Geographic Variation in Housing Filtering Rates

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Many properties ‘filter’ into affordable housing as they age

- Filtering in housing economics is the process by which properties, as they age, depreciate and thus tend to be purchased by lower-income households

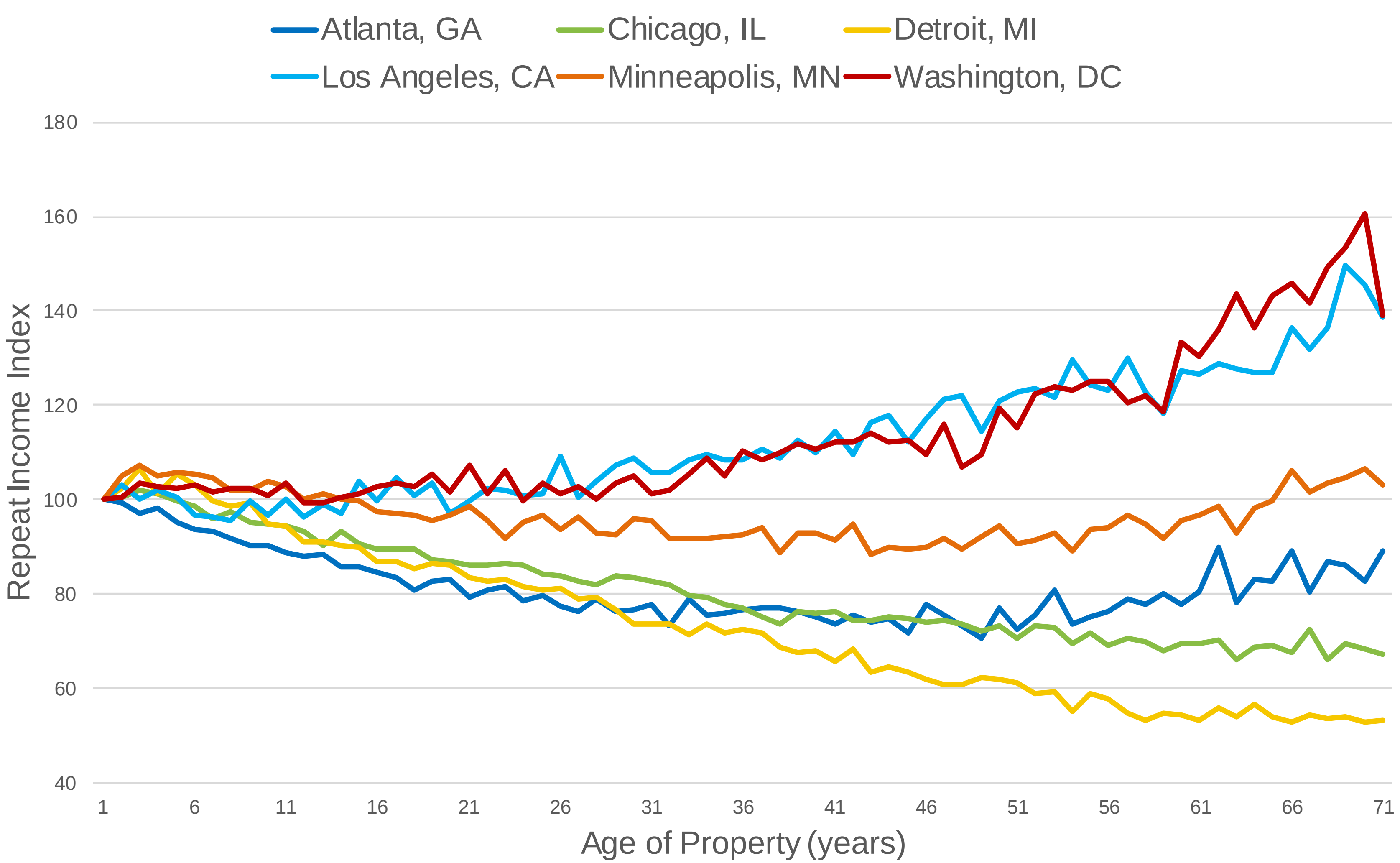
- Developers build very little unsubsidized affordable housing, but homes initially built for higher income households can ‘filter down’ to lower income households
  - Most ‘affordable’ housing is created through filtering

