

ONLINE APPENDIX

Place-Based Drivers of Mortality: Evidence from Migration

by Finkelstein, Gentzkow, and Williams

A Empirical Bayes Adjustment

Our Empirical Bayes adjustment follows Chetty and Hendren (2018). This appendix describes the approach in more detail.

Let γ_j be the true life expectancy treatment effects with mean 0. Let M be the average causal place effect which, by construction, is also 0. There is no measurement error in M . We assume that γ_j is a normally distributed random variable, so that

$$(A.1) \quad \gamma_j = M + \eta_j$$

with $\eta_j \sim N(0, \chi^2)$.

Further, assume that the unbiased estimates of γ_j are subject to idiosyncratic measurement error:

$$(A.2) \quad \hat{\gamma}_j = \gamma_j + v_j$$

where the estimation error $v_j \sim N(0, s_j^2)$ and s_j is the standard error of γ_j from the bootstrap.

Combining equations (A.1) and (A.2) implies:

$$(A.3) \quad \hat{\gamma}_j = M + \eta_j + v_j$$

and using OLS we are able to estimate $\text{Var}(\eta_j + v_j)$ as $\widehat{\text{Var}}(\eta_j + v_j)$. Note that in our setting, $\widehat{\text{Var}}(\eta_j + v_j) = \text{Var}(\hat{\gamma}_j)$.

With these assumptions, we are able to compute:

$$(A.4) \quad \chi^2 = \text{Var}(\eta_j) = \text{Var}(\eta_j + v_j) - E[s_j^2]$$

Optimal linear predictions We compute forecasts γ_j^{EB} of each CZ's true causal effect γ_j that minimize the mean squared prediction error:

$$(A.5) \quad \sum_{j=1}^J (\gamma_j^{EB} - \gamma_j)^2$$

Note that the (unobserved) true causal effect of moving to j can be written as:

$$(A.6) \quad \gamma_j = \beta_{1,j} \cdot M + \beta_{2,j} \cdot \hat{\gamma}_j$$

A hypothetical OLS regression across the 563 CZs to estimate the 563 $\beta_{1,j}$ coefficients and the 563 $\beta_{2,j}$ coefficients allows us to form predictions of the true causal effects, γ_j , using M and $\hat{\gamma}_j$, which we call γ_j^{EB} .

$$(A.7) \quad \gamma_j^{EB} = \hat{\beta}_{1,j} \cdot M + \hat{\beta}_{2,j} \cdot \hat{\gamma}_j$$

Note that these predictions, γ_j^{EB} , would minimize the objective function in equation (A.5). Given a way to estimate these coefficients, we can directly compute the optimal forecasts. However, because γ_j is unobserved, we cannot simply estimate the coefficients in an OLS regression. Instead, we use the derivation of these coefficients as in Chetty and Hendren (2018):

$$(A.8) \quad \gamma_j^{EB} = \frac{\chi^2}{\chi^2 + s_j^2} \cdot \hat{\gamma}_j + \frac{s_j^2}{\chi^2 + s_j^2} M$$

Because in our setting $M = 0$, this simplifies to:

$$(A.9) \quad \gamma_j^{EB} = \frac{\chi^2}{\chi^2 + s_j^2} \cdot \hat{\gamma}_j$$

Lastly, again following Chetty and Hendren (2018), we calculate the mean-squared error, e_j^2 , of the optimal prediction, $\hat{\gamma}_j^{EB}$, as:

$$e_j^2 = E[\hat{\gamma}_j^{EB} - \gamma_j]^2 = \frac{1}{\frac{1}{\chi^2} + \frac{1}{s_j^2}}$$

and compute the 95% credible interval as $\hat{\gamma}_j^{EB} \pm 1.96 \cdot e_j$.

B Microfoundation for Assumptions 1 and 2

In this section, we show a natural set of assumptions on the selection process under which Assumptions 1 and 2 are guaranteed to hold with constants $\varphi_1 = \varphi_2 = 1$. The key condition is that selection works only through the single index of overall health capital.

We begin with an underlying population of movers with health capital $\theta_i = h_i + \eta_i$, where h_i and η_i are observed and unobserved components respectively. For simplicity, we ignore the role of demographics and set $X_i\psi = 0$. Following the approach of Section I, we define η_i to be a residual orthogonal to h_i , so that any unobserved determinants of health capital correlated with the observed measures are absorbed in h_i , and η_i only includes the components not predictable from observables. We go beyond the structure imposed above to assume h_i and η_i are independently normally distributed in the population, with $h_i \sim N(0, \sigma_h)$ and $\eta_i \sim N(0, \sigma_\eta)$. We assume $E(\eta_i|o(i), j(i)) = \eta_{o(i)}^{orig} + \eta_{j(i)}^{dest}$ and $E(h_i|o(i), j(i)) = h_{o(i)}^{orig} + h_{j(i)}^{dest}$.

There is an unmodeled selection process under which each mover i is assigned an origin $o(i) \in \mathcal{J}$ and a destination $d(i) \in \mathcal{J}$. These assignments are potentially correlated with health capital. Such correlation could arise because health capital changes the relative appeal of living in different locations, because determinants of location choices are correlated with determinants of health capital, and/or because origin locations exert a causal effect on health capital as of the time of move.

The key assumption we impose on the selection process is that all such correlation operates only through overall health capital index $\theta_i = h_i + \eta_i$ and not differentially through h_i or η_i on their own. Formally, we assume that once we condition on overall health capital θ_i , origin and destination locations provide no further information about the values of h_i and η_i .

Assumption 1. (*Single index*) $E(h_i|\theta_i, o(i), j(i)) = E(h_i|\theta_i)$

Note that since $\eta_i = \theta_i - h_i$, Assumption 1 implies $E(\eta_i|\theta_i, o(i), j(i)) = E(\eta_i|\theta_i)$. This single index assumption naturally constrains the selection on h_i to be tightly related to selection on η_i .

