Health spillovers among hospital patients: Evidence from roommate assignments

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Abstract:

Background: The tendency of an individual to conform to or be affected by others has been reported for many health variables (mental health, obesity, mortality, etc.) and in a variety of social contexts (family, friends, co-workers, etc.). Examining social spillovers in health among hospital patients holds potential for better understanding and improving patient hospitalization experiences and outcomes. Goal: This study is an empirical examination of spillovers in health among patients hospitalized in an acute care hospital, using data on quasi-random hospital roommate assignments and a longitudinal measure of the patient's clinical condition. Mechanisms of transmission of social spillovers in health among hospital patients are also explored. Data and setting: The sample includes 1,392 females and 1,251 males who were discharged from a large urban teaching hospital during 6/1/11-12/31/11 and who had at least one roommate throughout the duration of their entire hospital stay. The clinical condition measure is the *Rothman Index*, an automatically generated and continuously updated score calculated based on a set of clinical variables using a novel clinically validated algorithm adopted by the study hospital. All data were obtained from the hospital's electronic medical records. Analysis: The study estimates a standard lagged linear-in-means peer influence model. The focus patient's clinical condition score at discharge (*t*) is regressed on the average admission clinical condition score (*t-1*) of his/her roommates weighted by the proportion of stay spent with each roommate, conditional on the patient's own clinical condition at admission (*t-1*) and a set of controls for the patient's characteristics and room assignments. Identification: Empirical studies of social spillovers face important identification challenges including unobserved selection bias, endogeneity (or reflection) bias, and bias from shared exposure to common environmental factors. The identifying source of variation in this study is variation in the clinical condition of the patient's roommates. Patients were assigned to rooms based on gender, diagnosis, and care needs. Balancing tests support that, conditional on a set of observable patient characteristics (gender, diagnosis) and room fixed effects, roommate assignments were plausibly exogenous (that is, the patient's clinical condition score at the time of admission was uncorrelated with the admission scores of his/her roommates). Conditional randomization of roommate assignments deals with unobserved selection, and using a pre-exposure measure of the roommate's clinical condition deals with confounding due to reflection and shared exposure to the common environment. Results: The study finds evidence of social spillovers in health for females – sharing a room with healthier patients lead to a better clinical condition at discharge (close to a half a point higher discharge patient condition score of the focus patient for every 1 standard deviation increase in the average clinical condition score of the roommates). Female patients with healthier roommates also had significantly lower odds of being readmitted back to the hospital after discharge. The study further shows that these effects are unlikely to be the result of indirect spillover effects through rivalry for care; rather, the spillovers appear to operate through psychological pathways. No similar effects were observed for male patients.

Keywords: peer effects, hospital roommates, natural experiment

JEL classifications: H1

I. Introduction

A large body of empirical literature suggests that a person's health is subject to social network effects, also referred to as social spillover effects or peer effects. The tendency for an individual to conform to, adopt, or imitate the behaviors of other individuals within some social contexts (family members, friends, neighbors, co-workers, etc.) has been reported in many health behaviors and outcomes, including smoking, drinking, exercise, diet, obesity, mental health, utilization of healthcare services, and even mortality. (Christakis, Fowler 2007; 2008; 2012; Cacioppo et al 2009; Fowler and Christakis, 2008; Eisenberg et al 2013; Yakusheva and Kapinos 2011; Yakusheva et al. forthcoming; Eagly and Chrvala 1986; Mears et al 1998; Kapinos and Yakusheva 2011; Fletcher in press.) Evidence of health spillovers is important from the policy perspective – in the presence of network externalities, a health-related intervention is capable of effecting a change in health beyond the group initially targeted by the policy. (Fowler and Christakis 2008.)

Examining health spillovers among patients in acute care holds potential for better understanding and improving patient hospitalization experiences and outcomes.