- Our research uses Freddie Mac data to estimate disaggregate filtering rates for owner-occupied properties and find:
  - Substantial variation in filtering rates across MSAs
  - Strong intra-MSA spatial patterns in filtering rates
  - Relationship between filtering, home improvements, and condition

Repeat income model of filtering rates

- Estimate filtering rates using the repeat income model (Rosenthal, 2014)
  - Estimate the model: $log(Y_t / Y_s) = I_t - I_s + \eta$
    - Where Y_t is the real income of the occupant at t and
    - I_t is the (log) income index for properties t years old
- Data
  - Owner-occupied 1-unit purchase mortgages funded by Freddie Mac
  - Year built data is from a combination of Black Knight and CoreLogic public records data and data from sellers of the mortgage
  - Includes mortgages originated from 1993 through 2018 for properties built after 1900
  - Only use pairs where the year built is the same for both sales to exclude teardowns
  - Final sample contains 1,321,756 repeat pairs for 1,204,665 properties
  - Real income is computed using qualifying income for the mortgage and national CPI

Repeat income filtering rates differ widely by MSA



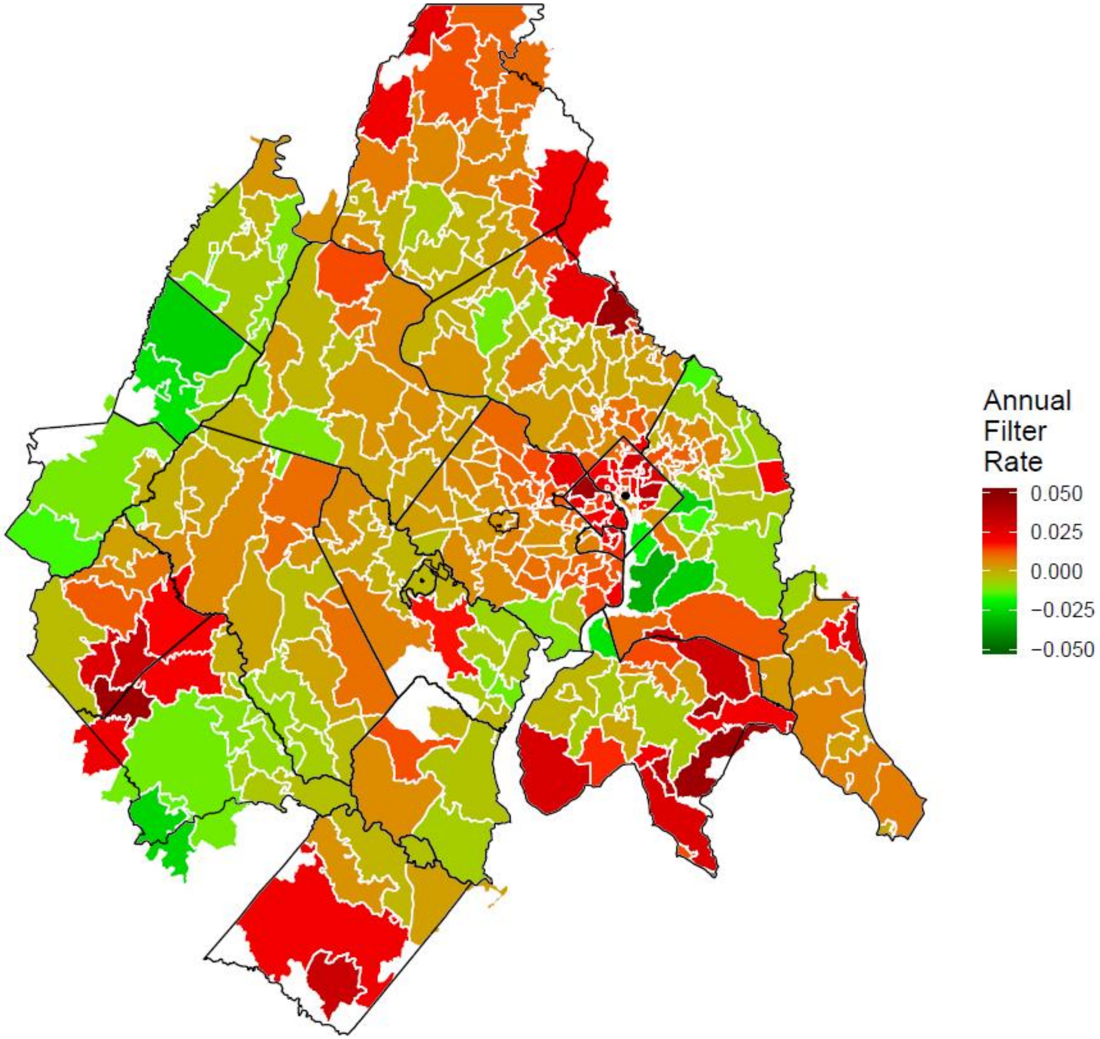
Large difference in filtering rates across MSAs in a linear model of filtering

