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James Cox
Georgia State University

Vjollca Sadiraj
Georgia State University

Kurt Schnier
University of California

John Sweeney
Emory University School of Medicine

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By James C. Cox[a], Vjollca Sadiraj[a], Kurt E. Schnier[b] and John F. Sweeney[c]

Abstract: This paper reports research on improving decisions about hospital discharges – decisions that are now made by physicians based on mainly subjective evaluations of patients' discharge status. We report an experiment on efficacy of our clinical decision support software (CDSS) which presents physicians with evidence-based discharge criteria that can be effectively applied at the point of care where the discharge decision is made. We report results from an experimental treatment that mandates physician attentiveness to the CDSS by replacing the default option of universal "opt in" to patient discharge with the alternative default option of "opt out" from the CDSS recommendations to discharge or not to discharge the patient on each day of hospital stay. We also report results from experimental treatments that implement the CDSS under varying conditions of time pressure on the subjects. The experiments were conducted using resident physicians and fourth-year medical students at a university medical school as subjects.

Keywords: Healthcare, Experiment, Clinical Decision Support System, Risk, Default Option

JEL Classification: C91, D81, I10

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a. Experimental Economics Center (E*x*CEN) and Department of Economics, Andrew Young School of Policy Studies, Georgia State University

b. School of Social Sciences, Humanities and Arts, University of California, Merced

c. Department of Surgery, Emory University School of Medicine

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1. Introduction

In 2010 Americans spent 17.6 percent of GDP on healthcare, which was eight percentage points above the OECD average (Organization for Economic Cooperation and Development, 2012).[1] The objective of decreasing medical costs, or at least reducing their outsized rate of increase, would seem to be well served by reducing hospital length of stay (LOS). If average LOS were to be reduced by 10 percent, the savings could approach $100 billion per year.[2] The research question we take up is how to assist physicians in making discharge decisions that decrease LOS and also lower the likelihood of *unplanned* readmissions, an indicator of low quality and a cost inflator. Physicians have rapidly increasing access to large amounts of raw data on each patient they treat through electronic medical record systems. The problem for improving discharge decision making is not shortage of data on the patient but, rather, absence of evidence-based discharge criteria that can be effectively applied at the point of care where the discharge decision is made.

Our central activity is a collaboration between physicians who make discharge decisions and (experimental and behavioral) economists – with expertise in research on decisions under risk and mechanism design – aimed at improving hospital discharge decision making. The objectives are to design, experimentally test, and disseminate a clinical decision support system (CDSS) that can be used to lower costs – by reducing average length of hospital stay – while increasing quality of medical care by decreasing the likelihood of unplanned readmissions.

An outline of current practice in hospital discharge decision making sheds light on the nature of the problem and a possible solution. Prior to deciding whether to discharge a patient, a physician examines the patient and reviews his or her electronic medical records. Criteria applied to making a discharge decision are derived from the physician's recall of his or her medical education and own previous practice and, perhaps, recommendations of one or more colleagues. The evidence base of these typical discharge criteria is extremely limited in comparison to the

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[1] Medicare, Medicaid, and CHIP (Children's Health Insurance Program) spending alone made up 21 percent of the 2012 federal budget (Center on Budget and Policy Priorities, 2013). In addition, both Medicaid and CHIP also require matching expenditures by the states.

[2] In 2010, 39 million patients spent on average 4.7 days in hospitals at a total cost in excess of $1.28 trillion (Agency for Healthcare Research and Quality, 2012).

voluminous information that could be derived from the electronic medical records of the patient *population* of a hospital. A typical hospital will serve many thousands of patients per year. Each surviving patient will be discharged from the hospital and it will subsequently be revealed, in most cases, whether the discharge was successful or unsuccessful (i.e., led to unplanned readmission within 30 days). The central question addressed in our research is how to use this mass of data – from current and former patients' electronic medical records and outcomes from previous discharges of patients – in developing evidence-based discharge criteria that can be effectively applied at the point of care where the discharge decision is made.

Our collaborative research began by analyzing a large sample of (de-identified) patient data to identify risk factors for unplanned hospital readmissions at a large southeastern teaching hospital (Kassin, et al. 2012). We subsequently elicited the hospital discharge criteria reported by physicians (Leeds, et al. 2013) and compared these self-reported criteria to (a) discharge criteria that can statistically explain actual discharges and (b) patient clinical and demographic data that predict successful or unsuccessful discharges (Leeds, et al. 2014). Although many self-reported criteria coincide with (statistically-explanatory) actual criteria, and many significant predictors of actual discharges coincide with significant predictors of successful discharges, various inconsistencies were identified which suggested the importance of research on creating and experimentally testing CDSS for improving discharge decision making. The present paper reports experimental testing of the authors' CDSS.

The research method for creating the CDSS proceeds as follows. We begin with the following question: Do the data profiles for patients who are successfully discharged differ in identifiable ways from the data profiles for patients who are unsuccessfully discharged? If the answer to this question is "yes" then that would open the possibility of building a decision support model that can inform discharge decisions for individual patients with the accumulated experience from discharging thousands of other patients. That is at the heart of our research agenda. We extract a large sample of de-identified data from the "data warehouse" of patient electronic medical records of a large southeastern teaching hospital. The data are used to build an econometric model, which provides the foundation for a decision support model that can be instantiated in software (i.e., the CDSS) and applied at the point of care. The CDSS presents the physician with a recommended discharge decision and with estimated daily readmission probabilities (and 80% confidence intervals); in addition, it provides information on dynamically-selected key clinical variables for the individual patient in a user friendly format.

Testing the CDSS for efficacy in improving discharge decision making includes both laboratory experiments and a planned field experiment, in the form of a hospital patient ward intervention. Ethical and practical considerations call for laboratory evaluation of the efficacy of the CDSS before its use in clinical intervention.

Cox, et al. (2014) reports details of development of the CDSS and results from a preliminary laboratory experiment with efficacy. The present paper reports results from a new experimental treatment that mandates physician attentiveness to the CDSS by replacing the default option of universal "opt in" to patient discharge with the alternative default option of "opt out" from the CDSS recommendations to discharge or not to discharge the patient on each day of hospital stay. We also here report results from new experimental treatments that implement the CDSS under varying conditions of time pressure on the subjects. The experiments were conducted using resident physicians and fourth-year medical students at a university medical school as subjects.

The organization of the paper is as follows. The following section discusses related literature, section 3 describes the CDSS, and sections 4 and 5 report on the experimental design and results from experimental tests of efficacy of the CDSS. A summary of the main findings and conclusions in section 6 completes the paper.

2. Related Economic and Medical Journal Literature

Hospital readmissions have recently become one of the critical healthcare quality metrics for American hospitals. In 2010, 19.2 percent of Medicare patients were readmitted within 30 days of discharge, resulting in additional hospital charges totaling $17.5 billion (Office of Information Products and Data Analytics, 2012). Hospitals and physicians are encountering increasing pressure to reduce hospital readmission rates, both from reputation effects of public disclosure of performance and from pay-for-performance reimbursement schemes that refuse payment for related readmissions.[3]

[3] Beginning in October 2012, the Centers for Medicare and Medicaid Services began publishing hospitals' readmission rates and penalizing those with "excess over expected" readmission rates for heart attack, heart failure and pneumonia patients. In 2012, a total of 2,217 hospitals were penalized; 307 of them were assessed the maximum penalty of 1 percent of their total regular Medicare reimbursements (*Kaiser Health News*, Oct 2, 2012). The scheduled penalties escalate in future years and apply to broader classes of treatment diagnosis codes.

The use of advanced information technology has been advocated as a method to increase healthcare quality and reduce costs (Cebul et al. 2008). Our research is part of a larger program in economics that aims at the creation of information technology for medical decision making and its application in clinical environments intended to improve quality and lower costs of healthcare. A seminal contribution by economists to improving healthcare is the mechanism design incorporated into information technology for kidney exchange by Roth, Sönmez, and Ünver (2004, 2007).[4] Their work provided a foundation for the New England Program for Kidney Exchange, and subsequent kidney exchange programs, which have led to increases in quality and length of life by matching patients with donors for transplant surgery while lowering the informational costs associated with organ matches. Support for improving medical decision making is needed in many additional areas. The present paper reports one such project. Our research targets improving physician discharge decision making through development of CDSS. Thus it lies at the intersection of healthcare cost and quality issues.

The topic of healthcare cost has been of considerable interest as the rate of growth in healthcare expenditures has exceeded the annual growth in real GNP per capita in the period since World War II (Newhouse 1992). Newhouse identified three demand-side and two supply-side factors that have influenced the cost of healthcare.[5] The supply side factors are physician-induced demand and low increase in productivity. To date little research has been conducted on the physician-induced demand causes of the increase in healthcare costs. However, it has been argued that the advent of the 468 Diagnosis Related Groups (DRG) payment mechanism implemented by Medicare in 1983 would help to mitigate the incentive problems that arise when physicians are compensated based on the level of healthcare provided (e.g., days in the hospital) rather than the health problem being addressed (e.g., appendicitis); see Pauly (1986). The recent actions by Medicare to reduce compensation when a hospital's rates of readmission are above reference levels is another effort to reduce the supplier-induced demand causes of the increase in healthcare costs. This action in effect lowers the effective DRG payment for treating a patient by reducing the amount of compensation a hospital receives if readmission rates are too high.

