Technology and the City

Photo by Bernard Gagnon

Three Big Questions

- How Does Technology Change the Demand for Cities?
  - Why have recent technological shifts been centripetal rather than centrifugal?
  - Will this continue?

- How Does Urbanism Change the Demand for Technology?
  - Cities are the absence of physical space between people and firms.
  - They exist to lower transport costs for goods, people and ideas.
  - Urbanism increases demand for technologies that thrive with density.
  - I focus more on the needs of the public “City” rather than private customers.

Centripetal Skyscrapers

The Chicago Home Insurance Building, built in 1885, is widely considered the world's first metal-framed skyscraper. This technology would come to dictate the shape of most cities in the twentieth century and beyond.

Chicago History Museum/Getty Images

Until nearby commercial structures began to dwarf it in 1890, Trinity Church had been New York's tallest building for forty years. The two buildings to the church's left held that honor for thirty years until they were destroyed in a terrible attack that ultimately illustrated the resilience of a great city.

Jeff Greenberg/ World of Stock

Centrifugal Cars (and Radios and TVs)

Cars and Highways Killed Urban Industry

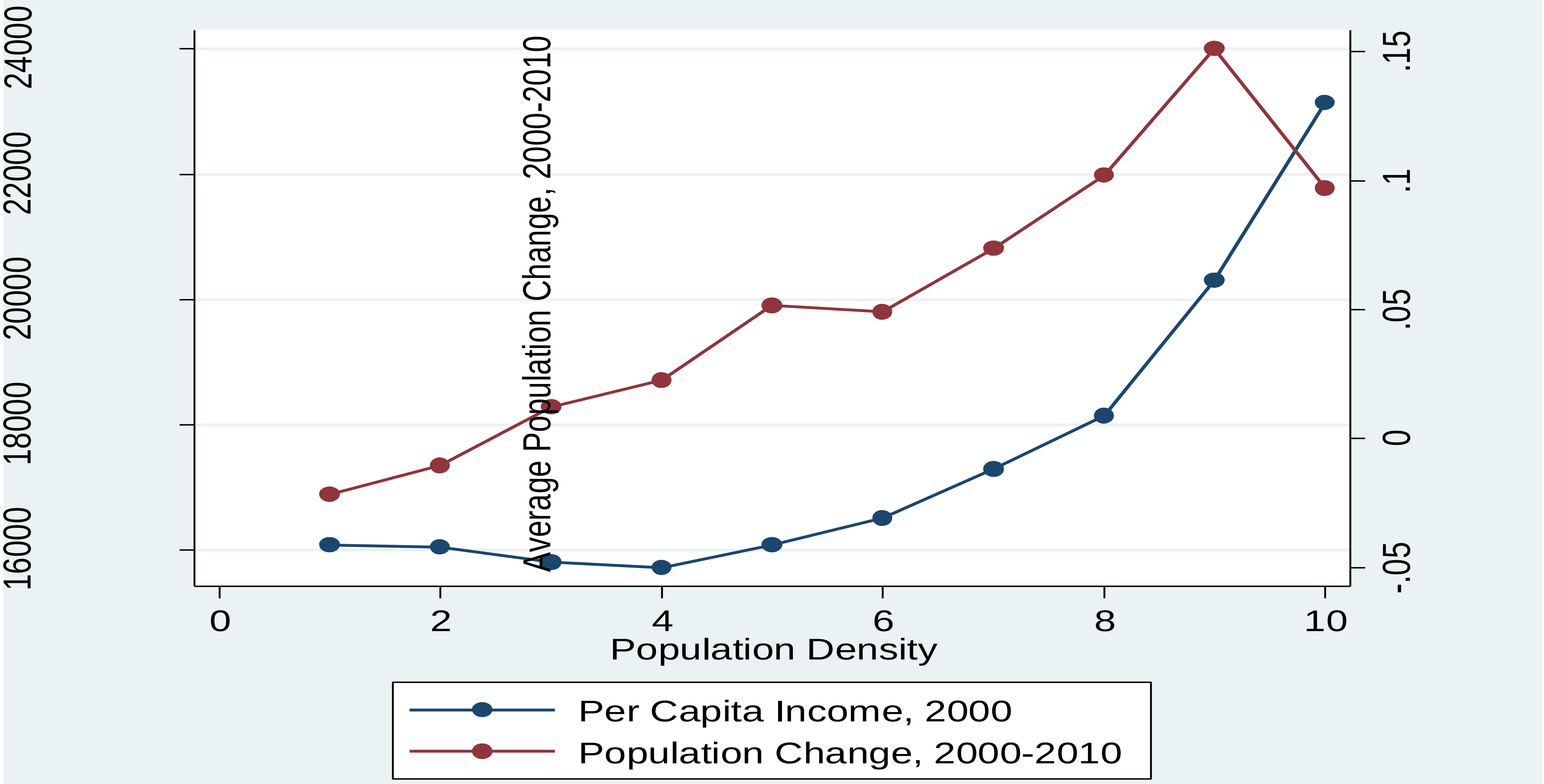
So Why Didn't These

Image by ChtiTux

Image by Danamania

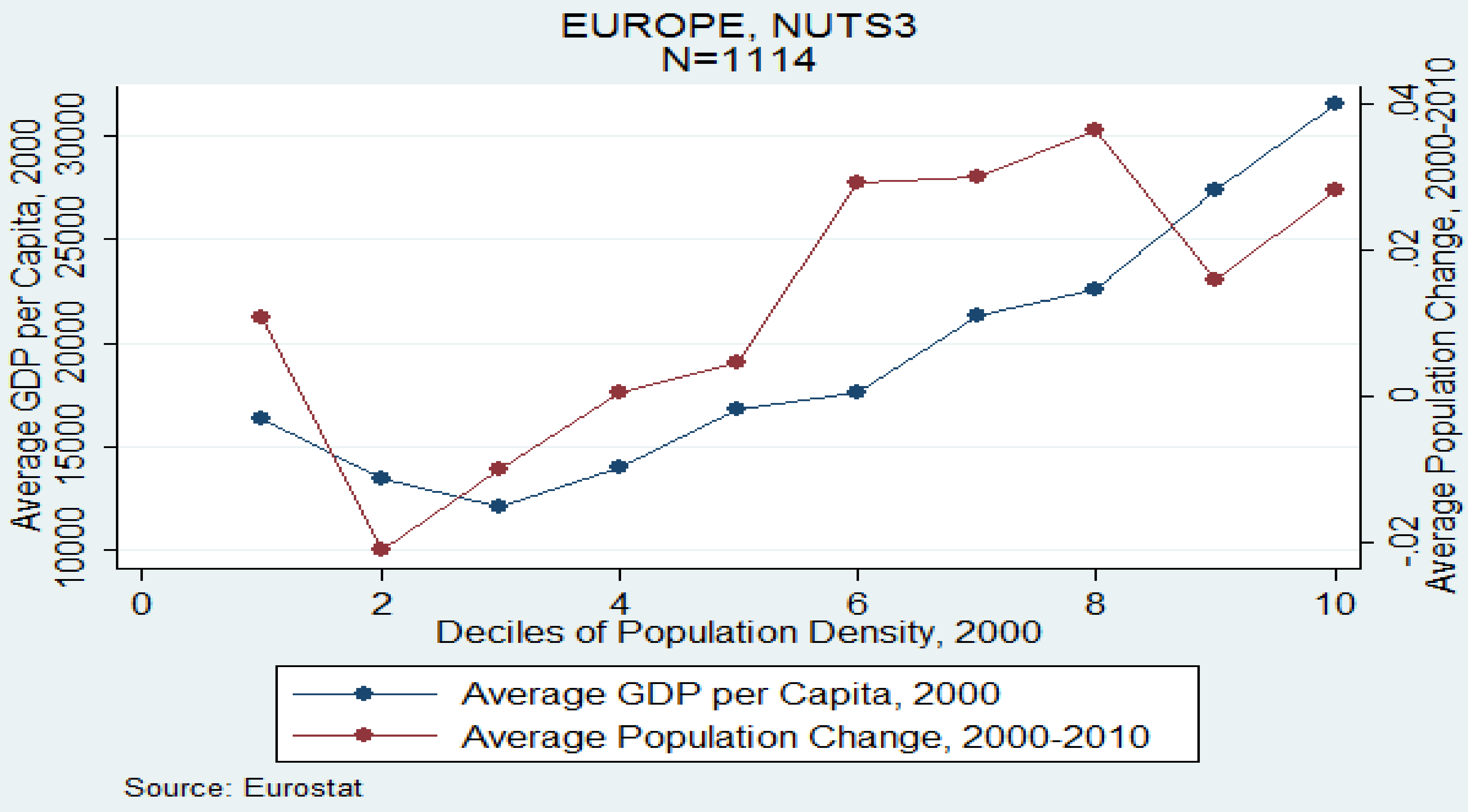
Kill Finance and Urban Information Industries

Photo by Runner1928

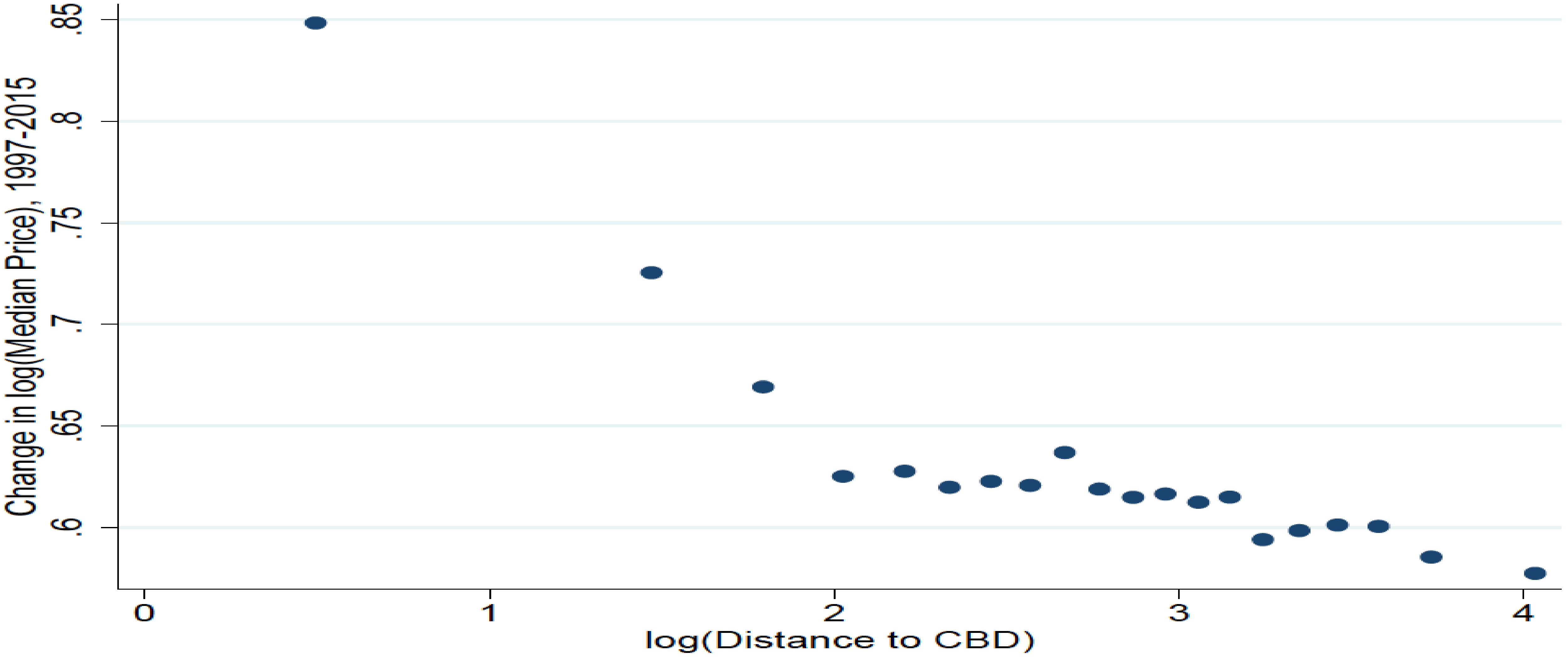


Source: U.S. Census


Employment rate by location
Employment Rate, percent
88
84
80
1980
1990
2000
2010
Year
Key
Major Metro Area
Other Metro Area
Non-Metro Area


EUROPE, NUTS3
N=1114
Average GDP per Capita, 2000
10000
15000
20000
25000
30000
Average Population Change, 2000-2010
-.02
0
.02
.04
0
2
4
6
8
10
Deciles of Population Density, 2000
Average GDP per Capita, 2000
Average Population Change, 2000-2010
Source: Eurostat

The Great Pro-City Price Tilt (U.S.)



Hipsman (2015) Using Zillow Sub-city

Will the last person to leave Seattle please turn out the lights?

