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ABSTRACT

Does the Marginal Hospitalization Save Lives? The Case of Respiratory Admissions for the Elderly*

Some commentators estimate that up to a third of U.S. medical spending may be wasted. This study focuses on the decision to hospitalize elderly Medicare patients who present at the emergency room (ER) with respiratory conditions. Failing to hospitalize sick patients could have dire consequences. However, in addition to generating higher costs, unnecessary hospitalization puts patients at risk of hospital acquired conditions and disrupts their lives. We use variation in the patient's nearest hospital's propensity to admit patients with similar observable characteristics as an instrument for the admission decision. While OLS estimates suggest that admitted patients are more likely to die, when we instrument for patient admission we find that the marginal hospital admission increases the number of hospital days by seven days and increases charges by $42,000 but has no effect on the risk of death in the course of the next year. The marginal hospitalization also reduces the risk of another emergency department visit in the next 30 days but increases outpatient visits over the same time horizon with no overall impact on charges. Longer term effects also include increased outpatient visits but effects on patient costs and health outcomes over the next year are minimal. Overall, these results lend support to the argument that in many cases the marginal hospitalization is unnecessary.

JEL Classification: I1
Keywords: hospital admission, respiratory emergency

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Some commentators estimate that up to a third of U.S. medical spending may be wasteful in the sense that it produces no health benefit and may at times even harm patients (Chandra and Skinner, 2012; Baicker, Chandra, Skinner, 2012; Berwick and Hackbarth 2012). Yet identifying wasteful spending and the factors that lead to it is difficult. Sheiner (2014) argues that approaches based on identifying high-spending areas are not a useful way to find inefficiencies. Similarly, Einav et al. (2018) argue that focusing on health care costs at the end of life is not helpful in identifying waste and suggest that researchers should focus on specific spending margins and on heterogeneity in the effects of spending across patients of different types.

This study focuses on the decision to hospitalize elderly Medicare patients who present at the emergency room (ER) with respiratory conditions and is one of the first to focus on the decision to hospitalize itself as an important margin for potentially wasteful medical care. We examine individuals aged 66 to 70 using hospital discharge records for New York State. Respiratory conditions are one of the most common classes of illnesses affecting these patients: 28 percent of all ER visits list a respiratory diagnosis as do 42 percent of hospitalizations. A little over half of these patients are admitted to hospital, meaning that clinicians are frequently called on differentiate between cases that require expensive hospital services and those that do not. Failing to hospitalize someone who needs to be admitted could lead to dire consequences, even death. But in addition to generating higher costs, unnecessary hospitalization puts patients at risk. McIntyre (2013) notes that patients who have been hospitalized experience "a period of generalized risk for a range of adverse health events" such as infection, metabolic disturbances, and falls. He describes a period of vulnerability due to sleep deprivation, poor nutrition, and pain that has been characterized as "post-hospital syndrome," and suggests that "admission to hospital could be considered a disease." Hospitalization often also has negative financial impacts (Dobkin et al. 2018).

The ideal setting for measuring the effect of the marginal hospitalization on outcomes would involve randomly assigning patients with symptoms around the severity threshold for admission to hospital either to hospital or to home care. We attempt to approximate this research design by using variation in the patient's nearest hospital's propensity to admit patients with similar observable characteristics as an instrument for the admission decision.[1]

We find, first, that there is considerable variation even within hospital in the probability of admission which seems unlikely to be explainable by purely medical risk factors. For example, conditional on observable diagnoses and comorbidities, women are less likely to be admitted than men; African-Americans and Hispanics are less likely to be admitted that non-Hispanic whites; and there is a sharp spike in admission probabilities at age 70.

Second, we find that there is considerable variation across hospitals in the probability that patients with different estimated severity levels will be admitted. Not surprisingly, this variation is greatest for patients in the middle of the severity distribution: For patients in the fifth decile of estimated severity, the probability of admission varies from 20 to 80 percent. These probabilities are calculated excluding small hospitals with fewer than 100 beds. The admission rate at the nearest large hospital for patients in the individual's predicted admission decile is a strong instrument for the individual's own admission to hospital. Since this instrument is based on the hospital's other patients, it is not affected by the patient's own health status. Simply put, if you live in some places, you are more likely to be hospitalized than others. We use the nearest large hospital to get around the endogeneity of hospital choice, and the instrument works because many people (45%) do in fact use the nearest large hospital.

[1] Card, Fenizia, and Silver (2019) employ a similar identification strategy.

Third, ordinary least squares estimates of the consequences of hospital admission suggest that admitted patients are more likely to die—the probability of death is one percentage point higher in the next week, rising to three percentage points higher over the next year. These estimates demonstrate the difficulty involved with trying to identify unnecessary hospitalizations given the data that is observable in administrative hospital records. On average clinicians are clearly choosing to admit the sicker patients among those presenting at the ER, indicating that they have additional information about the patient's condition that is superior to that available to us.

Finally, when we instrument for patient admission, we find that the marginal hospital admission increases the number of hospital days by seven days and increases charges by $42,240, but has no effect on the risk of death. The marginal hospitalization also reduces the risk of returning to the emergency department in the next 30 days, and increases the probability that care is received in an outpatient setting. It has minimal impacts on costs and health outcomes beyond 30 days.

The rest of this paper is laid out as follows. We first discuss some of the background literature related to unnecessary hospitalization. We then discuss the data and estimation strategy in the paper. Section V presents our main results, and several robustness checks are discussed in Section VI. Section VII concludes.

II. Background

A day in the hospital is expensive relative to other ways to deliver care and may have negative effects on patients, making the decision to hospitalize a patient a potentially important margin affecting health care costs and health outcomes. Yet, it is difficult to identify hospitalizations that may have been *ex ante* unnecessary even with detailed administrative data

(Einav et al, 2018). Some researchers have attempted to directly assess the extent to which hospitalizations were unnecessary. For example, Kemper (1988) conducted a retroactive evaluation of pediatric visits to the University of Wisconsin Hospital and deemed 21.4% of admissions inappropriate. These findings suggest that many hospital admissions may not be beneficial to patients, but detailed chart review is not feasible on a large-scale basis.

Other studies have examined the effect of additional hospital spending on patient health after patients are hospitalized. For example, Kaestner and Silber (2010) find a negative association between inpatient hospital spending and 30-day mortality for Medicare patients. Doyle (2005, 2011) and Doyle et al. (2015) examine patients with emergencies who end up being admitted to higher and lower spending hospitals. They find that patient outcomes are better in hospitals with higher average levels of in-patient spending. Almond, Doyle, and Kowalski (2010) and look at rules that mandate greater spending on newborns just above a birthweight threshold compared to newborns just below it, and again find that higher spending improves outcomes. However, using a similar design, Almond and Doyle (2011) find no impact of additional hospital days for maternity patients. More broadly, Alalouf, Miller, and Wherry (2019) study the impact of a marginal diagnosis of diabetes and find it leads to more spending on drugs and care but no improvement in health.

Few papers examine the decision to admit the marginal patient in the first place, even though this is a particularly important margin in terms of treatment and spending. In principal, we would like to compare two identical patients, one of whom was hospitalized and the other of whom was not. Because we cannot perfectly assess patient condition, we need to find an instrumental variable that predicts hospitalization but has no independent effect on outcomes.

Several previous papers have suggested that hospitals with empty beds are more likely to admit patients, other things being equal. In one of the earlier papers to address this phenomena, Fisher et al. (1994) examined future probabilities of hospital admission in Medicare patients in Boston and New Haven who had all been initially admitted for myocardial infarction, stroke, hip fracture, gastrointestinal bleeding, or potentially curative surgery for cancer. They found that the Boston patients had a 64 percent higher average readmission rate over the next three years compared to New Haven patients, but experienced no difference in mortality rates. They argue that this higher rate of future admissions cannot be explained by differences in severity of illness or differential use of nursing home care or Veterans Administration hospitals. They conclude that the most likely explanation is that a greater availability of beds per capita in Boston led to the higher admission rates and that the marginal admissions had little impact on health outcomes. These findings are echoed by Fisher et al. (2000) who look at a broader sample of Medicare patients. Similarly, Goodman et al. (1994) found that pediatric patients in zip codes with high per capita bed supply had 9% more admissions than children in areas with lower per capita bed supply.

More recently, Sharma, Stano and Gehrig (2008) study responses to short run variation in hospital demand in Oregon. They find that when demand for beds is relatively high, hospitals discharge patients earlier, but they do not find any effect on hospital admissions. Evans and Kim (2006) similarly find that hospitals respond to short run demand shocks by reducing length of stay rather than by altering admissions. Alexander and Currie (2017) show that flu prevalence is related to the probability that publicly insured children are admitted to hospital, but has relatively little effect on admissions of the privately insured.

These findings suggest that measures of demand relative to bed capacity may be of limited predictive value as instrumental variables for hospital admission in the Medicare population. Moreover, arguably, utilization rates could have independent effects on outcomes by, for example, affecting the quality of nursing care received (Evans and Kim, 2006). In his analysis of the effects of the availability of neonatal intensive care unit beds on admission to the NICU and patient outcomes, Freedman (2016) explicitly rejects the use of bed availability as an instrument on these grounds.

