**Online Supplement**

“Opt out” and Access to Anesthesia Care for Elective and Urgent Surgeries among United States Medicare Beneficiaries, Sun et al.

**Technical Appendix.**

In this technical appendix, we describe in detail the implementation of our difference-in-differences approach. In addition, we describe the methods used to produce the land area-adjusted distance measures shown in Figure 1 and Table 3.

*Difference-in-Differences Approach*

As discussed in the main body of the paper, a simple comparison of outcomes between “opt out” and non-“opt out” areas may suffer from confounding due to differences in observable and unobservable factors between the two groups, such as unobservable market factors and differences in patient health. Although we did control for a large set of plausible confounders including the patient demographics and comorbidities shown in table 2 of the main text, even this extensive set of controls might not fully account for all plausible confounders.

The difference-in-differences approach, which has been extensively used to evaluate the effects of policy,1 provides one way to reduce confounding. At heart, the difference-in-differences approach estimates the effect of “opt out” by performing two calculations. First, it evaluates the change in outcomes among “opt-out” states following the decision to “opt out,” rather than simply comparing “opt out” states to non-”opt out” states. By focusing on the changes in outcomes before and after “opt out” *within* a given state, the difference-in-differences approach eliminates much of the confounding that may occur due to differences in patients, and market factors across states. Indeed, for our analysis, we went a step further and used zip-code level effects. Thus, our analysis examines the change in outcomes within a *zip code* following “opt out.” Compared to state-level effects, the use of zip-code level effects should further reduce confounding as they allow us to control for unobservable factors occurring at the level of the zip code and not just at the level of the state.

However, this simple “before-after” comparison can also be confounded by secular trends (such secular trends in the opening/closing of hospitals). Our difference-in-differences approach addresses this possibility in two ways. First, we incorporate year effects, which will control for any unobservable secular effects occurring at the national level. In addition, we also added a set of controls for linear and quadratic time trends occurring at the state level.

We implemented our difference-in-differences approach using the following regression:

(1)

In equation (1), *i* indexes the individual, *j* is an index for the zip code of residence, *k* is an index for the county of residence, *l* is an index for the state, and *t* is an index for the year. is a fixed effect for zip code *I*, which, as noted above, controls for unobservable factors at the zip-code level. is a year effect that controls for unobservable time-varying factors at the national level, while and control for linear and quadratic trends at the state level. is a vector of patient characteristics (e.g., race, age, comorbidities), and county level characteristics (e.g., population and median income). is an indicator variable that equals 1 in “opt out” states for the years following “opt out” and zero otherwise.[[1]](#footnote-1)

Our coefficient of interest was , which reflected the effect of “opt out” on the specific outcome. For two of our outcomes, the dependent variable was an indicator variable. The indicator equaled one if the patient traveled outside their zip code for the given procedure (and zero otherwise). For the other outcome, the indicator equaled one if the patient received anesthesia (i.e., care by an anesthesiologist and/or CRNA) for their procedure (and zero otherwise). For these two outcomes, can be interpreted as the effect of “opt out” on the relevant outcome in absolute (percentage point) terms. For example, for the outcome of the patient receiving anesthesia for their procedure, if equaled 0.05, this would imply that “opt out” was associated with a five percentage point (absolute) increase in the proportion of patients receiving anesthesia for their procedure. Our third outcome was the distance (in kilometers) traveled by the patient to receive their procedure. For this outcome, can be interpreted as the effect of “opt out” on the mean ravel distance among patients who traveled outside their zip code. For example, if equaled -15, this would imply that “opt out” was associated with 15 km decrease in travel distances.

In using a linear regression to model the effect of “opt out” on the percentage of patients receiving anesthesia and the percentage of patients traveling outside of their zip code, our approach utilized a linear probability model, in contrast to a probit or logistic regression. We chose a linear probability primarily because the large number of indicator variables for our difference-in-differences model (e.g., one indicator for each zip code),[[2]](#footnote-2) led to impractically long computational times.[[3]](#footnote-3) However, an additional consideration was that that coefficients from the linear probability model are easier to interpret and directly correspond to the increase in probability that a patient received surgery. By contrast, it is harder to translate the coefficients from a logistic or probit regression into the change in probability for receiving surgery. For example, while the odds ratios that are easily estimated from a logistic regression represent the approximate changes in probability (i.e., relative risk) for rare outcomes,2,3 in our case, the “outcome” of interest (patients travelling outside their zip code for surgery) is extremely common. Therefore, the odds ratios will not approximate the relative risk.