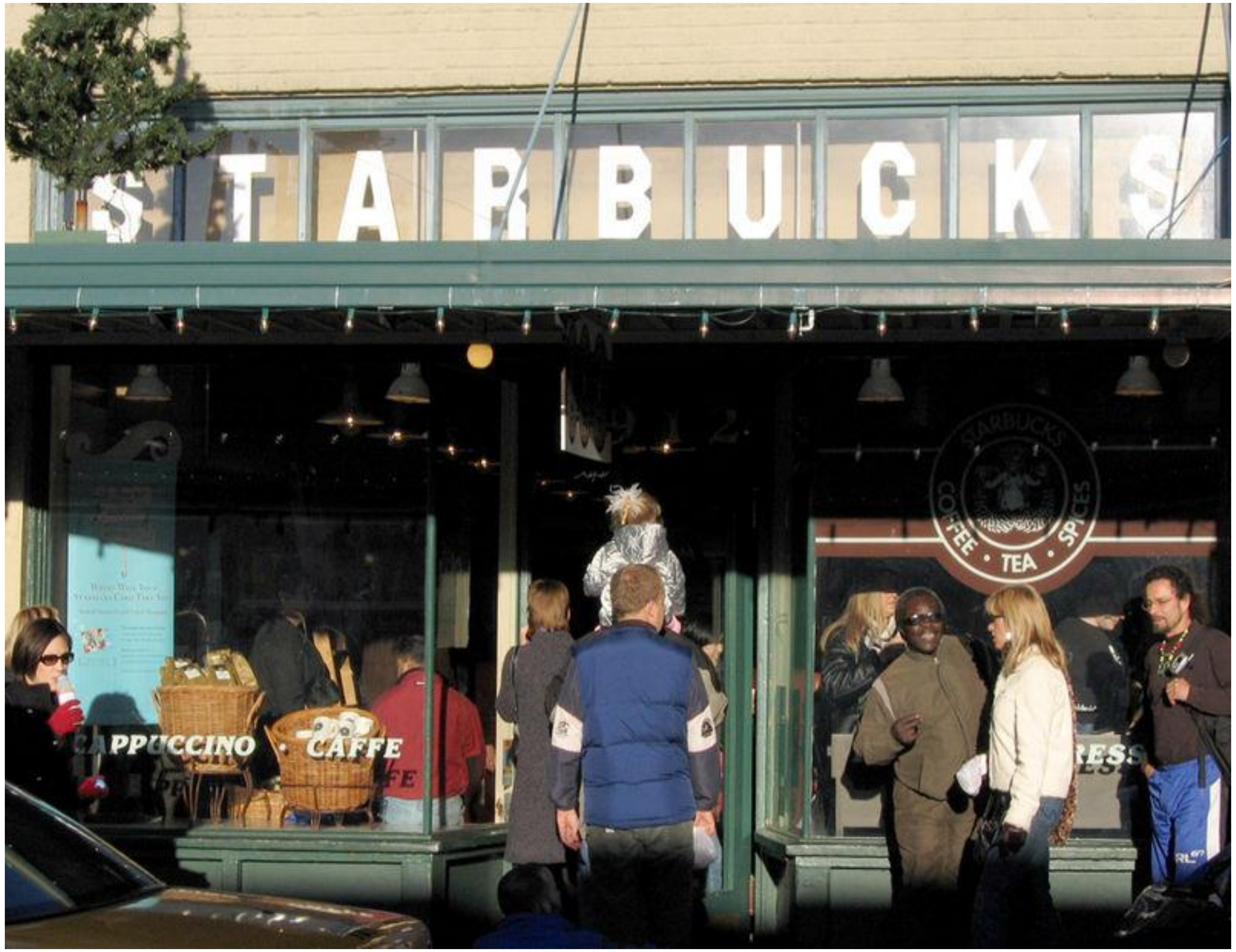
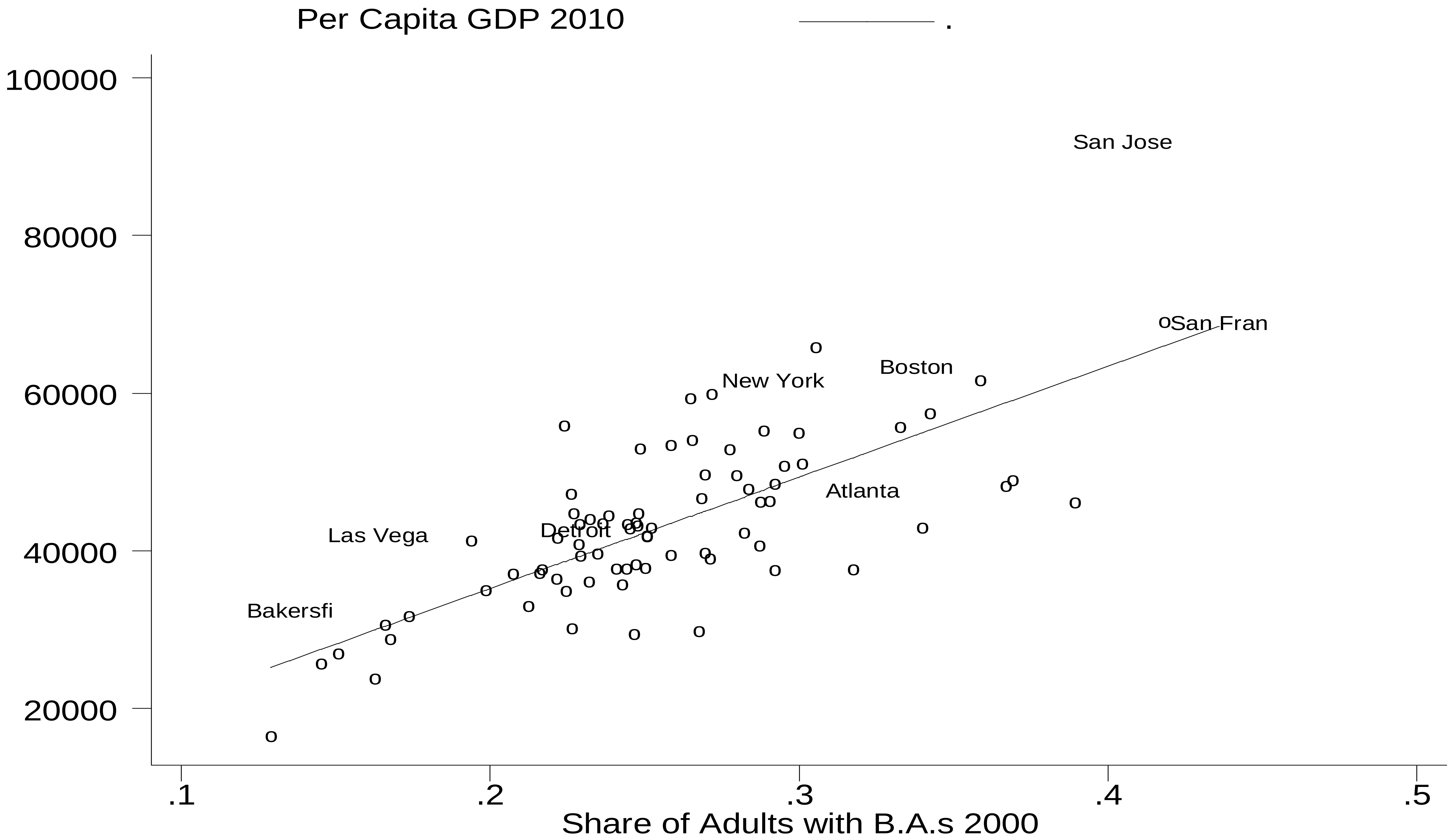
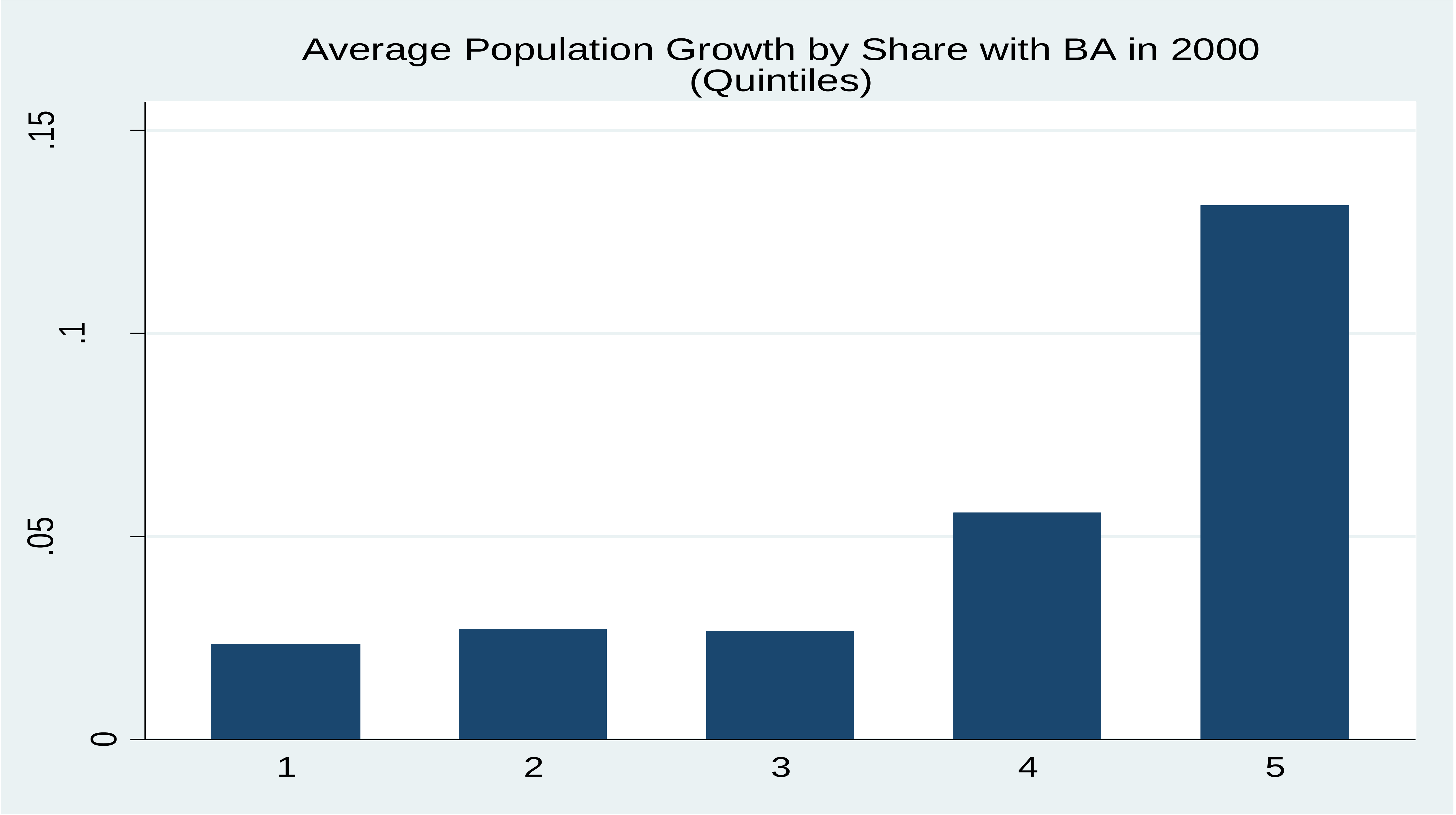


Photo by Postdil



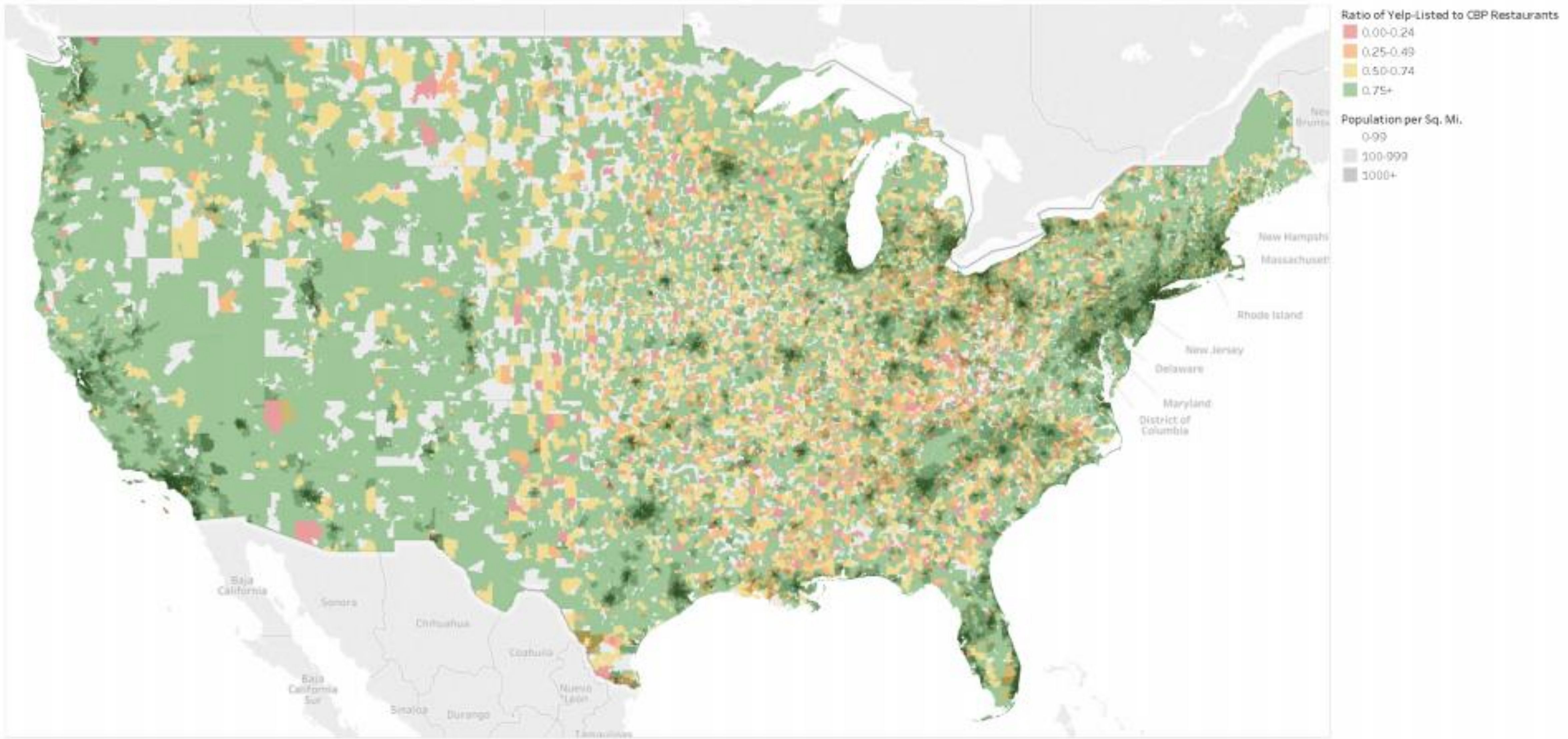
Per Capita GDP 2010
100000
80000
60000
40000
20000
San Jose
San Fran
Boston
New York
Atlanta
Las Vega
Detroit
Bakersfi
.1
.2
.3
.4
.5
Share of Adults with B.A.s 2000

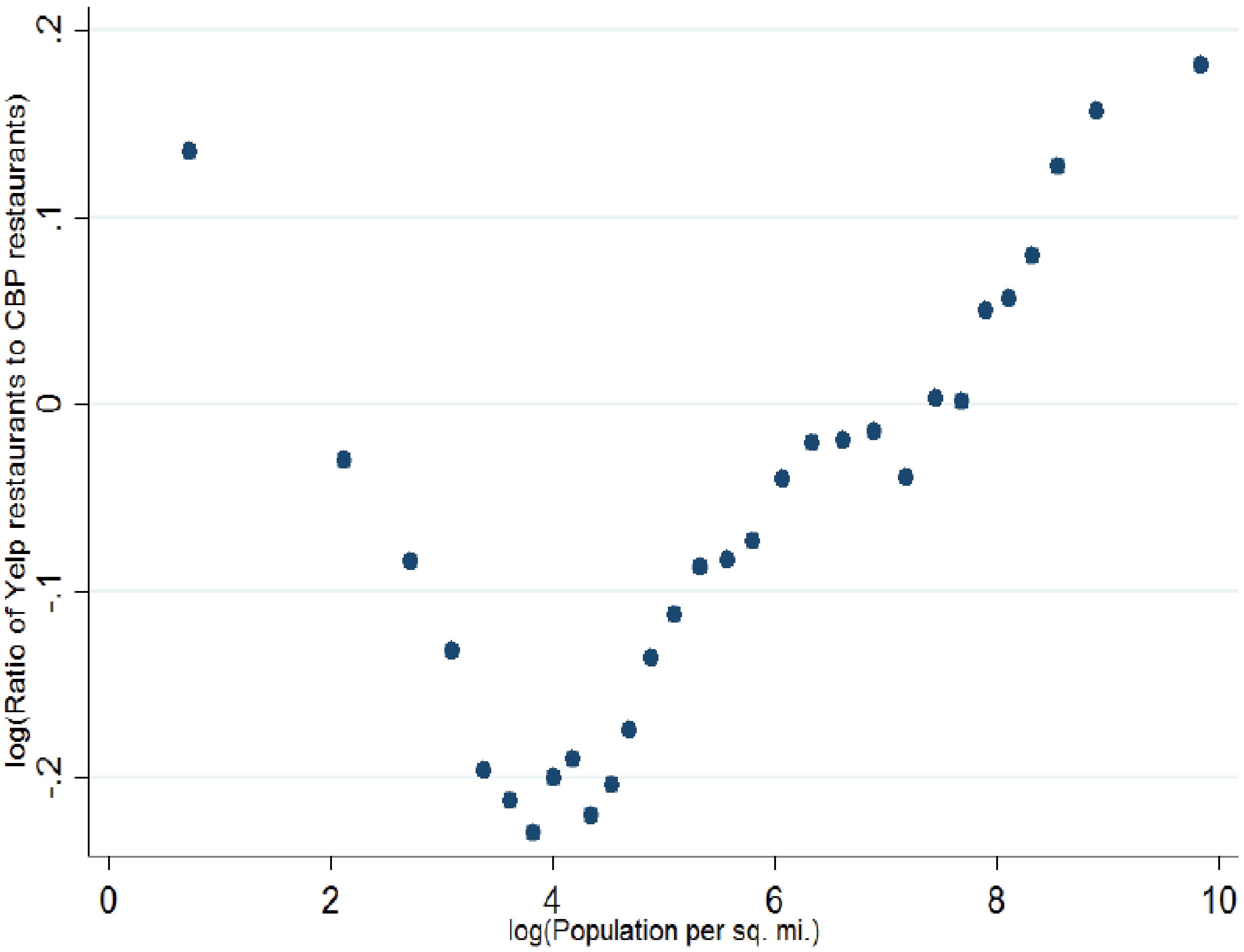

Average Population Growth by Share with BA in 2000
(Quintiles)
0
.05
.1
.15
1
2
3
4
5