This brief review of the literature suggests that the decision to hospitalize a patient is an important, yet relatively unexplored margin affecting hospital costs and patient outcomes, and that one of the main limitations on research is the difficulty in finding an appropriate instrument for hospital admission.

III. Data

The primary data source used in this paper is a restricted version of the hospital discharge data from the New York State Department of Health Statewide Planning and Research Cooperative System (SPARCS).[2] These data contain records for every hospital inpatient stay, hospital outpatient (emergency department, ambulatory surgery, and outpatient services) visit, and each ambulatory surgery and outpatient services visit to a hospital extension clinic and diagnostic and treatment center for the years 2005-2014. It has numerous advantages over the more commonly used Health Care Utilization Project (HCUP) data, including having information on the exact dates of arrival, admission, and discharge. These data include the zip code of the patients' residence, and an encrypted ID variable that makes it possible to link patients across discharges.

Since our project studies the decision to admit a patient from the emergency department, we rely on a key piece of information: an "emergency department indicator" variable. This enables us to identify inpatients who were admitted from the ER as well as patients who were treated in

[2] For further information about SPARCS see: https://www.health.ny.gov/statistics/sparcs/.

the ER and discharged without being admitted.

The SPARCS data also includes mortality variables which are derived from an internal match with state vital records. These variables tell us whether a particular patient died within a certain time frame. These data include all deaths (not only those in hospital) and so are a complete census of future mortality within the relevant time window.[3]

We combine the SPARCS data with time series data from the New York State Department of Health on the number of beds in each hospital. While current information on beds is freely available,[4] we had to request quarterly historical bed information, which was provided for the first quarter of 2008 through the second quarter of 2014, excluding the fourth quarter of 2011 which is unavailable for administrative reasons unrelated to our project.[5] To maintain a balanced panel of months, we use data from 2008-2013 as our primary sample.

We define our primary analysis sample as follows. First, we limit to individuals with the emergency department indicator. Second, we focus on individuals between the ages of 66 and 70. This is an age range that is sufficiently old to be at substantial risk for respiratory problems, but young enough that most people are expected to recover from an additional hospitalization. We start at age 66 rather than age 65 to ensure that all individuals have been eligible for Medicare for at least a year. In this way, we avoid changes in the propensity to be admitted and in the intensity of care that are associated with initial receipt of Medicare (see Card, Dobkin, and Maestas, 2008, 2009).

We then limit the sample to individuals with at least one respiratory diagnosis, using the

[3] In contrast, the HCUP data only has information on whether an individual died in the hospital.
[4]For further information about New York hospitals see: https://profiles.health.ny.gov/hospital/alpha.
[5] We were told in an email from our contact: "Note there was no update done in the 4th quarter of 2011 for, as I recall, bureaucratic reasons."

Clinical Classification Software's grouping of ICD-9 diagnosis codes.[6] Focusing on one specific category of diagnoses is one way to try to narrow the comparison of admitted and not admitted patients to those who are similar to each other without placing undue weight on the exact diagnosis code given. Respiratory diagnoses are common, and there is also often uncertainty about the appropriate exact diagnosis within that general category (Chan and Gentzkow, 2019).

For each individual with at least one respiratory diagnosis, we create indicators for whether each condition was present on arrival at the hospital.[7] We also use the diagnosis variables to create indicators for comorbidities.[8] Note that only co-morbidities that were present when the patient initially presented at the ER are included in this index.

We then link these individuals to all of their past and future discharge records, regardless of the diagnoses in these records. With these linked records, we create variables indicating whether an individual had a respiratory diagnosis in the past year (past 365 days), in an inpatient or outpatient setting, and the number of days in the past year that they spent in the hospital as an inpatient or in ambulatory surgery for any reason. We also identify any hospital acquired

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[6] See: https://www.hcup-us.ahrq.gov/toolssoftware/ccs/ccs.jsp, http://www.nber.org/data/icd-ccs-crosswalk.html. Specifically, we include codes 122-134, which correspond to pneumonia, influenza, tonsillitis, bronchitis, upper respiratory infections, chronic obstructive pulmonary disease, asthma, aspiration pneumonitis from food or vomiting, pleurisy; pneumothorax; pulmonary collapse, respiratory failure; lung disease due to external agents, lower respiratory disease, and upper respiratory disease.

[7] We assume all diagnoses on an emergency discharge record were present on arrival. For diagnoses on an inpatient file, there are separate variables indicating if the diagnosis was present on arrival.

[8] We do this by applying identifying the components of the composite comorbidity Charlson Index (Charlson et al. 1987), using the Stata function "charlson." Comorbidities include: acute myocardial infarction, congestive heart failure, peripheral vascular disease, cerebrovascular disease, dementia, chronic obstructive pulmonary disease, rheumatoid disease, peptic ulcer disease, liver disease (minor and moderate/severe), diabetes (with and without complications), hemiplegia or paraplegia, renal disease, and cancer (local and metastatic).

conditions (HACs) that an individual suffered from after admission.[9] These are conditions that the Centers for Medicaid and Medicare Services believes could have been prevented through the application of evidence-based guidelines.

Table 1 provides an initial overview of these data. Overall, 56.5 percent of the patients in our sample were admitted, suggesting that doctors have considerable discretion in who is admitted and who is not for these diagnoses as a class. Once admitted, the average length of stay is about four days. About 0.5 percent of patients suffer from a hospital acquired condition (though since hospitals are self-reporting these data and may suffer financial penalties in consequence, these data may be under-reported). Aside from the current episode of care, patients in our sample have an average of 11.1 additional hospital days in the next year. Death rates are high relative to the overall population in this age group: 4.3 percent of these patients die within the next week, and 17.8 percent die within the next year compared to a mortality rate of 1788.6 per 100,000 people 65 to 74 in the U.S. as a whole in 2016.[10]

IV: Methods

We seek to exploit variation in New York state's hospitals propensity to admit patients in similar condition to hospital. Hence, the first step in our analysis is to try to group patients with similar levels of morbidity. To do so, we first estimate the propensity that a patient will be admitted using all of the patients in our sample independent of what hospital they went to:[11]

[9] We use the definition of hospital acquired conditions available at https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/HospitalAcqCond/Hospital-Acquired_Conditions.html.
[10] See https://www.cdc.gov/nchs/products/databriefs/db293.htm.
[11] This procedure follows Currie, MacLeod, and Van Parys (2016) and Currie and MacLeod (2017).

$$P(admitted_{it} = 1) = F(\alpha + \mathbf{RespDiag}_{it} + \mathbf{Comorbidities}_{it} + \mathbf{PastDiag}_{it-1} + \mathbf{HospDays}_{it-1} + \mathbf{DayOfWeek}_{t} + \mathbf{Month}_{t} + \mathbf{Year}_{t} + \mathbf{X}_{i} + \mathbf{Zip}_{i} + \varepsilon_{it}), \quad (1)$$

where *admitted* for individual *i* is equal to one if the discharge record was in the inpatient discharge file, and is equal to zero if the record is in the outpatient file. **RespDiag** are indicators for respiratory diagnoses present at the current visit (as defined by the 13 CCS codes listed above) and **Comorbidities** are the categories from the Charlson index discussed above, also for the current visit. Together these variables provide an indication of the patient's current health condition.

The vector **PastDiag** includes indicators for respiratory diagnoses present on discharge records in the past year (i.e. past 365 days), while **HospDays** is the total number of inpatient hospital days in the past year. Together these variables summarize information about past health conditions of the patient that may be relevant to the current case. For example, if the patient has a history of asthma and some knowledge of how to manage it, they may be less likely to be hospitalized than if they have an asthma attack without such a history.

We also control for **DayOfWeek** (i.e., Sunday, Monday…) and **Month** indicators given previous evidence that admissions are sensitive to timing within the week and year (Lew, 1966; Barry, 2004), as well as calendar **Year** indicators in order to control for possible longer-term time trends in admissions.

Finally, we control for **X**, a vector of individual-level controls including as sex, indicators for race and ethnicity, and single-year-of-age fixed effects as well as for zip code fixed effects.[12] These variables may proxy for underlying differences in health status that could affect both the probability of hospital admission and outcomes. However, to the extent that estimated effects of

[12] Given that our primary specification for our admission propensity model is a logit, we drop any individuals from ZIP codes or hospitals where everyone or no one was admitted. This applies to less than 0.3% of the sample.

variables like race do not reflect underlying health, they arguably do not belong in this model. Hence, we discuss estimates computed without these variables in the robustness section below.

Robust standard errors (ε) are clustered at the zip code level in order to allow for correlations in unobservable factors among patients within zip codes. In what follows, we use a logit specification for F, though in the robustness section, we also report results computed using alternative approaches to developing an index, including machine learning techniques.