Peer effects among patients sharing a room during hospitalization is a largely unexplored domain of patient experiences. Studies of patient preferences regarding room type show that 10-30% of patients prefer a shared room, because they enjoy the companionship and shared experience or wish to avoid feelings of isolation. These patients tend to be elderly, have limited social support outside of the hospital, and suffer from medical conditions associated with a poor prognosis (e.g. oncology patients). (Hill-Rom 2002; White 2003; Contemporary Longterm Care 1997.) A study of patient experiences in multi-occupancy rooms in Norway describes substantial amounts of interaction among patients, including sharing information about their illnesses, treatments, or staff, and even offering help with daily tasks. It is also not uncommon for patients to provide informal surveillance by alerting medical staff to potential needs or safety concerns regarding their roommate. (Album 1998; 2010.) One study compared patient outcomes between private and semi-private rooms and found evidence of clinical benefits of the shared room for the elderly patients with delirium, including lower mortality, fewer falls, and less frequent use of medication. (Flaherty 2003.) In two other studies, assigning a pre-operative patient to share a room with a post-operative patient significantly reduced anxiety and sped up post-surgical recovery among coronary-bypass patients. (Kulik and Mahler 1987; Kulik et al. 1996.) While these findings point to the existence of peer effects among patients in acute care settings, they offer evidence that is largely descriptive and based on narrowly defined patient populations.

Empirical studies of peer effects face several identification challenges first laid out by Manski (1993). Sources of bias in peer influence estimates include unobserved peer selection (also referred to as homophily), endogeneity due to reciprocal nature of peer influence (also referred to as reflection), and spurious peer correlations driven by exposure to unobserved environmental and contextual effects. A variety of estimation strategies have been utilized in order to correct for these confounding factors, including lagged peer characteristic specifications and instrumental variable approaches to deal with selection and reflection, and aggregate-level fixed effects to deal with confounding from exposure to shared environmental influences. Several peer effect studies took advantage of a natural experiment involving random peer assignment (college roommate assignment, military squadron assignments) to overcome the selection bias, and used pre-assignment peer characteristics to avoid confounding from reflection and exposure to shared environment (Yakusheva and Kapinos, 2011; Yakusheva et al. forthcoming; Carrell and Hoekstra 2011). This study uses quasi-random assignment of hospital roommates to examine the importance of peer health effects among hospitalized patients.

A key contribution of this study is a focus on the role of peer effects for patient outcomes at discharge and during the immediate post-hospitalization period, using plausibly random variation in roommate characteristics and repeat measures of patient clinical condition which allows us to deal the abovementioned biases. Our results show significant peer effects for female patients – sharing a room with healthier patients leads to a greater improvement in own clinical condition during hospitalization, as well as reduced odds of readmission. We do not observe similar effects for males. We further find that these effects are not driven by having to compete for nursing care; rather, the mechanism of peer influence appears to operate through psychological pathways.

II. Data

The study follows adult patients hospitalized on medical and surgical units and sharing a hospital room with other patients from admission to discharge. The study uses proprietary data extracted from the electronic medical records of a non-profit tertiary medical center in New Haven, CT. The medical center is accredited by the Joint Commission and has been designated by the American Nurses Credentialing Center as a Magnet facility. It has 854 adult beds and close to 56,000 annual discharges. A total of 15 units (11 medical and 4 surgical) offer shared rooms; there are 93 shared rooms (86 two-bed rooms and 7 three-bed rooms) on these 15 units.

The data were extracted from three data bases within the study hospital's electronic information system: the Record Information Management System (RIMS) included data on utilization (hospitalizations prior to the index event and readmissions), mortality, patient characteristics (age, sex, diagnosis, insurance), and costs; the clinical data base from the electronic point of care system (Sunrise Clinical Manager (SCM), Allscripts, Chicago, IL) provided data on the patient's clinical condition that was updated multiple times on a daily basis throughout hospitalization; lastly, the Patient Activity Database (PAD) recorded and time-stamped the patient's point of admission, discharge, and every transfer/movement within the hospital and was used to track the patient's location throughout hospitalization and to match patients with their roommates based on overlaps in the dates and times (to ¼ of an hour) of in- and out- transfers for each room.

The data included 26,760 adult (18 and older) discharges that occurred between July 1 and December 31 of 2011. We exclude patients admitted for observation only, as well as patients admitted for psychiatric, pediatric, obstetric/gynecology, diagnostic imaging, and dentistry services, leaving us with the sample of 13,131 adult medical-surgical patients. We further limited the sample to patients who had at least one roommate (n=8,904) and who were with a roommate 90% or more of the total time they were in the hospital (n=3,417). Patients who spent a 10% or more of their stay in alone in a shared room or in a private room were excluded because decisions to isolate a patient are often driven by disease-related factors (e.g., infection) and insurance type and may correlate with outcomes of hospitalization. A total of 366 patients were excluded due to missing clinical data, and an additional 408 patient were excluded due being matched to roommates with missing clinical data, resulting in a final sample of 2,643 patients (1,392 females and 1,251 males).