Proposition 1. *Assumption 1 implies Assumptions 1 and 2 hold with $\varphi_1 = \varphi_2 = 1$.*

Proof. Normality of h_i and η_i as well as the fact that $\theta_i = h_i + \eta_i$ imply

$$\theta_i|h_i \sim N(h_i, \sigma_\eta).$$

Standard conjugate prior results for the normal distribution with known variance imply

$$\begin{aligned} E(h_i|\theta_i) &= \frac{\frac{1}{\sigma_h}}{\frac{1}{\sigma_h} + \frac{1}{\sigma_\eta}} \cdot 0 + \frac{\frac{1}{\sigma_\eta}}{\frac{1}{\sigma_h} + \frac{1}{\sigma_\eta}} \cdot \theta_i \\ &= \frac{\sigma_h}{\sigma_h + \sigma_\eta} \theta_i. \end{aligned}$$

It then follows that for any $o(i)$ and $j(i)$,

$$\begin{aligned}
h_{o(i)}^{orig} + h_{j(i)}^{dest} &= \mathbb{E}(h_i | o(i), j(i)) \\
&= \mathbb{E}_{\theta_i} [\mathbb{E}(h_i | \theta_i, o(i), j(i)) | o(i), j(i)] \\
&= \mathbb{E}_{\theta_i} [\mathbb{E}(h_i | \theta_i) | o(i), j(i)] \\
&= \mathbb{E}_{\theta_i} \left[\frac{\sigma_h}{\sigma_\eta + \sigma_h} \theta_i | o(i), j(i) \right] \\
&= \frac{\sigma_h}{\sigma_\eta + \sigma_h} \left(h_{o(i)}^{orig} + h_{j(i)}^{dest} + \eta_{o(i)}^{orig} + \eta_{j(i)}^{dest} \right),
\end{aligned}$$

where the third line uses Assumption 1. We therefore have $h_{o(i)}^{orig} + h_{j(i)}^{dest} = \frac{\sigma_h}{\sigma_\eta} \left(\eta_{o(i)}^{orig} + \eta_{j(i)}^{dest} \right)$. The fact that this must hold for all $o(i)$ and $j(i)$ implies

$$\begin{aligned}
h_{o(i)}^{orig} &= \frac{\sigma_h}{\sigma_\eta} \eta_{o(i)}^{orig} \\
h_{j(i)}^{dest} &= \frac{\sigma_h}{\sigma_\eta} \eta_{j(i)}^{dest}.
\end{aligned}$$

We therefore have $\frac{\text{StDev}(h_{o(i)}^{orig})}{\text{StDev}(\eta_{o(i)}^{orig})} = \frac{\text{StDev}(h_{j(i)}^{dest})}{\text{StDev}(\eta_{j(i)}^{dest})} = \frac{\sigma_h}{\sigma_\eta}$, which implies Assumption 2 with $\varphi_2 = 1$. We

also have $\frac{\text{StDev}(h_{j(i)}^{dest})}{\text{StDev}(\eta_{j(i)}^{dest})} = \frac{\sigma_h}{\sigma_\eta} = \frac{h_{j(i)}^{dest}}{\eta_{j(i)}^{dest}}$, so Assumption 1 with $\varphi_1 = 1$ follows by Proposition 1. \square

C Sample Restrictions, Mover Definition, and Characteristics of Moves

Appendix Table A.10 details the number of observations excluded by each of our sample criteria. Our analysis sample consists of almost 69 million Medicare enrollees whom we observe between the ages of 65 and 99. Of these, almost 62 million are non-movers; their zip code of residence does not change at any point over the years we observe them. The remaining 7 million are “potential movers,” in that their zip code of residence changes at least once. To the extent possible, we impose a parallel set of restrictions to the non-mover and mover samples.

Non-mover sample

To define our non-mover sample, we begin with the 62 million enrollees whose CZ of residence does not change over the years we observe them. We make several further restrictions that bring the non-mover sample down to just over 43 million. For each non-mover, we need to be able to define a year t_i^* as a counterfactual move year. Most importantly, this requires that they have a year $t_i^* - 1$ in which the non-mover was enrolled in Traditional Medicare, so that we can measure their healthcare utilization in year $t_i^* - 1$. We also exclude non-movers who do not have a $t_i^* - 1$ in which they are younger than 98 and that is before 2012. These restrictions decrease the number of eligible non-movers from 62 million to 52 million. We exclude non-movers who do not have a year $t_i^* - 1$ such that they survive through the end of year t_i^* , so that we are able to observe their mortality in year $t_i^* + 1$. This eliminates another 9 million non-movers. Finally, we exclude the small number of non-movers who do not have a remaining year $t_i^* - 1$ with data on controls of health utilization and chronic conditions. For the remaining non-movers, t_i^* is defined as their second year in the sample. In all of our analyses we work with a random 10% sample of these remaining 43 million non-movers.

Mover sample

To define our mover sample, we begin with the 7 million “potential movers” - i.e. individuals whose zip code of residence changes at least once. We make several further restrictions to the mover sample that bring the number of movers down to just over 2 million. First, we exclude individuals whose CZ residence changes more than once; this brings the 7 million potential movers down to 5.6 million. Second, we exclude movers who are enrolled in Medicare Advantage (MA) the year before move ($t_i^* - 1$) or the year after move ($t_i^* + 1$) since, as discussed, we cannot observe healthcare claims for MA enrollees and we need to observe the location of healthcare claims to define movers. Following the approach of Finkelstein et al. (2016), we exclude “movers” for whom the ratio of the number of claims located in their destination to the number located in either their origin or their destination does not increase by at least 0.75 in their post-move years relative to their pre-move years; these are individuals who, despite having a change of official address on file, do not appear to have really changed CZs based on their claims pattern.¹

¹The change in claim share is not defined for movers who do not have at least one claim both pre- and post-move. Following Finkelstein et al. (2016), we exclude these cases if: (i) they have no post-move claims and a pre-move destination claim share greater than 0.05; (ii) they have no pre-move claims and a post-move destination claim share less than 0.95.

The exclusion of movers who are on MA in $(t_i^* - 1)$ or $(t_i^* + 1)$ brings the number of movers down from 5.6 million to 4.2 million. The exclusion of “false” movers (i.e. those whose claim share does not increase by at least 0.75), further reduces the number of movers to 2.6 million. A few other exclusions for data reasons bring our final mover sample down to 2 million movers. Of the 2 million movers in our final sample, about 18% of them are on MA in at least one year. Given the number of total enrollee-years we observe, we estimate an average annual cross-CZ move rate for Medicare enrollees of about 0.5 percent.