Estimation of equation (1) tells us how the variables included in the model are treated, on average, by hospitals in New York state. Hence, we can use the admission propensity computed in equation (1) to ask whether a particular hospital is more or less likely than the average hospital to admit patients with a given vector of observable characteristics. In what follows, we use the estimated admission propensity index to divide patients into deciles. For each patient, we match the patient to the nearest general service hospital with over 99 beds which saw emergency respiratory patients age 66-70 in that person's decile in that year.[13] We then ask how likely that hospital is to admit a patient in that year in each admission probability decile. For this exercise, we use hospitals with over 99 beds because small hospitals can have small cell sizes that cause noise in their estimated propensities to admit patients from a particular decile. When computing the hospital's probability of admitting patients in a particular decile, we also exclude the index patient from the calculation. We therefore also exclude hospitals that only had 1 emergency respiratory patient age 66-70 in a given decile in a given year, as we wouldn't be able to calculate this leave-out index.

This exercise seeks to isolate variation in the probability of admission that stems from the

[13] An alternative specification that matches each ZIP code to the nearest hospital with over 99 beds and then drops any patients for whom that hospital had no patients in that year and decile yields very similar results, albeit with only 93% of the sample.

fact that a patient of a given type went to a hospital with a high or low probability of admitting other similar patients. We use the admission propensity for the nearest large hospital, whether or not the patient actually went there, because some patients might actively seek hospitals with high or low admission probabilities. Because most patients do in fact use the nearest hospital, the nearest hospital's propensity to admit patients of the index patient's type is predictive of the index patient's admission probability, without having been directly chosen by the index patient.

The first stage model that we estimate is given by:

$$admitted_{idht} = \alpha + admission\_prob_{dht} + \widehat{index}_{iht} + \mathbf{Decile}_d + \mathbf{Hosp}_h + \mathbf{DayOfWeek}_t + \mathbf{Month}_t + \mathbf{Year}_t + \mathbf{Zip}_i + \varepsilon_{idth}, \quad (2)$$

Here, admitted is an indicator equal to one if patient *i* from predicted admission decile *d* is admitted at time *t* to hospital h. The variable $admission\_prob_{dht}$ is the instrument discussed above, that is, the probability that a patient in the same decile of admission probabilities as the index patient was admitted to the nearest hospital with over 99 beds (where this probability is computed excluding the index patient). The variable $\widehat{index}$ is the predicted probability of admission for the index patient from equation (1). Note that we obtain much the same thing if we just include all of the variables from (1), but using $\widehat{index}$ instead improves the fit of the first stage, which makes sense because it incorporates additional information. **Decile** and **Hosp** are decile and hospital fixed effects, respectively.

Including decile fixed effects allows the patient's condition to have a flexible piecewise linear impact on both admission probabilities and outcomes, rather than being strictly linear in the admission index. Including hospital fixed effects means that we are identifying the effects of admission using within-hospital variations in the probability of admitting a patient in different deciles of the admission probability distribution. For example, as we show below, most hospitals admit patients in the highest decile of the distribution, but there is a wide range of responses to patients in the middle of the distribution. In the context of our model it is this within hospital gap in the probabilities of admission between deciles that identifies the effect of admission.

We then estimate the impact of an admission on health outcomes by estimating the following equation:

$$Outcome_{idht} = \alpha + \beta admitted_{idht} + \widehat{index}_{idht} + \mathbf{Decile}_d + \mathbf{Hosp}_h + \mathbf{DayOfWeek}_t + \mathbf{Month}_t + \mathbf{Year}_t + \mathbf{Zip}_i + \varepsilon_{idth}, \tag{3}$$

using both ordinary least squares (OLS) and the instrumental variables procedure described above. The outcomes we examine include length of stay, future hospital inpatient days, hospital acquired conditions, and mortality. Robust standard errors are clustered at the zip code level, to allow for unobserved correlations between patients residing in the same zip code..

OLS estimates of the coefficient of interest, β, will likely suffer from omitted variables bias given that the physician deciding whether to admit the patient has access to information that is not on the discharge record. If physicians are likely to admit the sickest patients, then one might expect a positive relationship between admission and outcomes such as mortality and readmission.

To proxy for the costs of care, we will use the total charges variable in the SPARCS data. While for patients with private insurance total charges may not always be strongly correlated with actual costs or reimbursements, virtually all of the individuals in our sample are on Medicare, so costs and reimbursements should be substantially correlated with charges.

V. Estimation Results

Table 2 shows the means and standard deviations of the variables included in the predicted admission model (1), as well as the average marginal effects of each variable, in both a logit specification and for comparison, in a linear probability model. The first section of the table shows that women are less likely to be admitted than men, conditional on all of the other information included in the model. Similarly, African Americans and Hispanics are less likely to be admitted than non-Hispanic whites. Because the models include zip code fixed effects, these results cannot be explained by where people live. The probability of admission rises with each year of age, but not smoothly: After increasing slightly from age 67 to 69, there is a sharp jump at age 70, suggesting that doctors may treat those in their 70s differently than those in their 60s.

Turning to current respiratory diagnoses and comorbidities, it appears that some diagnoses are much more likely than others to result in admittance. Specifically, pneumonia, pleurisy, respiratory failure, lung disease due to external agents, and other lower respiratory disease are strongly predictive of admission, while other upper respiratory disease and acute bronchitis are strongly negatively related to admission. Patients with serious comorbidities such as congestive heart failure, cerebrovascular disease, dementia, disease, diabetes with complications, renal disease, and cancer are much more likely to be admitted, while previous respiratory admissions in the past year generally have small effects that tend to be negative when they are statistically significant. Overall, the model predicts about 80 percent of admission decisions correctly (that is, the predicted probability of admission is less than 50 percent when the person was not admitted, and over 50 percent when they were admitted).

Panel A of Figure 1 shows the distribution of actual admission rates for patients across hospitals. There is one sub-figure for each decile, starting with the lowest decile of admission probabilities. Starting at the top left the figure shows for example, that the modal New York hospital admits no patients from the lowest decile of predicted admission probabilities, while a few hospitals admit more than 20 percent of such patients. The mass gradually shifts to the right as we move to higher predicted probability of admission deciles. Most hospitals admit all patients in the highest decile, though a few admit fewer than 90 percent of these patients. Not surprisingly, the greatest spread in admission probabilities occurs in the middle of the predicted probability of admission deciles. For example, at the fifth decile, the actual admission probabilities vary from less than 20 percent to almost 80 percent. Recall that we have eliminated the smallest hospitals from the figure. While some of the outliers in the figure may be attributable to noise due to small cell sizes, Figure 1 suggests that there is real variation across hospitals in their probabilities of admitting patients with similar observable characteristics.

Panel B shows the same data for the earliest (2008) and latest (2013) years in our sample. Here we see that while there is more variation over all (as the sample size is smaller), the two years are reasonably but not exactly consistent within deciles.

Table 3 shows estimates of the first stage of the instrumental variables regression, equation (2). The admission rate at the nearest large hospital for patients in individual *i*'s predicted admission decile is a strong predictor of an individual's own admission with a t-statistic of 8.27.[14] Overall the model explains about 45 percent of the variation in individual admission probabilities, and the fraction explained rises with the addition of the instrument.

Table 4 shows OLS estimates of the effects of hospital admission on outcomes. Not surprisingly, admission is associated with an increase in length of stay of 5.2 days and an additional $26,000 of charges. Admission also appears to increase the probabilities of future hospital days, hospital acquired conditions, and death in each of the time windows examined. The probability of

[14] We have also estimated similar equations treating empty beds and an index of flu prevalence as potential instruments. Consistent with past work, these variables are predictive of hospital admissions, but have t-statistics around 3.4, and adding them to the model does not increase the overall fraction of variation in admission probabilities that is explained.

death rises from an increase of about one percentage point in the next seven days to an increase of 3.5 percentage points in the next year. As discussed above, these estimates are likely to be driven by omitted variables bias since hospital personnel have information that does not appear in the administrative hospital records and are likely to be admitting the sickest patients. It is also possible that sicker patients choose to present at hospitals with higher admission probabilities.

Table 5 shows that when we account for omitted variables bias and endogenous hospital selection using our instrument, most results are quite different. Reassuringly, we find a similar effect on length of stay and total charges – it should be the case that admitting someone increases the length of stay in the current episode of care and the total charges.

Column (2) of Table 5 shows, however, that the instrumental variables estimates of the effect of admission on future hospital days, i.e. those not associated with the current episode of care, is strongly positive. Thus, as we saw in Table 2, being admitted is strongly predictive of future hospital admissions. Since equation (3) includes hospital fixed effects, this result cannot be explained by persistence in the patient's choice of hospital. Instead, the estimate suggests that even within hospital, a past hospitalization increases the probability of a future one.

This phenomenon might reflect a negative effect of hospitalization itself on people's health. Column (3) shows that while the estimated effect of admission on hospital acquired conditions is not statistically significant, it is four times larger than the OLS estimate in Table 4. Alternatively, doctors may take previous hospitalizations as a signal about the underlying health status of the patient that makes it more likely for them to decide on hospitalization in marginal cases. It is important to distinguish between these two hypotheses since the "hospitalization as disease" model suggests that the marginal hospitalization may be not only unnecessary but actively harming people, while in the signaling model, there is no necessary effect of a marginal hospitalization on health, and it could even be positive. The remaining columns of Table 5 show that the estimated effects of admission on the probability of death become negative but statistically insignificant once omitted variables bias and the endogeneity of hospital choice are accounted for.