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[4] They developed a model of paired-kidney exchange for living donors and illustrated the benefits of two-way, three-way and higher level matches.

[5] The demand side factors influencing medical costs are the increased size of our aging population, the spread of insurance and the increase in consumer income.

Our research begins with the premise that an integral component of achieving these cost reductions is the assimilation and dissemination of information to help physicians make better discharge decisions.[6] Our research is one of the first efforts to develop and test the efficacy of using information technology to address a supplier-induced increase in healthcare costs of primary interest to Medicare, high rates of hospital readmission. Our research endeavors to contribute to development of Comparative Effectiveness Research as well as testing the efficacy of its utilization.[7]

One of the earliest investigations of the determinants of hospital readmission in the medical literature was conducted by Anderson and Steinberg (1985) who found that a patient's disease history and diagnosis were important determinants of a patient's probability of readmission. More recent research has further illustrated the role that these patient-specific factors have on the probability of readmission (Demir 2014) and that the use of electronic medical record (EMR) data on a patient's vital signs and laboratory test results can be used to explain likelihood of readmissions (Amarasingham, et al. 2010). Amarasignham, et al.'s (2010) reported results are relevant to our research because: (1) they validate the use of electronic medical records data in recovering readmission probabilities; and (2) they highlight a fundamental flaw with the current Medicare regulations that generate expectations for readmission rates with models that do not contain clinical information. The importance of using clinical information to inform estimates of readmission rates is also supported by Lee et al. (2012), who study return visits to a pediatric emergency room within 72-hours. Both Amarasignham, et al. (2010) and Lee, et al. (2012) conclude that their research supports the importance of future development of CDSS to improve discharge decision making.

In a recent review of 148 studies, Bright, et al. (2012), conclude that the current CDSSs (mostly *not* for discharge decisions) are effective at improving healthcare when assisting with physician decision making at the point of care. None of these studies, however, reports a test of efficacy of *discharge* decision support software that (a) applies at the point of care and (b) mandates physician attentiveness by replacing the default option of universal "opt in" to patient

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[6] We are not the first to highlight the importance of information in lowering health care costs. Cebul, et al. (2008) show that increasing information flows will lower healthcare organizational costs whereas Phelps (1992) argues that dissemination of the information can reduce regional variation in care.

[7] For a detailed discussion of Comparative Effectiveness Research in the economics literature see the discussion of Chandra, et al. (2011).

discharge with the alternative default option of "opt out" from the CDSS recommendations to discharge or not to discharge the patient on each day of hospital stay. We develop and test decision support software that applies at the point of care and includes a version which requires justification for overriding the software's discharge recommendations.

3. Features of the CDSS

Details of development of the CDSS are reported in Cox, et al. (2014). We here summarize its features. The CDSS was developed from an econometric model that used data from (de-identified) electronic medical records for 3,202 surgery patients who had been discharged from a large southeastern hospital and subsequently readmitted or not readmitted with the same diagnosis code within 30 days. We used probit regression to estimate probabilities of readmission with data that included the average values of clinical variables during a patient's stay, the duration of time spent outside and within the normal range of values expected for a particular clinical variable, counts of medications, images and transfusions, as well as a full set of interaction terms between the laboratory test and vital sign variables. We also used census track data that could be linked to the patient charts in a procedure that conformed with HIPAA privacy rules.[8]

The electronic medical record and census track information were used to construct a data set that contained 48,889 unique patient-day observations that corresponded to the observed value of each patient's data for each day during the hospital stay. This data set was used with the estimated probit model to construct the CDSS that reports probability of readmission for each individual patient in a representative sample if the patient were to be discharged from the hospital on that day. Time-varying point estimates of readmission probabilities and 80% confidence intervals were obtained from the probit-estimated parameter distributions and displayed by the CDSS (see Figures 1, 3 and 4 below for examples). An 80% confidence interval was selected because it captures a 10% one-sided error on the decision criterion to discharge a patient on a given day. These daily readmission probabilities are used with targeted readmission rates that vary with patient diagnosis codes to determine the CDSS patient-specific daily discharge recommendations. The CDSS uses target readmission rates that are 10% reductions from historical readmission rates and are based on the targets stated by the Center for

[8] Our procedures conform to the "Safe Harbor" Method as defined by the HIPAA Privacy Rule Section 164.514 (B)(2).

Medicare and Medicaid Services in 2010. In addition to discharge recommendations and readmission probabilities, the CDSS dynamically displays six clinical variables that the probit model indicates are most significant for the discharge status of the individual patient on that day of the hospital stay. The clinical variables displayed in the six charts for a patient can change from one day to another day, reflecting the model's updated implications with changing data on patient status (see Figures 1, 3 and 4 below for examples).

4. Experimental Design and Protocol

In order to conduct our experiment we selected 30 (de-identified) patient charts from the sample of 3,202 patient electronic medical records in our sample. The entire sample was first partitioned into low, medium and high readmission risk categories.[9] We subsequently selected 10 patient charts from each of the three risk categories to provide a clear test of the efficacy of the software.

The experimental design "crosses" the presence or absence of a 45 day constraint on the number of "experimental days" with alternative information and default conditions. Inclusion of the 45 day constraint increases the opportunity cost of keeping a patient longer in the hospital; this feature of the experiment is a stylized way of capturing the effect of a hospital's "capacity" on discharge decision making. The alternative information and default conditions will be explained below. We first explain features of the experiment that are present in all treatment cells.

4.a Common Features of all Treatments

The information provided to subjects in all treatment cells includes clinical variables that are the same as they would get from a hospital's electronic medical records (EMR). Not only is the same information provided as in the hospital's EMR, we also use a graphical interface that is a facsimile of the EMR computer display screens.

[9] Target readmission rates that are 10% reductions from historically observed readmission rates for patients with different diagnosis codes were used for this partitioning. A "low risk" patient had a procedure with a target readmission rate less than 10%, a "medium risk" patient was between 10% and 17%, and "high risk" patient was greater than 17%. These are associated with the complexity of the surgery and the procedure-specific potential for infection and other complications; they are not patient-specific.

A subject begins each experimental day by selecting patients from a list on a screen that displays summary information from each of three patient charts that includes patient age, sex, and length of stay in the hospital (up to the current experimental day) taken from electronic medical records. After selecting a patient, a subject in the experiment gets access to that patient's chart information.

A subject in the experiment did not always have to review a patient's chart for the first few *calendar* days they were in the hospital if there was no realistic prospect for considering discharge during those days. The first "experiment day" on which a subject was asked to review a chart was randomly selected to be between one and four days before the discharge model would first recommend that the patient be discharged; this one to four day period was independently selected for each of the 30 patient charts. During an experimental session, the 30 patient charts were presented in a random order that was independently drawn for each subject.

In order to avoid leading the subjects towards making particular decisions, the dates of actual discharge of the patients were removed from the patient charts. Within the experiment it was, of course, possible that a patient could be retained longer than the observed length of stay in the EMR. Therefore, we constructed continuation charts for all 30 patients that imputed an extra five days of possible stay.[10] In all treatments, the subjects were informed that they should assume that a patient was being managed at the appropriate standard of care while in the hospital and that the subjects were *not* being asked to speculate about additional tests or procedures that they might want to order. Instead, they were asked to make the hospital discharge decisions on the basis of the clinical information contained in the patient chart.

At the beginning of an experiment session, the subjects were welcomed to the decision laboratory by one of the researchers who self-identified as a medical doctor and explained that the research was supported by an NIH grant.[11] Each subject was informed that they would make a series of choices between the two options, "Discharge Patient" and "Do NOT Discharge Patient." Any patient not discharged would return for consideration on the next experiment day with updated chart information. Any patient who was discharged could turn out to be successfully discharged or, alternatively, could be readmitted. The likelihood of readmission was

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[10] The percentages of patients discharged in the experiment that occurred during the continuation chart periods are 7.76, 8.77 and 7.48 in the baseline, information and default treatments.

[11] The subjects read and signed the IRB-approved consent form and subsequently began reading the subject instructions on their computer monitors. Subject instructions for the experiment can be found at http://excen.gsu.edu/jccox/subjects.html.

based on the estimated probit model.[12] Any patient readmitted in the experiment remained in the hospital for at least two experimental days during which the subject continued to view the updated chart.