Appendix Figure A.7 shows a mover’s claims in her destination CZ, as a share of those in either her origin or her destination, by relative year. There is a sharp change in the year of the move, and only a very small share of claims in the destination pre-move or in the origin post-move. The share of claims in the destination in the year of the move (relative year 0) is close to 0.5, suggesting that moves are made roughly uniformly throughout the year.

Characteristics of moves

We examined some of the characteristics of moves. The average distance between origin and destination zip code centroids of movers in our sample is 547 miles, with a median of 305 miles and a standard deviation of 601 miles. Roughly 66 percent of moves cross state boundaries, and 48 percent cross census division boundaries. Moves to Florida account for 12 percent of all moves, and moves to Arizona or California account for an additional 10 percent.

In our previous work (Finkelstein et al. 2016), we also used data from the Health and Retirement Survey to explore some of the time-varying correlates of moving in the Medicare population; widowhood and retirement were significant predictors of moving, and the most common self-reported rationale for moving was to be near one’s children.

D Data and Definitions for Place Characteristics

Here we describe the data and definitions used for the place characteristic measures that we correlate with treatment effects in Figure 6. Summary statistics for all of these measures can be found in Appendix Table A.11.

D.1 Healthcare Utilization

We follow Finkelstein et al. (2016) to construct our health care utilization measures. The utilization measure we use as a pre-period control in our estimation is created by aggregating care provided to Medicare beneficiaries as recorded in the inpatient and outpatient claims data. For the healthcare place characteristics in Figure 6, we use a 20% random sample of data from the inpatient, outpatient, and carrier files from Medicare year 2010. See Finkelstein et al. (2016) Online Appendix for more details on how utilization is computed. Our definitions of diagnostic tests and imaging tests also follow directly from Finkelstein et al. (2016) and detailed definitions of these variables can also be found in that paper’s Online Appendix.

D.2 Other Healthcare Characteristics

Share of hospitals that are non-profit and Hospital beds per capita are defined as in Finkelstein et al. (2016) using the 1998-2008 American Hospital Association’s annual survey of hospitals.

Specialists per thousand residents and PCPs per thousand residents are also defined as in Finkelstein et al. (2016) using counts of physicians from the 2011 AMA Physician Masterfile. CZ populations are computed by first aggregating county-level populations from the 2000 Census and 2007-2011 ACS, and then taking the simple average across the two.

Hospital Compare Score, a measure that reports the quality of hospitals, is derived from “process of care” measures that are publicly reported by CMS and uses quarterly data from 2005 to 2011. For a given measure (e.g., share of heart attack patients given aspirin at arrival or share of pneumonia patients given oxygenation assessment), we standardize the score by first taking a simple average across the quarterly measures within a year for a given hospital to get an annual measure. We then construct z-scores for each measure across hospitals in a given year. Lastly, for each hospital we take the simple average of the z-scores across measures within a year and then the simple average over years.

D.3 Non-healthcare Characteristics

Measures derived from Centers for Disease Control (CDC) data Many of our CZ-level measures of non-healthcare characteristics are derived from data downloaded from the CDC (<https://wonder.cdc.gov/>) and cover the years 2001-2011 (except pollution, for which records are only available beginning in 2003).

- Homicides and Auto Deaths are defined by the National Center for Health Statistics using ICD-9 and ICD-10 mortality codes and are reported per 100,000 people from 2001-2011 at the county level. We take the population-weighted average across counties to aggregate to the CZ level, with county populations based on an average from the 2000 Census and 2007-2011 ACS.

- Pollution is a measure of fine particulate matter and is reported in micrograms per cubic meter. For each county we have the daily average across all days from 2003-2011. We aggregate these single county-level measures to the CZ level by taking the population-weighted average across counties within each CZ, with county populations constructed as described above.

- Average Winter Temperature is defined as the average daily minimum air temperature during the months of January, February, and March for each county. For each county we take a simple average across all winter months from 2001-2011, and then aggregate these single county-level measures to the CZ level by taking the population-weighted average across counties within each CZ, with county populations constructed as described above.

- Average Summer Temperature is defined similarly to Average Winter Temperature, but uses the average daily maximum air temperature during the months of June, July, and August.

Measures derived from Chetty et al. (2016) data Our health behavior measures are derived from the health behavior data posted by Chetty et al. (2016) (<https://healthinequality.org/data>), as originally drawn from the Behavioral Risk Factor Surveillance Survey (BRFSS). The data cover 1996-2008 and are reported at the CZ level separately for each income quartile. We take the simple average of the four quartiles to get the average measure in each CZ.

- Smoking is the fraction of respondents who report currently smoking in each CZ of the pooled BRFSS sample over years 1996-2008.

- Obesity is the fraction of respondents who are obese ($BMI \geq 30$) in each CZ of the pooled BRFSS sample over years 1996-2008.

- Exercise is the fraction of respondents who have exercised in the past 30 days in each CZ of the pooled BRFSS sample over years 1996-2008.

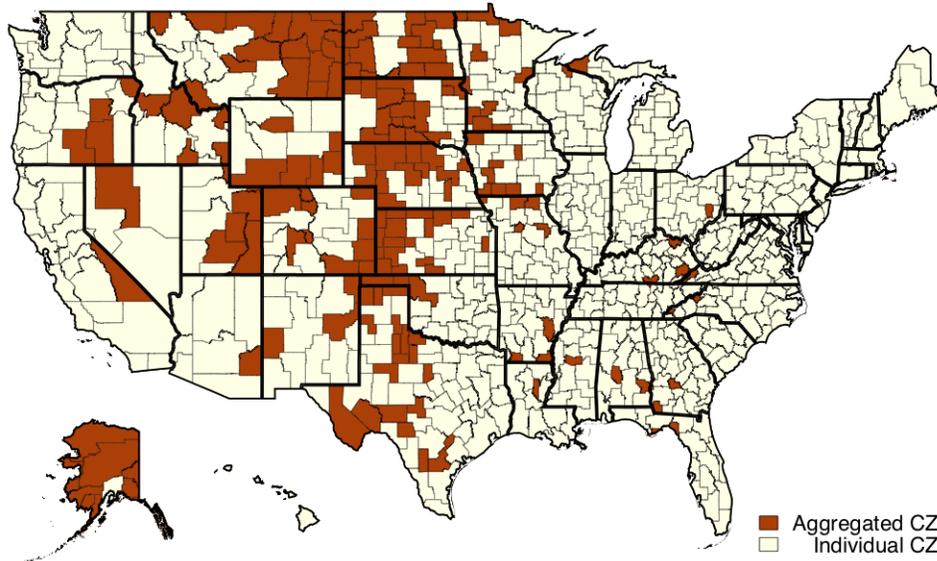
Measures derived from Census data Our other CZ level measures of non-healthcare characteristics are derived from Census data.

