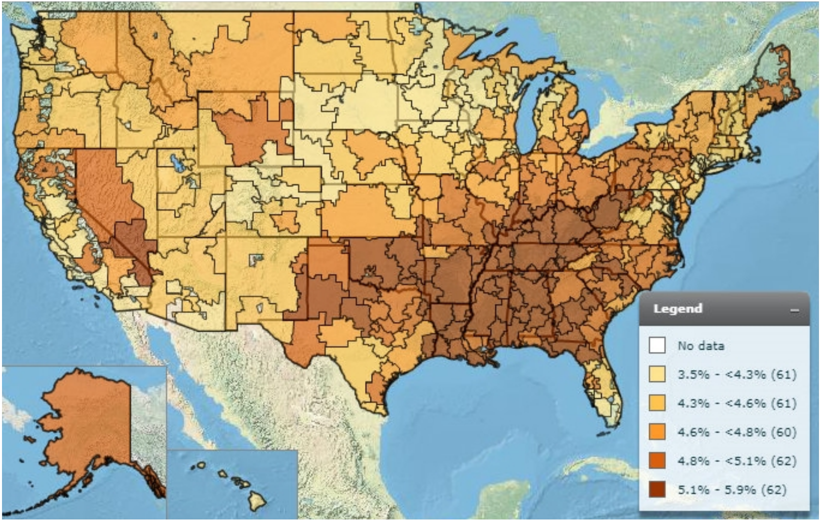
Geographic Variation in Health and Healthcare

Evidence from Migration

Amy Finkelstein, MIT and NBER

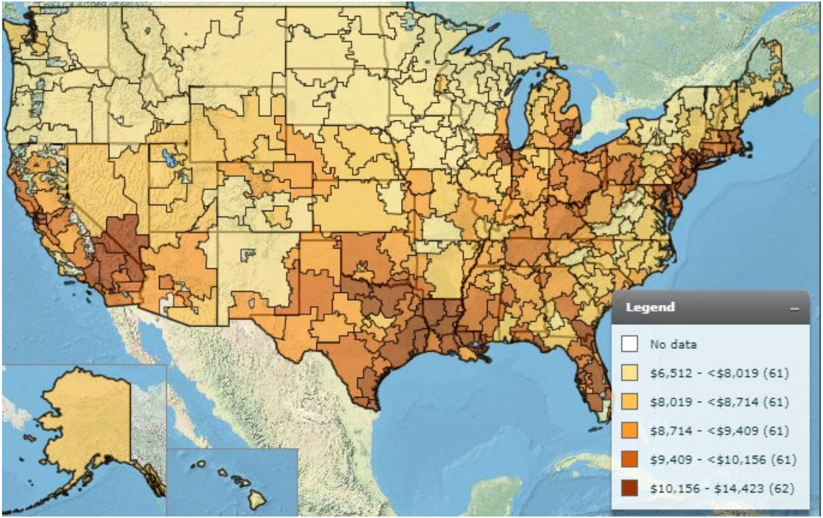
October 18, 2018

Geographic Variation in 1-Year Mortality



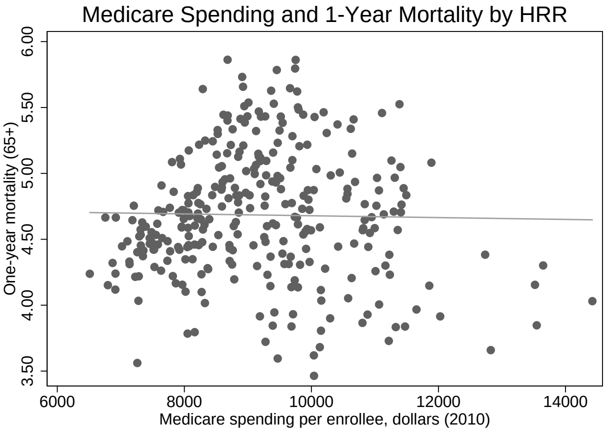
Source: *Dartmouth Atlas*; 1-year mortality of 65+ (2010; adjusted for age, sex, and race)

Geographic Variation in Healthcare Spending



Source: *Dartmouth Atlas*; Medicare spending per enrollee (2010; adjusted for age, sex, and race)

Healthcare Spending and Mortality



Substantial Geographic Variation in Health and Healthcare

- 4 year difference in life expectancy at age 40 among 100 most populous commuting zones (Chetty et al., 2016)

