Appendix: Sources of Geographic Variation in Health Care Spending Among Individuals with Employer Sponsored Insurance

Expanded Sample Construction

Using HCCI claims data, we constructed a sample of health care services provided in geographic areas across the country in each year from 2012 to 2016. The HCCI claims data are primarily organized at the claim line level. That is, for a service performed, the claim filed is broken up into multiple claim lines. To construct a service level sample from the claim line level data, we aggregated data from all claim lines associated with each service. This aggregated service will be referred to as a service claim.

Area Inclusion Criteria

To be included in our expanded sample, a claim line had to be associated with an individual from and a service provided within one of our analysis areas. We performed our analysis at the Core-Based Statistical Area (CBSA) level.

The CBSAs included in the study had to meet certain population, coverage, and utilization criteria. First, the sample CBSAs had to have a minimum average HCCI coverage of 10% over the 5-year period (2012-2016). Yearly HCCI coverage estimates were calculated by dividing HCCI's member years (total member months divided by 12) within a CBSA by the American Community Survey (ACS) 5-year average employer sponsored insurance (ESI) population in that same CBSA. Each sample CBSA had to have an average of at least 25,000 member years in the HCCI data from 2012-2016. Using data from the American Hospital Association (AHA), included CBSAs had to have a minimum of 5 distinct, non-governmental General Medical and Surgical Hospitals. This resulted in a final geographic sample of 112 CBSAs across 43 states.

Member Inclusion Criteria

We included all claim lines associated with members who were both in our study analysis CBSAs and a part of the sample population. For a member month to be included in the sample population, the member, in that given month, needed to be under the age of 65 and have an identifiable gender in the data. Additionally, they had to have ESI, non-individual coverage with one of the following plan types: Health Maintenance Organization, Preferred Provider Organization, Point of Service Plan, or Exclusive Provider Organization. Using these member months, we calculated our sample's member year totals by CBSA and by year to determine the CBSA sample.

We omitted members from our expanded sample who was associated with multiple health plans within any given month, did not have a full year of coverage, or had inconsistent demographic or plan information within any year.

We subsequently cleaned and analyzed remaining members' associated inpatient, outpatient, and professional service claims.

Aggregating claim lines to service claims

We define a service claim as all claim lines for an individual with common dates and service codes. We define service codes distinctly in each high-level service category (inpatient, outpatient). For inpatient claims, we define a service code as DRG codes. For outpatient claims, we define service codes as the combination of CPT code and CPT code modifier. For the remainder of this document, we use CPT code to refer to the combination of CPT code and CPT code modifier.

When aggregating claim lines to the service claim level, we summed all allowed amounts (the actual amount paid to for the claim) from each claim line associated with a particular service claim. Allowed amounts comprise both the insurer's payment to a provider as well as any out-of-pocket spending (copayments, coinsurance, or deductibles) by the patient. We define the sum of the these allowed amounts as the total spending on a service claim.

This sample of claims comprises our expanded sample. In total, our sample spans over 1.8 billion claims from 132 million member years across the study, 2012 - 2016.

Mover, Non-Mover Sample Inclusion Criteria

Our primary analysis sample was a subsample of our expanded sample described above. We restricted our analysis sample to individuals with at least four years of continuous enrollment between 2012 and 2016. We then constructed a sample of movers and non-movers. For our mover sample, we identified individuals who moved exactly once to and from one of our 112 metro areas, and for whom we observe at least two years of coverage prior to their move and one year following their move. This implied two cohorts of individuals who moved in either 2014 or 2015. For our non-mover sample, we compiled a 5-percent random sample of individuals who remained in the same sample metro area throughout the duration of their coverage. We then separated our sample of non-movers into two cohorts corresponding to our mover cohorts of individuals who moved in either 2014 or 2015. For non-movers whom we observe for exactly 4 years of data, we assigned them to the "move year" cohort corresponding to the second to last year we observe in the data. In this way, analogously to our sample of movers, we would observe them in two years prior to a hypothetical move and one year following. For non-movers whom we observe for 5 years in the data, we randomly assigned them to move year cohorts.

To measure individual medical spending for individuals in our analysis sample, we leveraged detailed information about the specific services rendered, including the place of service, procedure and diagnosis codes, and actual payments made by the insurer and/or patient in the HCCI data. We calculated total annual medical spending by summing the allowed amounts (which includes both payer and individual out-of-pocket spending) on each claim across all categories (inpatient, outpatient, professional services) in each calendar year. We defined claims by aggregating all claim lines for the service rendered to a patient on the same dates. For inpatient services, we combined claim lines with the same DRG and overlapping or contiguous service dates. For outpatient and professional services, we combined claim lines with the same CPT code and modifier on the same date.

Calculating Per-Person Spending in Each CBSA, Year

We computed total annual medical spending within our analysis sample, analogously to how we separately calculated total annual medical spending for everyone in our expanded sample. To provide a more complete picture of spending in each metro area, we did not want to restrict our CBSA spending measures to only summarize data from our analysis sample (a subset of our expanded sample).To compute per-person spending, we limited our expanded sample to only comprise data from individuals who maintained coverage in a single insurance plan in the same CBSA for the entire calendar year. We also omitted any individuals who had any claims with negative allowed amounts. For each metro area, then we calculated annual per-person spending by aggregating spending for all people living in the metro area and dividing by the number of members in each year.

