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

Medicare Spending and 1-Year Mortality by HRR

One-year mortality (65+)

Medicare spending per enrollee, dollars (2010)
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
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- People are different (shorthand: “demand” factors)
  - Health status (genetics, health behaviors, prior healthcare, etc.)
  - Preferences

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  - Economically intuitive: constant proportional effects
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Goal: estimate place-specific treatment effects (\( \gamma_j \)) 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 (\( \gamma_j \)) from person-specific factors (\( \theta_i \))
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Use people who move across areas to identify impact of place ($\gamma_j$) from person-specific factors ($\theta_i$)
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

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

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- \( \rho_{r(i,t)} \): fixed effects for “relative years” for movers (zero for non-movers)
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Allows movers to differ arbitrarily from non-movers in:
- Levels of log utilization (\( \alpha_i \))
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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 $\alpha_i$)
  - 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 $\rho_r$)
  - 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

Slope=.63

Movers Matched Non-Movers

Destination–Origin Difference in Average Log Utilization

Change in Log Utilization on Move

-.5 0 .5

Destination–Origin Difference in Average Log Utilization

Movers

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Event Study: Log Utilization

- Log Utilization (Coefficient)
- Year Relative to Move
Summary of Findings

- 40-50% of geographic variation due to patients, 50-60% due to place
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- Small role for demographics, persistence of past treatments, habit formation
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  - Small role for demographics, persistence of past treatments, habit formation
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- 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?
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 Houri, 2016; Rudd et al., 2016; GAO 1991).
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Large geographic variation: opioid prescription rates per capita are 4 times higher for the 75th than the 25th percentile county (McDonald et al., 2012)
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  - Demand factors (e.g. mental health, earnings potential) (e.g. Case & Deaton 2015, 2017)
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- 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”

Now focus on disabled Medicare enrollees (SSDI)

- Opioid use especially prevalent - roughly half of SSDI recipients 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

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Opioid “abuse” difficult to measure, even in a clinical 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

Change in Abuse Index Upon Move

Destination-Origin Diff in Abuse Index

Slope: 0.3515
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
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- In progress
  - Impacts on total opioid abuse (potential substitution to illegal opioids)
  - Implications for economic model of addiction
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

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  - And rarely before you move
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  - Thought experiment: Boston → Minneapolis or Houston
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- 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
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- Standard approaches (Altonji et al., 2005, Oster 2016) require two independent assumptions
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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
Empirical Bayes-adjusted estimates of life expectancy treatment effects
Treatment Effects vs. Cross Section

Slope = 0.07
(0.02)
## Largest and Smallest Treatment Effects

<table>
<thead>
<tr>
<th>HRR Name</th>
<th>Treatment Effect</th>
<th>Age 65 Life Expectancy</th>
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</tr>
</thead>
<tbody>
<tr>
<td>East Long Island, NY</td>
<td>0.79</td>
<td>85.27</td>
<td>Shreveport, LA</td>
<td>-0.47</td>
<td>82.41</td>
</tr>
<tr>
<td>Manhattan, NY</td>
<td>0.75</td>
<td>85.14</td>
<td>Las Vegas, NV</td>
<td>-0.48</td>
<td>82.91</td>
</tr>
<tr>
<td>White Plains, NY</td>
<td>0.74</td>
<td>85.58</td>
<td>Lincoln, NE</td>
<td>-0.48</td>
<td>84.28</td>
</tr>
<tr>
<td>Camden, NJ</td>
<td>0.74</td>
<td>84.25</td>
<td>New Orleans, LA</td>
<td>-0.51</td>
<td>79.47</td>
</tr>
<tr>
<td>Madison, WI</td>
<td>0.73</td>
<td>83.91</td>
<td>Amarillo, TX</td>
<td>-0.54</td>
<td>83.16</td>
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<tr>
<td>Morristown, NJ</td>
<td>0.70</td>
<td>85.11</td>
<td>Houston, TX</td>
<td>-0.64</td>
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<tr>
<td>Takoma Park, MD</td>
<td>0.67</td>
<td>85.97</td>
<td>Albuquerque, NM</td>
<td>-0.72</td>
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<tr>
<td>Fort Lauderdale, FL</td>
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  - 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:
  - 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:
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