**Online Supplemental Content**

**Figure A.1. : Sample Construction Flow Chart**

**

**Appendix Table A.1. Regulatory Environment for Nonphysician Anesthesia Providers**

|  |  |  |  |
| --- | --- | --- | --- |
|  | **AA** | **“Opt-out”** | **Year** |
| Alabama | Yes | No | 1998 |
| Alaska | No | Yes | 2003 |
| California | No | Yes | 2009 |
| Colorado | Yes | Yes | 2010 (“Opt-out”), 2012 (AA) |
| District of Columbia | Yes | No | 2004 |
| Florida | Yes | No | 2004 |
| Georgia | Yes | No | 1972 |
| Idaho | No | Yes | 2002 |
| Indiana | Yes | No | 2014 |
| Iowa | No | Yes | 2001 |
| Kansas | No | Yes | 2003 |
| Kentucky | Yes |  | 2002 (AA), 2012 (“Opt-out”) |
| Michigan | Yes | No | 1978 |
| Minnesota | No | Yes | 2002 |
| Missouri | Yes |  | 2003 |
| Montana | No | Yes | 2004 |
| Nebraska | No | Yes | 2002 |
| New Hampshire | No | Yes | 2002 |
| New Mexico | Yes | Yes | 2001 (AA), 2002 (“Opt-out”) |
| North Carolina | Yes | No | 2007 |
| North Dakota | No | Yes | 2003 |
| Ohio | Yes | No | 2000 |
| Oregon | No | Yes | 2003 |
| Oklahoma | Yes | No | 2008 |
| South Carolina | Yes | No | 2001 |
| South Dakota | No | Yes | 2005 |
| Texas | Yes | No | 1999 |
| Vermont | Yes | No | 2003 |
| Washington | No | Yes | 2003 |
| Wisconsin | Yes | Yes | 2005 (“Opt-out”), 2012 (AA) |
| **Table A.1** lists all states (and the District of Columbia) that have enacted legislation allowing for anesthesiologist assistant practice (“AA”) and/or that have chosen to “opt out” of federal regulation requiring physician supervision of nurse anesthetists. States not listed in the table have not chosen to “opt-out” of these federal regulation *and* have not enacted legislation allowing for anesthesiologist assistant practice. |

*Data Appendix*

The Medicare data are detailed and structured in a specific manner. The inpatient file contains claims submitted by the institution (e.g., the hospital) providing care for inpatients. The file contains data such as admission and discharge dates, demographic information (e.g., age, race, zip code) and diagnosis codes (International Classification of Disease, 9th edition; ICD), which can be used to draw inferences about a patient’s comorbidities as well as events (e.g., pulmonary embolism or myocardial infarction) that occurred during the stay. In addition, the inpatient file also contains procedure codes (ICD) describing the procedures performed during the admission, as well as the Diagnosis Related Group (DRG) billed by the facility. DRGs are collections of ICD diagnosis codes developed by CMS to facilitate payments to hospitals; CMS classifies DRGs as being “medical” or “surgical” in nature.1 Finally, the inpatient file contains data on the patient’s status at discharge—for example, noting whether the patient was transferred to another facility, died, or was discharged home.

 The carrier file contains claims submitted by healthcare providers (e.g., physicians) when they provide care for patients. Data from the carrier file include the date the service was performed and the Current Procedural Terminology code billed by the healthcare provider, which can be used to identify the procedure/service provided.[[1]](#footnote-1) The carrier file also contains data about the healthcare provider, such as the self-reported specialty (anesthesia providers can report anesthesiologist (MD), nurse anesthetist, or anesthesiologist assistant), as well as the provider’s taxpayer identification number (TIN). The latter can be used to identify the healthcare provider’s group practice.2-4

 Therefore, a patient admitted for inpatient surgery will have several claims in the Medicare data: at least one claim in the inpatient file from the hospital where the surgery was performed, as well as several claims in the carrier file from the healthcare providers who provided services for the patient—for example, claims submitted by the surgeon and the anesthesia provider. There are no explicit mechanisms to link the claims submitted by healthcare providers to the claim submitted by the institution; typically, researchers link claims from the healthcare providers to a given hospital claim using the dates of service reported on the healthcare providers’ claims and the admission and discharge dates, or procedure dates, listed on the institutional claim.