Spending Index Sample Construction

Claim Inclusion Criteria

To compute our spending, price and use indices we restrict which claims we included from our expanded sample to only use a subset which we will call our index data set. We apply distinct inclusion exclusion criteria for claim lines from each service category (inpatient, outpatient). For inpatient services, we exclude inpatient service claims with overlapping lengths of stays. For example, if the same individual had two claims on the same date (e.g., one for a service code indicating Simple Pneumonia and Pleurisy (DRG 193) and another service code indicating Heart Failure and Shock (DRG 291)) both service claims would be excluded from our sample. We also excluded inpatient service claims where any of the claim lines took place at a non-General Acute Care (GAC) hospital or if they were associated with a pre-Major Diagnostic Category (MDC) code. Included service claims needed to have consistent types of bill codes that indicated an inpatient hospital visit. Service claims were excluded if they did not take place at a GAC, non-governmental, non-military hospital found in the AHA data, or if there were claim lines which indicated the service claim took place at multiple hospitals.

For outpatient and professional services, the sample was limited to service claims that consisted of claim lines with only the following type of bill codes: hospital outpatient, hospital laboratory services, ambulatory surgery center, any of the eight types of clinics (rural health, hospital based or independent renal dialysis center, freestanding, outpatient rehabilitation, comprehensive outpatient rehabilitation, community mental health, federally qualified health, and other), or a freestanding emergency medical facility. We found the number of units most commonly associated with each CPT code in each year. Service claims with unit counts differing from their corresponding CPT code and year combination's mode of units were excluded to ensure reported prices were the price of the most typical visit for that service code in that year.

Additionally, we excluded claims with extreme length of stay or costs. We only included inpatient service claims with lengths of stay under 180 days. Outpatient services had to occur on a single day. Across both categories, we excluded service claims with a total charge amount less than or equal $1 or a total spending amount (the actual amount paid to the providers including any patient cost sharing) less than or equal to $1. We also excluded services with a total spending to total charge ratio less than or equal to 20 percent. Finally, the inpatient sample was further trimmed by removing the top and bottom 1% of service claims based off their total spending.

Identifying a Set of Common Services

To construct a set of common services we first aggregated the number of service claims for each service code within each calendar year for each category. We restricted the service codes included in our set of common service codes to meet two criteria: (1) a service code must appear in each year of our data and (2) a service code must be present in at least 80% of CBSAs in our sample. For each category, we then constructed a set of the most common service codes ("common services") observed in our base year (2012) meeting our inclusion criteria:

- Inpatient Services: the 100 DRG codes with the highest share of nationwide inpatient admissions in 2012
- Outpatient Services: the 500 CPT codes with the highest share of nationwide outpatient procedures in 2012
- Professional Services: the 500 CPT codes with the highest share of nationwide outpatient procedures in 2012

Calculating Spending, Price, and Use Indices

Calculating Per-person Spending, Use, Average Price

Using our index data set, we calculated the total spending and use for each service code within our sets of common services in each CBSA in each year. We define the total spending on a service code as the sum of the total spending on each service claim for that service code in each CBSA in each year. We define use as the count of claims (i.e., number of times a service code was provided) for a service code in each CBSA in each year. We then define the average price of each service code in each CBSA in each year as the total spending on each service divided by its use. More formally, given each service claim *c* in the set of service claims C_{tgs} for each service code *s*, in CBSA *g*, in year *t*, we define these measures as follows:

Total spending per-person on service code *s* in CBSA *g* in year *t* :

$$\text{PC Spend}_{\text{tgs}} = \frac{\text{Spend}_{\text{tgs}}}{\text{Member Years}_{\text{tg}}}\text{; Spend}_{\text{tgs}} = \sum_{\text{c}\in\text{C}_{\text{tgs}}} \text{Spend}_{\text{tgsc}}$$

$Member\ Years_{tg}$ is the sum of all member months in CBSA *g* in year *t* divided by 12.

Total use per-person of service code *s* in CBSA *g* in year *t* :

$$\text{PC Use}_{\text{tgs}} = \frac{\text{Use}_{\text{tgs}}}{\text{Member Years}_{\text{tg}}}\text{; Use}_{\text{tgs}} = \sum_{\text{c}\in\text{C}_{\text{tgsc}}} 1$$

Average price on service code *s* in CBSA *g* in year *t* :

$$\overline{\text{Price}}_{\text{tgs}} = \frac{\text{PC Spend}_{\text{tgs}}}{\text{PC Use}_{\text{tgs}}} = \frac{\text{Spend}_{\text{tgs}}}{\text{Use}_{\text{tgs}}} = \frac{\sum_{\text{c}\in\text{C}_{\text{tgs}}} \text{Spend}_{\text{tgsc}}}{\sum_{\text{c}\in\text{C}_{\text{tgs}}} 1}$$

We compute these measures at the national level for each year:

Total spending per-person on service code *s* nationally in year *t*

$$\text{PC Spend}_{\text{ts}} = \frac{\sum_{\text{g}\in\text{G}} \text{Spend}_{\text{tgs}}}{\sum_{\text{g}\in\text{G}} \text{Member Years}_{\text{tg}}}$$

Total use per-person of service code *s* nationally in year *t*

$$\text{PC Use}_{\text{ts}} = \frac{\sum_{\text{g}\in\text{G}} \text{Use}_{\text{tgs}}}{\sum_{\text{g}\in\text{G}} \text{Member Years}_{\text{tg}}}$$