<u>Variables:</u> the main measure of a patient's health is the *Rothman Index (RI)* score available in the hospital electronic health records. The RI score is a novel way of monitoring the patient's clinical condition throughout the course of hospitalization that was been adopted by the study site and available in the electronic health records. (Rothman et al. forthcoming; Rothman et al. 2012; Rothman et al. 2013.) The RI score is automatically calculated for each patient and updated multiple times on a daily basis, using proprietary software and an algorithm that has been clinically validated using different patient demographics and in multiple hospitals. The RI tracks each patient's condition metric over the course of hospitalization and is calculated by evaluating and integrating 26 medical measurements available in the electronic health records (EHR). The variables used in computing the RI are: vital signs (e.g., temperature, blood pressure, etc.), Braden Scale (a score used to assess the likelihood of skin

breakdown), heart rhythms (sinus bradycardia, sinus rhythm, etc.), lab tests, and nursing assessments (e.g., food/nutrition, psycho-social, etc.). The RI score is a subtraction index from 100 with a theoretical range of (-69 to 100) and higher values indicating better clinical condition. In previous studies, when the patient's RI score was less than 40, the patient experienced a five-fold increase in the risk of 14 day mortality, and the RI score of less than 70 at the time of discharge was associated with close to a 3-fold increase in the risk of an unplanned 30 day readmission. (Rothman et al., forthcoming; Bradley, Yakusheva et al., 2013.) We used the patient's RI score at the end of each roommate exposure spell, and the change in the RI score (difference between the RI score at the end and the RI score at the beginning of a roommate exposure spell) as the main outcome measures, and the patient's own RI score at the beginning of the roommate exposure spell as a control variable. We also examine other patient outcomes including: *unplanned readmission* (a binary indicator for having a record of an unplanned readmission to the same facility within 30 days of the discharge date); *length of stay* (number of days between the time of admission and the time of discharge); and c*ost of hospitalization* (total cost equal to the sum of direct and indirect costs estimated by the hospital's cost-accounting system).

Our main peer variable is the roommate's RI at the beginning of the exposure spell. We used the roommate's start-of-spell RI as a continuous variable and also categorized it into five bins based on the quintiles of the RI distribution (Very low (<60), Low (60-72.4), Medium (72.5-81.4), High (81.5-88), and Very high (>88). Control variables included the patient's demographic characteristics (age in years, sex), insurance type (Medicaid including managed Medicaid; Medicare including managed Medicare; Blue Cross or commercial including managed care commercial; and "other," which included self-pay, grant funded, and other insurance), reason for admission (medical or surgical), diagnosis fixed effects, and room fixed effects. The discharge diagnosis fixed effects categorized patients based on the diagnostic groups as defined by the Agency for Healthcare Research and Quality (AHRQ) Clinical Classification Software (CCS).[1] Table 1 shows the descriptive characteristics of the sample.

Room Assignments: The assignment of newly admitted patients to beds was conducted through computerized bed assignment software. A nurse manager logs into the system and is presented with a screen showing a diagram of the real-time status of all of the beds on the designated unit, as well as their location on the floor, type of room, and the proximity to the nurse station. (See Figure 1.) Beds are color-coded to show which were available or will soon become available, as well as, for shared rooms, the gender of the patient occupying the other bed and whether or not the patient is an isolation patient. The average occupancy rate on the study units was over 90%. Being located in an urban area with a large proportion of low-income uninsured patients, many hospital encounters were unplanned admissions through the emergency room. When a bed was unavailable at the time of admission, new patients were assigned to "virtual beds" (the grey squares underneath the unit chart) and placed in the hallways until a regular bed became available. Several of the hospital administrators we spoke with shared that bed assignments for non-infectious patients (those who not requiring isolation) were largely based on space availability; however, patients were almost always assigned to rooms with patients of the same gender, and, whenever possible, sicker patients requiring more care were placed in rooms located closer to the nursing station.

