases, surprisingly little is known about how much space is dedicated to roadway. Manville and Shoup (2005; 1997) trace a reported and widely shared 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 makes a similar, uncited claim (The Special Assistant for Public Works Planning, 1960, p. 35), as does Lewis Mumford (1961, p. 510). The 1924 Los Angeles highway plan, by contrast, faults downtown Los Angeles for dedicating just 21.5% of its land area to roads, compared to 44% in Washington, DC, 34.5% San Francisco, and 24% to 41% in a range

[1] The US federal government spends nearly $50 billion building, widening, rebuilding, and maintaining highways and arterials each year. States and local governments spend another $150 billion, making road investment the largest source of local government spending after education, public health, and general welfare programs. More than half of roadway expenditures goes to building, widening, and expanding roadways. The rest goes to maintenance and operations.

[2] 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 wort 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).

of other 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 provide more systematic estimates in a handful of US cities and counties. Using spatial parcel data, Millard-Ball (2022) estimates that 17% to 21% of land area is dedicated to residential streets in 20 urban counties, predominantly from California and Texas, with adequate parcel-level data. This 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). Estimated shares of roadway, however, likely vary substantially based on different measures of land area.

No systematic estimates exist of the total amount of land area dedicated to roadway in US urban areas or its value. Existing city-level estimates are disproportionately from the largest cities, like New York, Los Angeles, and San Francisco. Without an accounting for the amount and value of land dedicated to roadways, it is difficult to assess whether there is too much or too little roadway or even whether outcomes, such as commute times, wealth, or employment, vary with the amount of roadway. [3]

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[3] For all the benefits to motorists, roadway takes land that could otherwise be used for homes, businesses, shops, and open spaces. Major roads are also arguably a negative local amenity which bisect neighborhoods and bring accidents, noise, and pollution (Brinkman & Lin, 2020). Baum-Snow (2007), for example, estimates that each additional urban highway reduced central cities population by 18% on average. Highway planners have long recognized that the places where roads will attract the most trips are also the places with the highest land values. Asked by President Roosevelt to develop a plan to finance an interstate highway system with toll roads, the Bureau of Public Roads (1939) concluded that tolls would only raise enough revenues to cover costs on a few select segments. Rural and suburban roads did not have sufficient demand for vehicular traffic. Land costs were too high in the central urban areas with the highest demand. Land acquisition, for example, represented 90% of estimated costs to build Boston's Central Artery and a highway on Woodward Avenue in Detroit (Bureau of Public Roads, 1939, p. 94; Charles A. Maguire and Associates, 1948).

In this paper, we present a novel methodology for combining publicly available datasets to generate predictions of roadway widths by place and by roadway-class across US metropolitan areas. We then 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). Approximately 80% of the US population resides in these PMSAs.

We find that roadway accounts for around a quarter of all urbanized land in the US—the equivalent of the total land area of West Virginia. This roadway is worth approximately $5 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.

Land is an important component of the cost of providing roadway. Annualized, the land value of roadway is higher than total annual federal, state, and local expenditures on roadway. It is also slightly above the total estimated variable costs of the trucking sector and slightly below a commonly used estimate of the external costs of driving.

Conducting a back-of-the-envelope cost-benefit analysis, we find that dedicating more land to roadways likely leads to net losses in social welfare even without accounting for the external costs of driving. These results are driven largely by assumptions about the elasticity of speed with respect to roadway. New roads simply do not save people much time, as has been observed and documented across time and place (Metz, 2008). Even assigning a generous elasticity at the high end of existing estimates and ignoring externalities, we find that the costs of widening roadways exceed the benefits to drivers and truckers by a factor of three. In short, the US urban roadway system is overbuilt. As a result, 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.

Existing estimates of road space

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

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.), TIGER (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 quality of roadway in a geography. Most of these databases also contain geographic shape files, indicating the location of roadway networks. For example, the World Bank's Global Roads Inventory provides spatial data on the total roadway and roadway class of 21 million km of roadway in over 200 countries. 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 provide additional information, such as road widths and median widths.

These databases are commonly used to generate measures of roadway supply for a wide variety of purposes. In an early example, Ingram and Liu (1999) used national and city-level data on income, roadway, and motorization rates to examine the role of income on roadway provision and motorization. The length and organization of road networks from the above datasets are also commonly used in research examining a variety of topics, including 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).

Shoup and Manville (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. Even assuming a generous average lane width of 15 to 30 feet, the authors estimate a maximum of just 2% to 4% of land area dedicated to roadways. This amount is substantially lower than other estimates (Angel et al., 2016; Gwilliam, 2003; Meyer & Gómez-Ibáñez, 1981; Millard-Ball, 2022; UN Habitat, 2013) and likely stems from the large amounts of non-urbanized land captured in Census-based land area measurements as discussed later in this paper.

Our general 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.