- Share Urban is derived from the 2000 and 2010 Census data. Urban and total populations are available at the county level, and we aggregate these values within each CZ and compute the share of that population that is urban. We then take the simple average of these values across the two census surveys.

- Share over 60, Median household income, and High school graduation rate are computed similarly using the 2000 Census survey and 2007-2011 American Community Survey. Median household income and high school graduation rates are computed for people 25 and older.

Appendix Figures

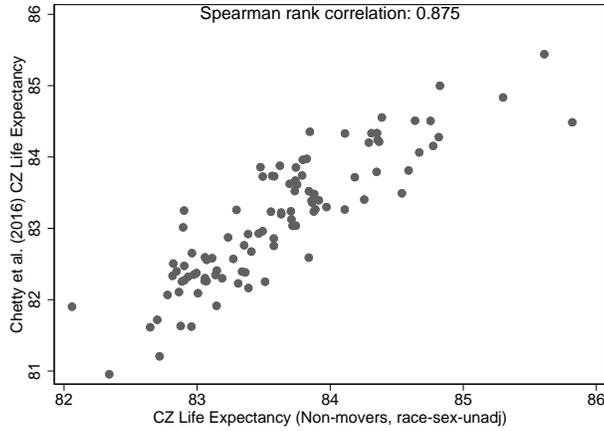
Figure A.1: Location of Small CZs



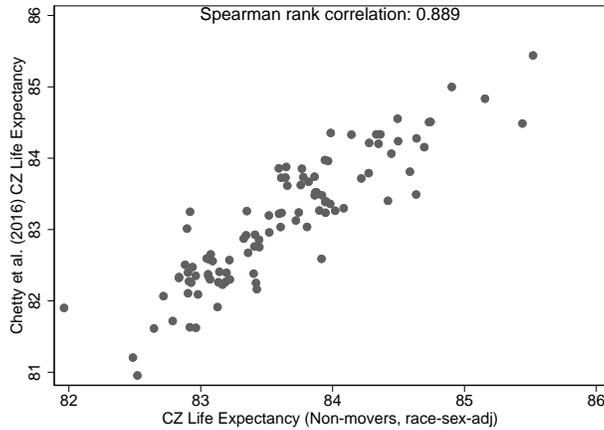
Notes: Figure shows the location of small CZs. Small CZs within the same state are combined and considered a single location, resulting in 35 aggregated CZs.

Figure A.2: Life Expectancy Correlations with Chetty et al. (2016)

(a): Unadjusted Life Expectancy



(b): Race-Sex Adjusted Life Expectancy (L_j)



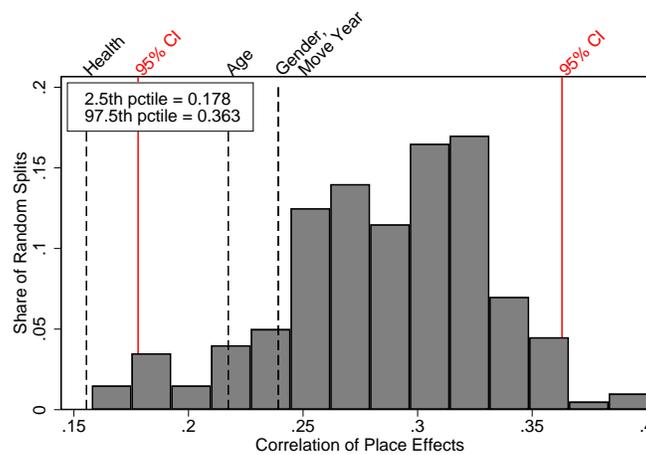
Notes: These figures compare our non-mover life expectancy at age 65 (L_j) to life expectancy estimates at age 40 from Chetty et al. (2016), among the 100 largest CZs by population in 2000. Panel (a) uses a version of L_j that is not adjusted for race and sex; specifically in panel (a), we set the elements of the vector associated with race and sex to the CZ average rather than the national average for each CZ. Panel (b) uses our race- and sex-adjusted L_j from Figure 1. These figures use the life expectancies from Chetty et al. (2016) that are not adjusted based on race or sex. Since their life expectancies are based on CZs as of 1990, we convert their estimates to CZs as of 2000 by taking an average of the 1990 CZ life expectancies, weighted by the proportion of the population in each CZ in 2000 who lived in the CZ in 1990. Correlation coefficients are based on the Spearman rank correlation, although results are similar when comparing life expectancies using the Pearson correlation coefficient.

Figure A.3: Distribution of Destination-Origin Difference in Average Life Expectancy