III. Analysis

We estimate a variant of the standard lagged linear-in-means peer influence model (Manski 1993) where the clinical condition of the focus patient is regressed on the peer group-average of the corresponding characteristic of the roommates. The conventional lagged linear-in-means equation has the following form:

[1] Categories with 10 or more patients were assigned a unique fixed effect, categories of less than 10 patients were combined into the reference category.

$$Y_{i1} = a_0 + \beta_0 \bar{Y}_0^{-i} + \gamma_0' Z_{io} + DX_i + R_i + u_i, \qquad (1)$$

where Y_{i1} is the focus patient's clinical condition at time 1 and $\bar{Y}_0^{-i}$ is the roommate group average clinical condition at some prior time 0; Z_{io} is a vector of patient controls (age, type of insurance, history of a prior hospitalization within 30 days, type of admission (medical or surgical) and patient i's own RI score at time 0); and DX_i and R_i are the diagnosis and room fixed effects. Due to documented gender differences in social network effects, we conduct all of our analyses by gender. The social spillover effect, or peer influence, is captured by coefficient β_0, which can be used to calculate the social multiplier, or the total effect of a unit change in the peer group average clinical condition, 1/(1-β_0).

In observational studies of naturally occurring peer settings (family, friends, neighborhoods), the coefficient β_0 is often biased due to unobserved peer selection, exposure to common environmental influences, and endogeneity. Although hospital patients do not choose their roommates, a selection bias may arise because the bed assignment process matched patients based on their diagnoses and care needs. A positive correlation between a patient's clinical condition and that of his roommate could then arise in the absence of peer effects, because similar patients are assigned to the same room (selection bias) or as a result of variation in nursing care quality (common environmental influence). Even when the correlation is due to peer effects, it may overstate the size of the true causal effect of the roommate's health status on the patient because the patient can influence the roommate (reflection or endogeneity bias). Examining social spillovers in health among hospital patients requires properly accounting for these confounding influences.

This study relies on quasi-randomized peer assignment process – bed assignments are determined based on a set of observable characteristics (gender, type of admission (medical vs. surgical), diagnosis, and room type including size, location on the floor, and type of equipment) as well as exogenous variation in occupancy space availability. Table 2 presents a set of balancing tests, by gender, before and after controlling for the type of admission, diagnosis fixed effects, and room fixed effects. The results show strong unconditional correlations in almost all of the clinical and demographic measures between the patients and the roommates (column 1). However, once the clinical factors used in the bed assignment process are controlled for, none of the conditional correlations between patients and their roommates remain statistically significant. These results support conditional randomization of hospital roommate assignments in our study. Furthermore, because the clinical condition is updated repeatedly from admission to discharge, we are able to use lagged pre-exposure peer measures of the roommates which deals with bias from endogeneity of influence and exposure to shared environment. Therefore, we are able to estimate the peer influence coefficient that is minimally confounded by biases many earlier peer effect studies struggled with.

Using the standard linear-in-means approach (1) on our data may have limitations due to the fact that patients are often not exposed to all of their roommates at the same time, nor are they necessarily exposed to each of their roommates for the same duration of time. For example, consider patient P hospitalized in a three-bed room, who shares the room with roommate R1 on days 1 and 2 and with roommate R2 on days 2, 3, and 4, of his four-day hospital stay. Using the average of the admission clinical condition scores of the roommates as the peer variable would ignore the fact that the second exposure spell was longer than the first, as well as the fact that R2 could not have exerted causal influence on the P's health trajectory during day 1.

To properly account for the specific data structure in our study, we estimate a dyadic peer influence model where a patient is linked to each of the roommates. For the patient in the above example, this approach results in two dyadic observations (P&R1), (P&R2). To adjust for unequal exposure spells and to avoid giving undue attention to patients with multiple roommates, we weight the data by the standardized proportion of stay spent with each roommate. In the above example, the first observation (P&R1) would receive the weight 2/(2+3) = 2/5, and the second observation (P&R2) would receive the weight 3/(2+3) = 3/5. Note that the weights add up to 1 and that the ratio of the weights reflects the ratio of the individual roommate exposures. The dyadic sample has 2,707 female and 2,170 male patient-roommate observations.

In order to align patient health outcomes with the timing of each of the roommate exposure spells, we link the patient's clinical condition score at the end of each of the exposure spells to the roommate's clinical condition score immediately prior to the beginning of the exposure spell, controlling for the patient's own clinical condition score immediately prior to the beginning of the spell. Our clinical condition measure, the RI score, is updated an average of 14 times daily, which allows us to establish accurate pre-exposure and end-of-exposure measurements within less than two hours of the actual beginning and ending of each roommate spell (average is 35 minutes).