Remote sensing

Researchers frequently estimate features of roadways using high resolution satellite imagery and other forms of remotely sensed data. In early examples, Mena and Malpica (2005) and Mokhtarzade and Zoej (2007) used 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. More recent applications have extended to additional and more complicated imagery with roadway distortions and urban features such as building edges that are more difficult to classify (Chaudhuri et al., 2012; Fakhri & Shah-Hosseini, 2022; Ghandorh et al., 2022). 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. Processing large amounts of high-resolution satellite imagery across multiple cities, moreover, introduces substantial computational challenges. 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.

Most published work focuses on predicting roadways using small samples of imagery or existing datasets of imagery. In one particularly relevant example, Engstrom, Hersh, and Newhouse (2017) used satellite imagery from Sri Lanka to estimate various urban features, such as number of buildings and the length and density of roadways. The authors found that features extracted from satellite imagery explained around 60% of the variance in poverty rates across 1,291 administrative units using ordinary least squares regression. Chao et al. (2021) extended this work and applied 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 also employ 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 assigned roads to different categories, such as local and major arterial. These hand calculations are then extrapolated to provide metropolitan estimates of the amount of 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 applied 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 applied 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.

Parcel data

The third general approach to estimating land areas relies on detailed parcel-level data. Millard-Ball (2022) collected spatial parcel data from 20 urban counties and used parcel areas to net out the amount of space dedicated to streets and match these to street line data from OpenStreetMap. Across counties, Millard-Ball (2022) reported a consistent range of 17% to 21% of land area dedicated to local streets. Matching localized land value data (Davis et al., 2021) to roadway area estimates resulted in 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.

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, land widths, shoulder lanes, and medians and apply this model to the 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 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.

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, width of left and right shoulder lanes, and width of the median lane. Since the universe of HPMS lanes excludes many local and service roads, we supplement the dataset with TIGER shapefiles. This required a combination of spatial joins, matching segments, cutting segments, and removing overlapping roadway segments from the dataset. We mapped and visually inspected the combined roadway segments for several dozen counties to ensure that combined roadway files represented the universe of roadways. We then assigned TIGER's code S1400 (Local Neighborhood Road, Rural Road, City Street) to HPMS' Local Road classification and S1640 (Service Drive, usually along a limited access highway) to HPMS' Minor Arterial classification.

Next, we assigned roadway segments geographically to Census block groups. In instances where segments cross multiple block groups, we assigned 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 the Census block groups, we used these fractions as weights. The final dataset uses the 2016 HPMS, 2016 TIGER, and 2016 5-year ACS data.

Predictor variables

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 tried segment length as a predictor but dropped this due to limited predictive power and inconsistencies across the HPMS and TIGER segment lengths. The final model predictors include the road's distance to the metropolitan center, median household income, fraction of White residents, median building age, and population density of the Census block group in which the road is located. We also have indicators for whether socioeconomic variables are missing and metropolitan-level indicator variables.

Modeling procedures

We estimated 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 use the default model parameters in the RandomForestClassifier methods, specifically, one hundred trees in the random forest, and Gini purity as the splitting measure. The nodes are expanded until all leaves are pure. We used the 20% remainder of the sample for testing model performance at the end.

Overall, we see significant improvements of the random forest model compared to traditional models such as multinominal logit and ordered logit. Since road-width features are ordinal, a wrong road width prediction that is closer to the true value should incur 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. Across road classes and road-width features (35 MAE scores), our model achieves an average MAE score of 0.082, with a standard deviation of 0.084. Therefore, our model on average predicts road width off by 8 percent. Compared with other road classes, local roads have the smallest training sample and lower MAEs in width-features such as median lane width and left and right shoulder lane widths.

Because the paper focuses on roadway distributions across cities, we further assess model performances at the more aggregate PMSA 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 0.04, and the 24 out of the 35 models have a standardized MAE less than 0.05 (5 percentage difference between the true and the predicted).

Finally, we tested 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.

Land value and land cover data

We supplement our prediction data 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' pooled cross-section estimates of "Land Value (Per Acre, As-Is)" from 2012 to 2019 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 is 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.) Block group land values are then assigned 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.

We use the impervious land cover data to supplement our own estimates of roadway area and to provide better estimates of urbanized land than the Census block group estimates, which often include desert, mountains, farmland, national parks, and other types of non-urbanized land. We provide additional details on the differences between the two land area measurements when discussing results below.

The land cover dataset provides estimates of impervious surface class, including three different roadway classifications, for 30-meter grid cells throughout the US. Estimated impervious land includes yards, small parks, and other urban features associated with urbanized land. In some instances, the measure captures substantial amount of water area adjacent to rivers, bays, and other bodies of water. As shown in the findings below, estimated land area from the US Census and the impervious Landsat estimates provide starkly different pictures of the amount of urban land dedicated to roadway in US cities and metropolitan areas.

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. Around 80% of US residents live in these PMSAs.

Findings

How much and what share?