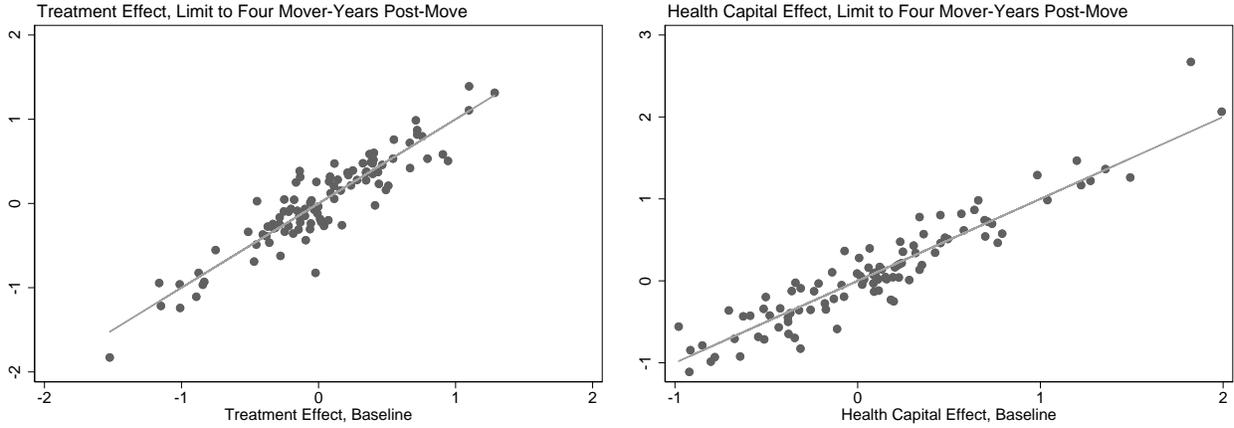
Notes: Figure shows the distribution across movers of the difference in average non-mover life expectancy at age 65 (L_j) between their origin and destination CZs. The sample is all movers (N = 2,033,263 movers).

Figure A.4: Heterogeneity in Place Effects



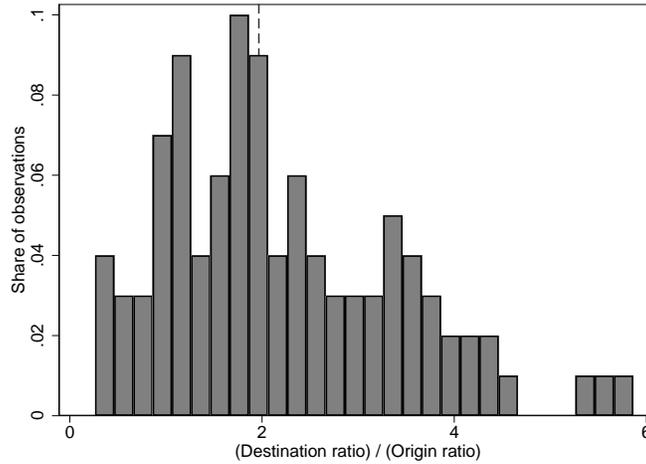
Notes: This histogram shows the distribution of correlation coefficients between place effects (γ_j) resulting from 200 random partitions that split the data into two equally sized groups, with separate estimation of the Gompertz model for each group. The place effects are corrected using the selection correction procedure. Red lines indicate the locations of the 2.5th and 97.5th percentiles; for values outside of this range, we reject the null hypothesis that the place effects are equal in the two groups.

Figure A.5: Constant Health Capital Assumption, Treatment and Health Effects Comparison



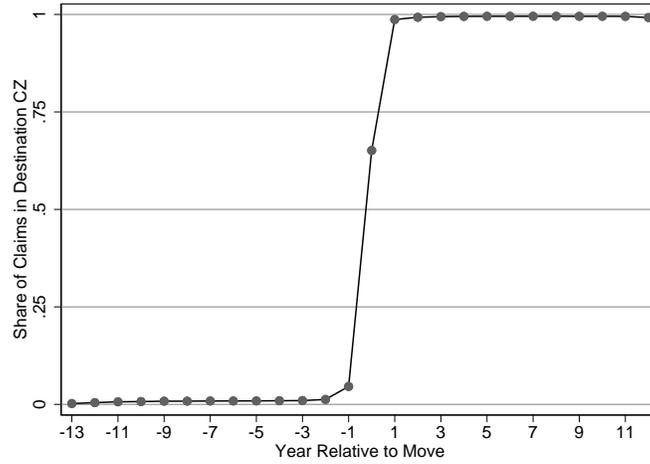
Notes: The left figure plots treatment effects from the sample that includes a maximum of four years post-move for each mover against the treatment effects from the baseline sample, using the 100 largest CZs by total population in 2000. The right figure plots health capital effects. Each point is one CZ. Solid lines indicate the 45-degree line.

Figure A.6: Histogram of (Destination ratio)/(Origin ratio)



Notes: This histogram plots the distribution of the ratio $\left(\frac{\text{StDev}(\eta_{j(i)}^{dest})}{\text{StDev}(h_{j(i)}^{dest})} \right) / \left(\frac{\text{StDev}(\eta_{j(i)}^{orig})}{\text{StDev}(h_{j(i)}^{orig})} \right)$ for 100 different subsets H_i^k of chronic conditions, using the same subsets as in Figure 7. For each k , H_i^k includes $\log(\text{overall utilization})$ and a random subset of thirteen of the twenty-seven chronic conditions. The dotted line shows the median of the distribution. All standard deviations are computed using the split-sample approach.

Figure A.7: Claims Share Graph



Notes: This figure shows the share of a mover's claims located in their destination CZ, among those in either their origin or their destination CZ. The sample is all enrollee-years ($N = 17,443,789$) in the 100% Denominator file for all movers in our baseline sample.

Appendix Tables

Table A.1: Predicting Mortality from Observables

	(1)	(2)	(3)
	Coefficient	(s.e.)	Average
Log(Utilization + 1)	0.028	(0.000)	3.67
Chronic Conditions:			
Acquired Hypothyroidism	-0.008	(0.003)	0.03
Acute Myocardial Infarction	-0.069	(0.009)	0.00
Alzheimer's	0.214	(0.008)	0.01
Alzheimer's and Related Disorders or Senile Dementia	0.474	(0.005)	0.03
Anemia	0.152	(0.002)	0.09
Asthma	-0.054	(0.005)	0.02
Atrial Fibrillation	0.222	(0.004)	0.03
Benign Prostatic Hyperplasia	-0.214	(0.004)	0.03
Breast Cancer	0.087	(0.005)	0.01
Cataract	-0.095	(0.002)	0.15
Chronic Kidney Disease	0.413	(0.005)	0.02
Chronic Obstructive Pulmonary Disease	0.484	(0.003)	0.05
Colorectal Cancer	0.048	(0.007)	0.01
Depression	0.188	(0.003)	0.04
Diabetes	0.342	(0.002)	0.08
Endometrial Cancer	0.115	(0.017)	0.00
Glaucoma	-0.063	(0.003)	0.05
Heart Failure	0.327	(0.003)	0.06
Hyperlipidemia	-0.221	(0.002)	0.15
Hypertension	0.042	(0.002)	0.25
Hip/Pelvic Fracture	0.042	(0.009)	0.00
Ischemic Heart Disease	0.099	(0.002)	0.13
Lung Cancer	0.772	(0.014)	0.00
Osteoporosis	0.032	(0.004)	0.03
Prostate Cancer	0.035	(0.005)	0.02
Rheumatoid Arthritis	-0.066	(0.003)	0.08
Stroke / Transient Ischemic Attack	0.205	(0.004)	0.02
N	6,345,989		