Subjects were informed that they could make at most a total of 30 choices of the Discharge Patient option. An unsuccessfully discharged patient "used up" one of these 30 feasible choices. A subject was paid $5 for each successful discharge and nothing for unsuccessful discharges. Each experiment session could last no more than two hours. The two-hour time limit, however, was not a binding constraint for any subject. In three treatment cells there was an additional constraint that the subject could not participate in more than 45 experiment days. In contrast, there was no limit on the number of experiment days that a subject could use to make up to 30 discharge decisions in the other three treatment cells. The purpose of the 45 experiment day constraint was to increase the opportunity cost of not discharging a patient. This 45 experiment day constraint was binding for some of the subjects in the three treatment cells in which it applied.

4.b Idiosyncratic Features of the Baseline, Information, and Default Treatments

In the Baseline Treatment, a subject makes the discharge decisions using only the information in the EMR. The default option in the Baseline Treatment is the same as in current medical practice: the patient remains in the hospital unless the physician with authority initiates entry of "discharge orders" in the EMR. The Information Treatment presents all of the EMR-facsimile screens used in the Baseline Treatment plus additional CDSS screens with selected patient information and a recommendation about the discharge decision. The default option in an Information Treatment is the same as in the Baseline Treatment. The Default Treatment presents all of the same information as in the Information Treatment, including a discharge recommendation, but uses a different default option. In the Default Treatment, the CDSS initiates

[12] In the case that a patient was readmitted after being discharged in the experiment the subject was presented with a readmission chart for the patient. The readmission chart was based on the observed complications following discharge within the population of patients served by the hospital. Subjects were informed of the complication that required readmission and the patient chart data were altered to be consistent with the presence of the complication as reflected in the empirical evidence reported in Kassin, et al. (2012). Each patient's chart was altered for only the first three to five days of their stay after readmission and the remaining chart days conformed to their observed data prior to being discharged.

discharge orders in EMR when it makes a positive discharge recommendation; an attending physician who did not accept the recommendation would have to enter reasons in the EMR for overriding the recommended decision. When the CDSS makes a negative recommendation, a physician would have to enter reasons for overriding the recommendation before entering discharge orders in EMR.[13]

The subjects enter their decisions on screens that differ across the Baseline and Default Treatments. The decision screen for the Baseline Treatment includes only the patient's ID, name, age, and sex and two buttons to be clicked in order to record a decision whether to discharge the patient on the experimental day recorded at the top of the screen. These buttons are labeled "Discharge Patient" and "Do NOT Discharge Patient." If the subject clicks on the Do NOT Discharge Patient button, the patient remains "in the hospital" and reappears in the subject's list of patients on the following experiment day. If the subject clicks on the Discharge Patient button, the patient is discharged. In the event of a successful discharge, the subject is paid five dollars. In the event of an unsuccessful discharge, the subject receives no payment and the patient is readmitted and reappears in the subject's list of patients.

There are three decision screens for the Default Treatment that will be described here (and three slightly different screens for the Information Treatment that will be described in footnotes). Which decision screen a subject encounters in the Default Treatment depends on the recommendation of the decision support software for the patient on that day. In case of a negative recommendation the decision maker encounters a decision screen like the one shown in Figure 1 that reports the recommendation "Do Not Discharge Patient" at the bottom left of the screen. The left side of the decision screen shows probabilities of readmission if the patient were to be discharged on any experiment day up to the present decision day (which is day 8, as shown on the horizontal axis). The dots at kinks in the piecewise linear graph show point estimates of the probabilities of readmission on days 1-8. The vertical dashed lines that pass through the dots (at kinks) correspond to the 80% confidence intervals of the readmission probability. The horizontal line shows the *target* readmission probability for patients with the diagnosis code of this patient. For the selected patient (Lucy Doe), the left part of the figure shows point estimates

[13] Note that the change in default option would *not* alter the fact that the attending physician has authority and responsibility for discharging the patient. This change in default option would change the procedure for entering discharge orders in the EMR.

that lie entirely above the horizontal line showing the target readmission rate; that is why the decision support software makes the negative recommendation. The six charts on the right two-thirds of the screen show the days 1-8 values of clinical variables that are probabilistically most important for the discharge decision for this specific patient on the present experiment day (which is day 8, in this case).

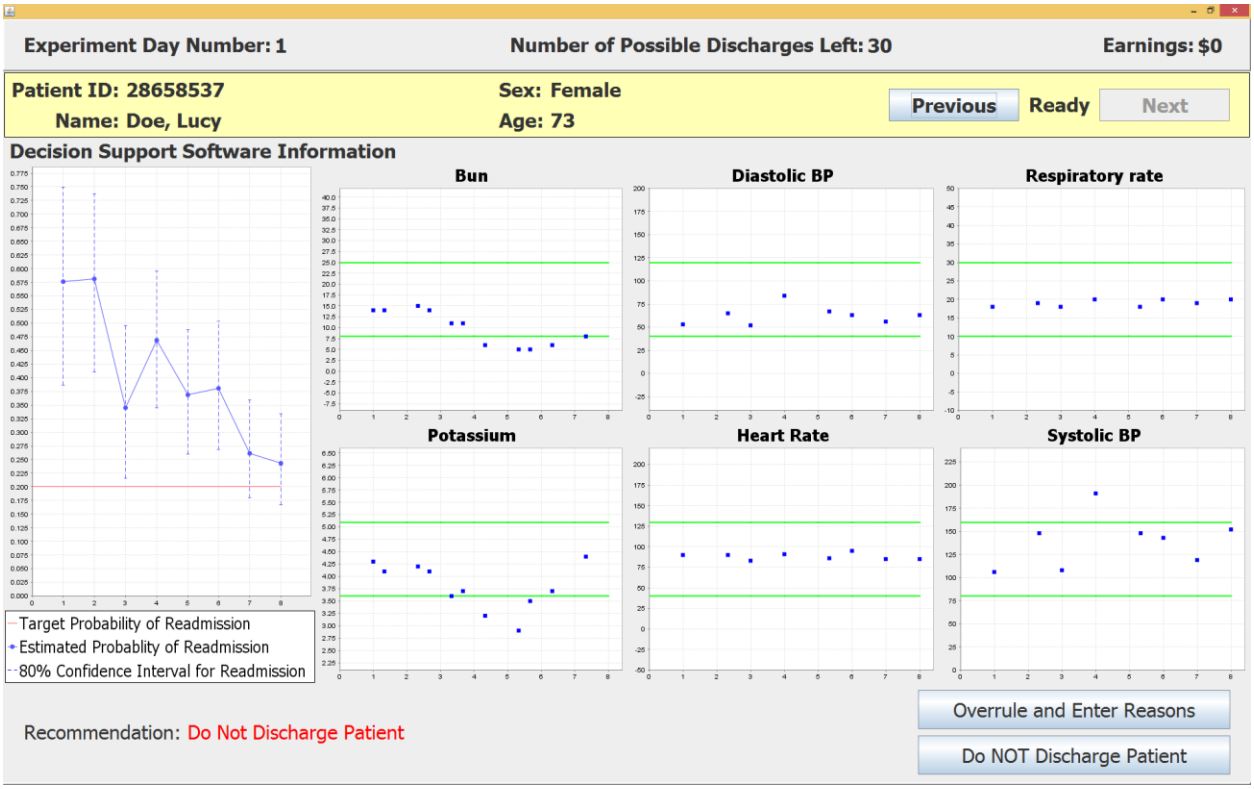

Figure 1. Default Treatment Decision Screen with Negative Recommendation

The subject enters her decision by clicking on one of the two buttons at the lower right of the screen. If the subject accepts the recommendation she clicks on the Do NOT Discharge Patient button. If the subject does not accept the negative recommendation he clicks on the Overrule and Enter Reasons button.[14] This choice causes the decision support software to open the screen shown in Figure 2 that requires the subject to enter her reasons for overruling the CDSS recommendation.[15] The reasons for overruling the recommendation can be recorded by

[14] The corresponding screen for the Information Treatment is identical to the one in Figure 1 except that the two buttons are labeled Discharge Patient and Do NOT Discharge Patient.
[15] In the Information Treatment there is no screen corresponding to the one in Figure 2.

clicking on (square) radial buttons on the left side of the screen and entering text on the right side of the screen.