In total, we estimate that there are 68,000 square kilometers (26,000sq miles) of roadway—roughly the total land area of West Virginia—in the US's 316 PMSAs. This corresponds to 0.07 hectares per household (a little under half of the average US single family lot size), 3.7% of all PMSA Census land area, and 25.5% of urbanized land estimated from the impervious Landsat data.

More dispersed settlement patterns generally require more roadway (Table 1.) On average, city cores and central cities—as defined in the subsection on geographic aggregation—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 cities and urban cores on average. Roadway in cities and city cores have an average of 22% of urbanized land used for roadway compared to 29% for PMSAs. The relationship is also non-linear. Within PMSAs, the share of impervious land covered by roadway tends to decrease from around 27% close to the CBD until about 23% at an average distance from the downtown and then increases substantially in block groups that are one to three standard deviations away from the average distance (Figure 1).

(Table 1 here)

(Figure 1 here)

The relationship between geography and the share of land dedicated to roadway, however, depends heavily on the denominator used. The average PMSA dedicates 29% of impervious land area to roadways, with 95% of PMSAs dedicating 15.5% to 58.0% of impervious land area to roadways. The average PMSA, by contrast has 4.3% of Census land area covered by roadway, with 95% of PMSAs having 1.5% to 10% 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 impervious area dedicated to roadway (Pearson's of -0.15). 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 impervious land data. Most of the Census land area is desert and includes multiple national parks and mountain ranges. Figure 2 shows the relationship between Census land area and urbanized land across the three geographies in Yuma, Arizona.

Outside of the core parts of Yuma, only a small fraction of Census land area is urbanized. Like in Las Vegas, desert, parkland, and mountains dominate the landscape. Second, more dispersed settlement patterns tend to include more rural and uninhabited land, with development occurring in spread out patterns along roadway.

(Figure 2 here)

The measures of roadway consumption also vary substantially across the 20 most populous PMSAs (Table 2). Large metropolitan areas tend to dedicate about a fifth to a third of urbanized land to roadway. Los Angeles is no exception and dedicates similar amounts of land area to roadway as New York, Chicago, Boston, and other large cities and PMSAs. 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 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 live 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. Data for the full 316 PMSAs and all variables presented in this paper are publicly available (Redacted).

(Table 2 here)

The estimated shares of impervious land area dedicated to roadway are also consistent with Millard-Ball's (2022, p. 37) estimates using county-level parcel files. While county and city are not always perfectly aligned, results are generally within a few percentage points. For example, Riverside has 16% of land area dedicated to roadway across both estimates. The share of Census land area dedicated to roadway, by contrast, is often substantially smaller than Millard Ball's

(2022) estimates, especially for counties that are similar or identical to PMSAs. For example, Orange County has 18% of its urban land dedicated to roadway by Millard-Ball's estimates. By our estimates, Orange County's roads accounts for 20% of impervious land but only 8% of Census land area.

On average, highways account for 8.4% of the land area consumed by roadways in metropolitan areas; arterial for 25%; and local roads for the remaining two-thirds (Table 3). Primary cities and city cores tend to have a higher share of highways and arterials than suburban areas.

(Table 3 here)

What is it worth?

We estimate that the land area dedicated to roads in US metropolitan areas is worth $5 trillion, 22% of national gross domestic product. Based on the share 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 $53,000 per PMSA household, $19,000 per person, and $736,000 per hectare ($298,000 per acre). 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 4). Since these more central locations are denser, however, the value per capita and per household is lower. Despite some extremely high value land areas, such as the core of New York City at $113 million per hectare, 95% of PMSAs have a road-area land value that falls between $67,000 and $3.2 million. Despite the greater variance in land values per hectare than land values per capita, the two are strongly proportionately related. The natural log of the land value per capita explains 62% to 88% of the variance in the natural log of land value per hectare at the three different geographies. Figure 3 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 4 here)

(Figure 3 here)

Table 5 provides the land value measurements for the twenty largest PMSAs in the sample. In some cities, such as Boston, New York, Washington DC, and Chicago, central land values are substantially higher than in suburban areas. 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 $8.4 million per hectare. In the case of Detroit, average land values are similarly low throughout the metropolitan area. In total, these 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 21.8% of the total value. The numbers are also generally consistent with Millard-Ball (2022) and Albouy et al.'s (2018, tbl. 2) estimates. For example, Albouy et al. estimate the New York PMSA's land to be worth roughly $14.4 million per hectare compared to our estimate of $13.1 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 for the most similar cities and counties of $20,000 to $275,000 per household.

(Table 5 here)

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 4). Despite lower land values, suburban areas tend to occupy substantially more land, with more of that land dedicated to roadways.

(Figure 4 here)

Is it worth it?