MSA	Filtering Rate (log)	Standard Error	40-Year (%)
Topeka, KS	-0.0158	0.0017	-46.74
Macon, GA	-0.0146	0.0020	-44.19
Fort Wayne, IN	-0.0145	0.0009	-43.94
Jackson, MS	-0.0144	0.0017	-43.72
Louisville, KY	-0.0136	0.0014	-42.00
Toledo, OH	-0.0133	0.0008	-41.19
Greensboro, NC	-0.0126	0.0008	-39.66
Terre Haute, IN	-0.0125	0.0018	-39.35
Spartanburg, SC	-0.0124	0.0017	-39.03
South Bend, IN	-0.0123	0.0013	-38.96

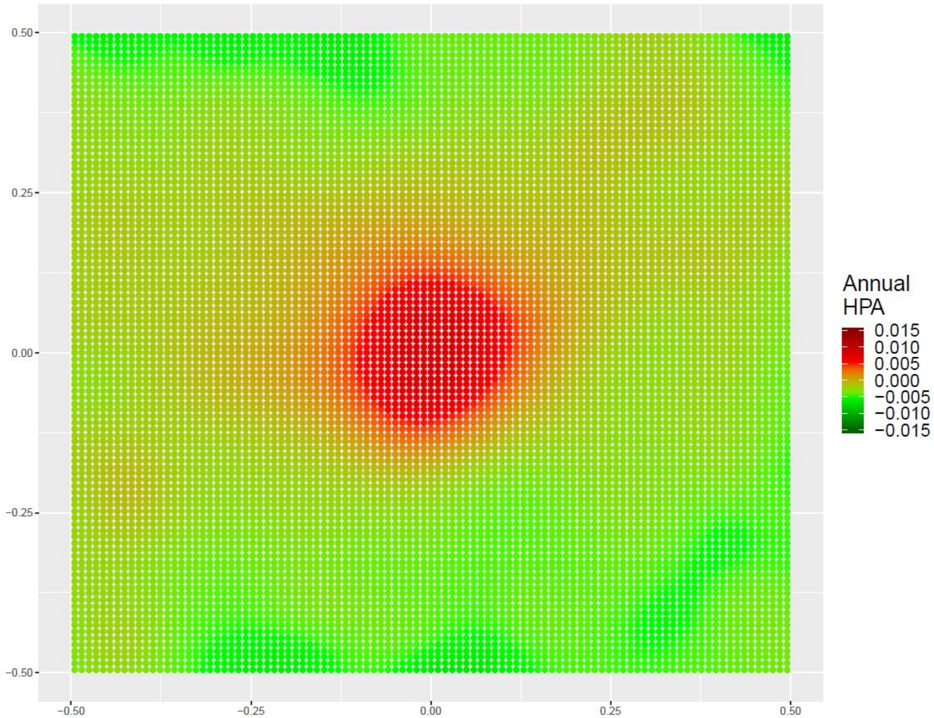
MSA	Filtering Rate (log)	Standard Error	40-Year (%)
Boulder, CO	0.0046	0.0009	20.20
Charlottesville, VA	0.0049	0.0017	21.65
Los Angeles, CA	0.0053	0.0004	23.57
San Diego, CA	0.0056	0.0006	25.31
Oxnard, CA	0.0057	0.0010	25.36
Seattle, WA	0.0064	0.0004	29.12
Santa Rosa, CA	0.0069	0.0013	32.00
San Jose, CA	0.0070	0.0008	32.21
San Francisco, CA	0.0074	0.0006	34.61
Midland, TX	0.0093	0.0015	44.77

