OREGON MODELING STEERING COMMITTEE
MWVCOG Conference Room
100 High St. SE, Suite 200, Salem Or
Wednesday, October 21, 2015
1:00 pm to 4:00 pm

Agenda

Welcome and Introductions	All	10 min
Conferences	All	5 min

TRB 95th Annual Meeting, January 10-14, 2016 Washington, D.C.
Use of Scenario Planning in Transportation Planning, June 2016 Portland, Oregon
Innovations in Travel Demand Modeling, May 1-4, 2016, Denver CO
National Tools of the Trade Conference, September 12-14, 2016 Charleston, SC
Others…

General Business	Walker	10 min

Approval of minutes from last meeting
(http://www.oregon.gov/ODOT/TD/TP/docs/OMSC/20150429Minutes.pdf)

Next meeting proposed date: **Wednesday, April 20, 2016**

Subcommittee Chairs' synopsis (summary of activity attached to Agenda):
Modeling Program Coordination Committee – Ray Jackson
Health Committee – Eric Main
Freight Committee – Derek Jaeger

New Business

OMSC Officers	Walker	10 min
New OMSC Facilitator	Knudson/Richardson	10 min
OMIP Activity	Knudson	15 min

BREAK

Presentations

PSU Pop Research Center Demographic Forecast	Ruan	30 min
Trade-offs Between Population Density and Household Transportation-Housing Costs	Palm/Wang	30 min
Oregon Trade Initiative	Drumm	30 min
Items for next meeting	All	5 min

Closing

REMOTE PARTICIPATION: If you want to join the meeting remotely, the call-in number is **503.540.1626.** Enter **8121** when asked for a conference room/number. Visual participation is available via JoinMe; the code will be provided over the phone.

DIRECTIONS/PARKING: **Parking**: Salem now has **three hour parking limits** downtown. Free parking is available at the parkades – Liberty Parkade is closest, one block west of the MWVCOG office at Liberty St and Ferry St. There are EV chargers available at all parkades. A map is available here: http://www.mwvcog.org:8080/2/about/Map_Downtown.jpg/view

Notes:

OREGON MODELING STEERING COMMITTEE

Wednesday, October 21, 2015

Subcommittee Reports

Modeling Program Coordination

The October MPC meeting is scheduled for the morning of October 21st. The following topics will be discussed:

- Using OHAS data to re-estimate "Joan" to update the current four step model
- Bicycle Safety Research
- Planned research activity

Transportation and Health Committee – June 2 Meeting Summary

1. **Subcommittee progress**

    a. TRB – OHA attended the special TRB conference in April and presented the OMSC subcommittee process. Many model developers were there. Discussed future of ITHIM. Big take away: very supportive of this work, and we can rely on them to continue. Another take away: interest outstrips resources for this work.

    b. Modeling poster – We'll present at the OAPA conference in October.

    c. ITHIM updates – Development of ITHIM 3 is underway, Woodcock is soliciting input on functions (OHA provided input). Neil Maizlish is near completion with providing ability for endless scenarios in spreadsheet version.

    d. Subcommittee goals & objectives – Better safety module would be desirable, but it's outside the scope of this project. Modular is important. What do we hope to get out of a pilot? Applying this in an RTP situation is ideal because it's actual investment. A pilot will help set up the flow of data between models. Regional travel model + ITHIM + dispersion model +… Can we develop a flow diagram that shows each of the modules/linkages? DLCD and ODOT are working with all MPOs to put their plans through GreenSTEP. Is there an opportunity to leverage that as a pilot? GreenSTEP doesn't account for some important outcomes (dispersion). We need something that will support regional models for long range planning (greenSTEP is not used in regional planning). Health outcomes at smaller geographies are a desirable outcome of a pilot. Much discussion about spreadsheet model vs. programmed. It will be programmed in a user-friendly interface. Unclear where the model will "live" at this point. It will be open source. Also not clear who will manage the contract. Many options for who runs the model – likely support from several state organizations. Pilot could start this summer, RFP next summer. There will be disclaimers; liability is

similar to existing models. Liability is limited – we are linking models, not creating new ones, and they will be one of many inputs for a given decision. OMSC can establish expectations for ABMs.

e. Pilot project location selection – Where is there already modeling work going on so that we wouldn't be creating a modeling work load. We could test packages of investments at the corridor level for mobility corridors in Metro. A scale appropriate for a dispersion model would be ideal for a pilot, since large scale projects might not be best. Testing the linkages of models is more important than testing sensitivity. 1000' buffer along arterials and freeways is what Eric and Phil used for dispersion. Ideas: Lane BRT, Metro mobility corridor suite of investments, Sunrise corridor, ODOT models don't really include active modes, so ODOT projects aren't helpful. Metro seems to be the best site. Metro + Eric will work on selecting a project.

2. **Recent Updates – September 24, 2015**

   a. SW Corridor was selected for the pilot project. Most of the data has been collected.

   b. OHA is providing input to ITHIM developers on the new version of ITHIM. Release of ITHIM 3 is at least 18 months way.

   c. ITHIM developers will provide R code for ITHIM if ODOT will provide R code for RSPM.

   d. CAL3QHCR is still under development.

   e. Eric is working on application flow diagram.

<u>Freight Committee</u>

No update.

Oregon Trade and Logistics Initiative

Oregon Modeling Steering Committee
October 21, 2015

business oregon | Oregon Department of Agriculture | Oregon Department of Transportation | PORT OF PORTLAND

Oregon Trade and Logistics Initiative

The Challenge:

- Loss of weekly container service and loss of market access
- Changes in the international maritime industry impacting all West Coast ports
- Significant impacts to farmers, manufacturers and transportation providers in Oregon and the Pacific Northwest
- Erosion of the benefits that have taken years to build-up

Oregon Trade and Logistics Initiative

Goals:

- Identify interim freight logistics solutions to help Oregon businesses move products and supplies to/from markets efficiently and cost-effectively, and
- Support long term service recovery at the Port of Portland's Terminal 6

Oregon Trade and Logistics Initiative

Elements:

- Trade Research
- Regional Shipper Workshops
- Freight Logistics Business Case Development
- Report to Legislature

Trade Research

Goals:

- Estimate cost, service, reliability and capacity impacts to Oregon importers and exporters
- Identify possible policies, initiatives and other measures to mitigate adverse impacts on Oregon businesses, and trade

Regional Workshops

- Portland – July 24
- Redmond – July 28
- Hermiston – July 29
- Ontario – Aug. 10
- Albany – Aug. 11
- Medford – Aug. 12

Trade Research Themes

- Preference for Portland
- Shipping adjustments
- Cost impacts
- Other impacts

Workshop Takeaways

- Each region's needs and solutions are different
- Disruption also impacts firms only shipping domestically
- Increased costs and transit time reduce competitiveness
- Roadway and port congestion combined with Hours of Service rules for truckers compound disruption
- Shortage of truck capacity and drivers to meet demand

Workshop Takeaways

- Loss of barge service reduces access to markets
- Increased access to rail is desired
- Solutions could range from information technology to hard infrastructure to container match-back programs
- Container service in the Columbia River is critical for managing costs and improving competitiveness

Freight Logistics Business Cases

Principles for Evaluation/Business Case Development:

- Reduce transportation costs and freight delays for Oregon exporters and importers
- Evaluate the feasibility of return on investments and cost considerations
- Benefit both Oregon exporters and importers who provide jobs
- Offer the opportunity for near term implementation
- Support the long-term economic interests of the state

Next Steps

- Trade Research – completed
- Freight Logistics Solutions Business Case Development – Sept.-Oct.
- Legislative and Agency briefings – Nov. 16-18
- Funding and Other Opportunities - ongoing

Current Activity

- Terminal Operator-Labor discussions
  - Ongoing
- Monthly Westwood service
  - July-Dec. 2015
- Weekly transpacific service recruitment
  - Key Origin & Destination markets: China, Japan, Korea
  - 3/4 target strings out of 38 transpacific services
  - Imports key to service recovery

Current Activity

- Port of Portland Carrier/Shipper Collaboration
  - Westwood Shipping Lines and Rivergate Depot
  - Upriver Barge/Rail

Questions and Answers

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Website:
www.oregontradesolutions.com

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Population Research Center (PRC) Oregon Population Forecast Program

Forecast Steering Committee, Oct. 2015

Xiaomin Ruan, Forecast Program Coordinator
Risa Proehl, Estimates Program Manager
Population Research Center (PRC)

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Oregon Population Forecast Program Project Team

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Population Forecast Program Coordinator

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GIS Research Analyst

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Research Assistant

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Web Technician

Population Research Center (PRC)

- Research Areas:
  - Oregon State Data Center (SDC)
  - Demographic Research and Advisory Services
  - Demography Instruction
  - Oregon Population Estimates Program
  - **Oregon Population Forecast Program**

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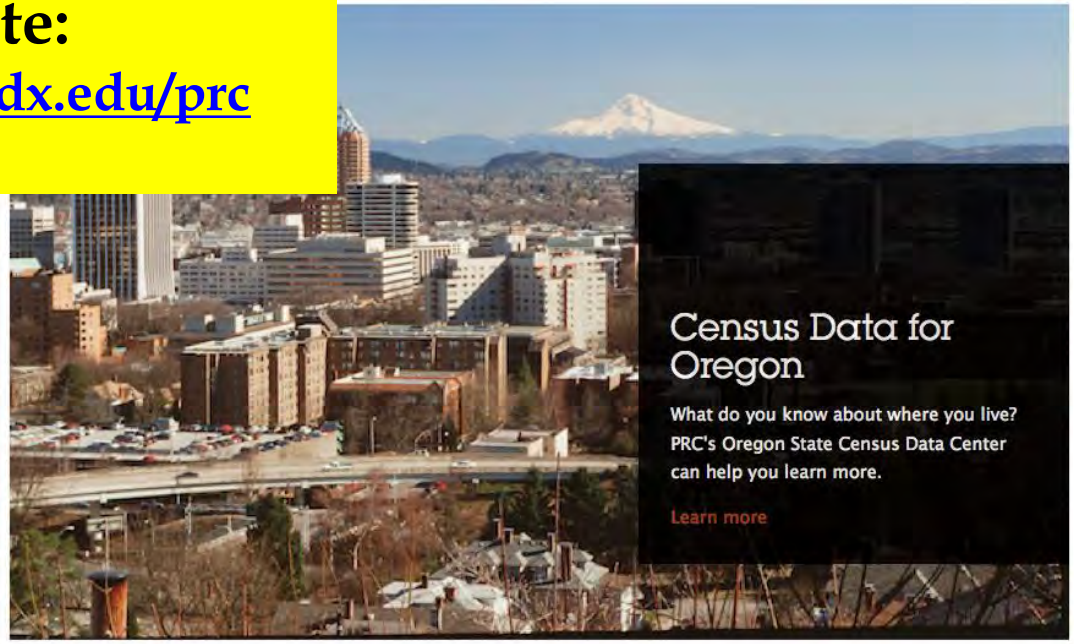
About PRC | News and Presentations | PRC Faculty | Annual Population Estimates | Research Areas | more

PRC Website:
http://www.pdx.edu/prc



Seeing the Future
Where will your city/town be in 50 years? PRC is...

Census Data for Oregon
What do you know about where you live? PRC's...

Population Estimates
The Census is conducted only every decade, but...

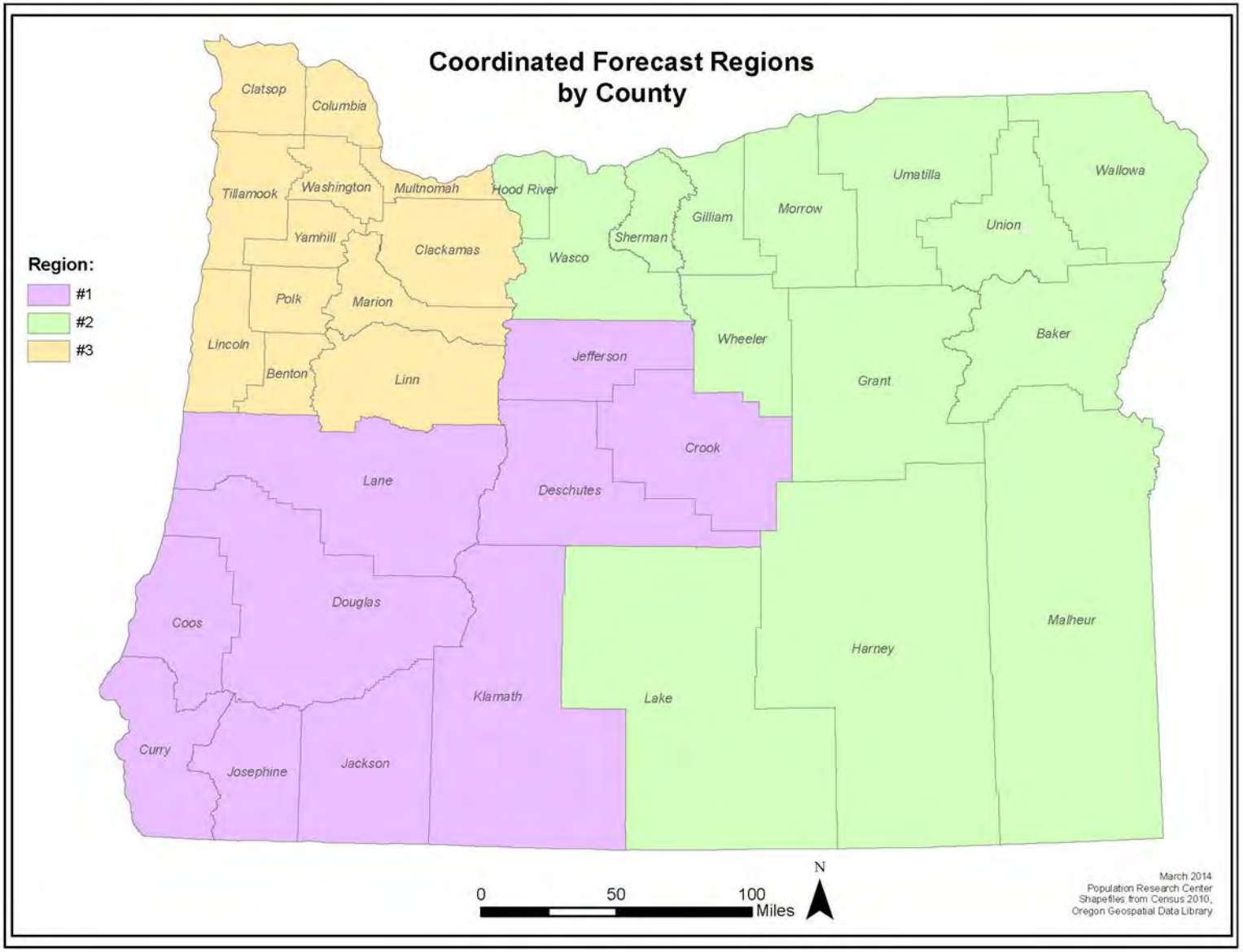
PRC Statewide Programs

- Oregon Census State Data Center
- Annual Population Estimates
- Oregon Population Forecast Program
- Mapping
- Geographic Analysis

The Population Research Center (PRC) is an interdisciplinary public service, research, and training unit for population-related data and research for the State of Oregon. The mission of PRC is to provide population data, information, and research analysis for Oregon and its communities. Center staff engage in a variety of demographic activities, including the Oregon State Data Center, the Oregon Population Estimates Program, and a variety of commissioned population projects. PRC staff also teach in the Nohad A. Toulan School of Urban Studies and Planning, supporting a graduate concentration in applied demography and a graduate certificate program in applied demography.