Given the tremendous extent and value of land dedicated to urban roadway, we investigate whether, at the margin, the value exceeds the costs on average. Before conducting a back-of-the-envelope cost benefit analysis, we present additional data on some of the costs and benefits of the transportation network to help put the $5 trillion dollar value of the 68,000 square kilometers of urban roadway in perspective (Table 6). Annualized conservatively at 5% of total land values, 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). This 5% figure is a typical value for public funds but substantially lower than a 9% figure for this type of super-core asset given to us by the manager of the infrastructure investment fund of a major US financial institution. The value is also a bit less than the inflation-adjusted estimates of the total external costs of travel estimated using figures from the Federal Highway Administration (n.d.) and Parry, Walls, and Harrington (2007), though more recent estimates of the external costs of greenhouse gas emissions alone (Tol, 2023) may be as high as $6,500 per household. 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 costs or benefits (US Bureau of Labor Statistics, 2016, 2017; U.S. Department of Transportation, 2017).

(Table 6 here)

Using these figures and conservative estimate of the elasticity of roadway with respect to speed and the elasticity of vehicle travel with respect to roadway supply, we conduct a back-of-the-envelope cost analysis of adding 10% road supply to US urban areas (Table 7). We choose 10% because it is substantial enough to see impacts but also because reducing a similar amount of roadway by downgrading arterials, removing lanes, or replacing urban highways is feasible without removing roadway access from land parcels altogether. In any case, the exercise is an abstraction and a general test of whether the US tends to have too much or too little urban roadway rather than a cost-benefit analysis of a specific roadway investment. We assign 0.1 as the elasticity of travel speed with respect to roadway, meaning that our 10% increase in urban roadway corresponds with a 1% travel times savings. This is on the high end of existing estimates (Akbar et al., 2023) and double our own estimates when matching our road supply database to speed data using similar approaches.

(Table 7 here)

To estimate the effect of roadway expansion on externalities, we assume a 0.7 elasticity of vehicle travel with respect to roadway. This is on the lower end of existing estimates (Cervero & Hansen, 2002; Downs, 2004; Duranton & Turner, 2011) and means that a 10% increase in roadway supply corresponds to 7% increase in vehicle travel and associated externalities.

Ignoring externalities entirely, the costs of expanding urban roadways exceeds the benefits by a factor of three. Including externalities results in costs that are five times higher than benefits. The poor economic performance of US roadway investments is robust to major changes in assumptions about the value of time, external costs of travel, or the value of trucking. The main assumption that drives the results is the increases in speeds associated with road investments. Ignoring externalities, speeds would have to increase by 3% for a 10% increase in urban roadway investments to have economic benefits exceed costs. Including externalities, the increased speeds would need to be closer to 5%.

By contrast, downgrading and removing urban roadways likely increases net social benefits. A 10% reduction in urban roadway from removing, narrowing, or downgrading roadway results in an estimated net benefit of $32.4 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 while also reducing pollution, greenhouse gas emissions, and traffic fatalities.

Conclusion

In this paper, we developed a predictive model to estimate the amount and share of land covered by roadway in US metropolitan areas. We then matched 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, we developed a back of the envelope cost-benefit analysis of the likely effects of a 10% increase in roadway capacity. Two key findings emerge.

First, the amount and value of land dedicated to roadway are substantial at about $5 trillion on the land area of West Virginia. Roadway in suburban areas tend to consume both a high share and high total amount of land and land value. Downtown roads generally consume 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 slightly less land dedicated to roadways than the average city.

Second, based even on generally optimistic assumptions, the costs of adding road capacity outweigh the benefits, substantially. This is unsurprising given the US history of building roadway to meet peak demand decades out into the future. Although number policy reforms have called for an emphasis on economic competitiveness, conservative roadway networks, and environmental protection, government agencies continue to pump billions of dollars into expanding 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 make our data publicly available at the county- and block-group-level in addition to the three summary geographies used in this paper. 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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Tables and Figures

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

	PMSA	City	Core
Roadway (m2) per capita	465.2	186.3	162.5
	(422.3)	(88.9)	(73.5)
Roadway (m2) per household	1222.8	479.5	410.9
	(1103.3)	(235.5)	(176.1)
Share of Census land area	0.04	0.13	0.18
	(0.11)	(0.06)	(0.07)
Share of impervious land area	0.29	0.22	0.22
	(0.08)	(0.06)	(0.07)

