

A close-up photograph of a branch with several bright pink flowers and buds. The flowers are wet, with water droplets visible on their petals. The background is a blurred natural setting with green foliage and grey rocks.

# Comparing Administrative Data to ACS Estimates of Income and Wealth

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ACS Data Users Conference | May 14-15 | Washington, DC



# Unlocking the (Neon Green) Door to Gentrification

Architecture is often the first chapter in the story of neighborhood change.



By Emily Badger

May 3, 2019





# NBER WORKING PAPER SERIES

## DO PEOPLE SHAPE CITIES, OR DO CITIES SHAPE PEOPLE? THE CO-EVOLUTION OF PHYSICAL, SOCIAL, AND ECONOMIC CHANGE IN FIVE MAJOR U.S. CITIES

Nikhil Naik  
Scott Duke Kominers  
Ramesh Raskar  
Edward L. Glaeser  
César A. Hidalgo



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DOI: 10.1177/0003122414535774  
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### Divergent Pathways of Gentrification: Racial Inequality and the Social Order of Renewal in Chicago Neighborhoods

Jackelyn Hwang<sup>a</sup> and Robert J. Sampson<sup>a</sup>

#### Abstract

Gentrification has inspired considerable debate, but direct examination of its uneven evolution across time and space is rare. We address this gap by developing a conceptual framework on the social pathways of gentrification and introducing a method of systematic social observation using Google Street View to detect visible cues of neighborhood change. We argue that a durable racial hierarchy governs residential selection and, in turn, gentrifying neighborhoods. Integrating census data, police records, prior street-level observations, community surveys, proximity to amenities, and city budget data on capital investments, we find that the pace of gentrification in Chicago from 2007 to 2009 was negatively associated with the concentration of blacks and Latinos in neighborhoods that either showed signs of disinvestment in 1995. Racial composition has a threshold effect on gentrification: the pace of change in a neighborhood is slower if the concentration of blacks is below a threshold, but faster if it is above that threshold.

### What Google Street View tells us about income

We often drive cars around town to flaunt wealth or image. But a surprising source - Google Street View - reveals deeper connections between cars and inequality.

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Owning Your Time

Affording Your Life

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[www.bbc.com/capital/story/20180105-how-your-car-signals-your-income](http://www.bbc.com/capital/story/20180105-how-your-car-signals-your-income)



$$\textit{income} = f(\textit{wealth}, \textit{other factors})$$



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The most  
sensitive  
question  
on the ACS



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The most  
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Most people  
hold most  
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their homes



$$\textit{income} = f(\textit{wealth}, \textit{other factors})$$

The most  
sensitive  
question  
on the ACS

Most people  
hold most  
wealth in  
their homes

Home value is  
publicly available  
administrative  
data



Restricted-Use  
ACS Microdata



County  
Assessed Value





1940 1% PUMS  
household  
wages & salaries



1940 1% PUMS  
estimated  
home value

2017 1% PUMS  
household  
wages & salaries



2017 1% PUMS  
estimated  
home value



# 1940

Log(Family Earnings)

	Null Model	Value Model
intercept	6.303 *	4.274 *
log(VALUE)		0.309 *
HHAGE	0.002	-0.010 *
HHAGE^2	0.000	0.000 *
NEARN	0.378 *	0.374 *
EMPLOY (1=employed)	0.596 *	0.493 *
METRO (1=nonmetro)	-0.503 *	-0.257 *
HHRACE (1=nonwhite)	-0.832 *	-0.507 *
SAMHOU (1=no move)	0.002	0.030 *

R-squared                      0.287                      0.391

\* significant at 0.01

- Only households:
- That own
  - Have 1+ earner
  - Not farms



# 1940

Log(Family Earnings)