In estimating our regression models, we clustered our errors at the state level. Although our sample consisted of a large number of observations, these observations may not be independent of each other. Therefore, a simple ordinary least squares (OLS) regression would tend to underestimate our standard errors (and overestimate the statistical significance of our regression coefficients). Calculating clustered standard errors is an appropriate approach to deal with this issue.4 In essence, clustering adjusts the standard errors based on the observed level of correlation within a given unit (cluster) defined by the investigator. Since we were primarily concerned with correlation within a given state, we clustered our standard errors at the state level.5 Clustering our standard errors also provides the additional benefit of producing standard errors that are robust to heteroscedasticity. While the use of a linear probability model generally results in unbiased estimates of the model parameters, using a straightforward ordinary least squares approach can lead to inconsistent estimates of the standard errors because the linear probability model violates the traditional assumptions on non-heteroscedasticity. Obtaining robust or clustered standard errors is a standard approach towards dealing with this issue.6

A crucial assumption of the difference-in-differences approach is that outcomes in the control group serve as a useful proxy for what outcomes in the treatment group “would have been” in the absence of treatment; an assumption known as the “parallel trends” assumption. While this assumption is required for a standard difference-in-differences approach, the approach outlined in equation (1) is robust to this assumption. Specifically, by incorporating group-specific time trends (the state-specific linear and quadratic time trends in equation 1), this approach—sometimes referred to as Comparative Interrupted Time Series approach, is a modified form of the difference-in-differences approach that is robust to violations of the “parallel trends” assumption. In essence, this approach compares the deviation from the existing trend among “opt out” states to the deviation for pre-existing trends in non-“opt out” states. Therefore, since this approach in effect accounts for differences in pre-existing trends, it is robust to the parallel trends assumption.7-9

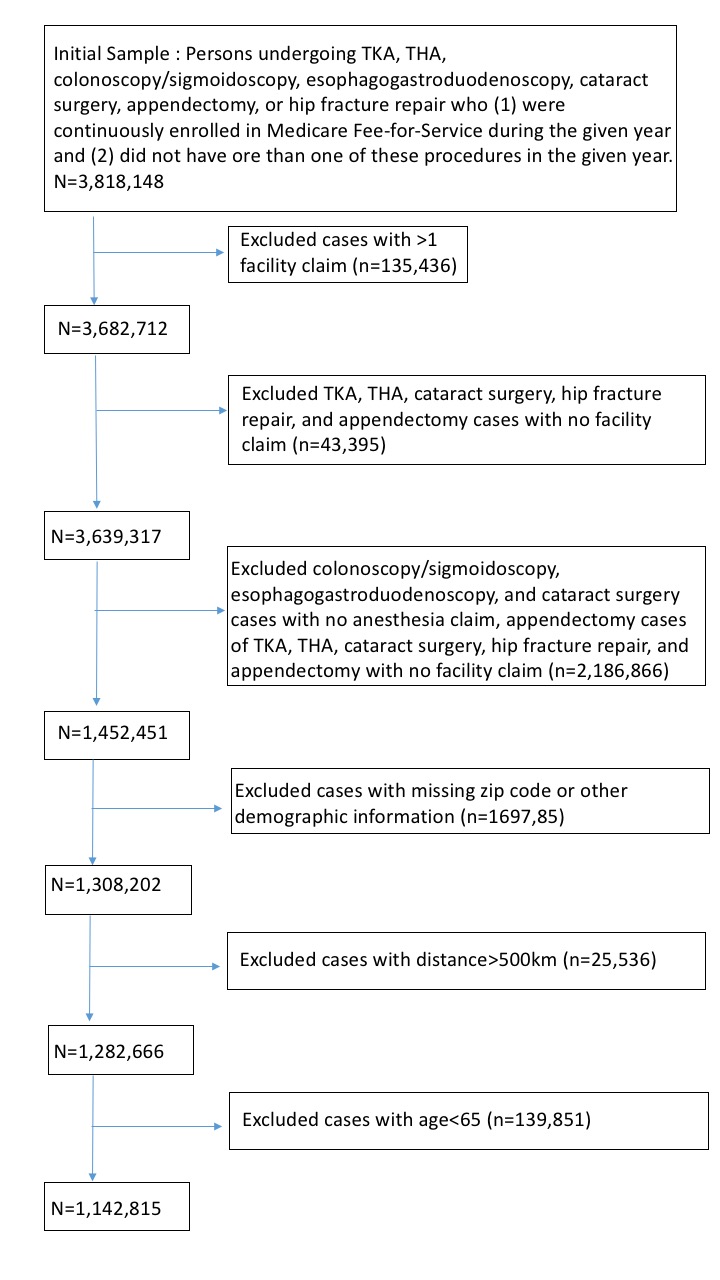
*Calculating Land-Area Adjusted Distance Measures*