*Technical Appendix*

 Our baseline analysis involved an instrumental variables approach that we implemented using a two stage least squares regression. As a first step, we estimated the following multivariable linear regression:

 (1)

In equation (1), *i* indexes the given patient, *j* indexes the diagnosis related group, *k* indexes the hospital, and *t* indexes the year of surgery. is a vector of year effects, is a vector of diagnosis related group fixed effects, is a vector of hospital fixed effects, is a vector of patient characteristics including sex, age, race, and the comorbidities listed in **Table 1** (e.g., diabetes, hypertension), and is the error term. is our independent variable of interest and is an indicator variable equaling 1 if the patient received care from a certified anesthesiologist assistant (AA) and 0 otherwise. is our instrument, which is the percentage of cases on the given date that were performed by AAs at hospital *k.* The goal of the first-stage regression is to estimate the extent to which changes in the daily percentage of cases performed by AAs—a number that is largely driven by scheduling decisions unlikely to be related to unobservable patient characteristics—affected the probability that the patient *actually* received care from a AA. Using the regression results from equation (1), we then estimated , which is the *predicted* probability that the patient would hav an AA involved in their care, given the percentage of cases that utilized AAs on the given day and the remaining variables shown in equation (1).

 The second stage regression was given by

 (2)

As with equation (1), *i* indexes the given patient, *j* indexes the diagnosis related group, *k* indexes the hospital, and *t* indexes the year of surgery. The variables , , , and are retained from equation (1). The dependent variable is the outcome of interest (e.g., survival, length of stay). is the predicted probability that an AA would be involved in the patient’s care, and is the error term. Our coefficient of interest is , which represents the expected change in the given outcome for cases with AA involvement (compared to cases with NA involvement).

In the case of survival, was modeled as an indicator variable equaling one if the patient died during the inpatient stay and zero otherwise. Thus, for survival, the statistical model outlined in equation (2) represents a linear probability model, and represents the absolute (i.e., percentage point) change in the probability of the outcome associated with receiving care from a AA. We chose a linear probability model because our analysis required the use of numerous indicator variables (e.g., the hospital and procedure fixed effects), which can lead to computational difficulties with logistic or probit regression.5 In addition, our instrumental variables model is unique because our endogenous regressor (whether the patient received care from a AA) *and* our clinical outcomes are discrete variables. In this circumstance, a two stage least squares regression is appropriate.6 Finally, in the setting of numerous fixed effects, nonlinear models such as the logit can be biased (the “incidental parameters problem”), while the linear probability model does not have this issue.7

In estimating our regression models, we clustered our errors at the hospital 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.8 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 hospital, we clustered our standard errors at the hospital level.9 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 in the case of survival 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.10

 Two crucial assumptions underlying out instrumental variables approach is that (a) our instrument is uncorrelated with unobservable factors that could be associated with patient outcomes (conditional on the other variables in our model) and (b) that our instrument has a strong association with whether an AA is involved in the patient’s care. While there is no way to statistically test the first assumption, it has face validity: it seems unlikely that higher-risk patients would be more likely to be scheduled on days when there are more AAs available to do cases. Indeed, as previously mentioned, many of the factors that influence the number of AAs available to do cases—such as scheduling decisions and the legal environment—are decided well in advance of the give day of surgery. Moreover, other factors that could influence the number of AAs available to do cases—such as illness—would also be highly unlikely to be correlated with factors that could influence the outcomes for an individual patient.

 The second assumption—that our instrument (the daily percentage of cases performed by AAs) be strongly correlated with whether the patient actually received care from an AA—also has face validity. The requirement for a strong correlation between these two variables is important because if the two are only *weakly* correlated, our instrumental variables approach could be biased 11. Here, there are formal statistical tests to test the association between our instrument and whether the patient actually received care from an AA; these tests are based on the F-statistic from equation (1) 11. The F-statistic from equation (1) was 2,783(see **Table A.1**), which is well in excess of the critical values for all the tests for a weak correlation between our instrument and whether the patient actually received care from an AA. Accordingly, we can easily reject the null hypothesis of a weak correlation between our instrument and whether the patient actually received care from an AA.

 The results of our main regressions are shown in **Table A.2**. In this table we display the regression coefficients for our instrumented independent variable of interest—an indicator of whether or not an AA provided care—as well as the regression constant. Coefficients for the year effects for years 2004-2011, age controls, procedure effects, hospital fixed effects, and the patient characteristics listed in **Table A.2** are available from the authors on request. The results from the first column suggest that AA care is associated with a 0.08 absolute (percentage point) reduction in inpatient mortality, compared to NA care, although this difference is statistically insignificant (p=0.47). In column (2), we present the results from a regression of inpatient length of stay on our instrument for AA care. The provision of AA care is associated with a 0.009 reduction in inpatient length of stay measured in days, although this effect is also statistically insignificant (p=0.89). Finally, in column (3) our dependent variable is inpatient spending. Here it can be seen that AA care was associated with a $59 reduction in inpatient spending, but this effect is also statistically insignificant (p=0.70).