Substantial Geographic Variation in Health and Healthcare

- 4 year difference in life expectancy at age 40 among 100 most populous commuting zones (Chetty et al., 2016)
- More than a factor of 2 difference in healthcare spending per Medicare enrollee (age/race/sex adjusted) (Dartmouth Atlas, 2010)
    - \$14,423 in Miami, FL vs. \$7,819 in Minneapolis, MN
    - \$13,648 in McAllen, TX vs. \$8,714 in nearby and demographically similar El Paso, TX (Gawande, 2011)

Substantial Geographic Variation in Health and Healthcare

- 4 year difference in life expectancy at age 40 among 100 most populous commuting zones (Chetty et al., 2016)
- More than a factor of 2 difference in healthcare spending per Medicare enrollee (age/race/sex adjusted) (Dartmouth Atlas, 2010)
  - $14,423 in Miami, FL vs. $7,819 in Minneapolis, MN
  - $13,648 in McAllen, TX vs. $8,714 in nearby and demographically similar El Paso, TX (Gawande, 2011)
- Higher area utilization not generally correlated with better patient outcomes

Two Broad Classes of Explanations

- People are different (shorthand: “demand” factors)
  - Health status (genetics, health behaviors, prior healthcare, etc.)
  - Preferences

Two Broad Classes of Explanations

- People are different (shorthand: “demand” factors)
  - Health status (genetics, health behaviors, prior healthcare, etc.)
  - Preferences
- Places are different (shorthand: “supply” factors)
  - Healthcare system (physical capital, human capital, hospital markets, etc.)
  - Other place-based factors (weather, crime, pollution, etc.)

Two Broad Classes of Explanations

- People are different (shorthand: “demand” factors)
  - Health status (genetics, health behaviors, prior healthcare, etc.)
  - Preferences

- Places are different (shorthand: “supply” factors)
  - Healthcare system (physical capital, human capital, hospital markets, etc.)
  - Other place-based factors (weather, crime, pollution, etc.)

- Different explanations have different implications
  - For policies aimed at improving health or reducing healthcare costs
  - For first steps toward welfare analysis

Large Existing Literature

- Geographic correlates with mortality suggest large role for person-specific factors - particularly health behaviors
  - Fuchs (1974) Utah vs. Nevada
  - Chetty et al. (2016) Use universe of tax records to analyze variation in life expectancy

Large Existing Literature

- Geographic correlates with mortality suggest large role for person-specific factors - particularly health behaviors
  - Fuchs (1974) Utah vs. Nevada
  - Chetty et al. (2016) Use universe of tax records to analyze variation in life expectancy
  - Consistent with *Dartmouth Atlas* - geographic variation in health not correlated with variation in healthcare use

Large Existing Literature

- Geographic correlates with mortality suggest large role for person-specific factors - particularly health behaviors
  - Fuchs (1974) Utah vs. Nevada
  - Chetty et al. (2016) Use universe of tax records to analyze variation in life expectancy
  - Consistent with *Dartmouth Atlas* - geographic variation in health not correlated with variation in healthcare use

- Geographic correlates with healthcare spending suggest large role for place-based factors (*Dartmouth Atlas* literature):
  - Controls for observable person characteristics do little to reduce geographic variation
  - Tentative conclusion has been that role of demand is limited

Large Existing Literature

- Geographic correlates with mortality suggest large role for person-specific factors - particularly health behaviors
    - Fuchs (1974) Utah vs. Nevada
    - Chetty et al. (2016) Use universe of tax records to analyze variation in life expectancy
    - Consistent with *Dartmouth Atlas* - geographic variation in health not correlated with variation in healthcare use

- Geographic correlates with healthcare spending suggest large role for place-based factors (*Dartmouth Atlas* literature):
    - Controls for observable person characteristics do little to reduce geographic variation
    - Tentative conclusion has been that role of demand is limited

- Policy influence: Visible role in public debate over Affordable Care Act ("Obamacare")
    - 2009 *Economic Report of President*: Large differences in spending with no outcome gradient suggest ~30% of spending could be cut without harm

Our Approach

- On-going research program with Matthew Gentzkow (Stanford) and Heidi Williams (MIT)

Our Approach

- On-going research program with Matthew Gentzkow (Stanford) and Heidi Williams (MIT)
- Exploit migration of Medicare enrollees to separate role of person vs. place
  - Thought experiment: Miami vs. Minneapolis

Our Approach

- On-going research program with Matthew Gentzkow (Stanford) and Heidi Williams (MIT)
- Exploit migration of Medicare enrollees to separate role of person vs. place
  - Thought experiment: Miami vs. Minneapolis
- Key advantage of this approach: can capture both observed and unobserved demand factors (e.g. unobserved health, preferences)