Notes: This table reports the coefficients of the components of H_i in our main estimating equation, equation (3). Standard errors are computed with 100 replications of the bootstrap. Column (3) reports the sample mean of $\log(\text{Utilization} + 1)$ in row (1) and, for all other rows, the share of beneficiaries with the indicated chronic condition in year $t_i^* - 1$. Utilization excludes physician services (“carrier files”) because these files are only available for a 20 percent subsample. As in the estimation, when computing the sample-wide shares, non-movers are upweighted by ten to account for our sampling procedure.

Table A.2: Number of Movers Received by CZ or Aggregate CZ

Statistics	# Movers to CZ
Minimum	48
10th Percentile	468
25th Percentile	781
Median	1,522
75th Percentile	3,534
90th Percentile	9,241
Maximum	45,360

Notes: This table summarizes the number of movers received by each of the 563 CZs or aggregated CZs.

Table A.3: Summary Statistics on Estimation Sample

	(1)	(2)
	Movers	Non-movers
Age:		
65-74	0.48	0.75
75-84	0.35	0.19
85+	0.18	0.06
Female	0.60	0.55
White	0.90	0.85
Region:		
Northeast	0.19	0.20
South	0.41	0.38
Midwest	0.21	0.25
West	0.19	0.17
On Medicaid	0.10	0.11
Avg. # of chronic conditions	3.05	1.33
1-year mortality	0.09	0.04
4-year mortality	0.27	0.15
Life expectancy at age 65	82.10	83.65
Number of individuals	2,033,263	4,312,726

Notes: These summary statistics are computed on all movers and non-movers in our Gompertz estimation sample. The reference year for movers is their move year, and the reference year for non-movers is set to be their second year in the sample. Rows for female, white, age, and region report the shares of individuals with the given characteristics. The life expectancy measure is conditional on surviving until age 65, and is calculated for 1,000 random 65-year-old enrollees within the sample indicated by each column. Time-varying characteristics are measured in the year prior to each enrollee's reference year.

Table A.4: Transition Matrix of Moves

Origin Decile	Destination Decile										Origin total
	1	2	3	4	5	6	7	8	9	10	
1	10%	13%	16%	17%	13%	12%	6%	5%	4%	4%	74,983
2	7%	10%	11%	14%	14%	13%	8%	8%	7%	9%	110,370
3	7%	9%	10%	16%	14%	14%	9%	8%	6%	6%	107,716
4	5%	7%	9%	12%	15%	13%	10%	9%	9%	10%	159,424
5	3%	6%	6%	12%	17%	14%	11%	11%	9%	10%	219,967
6	3%	6%	6%	9%	13%	14%	12%	14%	11%	13%	238,606
7	2%	4%	5%	8%	12%	15%	9%	16%	14%	15%	184,239
8	1%	4%	4%	7%	11%	12%	12%	14%	18%	17%	220,596
9	1%	3%	3%	6%	9%	11%	12%	21%	14%	19%	305,532
10	1%	4%	2%	6%	9%	10%	11%	15%	16%	27%	411,830

Notes: Table reports the percentage of moves in each row to each destination. The “origin total” column reports the total number of moves in each row. Each row is a (population-weighted) decile of CZ origin life expectancy. Each column is decile of CZ destination life expectancy. Q1 is the lowest life expectancy and Q10 is the highest. The sample is all movers (N = 2,033,263 movers).

Table A.5: Heterogeneity in Place Effects

Sample		
Baseline Standard Deviation of γ_j	0.054	[0.040, 0.069]
Move Year		
Standard Deviation of γ_j		
(i) Late	0.064	[0.000, 0.096]
(ii) Early	0.056	[0.034, 0.071]
Gender		
Standard Deviation of γ_j		
(i) Female	0.056	[0.031, 0.073]
(ii) Male	0.068	[0.034, 0.100]
Age		
Standard Deviation of γ_j		
(i) Young Movers	0.075	[0.050, 0.099]
(ii) Old Movers	0.038	[0.000, 0.067]
Individual Health		
Standard Deviation of γ_j		
(i) Good Health	0.101	[0.074, 0.117]
(ii) Poor Health	0.058	[0.024, 0.081]

Notes: The first row replicates baseline results (See Table 3) and the rest of the table summarizes splits of the main sample that approximately divide the number of movers into two equal groups. Each group includes all non-movers and the Gompertz estimation for each group controls for the same covariates as in the main estimation. “Late movers” includes all movers with a move year of 2005 or later (N = 909,901) and “early movers” includes all movers with a move year before 2005 (N = 1,123,362). There are 1,229,235 female movers and 804,028 male movers. Young movers move when they are 75 or younger (N = 1,038,585) and old movers move when they are older than 75 (N = 994,678). Movers with good health have a value of \hat{h}_i less than or equal to the median value among all movers (N = 1,016,631) and movers with poor health have a value of \hat{h}_i greater than the median value among all movers (N = 1,016,632). Standard deviations are calculated using the split-sample approach. Brackets show the 95% confidence intervals computed via 100 iterations of the Bayesian bootstrap. Since standard deviations cannot be negative, any split-sample approach that produces a negative result we set to 0.000.