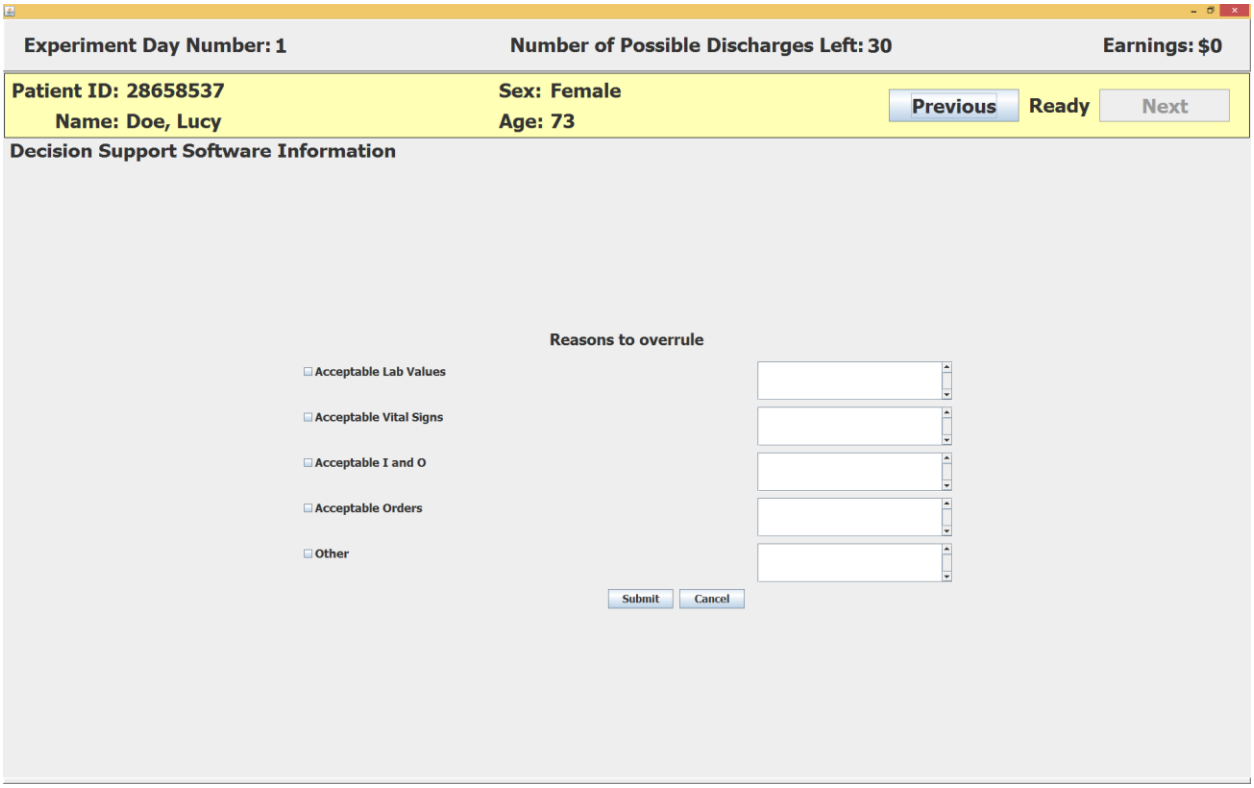

Figure 2. Reasons to Overrule a Negative Recommendation

Figure 3 shows data for a day on which the decision support software does not make a recommendation whether to discharge or not to discharge Lucy Doe; instead, it exhibits the "recommendation" for day 9 as Physician Judgment. A Physician Judgment "recommendation" occurs when the target readmission rate falls between the point estimate and the upper bound on the 80% confidence interval for the readmission probability. Although there is no recommended decision in this case, the software does provide decision support with the information in the readmission probabilities on the left side of the screen and the six dynamically-selected clinical variables on the right side of the screen.[16] The subject enters a decision on this screen by clicking on one of the two buttons in the bottom right corner of the screen shown in Figure 3.[17]

[16] The clinical variables exhibited in Figure 1 and Figure 3 are not all the same variables, which reflects the dynamic updating of the decision support model as patient variables change from one day to another in the electronic medical record for this patient.

[17] The corresponding screen for the Information Treatment is identical to the one in Figure 3.

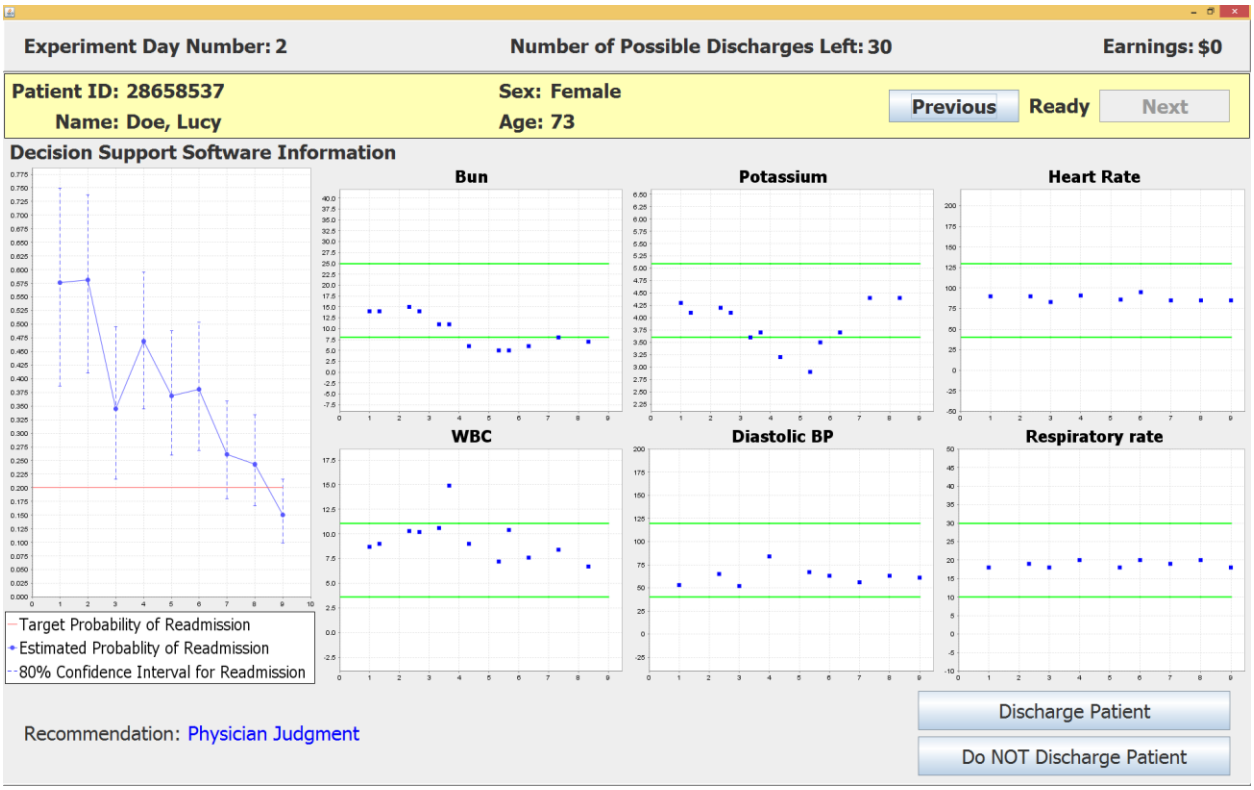

Figure 3. Default Treatment Decision Screen with Physician Judgment "Recommendation"

The CDSS first recommends that Lucy Doe be discharged on the experiment day in which the top of the 80% error bar dips below the target readmission rate. This conservative criterion reflects choice of an estimated 10% error for the positive recommendation. In the example shown in Figure 4, the first day on which the top of the error bar drops below the target readmission rate is experiment day 11. The software's recommendation on that day is Discharge Patient. The subject enters her decision by clicking on one of the two buttons at the lower right of the screen.[18] If the subject accepts the recommendation she clicks on the Discharge Patient button. If the subject does not accept the negative recommendation she clicks on the Overrule and Enter Reasons button. This choice opens the screen shown in Figure 5 that requires the subject to enter his reasons for overruling the software's positive recommendation.[19]

[18] The corresponding screen for the Information Treatment is identical to the one in Figure 4 except that the two buttons are labeled Discharge Patient and Do NOT Discharge Patient.
[19] In the Information Treatment there is no screen corresponding to the one in Figure 5.