Tables 6-9 study the impact of a marginal hospital admission on future health care. We utilize the claim type and emergency department indicator variables to construct dummy variables for several different types of future health care: Emergency Department (including patients that eventually ended up in ambulatory surgery or as inpatients), Inpatient (whether emergencies or not), and Non-Emergency Outpatient (including ambulatory surgery).[15] For each of these categories, we look at the probability of having at least one discharge in the 30 days post discharge, and in the 31 to 365 days post discharge.

Given the likely bias in the OLS results due to patient characteristics unobservable to us, we will focus on the IV results in Tables 7 and 9. In the first 30 days after discharge from the ER, we find that a marginal admission lowers the probability of another emergency department visit and increases the probability of a non-emergency outpatient visit but has minimal impact on future inpatient stays or charges. In the subsequent rest of the year, the IV results (in Table 9), still only show marginally statistically significant results, except that there is evidence of an increase in outpatient visits suggesting that the patient may be getting more follow up care in an outpatient setting.

[15] These categories are not quite mutually exclusive (as Emergency Department visitors that ended up as inpatients are counted in both of the first two categories). Still, we believe these are the most intuitive outcomes to consider.

VI. Robustness

The appendices contains three robustness checks on our main specification: 1) omitting race controls from the calculation of our admission propensity index; 2) using county fixed effects instead of zip code fixed effects in the calculation of the index; and 3) using LASSO for prediction instead of logit, also with county fixed effects. The use of county fixed effects instead of zip code fixed effects is for tractability with the LASSO procedure.

Our results are broadly consistent across our main specification and these three alternate specifications suggesting that they are not affected by small differences in procedures for predicting hospitalization.

VI. Conclusions

We examine hospital admission decisions using a sample of elderly Medicare patients from New York state. The previous literature has focused mainly on the intensive margin, i.e. on the marginal effect of additional days of hospitalization or more intensive spending on already hospitalized patients. Few previous authors have examined the impact of the hospitalization decision itself.

It is difficult to study the impact of hospitalization because of omitted variables bias and endogeneity in the hospitals that patients select. We propose an instrumental variables strategy to overcome these obstacles. Our instrument focuses on the nearest large hospital's propensity to admit patients who have observable characteristics similar to those of the index patient. Because we include zip code in all of our models and hospital fixed effects in our first stage and main equation, the identifying variation we use cannot be attributed to overall mean differences between hospitals, but can be thought of as an interaction between a hospital's propensity to admit and patient severity.

We find that there is considerable variation in the probability of admission for patients with similar observable medical risk factors. Conditional on observable diagnoses and comorbidities, women are less likely to be admitted than men; African-Americans and Hispanics are less likely to be admitted that non-Hispanic whites; and there is a sharp spike in admission probabilities at age 70. We also find that there is considerable variation across hospitals in the probability that patients in a particular decile of the predicted probability of admission will actually be admitted. The probability that the nearest large hospital's propensity to admit other patients in the patient's severity decile to hospital is a powerful instrument for the index patient's own admission.

While OLS estimates suggest that admitted patients are more likely to die, using our instrument we find that for the marginal patient a current hospital admission increases the number of hospital days by seven days and increases charges by $42,000. However it has no effect on the risk of death in the course of the next year. The marginal hospitalization also reduces the risk of another emergency department visit in the next 30 days but increases outpatient visits over the same time horizon with no overall impact on charges. Longer term effects on patient costs and health outcomes over the next year are minimal though the increase in outpatient visits appears to be maintained. Overall then our findings support the argument that in many cases the marginal hospitalization may be unwarranted, creating unnecessary costs for both the patient and the health care system.

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Table 1: Summary Statistics for Outcomes

	(1) Mean	(2) Standard Deviation
Admitted to the Hospital	0.565	
Length of Stay in Hospital (days)	4.067	8.343
Total Charges ($)	24,320	54,700
Any Hospital Acquired Condition in Next Year	0.00532	
Hospital Days in Next Year After This Episode	11.08	22.25
Died in the Next 7 days	0.0428	
Died in the Next 15 days	0.0506	
Died in the Next 30 days	0.0630	
Died in the Next 180 days	0.132	
Died in the Next 360 days	0.178	
0-30 days after discharge		
Emergency Department (No Admission)	0.131	
Emergency Ambulatory Surgery	0.00115	
Non- Emergency Ambulatory Surgery	0.0312	
Emergency Inpatient	0.158	
Non-Emergency Inpatient	0.0660	
Non-Emergency Outpatient	0.0914	
Total Charges ($)	12,930	47,240
31-365 days after discharge		
Emergency Department (No Admission)	0.390	
Emergency Ambulatory Surgery	0.00492	
Non- Emergency Ambulatory Surgery	0.195	
Emergency Inpatient	0.390	
Non-Emergency Inpatient	0.154	
Non-Emergency Outpatient	0.242	
Total Charges ($)	56,080	12,770

N=435,876

Table 2: Predicting Admission: Summary Statistics and Average Marginal Effects

	(1) Mean	(2) Coefficient from Linear Probability Model for Index	(3) Average Marginal Effect for Index from a Logit Regression
Information on current episode:			
Demographics:			
Female	0.551	-0.00626***	-0.00366**
		(0.00181)	(0.00162)
Age	67.98		
	(1.418)		
Age = 66		(reference)	(reference)
Age = 67		-0.000391	-0.000945
		(0.00215)	(0.00200)
Age = 68		0.00562**	0.00447**
		(0.00220)	(0.00207)
Age = 69		0.00709***	0.00489**
		(0.00234)	(0.00217)
Age = 70		0.0131***	0.0102***
		(0.00234)	(0.00221)
Nonhispanic White	0.575	0.0319***	0.0290***
		(0.00516)	(0.00472)
Nonhispanic Black	0.177	-0.0201***	-0.0208***
		(0.00557)	(0.00499)
Hispanic	0.128	-0.0232***	-0.0185***
		(0.00629)	(0.00558)
Diagnoses from Current Stay:			
Pneumonia	0.158	0.239***	0.265***
		(0.00252)	(0.00260)
Influenza	0.00633	0.0228***	0.0425***
		(0.00847)	(0.00691)
Acute bronchitis	0.00117	-0.0898***	-0.0324**
		(0.0165)	(0.0160)
Other upper respiratory infections	0.0320	-0.0444***	-0.0114**
		(0.00523)	(0.00478)
Chronic obstructive pulmonary disease and bronchiectasis	0.0729	-0.121***	-0.0696***
		(0.00332)	(0.00305)
Asthma	0.404	0.112***	0.0940***
		(0.00756)	(0.00628)

Aspiration pneumonitis; food/vomitus	0.212	0.0754***	0.0615***
		(0.00767)	(0.00647)
Pleurisy; pneumothorax; pulmonary collapse	0.0172	0.275***	0.578***
		(0.00459)	(0.0152)
Respiratory failure; insufficiency; arrest	0.0618	0.156***	0.183***
		(0.00432)	(0.00654)
Lung disease due to external agents	0.0978	0.183***	0.245***
		(0.00339)	(0.00510)
Other lower respiratory disease	0.00380	0.164***	0.180***
		(0.0100)	(0.0113)
Other upper respiratory disease	0.346	-0.158***	-0.125***
		(0.00359)	(0.00299)
Acute bronchitis	0.0699	-0.174***	-0.119***
		(0.00410)	(0.00359)
Comorbidity Diagnoses from Current Stay:			
Acute Myocardial Infarction	0.0405	-0.0374***	-0.0380***
		(0.00548)	(0.00566)
Congestive Heart Failure	0.185	0.208***	0.225***
		(0.00336)	(0.00393)
Peripheral Vascular Disease	0.0411	0.156***	0.205***
		(0.00325)	(0.00517)
Cerebrovascular Disease	0.0315	0.177***	0.185***
		(0.00479)	(0.00614)
Dementia	0.00518	0.136***	0.259***
		(0.00781)	(0.0159)
Chronic Obstructive Pulmonary Disease	0.603	0.0689***	0.0787***
		(0.00836)	(0.00700)
Rheumatoid Disease	0.0221	0.204***	0.204***
		(0.00513)	(0.00646)
Peptic Ulcer Disease	0.00960	0.239***	0.311***
		(0.00660)	(0.0146)
Mild Liver Disease	0.0139	0.173***	0.221***
		(0.00625)	(0.0110)
Diabetes	0.269	0.0941***	0.0776***
		(0.00357)	(0.00303)
Diabetes + Complications	0.0319	0.189***	0.304***
		(0.00372)	(0.00969)
Hemiplegia or Paraplegia	0.00594	0.174***	0.307***
		(0.00694)	(0.0184)
Renal Disease	0.121	0.178***	0.224***
		(0.00267)	(0.00345)
Cancer	0.0788	0.183***	0.194***
		(0.00321)	(0.00395)
Moderate/Severe Liver Disease	0.00731	0.136***	0.245***
		(0.00727)	(0.0160)
Metastatic Cancer	0.0369	0.172***	0.254***