- Impose an assumption of a linear (in logs) filtering index to increase the number of MSAs covered:
  - $\log\left(\frac{Y_{t+\tau}}{Y_t}\right) = g\tau + \eta$ where g is the log filtering rate, and τ is the time between purchases
- Results:
  - Filtering rates range from an upwards rate of 0.9% to a downwards rate of -1.6% per year
  - Using Uniform Appraisal Data for 1-unit single-family properties from 2012 through 2019:
    - MSAs with higher filtering rates have greater share with kitchen and bathroom improvements
    - Properties in upwards filtering MSAs are less likely to transition to lower condition

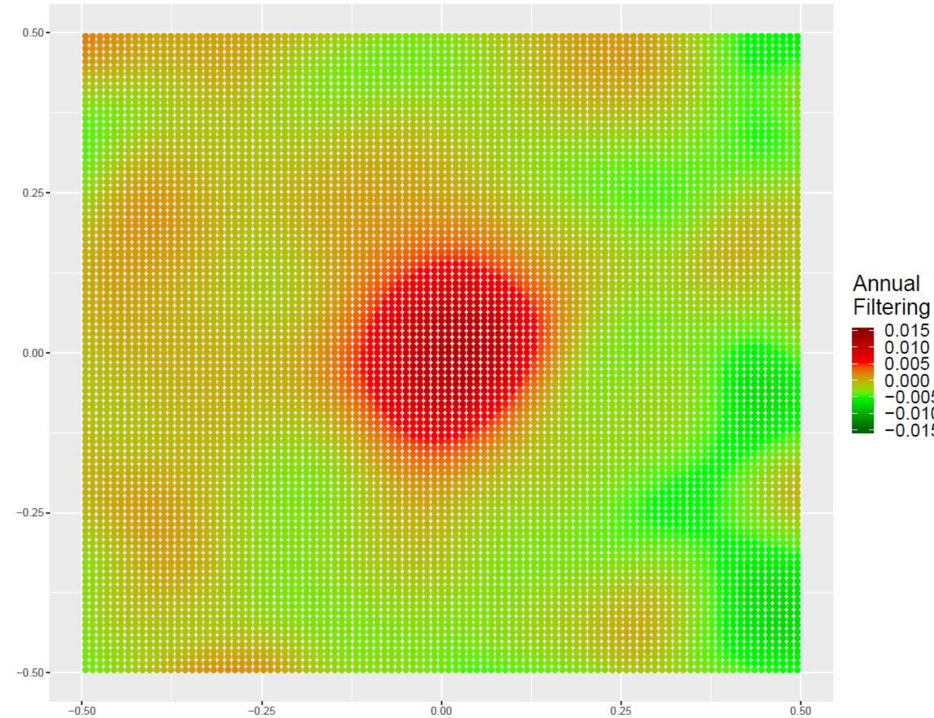
Spatial patterns of filtering rates within MSAs using a local linear (non-parametric) estimator: Washington, DC



HPA



Filtering



- Across MSAs, there is above average HPA and filtering close to the MSA center

Extensions

- Estimate structural model of filtering (Rosenthal, 2014)
  - » Filtering rates largely explained by depreciation and HPA
  - » Depreciation has become less important in the post-crisis years
- Demonstrate robustness of results
  - » When effective age is used
  - » When a linear spline functional form is used in the repeat income model
  - » After correcting for selection bias (because only use Freddie Mac's data)
    - – Utilize the National Mortgage Database (NMDB) for Heckman selection model
    - – Statistically significant selection effects
    - – Selection correction has only a small impact on estimated filtering rates
- Show gentrification is associated with slower filtering rates (less negative)
- Mixing of income over time for a given property
  - » Substantial volatility of income filtering around mean filtering rate
  - » Most new GSE affordable housing (LIP and VLIP) loans were for properties that transitioned from non-qualifying loans. Conversely, most LIP and VLIP loans transition out of goals qualifying status at the next sale.

Conclusions

- This analysis demonstrates the geographic heterogeneity of filtering rates
  - » There is substantial variation in filtering rates across MSAs
  - » There is even greater variation across ZIP Codes within MSAs
  - » The variability of filtering rates is largely explained by differences in house price appreciation within and across MSAs

- Even though each MSA has a unique complex pattern of HPA and filtering rates, there are identifiable patterns after averaging over MSAs
  - » Areas close to the city center have about a 1% higher annual rate of HPA, and the outskirts about 0.5% lower HPA relative to MSA averages
  - » Areas close to the city center have about a 1% higher filtering rate (towards filtering up) from the MSA average