Our Approach

- On-going research program with Matthew Gentzkow (Stanford) and Heidi Williams (MIT)
- Exploit migration of Medicare enrollees to separate role of person vs. place
  - Thought experiment: Miami vs. Minneapolis
- Key advantage of this approach: can capture both observed and unobserved demand factors (e.g. unobserved health, preferences)
- Use this approach to examine role of place-based factors in driving:
  - Healthcare spending (QJE 2016)
  - Prescription opioid abuse (in progress)
  - Life expectancy (working paper, 2018)

General Framework

$$log(y_{ijt}) = \gamma_j + \theta_i + x_{it}\beta + \varepsilon_{ijt}$$

- y_{ijt}: healthcare use or mortality of person i in geographic area j in year t

General Framework

$$log(y_{ijt}) = \gamma_j + \theta_i + x_{it}\beta + \varepsilon_{ijt}$$

- y_{ijt}: healthcare use or mortality of person i in geographic area j in year t
- Key economic assumption: additive separability of person-specific (θ_i) and place-specific (γ_j) factors
    - Economically intuitive: constant proportional effects
    - Empirically testable

General Framework

$$log(y_{ijt}) = \gamma_j + \theta_i + x_{it}\beta + \varepsilon_{ijt}$$

- y_{ijt}: healthcare use or mortality of person i in geographic area j in year t
- Key economic assumption: additive separability of person-specific (θ_i) and place-specific (γ_j) factors
  - Economically intuitive: constant proportional effects
  - Empirically testable
- Goal: estimate place-specific treatment effects (γ_j) for counterfactual analysis such as:
  - How much would geographic variation in healthcare spending be reduced if treatment effects were equalized?
  - Impact of moving from a low opioid abuse county to a high abuse county on prescription opioid abuse?
  - Impact of living in a 10th vs 90th percentile place on life expectancy?

General Framework

$$log(y_{ijt}) = \gamma_j + \theta_i + x_{it}\beta + \varepsilon_{ijt}$$

- y_{ijt}: healthcare use or mortality of person i in geographic area j in year t
- Key economic assumption: additive separability of person-specific (θ_i) and place-specific (γ_j) factors
    - Economically intuitive: constant proportional effects
    - Empirically testable
- Goal: estimate place-specific treatment effects (γ_j) for counterfactual analysis such as:
    - How much would geographic variation in healthcare spending be reduced if treatment effects were equalized?
    - Impact of moving from a low opioid abuse county to a high abuse county on prescription opioid abuse?
    - Impact of living in a 10th vs 90th percentile place on life expectancy?
- Use people who move across areas to identify impact of place (γ_j) from person-specific factors (θ_i)

Data

- All projects use (20% random sample of) Medicare claims data (~1998 - 2014)
  - Millions of enrollees per year
- Demographics (age, race, sex)
- Detailed health diagnoses / conditions
- Zip code of residence
  - Based on address in Medicare billing / Social Security each year
- Detailed medical claims data
- Date of death (if any)
- Roughly one-half of one percent of sample moves across an HRR each year
  - Observe hundreds of thousands of moves per year

Drivers of Variation in Healthcare Spending

Model of Utilization

$$log(y_{ijt}) = \gamma_j + \alpha_i + \tau_t + \rho_{r(i,t)} + x_{it}\beta + \varepsilon_{ijt}$$

- y_{ijt}: healthcare use of person i in geographic area j in year t
- $\rho_{r(i,t)}$: fixed effects for “relative years” for movers (zero for non-movers)
- x_{it}: fixed effects for five-year age bins

Model of Utilization

$$log(y_{ijt}) = \gamma_j + \alpha_i + \tau_t + \rho_{r(i,t)} + x_{it}\beta + \varepsilon_{ijt}$$

- y_{ijt}: healthcare use of person i in geographic area j in year t
- $\rho_{r(i,t)}$: fixed effects for "relative years" for movers (zero for non-movers)
- x_{it}: fixed effects for five-year age bins

- Allows movers to differ arbitrarily from non-movers in:
    - Levels of log utilization (α_i)
    - Trends in log utilization around their moves, e.g., due to health shocks ($\rho_{r(i,t)}$)

Model of Utilization

$$log(y_{ijt}) = \gamma_j + \alpha_i + \tau_t + \rho_{r(i,t)} + x_{it}\beta + \varepsilon_{ijt}$$

- y_{ijt}: healthcare use of person i in geographic area j in year t
- $\rho_{r(i,t)}$: fixed effects for "relative years" for movers (zero for non-movers)
- x_{it}: fixed effects for five-year age bins

- Allows movers to differ arbitrarily from non-movers in:
  - Levels of log utilization (α_i)
  - Trends in log utilization around their moves, e.g., due to health shocks ($\rho_{r(i,t)}$)