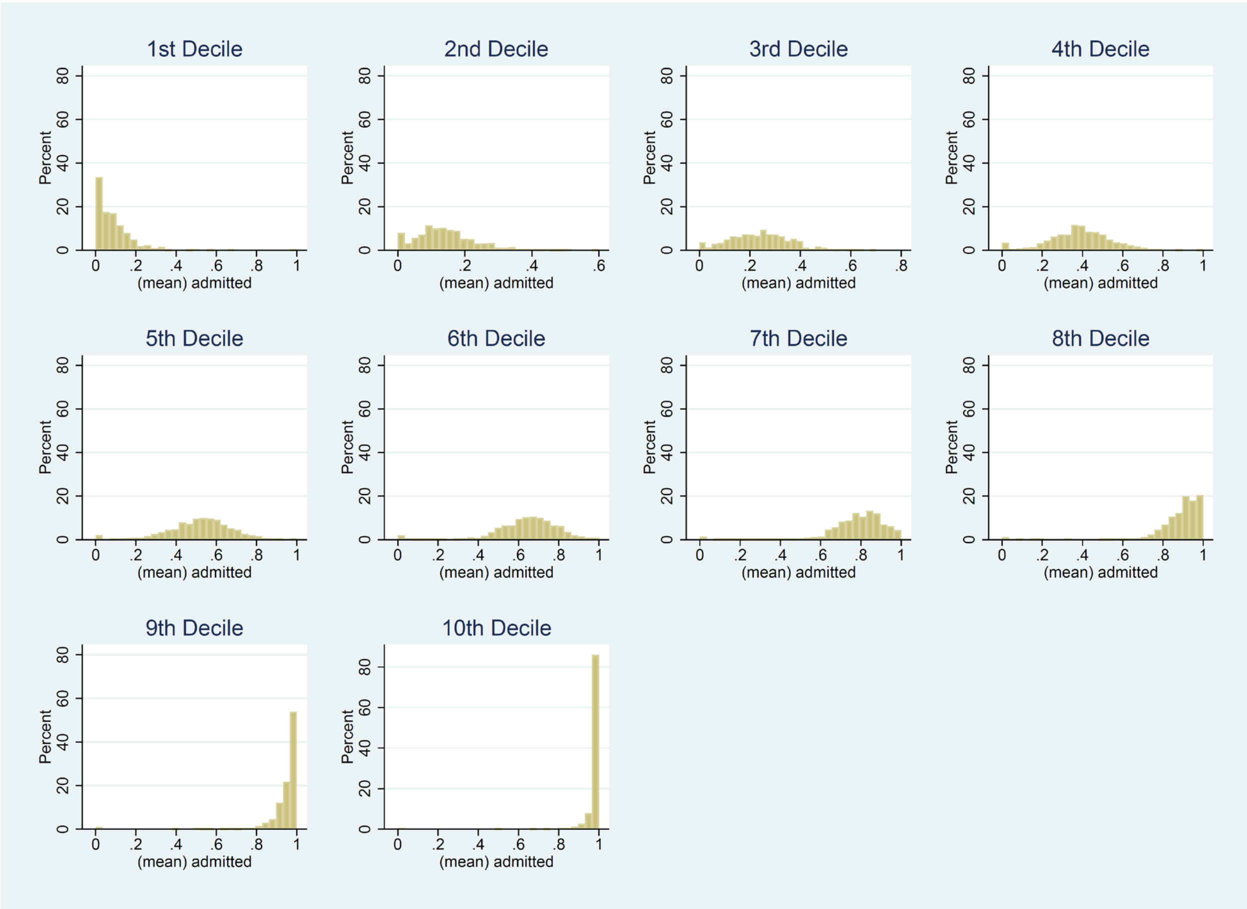
		(0.00361)	(0.00589)
Diagnoses from Stays in Past Year:			
Pneumonia	0.148	0.00257	0.000662
		(0.00255)	(0.00265)
Influenza	0.00458	0.000677	-0.00442
		(0.0120)	(0.0114)
Acute bronchitis	0.000902	-0.0240	-0.0174
		(0.0277)	(0.0267)
Other upper respiratory infections	0.0337	-0.0312***	-0.0255***
		(0.00538)	(0.00479)
Chronic obstructive pulmonary disease and bronchiectasis	0.0593	-0.0444***	-0.0356***
		(0.00398)	(0.00356)
Asthma	0.334	-0.0230***	-0.0238***
		(0.00214)	(0.00202)
Aspiration pneumonitis; food/vomitus	0.199	-0.0405***	-0.0347***
		(0.00278)	(0.00228)
Pleurisy; pneumothorax; pulmonary collapse	0.0165	0.0122*	0.000560
		(0.00737)	(0.00837)
Respiratory failure; insufficiency; arrest (adult)	0.0594	-0.0147***	-0.0169***
		(0.00404)	(0.00440)
Lung disease due to external agents	0.103	-0.00680*	-0.0133***
		(0.00360)	(0.00368)
Other lower respiratory disease	0.00441	-0.00985	-0.00174
		(0.0132)	(0.0133)
Other upper respiratory disease	0.285	-0.0102***	-0.0134***
		(0.00204)	(0.00198)
Acute bronchitis	0.0605	-0.0222***	-0.0201***
		(0.00346)	(0.00339)
Hospital Days in the Past Year	10.07	0.00101***	0.00113***
	20.24	(5.74e-05)	(6.38e-05)

N = 435,876

Notes: Models also include weekday, month, year, and zip FE. Standard deviation for variables that are not binary are shown in parenthesis.

Figure 1: Distribution of Actual Admission Rates Across Hospitals for Each Decile of Predicted Hospital Admission

Panel A: All Years



Panel B: 2008 and 2013

Notes: Each sub-figure represents a decile of the predicted admission probability from the logit shown in Table 2. The top left corner shows admission probabilities for the lowest decile of predicted admission, while the bottom right corner shows admission probabilities in the highest decile.

Table 3: First Stage Regressions

	(1)	(2)
Admission rate for patients in individual's predicted admission decile at closest hospital w/ >=100 beds and >= 2 visits in that decile & year		0.211***
		(0.0137)
Individual Predicted Probability of Admission	1.040***	1.030***
	(0.0221)	(0.0210)
Observations	435,876	435,876
R-squared	0.454	0.456

Notes: Robust standard errors are clustered at the zip code level *** p<0.01, ** p<0.05, * p<0.1. The individual's predicted probability of admission is computed using the estimates in Table 2. The instrument is the admission rate for patients in the individual's predicted admission decile at the closest general service hospital with over 99 beds, excluding the patient if he or she went to that hospital. Closest is measured using the patient's residential zip code centroid. All regressions contain decile, hospital, year, month, weekday, and zip code fixed effects.

Table 4: Ordinary Least Squares Estimates of Effects of Admission to Hospital for the Marginal Patient

	(1) Length of Stay	(2) Total Charges ($)	(3) Hospital Days in Next 365, Excluding Current Episode	(4) Hospital Acquired Condition in the next year	(5) Died in the Next 7 Days	(6) Died in the Next 15 Days	(7) Died in the Next 30 Days	(8) Died in the Next 180 Days	(9) Died in the Next 360 Days
Patient Admitted	5.169***	25,990***	1.384***	0.00144***	0.00974***	0.0109***	0.0134***	0.0273***	0.0347***
	(0.0354)	(409.60)	(0.143)	(0.000317)	(0.000705)	(0.000771)	(0.000860)	(0.00137)	(0.00180)
Predicted Admission Probability	3.189***	18,270***	13.65***	0.0104***	0.112***	0.132***	0.154***	0.265***	0.339***
	(0.307)	(1975.32)	(1.130)	(0.00315)	(0.00753)	(0.00854)	(0.00954)	(0.0142)	(0.0167)
N	435,876	435,876	435,876	435,876	435,876	435,876	435,876	435,876	435,876
R-squared	0.209	0.206	0.065	0.012	0.067	0.075	0.085	0.132	0.153

Notes: Robust standard errors are clustered at the zip code level. *** p<0.01, ** p<0.05, * p<0.1. The individual's predicted probability of admission is computed using the estimates in Table 2. All regressions contain decile, hospital, year, month, weekday, and zip code fixed effects.

Table 5: Instrumental Variables Estimates of Effects of Admission to Hospital for the Marginal Patient

	(1) Length of Stay	(2) Total Charges ($)	(3) Hospital Days in Next 365, Excluding Current Episode	(4) Hospital Acquired Condition in the next year	(5) Died in the Next 7 Days	(6) Died in the Next 15 Days	(7) Died in the Next 30 Days	(8) Died in the Next 180 Days	(9) Died in the Next 360 Days
Patient Admitted	6.681***	42,240***	4.434	0.00714	0.00457	-0.00488	-0.0167	-0.0257	-0.0199
	(0.648)	(3946.12)	(3.059)	(0.00698)	(0.0140)	(0.0159)	(0.0170)	(0.0292)	(0.0338)
Predicted Admission Probability	1.616**	1373.05	10.48***	0.00447	0.117***	0.149***	0.185***	0.320***	0.396***
	(0.775)	(4812.35)	(3.120)	(0.00794)	(0.0162)	(0.0187)	(0.0204)	(0.0335)	(0.0391)
N	435,876	435,876	435,876	435,876	435,876	435,876	435,876	435,876	435,876
R-squared	0.204	0.194	0.062	0.011	0.067	0.074	0.083	0.128	0.150

Notes: Robust standard errors are clustered at the zip code level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The individual's predicted probability of admission is computed using the estimates in Table 2. The instrument is the admission rate for patients in the individual's predicted admission decile at the closest general service hospital with over 99 beds and at least 2 patients in that decile in that year. Closest is measured using the patient's residential zip code centroid. All regressions contain decile, hospital, year, month, weekday, and zip code fixed effects.