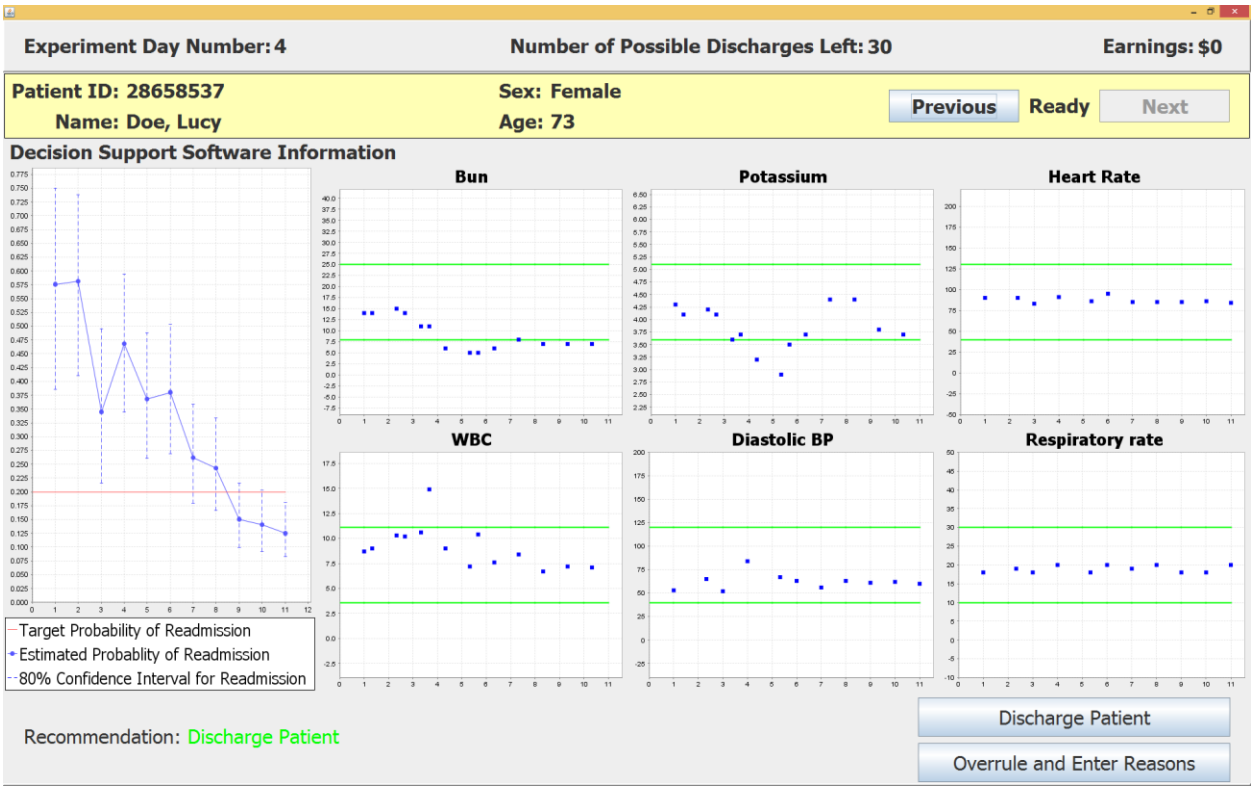

Figure 4. Default Treatment Decision Screen with Positive Recommendation

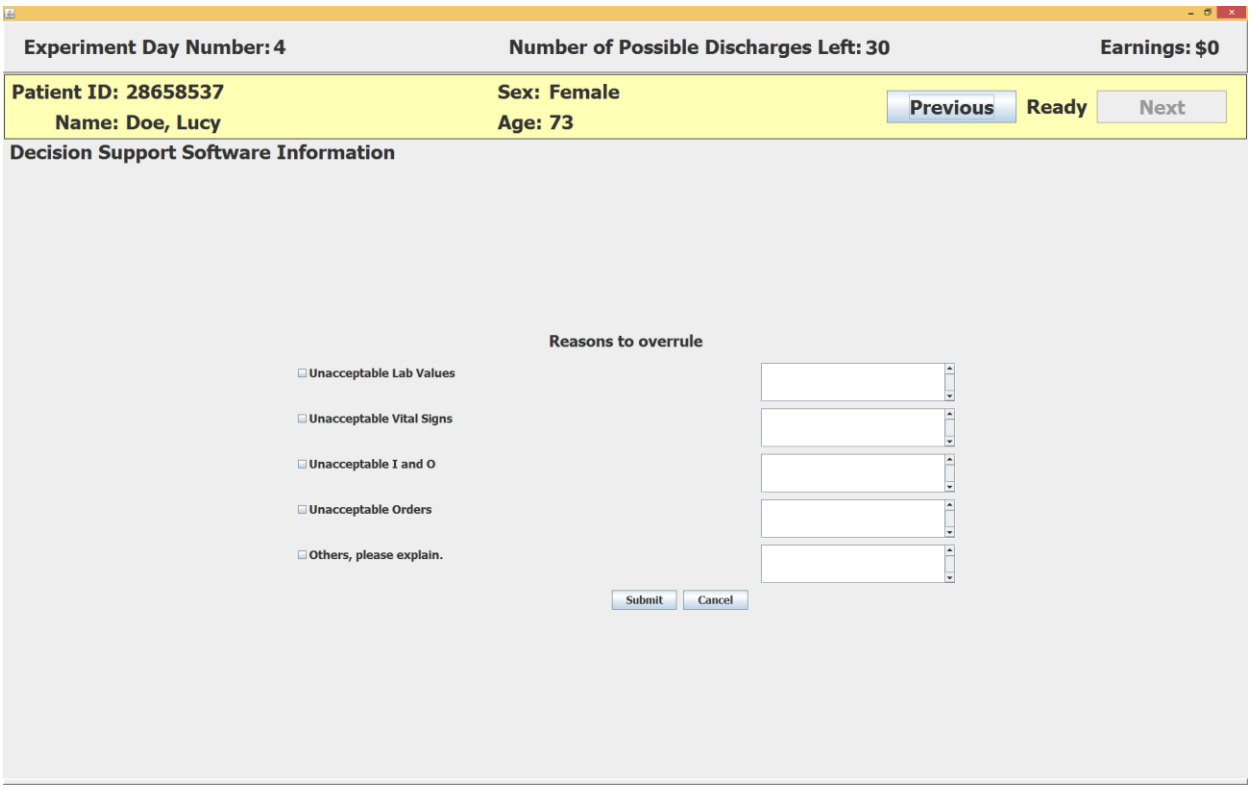

Figure 5. Reasons to Overrule a Positive Recommendation

5. Results from the Experiment

A total of one hundred and twenty-five subjects participated in the experiments; twenty of these subjects were resident physicians and the rest were fourth-year medical students. Subjects were distributed almost equally across the Baseline (43 subjects), Information (42 subjects), and Default (40 subjects) treatments. The overall number (64) of female participants was similar to the number (61) of male subjects, as was the gender composition across treatments ((21F, 22M), (20F, 22M) and (23F, 17M); Pearson chi2(2)=0.95, p-value=0.62). Academic performance of subjects who participated in different treatments was at comparable levels.[20]

After making their discharge decisions, subjects completed an online questionnaire that was embedded in the experiment software. The questionnaire elicited demographic information and also included hypothetical response questions about risk attitudes.[21] After completing the questionnaire, subjects exited the lab one at a time to be paid in cash in private. Average subject payoff was $131 for participation lasting, on average, 90 minutes.

We ran two designs that differ from each other only with respect to whether there was a constraint (of 45 days) on the number of experimental days. Fifty-four subjects (out of 125) participated in the design with the 45 experimental days constraint and 71 participated in the design with no constraint on the number of experimental days.

Data from our experiment provide support for efficacy of the decision support software with respect to four measures of performance: subject earnings, quality of service (readmission rate), hospital length of stay, and time efficiency (number of experimental days utilized to make a certain number of discharges). We report several ways of describing the data and statistical analysis for significance of treatment effects.

5.a Decision Time Efficiency and Daily Experiment Earnings

In the treatment cells without the 45 day constraint, subjects took on average 54 experimental days to finish the experiment (i.e. to make 30 discharges) in the Baseline Treatment but in the Information and Default Treatments they were able to complete the task of making 30 discharges

[20] Reported average grades in medical school of subjects in the Baseline, Information and Default Treatments were 3.59, 3.57 and 3.46 (Kruskal-Wallis test: chi2 = 3.32, p-value=0.19).
[21] The questionnaire can be found at http://excen.gsu.edu/jccox/subjects.html.

within 47 and 42 experimental days, respectively, an improvement in time efficiency of 7 and 12 experimental days. The null hypothesis of equal time efficiency across treatments is rejected (chi2=6.42; p-value=0.04 according to Kruskal-Wallis test).[22] Data from treatments in which the discharge decision support software is used are significantly more efficient than the Baseline but the effect is stronger in the Default Treatment (one sided p-values reported by the t-test are 0.043 or 0.004, respectively, when the Baseline is compared with the Information or Default Treatment). Figure 6 shows cumulative distributions of experimental days in the Baseline and Default Treatments.