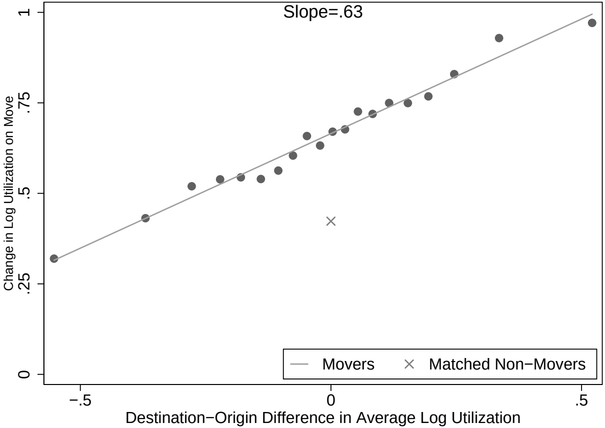
- Identifying assumption: No shocks to utilization that coincide exactly with the timing of the move and that are correlated with utilization in the origin and destination
  - Can investigate empirically using event study representation of estimating equation
  - $\hat{\delta}_i$ is the difference in the sample in average log utilization between the mover's destination and origin:

$$log(y_{it}) = \alpha_i + \lambda_{r(i,t)}\hat{\delta}_i + \tau_t + \rho_{r(i,t)} + x_{it}\beta + \varepsilon_{it}$$

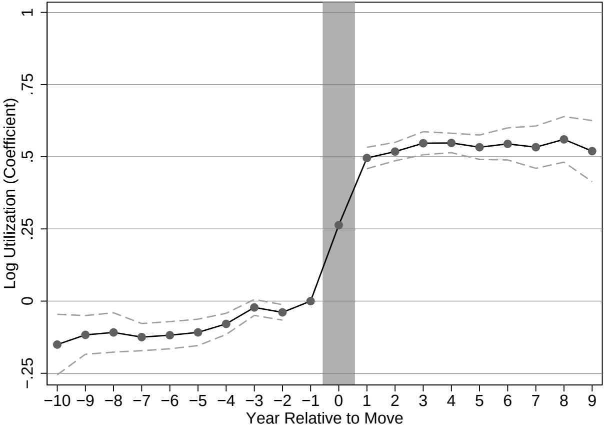
Movers and their Moves

- Movers are different from non-movers (fixed differences captured by α_i)
  - Slightly more likely to be female, white
  - Somewhat more educated, similar initial retirement rates (HRS)
- Time-varying correlates of moving (correlates of moving captured by ρ_r)
  - Top reason for moving "to be near/with children" (HRS)
  - Becoming widowed/retired associated with higher move probability; changes in self-reported health are not (HRS)
- Geography of moves (across HRRs)
  - Median move = 357 miles; IQ range = 120-913 miles
  - 68% of moves are cross-state
  - 12% have Florida as destination

Change In Log Utilization with Size of Move



Event Study: Log Utilization



Summary of Findings

- 40-50% of geographic variation due to patients, 50-60% due to place

Summary of Findings

- 40-50% of geographic variation due to patients, 50-60% due to place
- What underlying factors drive differences in patient demand?
  - Small role for demographics, persistence of past treatments, habit formation
  - Patient health can explain a substantial portion (50-80%)

Summary of Findings

- 40-50% of geographic variation due to patients, 50-60% due to place
- What underlying factors drive differences in patient demand?
  - Small role for demographics, persistence of past treatments, habit formation
  - Patient health can explain a substantial portion (50-80%)
- Area correlates of high place effects include:
  - Larger share of for-profit hospitals
  - Larger share of doctors who report a preference for aggressive care

What Drives Prescription Opioid Abuse?

US Opioid Crisis

- In 2016, opioid deaths were more than double homicides, and order of magnitude higher than cocaine-related deaths at height of crack epidemic (Frieden and Houry, 2016; Rudd et al., 2016; GAO 1991)

US Opioid Crisis

- In 2016, opioid deaths were more than double homicides, and order of magnitude higher than cocaine-related deaths at height of crack epidemic (Frieden and Houry, 2016; Rudd et al., 2016; GAO 1991)
- Large geographic variation: opioid prescription rates per capita are 4 times higher for the 75th than the 25th percentile county (McDonald et al., 2012)

US Opioid Crisis

- In 2016, opioid deaths were more than double homicides, and order of magnitude higher than cocaine-related deaths at height of crack epidemic (Frieden and Houry, 2016; Rudd et al., 2016; GAO 1991)
- Large geographic variation: opioid prescription rates per capita are 4 times higher for the 75th than the 25th percentile county (McDonald et al., 2012)
- Potential causes:
  - Demand factors (e.g. mental health, earnings potential) (e.g. Case & Deaton 2015, 2017)
  - Supply factors (e.g. physician prescribing behavior, pill mills, legal restrictions) (e.g. Barnett et al., 2017; Schnell and Currie, 2017; Meara et al., 2016)