Table 6: Ordinary Least Squares Estimates of Effects of Admission to Hospital on 30-Day Revisit and Readmission Outcomes

	(1) Emergency Department	(2) Inpatient	(3) Outpatient	(4) Total Charges ($)
Patient Admitted	-0.0367***	0.0280***	0.0000226	2057.78***
	(0.00265)	(0.00225)	(0.00172)	(212.89)
Predicted Admission Probability	0.139***	0.224***	-0.0491***	16,340***
	(0.0212)	(0.0193)	(0.0162)	(2012.28)
Observations	435,876	435,876	435,876	435,876
R-squared	0.026	0.048	0.096	0.034

Notes: Robust standard errors are clustered at the zip code level. *** p<0.01, ** p<0.05, * p<0.1. The individual's predicted probability of admission is computed using the estimates in Table 2. All regressions contain decile, hospital, year, month, weekday, and zipzip code fixed effects.

Table 7: Instrumental Variables Estimates of Effects of Admission to Hospital on 30-Day Revisit and Readmission Outcomes

	(1) Emergency Department	(2) Inpatient	(3) Outpatient	(4) Total Charges ($)
Patient Admitted	-0.136***	0.00577	0.128**	-1002.97
	(0.0433)	(0.0390)	(0.0555)	(4323.41)
Predicted Admission Probability	0.242***	0.247***	-0.183***	19,520***
	(0.0464)	(0.0440)	(0.0611)	(4789.71)
Observations	435,876	435,876	435,876	435,876
R-squared	0.019	0.048	0.075	0.033

Notes: Robust standard errors are clustered at the zip code level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The individual's predicted probability of admission is computed using the estimates in Table 2. The instrument is the admission rate for patients in the individual's predicted admission decile at the closest general service hospital with over 99 beds and at least 2 patients in that decile in that year. Closest is measured using the patient's residential zip code centroid. All regressions contain decile, hospital, year, month, weekday, and zip code fixed effects.

Table 8: Ordinary Least Squares Estimates of Effects of Admission to Hospital on 31-365-Day Revisit and Readmission Outcomes

	(1) Emergency Department	(2) Inpatient	(3) Outpatient	(4) Total Charges ($)
Patient Admitted	-0.0218***	0.0522***	-0.00952***	4485.68***
	(0.00263)	(0.00310)	(0.00250)	(742.78)
Predicted Admission Probability	0.0912***	0.233***	-0.0494**	63,500***
	(0.0255)	(0.0246)	(0.0239)	(6301.84)
Observations	435,876	435,876	435,876	435,876
R-squared	0.035	0.057	0.100	0.069

Notes: Robust standard errors are clustered at the zip code level. *** p<0.01, ** p<0.05, * p<0.1. The individual's predicted probability of admission is computed using the estimates in Table 2. All regressions contain decile, hospital, year, month, weekday, and zip code fixed effects.

Table 9: Instrumental Variables Estimates of Effects of Admission to Hospital on 31-365-Day Revisit and Readmission Outcomes

	(1) Emergency Department	(2) Inpatient	(3) Outpatient	(4) Total Charges ($)
Patient Admitted	-0.0498	0.0808	0.159**	21,710
	(0.0483)	(0.0509)	(0.0720)	(15,260)
Predicted Admission Probability	0.120**	0.203***	-0.224***	45,600***
	(0.0560)	(0.0567)	(0.0771)	(16,600)
Observations	435,876	435,876	435,876	435,876
R-squared	0.034	0.057	0.084	0.067

Notes: Robust standard errors are clustered at the zip code level. *** p<0.01, ** p<0.05, * p<0.1. The individual's predicted probability of admission is computed using the estimates in Table 2. The instrument is the admission rate for patients in the individual's predicted admission decile at the closest general service hospital with over 99 beds and at least 2 patients in that decile in that year. Closest is measured using the patient's residential zip code centroid. All regressions contain decile, hospital, year, month, weekday, and zip code fixed effects.

Appendix A: First Stage Regressions Using Alternative Indicies

Appendix Table A1: First Stage Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Logit with Race Controls & Zip Code FE		Logit without Race Controls but with Zip Code FE		Logit with Race Controls & County FE		LASSO with Race Controls & County FE	
Admission rate for patients in individual's predicted admission decile at closest hospital w/ >=100 beds and >= 2 visits in that decile & year		0.211***		0.209***		0.241***		0.242***
		(0.0137)		(0.0135)		(0.0146)		(0.0146)
Individual Predicted Probability of Admission	1.040***	1.030***	0.993***	0.985***	0.988***	0.981***	0.991***	0.983***
	(0.0221)	(0.0210)	(0.0213)	(0.0212)	(0.0213)	(0.0213)	(0.0211)	(0.0210)
Observations	435,876	435,876	435,876	435,876	435,876	435,876	435,876	435,876
R-squared	0.454	0.456	0.453	0.455	0.451	0.454	0.451	0.454

Notes: Robust standard errors are clustered at the zip code level *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The individual's predicted probability of admission is computed using the estimates in Table 2. The instrument is the admission rate for patients in the individual's predicted admission decile at the closest general service hospital with over 99 beds, excluding the patient if he or she went to that hospital. Closest is measured using the patient's residential zip code centroid. All regressions contain decile, hospital, year, month, weekday, and zip code or county fixed effects.

Appendix B: All Results Replicated Without Race Controls in the Prediction Equation

Appendix Table B1: Ordinary Least Squares Estimates of Effects of Admission to Hospital for the Marginal Patient

	(1) Length of Stay	(2) Total Charges ($)	(3) Hospital Days in Next 365, Excluding Current Episode	(4) Hospital Acquired Condition in the next year	(5) Died in the Next 7 Days	(6) Died in the Next 15 Days	(7) Died in the Next 30 Days	(8) Died in the Next 180 Days	(9) Died in the Next 360 Days
Patient Admitted	5.205***	26,710***	1.501***	0.00160***	0.00892***	0.0100***	0.0125***	0.0266***	0.0338***
	(0.0379)	(3902.2)	(0.144)	(0.000301)	(0.000766)	(0.000831)	(0.000927)	(0.00144)	(0.00191)
Predicted Admission Probability	4.006***	26,230***	11.48***	0.00867***	0.117***	0.136***	0.163***	0.288***	0.356***
	(0.0818)	(799.51)	(0.273)	(0.000703)	(0.00171)	(0.00185)	(0.00211)	(0.00326)	(0.00385)
N	435,876	435,876	435,876	435,876	435,876	435,876	435,876	435,876	435,876
R-squared	0.191	0.164	0.060	0.011	0.046	0.052	0.062	0.102	0.124

Notes: Robust standard errors are clustered at the zip code level. *** p<0.01, ** p<0.05, * p<0.1. The individual's predicted probability of admission is computed using the estimates in Table 2. All regressions contain decile, hospital, year, month, weekday, and zip code fixed effects.

Appendix Table B2: Instrumental Variables Estimates of Effects of Admission to Hospital for the Marginal Patient

	(1) Length of Stay	(2) Total Charges ($)	(3) Hospital Days in Next 365, Excluding Current Episode	(4) Hospital Acquired Condition in the next year	(5) Died in the Next 7 Days	(6) Died in the Next 15 Days	(7) Died in the Next 30 Days	(8) Died in the Next 180 Days	(9) Died in the Next 360 Days
Patient Admitted	6.586***	47,190***	1.673	0.00279	0.00576	-0.00521	-0.0146	-0.0270	-0.0485
	(1.105)	(6790.92)	(3.213)	(0.00740)	(0.0259)	(0.0289)	(0.0318)	(0.0508)	(0.0571)
Predicted Admission Probability	2.617**	5638.70	11.31***	0.00748	0.120***	0.151***	0.190***	0.342***	0.439***
	(1.108)	(6955.74)	(3.192)	(0.00742)	(0.0261)	(0.0290)	(0.0319)	(0.0509)	(0.0572)
N	435,876	435,876	435,876	435,876	435,876	435,876	435,876	435,876	435,876
R-squared	0.187	0.145	0.060	0.011	0.046	0.052	0.060	0.099	0.118

Notes: Robust standard errors are clustered at the zip code level. *** p<0.01, ** p<0.05, * p<0.1. The individual's predicted probability of admission is computed using the estimates in Table 2. The instrument is the admission rate for patients in the individual's predicted admission decile at the closest general service hospital with over 99 beds and at least 2 patients in that decile in that year. Closest is measured using the patient's residential zip code centroid. All regressions contain decile, hospital, year, month, weekday, and zip code fixed effects.