**Table A.1: AA Involvement and Daily Share of Cases, 2004-2011 (First-Stage Regression Results)**

|  |  |
| --- | --- |
|  | AA Care |
| Share of Cases (%) | 1.00(0.00079))p<0.001 |
| Constant | 0.00034(0.0028)p=0.90 |
| F-statistic | 2,783 |
| R-squared | 0.89 |
| N | 443,098 |

*Notes:* Table A.1 shows the results of our first stage regression using two stage least squares estimation. Regression coefficients are shown together with standard errors that are clustered at the hospital level (in parentheses) as well as p-values. We do not show coefficients for the year effects for years 2004-2011, age controls, procedure effects, hospital fixed effects, and the patient characteristics listed in Table 1. These are available from the authors on request. The table shows the results of a regression in which the dependent variable is the daily percentage of cases performed by AAs and the independent variable is whether an AA was involved in the patient’s care.

**Table A.2: Anesthesia Care Team Composition and Patient Outcomes, 2004-2011 (Second-Stage Regression Results)**

|  |  |  |  |
| --- | --- | --- | --- |
|  | Inpatient Mortality (%) | Length of Stay (Days) | Inpatient Spending ($) |
| AA Care | -0.08(0.2)p=0.47 | -0.009(0.06)p=0.89 | -56(142)p=0.70 |
| Constant | 1.6(0.34)p<0.001 | 4.3(0.17)p<0.001 | 42,318(513)p<0.001 |
| F-statistic | 99999 | 99999 | 99999 |
| R-squared | 0.07 | 0.36 | 0.54 |
| N | 443,098 | 443,098 | 443,098 |

*Notes:* Table A.2 shows the results of our second stage regression using two stage least squares estimation. Regression coefficients are shown together with standard errors that are clustered at the hospital level (in parentheses) as well as p-values. We do not show coefficients for the year effects for years 2004-2011, age controls, procedure effects, hospital fixed effects, and the patient characteristics listed in Table 1. These are available from the authors on request. Column (1) shows the results of a regression in which the dependent variable is inpatient mortality and the independent variable is the instrument for whether an AA was involved in the patient’s care. Column (2) shows the results of a regression in which the dependent variable is length of stay and column (3) shows the results of a regression in which the dependent variable is inpatient spending.

**Table A.3.: Anesthesia Care Team Composition and Additional Patient Outcomes, 2004-2011**

|  |  |  |
| --- | --- | --- |
| **Outcome** | **N** | **Regression Coefficient** |
| Death among patients admitted with Low-Risk DRGs | 64,070 | 0.04(-0.3 to 0.4)p=0.86 |
| Death among patients with serious treatable conditions (pneumonia, sepsis, shock, shock, or GI hemorrhage) | 24,499 | 2.0(-0.2 to 4.3)p=0.08 |
| Pneumothorax | 409,528 | 0.057(-0.004 to 0.1)p=0.07 |
| Acute Kidney Injury | 274,168 | 0.01(-0.4 to 0.5)p=0.95 |
| Post-operative respiratory failure | 231,026 | 0.1(-0.1 to 0.4)p=0.36 |
| Transfusion Reaction | 441,076 | \*\* |
| Anesthesia Complication | 443,098 | -0.006(-0.05, 0.04)p=0.78 |
| **Table A.3** presents the results of analyses examining the association between the given outcome and the use of an anesthesia care team with an anesthesiologist assistant (compared to care teams with nurse anesthetists). The analyses used are the same multivariable analyses described in the methods section. The reported regression coefficient is the absolute (percentage point) difference in the incidence of the given outcome associated with care teams that used anesthesiologist assistants. For example, in the case of death among patients admitted with low-risk DRGs, the incidence of death was 0.04 percentage points higher among anesthesia care teams with anesthesiologist assistants, compared to teams with nurse anesthetists. 95% confidence intervals shown in parentheses are adjusted for clustering at the hospital level. \*\*outcome could not be studied as it occurred only once in the entire sample.  |

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1. In the United States, individual healthcare providers bill for procedures using the CPT code system, while institutions use the ICD code system to describe the procedures that were performed during the inpatient admission. [↑](#footnote-ref-1)