US Opioid Crisis

- In 2016, opioid deaths were more than double homicides, and order of magnitude higher than cocaine-related deaths at height of crack epidemic (Frieden and Houry, 2016; Rudd et al., 2016; GAO 1991)
- Large geographic variation: opioid prescription rates per capita are 4 times higher for the 75th than the 25th percentile county (McDonald et al., 2012)
- Potential causes:
  - Demand factors (e.g. mental health, earnings potential) (e.g. Case & Deaton 2015, 2017)
  - Supply factors (e.g. physician prescribing behavior, pill mills, legal restrictions) (e.g. Barnett et al., 2017; Schnell and Currie, 2017; Meara et al., 2016)
- Relative importance of different causes
  - Uncertain
  - Important for policy

Approach

- Same estimating equation used for analyzing causes of “legitimate” healthcare use can also be used for causes of healthcare “abuse”

Approach

- Same estimating equation used for analyzing causes of “legitimate” healthcare use can also be used for causes of healthcare “abuse”
- Now focus on *disabled* Medicare enrollees (SSDI)
  - Opioid use especially prevalent - roughly half of SSDI recpients receive an opioid prescription each year (Meara et al. 2016)
  - Enrollment in Medicare provides rich panel data on prescription drug use (and residency changes)
  - Fixed level of government benefits and tight limits on additional earnings
    - can rule out large changes in income or employment around moves

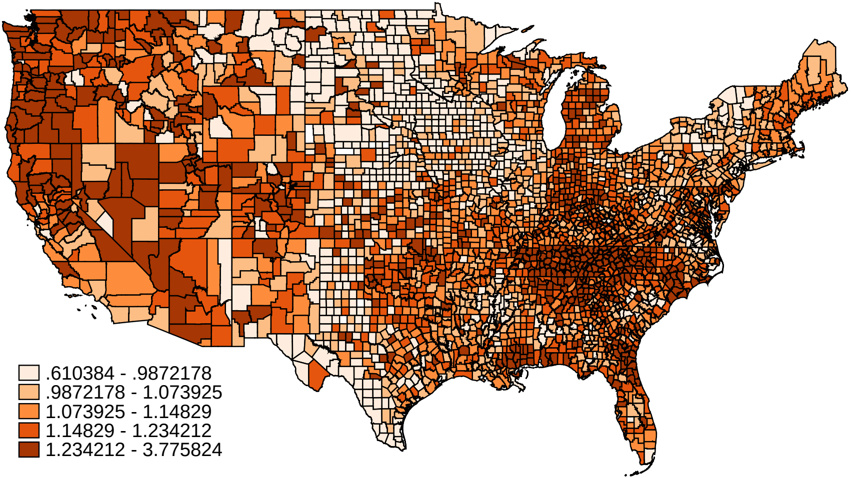
Approach

- Same estimating equation used for analyzing causes of “legitimate” healthcare use can also be used for causes of healthcare “abuse”
- Now focus on *disabled* Medicare enrollees (SSDI)
  - Opioid use especially prevalent - roughly half of SSDI recpients receive an opioid prescription each year (Meara et al. 2016)
  - Enrollment in Medicare provides rich panel data on prescription drug use (and residency changes)
  - Fixed level of government benefits and tight limits on additional earnings
    - can rule out large changes in income or employment around moves
- Geographic unit of analysis / migration: county

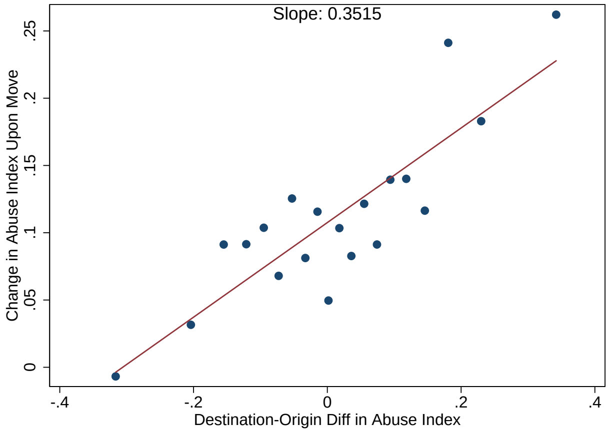
Measuring Prescription Opioid Abuse

- Opioid "abuse" difficult to measure, even in a clincial setting
- We follow existing literature's proxies for opioid abuse based on prescription data.
  - "Many prescribers": individuals filled prescriptions from four or more prescribers ("doctor shopping")
  - "High MED": average daily morphine-equivalent dosage of more than 120 mg in any quarter.
  - "Overlapping prescriptions": whether fill new prescription before previous one has run out
- Summary measure: "abuse index"
  - Combines above as well as more flexible functions of underlying prescriptions
  - Index weights are derived from a multivariate regression of an indicator for poisoning events (i.e. emergency room visits or inpatient hospital admissions for poisoning) on the prescription measures from the previous year.
  - Results from index very similar to results from individual measures

