Supplemental Online Content

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This supplementary material has been provided by the authors to give readers additional information about their work.

eMethods. Selection of matching variables

 We created our final analytic sample by matching telestroke vs. control patients from a given year-month period 1:1. Common matching methods include propensity score matching or Coarsened Exact Matching. The former matches patients using a summary score of covariates, while the later identifies matches that are exactly the same, discarding the rest. These approaches can lead to imbalances on specific covariates (even if balanced overall) or unnecessary and meaningful loss of sample.

 The approach we took is called cardinality matching—an approach that is less likely to suffer from these limitations—and employed it within a risk-set matching framework. As we describe in our methods section cardinality matching uses integer programming to find the largest possible set of matches that satisfy the level of balance we wanted to achieve, which was complete balance (ie, no differences) on four pre-specified variables and an acceptable level of balance (< .1 absolute standard deviations) on the remaining covariates ("mean balance" variables). We executed the matching routine within 6 month periods from 2008 through June 2017 (19 periods), stacking each period's matches together to form our final analytic sample.

 An important step in our study plan was the selection of which variables we would use to exact match on and which variables we would use to mean balance our telestroke and control samples. Our final decisions were based on literature review, which variables were available for 100% of our admissions, which variables were predictive of 180 day mortality (Table S2 below), and which variables our advisory panel believed were more predictive of 180 day mortality. This panel composed of vascular neurologists were given a list of eligible variables and asked to rank order them by their importance in explaining mortality after stroke.

 As shown in Table S2—which modeled 180 mortality in 2008 on patient demographics, original enrollment reason, Medicaid status, and 27 chronic condition indicators—age is the key predictor of mortality. Atrial fibrillation was also highly predictive and our advisory panel also recommended it as a key predictor. Combined, we had the initial lists of exact and mean balance variables as follows:

- Exact matching: age, sex, use of ambulance, h/o afib, rural location
- Matching with mean balance: race/ethnicity, h/o HL, hospital stroke volume, region, Medicaid dual status, h/o stroke/TIA, Coronary artery disease, carotid stenosis, diabetes mellitus, peripheral vascular disease, hypertension, hospital academic status

Use of ambulance was only available in a 20% sample, so we removed that variable and exact matched on age, sex, Atrial fibrillation, and rural residence (based on patient zip). We also added the patient's original reason for enrolling in Medicare to capture "disability", used a more detailed breakout of hospital region (using the 9 census divisions), and included hospital rurality as well.

eTable 1. Crosswalk of *ICD*-*9* to *ICD*-*10* acute stroke diagnosis codes

The International Classification of Diseases (ICD) transitioned from the Ninth Edition (ICD-9) to the Tenth Edition (ICD-10) in October 2015. Because our study period began in 2008 and ended in 2017, and because we used a patient's primary diagnosis code to identify an acute stroke, we had to use the acute stroke codes from both editions to build our analytic sample. Table S1 shows the crosswalk of acute stroke diagnosis codes—from ICD-9 to ICD-10—that we used in our study.

eTable 2. Coefficients in 180-day mortality model (admissions in 2008 only)

*** p<0.001, ** p<0.01, * p<0.05

The census division of the patient's first hospital was also used to match telestroke and control admissions. To save space in Table 1 we provide the detail above in Table S3.

 While not used directly as a match variable, we evaluated the balance we achieved by checking if our measure of 180 day predicted mortality from admission was similar after matching. We present this in Table S4 along with the remaining Charleston chronic conditions (CCWs) that *were not used* for matching, the total number of conditions per patient, and using a 20% sample only, ambulance use and distance traveled on the first day of an admission. These additional characteristics were not used as exact or mean balance covariates in our matching algorithm, but the averages and standardized differences shown in Table S4 below provide more evidence that our telestroke and control admissions were well balanced.

*Indicates variable on which exact matching conducted.

**Indicates variable on which mean balancing was conducted.

eTable 5. Outcome differences and risk ratios in telestroke vs control hospitals in the year prior to telestroke introduction

Averages for admissions that started in telestroke or control hospitals are shown in the first two columns, followed by their difference and the 95% CI around that difference.

*For statistical significance (p-values), we used McNemar's test for dichotomous outcomes and the Wilcoxson signed-rank test for continuous ones. Risk ratios for the dichotomous outcomes, along with their 95% CI, are shown in the last column.

^reperfusion treatment includes delivery of thrombolysis via alteplase or thrombectomy at the presenting hospital or after transfer † thrombolysis via alteplase delivered before admission a.k.a. "drip and ship" is recorded in the patient's diagnosis codes at the admitting hospital

 To assess if hospitals with telestroke capacity were different from control hospitals *before* they introduced telestroke, we constructed a separate analytic sample of "treated admissions" that were drawn from telestroke hospitals in the year before their telestroke programs were introduced and matched them to admissions from other control hospitals. The matching methods we used to create this pre-telestroke introduction matched sample were the same as described in our main analysis, where we employed cardinality and risk set matching and used the same covariates described in Tables 1 and S3 to do so. After creating our pre-telestroke sample we used the same statistical approach to analyze our matched pairs and we present those results above. Given this was the year prior to telestroke introduction, the expectation was that the outcomes would be similar between treatment and controls.