Table A.6: Constant Health Capital Assumption

	Baseline (Large CZs)	Limit to Mover-Years:		
		≤ 2 Years Post-move	≤ 4 Years Post-move	≤ 6 Years Post-move
(1) Number of movers	710,990	710,990	710,990	710,990
Cross-CZ standard deviation of:				
(2) Life expectancy (L_j)	0.66 [0.64, 0.68]	0.66 [0.64, 0.67]	0.66 [0.64, 0.68]	0.66 [0.64, 0.68]
(3) Treatment effects ($L_j^* - \bar{L}$)	0.47 [0.40, 0.53]	0.54 [0.40, 0.67]	0.47 [0.36, 0.56]	0.47 [0.37, 0.54]
(4) Health capital effects	0.53 [0.44, 0.59]	0.60 [0.43, 0.73]	0.56 [0.44, 0.64]	0.56 [0.46, 0.63]

Notes: This table assesses the constant health capital assumption with the specifications indicated in each column among the 100 largest CZs by total population in 2000. Columns for “Limit to Mover-Years” only include the indicated years for movers after the move year. Row (2) shows the cross-CZ standard deviation of life expectancy at 65 among non-movers in the indicated sample. All standard deviations are computed using the split-sample approach, giving equal weight to each CZ. 95% confidence intervals are computed using 100 iterations of the Bayesian bootstrap.

Table A.7: Panel vs. Cross-Section

	(1)	(2)	(3)
	Any hospital admission	Any emergency room visit	Any outpatient visit
(1) Mean of outcome	0.196	0.263	0.617
Cross-section standard deviations:			
(2) Outcome	0.027 [0.026, 0.028]	0.031 [0.031, 0.032]	0.098 [0.098, 0.099]
(3) Place effect, unadjusted (τ_j^{dest})	0.028 [0.025, 0.030]	0.029 [0.026, 0.031]	0.084 [0.083, 0.085]
(4) Place effect, adjusted (γ_j)	0.024 [0.021, 0.026]	0.026 [0.023, 0.029]	0.086 [0.085, 0.087]
(5) Panel standard deviation: place effect (γ_j)	0.020 [0.018, 0.021]	0.023 [0.021, 0.025]	0.101 [0.100, 0.102]

Notes: Each column reports results for a different outcome. Row (1) reports the mean of the dependent variable. Row (2) reports the cross-CZ standard deviation of the outcome. The estimates are reported in rows (3) through (5). All estimates are linear probability models; for the cross-sectional estimates (rows 3 and 4) we estimate equation (3) on the outcome one-year post-move. For the panel (row 5) we estimate the panel equation (7). The sample is different from our baseline sample ($N = 5,258,502$ enrollees instead of 6,345,989) because, to be consistent with our panel analysis, we exclude enrollees who do not have 12 months of Parts A and B coverage in relative year 1. For the panel estimation, we further exclude all enrollee-year observations for which an enrollee does not have 12 months of Parts A and B coverage as well as relative year 0 for movers. We also restrict our analysis to years 1999-2011. These exclusions together ensure that each outcome variable in this analysis always includes twelve months of Parts A and B coverage. In column (1), any hospital admission is defined as non-zero inpatient utilization. In column (2), any emergency room visit is defined as non-zero emergency room utilization. In column (3), any outpatient visit is defined as non-zero outpatient utilization. Each of these utilization measures is defined as in Finkelstein et al. (2016), except emergency room utilization, which is defined using only the inpatient and outpatient files (rather than the measure that includes the carrier files in Finkelstein et al. 2016). The mean of the outcome is the average over all enrollee-years in the sample. We compute the CZ level measure by first taking the average over non-movers within each CZ, then the simple average over years. 95% confidence intervals are computed using 100 iterations of the Bayesian bootstrap.

Table A.8: Alternative Selection Assumptions

	(1) φ	(2) StDev of Place Effects (γ_j)	(3) StDev of Treatment Effects ($L_j^* - \bar{L}$)
(1) Baseline	1.00	0.054 [0.040, 0.069]	0.44 [0.32, 0.55]
(2) Conceptual minimum	1.26	0.054 [0.039, 0.070]	0.43 [0.31, 0.56]
(3) Empirical median	1.97	0.064 [0.047, 0.083]	0.52 [0.37, 0.67]
Adjusted based on panel:			
(4) Any ER visit	1.75	0.059 [0.042, 0.077]	0.48 [0.34, 0.62]
(5) Any hospital admission	2.70	0.088 [0.069, 0.109]	0.71 [0.56, 0.89]
(6) Any outpatient visit	7.10	0.279 [0.247, 0.321]	2.27 [2.00, 2.62]
(7) Minimum difference across outcomes	2.80	0.091 [0.073, 0.113]	0.74 [0.60, 0.92]

Notes: This table reports the cross-CZ standard deviations of our place effects and treatment effects for various values of $\varphi = \varphi_1 \varphi_2$ as defined in equation (6). Row (1) corresponds to the baseline results where $\varphi = 1$. Row (2) shows results for the value of φ that minimizes the implied standard deviation of γ_j . Row (3) uses the median value of φ from Figure A.6. Rows (4)-(6) use the values of φ that minimize the absolute difference between the standard deviation of the place effects estimated via the panel approach and via the adjusted cross-sectional approach from Table A.7, for each of the indicated outcomes. Row (7) uses the value of φ that minimizes the average of this absolute difference across all three outcomes from rows (4)-(6). 95% confidence intervals are computed using 100 iterations of the Bayesian bootstrap.