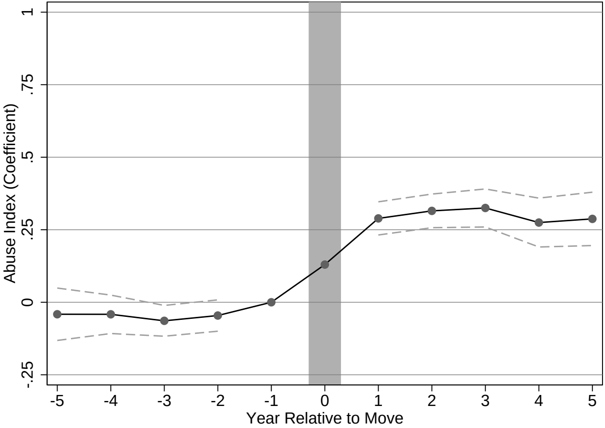
Geographic Variation in Prescription Opioid Abuse



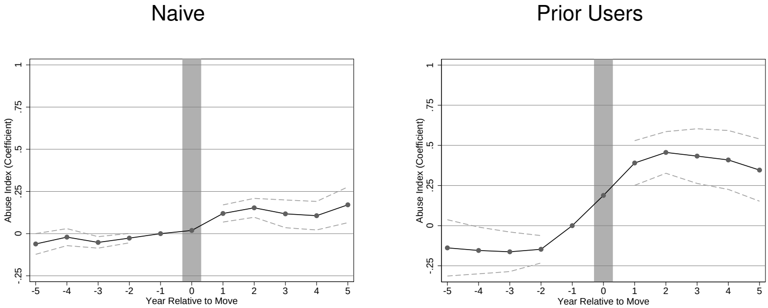
Change in Opioid Abuse by Size of Move



Event Study: Opioid Abuse



Event Studies: Opioid Abuse - Naive and Prior Users



Note: Naive movers are those with no opioid use in relative year -1, while prior users filled at least one opioid prescription in that year. We omit the approximately 20% of enrollee-years with no observations in relative year -1.

Summary of Findings

- Movement to a county with a 20 percent higher rate of prescription opioid abuse (equivalent to a move from a 25th to 75th percentile county) increases rate of abuse by 6 percent
    - Suggests roughly one-third of the gap between these areas is due to place-specific factors

Summary of Findings

- Movement to a county with a 20 percent higher rate of prescription opioid abuse (equivalent to a move from a 25th to 75th percentile county) increases rate of abuse by 6 percent
  - Suggests roughly one-third of the gap between these areas is due to place-specific factors
- Effects particularly pronounced for prior opioid users
  - Impact of move on opioid abuse four times larger than the increase for opioid naives

Summary of Findings

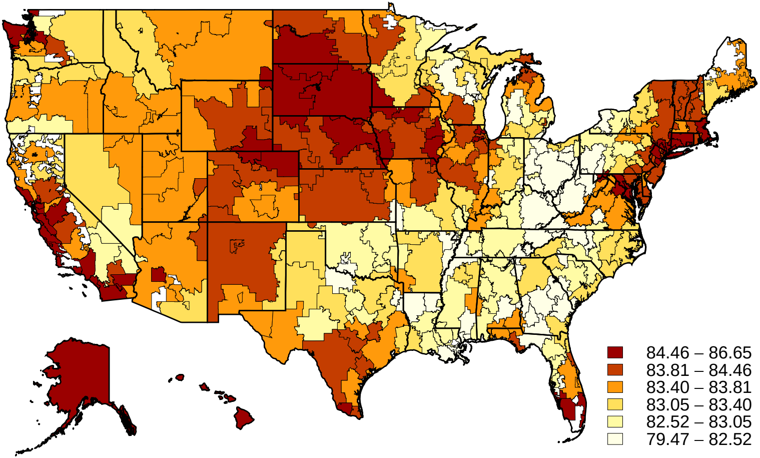
- Movement to a county with a 20 percent higher rate of prescription opioid abuse (equivalent to a move from a 25th to 75th percentile county) increases rate of abuse by 6 percent
  - Suggests roughly one-third of the gap between these areas is due to place-specific factors

- Effects particularly pronounced for prior opioid users
  - Impact of move on opioid abuse four times larger than the increase for opioid naives

- In progress
  - Impacts on total opioid abuse (potential substitution to illegal opioids)
  - Implications for economic model of addiction

Place-Based Drivers of Mortality

Age 65 Life Expectancy



Source: Authors' calculations from Medicare data; Average life expectancy in HRR is computed using average characteristics of Medicare beneficiaries in the HRR except for race and sex for which national averages are used.