Population Forecasts

- **Population Forecasts**
  - Provides a picture of future population based on historic and current trends, and assumptions about likely future events


Coordinated Forecast Regions
by County
Region:
#1
#2
#3
Clatsop
Columbia
Tillamook
Washington
Multnomah
Hood River
Yamhill
Clackamas
Polk
Marion
Lincoln
Benton
Linn
Wasco
Sherman
Gilliam
Morrow
Umatilla
Wallowa
Union
Jefferson
Wheeler
Baker
Grant
Crook
Lane
Deschutes
Douglas
Coos
Malheur
Harney
Klamath
Lake
Curry
Josephine
Jackson
0
50
100
Miles
N
March 2014
Population Research Center
Shapefiles from Census 2010,
Oregon Geospatial Data Library

Forecast Program: 4-Year Cycle

Year 1	Year 2	Year 3	Year 4
Program Development	Prepare County-Level Forecasts Region 1	Prepare County-Level Forecasts Region 2	Prepare County-Level Forecasts Region 3
	1st Set of Coordinated City-County Forecasts	2nd Set of Coordinated City-County Forecasts	3rd Set of Coordinated City-County Forecasts

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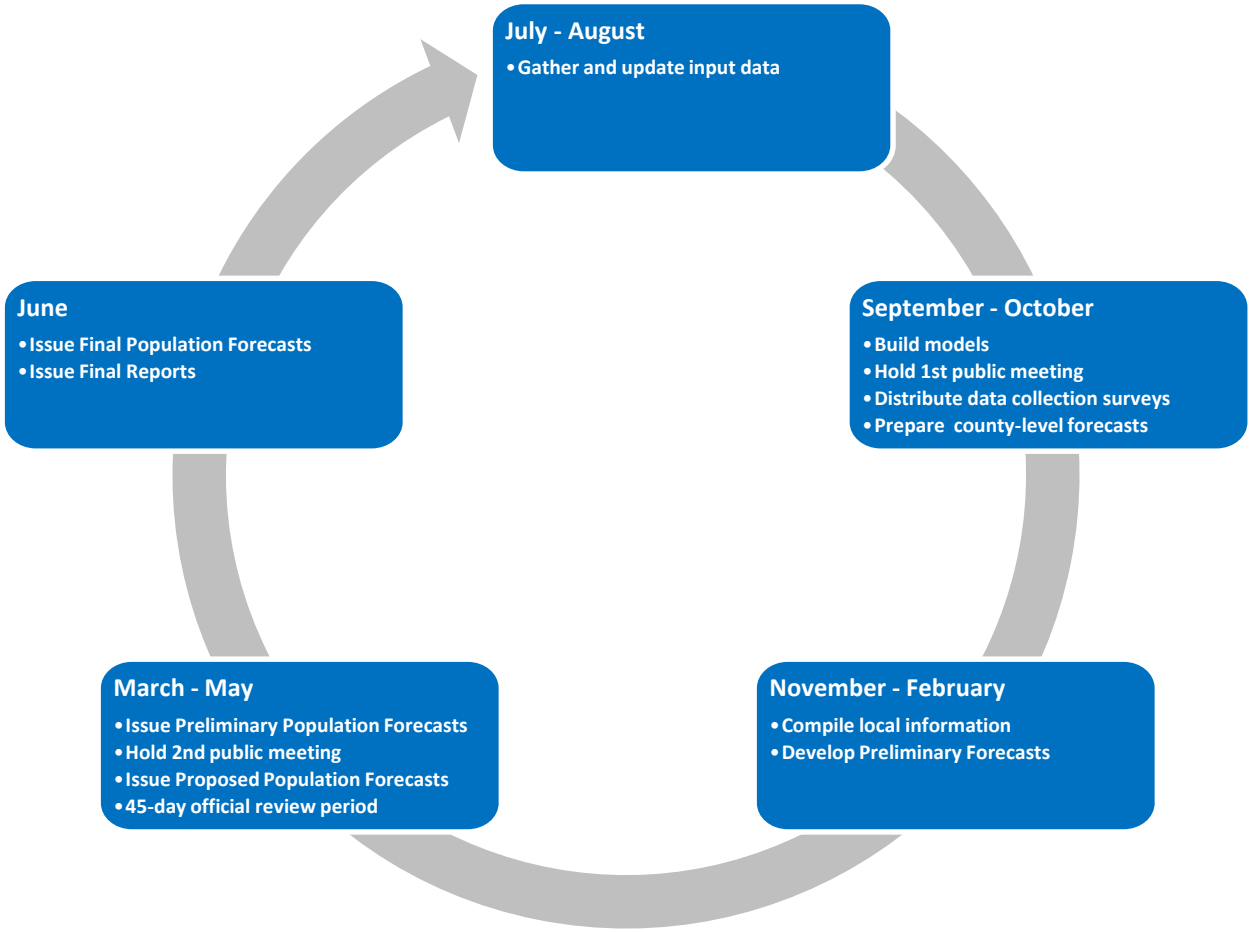
Coordinated Forecast: Annual Schedule



Process for Population Forecasts

- Develop and update demographic models using historic and recent data
- Analyze past and current population trends
  - Reasons for change, continuous or short-term?
- Gather information about existing and planned future housing, and about population change
  - Housing developments
  - Construction of new GQ facilities
  - New employers
- Make assumptions about future housing and population change
- Revise forecasts on a regular basis

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Process for Local Input

- Hold regional meetings
  - Receive input on:
    - Historical and current demographic and economic trends
    - Plans for future growth
  - Receive feed back on Preliminary Forecasts
- Local survey
  - Collect local observations
    - Population composition; recent change
    - Planned housing development plus group quarters facilities
    - Future employers
    - Infrastructure
    - Anything that might promote or hinder population growth
  - Survey will be posted on website and emailed to each jurisdiction
  - Issued in October each year
- Official review period for Proposed Forecasts

Population Forecast Methods

- Cohort-Component Method
  - Based on age-sex structure
  - Survival rates – Fairly constant over time
  - Fertility – Slightly more variable than survival rates
  - Migration Rates – Subject to greater fluctuation than mortality and fertility and more unpredictable
  - Generally works better for areas with larger populations

Population Forecast Methods

- Housing Unit Method
  - Generally works better for areas with smaller populations
  - Housing unit growth
  - Housing unit type
  - Persons per household (PPH)
  - Occupancy rates
  - Add group quarters population

Population Forecast Methods

- For comparison and to serve as a check
- Ratio Methods
- Trend Extrapolation
- Employment Conversion Model

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Population Forecast Data Sources

Primary Sources:

- U.S. Census Bureau, Decennial Censuses
- Population Research Center (PRC), Oregon Population Estimates Program
- Oregon Health Authority, Center for Health Statistics
- Counties, Assessors Office
- Incorporated cities, Community Development/Planning Department
- Oregon Geospatial Enterprise Office (GEO), Spatial Data Library

Secondary Sources:

- State of Oregon, Office of Economic Analysis
- U.S. Census Bureau, American Community Survey (ACS)
- U.S., Internal Revenue Service
- State of Oregon, Department of Revenue
- Oregon Department of Education
- U.S., Centers for Medicare and Medicaid Services
- State of Oregon, Employment Department

Deliverables

- Forecasts (50 year horizon, 5-year time intervals)
  - County-level forecasts (5-year age groups)
  - Coordinated UGB-level forecasts (Total population)
- Report containing:
  - Summaries of historic and future demographic trends, assumptions about future growth, and a compilation of information collected from city and county officials and the public
  - Short technical description of methods employed to produce the forecast

Possible Plans for Future?

- Statewide and all 36 counties forecasts?
- Other forecast needs?

THE TRADE-OFFS BETWEEN POPULATION DENSITY AND HOUSEHOLD'S TRANSPORTATION-HOUSING COSTS

PRESENTED BY

MATTHEW PALM (UC DAVIS) AND HAIZHONG WANG (OSU)