Standard deviations in parentheses

Table 2. Land consumption of roadways by the twenty most populous PMSAs

	PMSA			City			Core		
Primary City	Population	Share of impervious land area	Share of Census land area	Share of PMSA Population	Share of impervious land area	Share of Census land area	Share of PMSA Population	Share of impervious land area	Share of Census land area
Atlanta	5,437,374	0.17	0.06	0.09	0.17	0.13	0.03	0.20	0.19
Baltimore	2,780,873	0.24	0.07	0.22	0.26	0.24	0.10	0.27	0.27
Boston	6,502,249	0.27	0.08	0.10	0.31	0.29	0.06	0.37	0.37
Chicago	8,656,303	0.20	0.08	0.31	0.23	0.22	0.04	0.31	0.32
Dallas	4,682,683	0.20	0.05	0.30	0.19	0.13	0.03	0.26	0.24
Detroit	4,260,835	0.19	0.08	0.16	0.26	0.26	0.02	0.34	0.34
Houston	5,800,581	0.16	0.05	0.60	0.15	0.12	0.03	0.26	0.26
Los Angeles	10,057,155	0.23	0.08	0.39	0.21	0.18	0.04	0.25	0.25
Minneapolis	3,420,041	0.47	0.11	0.12	0.49	0.33	0.07	0.49	0.48
Nassau	2,854,931	0.19	0.12	0.02	0.25	0.25	0.08	0.23	0.23
New York	9,853,240	0.25	0.14	0.86	0.28	0.26	0.08	0.29	0.29
Irvine	3,132,211	0.21	0.13	0.08	0.20	0.11	0.07	0.21	0.21
Philadelphia	5,393,549	0.21	0.08	0.29	0.27	0.24	0.09	0.36	0.35
Phoenix	4,486,153	0.29	0.03	0.35	0.21	0.11	0.02	0.22	0.21
Riverside	4,430,646	0.28	0.02	0.08	0.16	0.12	0.03	0.17	0.15
San Francisco	3,253,356	0.19	0.04	0.44	0.19	0.11	0.06	0.21	0.21
Seattle	2,918,312	0.30	0.06	0.23	0.31	0.30	0.07	0.36	0.36
St. Louis	2,759,413	0.13	0.05	0.11	0.15	0.30	0.03	0.12	0.23
Tampa	2,927,714	0.17	0.07	0.13	0.19	0.15	0.04	0.22	0.22
Washington, DC	6,139,769	0.25	0.06	0.11	0.24	0.22	0.06	0.27	0.25

Table 3. Average share of roadway area by roadway type

	PMSA	City	Core
Share highway	0.084	0.101	0.101
	(0.044)	(0.064)	(0.072)
Share arterial	0.249	0.287	0.306
	(0.064)	(0.066)	(0.067)
Share local road	0.666	0.612	0.593
	(0.075)	(0.082)	(0.088)

Standard deviations in parentheses

Table 4. Roadway land value across metropolitan areas

	PMSA	City	Core
Road value per capita	$14,728	$11,760	$12,025
	($18,572)	($20,483)	($18,580)
Road value per household	$40,037	$29,908	$29,684
	($52,932)	($47,316)	($42,674)
Road value per hectare	$579,864	$1,119,943	$1,593,219
	($1,491,035)	($3,171,815)	($7,259,282)

Table 5. 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	$4,648	$13,087	$275,505	$12,497	$30,116	$1,222,119	$15,485	$37,685	$1,839,579
Baltimore	$16,497	$44,084	$947,789	$17,074	$43,737	$2,090,903	$27,418	$68,273	$4,156,942
Boston	$25,852	$68,435	$1,216,803	$56,966	$144,606	$10,327,914	$91,791	$222,534	$16,631,555
Chicago	$13,636	$37,618	$1,082,496	$19,035	$49,565	$3,850,415	$51,382	$100,671	$10,737,860
Dallas	$9,154	$25,898	$531,799	$11,172	$29,502	$952,531	$19,699	$42,975	$1,538,890
Detroit	$5,446	$13,971	$300,839	$3,490	$9,282	$258,854	$7,066	$14,424	$354,557
Houston	$9,515	$27,838	$712,463	$11,450	$32,411	$1,212,331	$48,295	$105,466	$4,305,651
Los Angeles	$44,317	$135,808	$5,424,335	$41,735	$120,619	$7,564,006	$26,429	$78,673	$6,578,981
Minneapolis	$23,231	$60,358	$484,706	$23,352	$55,870	$1,311,027	$17,058	$40,307	$1,197,429
Nassau	$25,987	$79,777	$1,924,200	$8,707	$30,501	$1,991,062	$25,326	$84,484	$3,385,096
New York	$53,635	$146,670	$13,100,868	$59,054	$159,741	$25,120,381	$153,860	$335,596	$113,397,787
Irvine	$69,029	$212,597	$8,365,459	$140,251	$383,625	$12,426,314	$48,914	$170,222	$7,221,255
Philadelphia	$11,252	$30,411	$779,331	$17,001	$45,522	$3,157,424	$35,237	$88,631	$7,033,683
Phoenix	$13,409	$37,676	$582,515	$9,707	$27,981	$824,367	$16,214	$43,450	$1,002,278
Riverside	$23,696	$79,259	$819,828	$11,412	$39,932	$1,269,905	$11,534	$39,717	$1,328,801
San Francisco	$37,439	$110,415	$3,090,825	$48,658	$137,615	$5,867,239	$63,035	$149,932	$8,894,918
Seattle	$38,163	$97,351	$1,685,261	$62,920	$138,439	$6,519,731	$75,320	$142,190	$7,715,257
St. Louis	$7,324	$18,541	$226,574	$8,266	$18,644	$543,851	$9,305	$21,407	$557,523
Tampa	$8,768	$22,094	$579,858	$14,869	$37,475	$1,107,435	$20,528	$48,542	$1,654,591
Washington, DC	$29,322	$81,717	$1,691,291	$69,378	$165,328	$13,325,003	$91,628	$197,865	$19,425,136