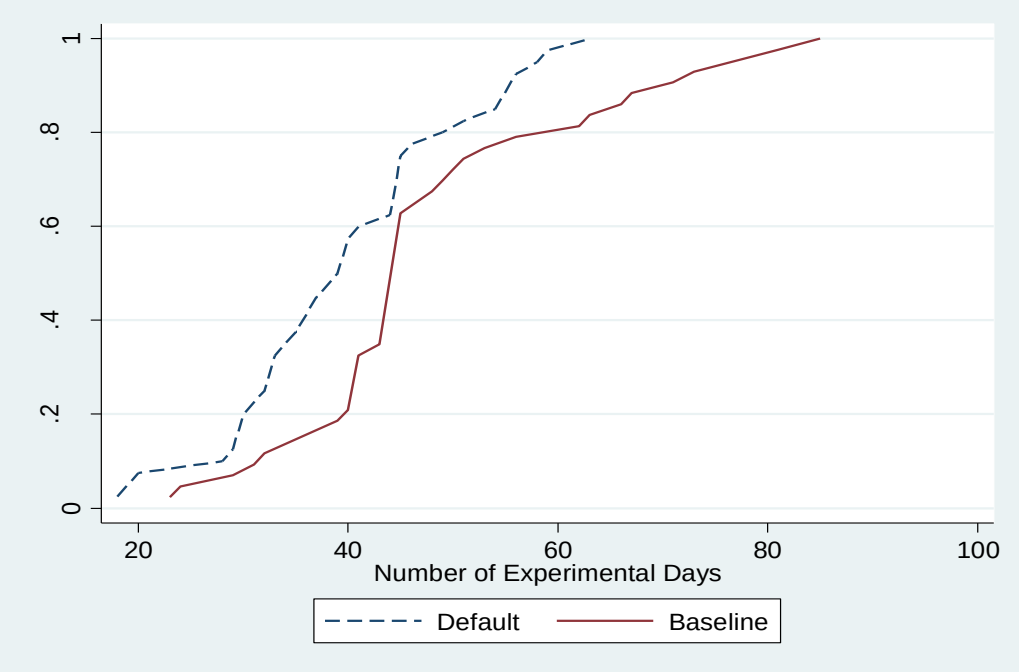

Figure 6. Cumulative Distributions of Observed Experimental Days

Average subject earnings per experimental day were $2.83, $3.15 and $3.62 in the Baseline, Information and Default Treatments, as reported in the top panel of Table 1 (with standard deviations in braces).[23] Subjects' daily earnings are highest in the Default Treatment

[22] Since in the 45-day-constraint design subjects couldn't go above 45 days we are excluding these data in the analysis of time efficiency in the main text because of potential bias. If we include those data, the task of 30 discharges takes 49, 44, and 40 experimental days, respectively, for the baseline, information, and default treatments. According to the Kruskal-Wallis test, the null hypothesis of equal distributions of experimental days across treatments is rejected (chi2 = 8.32, p-value = 0.016).

[23] These "experimental day" payoff amounts are average amounts paid for the time taken to review three patient charts and consider making a discharge decision for each of the patients (during an "experimental

and lowest in the Baseline Treatment. We ran one-way analysis of variance by ranks (Kruskal-Wallis tests) to ascertain whether daily earnings across different treatments come from the same distribution. The null hypothesis (of the same earnings) is rejected by this test (chi-squared statistic is 12.33, two-sided p-value is 0.002).

Next, we ask which treatments are responsible for this rejection. The means of the ranks of daily earnings of three treatments are shown in the lower panel of Table 1. The p-values for each pairwise comparison are shown in the bottom two rows. Using (Bonferroni) adjusted p-values for multiple comparisons, we conclude that baseline and default data on earnings per day are coming from different distributions; subjects in the Default Treatment are earning more per experimental day than subjects in the Baseline Treatment.

Table 1. Comparisons of Daily Earnings across Treatments

	Baseline	Information	Default
Number of Subjects	43	42	40
Mean {st.dev.}	$2.83 {0.94}	$3.15 {0.94}	$3.62 {1.16}
Kruskal-Wallis Test			
RankMean	49.22	63.64	77.14
Information	0.033	--	
Default	0.0002***	0.046	--

(Rank Means and p-values correspond to Kruskal-Wallis test; the adjusted p-value for multiple comparisons is 0.008 in case of all pairwise comparisons and 0.0125 in case the baseline is treated as a control group, i.e. comparing the baseline to the other two.)

We are also interested in other features of the experimental design and individuals' characteristics that are correlated with higher daily earnings. So we ran linear regressions (with robust standard errors) of daily earnings as a dependent variable and Information and Default Treatment dummies, a dummy for the 45-day constraint, and subject demographic variables as right-hand variables. The parameter estimates are as follows (standard errors in braces):[24]

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day"). They are *not* the average amount paid to subjects for participation in an experiment session which, as reported above, was $131.

[24] F(10,108)=2.94 (p-value=0.003), 119 observations. Six observations were dropped during the regression because of incomplete demographics responses. The estimates of the robust regression without demographics for the information and default treatments are 0.31 (p-value = 0.10) and 0.65 (p-value = 0.001) and F(4,120)= 4.08 (p-value=0.004).

$$Daily\ Earnings = \underset{\{1.424\}}{3.63^{**}} - \underset{\{0.164\}}{0.28^{*}} \times D_{45day} - \underset{\{0.231\}}{0.46^{*}} \times D_{resident} - \underset{\{0.366\}}{0.15} \times GPA_{undergrad} + \underset{\{0.142\}}{0.15} \times GPA_{med}$$
$$- \underset{\{0.152\}}{0.09} \times D_{music} - \underset{\{0.172\}}{0.06} \times D_{athlete} - \underset{\{0.153\}}{0.47^{***}} \times D_{female} + \underset{\{0.043\}}{0.02} \times risk + \underset{\{0.186\}}{0.72^{***}} \times D_{default} + \underset{\{0.180\}}{0.31^{*}} \times D_{info}$$

Daily earnings are lower for residents (by 46 cents) and female physicians (by 47 cents); they are also lower (by 28 cents) in the treatment with the 45-day constraint on the maximum number of experimental days. There are insignificant effects of musical training and record of competitive athletics (although such characteristics are selected for in admissions to the surgical specialty). With respect to treatment effects, consistent with findings at the aggregate level of data analysis, daily earnings of subjects in the Default and Information Treatments are 20% and 9% higher than in the Baseline (p-values are 0.000 and 0.087).[25] Subjects are also making more money per experimental day in the Default Treatment than in the Information Treatment.[26] We conclude that:

Result 1. *Use of the CDSS, with or without making the CDSS's recommendation the default option, increases: (a) decision time efficiency; and (b) daily earnings.*

One may wonder whether the increased decision time efficiency that we observe in the treatments has a negative effect on the quality of care. Given the design of our experiment, lower quality would be manifested in higher readmissions. Readmission rate is one of the factors that affect the ranking of a hospital and it is also one that has attracted increasing attention from Medicare, including fines for excess readmissions beginning in October 2012. In the following section we look closely at the interaction between different treatments and readmission rates in our experiment.

5.b Readmissions as an indicator of the quality of care

An earlier discharge is not an indicator of better discharge decision making if it decreases the quality of care. An indicator of the quality of care is the readmission rate since a premature discharge increases the likelihood of an unplanned but necessary readmission. Averages of

[25] Note that 0.72/3.63 ≅ 0.20 and 0.31/3.63 ≅ 0.09 using the coefficient estimates.
[26] Estimates for the information and default treatments are different from each other (F(1,108)=4.80, p-value=0.031.)

readmission rates of all regular patients[27] observed across treatments are 10.21%, 10.40% and 9.84%, respectively, for the Baseline, Information and Default Treatments. For regular patients with high levels of *targeted* readmission probabilities (at least 17%) the mean readmission rates are 13.49%, 12.70% and 10.80% for the Baseline, Information and Default Treatments.[28] Means tests imply that use of the CDSS combined with change in the default option significantly reduces the overall mean of readmissions by 3.6% and the rate for high risk patients by 20%. In contrast, the means test implies no significant difference between the Baseline and Information Treatments.

We ran probit regressions with binary dependent variable that takes value 1 if a regular patient is readmitted. Covariates include subjects' demographics, a risk aversion index,[29] patients' targeted readmission probabilities, whether the patient was discharged before the first recommended discharge day (Understay = 1) or after that day (Overstay = 1), and the recommended length of stay until first discharge recommendation (Rec. LOS). Table 2 reports the estimated coefficients (and p-values of the probit regressions) with clusters at the subject level using data for the high risk patients (columns (1) and (2)) and all patients (columns (3) and (4)). The probit regressions reported in columns (2) and (4) include the Rec. LOS variable, reported in the first row of the table, while regressions reported in the other columns exclude it.

[27] A patient is called "regular" if he has not previously been readmitted.
[28] One third of "patients" in our experiments had a targeted probability of readmission higher than 0.17; we call such patients "high risk" patients.
[29] In the hypothetical ten ordered tasks in the post-experiment survey, a risk neutral subject switches from the safer option to the riskier option in task 5. The risk index variable that we constructed is the difference between the number of the task that a subject switches (for the first time) from choosing the safer option to choosing the riskier one and task five. Hence, the risk index is negative for a risk lover and positive for a risk averse subject (the later the switch the lower the subject's tolerance to risk).