OCT. 21ST, 2015

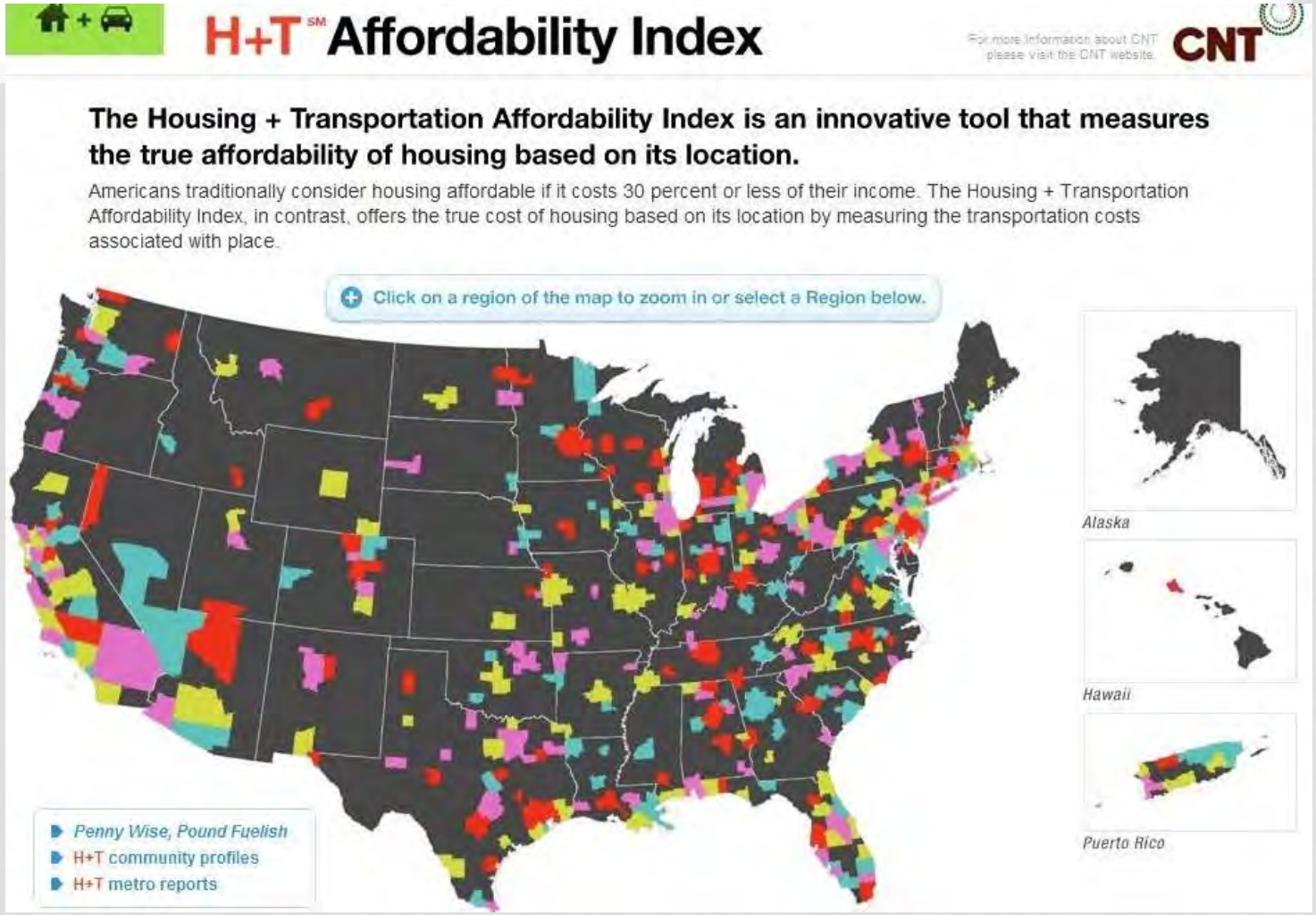
TRANSPORT POLICY

Volume 36, November 2014, Pages 160-172

http://www.sciencedirect.com/science/article/pii/S0967070X14001504

THE MOTIVATION

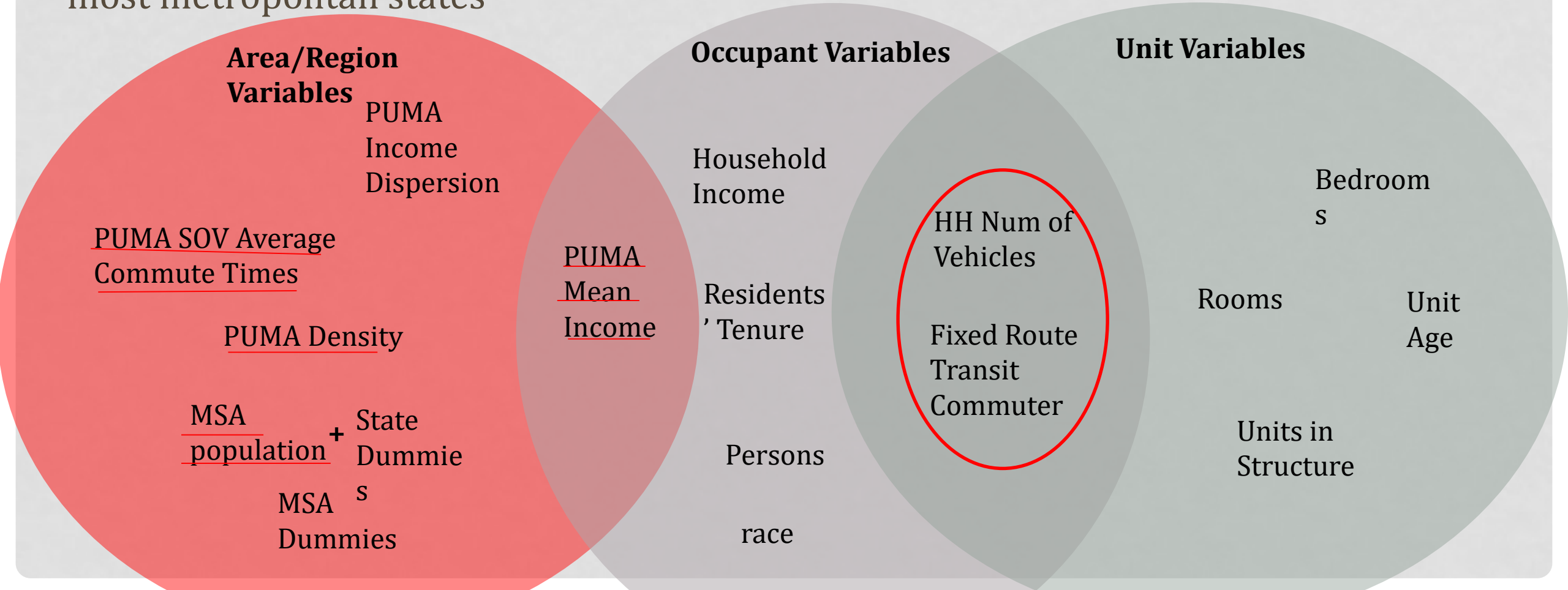
- Integration of Land Use (housing) and Transport planning:
- CA: SB 375
- OR: SB 100
- MRCOG: Proposed BRT lines
- US: HUD's TOD Monies



http://agbeat.com/housing-news/interactive-housing-transportation-affordability-maps/

THE METHOD, DATA, AND VARIABLES:

- **Data**: from **Public Use Micro- Sample (PUMS)** data
- **Limitations**: only units in urbanized **Public Use Micro Sample Areas (PUMAs)** in 22 most metropolitan states



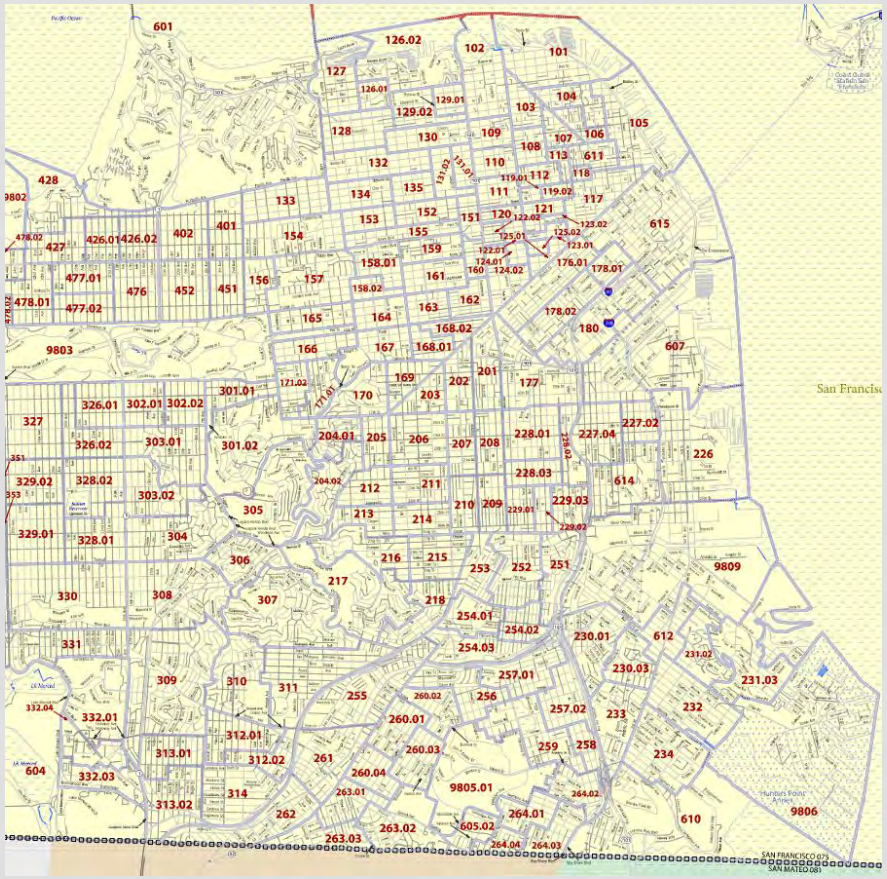
KEY DEFINITIONS:

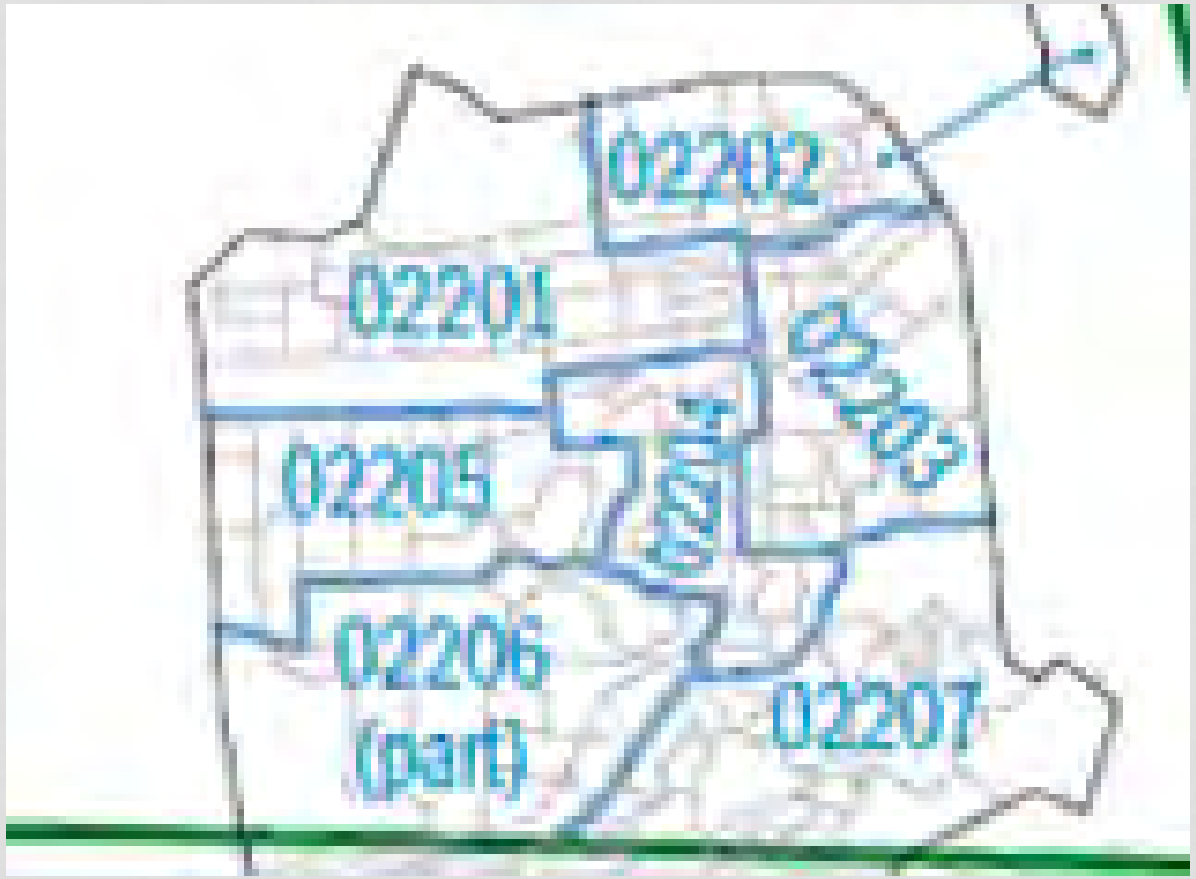
- Depended variable: "**Housing Costs**"--The amount a household spends on housing.
  - For Home owners: Mortgage + utilities + insurance + taxes
  - For Renters: Rent + insurance + utilities

THE METHOD, DATA, AND VARIABLES (2):

- **Questions:**
  - Does density correlate with housing costs?
  - Does proximity to transit use with housing costs?
  - Do PUMA SOV commute times correlate with housing costs?
- **Model Format:**
  - **Log-Log: results produce an elasticity of rent with respect to density, transit, commute times.**
- **Model Disaggregation:**
- **Two models predicting Gross Rent: one for Single Family Renters ,one for Apartments**
- **Two models predicting Single family home owner costs: one for housing unit value, one for monthly mortgage payment**

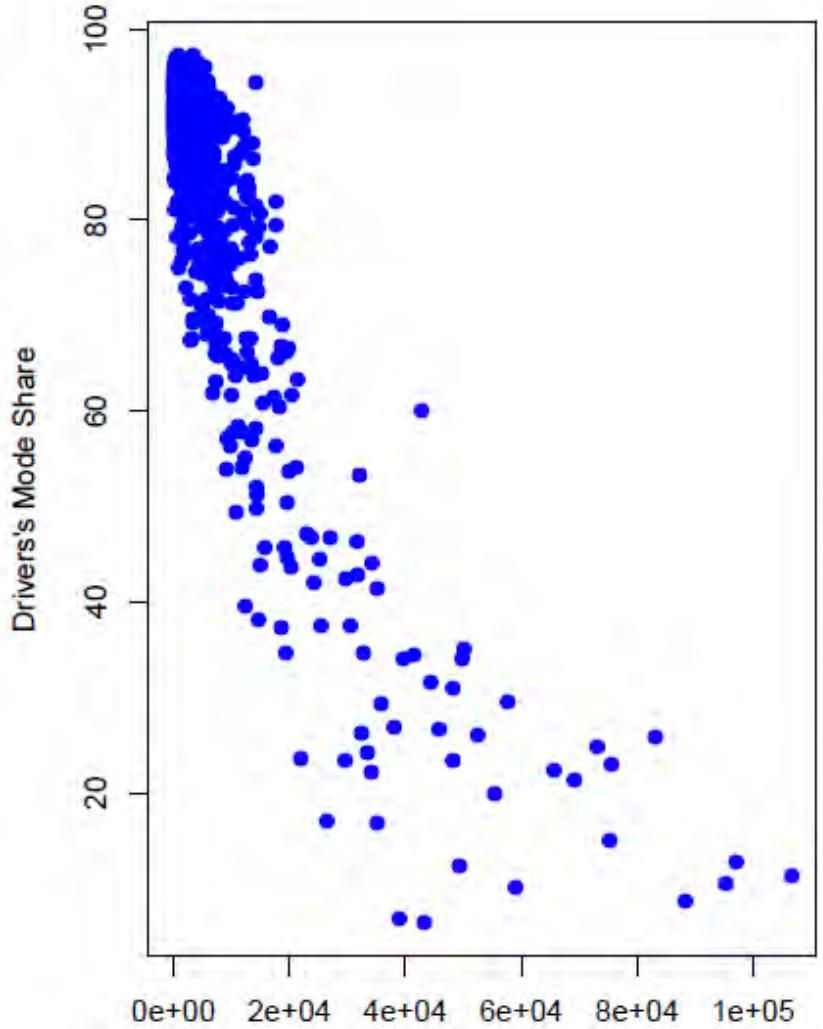
TRACTS VERSUS PUMAS:





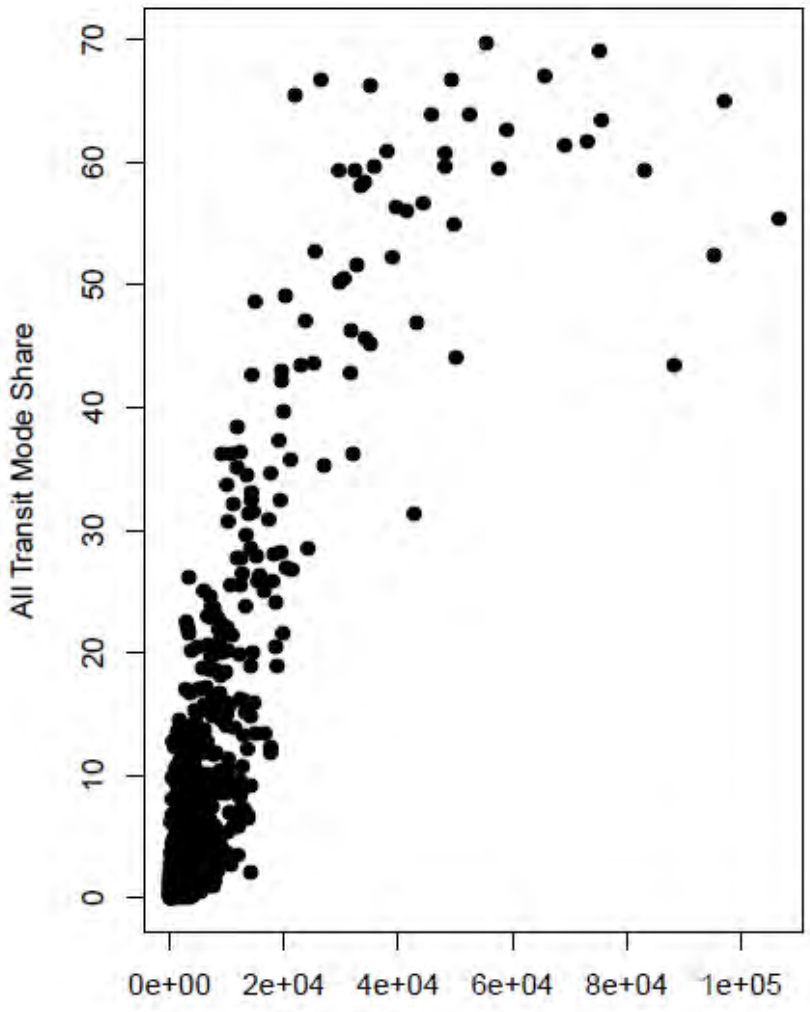
http://www2.census.gov/geo/maps/dc10map/tract/st06_ca/c06075_san_francisco/DC10CT_C06075_004.pdf

SOV Mode Share By Density



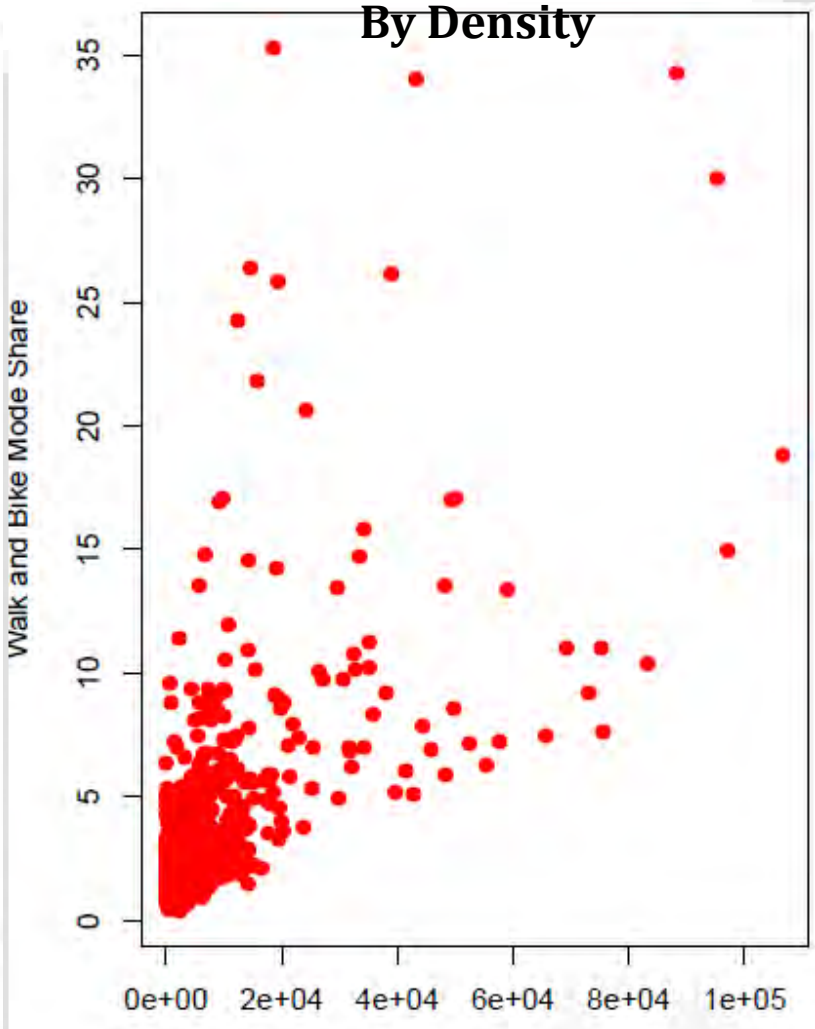
PUMA Density

Transit Mode Share By Density



PUMA Density

Walk/Bike Mode Share By Density



PUMA Density

MODEL RESULTS*

	Label	Multi-Family Rent	Single Family Rent	Single Family Mortgage (Owned <1 yr)	Single Family Unit Value (Owned <1 yr)
		Beta	Beta	Beta	Beta
State-Indicator Model Runs	PUMA Pop. Density	.05***	.04***	.05***	.04***
	Fixed Route Commuter	.07***	.03***	.04***	.08***
	Avg SOV Commute Time	-.05*	-.06**	-.20**	-.45**
	MSA Size	.03***	.04***	.08***	.11***
	R-Squared	.38	.42	.44	.53
					.08***
MSA-Indicator Model Runs	PUMA Pop. Density	.06***	.05***	.06***	.07***
	Fixed Route Commuter	.08***	.04***	.06***	-.45***
	Avg SOV Commute Time	.12**	-.01	-.29**	.49
	R-Squared	.36	.41	.48	
					116,050
	N-Observations	504,371	267,483	108,229	1010
	K-Clusters	1015	1015	1010	

Not Shown: Indicator variables, other IVs

MSA-SPECIFIC ELASTICITIES*

	Label	New York City	San Francisco	Los Angeles	Charlotte
		Beta	Beta	Beta	Beta
MSA-Indicator Model Runs	PUMA Pop. Density	.11***	.04***	.07***	.05***
	Fixed Route Commuter	-.02***	-.02	.03	N/A
	Avg SOV Commute Time	-.02	-.21**	-.44***	.15**
	R-Squared	.22	.27	.26	.38
					.
		San Diego	Seattle	Indianapolis	Houston
MSA-Indicator Model Runs	PUMA Pop. Density	-.46***	.03***	.01	.03***
	Fixed Route Commuter	.39***	.03*	.21	N/A
	Avg SOV Commute Time	.03	-.19***	-.68***	-.91***
	R-Squared	.26	.41	.42	.37

Not Shown: Indicator variables, other IVs

2006-2010 ACS MODEL RESULTS*

Transform	Variable	Multi-Family Renters--ALL				Multi-Family Renters <1 year (new renters)			
Log	2000 Driver Commute times	-.011^	-.025***	-.15***	-.056**	.02*	.000	-.19**	-.48**
Log	2000 PUMA Density	.049***				.06*			
Log	2010 PUMA Density		0.051***				.067***		
Log	Change in PUMA Density 00-10			.023***				.036***	
Log	PUMA Area				-.05**				-.07**
Normal	PUMA POP Change 00-10				-.02*				-.0000001**
Log*Normal	Interaction Area*Pop Change				.04e^-6*				.05e^-5*
	R^2	.333	.334	.325	0.334	.40	.39	.39	0.4

*full results available upon request

Not Shown: Indicator variables, other IVs

2006-2010 ACS MODEL RESULTS*

Transform	Variable	Single Family Renters				Single Family Renters <1 year (new renters)			
Log	2000 Driver Commute times	.06	.04	-.12**	.032	.06	.05	-.06	.01
Log	2000 PUMA Density	.035***				.03***			
Log	2010 PUMA Density		.035***				.03***		
Log	Change in PUMA Density 00-10			.02***				.02***	
Log	PUMA Area				-.04***				-.03***
Normal	PUMA POP Change 00-10				-2e^-6***				-.1^e^-7
Log*Normal	Interaction Area*Pop Change				4e^-7*				2.3e^-7
	R^2	.26	.26	.26	0.26	.26	.26	.26	0.26

*full results available upon request

Not Shown: Indicator variables, other IVs

TAKEAWAYS:

- Housing costs may be very inelastic with respect to density
- Impacts of "density" on "affordability" often cited may in fact be the impacts of density **and** regional economies of scale (accessibility) as opposed to density promoting policies alone like infill development.

Infill in San Francisco

≠

Infill in Corvallis

TAKEAWAYS (2)

- The "transit premium" can be captured just by identifying units with FRT commuters.
  - Our elasticities of .03 to .07 are going to be **underestimates.**
- PUMS data useful in measuring affordable housing goals over time

Source: http://www.valleymetro.org/metro_projects_planning/transit_oriented_development

TAKEAWAYS (3)

- Home owners in neighborhoods with lower SOV commute times pay higher mortgages
  - This is especially true and more significant in **the sunbelt**.

Source: http://www.city-data.com/forum/general-u-s/843161-best-city-southwest-3.html

POLICY IMPLICATIONS

- "Density" itself is not a major driver of prices
  - Certain types of policies intended to promote density may increase housing in the medium term (0-30 years), particularly urban growth boundaries.
  - Other policies may yield less negative impacts
- Construction of Fixed Route Transit systems *may* significantly change affordability along routes
  - This has not been proven or explored for Bus Rapid Transit, however.

Source: ttp://www.mercurynews.com/business/ci_24857532/san-francisco-tech-bus-protests-deal-charge-fees

THANK YOU

Questions? Comments?

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journal homepage: www.elsevier.com/locate/tranpol

The trade-offs between population density and households' transportation-housing costs

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ARTICLE INFO

Keywords:
Density
Housing costs
Smart growth
Transit

ABSTRACT

As metropolitan area governments and others promote density-promoting "smart growth" policies, finer analysis is needed to quantify the impact of such policies on households transportation and housing costs. Existing research suggests that households in urban areas trade-off between housing costs and transportation costs, but does not explore how policies to increase urban densities might explicitly impact this balance. Furthermore, the research does not adequately distinguish between the effect of urban area density and the effects of other factors associated with urban area density (e.g metropolitan area size and household incomes) on housing costs. This paper uses the 2000 Census Public Use Micro Sample (PUMS) person and household data from 23 of the nation's most densely populated states to identify the impact of increased population density on three housing cost measures: household rents, housing unit values, and monthly mortgage payments. Log linear models were estimated for each housing cost measure using least-squares regression. Dependent variables included household, housing unit, and geographic area characteristics, including population density. The models were found to be very similar to one another in terms of the statistical significance and values of estimated model parameters. Population density (measured at the PUMS area level) was found to be statistically significant at the 0.01 level for all housing cost measures. Although significant, the parameter estimates show that the elasticity of housing cost with respect to population density is low, ranging from 0.041 to 0.05. This research also explores the relationship between housing costs and accessibility. Results show that households living in areas closer to jobs (as indicated by shorter average commute times) and households utilizing fixed route transit systems have marginally higher housing costs.

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1. Introduction

1.1. Background

Several large metropolitan areas are currently debating or implementing regional plans that will dramatically increase their communities' population densities and the number of residents living in multi-family units near transit stations. Most recently, the Association of Bay Area Governments (ABAG) in Northern California adopted a plan for transforming many existing communities into transit-oriented neighborhoods with densities as high as Manhattan in New York City (Association of Bay Area Governments, 2013). The rationale for this is to reduce vehicle miles traveled (VMT) and greenhouse gas emissions by increasing population densities and transit oriented development (TOD).

Although urban area VMT can be reduced by increasing urban population density, doing so may also increase the cost of housing as a consequence of limiting the supply of developable land. This could impede efforts to increase urban population density. It could also result in the unintended consequence of stimulating exurban and bedroom community development, and undermine the objective of reducing VMT and greenhouse gas emissions. Therefore, in order to fully understand the potential consequences of increasing urban area population density, it is important to understand the relationship between population density and housing cost. This paper quantifies that relationship by examining three housing cost measures: household gross rents, household monthly mortgage costs, and housing unit values.

Unlike prior research, models are constructed using a very large sample of household-level data collected from 23 states using the Census Public Use Microdata Sample (PUMS). The highly disaggregate

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nature of the PUMS data enabled the models to control for a number of urban area, household and housing unit factors that confound the relationship between density and housing cost. Multiple density-promoting policies are available for city and regional governments, including building height restrictions (Brueckner and Sridhar, 2012), land use and planning regulations (Geshkov and DeSalvo, 2012), and property taxes (Song and Zenou, 2006). Quantifying the effects of these specific policies is not the aim of this paper, however, our models provide a tool to see how density changes from such policies increases would impact rents, mortgage costs and housing unit values. Our paper raises the possibility that PUMS data could be used to model specific impacts from these policies in the future.

The models developed produce elasticities of the relationship between densities on these dependent variables for specific market segments: single-family units and multi-family units for renters and home buyers. One set of models is put forward explicitly as a tool for urban and state governments to model impacts of density on rents and mortgage payments in their communities.

1.2. Paper organization

The paper is organized as follows. Section 2 reviews prior work that quantifies the impacts of population density either explicitly or in the form of pedestrian accessibility on higher housing prices. Section 3 provides an overview of the data source, cleaning and preparation. Models and specifications are presented and discussed in Section 4, followed by the results in Section 5 which includes alternative specifications. Section 6 presents the validation and explores the results of testing the models developed on half of the data in predicting depending variables on the other half of the data. The model diagnostics and discussion section is provided in Section 7 and Section 8 concludes this research with future remarks.

2. Literature review

A key objective of increasing urban population density is to reduce VMT and associated adverse consequences such as greenhouse gas emissions. The literature supporting the correlation of increased density with reduced VMT at the household level is extensive and detailed (Hotzclaw et al., 2002; Handy, 2005). Although some research has raised issues regarding the confounding effect of residential self-selection, more recent research has confirmed the effect of population density on travel behavior by attempting to control for self-selection effects (Handy and Mokhtarian, 2005; Brownstone and Golob, 2009; Valle, 2011). In one study, Qing (2011) controlled for supply conditions and selection effects and still found a significant and negative impact of density on fuel usage. The literature on how this affects housing in terms of prices, rents and mortgage payments, however, is less conclusive.