Average price on service code *s* nationally in year *t*

$$\overline{\text{Price}}_{\text{ts}} = \frac{\text{PC Spend}_{\text{ts}}}{\text{PC Use}_{\text{ts}}} = \frac{\text{Spend}_{\text{ts}}}{\text{Use}_{\text{ts}}}$$

Calculating Weighted Service Price, Use, and Total Spending for Service Category

We computed weighted measures for each service category (inpatient, outpatient, professional Services). We calculated each service code's weight as the total spending (nationally) on that service code divided by the total spending (nationally) on all of our common services in our base year, 2012. For a given service code, our service weights should be interpreted as the share of total spending on our set of common services. More formally, for a service code *s* belonging to our set of common services *S* in our base year (2012), we defined the service weight for service code *s* as follows:

$$\mathrm{w_s} = \frac{\sum_{\mathrm{g \in G}} \mathrm{Spend}_{\mathrm{2012gs}}}{\sum_{\mathrm{s \in S}} \sum_{\mathrm{g \in G}} \mathrm{Spend}_{\mathrm{2012gs}}}$$

Using our service weights, we computed weighted price, per-person service use of, and per-person total spending on our common set of services for each category. To do so, we took the weighted product of the average price, per-person use, and per-person total spending on each service code within our set of common services.

Weighted per-person spending in CBSA *g* in year *t* :

$$\mathrm{w\ PC\ Spend_{tg}} = \prod_{\mathrm{s \in S}} \left[\mathrm{PC\ Spend_{tgs}}\right]^{\mathrm{w_s}}$$

Weighted per-person use in CBSA *g* in year *t* :

$$\mathrm{w\ PC\ Use_{tg}} = \prod_{\mathrm{s \in S}} \left[\mathrm{PC\ Use_{tgs}}\right]^{\mathrm{w_s}}$$

Weighted price in CBSA *g* in year *t* :

$$\mathrm{w\ \overline{Price}_{tg}} = \prod_{\mathrm{s \in S}} \left[\mathrm{\overline{Price}_{tgs}}\right]^{\mathrm{w_s}}$$

These measures can be interpreted as the price of a representative service (within our set of common services) in each category of services, the per-person use of that representative service, and the per-person total spending on that representative service.

Using Weighted Measures to Construct Spending, Price and Use Indices for Each Service Category

We calculated indices using our weighted measures by comparing the weighted spending, use, and price measures in each CBSA to a national-level, static reference point. To calculate a reference point, we similarly constructed weighted spending, use and price measures at the national level in 2012 (the study's base year).

Weighted per-person spending nationally in year *t* :

$$\text{w PC Spend}_{2012} = \prod_{s \in S} [\text{PC Spend}_{2012s}]^{w_s}$$

Weighted per-person use nationally in year *t* :

$$\text{w PC Use}_{2012} = \prod_{s \in S} [\text{PC Use}_{2012s}]^{w_s}$$

Weighted price nationally in year *t* :

$$\text{w } \overline{\text{Price}}_{2012} = \prod_{s \in S} [\, \overline{\text{Price}}_{2012s}]^{w_s}$$

Using our weighted CBSA level measures and weighted national level measures, we constructed our spending, use and price indices:

Per-person Spending Index:

$$\text{T}_{\text{tg}} = \frac{\text{w PC Spend}_{\text{tg}}}{\text{w PC Spend}_{2012}} = \frac{\prod_{s \in S}[\text{PC Spend}_{\text{tgs}}]^{w_s}}{\prod_{s \in S}[\text{PC Spend}_{2012s}]^{w_s}} = \prod_{s \in S}\left[\frac{\text{PC Spend}_{\text{tgs}}}{\text{PC Spend}_{2012s}}\right]^{w_s}$$

Per-person Use Index:

$$\text{U}_{\text{tg}} = \frac{\text{w Use}_{\text{tg}}}{\text{w Use}_{2012}} = \frac{\prod_{s \in S}[\text{PC Use}_{\text{tgs}}]^{w_s}}{\prod_{s \in S}[\text{PC Use}_{2012s}]^{w_s}} = \prod_{s \in S}\left[\frac{\text{PC Use}_{\text{tgs}}}{\text{PC Use}_{2012s}}\right]^{w_s}$$

Price Index:

$$\text{P}_{\text{tg}} = \frac{\text{w}\overline{\text{Price}}_{\text{tg}}}{\text{w } \overline{\text{Price}}_{2012}} = \frac{\prod_{s \in S}[\overline{\text{Price}}_{\text{tgs}}]^{w_s}}{\prod_{s \in S}[\overline{\text{Price}}_{2012s}]^{w_s}} = \prod_{s \in S}\left[\frac{\overline{\text{Price}}_{\text{tgs}}}{\overline{\text{Price}}_{2012s}}\right]^{w_s}$$