Table 6. Summary of annual roadway transportation costs and benefits in 2016

	Per household	Total (billions)
Government spending on roads	$1,590	$200
Consumer spending on cars	$8,427	$1,092
Time costs (urban households)	$11,026	$1,075
Variable Costs of Urban Freight Trucking	$2,521	$246
Land value of urban roads	$2,653	$252
External costs of urban VMT	$3,020	$295

Table 7. Estimated costs and benefits per urban household of a 10% increase in urban roadway capacity

Benefits	
Time savings	$110.26
Freight trucking	$25.21
Direct costs	
Government spending	$158.96
Land value	$263.80
Benefit-cost ratio	**0.32**
Externalities	$211.39
Benefit-cost ratio	**0.21**

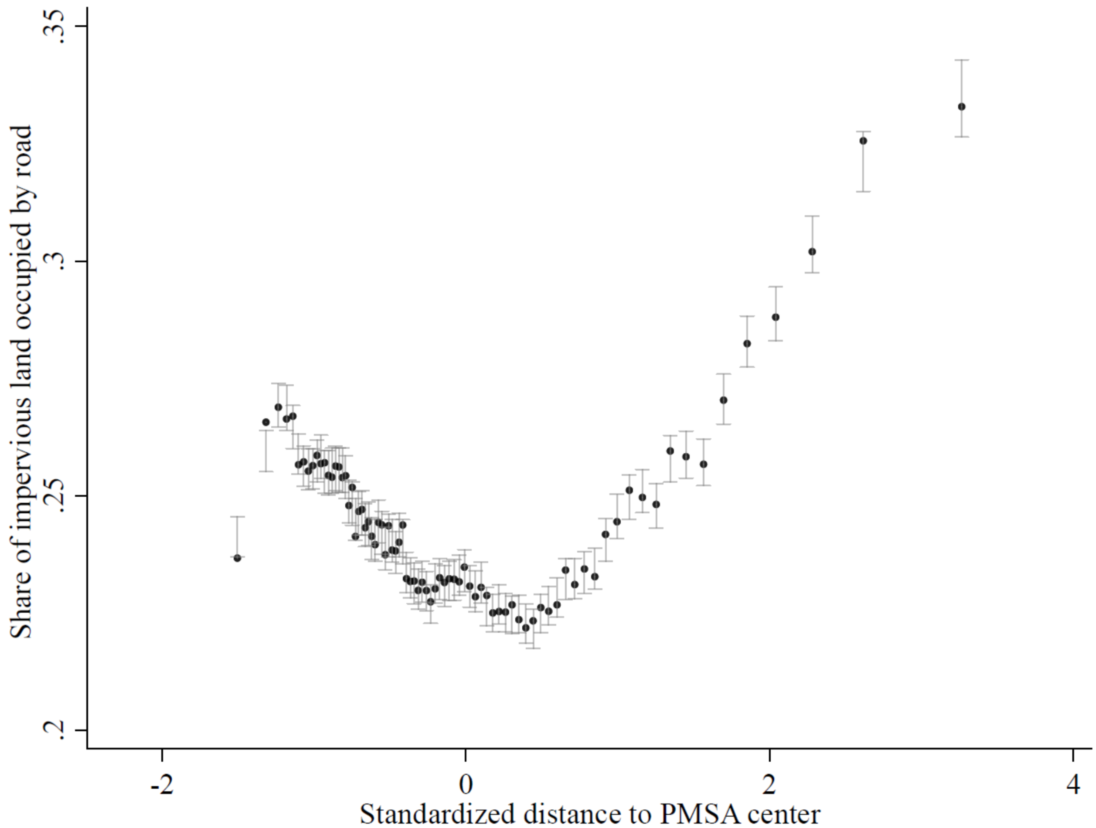

Figure 1. Roadways' impervious land share against standardized distance from center

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.