Several studies have identified how the transportation related benefits of density are associated with increasing housing costs. Studies looking at the impact of walkability indexes on housing unit values and sales prices have found that housing units located in areas which enable residents to walk to meet most or all daily needs see increased prices and rents (Leingberger and Alfonzo, n.d.; Cortright, 2013). Because walkability is a measure of the number of amenities and employment within walking distance of a unit, it can be interpreted in this context as a proxy for immediate neighborhood densities. Research by the Center for Neighborhood Technology (CNT) found that while average residential unit sales values declined from 2006 to 2011, they rose for units with proximity to transit during that same period in Phoenix, Chicago, Boston, Minneapolis and St. Paul, and San Francisco (Becker et al., 2013). A recent overview of the literature supports the idea that households taking fixed route transit, especially those in transit oriented developments, pay a premium for that greater accessibility (Wardrip, 2012).

Other studies suggest that prices should rise with density because density reflects the demand to live near employment centers. This is based on the 'monocentric' model of a city, which posits a concentric city with a central business district (CBD) at its core and assumes that households prefer to live near the CBD to minimize their travel costs. Household demand for proximity to the CBD causes land and housing prices and rents to be higher there than in more distant locations. Developers respond by increasing the density of their development projects in order to capitalize on household unit demand and to reduce the cost of land per developed unit (Alonso, 1964; Muth, 1969; Mills, 1967). Recent applications of the model have confirmed the hypothesis that population density and housing costs decline as distance from the CBD increases. Kulish et al. (2011) tested the model's assumptions on postal code level median housing prices in major cities in Australia and found distance to CBD a significant and negative predictor of housing prices.

Research using hedonic price and rent models has produced mixed findings regarding the impact of density on housing prices and rents. Several researchers found positive relationships between population density and housing prices. Ottensmanna et al. (2008) found a significant positive correlation between the distance to multiple employment centers and housing prices using a series of hedonic housing price models in a study of Marion County, Indiana. Fisher et al. (2009) found a highly significant log–log density coefficient for rents in the greater Boston area of 0.03 for single family units and 0.024 for condominiums.

The opposite relationship was found by one study of owner-occupied housing values in Portland, Oregon. Using housing data at the census block level from 1990 and 2000, Jun (2006) estimated hedonic housing price models for housing units in the Portland metropolitan area's three counties. A dummy variable was included which identified whether the census block-group was contained within the urban growth boundary (UGB). The dummy variable was found to be insignificant, but a block group population density variable was found to be significant and have a negative coefficient. Although this finding suggests that housing prices decline with increasing population density, caution is advised for several reasons. First the study's use of block groups as the unit of analysis means that the model relates block-group averages of household and housing unit attributes. The resulting ecological correlations may not reflect actual relationships between housing costs and household and housing unit characteristics. In addition, the analysis does not appear to differentiate between owner-occupied housing for single-family detached units, attached units and units in a multi-unit structure so observed price differences between census block groups could be reflecting unit composition differences.

Density itself may contribute to the growth of certain amenities in an area that in turn further population growth in that area, including specialized employment opportunities and consumptive amenities like restaurants, museums and other cultural amenities. Schiff (2012) finds population density, along with demographic variables, positively correlates with the diversity of unique cuisines available at the MSA level, noting that overall population of MSAs and their densities jointly predict restaurant diversity. This suggests that a combination of a large population with large concentrations of people together yield the positive returns to density for households that may be associated with gentrification and rising housing costs–restaurants, "hip" social establishments, etc. Rappaport (2008) finds a powerful correlation between MSA density and a broad range of consumer amenities including–outdoor recreational opportunities,

artistic institutions, educational institutions and good climate. Rappaport concludes that population density of cities may be determined by households' desire to locate in areas with appealing amenities and a better "quality of life" in spite of the negative quality of life impacts of density like congestion and crowding.

The amenity variables are not statistically teased out or controlled for in this paper, as they are part of the reason why density would correlate with housing prices at all and our intent is not to provide a pure and exclusive effect of density on prices beyond what density endogenously promotes in an urban society. The intent of this paper is not to identify how specific density-promoting policies mentioned above may impact rents, mortgage payments and home values. Rather, it is designed for use by professionals and researchers who may know the impact of a policy on density, and who need to model that additional density effect on housing affordability in the area receiving the policy treatment.

The research presented in this paper differs from research presented above in several important respects. First, it uses disaggregate household and housing unit data from the Census PUMS so that correlations properly reflect relationships at the household and housing unit level. Because the data are highly disaggregate with regard to characteristics of the households and the structures in which they reside, it is possible to control for the effect of a number of factors that potentially confound the relationship between population density and housing cost. Second, rather than using the data from one or a few metropolitan areas, this study uses hundreds of thousands of household records from metropolitan areas across 23 states. This expansive dataset supports robust statistical analysis and conclusions drawn from the analysis. There are some drawbacks resulting from the limitations of the dataset as explained below.

3. Data source and preparation

The study used PUMS 5% sample data for the year 2000 for metropolitan counties in 23 states around the country, including the most populous and densely populated states. The metropolitan statistical areas included in this study ranged in size from 406,934 people to over 21 million people. In total, they represented a population of over 101 million residents, over a third of the United States population in the year 2000. The 2000 PUMS data is used rather than more recent data to avoid housing market distortions caused by the housing bubble and subsequent crash. Table 8 in Appendix lists the states included in the study. The very large size of the datasets enabled portions of the data to be reserved for validation purposes. Half of the data points were selected randomly for use in model estimation. The other half were used for model validation.

3.1. Dependent variables

State datasets were extracted from the Census Bureau FTP site and recombined into several national datasets separated by unit and tenure type. The three dependent variables used to operationalize housing costs are gross monthly rents, primary mortgage payments and housing unit values:

- Monthly rents were derived from the PUMS variable GRENT, for gross monthly rents.
- Primary mortgage payments were derived from the variable MRT1AMT in the PUMS dataset. Household's annual tax amounts (TAXAMT) were divided by 12 and added to household's mortgage payment values for those households which did not have taxes included in their payments (TAXINCL). Units which had insurance included in their mortgage payment (INSINCL) had their annual insurance amount (INSAMT) divided by 12 and subtracted from their mortgage payments.
- Housing unit values are coded categorically in the PUMS datasets by the HVAL variable. Each unit's HVAL value was recoded to the midpoint value of the category it fell into. Because this is a categorical variable that was recoded into a numeric variable, some caution in interpreting the results is warranted.

In the PUMS dataset, both the mortgage payment (MRT1AMT) and unit value (HVAL) variables have "top-code" values. For the former case, the top-coded values were coded as the state-level mean of all mortgage payments in the dataset above $3,000 a month. Because this top-coding introduced bias into the data, the authors removed these units from the final analysis. They represented 2.7% of the data and the authors ran auxiliary analysis which included them that did not produce differences in coefficient signs or significance levels.

3.2. Key independent variables

Density was calculated as the residential population per square mile by Public Use Microdata Area (PUMA) . This was a matter of necessity because the PUMA, or Public Use Micro-Sample Area, is the lowest geographic unit associated with individual household responses in PUMS datasets in order to protect anonymity. Each PUMA from the year 2000 is designed to encompass a minimum 100,000 residents counted in the 2000 Census, with a priority placed by designers on ensuring PUMAs line up consistently with county and city boundaries to the best extent possible (Missouri Census Data Center, 2011).

The lack of detailed geographic specificity is the most significant information trade-off of the research approach and is a consequence of how household and housing unit data is published by the U.S. Census Bureau. These data provide the most extensive and consistent record on household and housing unit characteristics. The Census Bureau protects anonymity by limiting the geographic specificity of disaggregate household and housing unit information and by providing only aggregate data for more specific geographic areas (e.g. tract, block group). This poses a dilemma for researchers using Census data to study housing cost relationships. On the one hand, using more geographically specific data enables the researcher to supplement the Census data and control for neighborhood-level attributes such as walkability. However, a researcher using that approach would be modeling relationships among the average characteristics of geographical areas, and therefore the relationships of household and housing unit characteristics represented in the model would be ecological and unlikely to accurately reflect the actual relationships. On the other hand, using the PUMS data would enable the researcher to accurately reflect household and housing unit relationships in the model but would not enable the data to be supplemented with neighborhood-level attributes.

The authors chose the disaggregate modeling approach based on their belief that for the purposes of the study, accurately representing household and housing unit relationships in the model is more important than representing neighborhood characteristics. Household characteristics such as the number of persons in the household, and housing unit characteristics such as the number of rooms, are strongly related to housing cost (as shown below) and cannot be represented adequately in an aggregate model. On the other hand, the authors believe that population density at the PUMA level can adequately represent the relationship between density and housing cost. Although PUMAs contain relatively large populations, they still provide an adequate

level of discrimination among portions of a metropolitan area. For example, the City of San Francisco is divided into 7 PUMAs and Manhattan Island is divided into 10 PUMAs. The authors believe that this is an adequate level of geographic detail to represent the effects of population density on the housing market.

The use of a PUMA-level measure of density rather than a more geographically detailed measure may also help to reduce the potential effects of excluded variable bias. Because of data limitations, this research could not include neighborhood level characteristics like walkability and school quality that can affect housing costs. The exclusion of such variables from the analysis introduces the possibility that the estimated coefficient for the density variable may capture some of the effects of other variables and thus overstate the effect of density on housing cost. This potential error is mitigated to some extent by using a PUMA-level density measure, rather than a more geographically detailed measure, because the covariance between the density measure and any unmeasured neighborhood-level variable is reduced the greater the area over which density is measured.

Two variables capturing transportation and commuting are also included in the dataset. First, to capture the effect of proximity to fixed route transit systems on housing costs, the authors produced a dummy variable equaling one if the household had a commuter who travels to work by streetcar, railroad, subway or ferry. Second, the authors included the mean average commute times of all vehicle drivers at the PUMA level. The authors explored alternative commute measures: household specific average vehicle commute times, and household-specific maximum and minimum commute times. Because inclusion of these variables systematically left out households without employment or without vehicle commuters, these variables were rejected for exploration in the analysis. Regardless, their inclusion or exclusion did not impact the sign or significance of population density.

4. Model specifications

Ordinary least squares (OLS) was used to estimate log-linear housing cost models by tenure, building type, and purchase date as follows: monthly rents for single-family dwellings, monthly rents for units in multifamily dwellings, house value for owner-occupied single-family dwellings, house value for recently purchased owner-occupied single-family dwellings, monthly mortgage payments for owner-occupied single-family dwellings, and monthly mortgage payments for recently purchased owner-occupied single-family dwellings. Because the independent variable of most interest is population density defined at the PUMA level, the authors opted to apply more statistically punitive measures of significance by applying cluster-robust standard errors to models produced. Cluster robust standard errors do not calculate standard errors by $N-1-K$ degrees of freedom but by $Z-1-K$ degrees of freedom where Z is the number of clusters. In this case, the clusters were PUMAs, the geographic level at which two variables of interest were defined: vehicle commute times and population density.

4.1. Primary models: state-level indicator controls

A standard hedonic model is developed around a set of state-level indicator variables for statewide modeling, otherwise following Ottensmanna et al. (2008) with independent variables of interest included. Additional control variables of housing unit and household attributes included in the models from the PUMS dataset are

- Household Income (HINC): reflecting the ability to pay, as housing is a normal good which households pay more for as their income rises.
- Number of Persons in the household (PERSONS): reflects the demand for living space.
- Number of Vehicles (VEHICL): a proxy for demand for space outside the unit for parking.
- Number of Years Living in the Housing Unit (derived from TENURE): a mean coding of the categorical variable. For rental units this captures the effect of fixed rental increases and rents at the time of first renting. For home-owner units this captures the effects of market conditions and interest rates at the time of home purchase.
- Number of Rooms in Housing Unit (ROOMS): reflects the housing unit size.
- Age of Structure (derived from YRBUILT): captures the effect of age on a unit's value. Ages are mean-coded from the categories of the original variable. For the top code category of unit built before 1935 the authors selected a value of 70 years.
- Number of Units in Structure (derived from BLDG): derived from the variable on structure type (BLDG), apartments receive a mean code for the range of the apartment category they fall into. This variable is excluded for single-family unit models.
- A dummy variable for if the unit sat on one to ten acres of land, and another dummy for if the unit sat on over ten acres of land. Derived from ACRES variable in the PUMS dataset. These were excluded from the single-family rent model when the authors found systematic differences between the one third of single family renters without this variable reported and the rest that did. However, an alternative model which included the variables did not change the sign or significance of population density.
- MSA population, pulled from the Census, captures the effect of the size of the MSA on housing costs. Research has confirmed that large cities which support better amenities have higher housing costs (Glaeser et al., 2000).
- State level dummies: a dummy for each state in the dataset with Alabama as the baseline, designed to capture the effect of state-level policies on housing

The model also contains a PUMA level control variable, the weighted mean of household incomes at the PUMA level derived from the household income variable (HINC). For models predicting rents, this variable is substituted with the weighted mean of all renters' household incomes at the PUMA level. This is intended capture the market area pressures of household incomes on housing costs (e.g. a middle income household living in a higher income area is likely to pay more for housing than that same household living in a lower income area). This variable also captures the effects of other community attributes that may affect housing costs. School quality is correlated with local incomes (Chetty and Friedman, 2013). Crime rates are also correlated with poverty and low income (Pratt, 2001).

4.2. MSACMSA level indicator control models

Since density may be influenced by various land use policies referenced in Geshkov and DeSalvo (2012), Brueckner and Sridhar (2012) and Song and Zenou (2006), we introduce a second set of models with indicator variables serving as fixed effects at the geographic scale available in the PUMS data that most closely matches those of those studies: the MSA. The MSA-indicator models include the following additional controls.

- MSA level dummies (MSACMSA1): used alternatively to control for regional differences in means within states at the metropolitan area level.
- Number of Bedrooms in the Unit (BEDROOMS): also reflects the unit's size relative to residents, this variable was left out of final analysis but included in auxiliary regressions.