Appendix Table B3: Ordinary Least Squares Estimates of Effects of Admission to Hospital on 30-Day Revisit and Readmission Outcomes

	(1) Emergency Department	(2) Inpatient	(3) Outpatient	(4) Total Charges ($)
Patient Admitted	-0.0366***	0.0285***	-0.000274	2094.30***
	(0.00270)	(0.00226)	(0.00173)	(211.93)
Predicted Admission Probability	0.139***	0.232***	-0.0228	15,090***
	(0.0219)	(0.0195)	(0.0164)	(1871.13)
Observations	435,876	435,876	435,876	435,876
R-squared	0.026	0.048	0.096	0.034

Notes: Robust standard errors are clustered at the zip code level. *** p<0.01, ** p<0.05, * p<0.1. The individual's predicted probability of admission is computed using the estimates in Table 2. All regressions contain decile, hospital, year, month, weekday, and zip code fixed effects.

Appendix Table B4: Instrumental Variables Estimates of Effects of Admission to Hospital on 30-Day Revisit and Readmission Outcomes

	(1) Emergency Department	(2) Inpatient	(3) Outpatient	(4) Total Charges ($)
Patient Admitted	-0.131***	0.0130	0.126**	-1825.57
	(0.0447)	(0.0407)	(0.0571)	(4397.67)
Predicted Admission Probability	0.233***	0.247***	-0.148**	18,990***
	(0.0478)	(0.0436)	(0.0604)	(4631.53)
Observations	435,876	435,876	435,876	435,876
R-squared	0.020	0.048	0.076	0.033

Notes: Robust standard errors are clustered at the zip code level. *** p<0.01, ** p<0.05, * p<0.1. The individual's predicted probability of admission is computed using the estimates in Table 2. The instrument is the admission rate for patients in the individual's predicted admission decile at the closest general service hospital with over 99 beds and at least 2 patients in that decile in that year. Closest is measured using the patient's residential zip code centroid. All regressions contain decile, hospital, year, month, weekday, and zip code fixed effects.

Appendix Table B5: Ordinary Least Squares Estimates of Effects of Admission to Hospital on 31-365-Day Revisit and Readmission Outcomes

	(1) Emergency Department	(2) Inpatient	(3) Outpatient	(4) Total Charges ($)
Patient Admitted	-0.0228***	0.0525***	-0.00985***	4539.92***
	(0.00266)	(0.00313)	(0.00249)	(750.46)
Predicted Admission Probability	0.124***	0.281***	-0.0562**	56,720***
	(0.0256)	(0.0247)	(0.0237)	(6153.67)
Observations	435,876	435,876	435,876	435,876
R-squared	0.035	0.057	0.100	0.069

Notes: Robust standard errors are clustered at the zip code level. *** p<0.01, ** p<0.05, * p<0.1. The individual's predicted probability of admission is computed using the estimates in Table 2. All regressions contain decile, hospital, year, month, weekday, and zip code fixed effects.

Appendix Table B6: Instrumental Variables Estimates of Effects of Admission to Hospital on 31-365-Day Revisit and Readmission Outcomes

	(1) Emergency Department	(2) Inpatient	(3) Outpatient	(4) Total Charges ($)
Patient Admitted	-0.0319	0.0915*	0.171**	17,190
	(0.0504)	(0.0520)	(0.0745)	(15,250)
Predicted Admission Probability	0.133**	0.243***	-0.236***	44,160***
	(0.0555)	(0.0547)	(0.0769)	(16,220)
Observations	435,876	435,876	435,876	435,876
R-squared	0.035	0.056	0.081	0.068

Notes: Robust standard errors are clustered at the zip code level. *** p<0.01, ** p<0.05, * p<0.1. The individual's predicted probability of admission is computed using the estimates in Table 2. The instrument is the admission rate for patients in the individual's predicted admission decile at the closest general service hospital with over 99 beds and at least 2 patients in that decile in that year. Closest is measured using the patient's residential zip code centroid. All regressions contain decile, hospital, year, month, weekday, and zip code fixed effects.

Appendix C: All Estimates Using County Fixed Effects vs. Zip Code Fixed Effects

Appendix Table C1: Ordinary Least Squares Estimates of Effects of Admission to Hospital for the Marginal Patient

	(1) Length of Stay	(2) Total Charges ($)	(3) Hospital Days in Next 365, Excluding Current Episode	(4) Hospital Acquired Condition in the next year	(5) Died in the Next 7 Days	(6) Died in the Next 15 Days	(7) Died in the Next 30 Days	(8) Died in the Next 180 Days	(9) Died in the Next 360 Days
Patient Admitted	5.167***	26,000***	1.486***	0.00147***	0.00971***	0.0109***	0.0134***	0.0275***	0.0351***
	(0.0354)	(412.97)	(0.145)	(0.000312)	(0.000703)	(0.000769)	(0.000859)	(0.00137)	(0.00179)
Predicted Admission Probability	3.198***	21,380***	9.494***	0.00990***	0.103***	0.121***	0.146***	0.262***	0.341***
	(0.310)	(1949.61)	(1.109)	(0.00332)	(0.00733)	(0.00831)	(0.00947)	(0.0143)	(0.0173)
N	435,876	435,876	435,876	435,876	435,876	435,876	435,876	435,876	435,876
R-squared	0.209	0.206	0.064	0.012	0.068	0.076	0.086	0.132	0.154

Notes: Robust standard errors are clustered at the zip code level. *** p<0.01, ** p<0.05, * p<0.1. The individual's predicted probability of admission is computed using the estimates in Table 2. All regressions contain decile, hospital, year, month, weekday, and zip code fixed effects.

Appendix Table C2: Instrumental Variables Estimates of Effects of Admission to Hospital for the Marginal Patient

	(1) Length of Stay	(2) Total Charges ($)	(3) Hospital Days in Next 365, Excluding Current Episode	(4) Hospital Acquired Condition in the next year	(5) Died in the Next 7 Days	(6) Died in the Next 15 Days	(7) Died in the Next 30 Days	(8) Died in the Next 180 Days	(9) Died in the Next 360 Days
Patient Admitted	6.276***	40,980***	4.744*	0.00890	0.00757	0.00462	-0.00641	-0.000647	-0.00300
	(0.548)	(3735.91)	(2.606)	(0.00601)	(0.0119)	(0.0134)	(0.0145)	(0.0257)	(0.0293)
Predicted Admission Probability	2.102***	6572.41	6.274**	0.00255	0.105***	0.127***	0.165***	0.289***	0.379***
	(0.633)	(4405.24)	(2.881)	(0.00682)	(0.0141)	(0.0160)	(0.0173)	(0.0293)	(0.0335)
N	435,876	435,876	435,876	435,876	435,876	435,876	435,876	435,876	435,876
R-squared	0.207	0.196	0.061	0.011	0.068	0.076	0.085	0.131	0.152

Notes: Robust standard errors are clustered at the zip code level. *** p<0.01, ** p<0.05, * p<0.1. The individual's predicted probability of admission is computed using the estimates in Table 2. The instrument is the admission rate for patients in the individual's predicted admission decile at the closest general service hospital with over 99 beds and at least 2 patients in that decile in that year. Closest is measured using the patient's residential zip code centroid. All regressions contain decile, hospital, year, month, weekday, and zip code fixed effects.

Appendix Table C3: Ordinary Least Squares Estimates of Effects of Admission to Hospital on 30-Day Revisit and Readmission Outcomes

	(1) Emergency Department	(2) Inpatient	(3) Outpatient	(4) Total Charges ($)
Patient Admitted	-0.0351***	0.0290***	0.000336	2103.58***
	(0.00268)	(0.00226)	(0.00172)	(212.80)
Predicted Admission Probability	0.106***	0.221***	-0.0119	15,650***
	(0.0226)	(0.0207)	(0.0162)	(2091.79)
Observations	435,876	435,876	435,876	435,876
R-squared	0.026	0.048	0.096	0.034

Notes: Robust standard errors are clustered at the zip code level. *** p<0.01, ** p<0.05, * p<0.1. The individual's predicted probability of admission is computed using the estimates in Table 2. All regressions contain decile, hospital, year, month, weekday, and zip code fixed effects.

Appendix Table C4: Instrumental Variables Estimates of Effects of Admission to Hospital on 30-Day Revisit and Readmission Outcomes

	(1) Emergency Department	(2) Inpatient	(3) Outpatient	(4) Total Charges ($)
Patient Admitted	-0.113***	0.0473	0.0801*	2254.42
	(0.0388)	(0.0357)	(0.0451)	(3961.60)
Predicted Admission Probability	0.183***	0.203***	-0.0907*	15,500***
	(0.0435)	(0.0397)	(0.0466)	(4461.06)
Observations	435,876	435,876	435,876	435,876
R-squared	0.022	0.048	0.088	0.034

Notes: Robust standard errors are clustered at the zip code level. *** p<0.01, ** p<0.05, * p<0.1. The individual's predicted probability of admission is computed using the estimates in Table 2. The instrument is the admission rate for patients in the individual's predicted admission decile at the closest general service hospital with over 99 beds and at least 2 patients in that decile in that year. Closest is measured using the patient's residential zip code centroid. All regressions contain decile, hospital, year, month, weekday, and zip code fixed effects.