Information Sharing Technologies Complement Urbanism

- Urban systems are complex and dense: they need information and have more potential to crowdsource information.
  - Yelp and Waze are both crowd-sources information providers.
- Urban labor markets have more workers and firms -- matching is harder.
  - Indeed, Careerbuilder, Glassdoor
- Urban density enables service industries – this increases the potential for service sector entrepreneurs and entrepreneurs that enable small-scale private service providers.
  - Uber and Lyft
- Density makes it possible to share more physical space and things – this increases the benefit of services that enable sharing.
  - Airbnb, Zipcar

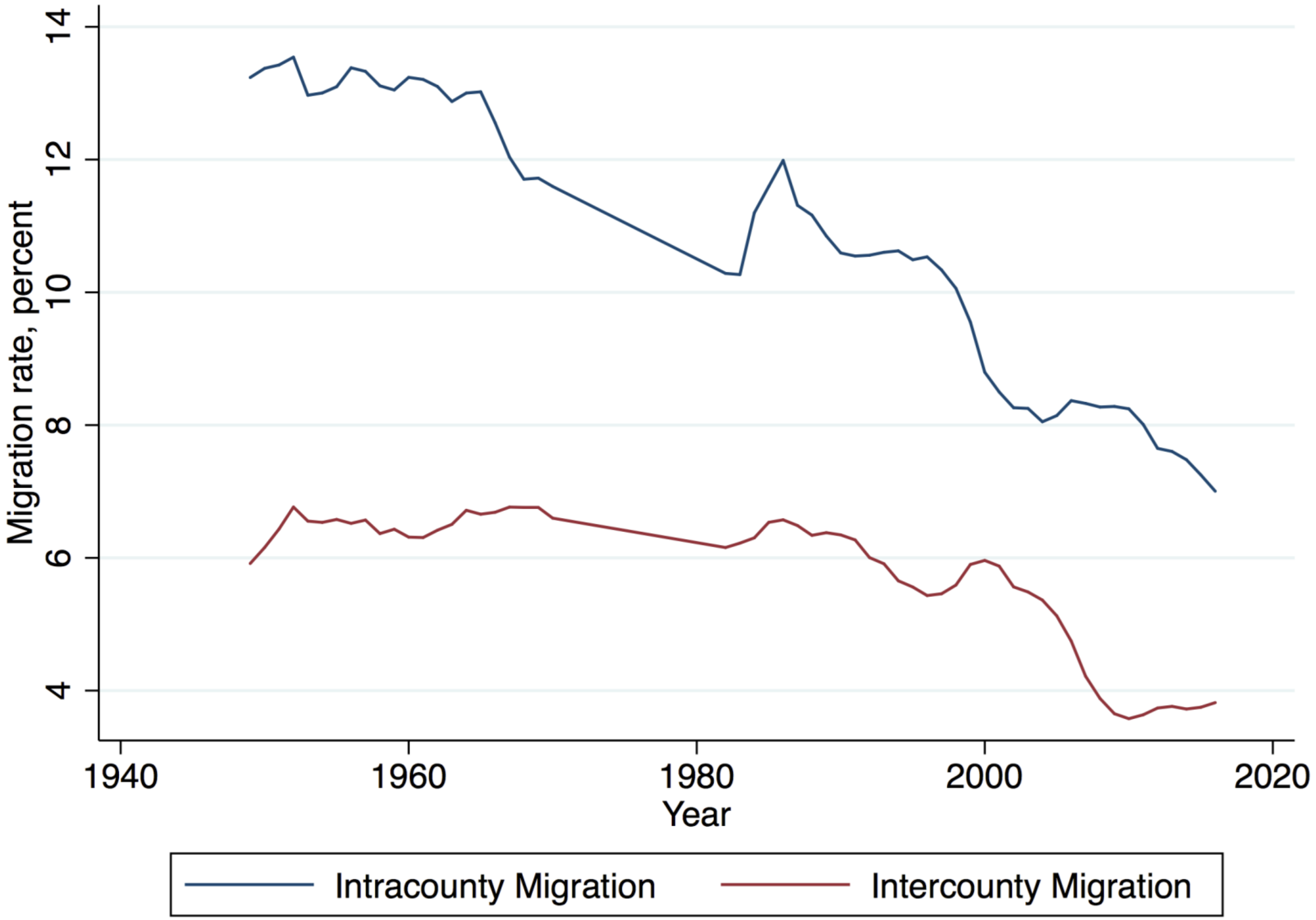
Yelp Coverage of Restaurants in 2015



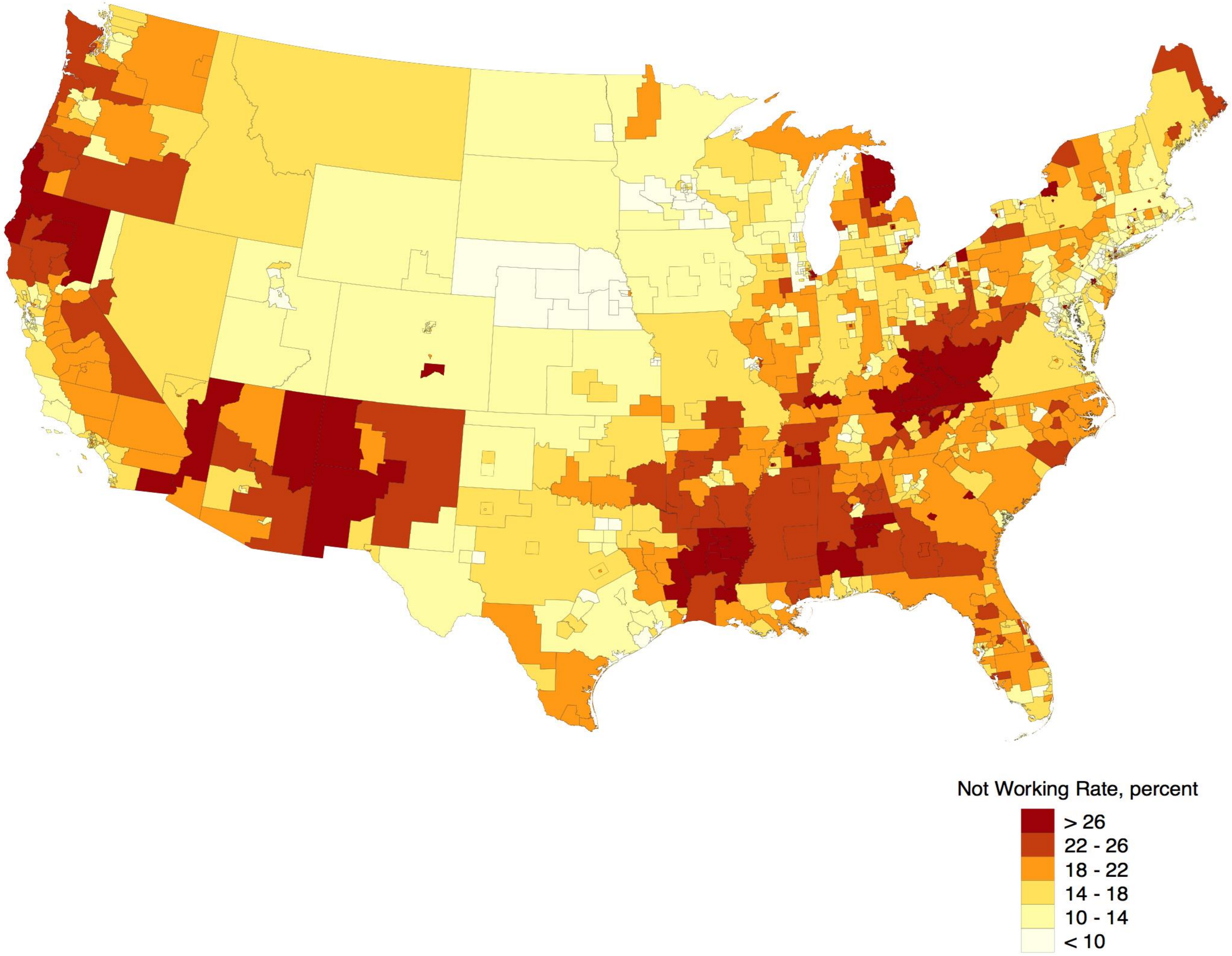


log(Ratio of Yelp restaurants to CBP restaurants)
.2
.1
0
-.1
-.2
0
2
4
6
8
10
log(Population per sq. mi.)

Can technology help explain the decline in migration?



Service Employment and the Geography of Jobless America: Prime Aged Men 2015



Technological and Urban Sharing: Zipcar and Airbnb

Photo by Mario Roberto Duran Ortiz

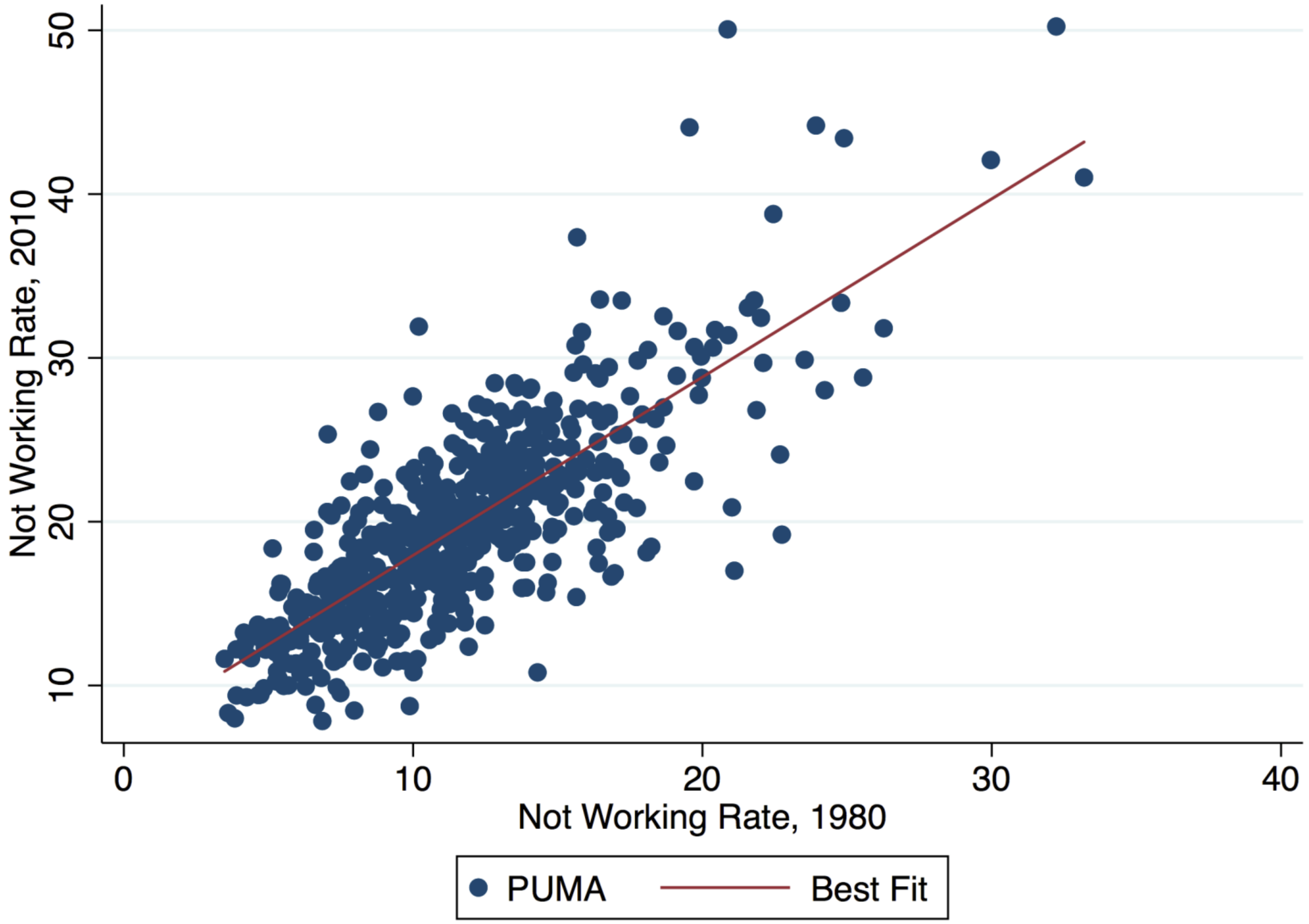
Photo by Ritusaheb

Uber in the 1970s?

What Does the Public Sector Need?

- Employment in less skilled cities
- Upward Mobility in all cities (from Chetty et al. data)
- More affordable housing in high skill areas
- What needs to change for technology to do better at solving these problems?
- What can technology deliver? Measurement.
- Measurement helps but it does not fix the mega-problems.
- I'm going to focus on three measurement problems: (1) potholes, (2) gentrification and (3) neighborhood streetscapes.