Table 2. Probit Regressions of Readmissions for Regular Patients

VARIABLES	High Risk Patients		All Patients	
Rec. LOS	…	0.005	…	-0.009***
	…	(0.185)	…	(0.000)
Understay	0.004	0.000	0.016***	0.025***
	(0.617)	(0.976)	(0.000)	(0.000)
Overstay	-0.005	-0.003	-0.004	-0.004
	(0.498)	(0.660)	(0.311)	(0.252)
Information	-0.020	-0.019	-0.000	0.001
	(0.386)	(0.397)	(0.972)	(0.958)
Default	-0.047**	-0.045**	-0.015	-0.015
	(0.022)	(0.027)	(0.211)	(0.190)
Female	-0.013	-0.015	-0.006	-0.004
	(0.492)	(0.439)	(0.570)	(0.723)
Athlete	0.019	0.019	0.006	0.007
	(0.384)	(0.396)	(0.592)	(0.563)
Musical	-0.034*	-0.035*	-0.023**	-0.021**
	(0.075)	(0.066)	(0.027)	(0.040)
Medical GPA	0.013	0.013	0.006	0.007
	(0.297)	(0.314)	(0.537)	(0.508)
Undergrad GPA	0.003	0.004	-0.017	-0.021
	(0.949)	(0.929)	(0.511)	(0.431)
Risk Avers. Index	-0.017***	-0.017***	-0.003	-0.003
	(0.003)	(0.002)	(0.200)	(0.262)
Resident	-0.013	-0.016	0.010	0.014
	(0.629)	(0.563)	(0.597)	(0.446)
Target Probability	4.207***	4.480***	0.762***	0.954***
	(0.000)	(0.000)	(0.000)	(0.000)
45 Day Constraint	0.051**	0.050**	0.044***	0.043***
	(0.030)	(0.031)	(0.000)	(0.001)
Nobs	1,063		3,197	

Results reported in Table 2 show treatment effects that are consistent with the aggregated data figures reported above; the Default Treatment induces a significant reduction in the readmissions of high risk patients. Probabilities of readmissions in the Default (holding all other covariates at the means) are 4.5% to 4.7% lower than in the Baseline for the high risk patients.[30] We conclude that:

[30] Probabilities of readmissions of regular patients in the information and default treatments (holding all other covariates at the means) are 1.7% and 0.57% lower than in the baseline, but these figures are not statistically different from 0.

Result 2. *Use of the CDSS and making the CDSS's recommendation the default option reduces readmissions of high risk patients.*

Referring to the estimates of Understay and Overstay in Table 2, we find that for data from all patients (right two columns) the patient Understay variable has a positive effect on readmission while the estimate of the Overstay variable is insignificant. This gives us the third result:

Result 3. *Discharging a patient earlier than recommended by the CDSS significantly increases the likelihood of unplanned readmission while later-than-recommended discharge does not significantly decrease it.*

Readmissions are significantly higher in the design with a constraint (of 45 days) on the maximum number of experimental days. Subjects with musical training have lower readmissions for all patients and high risk patients while those with a higher risk aversion index have lower readmissions with high risk patients. The recommended hospital length of stay (Rec. LOS) also has a significantly negative effect on readmissions[31] but the effect disappears when only the high risk patients are considered. We next turn our attention to hospital length of stay (LOS) across treatments.

5.c Hospital Length of Stay

The average figures for observed LOS of regular patients are 7.72, 7.15 and 6.64 for the Baseline, Information and Default Treatments.[32] The OLS estimates (and robust standard errors in braces) of the hospital length of stay for regular patients are[33]

$$\underset{\{2.053\}}{\mathrm{LOS} = 7.75^{**}} - \underset{\{0.248\}}{0.32} \times D_{45day} + \underset{\{0.301\}}{0.84^{***}} \times D_{resident} - \underset{\{0.548\}}{0.29} \times GPA_{undergrad} - \underset{\{0.126\}}{0.13} \times GPA_{med}$$
$$+ \underset{\{0.220\}}{0.40^{*}} \times D_{music} - \underset{\{0.285\}}{0.08} \times D_{athlete} + \underset{\{0.217\}}{0.71^{***}} \times D_{female} + \underset{\{0.072\}}{0.06} \times risk - \underset{\{0.305\}}{0.92^{***}} \times D_{default} - \underset{\{0.275\}}{0.50^{*}} \times D_{info}$$

[31] The estimated marginal effect is - 0.01 (std. error is 0.002) for the model reported in the right-most column of Table 2.

[32] If we include days in the hospital after a patient is readmitted in LOS then we get the following average hospital lengths of stay for the baseline, information and default treatments: 8.60, 8.11 and 7.42.

[33] F(10,118)=6.35 (p-value=0.00), nobs=3274, 119 clusters. If we include in LOS days in the hospital as a readmitted patient we still get similar results; the estimates for the information and the default treatments are -0.48 and -1.05.

Female subjects and resident physicians kept their patients in the hospital longer but their readmissions were not lower than others (as shown in Table 2). The hospital length of stay of regular patients is lower in both the Information (by a half day) and Default (by almost one day) treatments while there are no higher readmission rates in these treatments (see Table 2 estimates for the Information and Default dummy variable parameters). We conclude that:

Result 4. *Use of the CDSS, with or without making the CDSS's recommendation the default option, reduces hospital length of stay without increasing readmissions.*

5.d Value of Decision Support Information

After completing all discharge decisions, subjects who participated in the Default and Information Treatments were asked (by the experiment software) to report their ranking on a five-point Likert scale (where higher is better) of the usefulness of being provided information on the estimated readmission probabilities and the 80% confidence intervals. Half of the subjects reported a score 3 or higher for both the point estimate and the 80% confidence interval.

The difference between daily earnings of the subjects who gave a score of three or higher for the usefulness of the point estimate (call it group H) and the average daily earnings of those who reported a lower score than three (call it group L) can be used as an economic measure of the effects of subjects' acceptance of the value of the readmission probability information. The mean daily earnings are $3.15 and $3.53 for groups L and H; the median figures are $2.87 and $3.42 for groups L and H. The Kolmogorov-Smirnov test rejects at 1% significance level (p-value is 0.001) the null hypothesis of daily earnings of the two groups being drawn from the same distribution. Similarly, the difference between days a patient is kept in the hospital by subjects of groups L and H can be used as an indicator of acceptance of the value of the information. The means are 3.43 and 2.82 days for groups L and H. Hence, in our experiment, a result from subjects' recognizing the value of the information is a reduction of length of stay of 0.61 days per patient, a decrease of 18%. The Kolmogorov-Smirnov test rejects at 1% significance level (p-value is 0.000) the null hypothesis that the distributions of observed length of stay (from the first day the patient is seen by subjects) are the same for the L and H groups of subjects. We conclude that:

Result 5. *Subjects who report they place relatively high value on usefulness of reported readmission probabilities: (a) keep their patients significantly fewer days in the hospital; and (b) earn significantly higher payoffs per experimental day.*

We also looked at the economic significance of following a recommendation. If we exclude rounds when the software reports Physician Judgment, we find that the (average) compliance rates are 80.78% and 81.44% in the Information and Default Treatments. In those treatments, subjects who discharged a patient when the recommendation was *not* to discharge earned $4.06 for serving that patient whereas those subjects who discharged a patient when the recommendation was to discharge earned $4.75, an increase of 17%. Tobit estimates of the determinant of earnings are[34]

$$Earnings = \underset{\{23.73\}}{49.57^{**}} + \underset{\{11.26\}}{30.70^{***}} \times complyRate - \underset{\{2.71\}}{18.17} \times D^{***}_{45day} - \underset{\{4.00\}}{1.01} \times D_{resident} + \underset{\{6.01\}}{18.59^{***}} \times GPA_{undergrad}$$
$$- \underset{\{1.98\}}{0.469} \times GPA_{med} + \underset{\{2.44\}}{3.04} \times D_{music} - \underset{\{2.73\}}{3.56} \times D_{athlete} - \underset{\{2.62\}}{3.91} \times D_{female} + \underset{\{0.68\}}{0.49} \times risk + \underset{\{0.20\}}{3.31} \times D_{default}$$

where the "complyRate" variable is the rate of compliance, defined as the number of times that a subject's decisions were the same as the decision recommended by the CDSS divided by the total number of the subject's decisions.[35] The coefficient estimate for the complyRate variable is positive and significantly different from 0 (p-value is 0.008). We conclude that:

Result 6. *Subjects who comply with the CDSS's recommendations have significantly higher earnings.*

Together, Results 5 and 6 inform us that subjects obtain higher earnings in the experiment when they: (a) report that they place relatively high value on usefulness of the CDSS readmission probability estimates; or (b) comply with the CDSS's recommendations to discharge or not to discharge patients. These conclusions are stronger for the Default Treatment.

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[34] Log-likelihood is -282, LR chi2(10) is 58.04, number of observations is 79. There are five right-censored observations for subjects who earned the maximum amount of money, $150. Three observations were dropped because of incomplete demographic responses. Tobit estimate of the complyRate variable when demographics are not included (all 82 observations included) is 35.18 (p-value=0.002).

[35] In the construction of the variable complyRate, subjects' decisions when the recommendation is Physician Judgment are not included.