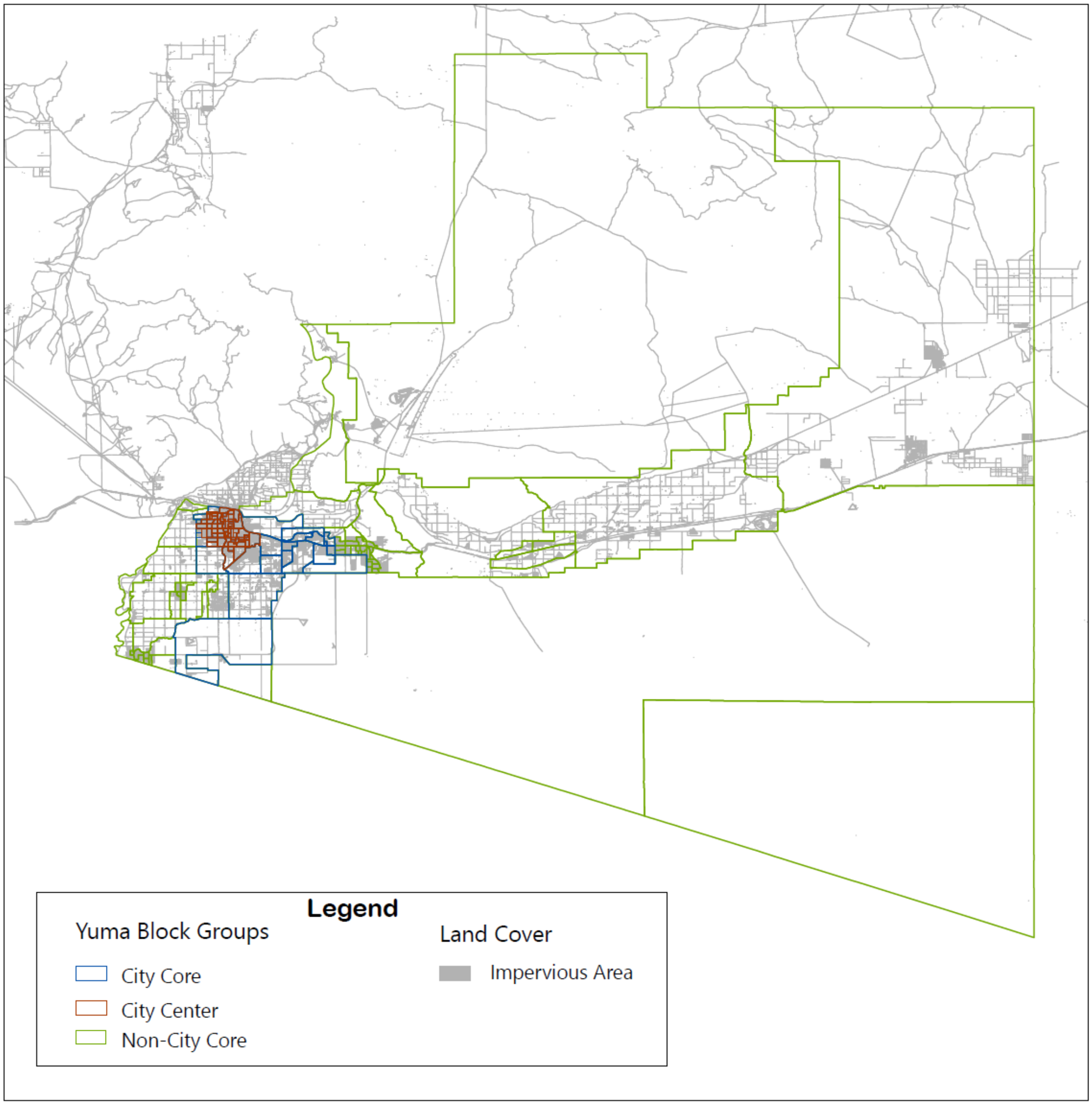

Figure 2. Census block groups in Yuma PMSA and impervious land area estimates

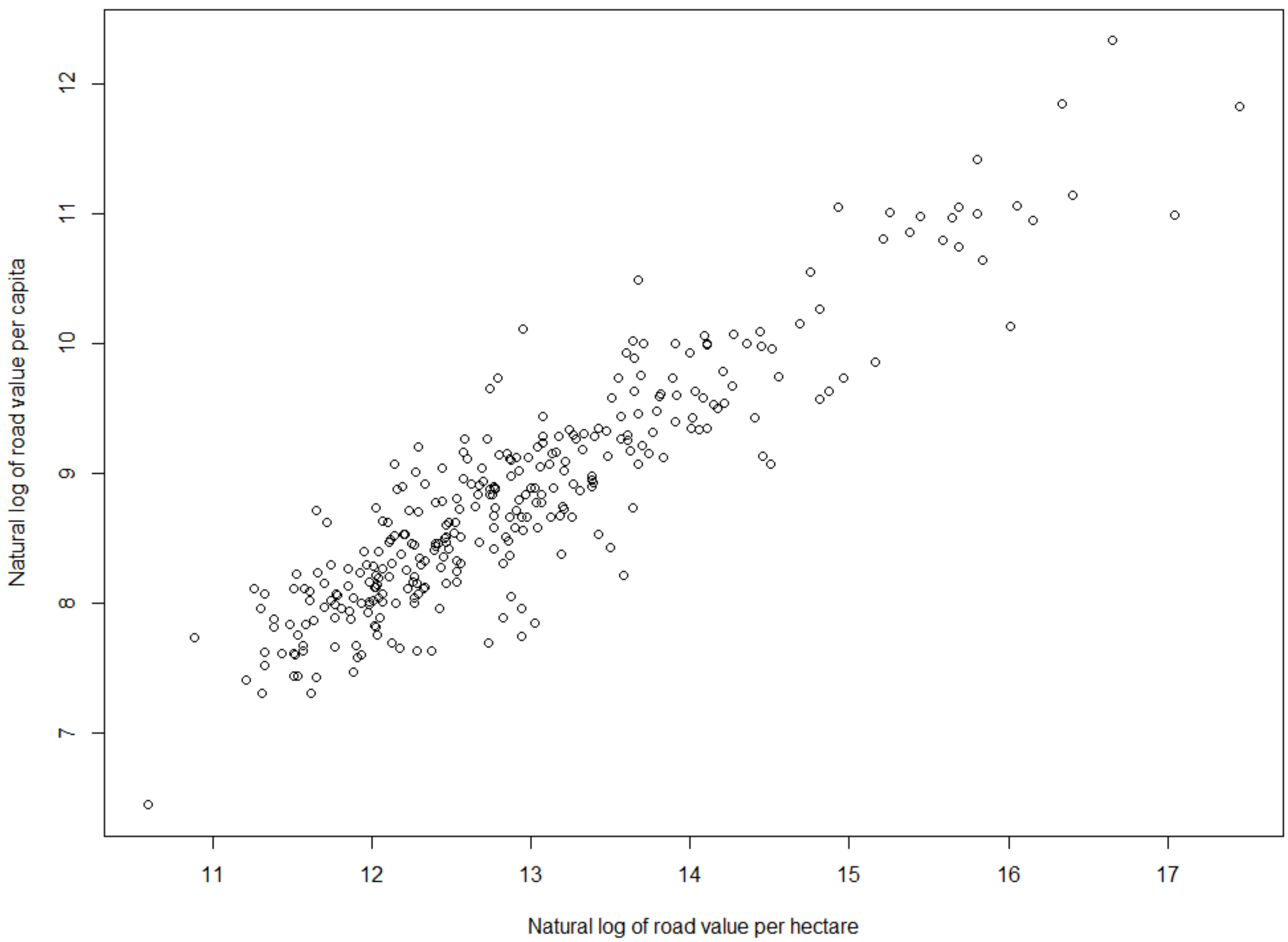

Figure 3. Relationship between land value per hectare and