Persistence of not working rates



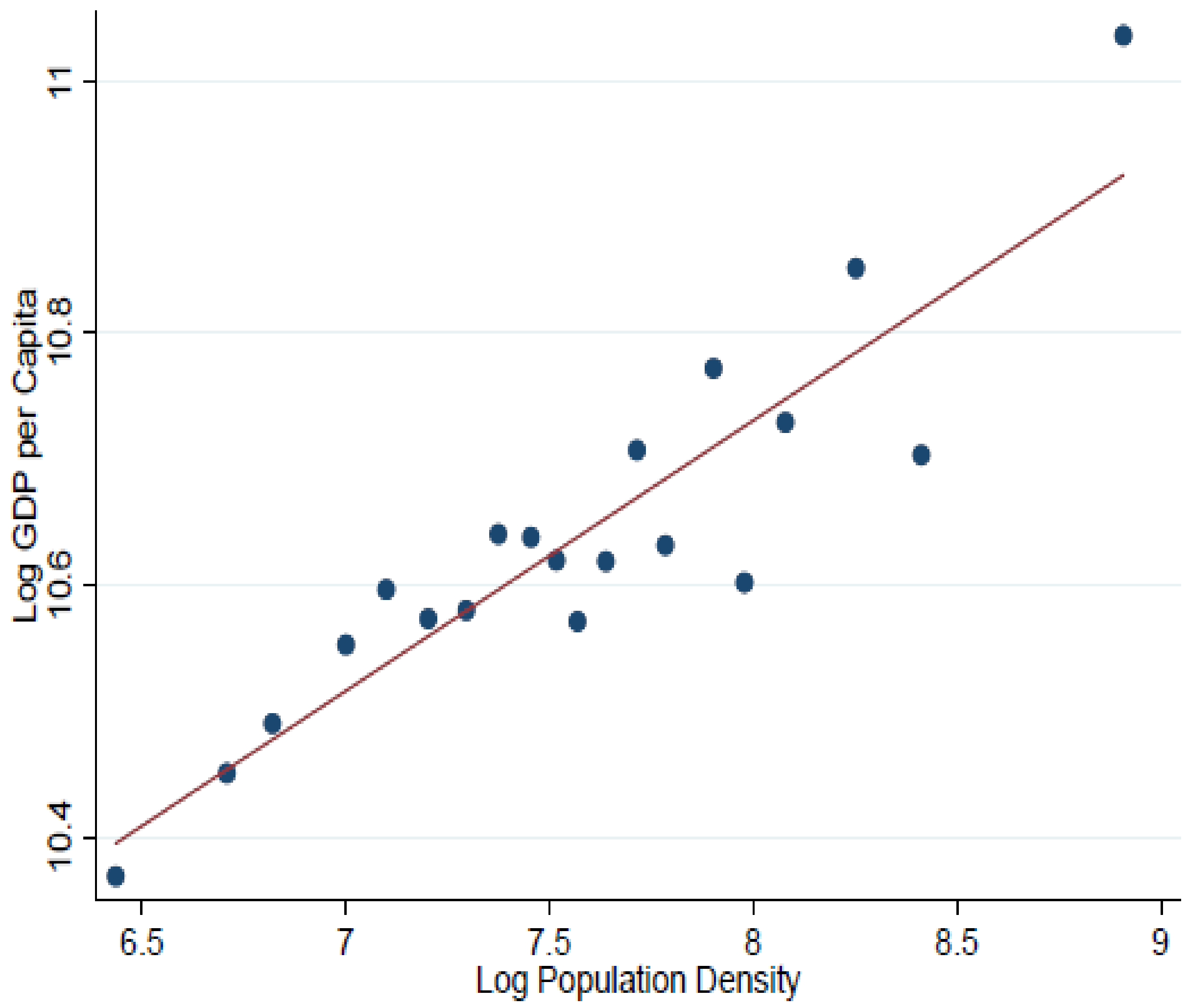


FIGURE 1. RELATIONSHIP BETWEEN DENSITY AND PER CAPITA GDP

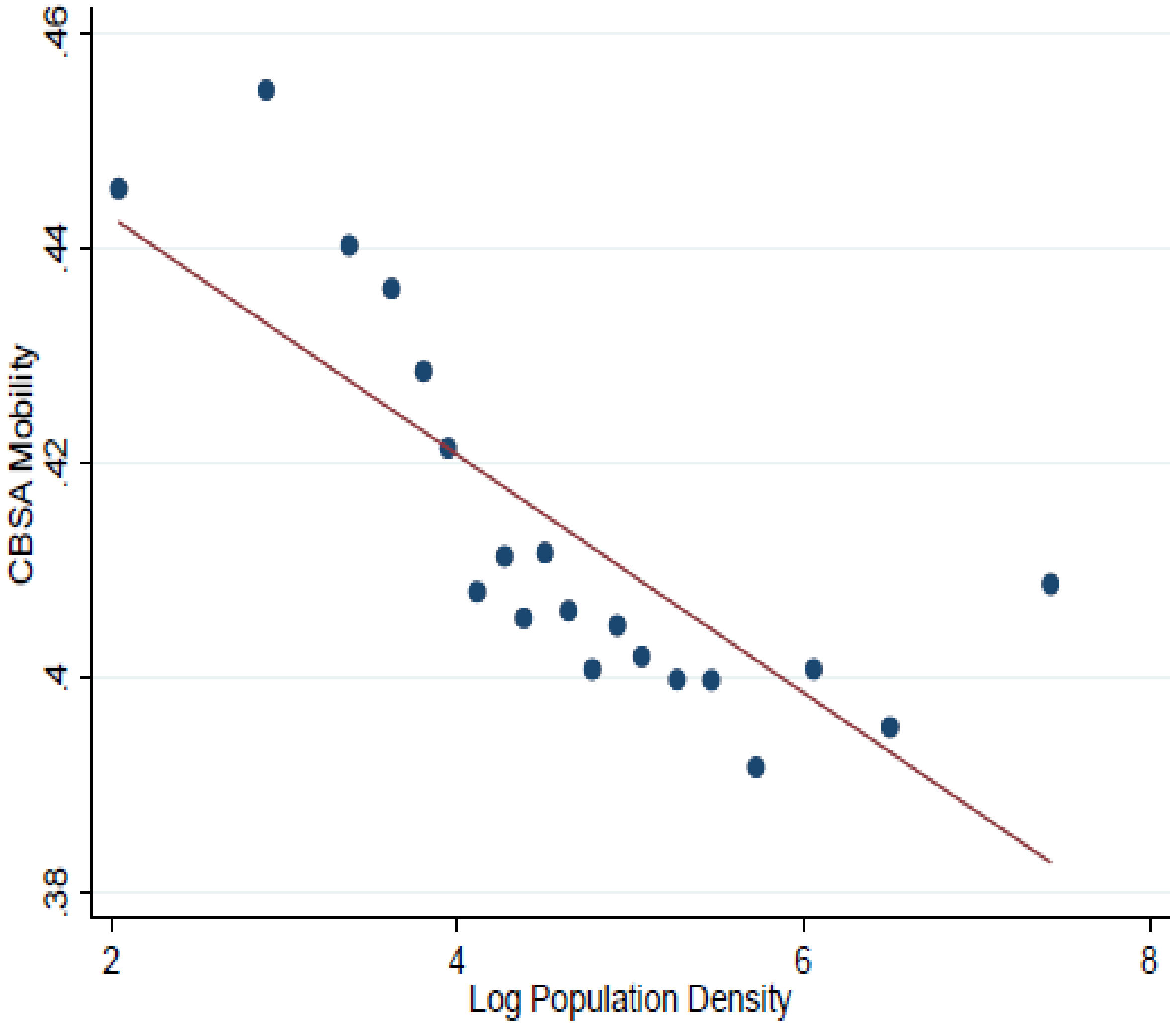


FIGURE 3. RELATIONSHIP BETWEEN DENSITY AND METRO AREA MOBILITY

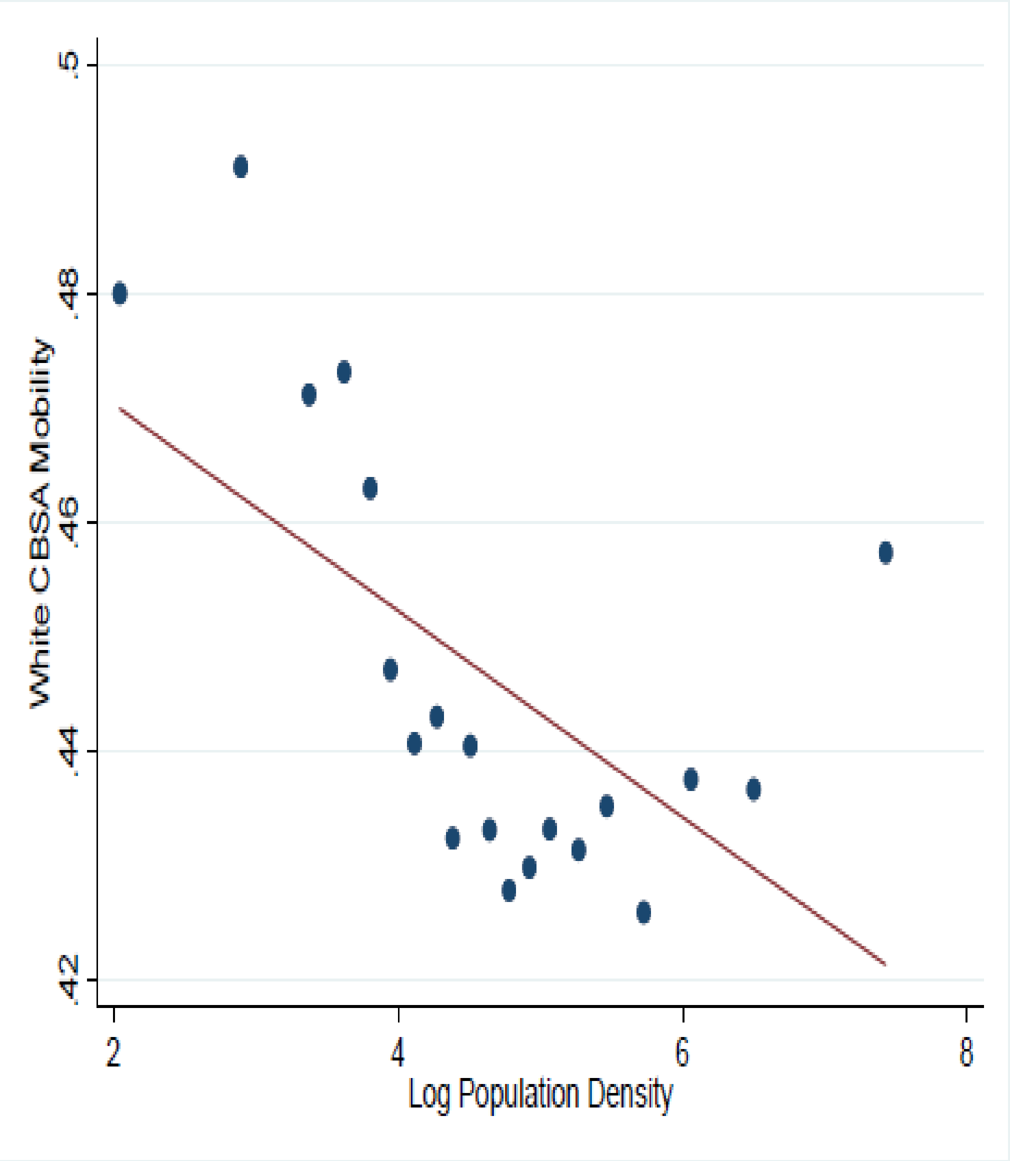


FIGURE 3a. RELATIONSHIP BETWEEN DENSITY AND WHITE METRO AREA MOBILITY

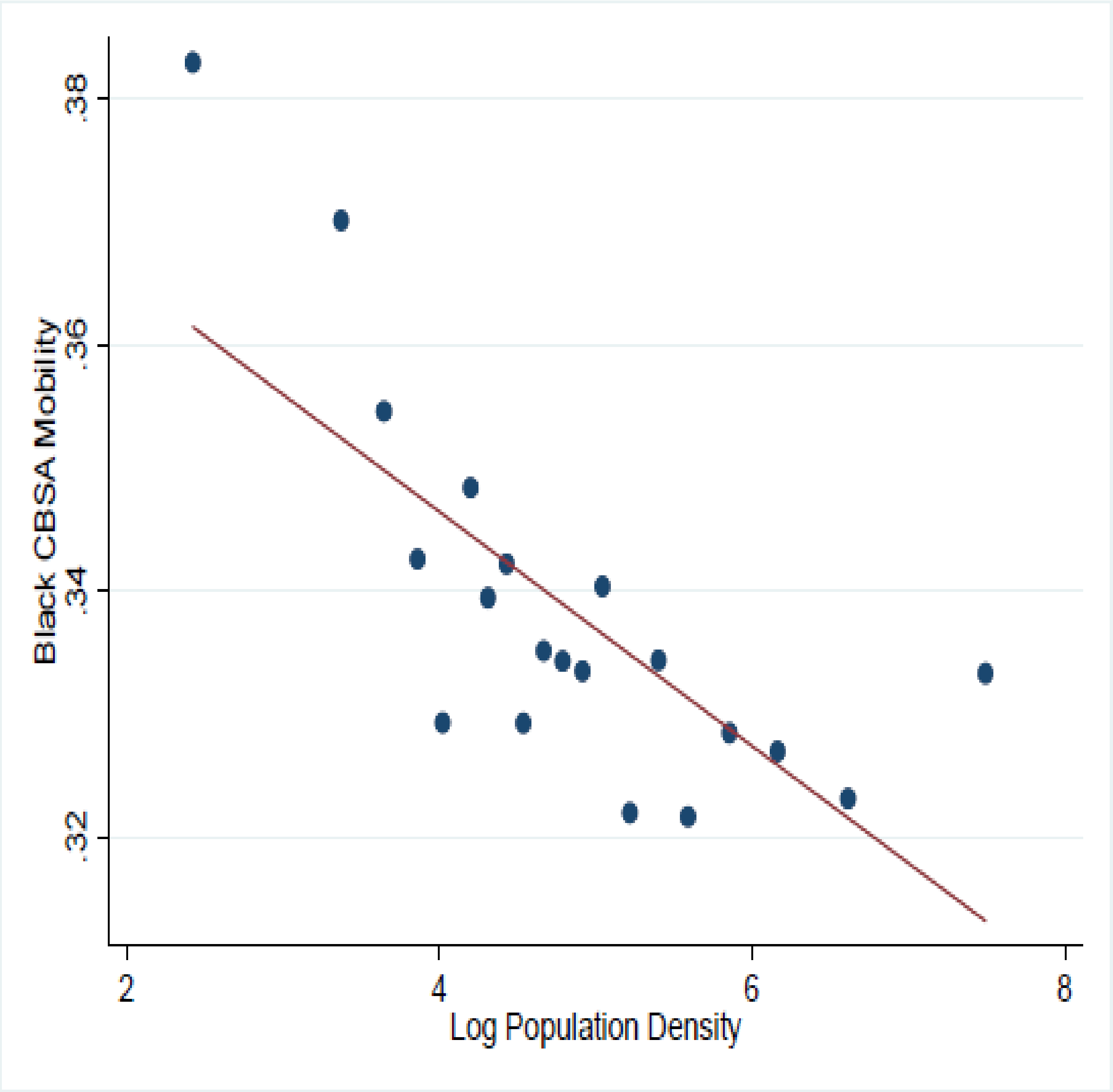


FIGURE 3b. RELATIONSHIP BETWEEN DENSITY AND BLACK METRO AREA MOBILITY

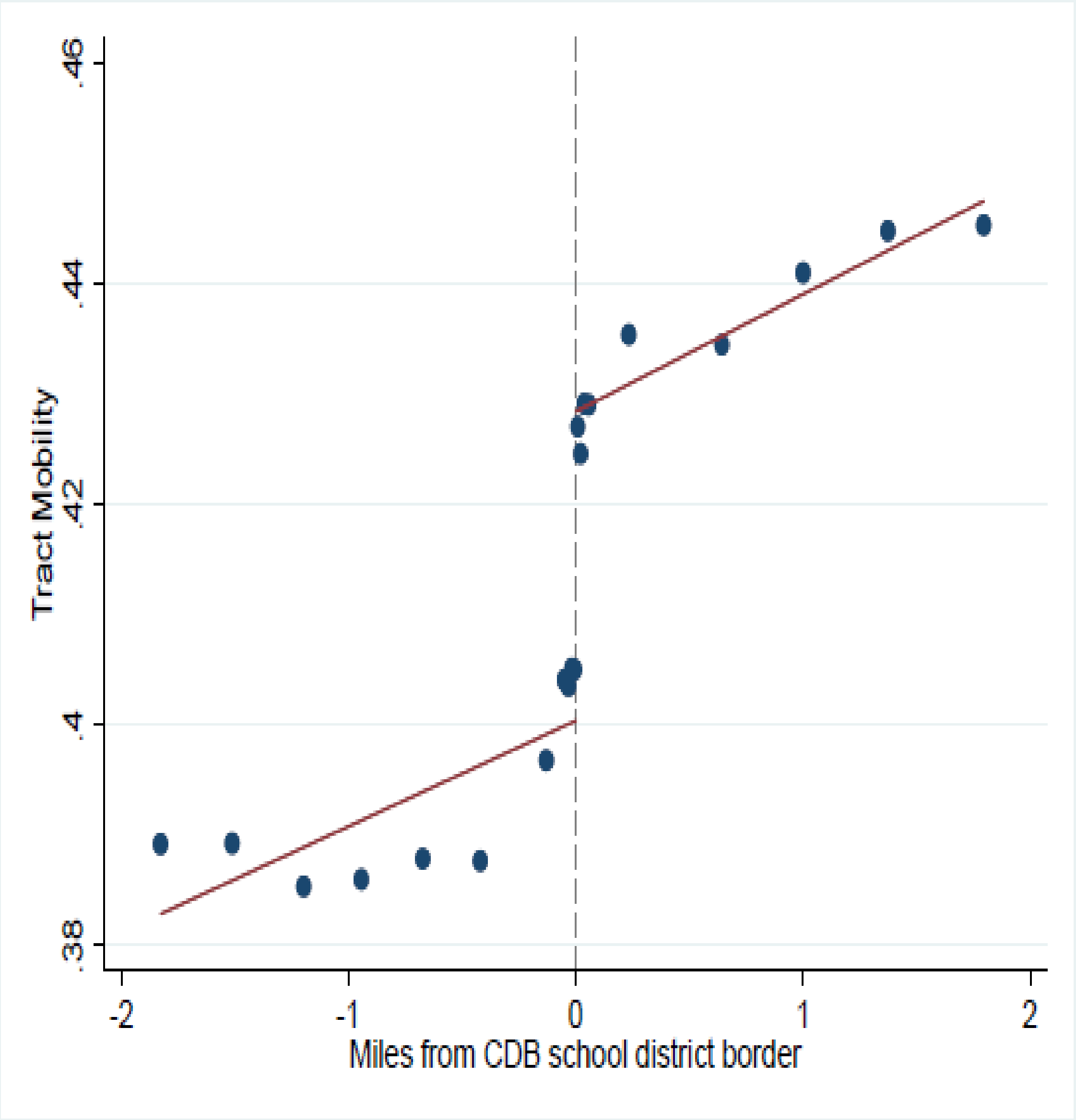
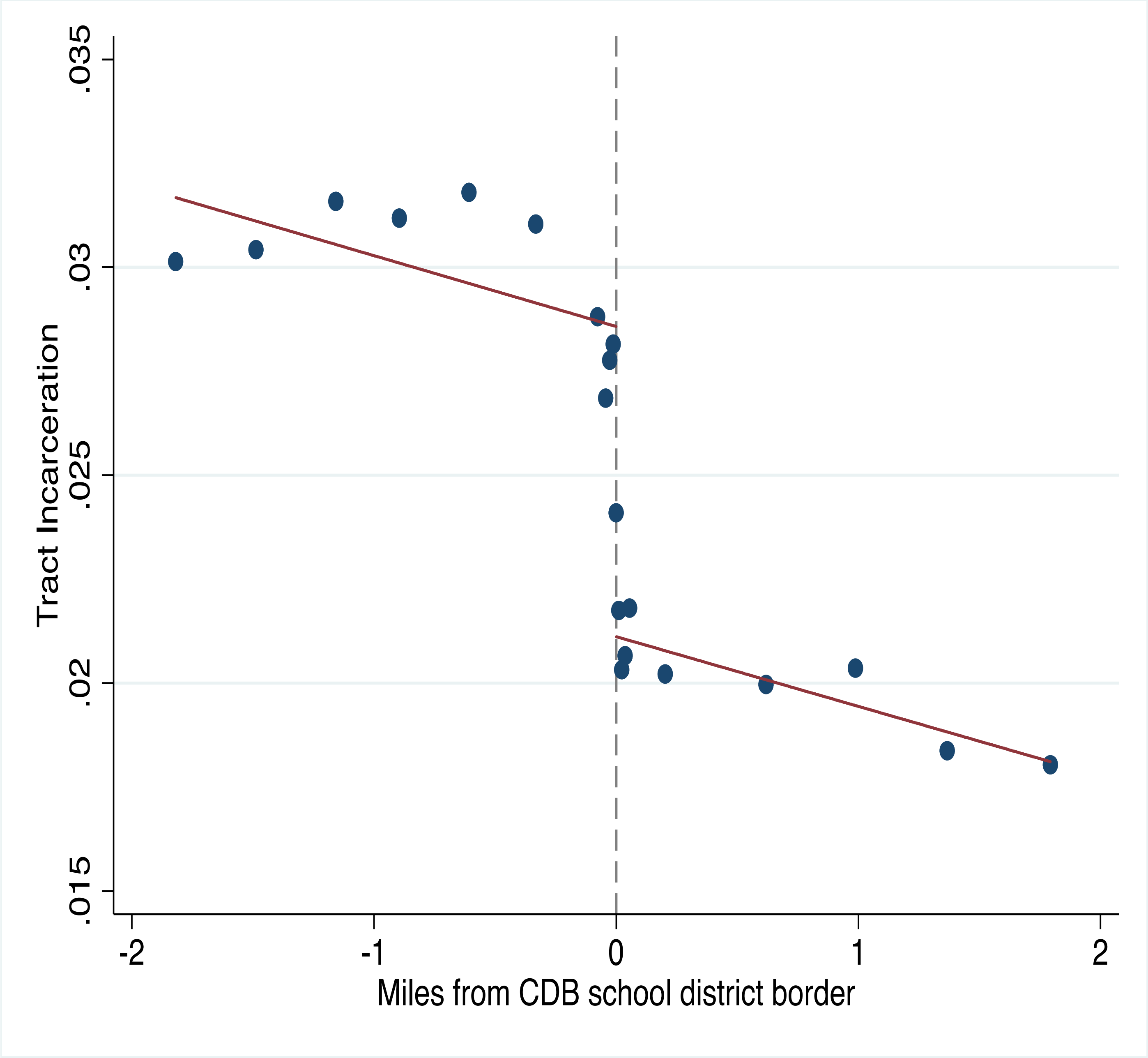


FIGURE 6. MOBILITY AT THE BORDER OF A CENTRAL CITY SCHOOL DISTRICT



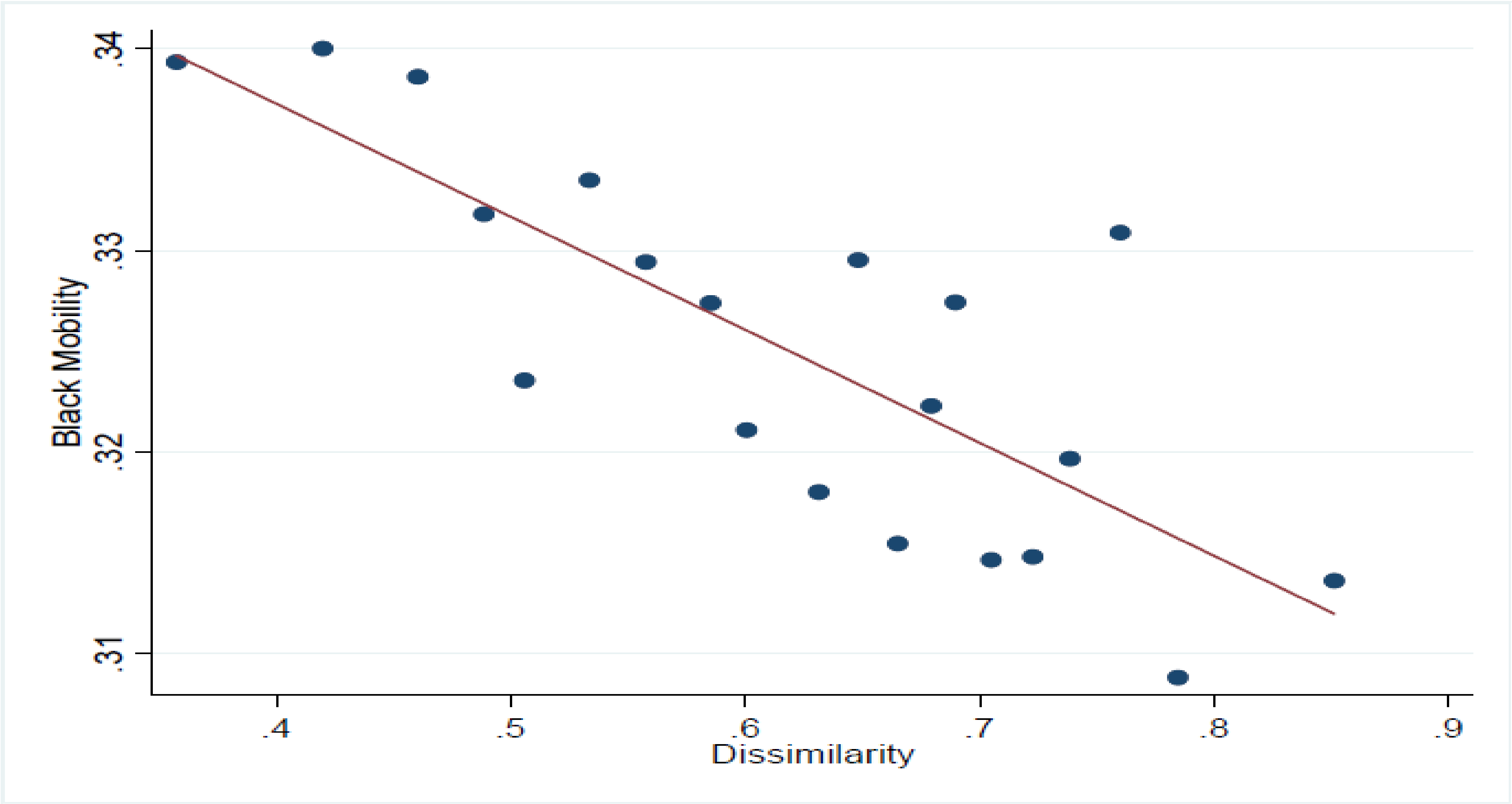
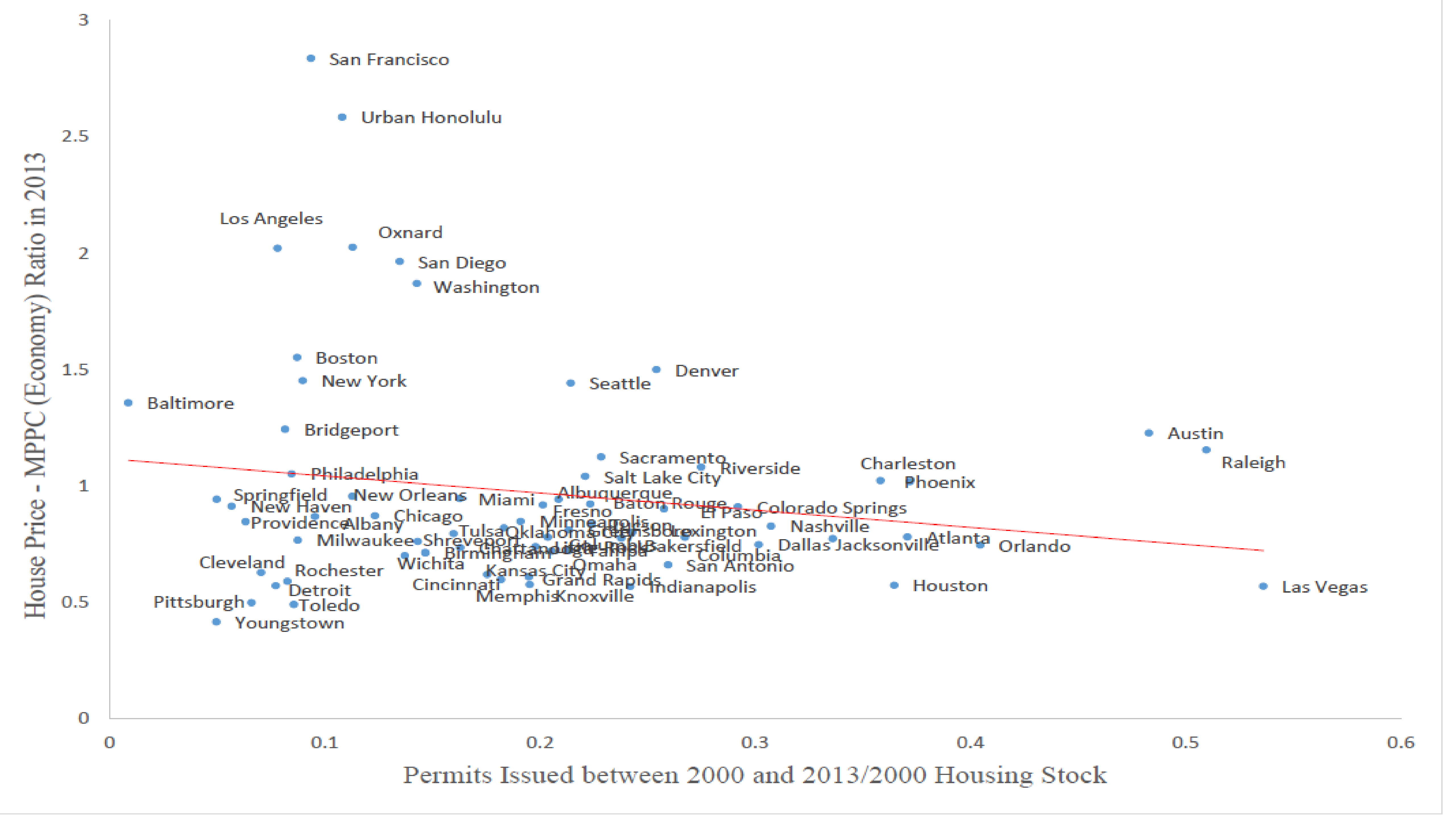


FIGURE 8. RELATIONSHIP BETWEEN SEGREGATION AND BLACK MOBILITY



House Price - MPPC (Economy) Ratio in 2013
Permits Issued between 2000 and 2013/2000 Housing Stock
3
2.5
2
1.5
1
0.5
0
0
0.1
0.2
0.3
0.4
0.5
0.6
San Francisco
Urban Honolulu
Los Angeles
Oxnard
San Diego
Washington
Boston
New York
Baltimore
Bridgeport
Seattle
Denver
Austin
Raleigh
Sacramento
Riverside
Salt Lake City
Charleston
Phoenix
Philadelphia
Springfield
New Haven
New Orleans
Miami
Albuquerque
Baton Rouge
Colorado Springs
El Paso
Fresno
Chicago
Providence
Albany
Tulsa
Lexington
Nashville
Milwaukee
Shreveport
Bakersfield
Dallas
Jacksonville
Atlanta
Orlando
Columbia
Cleveland
Rochester
Wichita
Omaha
San Antonio
Kansas City
Grand Rapids
Cincinnati
Detroit
Indianapolis
Houston
Las Vegas
Memphis
Knoxville
Pittsburgh
Toledo
Youngstown