One convenient property of this methodology is that the per-person spending index is equal to the product of the price and use indices:

$$\text{P}_{\text{tg}} = \prod_{s \in S}\left[\frac{\overline{\text{Price}}_{\text{tgs}}}{\overline{\text{Price}}_{2012s}}\right]^{w_s} = \prod_{s \in S}\left[\frac{\left(\frac{\text{PC Spend}_{\text{tgs}}}{\text{PC Use}_{\text{tgs}}}\right)}{\left(\frac{\text{PC Spend}_{2012s}}{\text{PC Use}_{2012s}}\right)}\right]^{w_s} = \frac{\prod_{s \in S}\left[\frac{\text{PC Spend}_{\text{tgs}}}{\text{PC Spend}_{2012s}}\right]^{w_s}}{\prod_{s \in S}\left[\frac{\text{PC Use}_{\text{tgs}}}{\text{PC Use}_{2012s}}\right]^{w_s}} = \frac{\text{T}_{\text{tg}}}{\text{U}_{\text{tg}}}$$

$$\text{T}_{\text{tg}} = \text{P}_{\text{tg}} * \text{U}_{\text{tg}}$$

Changes in Plan Characteristics Concurrent with Individuals Moving

It is important to note that observing an individual within the HCCI data over time does not necessarily require that individual to maintain coverage through the same insurance plan – whether or not an individual moves. That is, an individual we observe over time could change employers and therefore plans, or maintain the same employer but switch from an HMO plan to a PPO, for example.

Below we report descriptive statistics on how frequently individuals in our sample – both movers and non-movers –experience changes in their plan enrollment over time. Specifically, we identify whether over our sample time period individuals change their group ID (e.g., employer), change their subscriber status (e.g., whether individuals are enrolled as self, spouse, child, other), or plan type (e.g., EPO/HMO/POS/PPO). We also identify whether individuals change whether they are enrolled in a consumer directed health plan (CDHP) for more months before or after their move year (for non-movers we use their assigned "move year").

While not all movers changed plans over our sample time period, we do observe that about 65% of individuals experienced some change in their plan status (Table Below). For context, this is only slightly higher than individuals who do not move (61%). Most movers (56%) have a change in their group ID indicating a change in their employer. A smaller proportion have changes in their plan type (e.g., HMO/PPO/POS) or whether they are in a Consumer Directed Health Plan.

Appendix Table A1: Frequency of Changes in Individuals' Plan Enrollment for Movers, Non-Movers

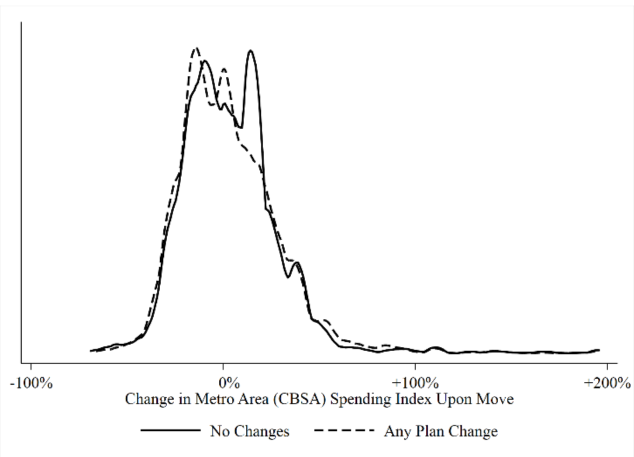
	Non-Movers		Movers		
	Mean	Standard Deviation	Mean	Standard Deviation	P-Value
Any Change	0.613	0.487	0.655	0.475	< 0.001
Change In…					
Group ID	0.549	0.498	0.560	0.496	< 0.001
Subscriber Status	0.005	0.069	0.029	0.167	< 0.001
Plan Type	0.070	0.255	0.065	0.247	< 0.001
High-Deductible Months	0.103	0.312	0.204	0.441	< 0.001
Observations	518,242		71,101		

Notes: We created a series of indicator variables for whether over our sample time period individuals change their group ID (e.g., employer), change their subscriber status (e.g., whether individuals are enrolled as self, spouse, child, other), or plan type (e.g., EPO/HMO/POS/PPO). We also identify whether individuals change whether they are enrolled in a consumer directed health plan (CDHP) for more months before or after their move year (for non-movers we use their assigned "move year"). We report the mean and standard deviations of these indicator variables. We present the result of a t-test for whether the means are statistically different for our sample of movers and non-movers.

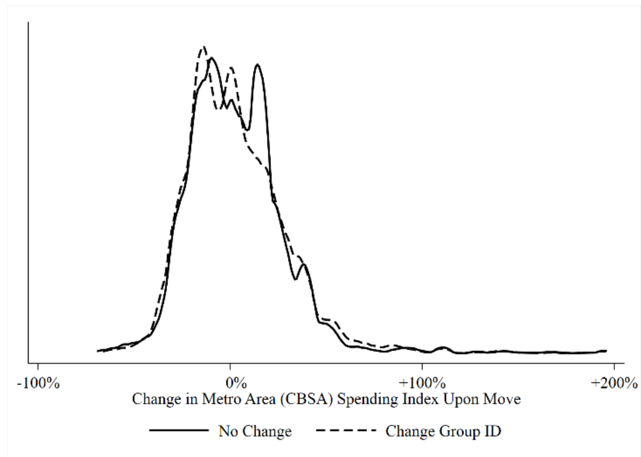
As individuals may change plan characteristics over time, one potential concern is that individuals who change their plan enrollment may differentially move to relatively higher or lower spending metro areas. However, we find that this is not the case. As seen below, the distribution of changes in metro area spending are similar and relatively balanced around zero for individuals who do and do not have any changes in their plan characteristics over our sample time period (Appendix Figure A1). We repeat this exercise separating individuals with or without changes in any plan characteristic as well as changes in individual plan characteristics:

Figure A1: Distribution of Changes in CBSA Spending Index Upon Move by Changes in Plan Characteristics

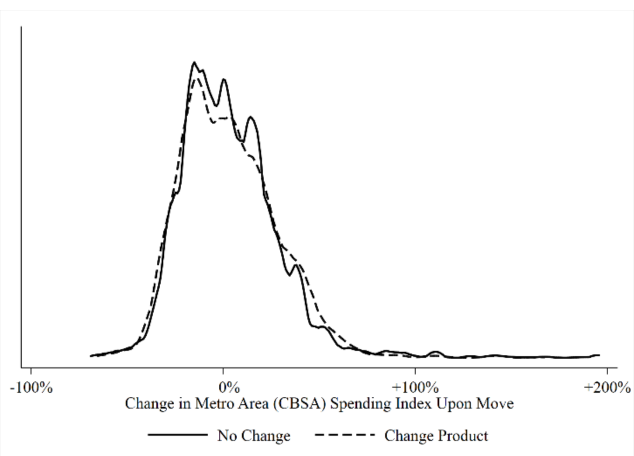
A. Any Change in Plan Upon Move



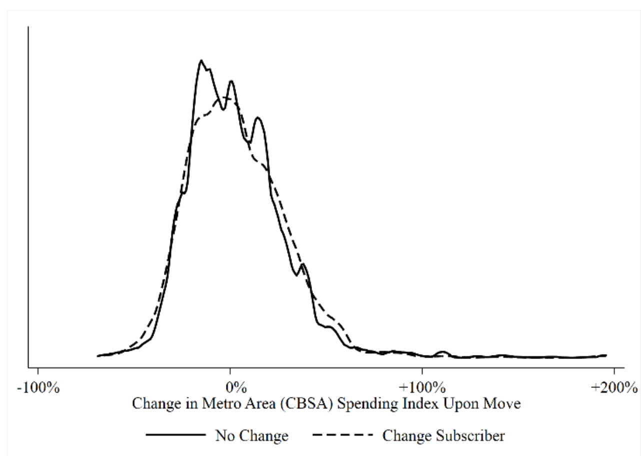
B. Change in Group ID Upon Move (i.e., Employer)



C. Change in Plan Product (EPO/HMO/POS/PPO)



D. Change in Plan Subscriber (Self/Spouse/Child/Other)



To further address this concern, we test whether our coefficient estimates could be biased by including individuals who have changes in their plan characteristics which reflect changes in unobservable factors potentially related to spending. Specifically, we re-estimate our event study specification limiting our sample to individuals with no changes in their plan characteristics (Appendix Table A2, below). We found that the coefficient estimates from this specification (Appendix Table A2, Specification 3) were not statistically different from our baseline specification (Appendix Table A2, Specification 1). In other words, we do not find evidence that including individuals who move and also have concurrent changes in their plan design are biasing the coefficient estimates we report.

Event Study Analysis

First, we followed an event study specification derived by Finkelstein et al. (2016) to estimate the effect of a change in an individual's metro area log spending level due to a move ($\hat{\delta}_i^{Spend}$) on their log medical spending (y_{it}). This specification allowed us to see whether an individual's medical spending changed in response to a change in their metro area's level of spending, and if the effect varied over time relative to their move. Specifically, we estimated log medical spending by individual i in year t in our movers sample using the following specification:

$$y_{it} = \alpha_i + X_{it}\beta + \tau_t + \theta_{r(i,t)}\hat{\delta}_i^{Spend} + \varepsilon_{it} \tag{A.1}$$

Here, α_i is a vector of individual fixed effects which account for all time invariant, individual factors. X_{it} is a vector of time varying individual characteristics, including age band, plan characteristics (product, market, relation to subscriber, prescription drug coverage, and mental health coverage), and indicators for year relative to move $r(i,t)$.[1] We also included a vector of year fixed effects (τ_t) to account for time varying non-individual specific factors (for example, inflation).