Appendix Table C5: Ordinary Least Squares Estimates of Effects of Admission to Hospital on 31-365-Day Revisit and Readmission Outcomes

	(1) Emergency Department	(2) Inpatient	(3) Outpatient	(4) Total Charges ($)
Patient Admitted	-0.0195***	0.0546***	-0.00902***	5066.14***
	(0.00265)	(0.00313)	(0.00251)	(749.48)
Predicted Admission Probability	0.0688***	0.172***	-0.0689***	39,490***
	(0.0252)	(0.0237)	(0.0248)	(5988.32)
Observations	435,876	435,876	435,876	435,876
R-squared	0.035	0.057	0.100	0.069

Notes: Robust standard errors are clustered at the zip code level. *** p<0.01, ** p<0.05, * p<0.1. The individual's predicted probability of admission is computed using the estimates in Table 2. All regressions contain decile, hospital, year, month, weekday, and zip code fixed effects.

Appendix Table C6: Instrumental Variables Estimates of Effects of Admission to Hospital on 31-365-Day Revisit and Readmission Outcomes

	(1) Emergency Department	(2) Inpatient	(3) Outpatient	(4) Total Charges ($)
Patient Admitted	-0.0612	0.0740*	0.136**	27,300**
	(0.0408)	(0.0431)	(0.0597)	(12,920)
Predicted Admission Probability	0.110**	0.153***	-0.212***	17,520
	(0.0473)	(0.0486)	(0.0627)	(14,210)
Observations	435,876	435,876	435,876	435,876
R-squared	0.034	0.057	0.088	0.065

Notes: Robust standard errors are clustered at the zip code level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The individual's predicted probability of admission is computed using the estimates in Table 2. The instrument is the admission rate for patients in the individual's predicted admission decile at the closest general service hospital with over 99 beds and at least 2 patients in that decile in that year. Closest is measured using the patient's residential zip code centroid. All regressions contain decile, hospital, year, month, weekday, and zip code fixed effects.

Appendix D: Using LASSO for the Prediction Equation instead of Logit (Also Using County vs. Zip Code Fixed Effects)

Appendix Table D1: Ordinary Least Squares Estimates of Effects of Admission to Hospital for the Marginal Patient

	(1) Length of Stay	(2) Total Charges ($)	(3) Hospital Days in Next 365, Excluding Current Episode	(4) Hospital Acquired Condition in the next year	(5) Died in the Next 7 Days	(6) Died in the Next 15 Days	(7) Died in the Next 30 Days	(8) Died in the Next 180 Days	(9) Died in the Next 360 Days
Patient Admitted	5.167***	25,990***	1.483***	0.00147***	0.00971***	0.0109***	0.0134***	0.0275***	0.0351***
	(0.0354)	(412.92)	(0.145)	(0.000313)	(0.000703)	(0.000769)	(0.000858)	(0.00137)	(0.00179)
Predicted Admission Probability	3.177***	21,310***	9.663***	0.0106***	0.104***	0.122***	0.148***	0.267***	0.347***
	(0.309)	(1944.17)	(1.103)	(0.00329)	(0.00733)	(0.00831)	(0.00950)	(0.0145)	(0.0174)
N	435,876	435,876	435,876	435,876	435,876	435,876	435,876	435,876	435,876
R-squared	0.209	0.206	0.064	0.012	0.068	0.076	0.086	0.132	0.154

Notes: Robust standard errors are clustered at the zip code level. *** p<0.01, ** p<0.05, * p<0.1. The individual's predicted probability of admission is computed using the estimates in Table 2. All regressions contain decile, hospital, year, month, weekday, and zip code fixed effects.

Appendix Table D2: Instrumental Variables Estimates of Effects of Admission to Hospital for the Marginal Patient

	(1) Length of Stay	(2) Total Charges ($)	(3) Hospital Days in Next 365, Excluding Current Episode	(4) Hospital Acquired Condition in the next year	(5) Died in the Next 7 Days	(6) Died in the Next 15 Days	(7) Died in the Next 30 Days	(8) Died in the Next 180 Days	(9) Died in the Next 360 Days
Patient Admitted	6.258***	40,920***	4.783*	0.00882	0.00641	0.00296	-0.00759	-0.00212	-0.00476
	(0.546)	(3715.53)	(2.606)	(0.00598)	(0.0118)	(0.0134)	(0.0145)	(0.0256)	(0.0292)
Predicted Admission Probability	2.096***	6515.54	6.391**	0.00327	0.107***	0.130***	0.169***	0.296***	0.387***
	(0.634)	(4385.84)	(2.869)	(0.00680)	(0.0141)	(0.0161)	(0.0174)	(0.0294)	(0.0336)
N	435,876	435,876	435,876	435,876	435,876	435,876	435,876	435,876	435,876
R-squared	0.207	0.196	0.061	0.011	0.068	0.076	0.085	0.131	0.152

Notes: Robust standard errors are clustered at the zip code level. *** p<0.01, ** p<0.05, * p<0.1. The individual's predicted probability of admission is computed using the estimates in Table 2. The instrument is the admission rate for patients in the individual's predicted admission decile at the closest general service hospital with over 99 beds and at least 2 patients in that decile in that year. Closest is measured using the patient's residential zip code centroid. All regressions contain decile, hospital, year, month, weekday, and zip code fixed effects.

Appendix Table D3: Ordinary Least Squares Estimates of Effects of Admission to Hospital on 30-Day Revisit and Readmission Outcomes

	(1) Emergency Department	(2) Inpatient	(3) Outpatient	(4) Total Charges ($)
Patient Admitted	-0.0352***	0.0290***	0.000317	2100.34***
	(0.00268)	(0.00226)	(0.00172)	(212.82)
Predicted Admission Probability	0.111***	0.224***	-0.00898	15,890***
	(0.0226)	(0.0204)	(0.0162)	(2072.29)
Observations	435,876	435,876	435,876	435,876
R-squared	0.026	0.048	0.096	0.034

Notes: Robust standard errors are clustered at the zip code level. *** p<0.01, ** p<0.05, * p<0.1. The individual's predicted probability of admission is computed using the estimates in Table 2. All regressions contain decile, hospital, year, month, weekday, and zip code fixed effects.

Appendix Table D4: Instrumental Variables Estimates of Effects of Admission to Hospital on 30-Day Revisit and Readmission Outcomes

	(1) Emergency Department	(2) Inpatient	(3) Outpatient	(4) Total Charges ($)
Patient Admitted	-0.112***	0.0462	0.0814*	2099.64
	(0.0387)	(0.0354)	(0.0449)	(3937.85)
Predicted Admission Probability	0.188***	0.207***	-0.0894*	15,890***
	(0.0435)	(0.0396)	(0.0466)	(4439.67)
Observations	435,876	435,876	435,876	435,876
R-squared	0.022	0.048	0.088	0.034

Notes: Robust standard errors are clustered at the zip code level. *** p<0.01, ** p<0.05, * p<0.1. The individual's predicted probability of admission is computed using the estimates in Table 2. The instrument is the admission rate for patients in the individual's predicted admission decile at the closest general service hospital with over 99 beds and at least 2 patients in that decile in that year. Closest is measured using the patient's residential zip code centroid. All regressions contain decile, hospital, year, month, weekday, and zip code fixed effects.

Appendix Table D5: Ordinary Least Squares Estimates of Effects of Admission to Hospital on 31-365-Day Revisit and Readmission Outcomes

	(1) Emergency Department	(2) Inpatient	(3) Outpatient	(4) Total Charges ($)
Patient Admitted	-0.0196***	0.0545***	-0.00903***	5051.26***
	(0.00265)	(0.00313)	(0.00251)	(749.54)
Predicted Admission Probability	0.0738***	0.177***	-0.0690***	40,470***
	(0.0249)	(0.0239)	(0.0253)	(5977.67)
Observations	435,876	435,876	435,876	435,876
R-squared	0.035	0.057	0.100	0.069

Notes: Robust standard errors are clustered at the zip code level. *** p<0.01, ** p<0.05, * p<0.1. The individual's predicted probability of admission is computed using the estimates in Table 2. All regressions contain decile, hospital, year, month, weekday, and zip code fixed effects.

Appendix Table D6: Instrumental Variables Estimates of Effects of Admission to Hospital on 31-365-Day Revisit and Readmission Outcomes

	(1) Emergency Department	(2) Inpatient	(3) Outpatient	(4) Total Charges ($)
Patient Admitted	-0.0636	0.0716*	0.139**	27,270**
	(0.0408)	(0.0429)	(0.0596)	(12,920)
Predicted Admission Probability	0.117**	0.160***	-0.215***	18,450
	(0.0470)	(0.0483)	(0.0626)	(14,250)
Observations	435,876	435,876	435,876	435,876
R-squared	0.034	0.057	0.088	0.065

Notes: Robust standard errors are clustered at the zip code level. *** p<0.01, ** p<0.05, * p<0.1. The individual's predicted probability of admission is computed using the estimates in Table 2. The instrument is the admission rate for patients in the individual's predicted admission decile at the closest general service hospital with over 99 beds and at least 2 patients in that decile in that year. Closest is measured using the patient's residential zip code centroid. All regressions contain decile, hospital, year, month, weekday, and zip code fixed effects.