Improving Understanding through Measurement

Surveys & Records

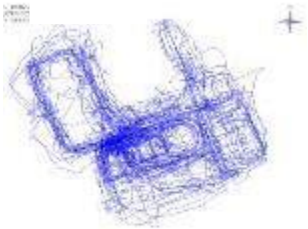
United States Census Bureau

Field Surveys

New Sources

Human Activity

Cellphone Records



Mobility Data

Social Networks

Built Environment

Street-level Imagery

Aerial Imagery

Satellite Imagery

Nowcasting Gentrification (joint with Mike Luca and other co-authors)

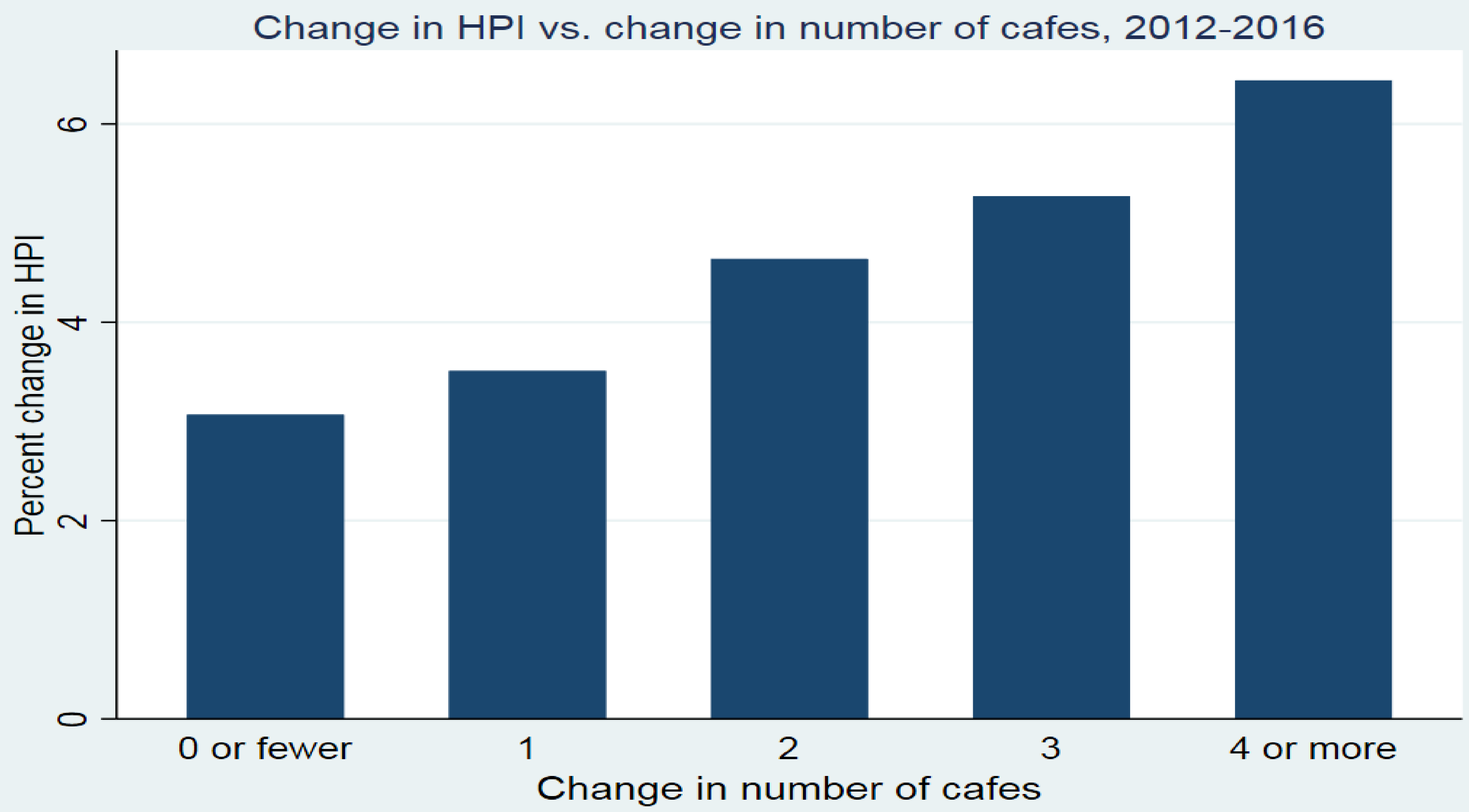
- Cities are wracked with the agonies of success– but data on gentrification often appears with a lag.
- Can Yelp nowcast housing price increases, demographic change and the physical change of each neighborhood?
  - We do demographic change for NYC and a few other large cities.
- This also creates a snapshot of what gentrification looks like.

	(1)	(2)	(3)
	% Change in HPI	% Change in HPI	% Change in HPI
Yelp Starbucks Growth (lag1)	0.482***		0.291***
	(0.087)		(0.079)
Yelp Starbucks Growth (lag2)	0.260***		0.155*
	(0.070)		(0.066)
% Change in HPI (lag1)		0.324***	0.323***
		(0.013)	(0.013)
% Change in HPI (lag2)		0.076***	0.076***
		(0.011)	(0.011)
Constant	-0.890***	0.900***	0.835***
	(0.060)	(0.065)	(0.068)
Year FE	Yes	Yes	Yes
Observations	24865	24819	24819
Adjusted R^2	0.239	0.332	0.333

All regressions include a full set of calendar year dummies and cluster standard errors at the ZIP Code level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

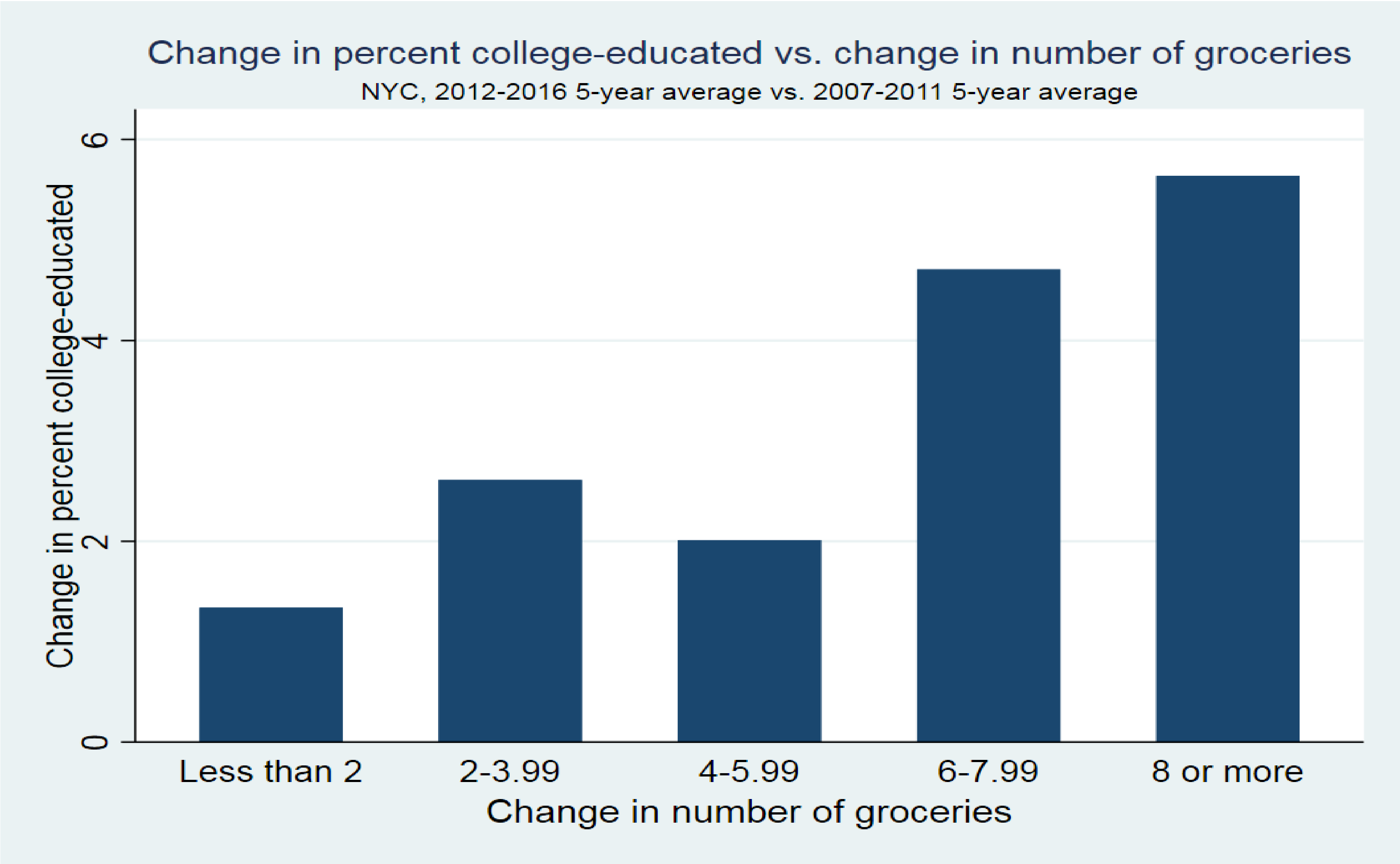
	(1)	(2)	(3)
	Yelp Starbucks Growth	Yelp Starbucks Growth	Yelp Starbucks Growth
% Change in HPI (lag1)	0.002**		0.002**
	(0.001)		(0.001)
% Change in HPI (lag2)	0.001		0.001
	(0.001)		(0.001)
Yelp Starbucks Growth (lag1)		-0.007	-0.008
		(0.011)	(0.011)
Yelp Starbucks Growth (lag2)		0.004	0.003
		(0.010)	(0.010)
Constant	0.135***	0.126***	0.135***
	(0.006)	(0.006)	(0.006)
Year FE	Yes	Yes	Yes
Observations	24907	24907	24907
Adjusted R^2	0.026	0.026	0.026

All regressions include a full set of calendar year dummies and cluster standard errors at the ZIP Code level. * p<0.10, ** p<0.05, *** p<0.01.



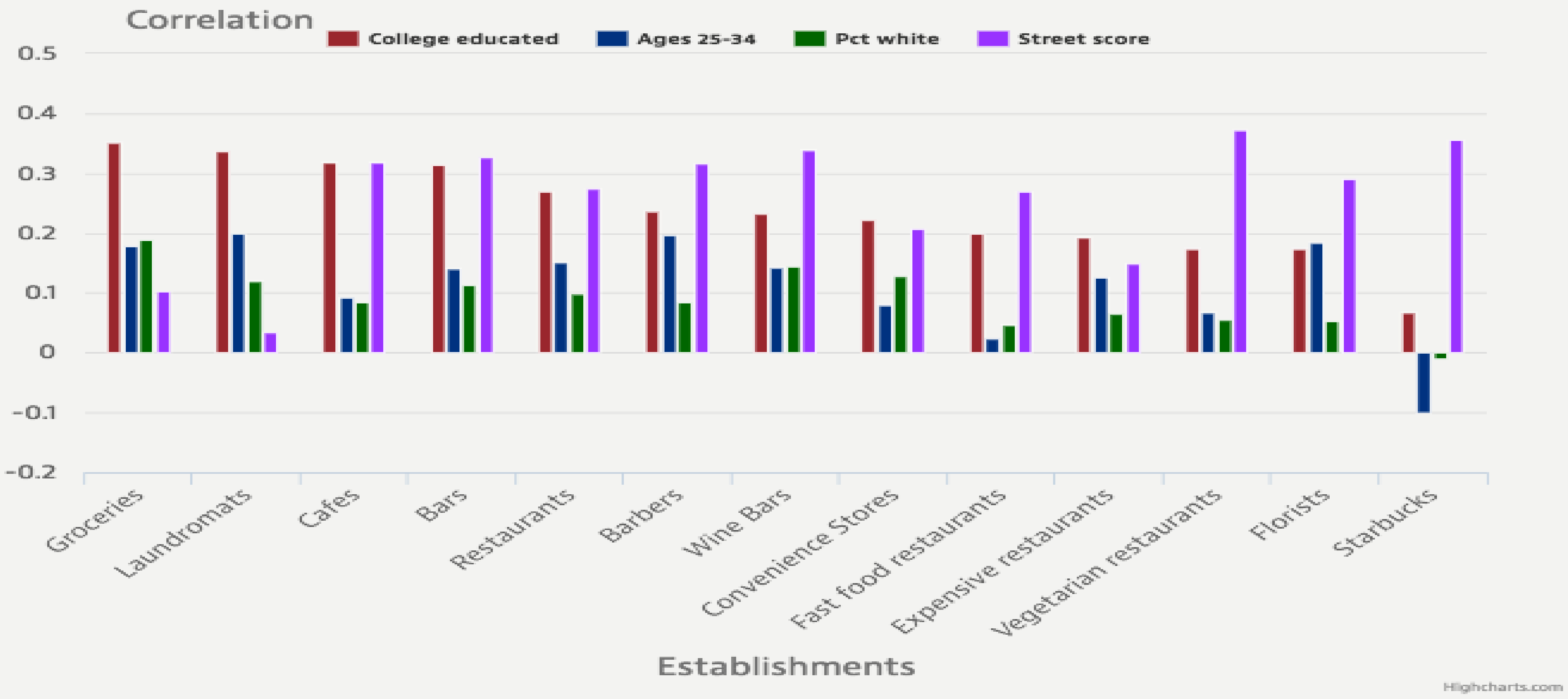
Change in HPI vs. change in number of cafes, 2012-2016
Percent change in HPI
0
2
4
6
0 or fewer
1
2
3
4 or more
Change in number of cafes

Nowcasting Demographics



Signs of gentrification

The growth of certain types of businesses in a neighborhood can be early signs of gentrification on the horizon. Below are how increases in certain types of establishments were correlated with demographic changes and perceptions of safety in New York City.