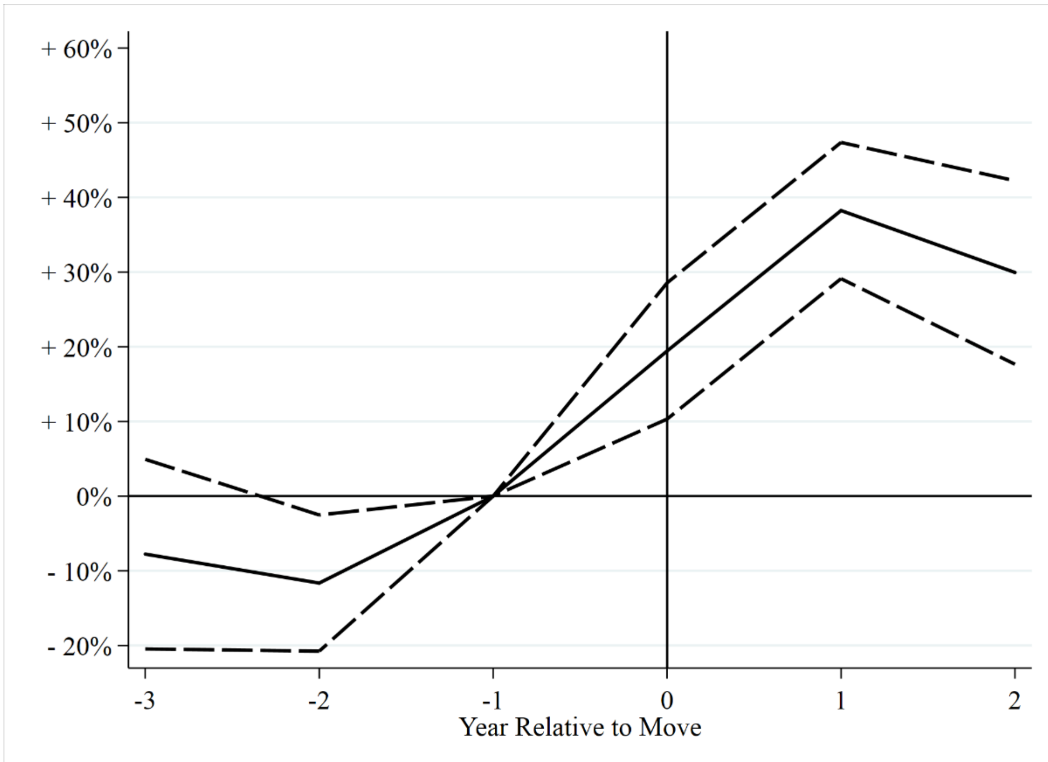
Our coefficients of interest were captured by the vector $\theta_{r(i,t)}$ which represent the effect of the difference in log spending levels between an individual's destination and origin metro area $\hat{\delta}_i^{Spend}$ by year relative to their move.[2] We estimated this specification where we measured changes in individuals' metro area spending levels as the log difference of both per-person spending level and index spending level.

[1] An individual was grouped into one of the following age-bands in each year according to their age: 0-18 years old, 19-24, 25-34, 35-44, 45-54, or 55-64. We include indicators for whether an individual *i* in year *t* is in an Exclusive Provider Organization (EPO), Health Maintenance Organization (HMO), Preferred Provider Organization (PPO), or a Point-of-Service (POS) plan. We include indicators for whether an individual *i* in year *t* is part of a Large or Small Group plan. We include variables that look at the number of months individual *i* in year *t* is enrolled in an Administrative Services Only (ASO) plan, plan with prescription drug coverage, mental health coverage. Lastly we include a variable for the number of months individual *i* in year *t* is enrolled in a consumer-directed health plan (defined as a plan identified by the HCCI data contributors as a high deductible plan associated with either a Health Savings Account or Health Reimbursement Arrangement).

[2] $\theta_{r(i,t)}$ is equivalent to the coefficients for the interaction terms between a vector of indicators for year relative to move and $\hat{\delta}_i^{Spend}$, the change in an individual's origin and destination CBSAs' levels of spending. Note that the un-interacted terms were both separately included in this specification ($\boldsymbol{\alpha_i}$ accounts for $\hat{\delta}_i^{Spend}$ because it is time invariant, and X_{it} includes $r(i,t)$).

Figure A2: Effect of Moving to Metro Area with 10% Higher Spending on Individual's Annual Medical Spending

Change in Individual Medical Spending



Notes: The coefficient estimates plotted in this figure are from estimating Equation A.1 reported in Table A2.

As seen in Figure 2, we found a significant positive effect of moving to an area with higher spending on an individual's medical spending (the coefficient estimates are presented below in Table A2). This finding is consistent across our various measures of changes in spending. Our results imply that an individual who moved to an area with 10% higher spending on average, all else equal, would have a 3.8% increase in their spending in the year following their move than in the year prior to their move.[3] This coefficient estimate is stable whether we measure a metro area's spending level using per-person spending or the spending index, and whether we measure the change in spending using the log difference in five-year average of destination and origin spending levels or the log difference between destination metro area spending level in the year

[3] This coefficient estimate is from specification 3 in Table 3. This specification measures the change in spending as the log difference in an individual's destination and origin metro areas' average spending index values. As we explain in the text, this is our preferred specification. Recall that the majority of our movers experienced a larger than 10% change in their metro area spending level upon moving (Table 2).

following the move and the origin metro area spending level in the year prior to the move (Table 3). Given this finding, we proceeded using the log difference between an individual's destination and origin metro area spending index five-year averages as our preferred specification. This specification will allow us to later decompose the effect of place-specific spending levels on individual spending into separate price and use effects, and is also our most conservative estimate.

In addition to a significant positive effect of a change in spending levels on individual spending in the first year following a move, we also found a significant positive effect in the second year following a move. The coefficients in each year following the move were not significantly different from each other, however, which provided empirical support for using a binary pre-post design rather than an event study which would allow the coefficients to vary over time.

One potential limitation of using a binary pre-post design, however, is that it may be confounded by a pre-trend. In our event study specification, it appeared that there was a significant increase in an individual's spending in the year prior to their move.[4] Thus, our binary pre-post design may have an upward-biased coefficient estimate. Interestingly, this finding mirrors a pre-trend of similar magnitude and significance found by Finkelstein et al. (2016) in a sample of movers from the Medicare population. Indeed, our point estimates from the event study specification were slightly lower than the binary pre-post design, which could be due to the significant pre-trend we observed in our event study. However, the magnitude of this difference is small in absolute terms and the event study coefficients in each post year and the coefficients in our binary pre-post design have overlapping confidence intervals; we cannot necessarily conclude they are statistically different. Thus, using an event study design does not lead to qualitatively or quantitatively different conclusions or implications than using a binary pre-post design.