Our main estimation model, therefore, is the following:

$$Y_{ij1} = a_1 + \beta_1 \bar{Y}_{ij0} + \gamma_1' Z_{io} + DX_i + R_i + u_{ij}, \qquad (2)$$

where Y_{ij1} is patient i's RI score at the end of patient i's exposure to roommate j, $\bar{Y}_{ij0}$ is roommate j's RI immediately prior to the beginning of patient i's exposure to roommate j, Z_{io} is a vector of patient i's controls including i's own RI prior the beginning of spell, and DX_i and R_i are the diagnosis and room fixed effects. The model is weighted as described above and the standard errors are clustered at the patient level.

As a robustness check, we also estimate a second variants of model (2), a change model instead of a level model, using the change in RI during the exposure spell of patient i to roommate j, ΔY_{ij}, as the dependent variable:

$$\Delta Y_{ij1} = a_1 + \beta_1 \bar{Y}_{ij0} + \gamma_1' Z_{io} + DX_i + R_i + u_{ij}. \qquad (2')$$

Here, all of the notation is the same as above, with the only exception that vector Z does not include the patient's own RI score at the beginning of the roommate exposure spell.

The social spillover effect is captured by coefficient β_1, which reflects, in both models (2) and (2'), the statistical effect of a unit change in the roommates' average starting RI on the patient's RI change during the exposure spell (model (2) controls for the patient's beginning-of-spell RI; therefore the coefficient is interpreted as it is in the change model). Because of the inverse frequency weighting, the peer effect estimate is qualitatively equivalent to the conventional social spillover estimate $\beta_0$in model (1) and can be made quantitatively equivalent by adjusting for the proportion of an average roommate spell in the total length of hospital stay. A positive and significant coefficient would suggest that sharing a room with healthier patients is associated with a greater improvement in clinical condition during hospitalization and it would be consistent with positive spillovers in health,.

In addition to the patient's clinical condition, we also examine several other outcomes of hospitalization including the length of hospital stay, the total cost of hospitalization, and the likelihood of readmission within 30 days post-discharge. Due to the skewedness of the distributions of the length of stay and costs, we log-transform these variables prior to estimation and use a linear regression model similar to model (2). We use a logistic regression for readmission, after limiting our sample to first admissions (no prior admission within 30 days) that did not end in a death.

IV. Mechanisms of transmission

Traditionally, peer effect studies focus on *direct* peer influence conceptualized as changes in an individual's behaviors or outcomes that occur as a result of observing and adopting similar behaviors or outcomes of the peers. This direct peer influence is typically hypothesized as being due to learning (information sharing about adoption of positive behaviors/outcomes or avoidance of negative behaviors/outcomes), social norm creation (desire to conform with a social norm or expectation), and economies of scale (reduced cost of engaging in a behavior together with peers). While direct peer influences due to economies of scale are unlikely to be present in an acute care setting, patients may receive information from their roommates about positive disease management techniques (learning), or they may feel better when they observe their roommates coping effectively during hospitalization (social norm effects).

An acute care setting can offer another mechanism of transmission of peer influence whereby peer effect could occur *indirectly* through rivalry in access to limited resources. For example, it is possible that having healthier roommates may benefit a patient even in the absence of any direct peer influence effects, simply because they utilize fewer hospital resources thus allowing clinicians to more effectively attend to the patient's needs. This indirect peer influence through rivalry in access to care is a peer effect in a sense that an exogenous change in the roommate characteristic can resulting in better or worse outcomes for the patient. However, unlike direct peer influence, the indirect peer effect has limited policy implications because it does not involve an underlying behavioral change and will not generate policy multipliers.

We examine our data for the evidence of both direct and indirect peer effects. In order to examine indirect peer effects, we create a variable equal to the daily count of RI updates during each roommate exposure spell. Because the RI updates are prompted by the entry of new data into the system (lab tests, nursing assessment inputs, physician assessments, vital signs updates, etc.), a higher count of updates is indicative of a more frequent care activity. (Table 1.) We use this variable as the left hand side variable in model (2) to estimate the effect of the roommate's clinical condition on the amount of daily care activity received by the focus patient during the roommate exposure spell, conditional on the patient's own clinical condition at the beginning of the spell.