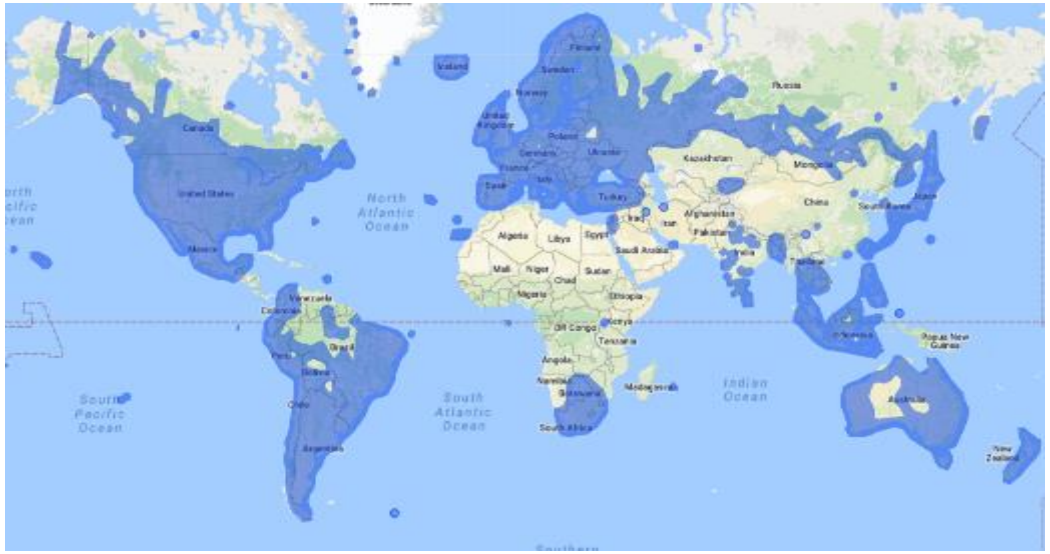


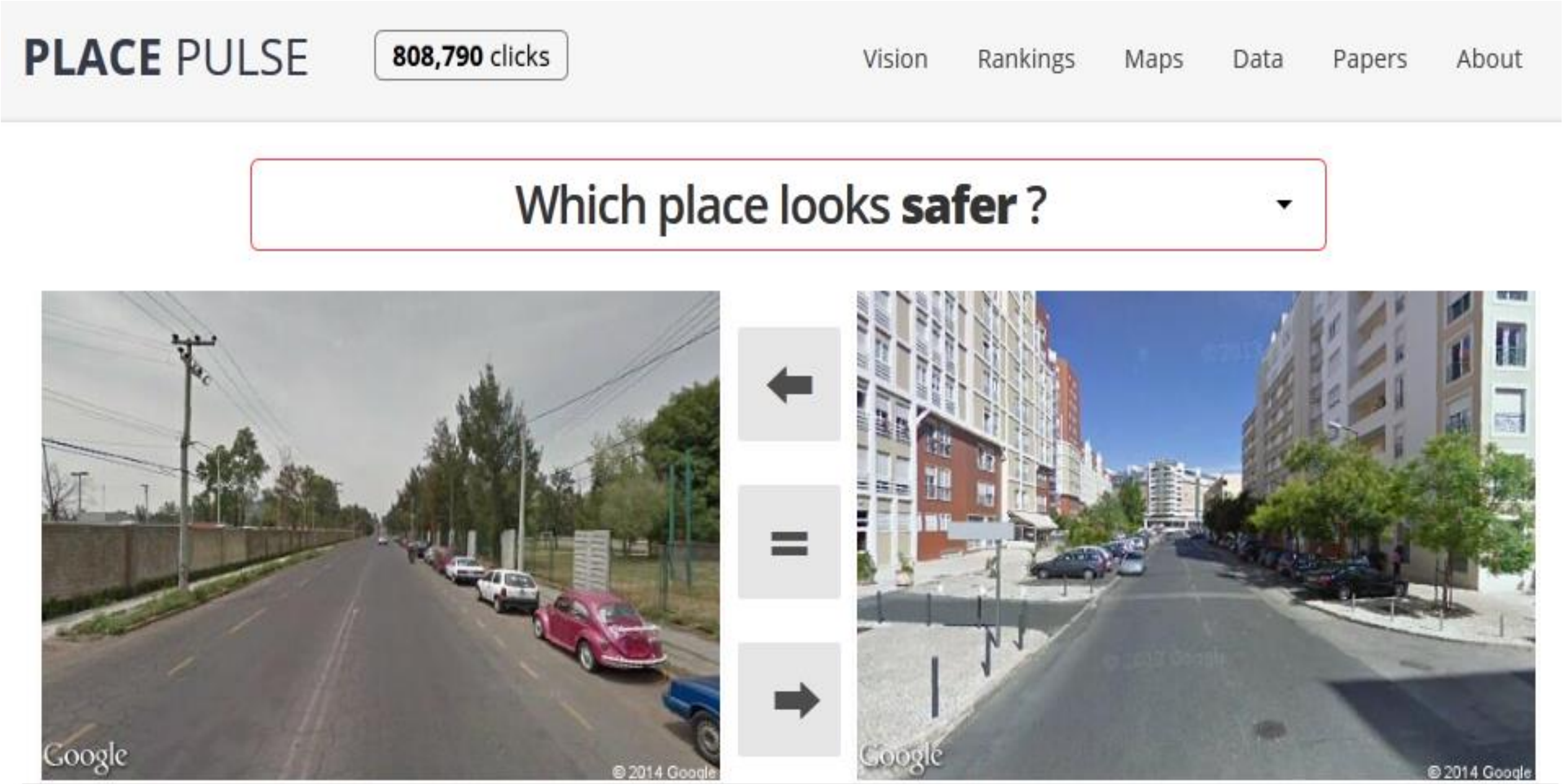
Source: author data

Boston, Chicago, LA, SF

	Change in percent of college educated	Change in percent of ages 25 to 34	Change in percent white	Obs.
Change in the number of florists	0.322***	0.219**	0.124	146
	(0.00007)	(0.008)	(0.135)	
Change in the number of vegetarian restaurants	0.227**	0.052	-0.139	131
	(0.009)	(0.556)	(0.114)	
Change in the number of cafes	0.221**	0.143	-0.012	161
	(0.005)	(0.071)	(0.880)	
Change in the number of restaurants	0.217**	0.110	0.054	165
	(0.005)	(0.161)	(0.487)	
Change in the number of bars	0.202*	0.170*	0.041	159
	(0.011)	(0.032)	(0.612)	
Change in the number of winebars	0.196*	0.101	-0.015	130
	(0.025)	(0.255)	(0.867)	
Change in the number of barbers	0.156	0.109	0.029	155
	(0.052)	(0.178)	(0.723)	
Change in the number of convenience stores	0.102	0.003	0.069	154
	(0.206)	(0.967)	(0.392)	
Change in the number of restaurants opened	0.091	-0.011	-0.035	165
	(0.244)	(0.886)	(0.654)	
Change in the number of Starbucks	0.090	-0.041	-0.013	125
	(0.318)	(0.646)	(0.884)	
Change in the number of groceries	0.039	0.019	0.008	163
	(0.621)	(0.813)	(0.917)	
Change in the number of fastfood	0.039	-0.023	0.117	159
	(0.623)	(0.773)	(0.141)	

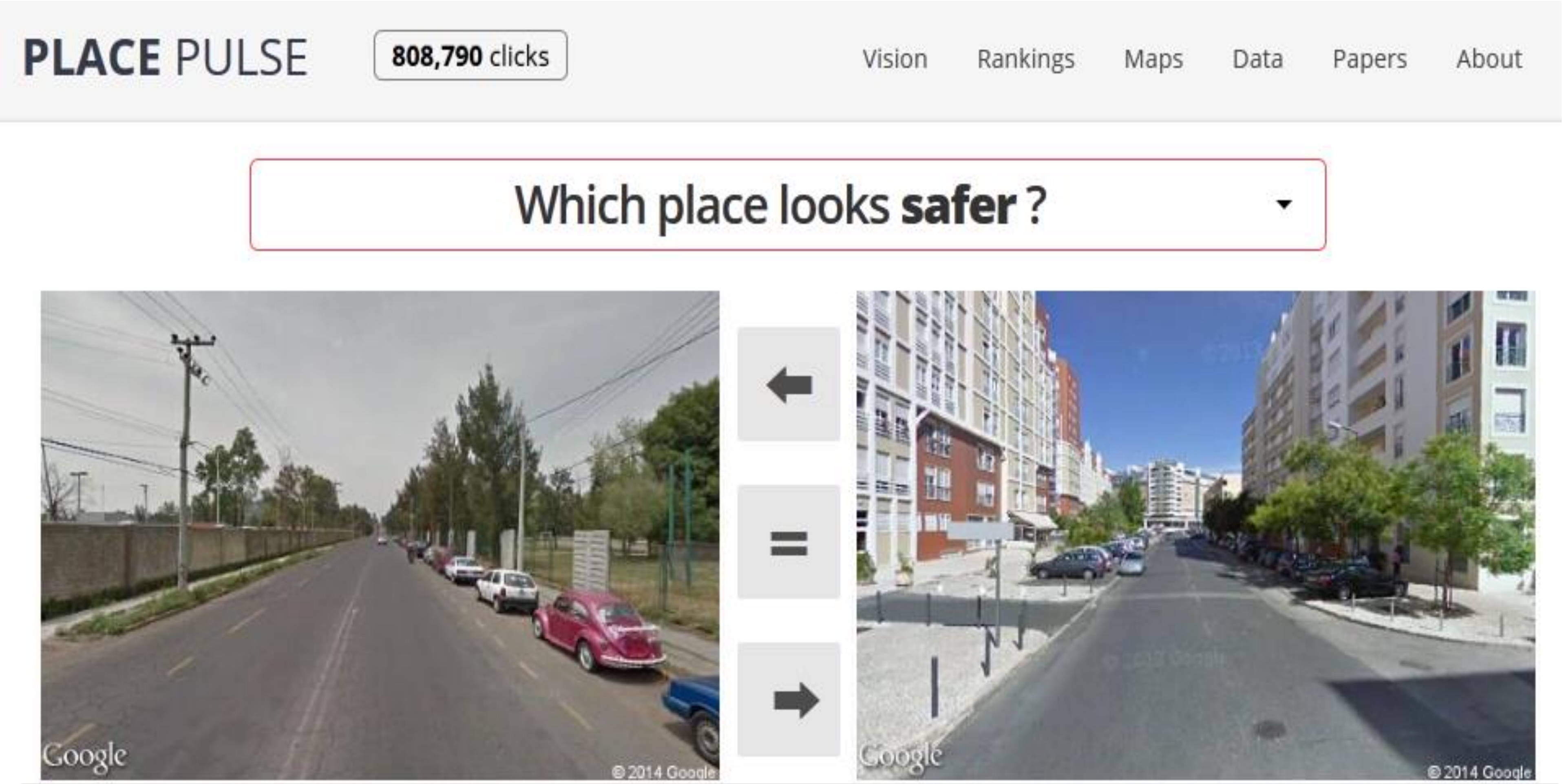
Google Street View: Street-level Imagery (joint with Nikhil Naik and co-authors)





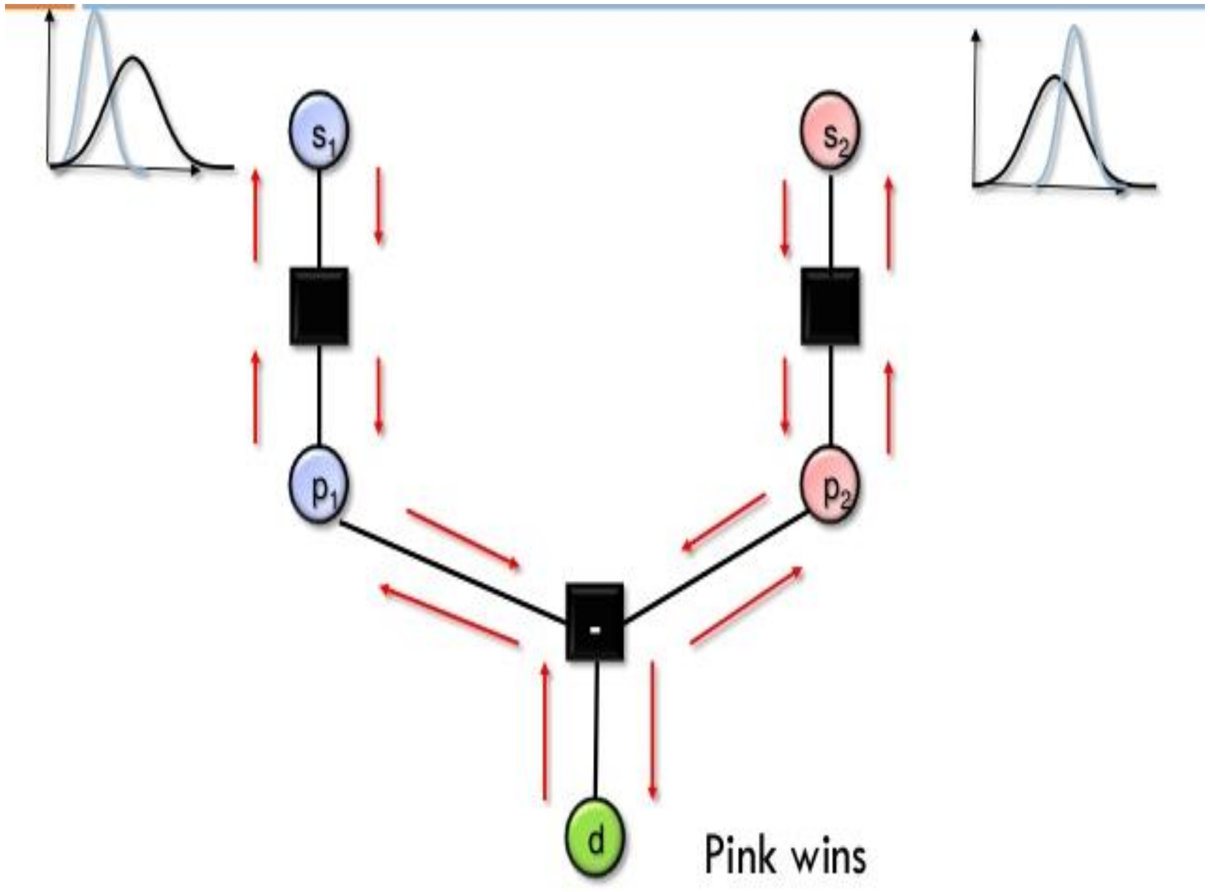
pulse.media.mit.edu
Salesses, Schechtner, and Hidalgo (2013)

Crowdsourced urban appearance survey



4,000 Images From New York, Boston, Linz and Salzburg
More than **8,000** Unique Participants from **91** countries
More than **200,000** Pairwise Comparisons

Converting Pairwise Comparisons to Ranked Scores



MIcrosoft Trueskill [Herbrich et al.2007]