To calculate the land-area adjusted distance measures shown in table 3 and Figure 1, we estimated the following linear regression model:

(2)

where *I* indexed patients, *j* indexed the zip code, and *t* indexed the year. was the land area (in square kilometers) for the zip code, which we obtained from the United States Census.[[4]](#footnote-4) was a dummy variable that equaled one if the zip code is located in an “opt out” state and zero otherwise. Note that for the purposes of this regression, the variable was defined based on whether a state ultimately became an “opt out” or not, and therefore did not vary over time. For example, Iowa chose to “opt out” in 2001 and therefore the value of for any Iowa zip code was equal to one. As above, was either (1) an indicator variable for whether the patient obtained their procedure outside of their given zip code or (2) the distance traveled by the patient for patients traveling outside of their zip code. After estimating equation (2) for a given procedure, we obtained the land area-adjusted values shown in table 3 and figure 1 by calculating the predicted values by “opt out” status (e.g., the predicted values when equaled one or zero). In calculating these predicted values, we set equal to the average land area across “opt out” and non-“opt out” states.

**Appendix Figure 1 – Sample Construction Flow Diagram**

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**Appendix Table A. List of Procedure (Current Procedural Terminology®) Codes**

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| --- | --- | --- |
|  | Current Procedural Terminology® Codes | |
|  | Surgical | Anesthesia10 |
| Cataract Surgery11 | 66982-66984, 66850, 66920, 66930, 66940 | 00142 |
| Colonoscopy/Sigmoidoscopy12 | 45305, 45308, 45309, 45315, 45320, 45331, 45380, 45384, 45385 | 00810 |
| Esophagogastroduodenoscopy13 | 43235, 43239 | 00740 |
| Total Knee Arthroplasty14 | 27447 | N/A |
| Total Hip Arthroplasty15 | 27130 | N/A |
| Appendectomy16 | 44950, 44960, 44970, 44979 | N/A |
| Hip Fracture17 | 27236, 27244, 27245, 27248, 27254, 27506, 27507 | N/A |
| **Appendix Table A** shows the procedure (Current Procedural Terminology®) codes used to identify the procedures analyzed in our study. The first column shows the procedure codes used to identify the procedures itself. For cataract surgery, colonoscopy, and esophagogastroduodenoscopy, the second column also shows the procedure codes used to identify whether anesthesia care was provided. The table also shows the references used to identify the codes for each procedure. | | |

**Appendix Table B** – List of “Opt Out” States

|  |  |
| --- | --- |
| **State** | **“Opt out” Date** |
| Iowa | December 2001 |
| Nebraska | February 2002 |
| Idaho | March 2002 |
| Minnesota | April 2002 |
| New Hampshire | June 2002 |
| New Mexico | November 2002 |
| Kansas | April 2003 |
| North Dakota | October 2003 |
| Washington | October 2003 |
| Alaska | October 2003 |
| Oregon | December 2003 |
| Montana | January 2004 |
| South Dakota | March 2005 |
| Wisconsin | June 2005 |
| California | June 2009 |
| Colorado | September 2010 |
| Kentucky | April 2012 |
| **Appendix Table B** shows the list of states “opting-out” of federal regulations requiring physician supervision of nurse anesthetists. | |