- A dummy variable for if the household was white: something that might correlate with density in some form given the highly segregated nature of America's inner cities and which might capture the lingering effects of discrimination in mortgage lending practices (Sykes, 2008).
- Income inequality within the PUMA: the authors applied an income differential variable to capture the effect of an unusually large share of high-end incomes on an area's housing market. This was captured by logging the difference between the 95th percentile income in a PUMA from the 40th percentile income in a PUMA. The usual measure, the standard deviation of income, was not selected due to high multi-collinearity issues with the mean income variables. Some research suggests that density may correlate with income inequality because it may exacerbate it (Pendall and Carruthers, 2003).

The individual state datasets were split into subsets by tenure. The state datasets were then combined into national datasets by tenure. The multi-state datasets were used to estimate the models for the following variables:

4.3. OLS and other explanatory variables

OLS regression was used to estimate the housing cost models. Because of the large number of observations, the authors split the data randomly into estimation and validation datasets. Half of the observations were used to estimate the models. The other half were used for model validation. The housing cost models have the following form:

$$V_i = \beta_0 + \beta_{i1}S + \beta_{i2}H + \beta_{i3}N + \beta_{i4}L + \epsilon_i \quad (1)$$

$$R_j = \beta_0 + \beta_{j1}S + \beta_{j2}H + \beta_{j3}N + \beta_{j4}L + \epsilon_j \quad (2)$$

$$P_k = \beta_0 + \beta_{k1}S + \beta_{k2}H + \beta_{k3}N + \beta_{k4}L + \epsilon_k \quad (3)$$

in which V is a vector of housing values, R is a vector of monthly gross rents, and P is a vector of primary mortgage monthly payments. S is a vector of state dummy variables with Alabama as a baseline. H is a matrix of unit or structure characteristics, N is a matrix of household characteristics, and L is a matrix of PUMA-wide and MSA characteristics. The β_0 is the constant term vector, β_H, β_N, and β_L are matrices of the corresponding parameters, and ϵ is a vector of error terms. Since house prices are skewed, the authors assume that rents, mortgage payments and housing unit values will also be skewed and thus adopt from the literature a transformation of the dependent variables into natural log form (Ottensmanna et al., 2008). This is the most commonly used specification in hedonic housing price models (Ottensmanna et al., 2008). The log transformation can reduce the heteroscedasticity associated with the use of highly skewed price and cost variables.

4.4. Clustered robust standard errors

This model requires clustered robust standard errors because a vector of independent variables in the model, vector L, are defined at the PUMA level and not the level of the household, which is the level at which observations are defined. Wooldrige (2003) lays out the case for robust clustered standard errors in situations where observations are pooled into non-overlapping groups-like schools, employers, or PUMAs, that exert their own effects on observations at that level. The following variance estimators demonstrate the difference between the traditional OLS estimator and one that is cluster robust:

$$V_{OLS} = s^2 \sum_{i=0}^{n} (x'x)^{-1} \quad (4)$$

$$V_{cluster} = (x'x)^{-1} \sum_{j=0}^{n_c} u_j' u_j (x'x)^{-1} \quad (5)$$

$$u_j = \sum_j e_j x_i \quad (6)$$

Eq. (4) shows the derivation of the variance in ordinary least squares where s is the variance of the residuals of the regression and x is a vector of independent variables. In Eq. (5), u is the cluster level variance of the residuals calculated in Eq. (6). Cluster-robust standard errors therefore punish our beta coefficients by calculating their standard errors by $K-1$ degrees of freedom instead of $N-1$, where K is the number of clusters.

5. Model results

Six housing cost models were estimated: rents for single-family renters, rents for multi-family renters, housing values for all single-family home owners, housing values for recent single-family home purchasers, mortgage payments for all single-family home owners, and mortgage payments for recent single-family home purchasers. The housing value and mortgage models were estimated for recent purchasers, in addition to all purchasers, because home values and mortgage payments reflect housing prices, interest rates, and transportation characteristics (e.g. commute time) existing at the time of purchase. Recent purchasers were defined as home owners who purchased their houses within a year of data collection. Housing cost models for owners of multifamily dwelling units were not estimated because of insufficient observations in many PUMAs and MSAs.

Tables 1–3 present the results of the models run with state dummies, intended to enable the modeling of density-increasing state-wide policies on housing costs.

The signs on the model coefficients are consistent across all models with the exception that the number of residents is positively correlated with rents and mortgage payments and negatively

Table 1
Single and multi-family rent models.

	Single family rent		Multi-family rent	
	b	Cluster robust *t*-stat	*b*	Cluster robust *t*-stat
Attached	−0.08	−27.63		
Log Rooms	0.29	68.99	0.16	37.44
Log Building Age	−0.06	−27.63	−0.04	−16.53
Log Units			−0.02	−9.02
Log Years There				
Land 1–9.9 Acres				
Land 1–9.9 Acres			0.10	26.18
Log Income	0.03	30.26	0.03	25.61
Log Residents	0.05	17.79	0.03	7.92
Log Vehicles	0.17	51.36	0.27	55.74
Fixed Route Commuter	0.03	9.46	0.07	15.84
Log Density	0.04	16.13	0.05	16.8
Log Puma Mean Inc				
Log Puma Mean Renter Inc	0.64	49.54	0.67	46.98
Log MSA Population	0.04	8.87	0.03	5.59
Log Puma Drivers Ave Commute	−0.06	−2.54	−0.05	−1.81
N	267,483		504,371	
K (Clusters)	1015		1015	
R Squared	0.42		0.38	
Adjusted *R* Squared	0.42		0.38	

Table 2
Single Family Home Owner Models.

	Housing value all owners		Housing values recent buyers	
	b	Cluster robust *t*-stat	*b*	Cluster robust *t*-stat
Attached				
Log Rooms	0.74	50.08	0.57	62.44
Log Building Age	−0.15	−30.74	−0.06	−36.31
Log Units				
Log Years There	−0.04	−21.34		
Land 1–9.9 Acres	0.12	32.16	0.10	26.18
Land 10 Plus Acres	0.31	46.34	0.18	20.39
Log Income	0.10	53.31	0.08	27.95
Log Residents	0.08	18.98	−0.03	−5.55
Log Vehicles	0.22	29.62	0.08	14.5
Fixed Route Commuter	0.07	7.32	0.08	14.5
Log Density	0.11	11.85	0.04	6.86
Log Puma Mean Inc	1.18	25.8	0.69	27.58
Log Puma Mean Renter Inc				
Log MSA Population			0.11	8.73
Log Puma Drivers Ave Commute	−0.15	−1.23	−0.45	−6.98
N	1,183,391		116,050	
K (Clusters)	1015		1010	
R Squared	0.50		0.53	
Adjusted *R* Squared	0.49		0.53	

Table 3
Single Family Mortgage Models.

	Mortgage payments all payers		Mortgage payments recent buyers	
	b	Cluster robust *t*-stat	*b*	Cluster robust *t*-stat
Attached				
Log Rooms	0.41	59.39	0.41	51.5
Log Building Age	−0.07	−42.3	−0.05	−36.57
Log Units				
Log Years There	−0.09	−67.2		
Land 1–9.9 Acres	0.05	23.16	0.04	13.17
Land 10 Plus Acres	0.10	22.07	0.07	9.07
Log Income	0.08	46.15	0.08	25.56
Log Residents	0.04	13.8	0.02	3.75
Log Vehicles	0.07	19.27	0.08	13.3
Fixed Route Commuter	0.03	11.53	0.04	11.71
Log Density	0.05	41.64	0.05	34.54
Log Puma Mean Inc			0.69	27.58
Log Puma Mean Renter Inc				
Log MSA Population	0.06	10.04	0.08	9.24
Log Puma Drivers Ave Commute	−0.16	−4.8	−0.20	−4.69
N	457,947		108,229	
K (Clusters)	1015		1010	
R Squared	0.43		0.44	
Adjusted *R* Squared	0.43		0.44	

correlated with housing values. It is expected that the sign would be positive because larger households would presumably be interested in having more space. The signs on all the other control variables that are shared across models are consistent and as expected. Housing costs increase with the number of rooms, lot size, household income, number of residents, number of vehicles, mean income in the area, and MSA population. Housing costs decrease with building age and length of tenure. The variables with the largest elasticities are mean household income for the PUMA (0.53–0.69), number of rooms (0.16–0.57), and number of vehicles (0.07–0.27).

The primary independent variables of interest confirm in sign and significance the existence of a housing and transportation cost

Table 4
MSA-fixed effects, single and multi-family rent models.

	Single family rent		Multi-family rent	
	b	Cluster robust *t*-stat	*b*	Cluster robust *t*-stat
Log Bedrooms	0.16	24.81	0.13	16.93
Log Rooms	0.18	34.08	0.06	12.52
Log Building Age	−0.05	−24.99	−0.04	−16.21
Log Units			−0.02	−9.44
Log Years There	−0.06	−54.81	−0.08	−27.9
Land 1–9.9 Acres				
Land 10 Plus Acres				
Log Income	0.27	31.3	0.04	28.78
Log Residents	0.06	25.14	0.04	10.32
Log Vehicles	0.16	48.26	0.28	50.16
White Household	0.03	20.78	0.05	16.85
Fixed Route Commuter	0.04	5.79	0.08	16.13
Log Density	0.05	20.92	0.06	21.12
Log Puma Mean Inc				
Log Puma Mean Renter Inc	0.53	37.49	0.64	33.71
Log Income Difference	0.07	5.88	−0.01	−0.04
Log Puma Drivers Ave Commute	−0.01	−0.46	0.12	3.05
N	220,676		511,146	
K (Clusters)	1015		1015	
R Squared	0.41		0.36	
Adjusted *R* Squared	0.41		0.36	

trade-off. Rents, housing values and mortgage payments are all significantly correlated with population density. The signs are positive, as expected with elasticities that range from 0.04 to 0.05. Households that use a fixed route transit system to commute have higher housing costs than households that do not, cetaris paribus. This effect is consistent and significant across all models with elasticities ranging from 0.028 to 0.07. The relationship between average driver commute time and housing cost is negative as expected; households near employment are willing to pay more for housing than those living farther away. The elasticities are consistent for the single family and multi-family rental markets, −0.058 and −0.05 respectively. The elasticities are much higher for the owner-occupied housing market: −0.16 to −0.20 for mortgage payments, −0.45 for housing value.

Interestingly, the coefficient on the number of units in the building is negatively correlated with rents for multi-family rental housing. This suggests that increasing the size of a multi-family building tends to lower costs independent of density. In other words, building costs do not appear to be the mechanism for increasing housing costs as density increases. Rather they appear to be a mechanism that mitigates the effect of density on housing costs.

Tables 4–6 presents the results of the alternative model specifications. The coefficients on population density neither lose significance nor change signs. The inclusion of additional variables on race, income dispersion and the number of bedrooms have little effect on the density variable.

The coefficients for the fixed route transit commuting variable remain positive and highly significant for all models. The coefficients indicate that renter households use commute by fixed-route transit pay between 4.7% and 6.4% more on rents than households that do not. Single family home owners paid about 2% more for mortgage payments and their homes were worth about 7% more. The relationship between vehicle commute times and monthly rent was not significant for single-family renters, but significant and positive for multifamily renters. That result is inconsistent with expectations and the multifamily renter model presented in Table 1. The vehicle commute time and housing cost relationship was negative and highly significant for recent home buyers, both

Table 5
MSA-fixed effects, single family housing owner models.

	Housing value all owners		Housing value recent buyers	
	b	Cluster robust *t*-stat	*b*	Cluster robust *t*-stat
Log Bedrooms	0.18	12.03	0.18	8.11
Log Rooms	0.74	50.28	0.64	37.02
Log Building Age	−0.15	−30.74	−0.10	−34.2
Log Units				
Log Years There	−0.042	−21.34		
Land 1–9.9 Acres	0.12	32.16	0.10	21.89
Land 10 Plus Acres	0.31	46.34	0.25	21.92
Log Income	0.10	53.31	0.12	29.52
Log Residents	−0.08	−18.98	−0.06	−8.4
Log Vehicles	0.22	29.62	0.2	16.64
White Household	0.12	24.53	0.09	21.08
Fixed Route Commuter	0.07	7.32	0.07	5.97
Log Density	0.11	11.85	0.08	9.8
Log Puma Mean Inc	1.18	25.8	1.02	24.44
Log Puma Mean Renter Inc				
Log Income Difference	−0.06	−1.59	−0.02	−0.04
Log Puma Drivers Ave Commute	−0.015	−1.23	0.45	−4.15
N	1,183,391		109,902	
K (Clusters)	1015		1010	
R Squared	0.50		0.49	
Adjusted *R* Squared	0.50		0.49	

Table 6
MSA-fixed effects, single family mortgage models.

	Mortgage payments all payers		Multi-family rent	
	b	Cluster robust *t*-stat	*b*	Cluster robust *t*-stat
Log Bedrooms	0.08	9.88	0.12	10.41
Log Rooms	0.41	59.39	0.39	39.33
Log Building Age	−0.00	−27.1	−0.00	−22.68
Log Units				
Log Years There	−0.11	−88.3		
Land 1–9.9 Acres	0.06	27.59	0.05	17.1
Land 10 Plus Acres	0.13	30.9	0.10	13.01
Log Income	0.09	55.38	0.10	29.97
Log Residents	0.03	14.15	0.01	1.56
Log Vehicles	0.16	48.26	0.28	8.83
White Household	0.05	17.55	0.05	16.85
Fixed Route Commuter	0.02	11.06	0.02	11.04
Log Density	0.06	14.67	0.06	6.26
Log Puma Mean Inc	0.58	33.31	0.59	27.94
Log Puma Mean Renter Inc				
Log Income Difference	0.04	2.73	0.04	2.4
Log Puma Drivers Ave Commute	−0.12	−1.85	−0.29	−4.18
N	864,837		10,281	
K (Clusters)	1015		1010	
R Squared	0.46		0.48	
Adjusted *R* Squared	0.46		0.48	

for home values and for mortgage payments. The relationship is not significant at the 5% level for all home owners. This makes sense because vehicle commute times reflect community attributes at or near the time when a household purchases their home.