#Total Street blocks
~1,000,000

#Sampled Street blocks
1,700

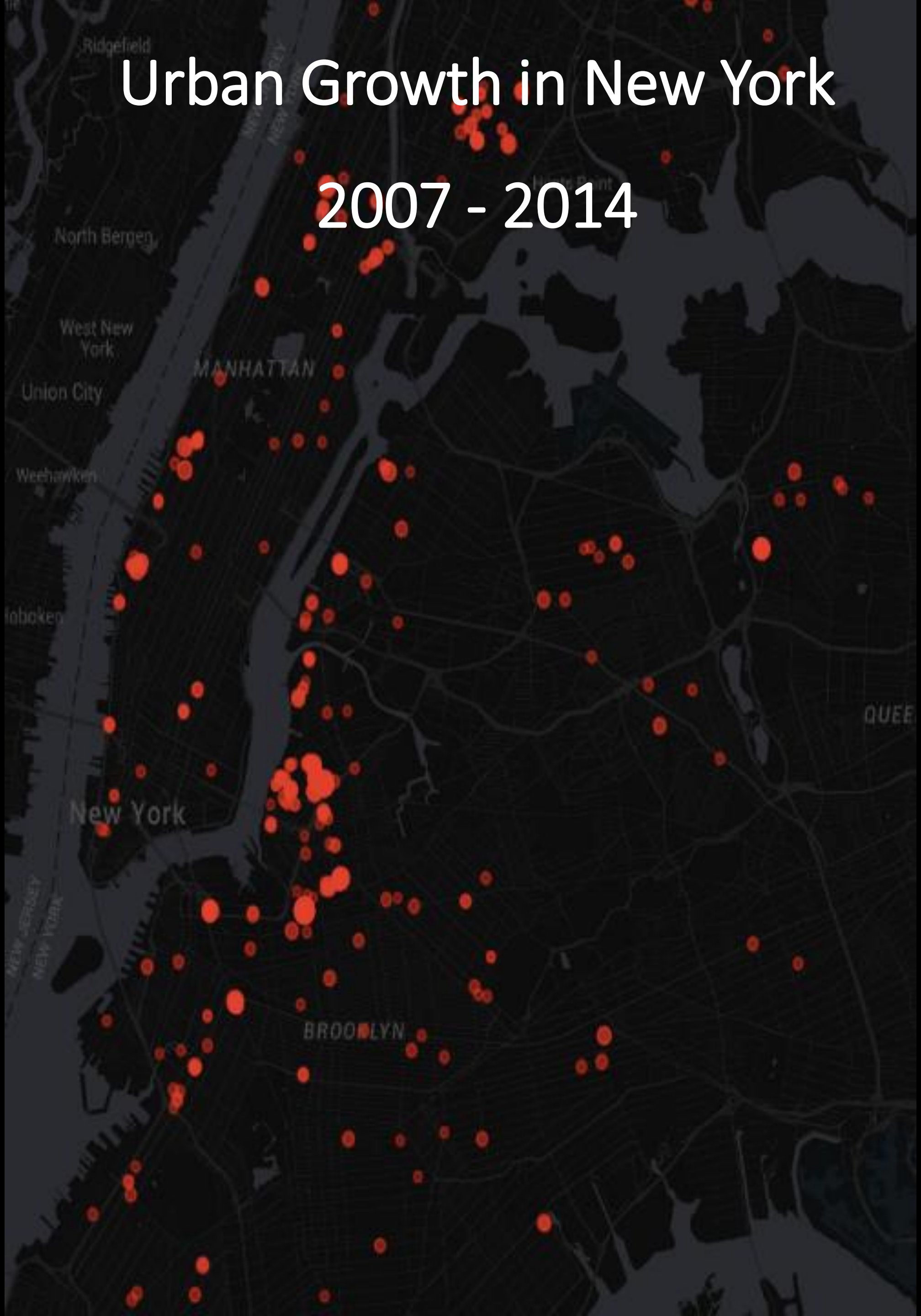
This is Nikhil Naik's big innovation

Example Images – Low Streetscore

Example Images – High Streetscore

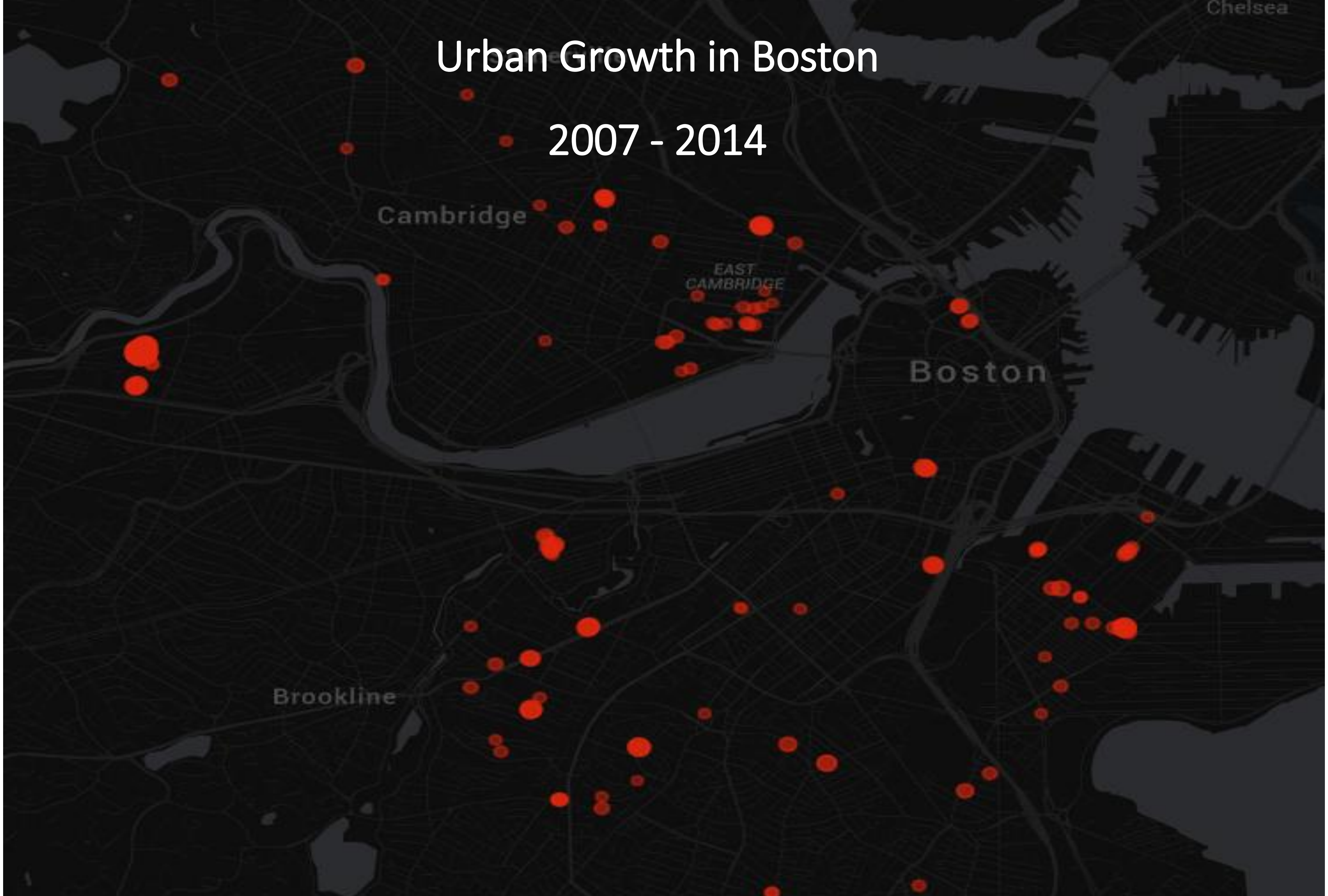
Urban Growth in New York

2007 - 2014



Urban Growth in Boston

2007 - 2014



Predicting Income from Imagery

Proof-of-concept experiment for the U.S.

Median Income of the Census Block group: $60,000

Training Examples

Computer Vision

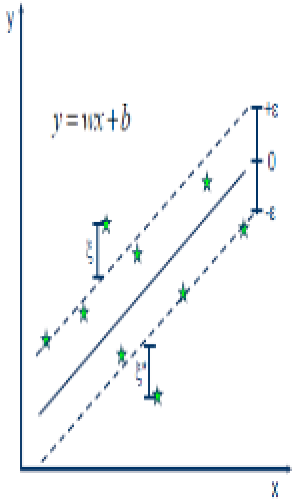


Image Features Derived from Pixels

Predicted Income

$54,000


New York City
R^2 = 0.81

Boston
R^2 = 0.86

Housing Price Evaluation (joint with Naik and Kincaid)

- Obvious interest in evaluation for property tax assessors in the U.S. and elsewhere.
- Property values are also interesting – but often because we want to place a dollar value on local public goods.
- Visual recognition can help this if we have an independent price measure (in this case, the visuals become the hedonic attribute).
- Predicted price may or may not be useful as outcomes.

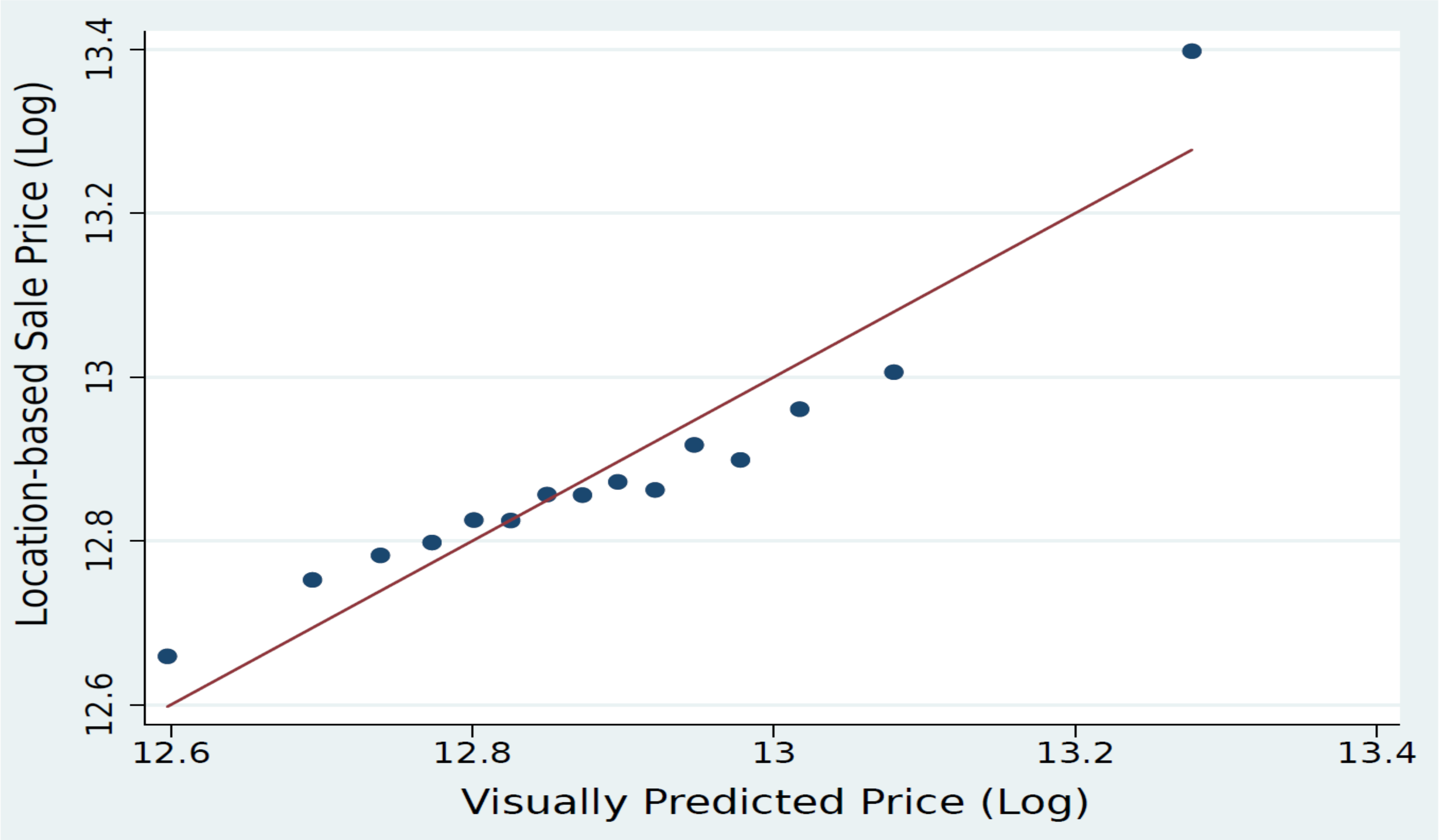
Predicting Property Prices from Imagery

Ongoing Work: Boston Property Prices Dataset

Glaeser, Kincaid, Naik

- 47918 Single Family Homes, 25723 condominiums from Greater Boston area.
- Sold between 1986-2016
- Includes data on both physical characteristics, and subjective measures of quality from city assessor's office.
- Includes "Streetscore" measures for all properties, evaluated from images captured between 2009 and 2014.

Valuing Housing using Streetview Images



A Policy Question

- The value of aesthetic appeal to the owner has little or no policy relevance whatsoever.
- The value of aesthetic appeal to the neighbor matters for many policies.
  - Zoning, historic preservation, local style based policies are justified based on aesthetic externalities.
- The problem is omitted area characteristics (nice homes mean rich neighbors).

	(1) 4 NN (Images)	(2) 4 NN (Images) Same Street	(3) 4 NN (Images) Different Street	(4) 4 NN (Assessor)	(5) 4 NN (Assessor) Same Street	(6) 4 NN (Assessor) Different Street
First-stage F-stat	533.192	46.595	158.103	77.725	82.25	34.44
2SLS	0.387***	0.399***	0.274***	0.560***	0.607***	0.309
	(0.012)	(0.047)	(0.071)	(0.062)	(0.033)	(0.228)
OLS	0.725***	0.734***	0.755***	0.821***	0.807***	0.948**
	(0.016)	(0.071)	(0.137)	(0.037)	(0.104)	(0.239)
First Stage; Basic Features	Yes	Yes	Yes	Yes	Yes	Yes
First Stage: Neighbor Exterior Image Features	Yes	Yes	Yes	No	No	No
First Stage: Neighbor Exterior Condition Rating	No	No	No	Yes	Yes	Yes
Observations	1546	765	765	1546	765	765

Notes: This table reports the 2SLS estimates of the log sale price, residualized on location. The endogenous variable is average assessed value of 4 neighbors from 2014, instrumented with average features of neighbor's street view image features in columns (1–3) and average features of neighbor's exterior condition, building style, structure class, and exterior finish in columns (4–6). Additional controls are included as shown. Standard errors are clustered by neighborhood.

$***p < 0.01, **p < 0.05, *p < 0.1$

Visuals as an Outcome

- Sometimes we have direct measures of home investment, but visuals provide us with a means of assessing investment.
- With this we can test hypotheses about how incentives impact home investment.
- Some have claimed that the foreclosure effect is due to destruction of the physical home.
- We take Boston homes that were foreclosure from 2007-2009.
- We match with 5 nearest neighbors using a propensity score based either on initial visuals or initial visuals plus other characteristics (including location).

Visual Index Growth 2009-2016
-.05
0
.05
.1
.15
11
12
13
14
15
Log Sale Price 2009

Matching Model	Treatment (#Samples)	Control (#Samples)	Treatment (After–Before)	Control (After–Before)	Diff in Diff	Standard Error	Z-score
(1) Effect of Remodeling on Visually-predicted Price							
Vis. Index	1025	5576	0.017	-0.000	0.030***	0.011	2.75
Vis. Index + Basic Features					0.041***	0.001	3.47
(2) Effect of Remodeling on Visually-Predicted Price (Single Family Homes)							
Vis. Index	424	2073	0.046	0.006	0.024	0.018	1.35
Vis. Index + Basic Features					0.049***	0.019	2.60
(3) Effect of Foreclosures on Visually-predicted Price							
Vis. Index	1256	3601	-0.018	0.003	-0.023***	0.008	-2.81
Vis. Index + Basic Features					-0.030**	0.009	-3.16
(4) Effect of Foreclosures on Visually-predicted Price (Unremodeled Homes)							
Vis. Index	890	2788	-0.022	0.004	-0.024***	0.009	-2.60
Vis. Index + Basic Features					-0.035***	0.011	-3.18
(5) Effect of Foreclosures on Visually-predicted Price (Single Family Homes)							
Vis. Index	363	1987	-0.021	0.015	-0.032**	0.014	-2.22
Vis. Index + Basic Features					-0.040***	0.016	-2.46
(6) Effect of Foreclosures on Visually-predicted Price (Single Family Unremodeled Homes)							
Vis. Index	281	1537	-0.021	0.017	-0.038***	0.015	-2.49
Vis. Index + Basic Features					-0.047***	0.019	-2.36

es: All price variables are in log dollars, residualized on location. In the Vis. Index matching model, a propensi
e is constructed on the basis of a home's visually-predicted log price (based on Street View features). In t
Index + Basic Features model, a neighborhood dummy, log living area, year built (normalized), and owr
ıpied flag is added to the set of covariates used for matching. The table reports the Abadie–Imbens standa

But this won’t solve the affordability crisis

- The flood of new data enables us to measure things that we never could before.
- In some cases (Opportunity Insights), the new data speaks directly to major urban problems, but even then it doesn’t always generate clear answers.
- In other cases (pothole and gentrification measurement), it provides at best a targeted spotlight.
- Yet if technology firms are going to be seen as friends of urban America, it makes sense to use a little of their genius to actually think about how to solve the big urban problems (and ideally make money at the same time).