[4] Across specifications, we observe that movers' spending is lower two and three years prior to the year before their move. In other words, there appeared to be an increase in individuals' spending in the year prior to moving relative to previous years.

Event Study Robustness Checks

The primary threat to our identification is that individual's choice of destination metro area may be related to changes in unobserved factors also correlated with changes in their medical spending. As discussed above ("Changes in Plan Characteristics Concurrent with Individuals Moving"), one concern is that our coefficient estimates could be biased by including individuals who have changes in their plan characteristics which reflect changes in unobservable factors potentially related to spending. To address this concern, we show that the distribution of changes in metro area spending are similar and relatively balanced around zero for individuals who do and do not have any changes in their plan characteristics over our sample time period (Appendix Figure A1). We repeat this exercise separating individuals with or without changes in any plan characteristic as well as changes in individual plan characteristics. We also then re-estimate our event study limiting our sample to individuals with no changes in their plan characteristics. The coefficient estimates for individuals who maintain the same insurance plan (specification 3) are similar and have overlapping confidence intervals with the coefficient estimates from baseline event study which includes individuals with plan changes (specification 1). Both pieces of evidence suggest that including individuals with changes in plan characteristics are not biasing our coefficient estimates.

A related concern given our sample demographics – commercially insured under 65 population – is that there may be changes in unobserved medical status correlated with both the choice of destination metro area and changes in medical spending. In particular, there is a concern that an including individuals with an anticipated medical condition with an anticipated increase in medical spending such as pregnancy could bias our coefficient estimates. To test this specific case, we limit our analysis to only males. We do not find evidence that including females biases our coefficient estimates (Appendix Table A2).

One further concern is that the HCCI data is a convenience sample which may not capture a full picture of the commercial insurance market in every metro area. To this end, we limit our analysis to only pairs of destination and origin metro areas where HCCI data contributors represent at least 25% of the commercial insurance market. Our coefficient estimates on this specification, while nosier, are similar to our baseline specification (Appendix Table A2).

Table A2: Event Study Robustness Tests

Outcome Variable:	Individual Medical Spending				
Robustness Check:	N/A	Exclude Move Year	Maintain Same Plan	Excluding Females	High HCCI Coverage Areas
	(1)	(2)	(3)	(4)	(5)
Effect of Moving to a Metro Area with a 1% Difference in Spending Level by Year Relative to Move					
Year - 3	-0.078	-0.069	-0.110	-0.006	-0.210
	(0.065)	(0.066)	(0.109)	(0.097)	(0.142)
Year - 2	-0.116**	-0.117**	-0.213***	-0.112	-0.011
	(0.047)	(0.047)	(0.079)	(0.070)	(0.103)
Year + 0	0.194***		0.119	0.192***	0.444***
	(0.047)		(0.079)	(0.070)	(0.103)
Year + 1	0.382***	0.380***	0.442***	0.386***	0.364***
	(0.047)	(0.047)	(0.079)	(0.070)	(0.104)
Year + 2	0.300***	0.288***	0.336***	0.218***	0.562***
	(0.063)	(0.064)	(0.110)	(0.093)	(0.138)
Demographic Controls	X	X	X	X	X
Year FE	X	X	X	X	X
Patient FE	X	X	X	X	X
Obs.	343,529	272,440	117,659	176,169	99,486
Unique Patients	71,101	71,101	24,501	36,447	20,521

Notes: We estimate each specification excluding observations for non-movers. As in Table 3, we measure the change in metro area spending level by the log difference between the 5-year average spending index for each mover's destination and origin metro area. In each specification, the omitted year relative to move is the year prior to an individual's move. Demographic controls included are as outlined in Table 3. Significance: * p < 0.10, ** p < 0.05, *** p < 0.01.Significance: * p < 0.10, ** p < 0.05, *** p < 0.01.

Measuring Metro Area Spending Level by Per Capita Spending Versus Spending Index

i. Measuring CBSA Spending Level: Per-person spending

We defined individual spending as the sum of all expenditures on medical services (inpatient, outpatient, and professional) during the calendar year, including both payer and patient shares. For each metro area, we calculated annual per-person spending by aggregating spending for all people living in the metro area and dividing by the number of members in each year. Similar to Finkelstein et al. (2016) we use these annual per-person spending measures to calculate the average across all five-years of our sample. We define these per-person spending measures as the "per-person" spending levels for each CBSA.

When computing CBSA per-person spending levels, we limited our expanded sample to only comprise data from individuals who maintained coverage for the entire calendar year. Because our analysis sample consists of individuals who maintain continuous coverage, we felt this provided a better comparison for average spending within a metro area.

ii. Measuring Changes in metro area spending levels upon move

We measure the log difference between the per-person spending level of a mover's destination and origin metro areas. This approach is analogous to Finkelstein et al. (2016).

iii. Event Study Analysis

Using our measure of changes in CBSA spending level – measured via per capita spending rather than our spending index we re-estimate equation 4.1. As seen below, the estimates for our coefficients of interest stable whether we measure an area's spending via per-person spending or our spending index, and whether we include or exclude movers. Given this finding, we proceeded using the log difference between an individual's destination and origin metro area average spending index level as our preferred specification.