**Appendix Table C: “Opt out” And Procedure Travel Distance, 1999-2011**

|  |  |  |  |
| --- | --- | --- | --- |
|  | Change in Minimum Travel Distance (km) | | |
|  | Minimum | 5th Percentile | 10th Percentile |
| Total Knee Arthroplasty (N=87,949) | 0.500  (-2.15, 3.15)  p=0.707  N=87,949 | 0.500  (-2.15, 3.15)  p=0.707  min=100% | 0.498  (-2.15, 3.15)  p=0.708  min=99.8 |
| Total Hip Arthroplasty (N=49,025) | 1.00  (-7.28, 9.28)  p=0.809  N=49,025 | 1.00  (-7.28, 9.28)  p=0.809  min=100% | 1.00  (-7.28, 9.28)  p=0.809  min=100 |
| Cataract Surgery (N=141,432) | 1.06  (-0.804, 2.93)  p=0.259  N=141,432 | 1.04  (-0.807, 2.86)  p=0.259  min=99.4% | 1.04  (-0.851 2.92)  p=0.275  min=94.0 |
| Colonoscopy/Sigmoidoscopy (N=72,021) | 1.74  (-0.643, 4.13)  p=0.149  N=72,021 | 1.74  (-0.644, 4.13)  p=0.149  min=99.2% | 1.74  (-0.654, 4.12)  p=0.151  min=94.5 |
| Esophagogastroduodenoscopy (N=73,041) | -1.50  (-5.63, 2.63)  p=0.469  N=73,041 | -1.50  (-5.63, 2.63)  p=0.469  min=99.4% | -1.50  (-5.64, 2.63)  p=0.470  min=94.5 |
| Appendectomy (N=17,304) | -7.06  (-16.2, 2.10)  p=0.128  N=17,304 | -7.06  (-16.2, 2.10)  p=0.128  min=100% | -7.06  (-16.2, 2.10)  p=0.128  min=100 |
| Hip Fracture Repair (N=77,089) | -1.73  (-6.12, 2.65)  p=0.431  N=77,089 | -1.73  (-6.12, 2.65)  p=0.431  min=100% | -1.73  (-6.12, 2.65)  p=0.431  min=100 |
| **Appendix Table C** presents the effect of “opt out” on the *minimum* distance traveled by patients living in a given zip code. The analysis incorporated a variety of controls including zip code effects, year effects, and controls for patient demographics and comorbidities. 95% confidence intervals shown in parentheses are adjusted for clustering at the state level. For this set of analyses, the unit of analysis is a zip code-year pair. As described in the methods section, for the 5th and 10th percentile of distance, we used the minimum distance traveled if there were insufficient observations in s zip code-year pair to estimate these distances without bias. “min” shows the percentage of zip codes for which there were insufficient observations to estimate the given percentile of distance without bias. Thus, for example, for total hip arthroplasty, 100% of zip codes had 9 or fewer patients, which is why all 3 columns are identical). | | | |

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1. Note that “opt out” takes place during the year (e.g., December 2001 for Iowa). However, our analysis is at the yearly level (as opposed to monthly or quarterly level). Therefore, for our analysis, we treated the “opt out” year as the earliest *full* year following “opt out” (e.g., for our analysis, the “opt out” year for Iowa was 2002). [↑](#footnote-ref-1)
2. With one indicator variable for each zip code, our model contains well over 30,000 variables for over one million patients, which makes results in impractically long computational times. In addition, given the large number of variables, providing a table with the coefficients for each variable is impractical. However, interested readers should contact the authors directly if they are interested in more detailed regression results. [↑](#footnote-ref-2)
3. Over one week on a large network server, and even then, the model had not been estimated [↑](#footnote-ref-3)
4. See https://www.census.gov/geo/maps-data/data/gazetteer.html [↑](#footnote-ref-4)