Added Empirical Challenge

- You Only Die Once

Added Empirical Challenge

- You Only Die Once
  - And rarely before you move

Added Empirical Challenge

- You Only Die Once
  - And rarely before you move
  - Can’t use prior panel analysis approach

Added Empirical Challenge

- You Only Die Once
  - And rarely before you move
  - Can't use prior panel analysis approach

- Once again, exploit migration
  - Thought experiment: Boston –> Minneapolis or Houston

Added Empirical Challenge

- You Only Die Once
  - And rarely before you move
  - Can't use prior panel analysis approach
- Once again, exploit migration
  - Thought experiment: Boston –> Minneapolis or Houston
- Steps toward identification
  - Origin fixed effects
  - Rich controls for observable, pre-move health
  - Novel strategy to adjust for remaining selection on unobservables (extending Altonji et al., 2005, Oster 2016)

Adjusting for Selection on Unobservables

- Look at selection of movers' destinations on **observed** health
- Use this to gauge likely selection on **unobserved** health

Adjusting for Selection on Unobservables

- Look at selection of movers' destinations on **observed** health
- Use this to gauge likely selection on **unobserved** health

- Standard approaches (Altonji et al., 2005, Oster 2016) require two independent assumptions

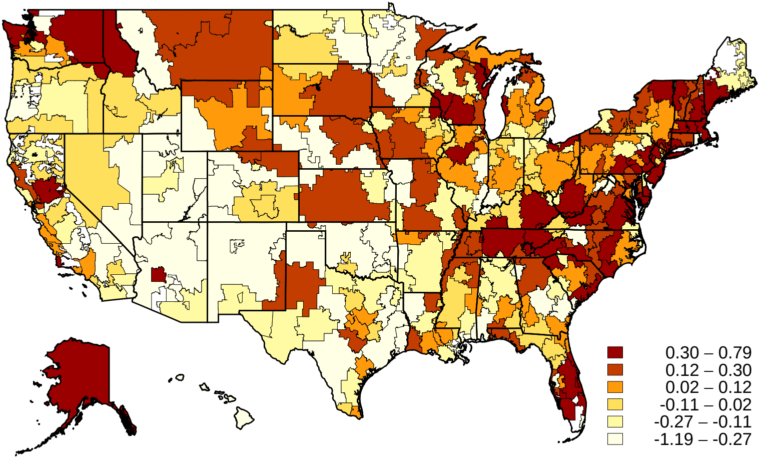
Adjusting for Selection on Unobservables

- Look at selection of movers' destinations on **observed** health
- Use this to gauge likely selection on **unobserved** health

- Standard approaches (Altonji et al., 2005, Oster 2016) require two independent assumptions
  - "Equal selection" of observables and unobservables
  - Variance explained by unobservables relative to observables ("R^2 assumption")

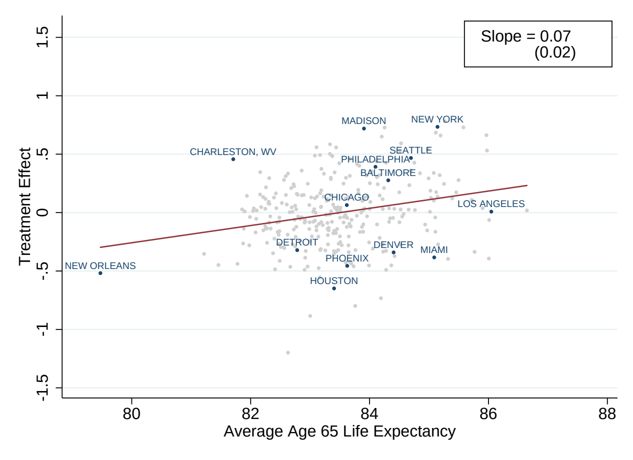
- In our setting, because we can recover variance of origin component of unobserved health, we can weaken the R^2 assumption:
  - "Relative importance": relative variance of unobservables and observables is the same in origin as in destination