Appendix Table A3: Discrete Event Study Analysis

Outcome Variable:	Individual Medical Spending			
Measure of Change in Metro Area 5-Year Average Spending Leve ($\hat{\delta}_i^{\text{Spend}}$):	Log Difference in Destination, Origin		Log Difference in Destination, Origin	
	Spending Index		Per-Person Spending	
	(1)	(2)	(3)	(4)
Effect of Moving to Metro Area with 1% Difference in Spending Level (θ^{Spend})	0.416***	0.427***	0.560***	0.548***
	(0.036)	(0.034)	(0.045)	(0.043)
Demographic Controls	X	X	X	X
Year FE	X	X	X	X
Patient FE	X	X	X	X
Include Non-Movers		X		X
Obs.	272,440	2,206,843	272,440	2,206,843
Unique Patients	71,101	589,343	71,101	589,343

Notes: Each specification is estimated separately with specifications 1,3 estimated on a sample of exclusively movers and specifications 2,4 estimated with both movers and non-movers. In each specification, we omit observations from the year associated with the move for both movers and non-movers. Note Specifications 1 and 2 are identical to Table 3. Non-movers were randomly assigned to move year cohorts corresponding with the move year cohorts in the mover sample. Demographic controls included are as outlined in Table 3. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Descriptive Evidence: Spending Trends for Movers by Relative Spending Levels of Origin, Destination

Appendix Table A4: Per-Person Medical Spending by Year Relative to Move for Movers

	Move to Lower Spending Area		Move to Higher Spending Area		
	Mean	Standard Deviation	Mean	Standard Deviation	P-Value
Years Relative to Move					
- 3	2984.36	12244.19	2736.83	12035.62	0.067
- 2	3386.85	12452.50	2973.50	17410.26	<0.001
- 1	3493.85	13139.95	2987.71	12909.92	<0.001
+ 0	3331.58	14471.04	3173.91	21039.16	0.245
+ 1	3744.31	14841.80	3790.37	14873.78	0.679
+ 2	3766.52	17634.67	3717.87	15754.42	0.797
Observations	35,236		35,865		

Notes: This table reports the average medical spending (sum of allowed amounts on medical services) per-person by year for our sample of non-movers and movers. We split our mover sample based on whether the 5-year average spending index in their destination metro area was higher than in their origin metro area ("Move to Higher Spending Area") or lower ("Move to Lower Spending Area").

Decomposing the Place-Specific Effect on Individual Spending in to Price and Use Effects

Recall that our spending index (T_{tg}) can be decomposed as the product of our price (P_{tg}) and use indices (U_{tg}). For a metro area *g* in year *t*:

$$T_{tg} = P_{tg} * U_{tg}$$

And, because we compute our average spending, price, and use indices across years as geometric products, we can decompose the average spending index value in each metro area g as the product of the average price and use index value for that metro area:

$$\overline{T}_g = \prod_t T_{gt}^{\frac{1}{5}} = \prod_t T_{gt}^{\frac{1}{5}} * \prod_t U_{gt}^{\frac{1}{5}} = \overline{P}_g * \overline{U}_g$$

Therefore, we can re-write the change in 5-year spending index due to a move – the log difference between the 5-year average of an individual's destination ($D(i)$) and origin ($O(i)$) metro area – as the sum of log differences in metro area price and use levels:

$$\begin{aligned}
\hat{\delta}_i^{Spend} &= \log\left(\overline{T}_{D(i)}\right) - \log\left(\overline{T}_{O(i)}\right) \\
&= \log\left(\overline{P}_{D(i)} * \overline{U}_{D(i)}\right) - \log\left(\overline{P}_{O(i)} * \overline{U}_{O(i)}\right) \\
&= \log\left(\overline{P}_{D(i)}\right) + \log\left(\overline{U}_{D(i)}\right) - \log\left(\overline{P}_{O(i)}\right) + \log\left(\overline{U}_{O(i)}\right) \\
&= \left[\log\left(\overline{P}_{D(i)}\right) - \log\left(\overline{P}_{O(i)}\right)\right] + \left[\log\left(\overline{U}_{D(i)}\right) - \log\left(\overline{U}_{O(i)}\right)\right] \\
&= \hat{\delta}_i^{Price} + \hat{\delta}_i^{Use}
\end{aligned}$$

Using this decomposition, we modified Equation (5.1) to separate the effect of a change in metro area spending level into a price and use effects by substituting in for $\hat{\delta}_i^{Spend}$:

$$\begin{aligned}
y_{it} &= \alpha_i + X_{it}\beta + \tau_t + \theta^{Spend} * \text{Post Move}_{it} * \hat{\delta}_i^{Spend} + \varepsilon_{it} \\
&= \alpha_i + X_{it}\beta + \tau_t + \theta^{Spend} * \text{Post Move}_{it} * (\hat{\delta}_i^{Price} + \hat{\delta}_i^{Use}) + \varepsilon_{it} \\
&= \alpha_i + X_{it}\beta + \tau_t + \tilde{\theta}^{Price} * \text{Post Move}_{it} * \hat{\delta}_i^{Price} + \tilde{\theta}^{Use} * \text{Post Move}_{it} * \hat{\delta}_i^{Use} + \omega_{it}
\end{aligned}$$

Here ω_{it} represents the resulting error term. Note that because price and use indices are correlated with each other we should not necessarily expect $\tilde{\theta}^{Price} = \tilde{\theta}^{Use} = \tilde{\theta}^{Spend}$.