Variance inflation factor tests for multicollinearity revealed no systematic problems of multi-collinearity in the regressions, and the use of cluster-robust standard errors ensures very strict corrections for assumed heteroscedasticity, lending confidence model validity.

6. Validation

Validation of the models was carried by running the estimated models on the data reserved for model validation and comparing the modeled results with the observed results. The modeled and observed results were compared at the PUMA level as that is the geographic level at which the key density and travel time variables were estimated. Fig. 1 presents a comparison of observed distributions of PUMA mean values for the housing cost variables versus the distributions of the predicted values for those variables. Fig. 1 shows that the modeled distributions of rents match the observed distributions very well. The modeled and observed distributions of home values and mortgage payments are also very close, but not as close as for rents.

Fig. 2 compares the observed and predicted PUMA mean values where the observed values are plotted on the *x*-axis and predicted values are plotted on the *y*-axis. The figure also compares a linear fit between the predicted and observed PUMA mean values against an ideal, 1:1 linear relationship. The tight clustering and high R-Squared values show that the models explain a very large amount of the variation in housing costs at the PUMA level. This is particularly evident for the rental models.

The slopes of the linear fits between observed and predicted values are less than 1:1. In other words, the models' predictions are high at lower housing costs and low at higher housing costs. The deviations are small for rental housing, more so for owner-occupied housing.

7. Model diagnostics and discussion

Plots presented after the conclusion show regression diagnostics produced in R. Fig. 3 shows the model diagnostics with the full single family rent sample, wherein the land dummies were excluded from the model. The figure on the top left corner of Fig. 3 shows the residuals of the observations plotted against their fitted values. Under the assumption of homoscedasticity, the red line representing the relationship between these variables should be completely flat. In Fig. 3, it is very close flat, with the appearance of some heteroscedasticity at either end of the distribution of fitted values. This is not of concern, as the use of cluster-robust standard errors was an especially punative control for how such heterscedasticity might artificially inflate significance (Verbeek, 2012). The Normal *Q*–*Q* plot on the topright is a plot of the model's standardized residuals against the theoretical quantiles of the distribution given a normal distribution. The results suggest that at one end of the distribution the residuals are not normally distributed. The scale–location plot on the bottom left corner is a plot of the fitted values against the square root of their residuals. Again, the lack of any relationship or discernible pattern in the relationship lends confidence to the model following the assumptions of OLS. Lastly, the bottom right plot of the residuals against each observation's leverage is a measure of potentially influential observations. The three household points labeled by R are labeled because they can be defined statistically as outliers. None of them appear to hold leverage in the model warranting concern.

The scale–location and residuals versus fitted values plots demonstrate severe and confusing heterscedasticity. The author suspects that this is due to the original categorical nature of the housing value data.

Fig. 4 shows the diagnostics of the multi-family and single family renter models. These models perform better in normality of residuals and heteroscedasticity.

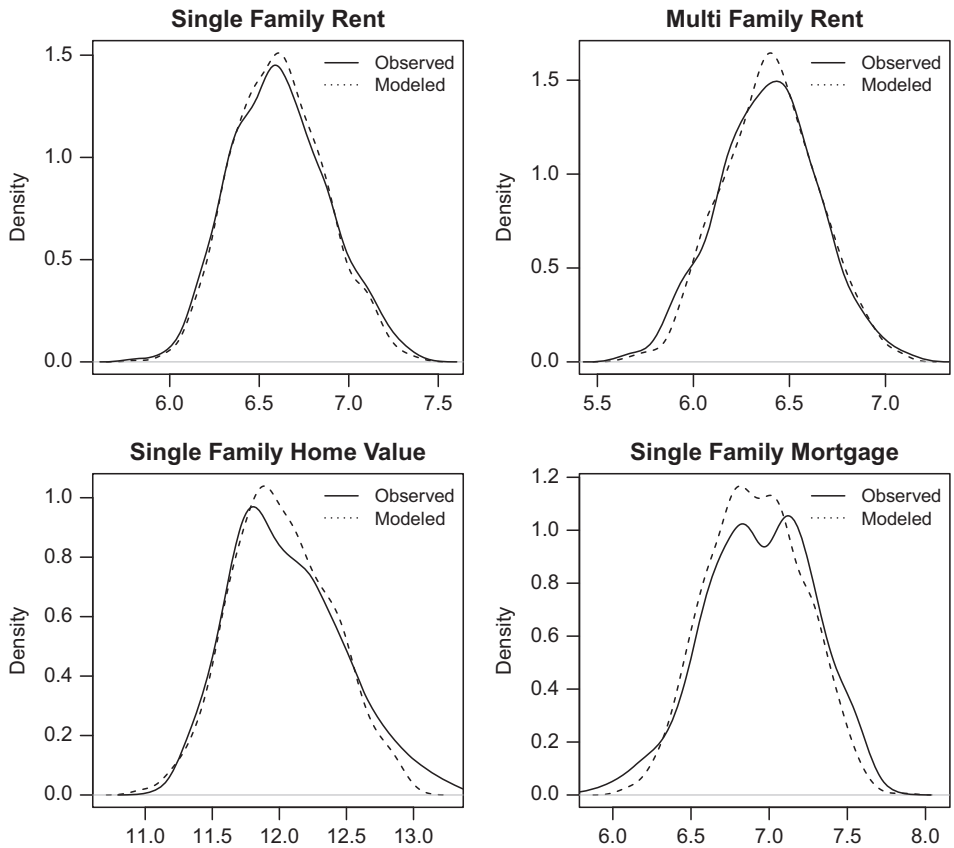

Fig. 1. PUMA mean distribution.

8. Conclusion and future work

This research completed a highly disaggregate analysis of housing costs on a very large sample of households representing over one third of the population of the United States. This enabled many factors to be controlled for at the household and housing unit level. It also enabled strong model validation tests to be completed (Fig. 5).

The research found that population density is strongly correlated with rents, housing values and mortgage payments. However, it was also found that the sensitivity of housing costs to population density is very low with elasticities in the range of 0.041–0.05. The significance and sensitivity of the effect is consistent across all of the housing markets studied. The significance and sensitivity of the effect is consistent across all of the housing market segments studied. The range of density coefficients is presented in Table 7.

These results may be surprising to some readers given the substantial housing price differences between large dense cities like San Francisco and smaller, less dense urban areas. This perhaps unexpected result can be explained by the models presented in this paper along with supporting research on the causes and consequences of metropolitan area growth. What some may conclude through cursory examination as the effect of density on housing cost is much more likely a consequence of the effect of metropolitan area population size on other factors, notably household income, that affect housing cost.

With regard to density, although the metropolitan-wide population density of large metropolitan areas varies considerably (e.g. Atlanta vs. Chicago), the probability that a household will reside in a higher density area will be greater in a larger metropolitan area than in a smaller metropolitan area, ceteris paribus. This is a consequence of the locational advantages of clustering, from the demand side (e.g. advantages to shoppers of retail clustering) and from the production side (e.g. advantages of industry clusters for exchanging information, services and/or products) (Mills, 1992). The incentive for clustering is greater in larger metropolitan areas because those areas can support more specialized services and a larger variety of services. As presented earlier in the paper, the clustering of employment within the metropolitan area also tends to drive the clustering of residential development as households bid up the price of housing in more accessible locations and developers respond by building more housing units in those areas.

Increasing metropolitan area size is also related to several other characteristics shown by the models to significantly affect housing costs. The first among these is household income. In all of the models presented, the PUMA average household income has the greatest effect on housing cost with elasticities ranging from 0.53 to 0.69. A household living in a higher income area will pay substantially more for housing independent of their income. In addition, the models show that households will spend more for housing if they have more income. In the case of owner-occupied single family housing, the elasticity of this effect ranges from 0.08 to 0.10.

Household income is related to metropolitan area size. Larger metropolitan areas have higher per capita incomes because of greater levels of productivity stemming from economics of agglomeration, specialization, and division of labor. In addition, because of the opportunities offered by specialization, larger metropolitan attract more highly educated and skilled workers who can command higher wages (Beeson, 1992). As a result, households living in metropolitan areas tend to have higher wages and are competing for housing with other workers who are likely to have much higher incomes than households living in smaller metropolitan areas. As the models show, this has a substantial effect on housing cost.

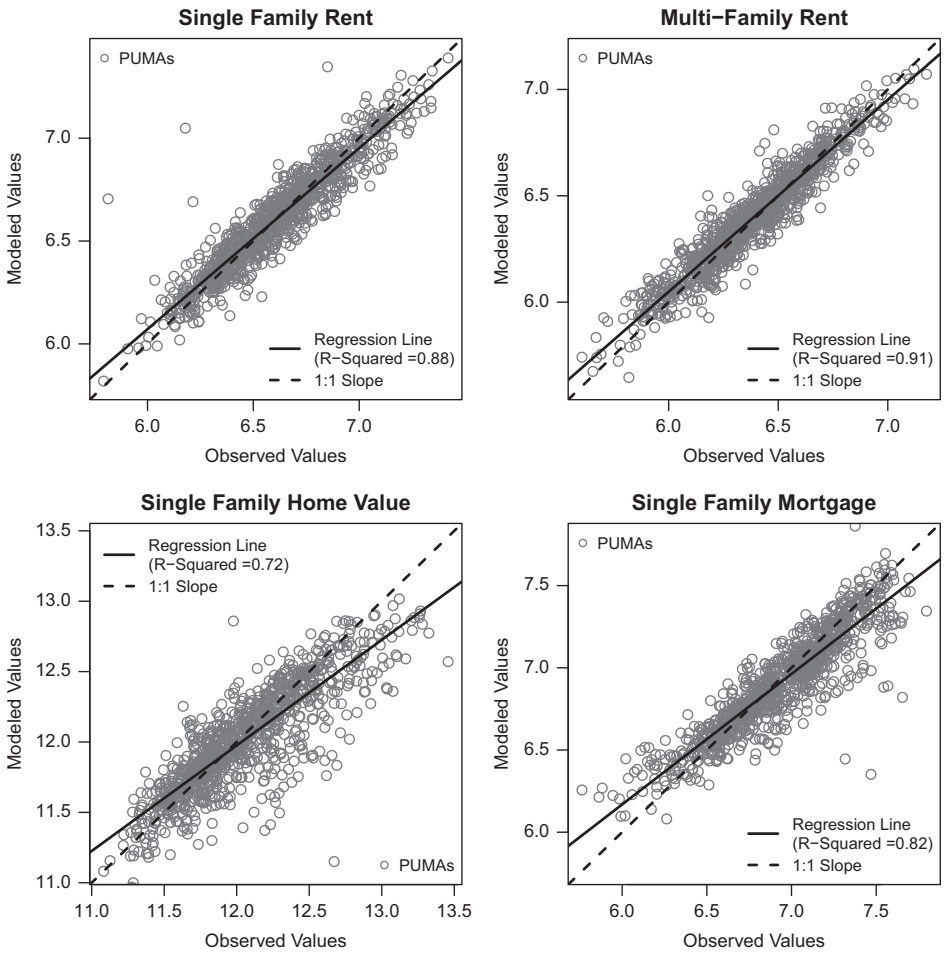

Fig. 2. PUMA mean scatters.

The research also supports the principle that households trade-off housing and commuting costs. The monthly mortgage costs and housing values of recent home purchasers were lower in places where average automobile commute times were higher. The sensitivity of rents to auto commute times was found to be relatively low with elasticities in the range of −0.05 to −0.06. The sensitivity of mortgage payments and home values for recent home buyers was found to be much greater, with elasticities of −0.20 for mortgage payments and −0.45 for home values. A similar trade-off is evident for fixed-route transit accessibility. Households using fixed-route transit service to commute to work paid more for housing, ceteris paribus. It is notable that this relationship between fixed-route transit access and housing cost are evident in the 2000 Census data. This is almost a decade before the difference in values noted for housing units with transit access during the most recent recession, as identified by Becker et al. (2013). The results confirm views expressed by the Center for Neighborhood Technology, the Brookings Institution, and others, that housing affordability should be thought of in the context of this trade-off between housing cost and transportation cost (Hass et al. 2006)

It is also interesting to note that for renters, the absolute values of the elasticities of housing cost with respect to auto commute time and housing cost with respect to density are nearly the same. This may indicate a very close relationship between housing cost, density and commuting time. The elasticities are not close for single-family home mortgage payments and values, but that may reflect the longer-term asset value aspects of home ownership.

The estimated elasticities of rents, housing values, and mortgage costs with density are smaller when a MSA population size variable is included in the respective models than when that variable is excluded. This suggests the possibility of an interaction between density and MSA size, with the effect of density on housing prices and rents possibly being lower in smaller MSAs compared to larger ones. These results have significant implications for the implementation of smart growth policies. Increasing urban area densities will most likely result in increasing housing costs, however the amount of the increase is likely to be small unless very large increases in density are planned over substantial areas. The models presented in this paper can be used to estimate the amount of effect that smart growth policies may have on housing costs in a metropolitan area. Because the results of this research are cross-sectional, the authors hesitate to claim this is the last word on the subject. Future work should incorporate this data with data from future years to track this relationship over time.

In addition to shedding light on the relative effect of population density on housing costs, this research provides strong models to enable urban analysts and planners to estimate the potential effects of smart growth policies on housing costs. Moreover, it shows the potential for using the massive PUMS datasets for carrying out additional research. These datasets and supporting datasets are readily available and were easily downloaded, processed and analyzed with scripts developed in the R software environment for statistical programming (R Core Team, 2013). The methods used in this research could be readily extended to include more states, evaluate more market segments, and augment the dataset with additional variables. Such efforts would provide additional understanding of how household and urban area characteristics affect housing costs and would help to provide better housing cost models.