	Null Model	Value Model
intercept	6.303 *	4.274 *
log(VALUE)		0.309 *
HHAGE	0.002	-0.010 *
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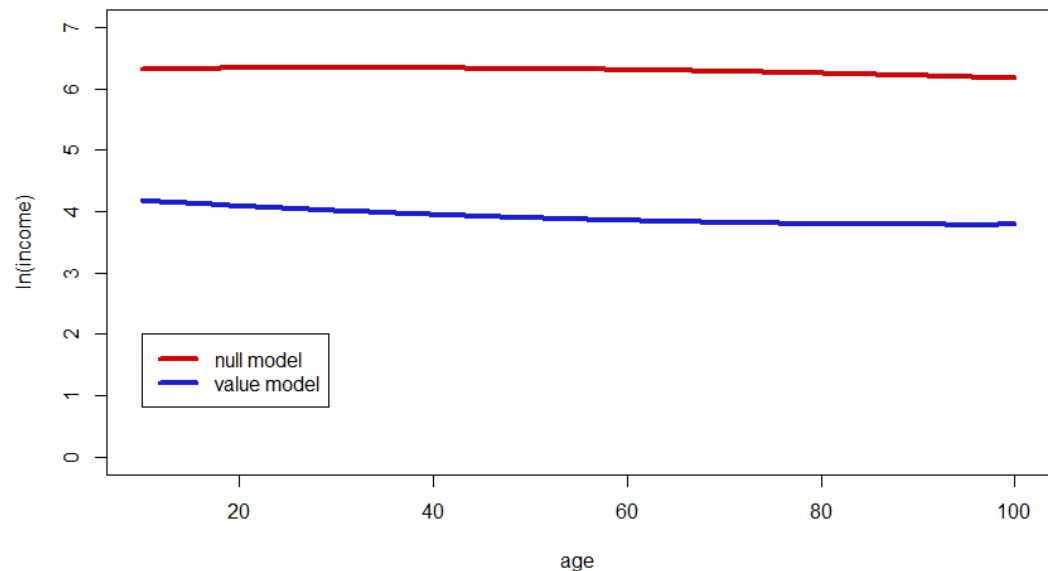
R-squared

0.287

0.391

\* significant at 0.01

Age changes signs



# 1940

Log(Family Earnings)	Null Model	Value Model
intercept	6.303 *	4.274 *
log(VALUE)		0.309 *
HHAGE	0.002	-0.010 *
HHAGE^2	0.000	0.000 *
NEARN	0.378 *	0.374 *
EMPLOY (1=employed)	0.596 *	0.493 *
METRO (1=nonmetro)	-0.503 *	-0.257 *
HHRACE (1=nonwhite)	-0.832 *	-0.507 *
SAMHOU (1=no move)	0.002	0.030 *
R-squared	0.287	0.391

\* significant at 0.01

Coefficients for number of earners & employment of head of household remain similar



# 1940

Log(Family Earnings)

	Null Model	Value Model
intercept	6.303 *	4.274 *
log(VALUE)		0.309 *
HHAGE	0.002	-0.010 *
HHAGE^2	0.000	0.000 *
NEARN	0.378 *	0.374 *
EMPLOY (1=employed)	0.596 *	0.493 *
METRO (1=nonmetro)	-0.503 *	-0.257 *
HHRACE (1=nonwhite)	-0.832 *	-0.507 *
SAMHOU (1=no move)	0.002	0.030 *
R-squared	0.287	0.391

\* significant at 0.01

Less effect of metro status & race

More effect for not moving





# 1940

Log(Family Earnings)

	Null Model	Value Model	Standardized Betas	Value Model
intercept	6.303 *	4.274 *		
log(VALUE)		0.309 *	0.366	
HHAGE	0.002	-0.010 *	-0.143	
HHAGE^2	0.000	0.000 *	0.076	
NEARN	0.378 *	0.374 *	0.315	
EMPLOY (1=employed)	0.596 *	0.493 *	0.207	
METRO (1=nonmetro)	-0.503 *	-0.257 *	-0.132	
HHRACE (1=nonwhite)	-0.832 *	-0.507 *	-0.121	
SAMHOU (1=no move)	0.002	0.030 *	0.016	

R-squared

0.287

0.391

\* significant at 0.01

The biggest single predictor of income is home value



# 2017

Log(Family Earnings)

	Null Model	Value Model	Standardized Betas Value Model
intercept	10.140 *	5.508 *	
log(VALUE)		0.403 *	0.492
HHAGE	-0.036 *	0.023 *	0.386
HHAGE^2	0.000 *	0.000 *	-0.397
NEARN	0.367 *	0.309 *	0.275
EMPLOY (1=employed)	-0.092 *	0.065 *	-0.029
METRO (1=nonmetro)	-0.306 *	-0.066 *	-0.037
HHRACE (1=nonwhite)	-0.139 *	-0.130 *	-0.057
SAMHOU (1=no move)	0.056 *	-0.002 *	-0.001
R-squared	0.148	0.362	