In order to examine direct peer influence, we examine the patient's psychosocial assessment as an outcome in model (2). Psychosocial assessment is part of a standard nursing assessment that usually occurs twice daily and is one of the components in the RI computation. During the assessment, the nurse is asked to "agree," "agree with comments noted," or "disagree" with the statement that reads, "Patient/family coping effectively." (Table 1.) Unfortunately, the study hospital was unable to provide the nurse assessment sub-components of the RI scores for the entire study sample. Additionally, because of the low frequency of nursing updates, our ability to link the patient's psychosocial status to each individual roommate spell was limited. Therefore, we create a binary indicator equal to 1 if the nurse disagreed with the statement at the time of the last assessment before discharge, and estimate a logistic model similar to model (2) on the subsample of 923 females (1,523 observations) and 856 males (1,373 observations) for whom the nursing assessment component was available.

V. Results

Sample descriptive characteristics: The average patient was 59.79 years old, with 29% patients being privately insured, 22% and 46% of patients being on Medicare and Medicaid, respectively, and 12% uninsured. Surgical admissions constitute 22% of the sample, and close to 13% of the sample had another admission within 30 days prior to the index admission. The average RI at admission was 80.77 (SD=13.36, range 15.3-99.6), and the average RI at discharge was 81.94 (SD=12.97, range 9-99.3). The length of stay and costs were skewed to the right with the average of 2.97 days (SD=2.99, range 1-66) and $9,391 (SD=10,557.38, range 0-185,331.90), and the log-transformed means were 2.3 days and $6,682.82, respectively. A total of 12.3% of the admissions were followed by a readmission within 30 days post-discharge.

On average, a patient was exposed to 1.85 roommates during hospitalization, and the average proportion of stay spent with each roommate was 0.72. Roommate's demographic characteristics were similar to those of the focus patients; however the roommates, on average, had significantly lower RI scores, were older, and were more likely to be on Medicaid. This is due to the fact that, by limiting our sample to patients who spent 90% or more of their stay in shared rooms, we eliminated patients who spent a significant part of their stay in isolation or intensive care therefore increasing the sample proportion of healthier patients.

<u>Roommate effects on clinical condition</u>: The main estimation results for social spillover in clinical condition (model 2) are presented in Table 3. The first four columns of results are for female patients, and columns 5-8 are estimates for male patients. Columns 1 (females) and 5 (males) show the estimates of the main peer influence model in levels (model 2), and columns 2 (females) and 6 (males) are for the change model (model 2'). The rest of the columns show the results with the roommate's clinical condition measure categorized into 5 quintiles (lowest omitted) instead of the continuous RI variable, and they are arranged in the same manner.

The results show a positive statistically significant peer effect for female patients, but not for male patients. For female patients, a 1 point increase in the roommate's average beginning-of-spell RI score is associated with a 0.026 point greater change in RI over the course of an average roommate spell ($p<0.05$). Given than average roommate spell is 0.72 of the hospitalization, this estimate is equivalent to 0.036 point increase over the course of hospitalization for every 1 point greater RI score of the roommate, or 0.505 points greater change in RI over the course of hospitalization for a standard deviation change in roommate's RI (SD=14.04). In the categorical model, compared to patients whose roommates were in the lowest RI category (RI<60), those with roommates in the high (81.5-88) and very high (>88) RI categories experienced more than a 1.3 point greater change in RI.

These results suggest that a female patient's hospitalization experience is determined, in part, by the clinical condition of her roommates, and are consistent with the ideal of social spillovers in health. While the magnitude of the estimate in our study is small, suggesting a social multiplier of only 1.037 (=1/(1-0.036)), it needs to be noted that these effects were estimated based on a small group of peers (less than two roommates, on average) and over a very short amount of time (2-3 days). Therefore, they are indicative of potentially much larger effects in broader contexts.

Roommate effects on length of stay, costs, and readmission: Estimates of roommate effects on other outcomes of hospitalization (length of stay, costs, and readmission) are presented in Table 4A (females) and Table 4B (males). For female patients, we observe no significant effects on length of stay or costs; however female patients with healthier roommates are significantly less likely to be readmitted. A one point increase in the roommates' average RI score is associated with 0.984 ($p<0.05$) odds of an unplanned readmission; compared to patients with roommates in the lowest quintile of the RI distribution, patients with roommates in the three highest quintiles have the odds of 0.44-0.57 ($p<0.05$) of being readmitted within 30 days following discharge.