 As shown in Table S5, there were no statistically significant differences. The trend was that patients that presented to telestroke hospitals in the year before telestroke introduction were less likely to have reperfusion treatment and slightly more likely to die within 30 days of admission. In other words, we find no evidence that care was already superior at the hospitals that introduced telestroke programs; rather, these data suggest that care may have been slightly worse before telestroke was introduced.

eTable 6. Sensitivity of unobserved factors using Rosenbaum bounds

As shown in Table 1 of the paper and in Table S3 above, after matching the standardized difference in sample means between telestroke admissions and control admissions for our covariates did not exceed 0.1 absolute standard deviations, a commonly accepted threshold for balance. For some key covariates such as age we matched exactly and thus the standardized differences were 0. While we balanced all the covariates believed to be important determinants of the outcomes, it is always possible that an unobserved covariate which is not captured in our data set is confounding our effect estimates. In other words, in an observational study it is always possible that an unobserved covariate that affects both the treatment (telestroke capacity) and the outcomes (i.e., mortality) can explain away a statistically significant finding. As we acknowledged in the paper these could include measures of stroke severity (though as described below, in the limited sample of cases there is balance in stroke severity).

We used Rosenbaum bounds to evaluate how sensitive our statistically significant results (p-value < 0.05 in Table 2) are to such hidden biases.¹ For a formal derivation of the bounds, please see Chapter 4 of Rosenbaum (2002; Observational Studies, Springer).² For a general discussion of the interpretation and validation of the bounds using examples, please see chapters 3 and 14 of Rosenbaum (2020; Design of Observational Studies, Springer).³ This sensitivity analysis sequentially increases the magnitude of bias due to a generic unobserved covariate and measures the resulting p-value. This magnitude of bias is captured by the parameter Γ, which bounds the odds ratio of the probabilities of receiving treatment of two units that have been matched for their observed covariates. The larger the value of Γ, the more insensitive the results are to hidden biases due to unobserved covariates. Table S6 above presents the results showing that some results are insensitive to hidden biases of moderate size (thrombolysis and transfer, thrombectomy), whereas others are insensitive to small biases only (reperfusion treatment, thrombolysis via alteplase). Mortality from admission was sensitive to small biases.

¹ Rosenbaum, P.R., 1987. Sensitivity analysis for certain permutation inferences in matched observational studies. Biometrika, 74(1), pp.13-26

² Rosenbaum PR. Observational studies. 2nd ed. New York: Springer; 2002

³ Rosenbaum, PR. Design of observational studies (Vol. 10). New York: Springer, 2020

eFigure 1. Sample of study hospitals

We identified 5085 unique critical access or short term acute care hospitals with at least 1 inpatient or outpatient (hospital department) claim over the period 2008 through 2017 (see box 1 above). As described in the Methods section, we excluded hospitals from our analysis that either (a) never (or almost never) billed for an acute stroke over the period 2008-2017, or conversely (b) likely had substantive on-site stroke expertise (described in Figure S1 above). Comprehensive or primary stroke centers were those currently certified by the Joint Commission (or another regional certifying organization including HFAP, DNV, and CIHQ) manually identified from the websites of these certifying organizations. Academic teaching hospitals were members of the Council for Teaching Hospitals (COTH) over the period 2015-2017. Thrombectomy hospitals performed one or more thrombectomy (identified by ICD-10 procedure codes: 3E03317-3E08317, 03CG3ZZ - 03CV3ZZ) in 2016/7.

After making these exclusions there were 765 hospitals we identified with telestroke capacity and another 2441 potential controls.⁴ To ensure potential controls did not have telestroke capacity, we excluded 1461 hospitals that reported they have a telestroke program on the 2016 or 2017 Emergency Department Inventory survey or did not respond to either or both of the surveys.⁵ In other words potential controls were only those that responded no to both surveys.

⁴ Telestroke capacity was identified from data provided by 15 telestroke networks including Blue Sky Neurology, Integris, InTouch, Mayo Clinic, Medical University of South Carolina, Northwestern Memorial Hospital, Partners HealthCare, Providence Health, SOC Telemed (formerly Specialists on Call), Stanford Health Care, University of Pittsburg Medical Center, University of Utah Hospital, Vanderbilt University Medical Center, Virginia Mason, and Wake Forest Baptist Health.

⁵ For a description of the survey see Zachrison KS, Boggs KM, M Hayden E, Espinola JA, Camargo CA. A national survey of telemedicine use by US emergency departments. J Telemed Telecare. 2020;26(5):278-284.

 Starting in October 2016, NIH stroke severity scores can now be recorded using ICD10 diagnosis codes on inpatient and outpatient claims. Scores are based on 11 criteria and range from 0 to 42 (the max score). Each claim can have multiple scores and a single episode of stroke can have multiple claims with different scores.

 Using only the final 6-month period in our data, we evaluated whether severity scores in telestroke hospitals were different from severity scores in control hospitals and found very little difference in both the averages (7.93 in telestroke hospitals vs 8.01 in controls; standardized difference in means -0.00995) and their distributions (Figure S2). We note that the telestroke sites were more likely to report a stroke severity score (17% vs 14.4%; standardized difference in means 0.0726), which may explain the very small difference in stroke severity we do see.

We decided not to include stroke severity in our analysis . Across our entire roughly 10 year study period, NIH stroke severity scores could only be recorded for 6 months and of these cases, only 15.7% had a score recorded. Therefore, of the total analytic sample, scores from this final semester only cover 1.4% of the final matched sample. Given this very limited sample, we did not feel like it added value to the manuscript. However, as we show above, for the limited sample that did have a severity score recorded we found no evidence of imbalance.