Table A.9: Robustness Checks

Specification	(1) Movers	(2) StDev of life expectancy (L_j)	(3) StDev of treatment effects ($L_j^* - \bar{L}$)	(4) $Corr(L_j^* - \bar{L}, \text{baseline})$	(5) $Corr(L_j^* - \bar{L}, L_j)$
(1) Baseline (Large CZs)	710,990	0.66 [0.64, 0.68]	0.47 [0.40, 0.53]	1.00	0.41 [0.35, 0.47]
(2) Heterogeneity by mover status	710,990	0.66 [0.64, 0.67]	0.47 [0.41, 0.52]	0.98 [0.97, 0.98]	0.43 [0.37, 0.50]
(3) Interacting H components with age	710,990	0.63 [0.61, 0.65]	0.42 [0.35, 0.47]	0.99 [0.97, 0.99]	0.38 [0.31, 0.45]
(4) Interacting gender with age	710,990	0.66 [0.64, 0.68]	0.47 [0.40, 0.53]	1.00 [1.00, 1.00]	0.41 [0.34, 0.47]
(5) Controlling for origin county mortality rates	710,990	0.67 [0.65, 0.68]	0.49 [0.43, 0.55]	0.98 [0.97, 0.99]	0.45 [0.38, 0.51]
(6) Move distance greater than 100 miles	558,367	0.67 [0.65, 0.68]	0.45 [0.36, 0.53]	0.96 [0.92, 0.97]	0.41 [0.33, 0.48]
(7) Movers age 70 or older moving after 2003	347,055	0.66 [0.64, 0.67]	0.44 [0.29, 0.55]	0.87 [0.76, 0.89]	0.33 [0.20, 0.46]
Destination-origin difference in L_j :					
(8) Greater than median difference	341,469	0.66 [0.64, 0.68]	0.53 [0.39, 0.64]	0.91 [0.83, 0.90]	0.48 [0.37, 0.58]
(9) Less than median difference	369,521	0.67 [0.64, 0.68]	0.49 [0.00, 0.89]	0.84 [0.59, 0.83]	0.42 [0.11, 0.74]
Excluding moves to:					
(10) Adjacent CZs	554,420	0.67 [0.65, 0.68]	0.48 [0.40, 0.56]	0.97 [0.93, 0.97]	0.41 [0.34, 0.49]
(11) Florida, Arizona, and California	485,389	0.61 [0.59, 0.63]	0.47 [0.35, 0.54]	1.00 [0.99, 1.00]	0.37 [0.29, 0.46]
(12) Years 1999-2003	325,041	0.61 [0.59, 0.63]	0.46 [0.36, 0.55]	0.92 [0.83, 0.92]	0.44 [0.32, 0.54]
(13) Years 2004-2012	385,949	0.69 [0.67, 0.73]	0.48 [0.36, 0.61]	0.86 [0.57, 0.76]	0.34 [0.20, 0.44]

Notes: Table reports results for alternative specifications. Estimates in all rows are computed on the 100 largest CZs by total population in 2000. The first row reports the baseline estimates, and each additional row represents a single deviation from the baseline, which are described in Section VI. All treatment effects are treatment effects on life expectancy, and are not adjusted using an empirical Bayes correction. Column (1) shows the number of movers who remain in each specification. In all rows, we estimate treatment effects for 100 CZs, other than Row (11) (79 CZs). Columns (2) and (3) show cross-CZ standard deviations of age-65 non-mover life expectancy and treatment effects, computed using the split-sample. Column (4) shows the cross-CZ correlation between treatment effects and the baseline treatment effects. The cross-CZ correlation of treatment effects and life expectancy in column (5) is computed as the coefficient of the regression of the non-adjusted treatment effect on age-65 non-mover life expectancy. 95% confidence intervals are computed using 100 iterations of the Bayesian bootstrap.

Table A.10: Sample Restrictions

	(1)	(2)
	Enrollees	Enrollee-years
Original sample	80,708,181	665,131,064
Excluding enrollee-years with age < 65 or age > 99	69,330,956	560,057,853
Excluding enrollee-years with incomplete data ¹	68,935,110	556,340,988
Number of non-movers after sample-wide drops	61,899,201	
Excluding non-movers without a valid relative year -1 with Traditional Medicare	52,448,582	
Excluding non-movers without a relative year -1 with 1-year mortality observed	43,147,931	
Excluding non-movers without a relative year -1 with pre-period controls ²	43,145,670	
Number of movers after sample-wide drops	7,035,909	
Excluding movers with more than one move	5,609,064	
Excluding movers on MA during relative years -1 or 1	4,204,679	
Excluding “false” movers ²	2,564,376	
Excluding movers for whom we cannot observe 1-year mortality	2,033,333	
Excluding movers with missing pre-period controls	2,033,263	

Notes: (1) Data is incomplete if the CZ is missing for an enrollee-year, or an enrollee has gaps in the years they are observed. (2) Pre-period controls consist of health utilization and chronic conditions. (3) False movers are those movers for whom the ratio of the number of claims located in their destination to the number located in either their origin or their destination does not increase by at least 0.75 in their post-move years relative to their pre-move years.

Table A.11: CZ Summary Statistics

	(1)	(2)	(3)
	Mean	S.D.	N
Healthcare Characteristics:			
Hospital Compare Score	-0.13	0.50	559
Specialists per capita	1.47	1.08	563
PCPs per capita	0.90	0.30	563
Hospital beds per capita	2.70	1.17	560
Share non-profit hospitals	0.82	0.20	560
Imaging tests	1.84	0.92	563
Diagnostic tests	4.12	2.82	563
Mean utilization	4150.60	1396.57	563
Non-healthcare Characteristics:			
Pollution (μg per cubic meter)	11.84	1.71	559
Summer Temperature($^{\circ}F$)	84.70	6.79	559
Winter Temperature($^{\circ}F$)	30.72	10.11	559
Auto Deaths (per 100,000)	19.46	7.07	563
Homicides (per 100,000)	5.50	3.18	490
Smoking	0.20	0.04	557
Obesity	0.27	0.05	557
Exercise	0.75	0.05	557
High School Graduation Rate	0.82	0.06	563
Household Income	40,724	7,950	563
Share 60+	0.20	0.04	563
Share Urban	0.56	0.22	563

Notes: This table reports the simple average across the (aggregated) CZs of the place characteristics in Figure 6. See Appendix D for detailed definitions of these place characteristics.

References

- Chetty, Raj and Nathaniel Hendren**, “The Impacts of Neighborhoods on Intergenerational Mobility II: County-Level Estimates,” *The Quarterly Journal of Economics*, 2018, 133 (3), 1163–1228.
- , **Michael Stepner, Sarah Abraham, Shelby Lin, Benjamin Scuderi, Nicholas Turner, Augustin Bergeron, and David Cutler**, “The Association Between Income and Life Expectancy in the United States, 2001-2014,” *Journal of the American Medical Association*, 2016, 315 (16), 1750–1766.
- Finkelstein, Amy, Matthew Gentzkow, and Heidi Williams**, “Sources of Geographic Variation in Health Care: Evidence From Patient Migration*,” *The Quarterly Journal of Economics*, 2016, 131 (4), 1681.