land value per capita across central cities

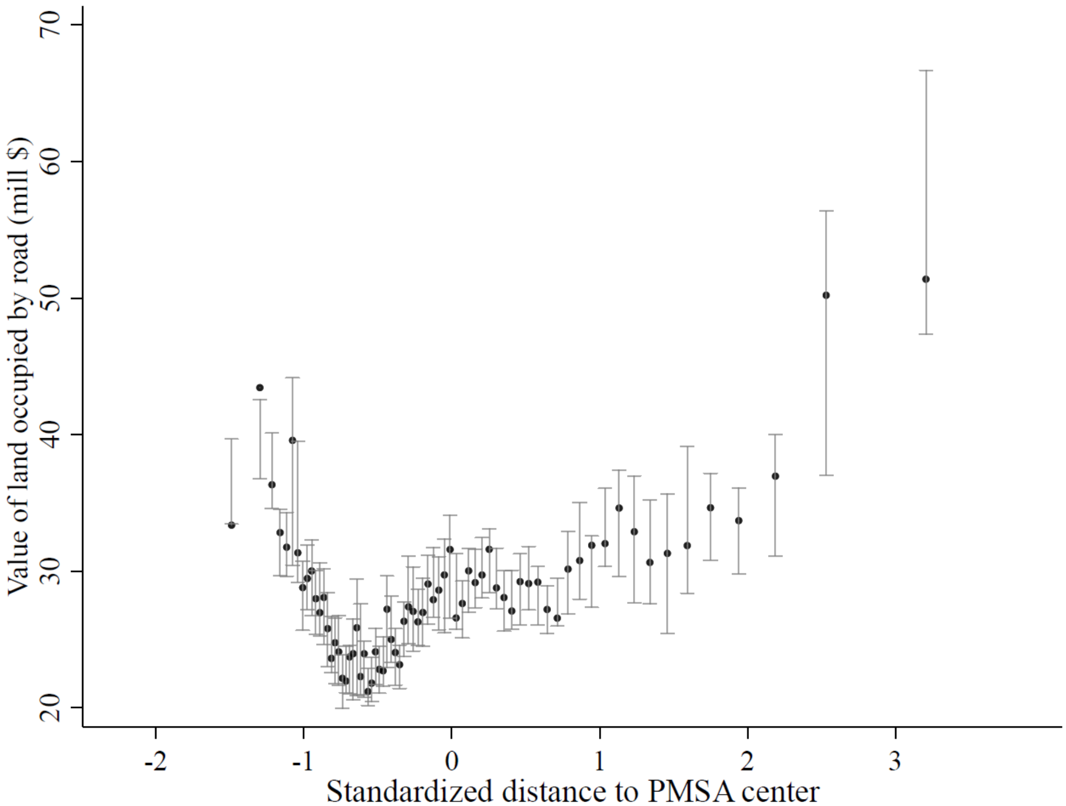

Figure 4. Total land value of roadway against standardized distance from center

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.