Life Expectancy Treatment Effects



Empirical Bayes-adjusted estimates of life expectancy treatment effects

Treatment Effects vs. Cross Section



Largest and Smallest Treatment Effects

Ten Largest			Ten Smallest		
HRR Name	Treatment Effect	Age 65 Life Expectancy	HRR Name	Treatment Effect	Age 65 Life Expectancy
East Long Island, NY	0.79	85.27	Shreveport, LA	-0.47	82.41
Manhattan, NY	0.75	85.14	Las Vegas, NV	-0.48	82.91
White Plains, NY	0.74	85.58	Lincoln, NE	-0.48	84.28
Camden, NJ	0.74	84.25	New Orleans, LA	-0.51	79.47
Madison, WI	0.73	83.91	Amarillo, TX	-0.54	83.16
Morristown, NJ	0.70	85.11	Houston, TX	-0.64	83.40
Takoma Park, MD	0.67	85.97	Albuquerque, NM	-0.72	84.19
Fort Lauderdale, FL	0.67	85.19	Mesa, AZ	-0.79	83.76
Salisbury, MD	0.66	84.21	Tampa, FL	-0.87	83.00
Fort Meyers, FL	0.60	84.53	San Bernardino, CA	-1.19	82.63

Summary of Findings

Treatment effects of place are...

Summary of Findings

Treatment effects of place are...

- Quantitatively important
  - Move from 10th to 90th percentile would increase life expectancy at 65 by 1.3 years

Summary of Findings

Treatment effects of place are...

- Quantitatively important
  - Move from 10th to 90th percentile would increase life expectancy at 65 by 1.3 years
- Imperfectly correlated with life expectancy in the cross-section
  - e.g. Miami, Charleston WV
  - Equalizing current place effects would reduce cross-sectional variation by 25 percent

Summary of Findings

Treatment effects of place are...

- Quantitatively important
  - Move from 10th to 90th percentile would increase life expectancy at 65 by 1.3 years
- Imperfectly correlated with life expectancy in the cross-section
  - e.g. Miami, Charleston WV
  - Equalizing current place effects would reduce cross-sectional variation by 25 percent
- Correlated (mostly intuitively) with observables

Summary of Findings

Treatment effects of place are...

- Quantitatively important
  - Move from 10th to 90th percentile would increase life expectancy at 65 by 1.3 years
- Imperfectly correlated with life expectancy in the cross-section
  - e.g. Miami, Charleston WV
  - Equalizing current place effects would reduce cross-sectional variation by 25 percent
- Correlated (mostly intuitively) with observables
  - More favorable where hospital *quality* is high, more physicians per capita
  - Unrelated to healthcare *quantity*
  - Less favorable where temperature, homicides, auto fatalities high

Summary and Implications

Updating Based on Our Findings

- Conventional Wisdom - based on geographic correlates:

Updating Based on Our Findings

- Conventional Wisdom - based on geographic correlates:
  - Place matters a lot for healthcare

Updating Based on Our Findings

- Conventional Wisdom - based on geographic correlates:
  - Place matters a lot for healthcare
  - Place matters little for life expectancy

Updating Based on Our Findings

- Conventional Wisdom - based on geographic correlates:
  - Place matters a lot for healthcare
  - Place matters little for life expectancy
  - Role of place in opioid abuse - actively under investigation

Updating Based on Our Findings

- Conventional Wisdom - based on geographic correlates:
  - Place matters a lot for healthcare
  - Place matters little for life expectancy
  - Role of place in opioid abuse - actively under investigation
- Our findings - based on mover design:

Updating Based on Our Findings

- Conventional Wisdom - based on geographic correlates:
  - Place matters a lot for healthcare
  - Place matters little for life expectancy
  - Role of place in opioid abuse - actively under investigation

- Our findings - based on mover design:
  - Place matters a lot for all three
  - But still room for person-specific factors

Where do we go from here?

- Results point to large causal impact of place on health and healthcare use

Where do we go from here?

- Results point to large causal impact of place on health and healthcare use
- Need to get inside the “black box” of place
  - What place-based factors are important?
  - Important for policy and welfare
  - Thus far have only looked at area correlates of place effects

Where do we go from here?

- Results point to large causal impact of place on health and healthcare use

- Need to get inside the "black box" of place
  - What place-based factors are important?
  - Important for policy and welfare
  - Thus far have only looked at area correlates of place effects

- Focusing now on role of physician in affecting healthcare use (in progress, with Gentzkow, Hull and Williams)

Where do we go from here?

- Results point to large causal impact of place on health and healthcare use
- Need to get inside the “black box” of place
  - What place-based factors are important?
  - Important for policy and welfare
  - Thus far have only looked at area correlates of place effects
- Focusing now on role of physician in affecting healthcare use (in progress, with Gentzkow, Hull and Williams)
- More work needed!