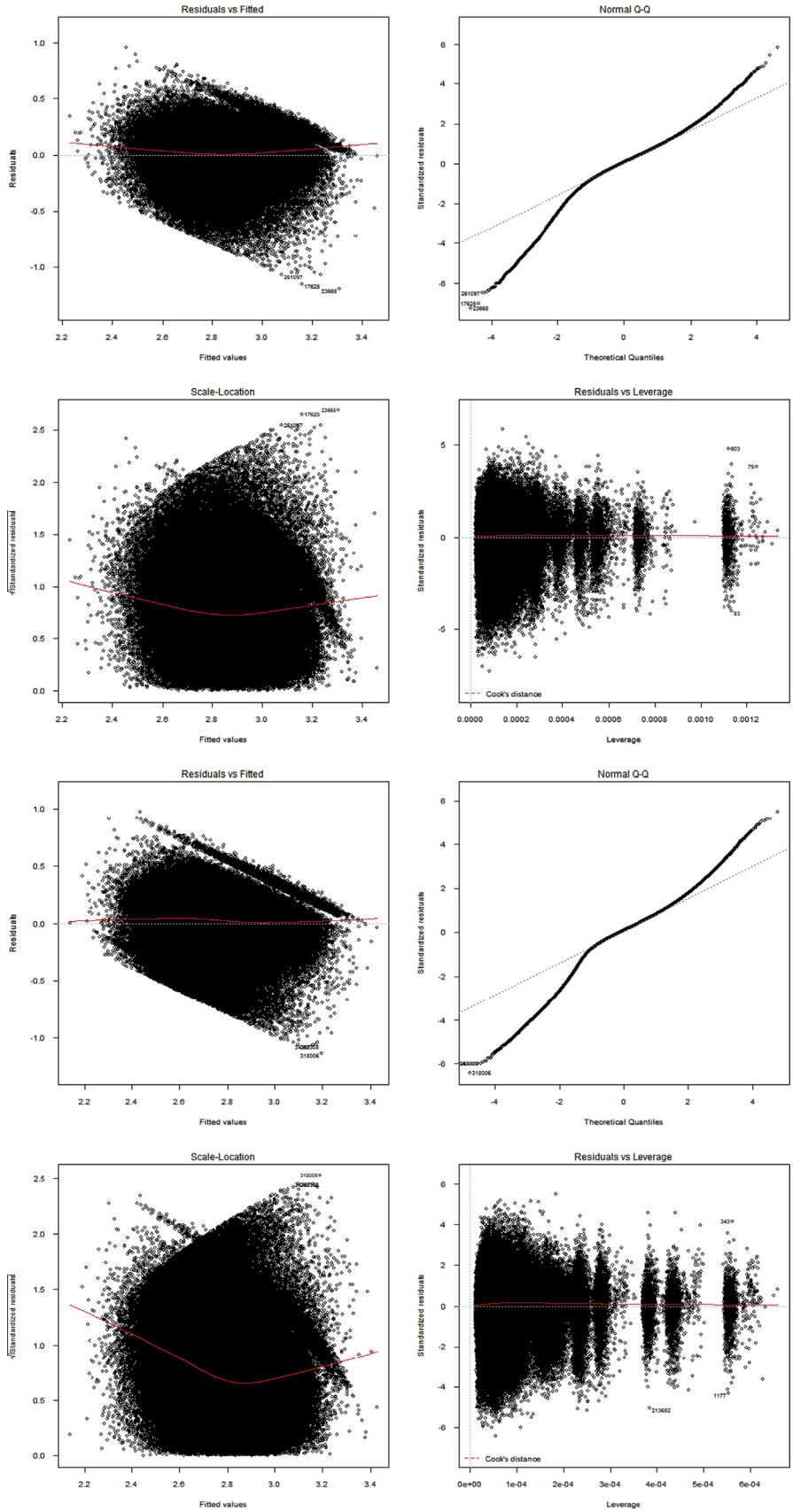

Fig. 3. Single and multi-family model diagnosis. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this paper.)

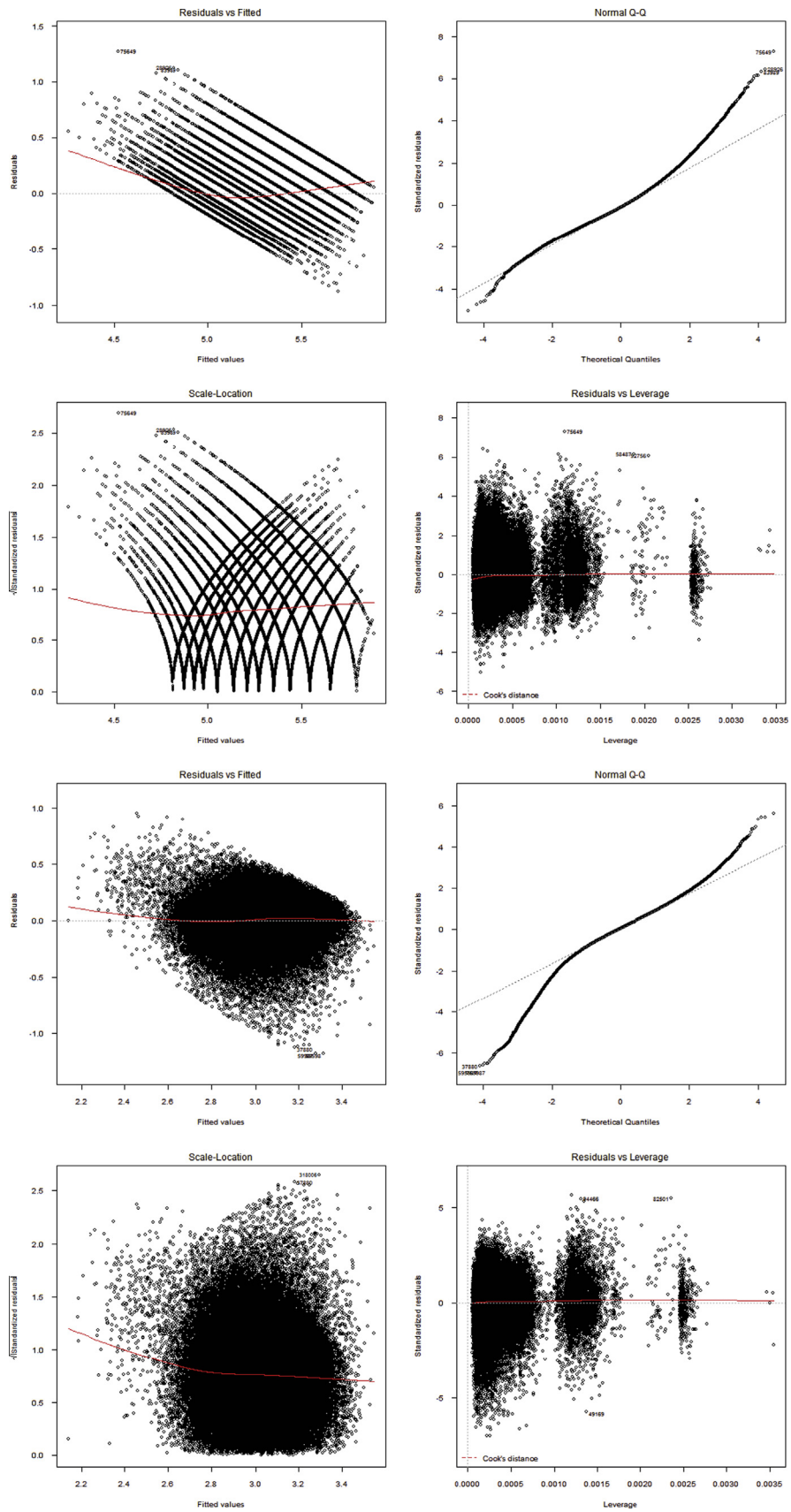

Fig. 4. Single and multi-family model diagnosis.

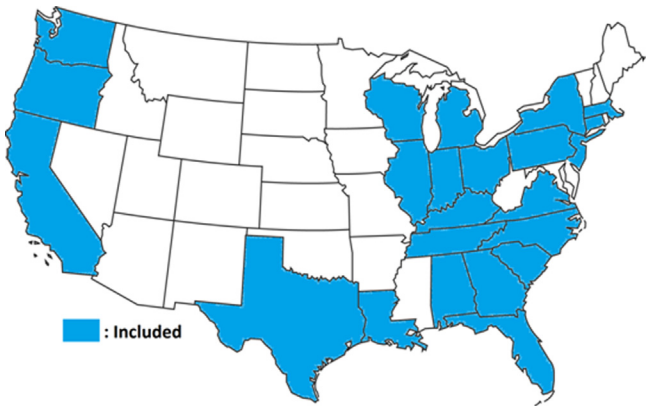

Fig. 5. States included in this study as presented in Table 8.

Table 7
Density coefficients across models, all significant.

	State fixed effects	MSA fixed effects
Single family rents	0.041	0.047
Multi-family rents	0.05	0.064
Single family mort payments	0.053	0.059
Recent buyer single family mort payments	0.053	0.056
Single family housing unit value	0.108	0.108
Recent buyer single family unit value	0.043	0.084

Table 8
States included in the study.

Alabama	Indiana	New York	Tennessee
California	Kentucky	North Carolina	Texas
Connecticut	Louisiana	Ohio	Virginia
Florida	Massachusetts	Oregon	Washington
Georgia	Michigan	Pennsylvania	Wisconsin
Illinois	New Jersey	South Carolina	

Table 9
Single family mortgage model.

	New York		Bay Area		Log Angeles	
	Beta	SE	Beta	SE	Beta	SE
Intercept	−0.53	0.05***	−0.25	0.09*	0.00	0.02
LogRooms	0.33	0.05***	0.31	0.01***	0.25	0.006***
Log Bldgage	−0.05	0.007***	−0.04	0.003***	−0.04	0.002***
Log Yrsthere	−0.13	0.002***	−0.17	0.002***	−0.13	0.002***
Land	0.10	0.003***	0.09	0.01***	0.07	0.004***
Land 10 plus	0.10	0.01***	0.13	0.01***	0.04	0.01*
Log HINC	0.06	0.002*	0.09	0.03***	0.09	0.002***
Log Persons	0.10	0.002***	0.07	0.01***	0.06	0.003***
Log Vehicle	−0.01	0.006	0.04	0.01***	0.07	0.006***
Fixed Route Commuter	−0.02	0.006***	−0.02	0.17	0.03	0.05
LogMean Inc	0.56	0.007***	0.61	0.01***	0.62	0.007***
Log POPSQMI	0.11	0.00***	0.04	0.002***	0.07	0.002***
Log Pumadriversavetime	0.03	0.02	−0.21	0.03***	−0.44	0.03***
N	99,715		45,361		90,084	
R Squared	0.2177		0.2666		0.2566	
Adjusted *R* Squared	0.2176		0.2664		0.2565	

**Significance level of 0.01.
*** Significance level of 0.001.
* Significance level of 0.05.

Table 10
Single family mortgage model.

	Houston		Chicago		Charlotte	
	Beta	SE	Beta	SE	Beta	SE
Intercept	0.96	0.089***	−1.72	0.096*	0.028	0.20
LogRooms	0.54	0.01***	0.35	0.01***	0.69	0.03***
Log Bldgage	−0.01	0.003***	−0.05	0.002***	−0.06	0.006***
Log Yrsthere	−0.08	0.002***	−0.01	0.002***	−0.11	0.006***
Land	0.02	0.004***	0.06	0.004***	0.03	0.01*
Land 10 plus	0.09	0.01***	0.06	0.01***	−0.08	0.04
Log HINC	0.08	0.002***	0.08	0.002***	0.09	0.007***
Log Persons	0.03	0.003***	0.04	0.005***	0.03	0.01***
Log Vehicle	0.08	0.01***	0.03	0.008***	0.08	0.03***
Fixed Route Commuter	N/A	N/A	0.03	N/A	N/A	N/A
LogMean Inc	0.54	0.01***	0.66	0.01***	0.34	0.03***
Log POPSQMI	0.03	0.003***	0.11	0.002***	0.05	0.01***
Log Pumadriversavetime	−0.91	0.06***	0.39	0.02***	0.15	0.10***
N	27,301		52,329		4,975	
R Squared	0.3657		0.3114		0.3769	
Adjusted *R* Squared	0.3655		0.3113		0.3755	

*Significance level of 0.05.
***Significance level of 0.01.

Table 11
Single family mortgage model.

	San Diego		Seattle-Tacoma		Indianapolis	
	Beta	SE	Beta	SE	Beta	SE
Intercept	1.22	0.198	0.09	0.17	0.31	0.026
LogRooms	0.33	0.015***	0.3	0.01***	0.58	0.02***
Log Bldgage	−0.05	0.005***	−0.04	0.003***	−0.1	0.004***
Log Yrsthere	−0.14	0.004***	−0.13	0.003***	−0.08	0.004***
Land	0.09	0.01***	0.05	0.00***	0.06	0.006***
Land 10 plus	0.10	0.02***	0.06	0.02***	0.13	0.02*
Log HINC	0.05	0.01*	0.09	0.00***	0.11	0.01***
Log Persons	0.08	0.01***	0.05	0.01***	0.01	0.005***
Log Vehicle	0.03	0.11	0.03	0.01***	0.06	0.02***
Fixed Route Commuter	0.39	0.02***	0.03	0.11	0.21	0.14
LogMean Inc	0.02	0.01***	0.52	0.02***	0.55	0.02***
Log POPSQMI	−0.46	0.08***	0.03	0.01***	0.01	0.01
Log Pumadriversavetime	0.03	0.02	−0.19	0.06***	−0.68	0.16***
N	16,309		23,236		9,842	
R Squared	0.2563		0.2472		0.4216	
Adjusted *R* Squared	0.2557		0.2468		0.4208	

*Significance level of 0.05.
***Significance level of 0.01.

Appendix

Single family mortgage models are given in Tables 8–11.

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