\* significant at 0.01

Home value  
an even more  
important  
predictor



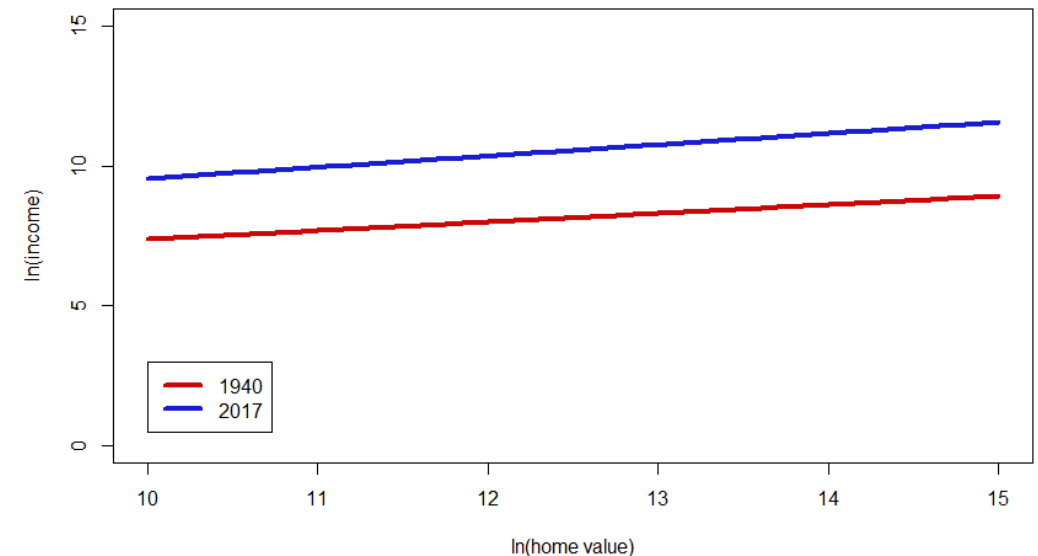
# 1940 & 2017

Log(Family Earnings)

	1940 Model	2017 Model
intercept	4.274 *	5.508 *
log(VALUE)	0.309 *	0.403 *
HHAGE	-0.010 *	0.023 *
HHAGE^2	0.000 *	0.000 *
NEARN	0.374 *	0.309 *
EMPLOY (1=employed)	0.493 *	0.065 *
METRO (1=nonmetro)	-0.257 *	-0.066 *
HHRACE (1=nonwhite)	-0.507 *	-0.130 *
SAMHOU (1=no move)	0.030 *	-0.002
R-squared	0.391	0.362

\* significant at 0.01

Home value  
has a similar  
relationship



# 1940 & 2017

Log(Family Earnings)

	1940 Model	2017 Model
intercept	4.274 *	5.508 *
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HHAGE	-0.010 *	0.023 *
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Age switches  
signs but  
remains flat



# 1940 & 2017

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SAMHOU (1=no move)	0.030 *	-0.002

R-squared

0.391

0.362

\* significant at 0.01

The number of earners has a similar relationship





# 1940 & 2017

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intercept	4.274 *	5.508 *
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Employment of  
HH head has a  
much smaller  
impact



# 1940 & 2017

Log(Family Earnings)

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log(VALUE)	0.309 *	0.403 *
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SAMHOU (1=no move)	0.030 *	-0.002

R-squared

0.391

0.362

\* significant at 0.01

Metropolitan  
status also  
similarly drops



# 1940 & 2017

Log(Family Earnings)

	1940 Model	2017 Model
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SAMHOU (1=no move)	0.030 *	-0.002
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\* significant at 0.01

Race also has  
a smaller  
impact



# 1940 & 2017

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	1940 Model	2017 Model
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R-squared	0.391	0.362

\* significant at 0.01

Moving houses  
no longer  
significant



# Conclusions

$$\textit{income} = f(\textit{wealth}, \textit{other factors})$$

- Home value and income appear highly related
- The relationship appears fairly stable over time





# Next Steps

- Obtain 1940 Microdata & assessors data
- Break apart income in 2017 into its components



# Outstanding Questions

- How does income relate to property value for renters?
- How does moving relate to income?
- What is the best way to specify race?





# Thank you.

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