These results suggest another question concerning the reasons why the CDSS leads to better discharge decisions in the experiment. Does this occur because a high proportion of subjects are reluctant to overrule CDSS recommendations, most especially when they have to enter reasons for doing so? Some insight into this question is provided by analyzing only that subset of the data in which the CDSS provides probability information and six dynamically selected patient charts but does *not* provide a recommendation to discharge or not to discharge the patient; these are the experimental days in patient charts in which the CDSS's "recommendation" is Physician Judgment. We compare the performance measures of decisions in the Baseline and Default Treatments using only the data from experimental days in which the "recommendation" is Physician Judgment and find that: mean total payoff is higher in the Default Treatment; mean experimental days is lower in the Default Treatment; and mean readmission rate for high risk patients is lower in the Default Treatment. Furthermore, payoff per experimental day is significantly higher in the Default Treatment and the total number of experimental days is significantly lower in the Default Treatment. In this way we find that the information provided by the CDSS improves discharge decision making even in the absence of a definitive recommendation about discharge, at least in the context of the Default Treatment. This suggests that the Default Treatment may better focus decision makers' attention on the new information (shown in the decision screen charts) provided by the CDSS even when it does not report a recommended decision.

5.e Effects of Capacity Constraint

The probit regressions in Table 2 show higher readmission rates in the presence of the 45-day constraint. The OLS regression shows, however, that LOS of regular patients is not affected by the 45-day constraint. But these figures are confounded with differences in numbers of patients discharged between the no-constraint and 45-day constraint treatments. We seek to isolate the effects on readmissions per patient discharged. For each subject we constructed a new variable, ReadmissionRate, which is the number of patients readmitted divided by the total number of discharges. Figure 7 shows kernel densities of this variable for both designs, with and without the 45-day constraint. It can be easily seen that the readmission rates are higher for subjects who were making discharge decisions under the 45-day constraint. The mean readmission rates are 7.5% and 11.9%, respectively, in the no-constraint and 45-day constraint treatments; the

differences are statistically significant at 1% (p-value reported by t-test is 0.0001; nobs are 51 and 54).[36]

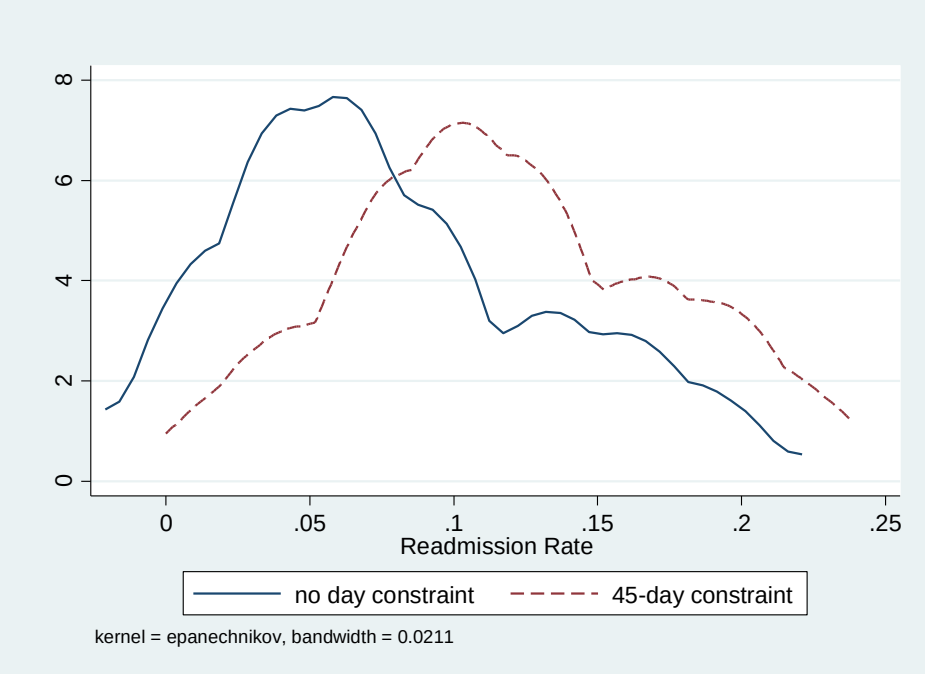

Figure 7. Kernel Densities for Readmissions/Discharges

5.f Reduction in Length of Stay

According to their electronic medical records, the 30 patients whose de-identified charts are used in our experiment were kept in the hospital an average of 9.37 days. In our Baseline Treatment, the average length of stay (LOS) was 8.6 days. This reduction may have resulted from the exclusive focus on the discharge decision created by the experimental environment. The average LOS in the Default Treatment was 7.42 days, which is 14% lower than the Baseline number of 8.6 days. This reduction in LOS did not produce higher readmission rates since the rates for the Baseline and Default Treatments were, respectively, 10.2% and 9.8% .

[36] If we include residents (who participated only in the no-constraints design), we still find that the mean readmission rates are 7.8% and 11.9% respectively in the no-constraint and 45-day constraint treatments. The t-test rejects the null hypothesis in favor of the alternative hypothesis of higher readmissions in the presence of the 45-day constraint at 1% (p-value is .0001). Numbers of observations are 71 and 54 in the no-constraint and 45-day constraint treatments.

6. Summary and Concluding Remarks

The hospital discharge decision plays a central role in the increasingly important interplay between the quality of healthcare delivery and medical costs. Premature discharge can lead to unplanned readmission with higher costs and questionable quality of care. Needlessly delayed discharge wastes increasingly expensive healthcare resources.

Our research program has analyzed patient data to identify risk factors for unplanned hospital readmissions (Kassin, et al. 2012), elicited physicians' stated criteria for discharge decisions (Leeds, et al 2013), estimated predictors of physicians' actual discharge decisions (Leeds, et al. 2014), and estimated clinical and demographic patient variables that predict successful vs. unsuccessful discharges (Leeds, et al. 2014). Inconsistencies between stated criteria, statistically-explanatory actual criteria, and predictors of successful discharge suggest that discharge decision making might be improved by application of large-sample, evidenced-based discharge criteria at the point of care where the discharge decision is made. Our approach to providing a tool for improving discharge decision making is to develop and test a Clinical Decision Support System (CDSS) for hospital discharges.

Cox, et al. (2014) reports development of the CDSS and a preliminary laboratory experiment on its efficacy. The present paper reports a laboratory experiment with efficacy of the CDSS in a treatment that makes the recommendation of the CDSS the default option. We also report results from a treatment that places time pressure on decision makers and analyze data from all laboratory experiments with the CDSS to date.

Taken together, our laboratory experiments produce data for treatment cells in a 2 by 3 design that crosses presence or absence of a 45 experimental day constraint with Baseline, Information, and Default Treatments. The Baseline Treatment presents subjects only with the kind of information that they receive from currently-used electronic medical records (EMR); indeed, the subject screens used in the Baseline Treatment are facsimiles of EMR screens. The Information Treatment uses these same EMR-facsimile screens plus a new screen that reports information provided by the decision support model. The information screen shows point estimates of marginal readmission probabilities and their 80 percent error bounds for experimental days prior to and including the relevant experimental decision day. The information screen displays six charts of dynamically-selected clinical variables that the probit regression model indicates have the highest marginal effects for predicting outcomes from discharge of that patient on that day during their hospital stay. Finally, the information screen shows one of three

recommendations (discharge, physician judgment, or do not discharge) that are based on the relationship between Medicare's target readmission probability for patients with the relevant diagnosis code and the readmission probability point estimate and 80 percent confidence interval for the patient whose data are under consideration. The Default Treatment differs from the Information Treatment by changing the default option for patient discharge. In the Information Treatment, the default option is that the patient remains in the hospital unless the responsible decision maker initiates an affirmative discharge order. In contrast, in the Default Treatment the patient is discharged or *not* discharged according to the recommendation of the decision support software unless the decision maker overrides that recommendation and provides reasons for rejecting it.

Data from our experiment provide support for efficacy of the CDSS with respect to the two central performance measures for hospital discharge decision making, lower readmission rate and shorter length of stay. The data also provide support for effectiveness of the CDSS in promoting time efficiency in making discharge decisions and for the traditional experimental economics performance measure of subject earnings in the experiment. The CDSS is more effective in the Default Treatment than in the Information Treatment; in other words, combining the information provided by the CDSS with making the software's recommendation the default option is more effective in promoting better discharge decisions than simply providing the information. Superior outcomes with the Default Treatment occur even for the subset of experimental days in which the CDSS does not offer a recommended decision; hence it is not solely subjects' conformance to recommendations that accounts for the treatment effect. Subjects perform generally better in the absence than presence of a ("45 experimental day") constraint that puts them under time pressure. Subjects who report they place relatively high value on information provided by the CDSS make better discharge decisions.

Further research collaboration is in progress. The next stage of research on the hospital discharge decision involves patient ward intervention. This requires development of a version of the CDSS that can interact with electronic medical records systems in real time and development of the protocol for the intervention.

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