We do not observe similar effects for male patients; however male patients show a negative association between the length of stay and the roommate's clinical condition, -0.00263 ($p<0.01$) or a 0.3% reduction in the length of stay for a 1 point increase in the roommates' average RI score; relative to the lowest roommate RI category, the length of stay was 8-10% shorter when a male patient had roommates in the top two RI quintiles. In combination with a lack of significant differences in clinical condition or likelihood of readmission, this finding might suggest that male patients with healthier roommates may be recovering quicker prompting a sooner discharge without sacrificing the quality of care. The absence of cost savings could be explained by the current claims and reimbursement schemes where cost computations are based on the discharge diagnosis and may not accurately reflect the actual utilization of resources in each individual case. Therefore, while the evidence of peer influences is weak for male patients, the results in Table 3 are consistent with the overall notion of positive social spill-overs in health.

Mechanisms: The results do not support the notion that the peer effects observed in our sample were driven by indirect effects through care delivery. (Table 5.) On the contrary, patients with healthier roommates appear to receive care less frequently than patients with sicker roommates (-0.0570, p<0.01). Compared with patients sharing the room with roommates in the lowest RI quintile, patients sharing a room with roommates in the top 3 quintiles receive care 1.3-1.9 times per day less frequently, conditional on their own care needs. This may be due to the existence of economies of scale in care delivery, whereby providing care to a sicker patient reduces the marginal cost of care delivery to *all* patients sharing the room, resulting in more frequent attention for all patients. It is also possible that more frequent visits of clinicians to the room to attend to a sick patient make other patients more likely to voice their concerns or ask that their own care needs are met more frequently. These effects are similar for male patients, but they are smaller in magnitude, (-0.0239, p<0.10).

Lastly, we explore direct peer effects on the patient's psychosocial assessment in Table 6. The results show some evidence that patients sharing a room with healthier roommates are more likely to cope effectively with their condition during hospitalization. In particular, female patients are 1.36% (p<0.10) less likely to be assessed as coping poorly at the time of discharge for every 1 point increase in the clinical condition of their roommates, and patients with roommates in the highest RI quintile (RI>88) are almost 4% (p<0.10) less likely to be assess as not coping effectively. Given that the overall prevalence of poor coping at discharge in the sample, 8.4%, this represents a large effect size, and is consistent with direct social spillovers in health. We observe no similar effects for males.

VI. Limitations

Although the present study was able to examine social spill-overs in health in a setting with plausibly exogenous peer assignments, we would like to point out several limitations. Our main outcome measure, the Rothman Index, is a measure of clinical condition and may not accurately reflect the patient's overall health status. The data come from a single facility and do not allow to examine readmissions to other facilities. Due to the sample restriction of >90% of hospital stay in a shared room, patients included in the study had lower severity of illness compared to the typical patient population; mortality rates were insufficient for analysis. Follow-up data after discharge were not available which precluded the study of longer-term effects. The inclusion of diagnosis and room fixed effects was necessary to insure conditional randomization of roommate assignments; however it reduced signal and power to detect small and medium effect sizes, particularly in the psychosocial condition model where the sample size is smaller. The sample used in the study was chosen to insure internal validity of our estimates; however the results may not be generalizable to other populations, including other patient populations.

VII. Summary and conclusions

The study examined social spillovers in health among hospital patients using quasi-random assignment of hospital roommates as a natural experiment. Using a lagged weighted dyadic peer influence model with diagnosis and room fixed effects, and longitudinal clinical condition data for sample of 1,392 female and 1,251 male adult medical and surgical hospital patients, the study found strong evidence of social spillover effects in health for female patients. Female patients sharing a room with healthier roommates experienced a greater improvement in clinical condition during hospitalization and reduced odds of readmission after discharge. These findings were not driven by indirect peer effects through rivalry for healthcare resources; rather they appeared to be the result of direct peer effects, in particular effect on psychosocial condition and ability to cope. The findings of this study suggest that health policy is capable of producing significant multiplier effects, and open new directions for healthcare researchers and policy makers in improving patient outcomes and reducing costs of care.

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Figure 1. Room assignments

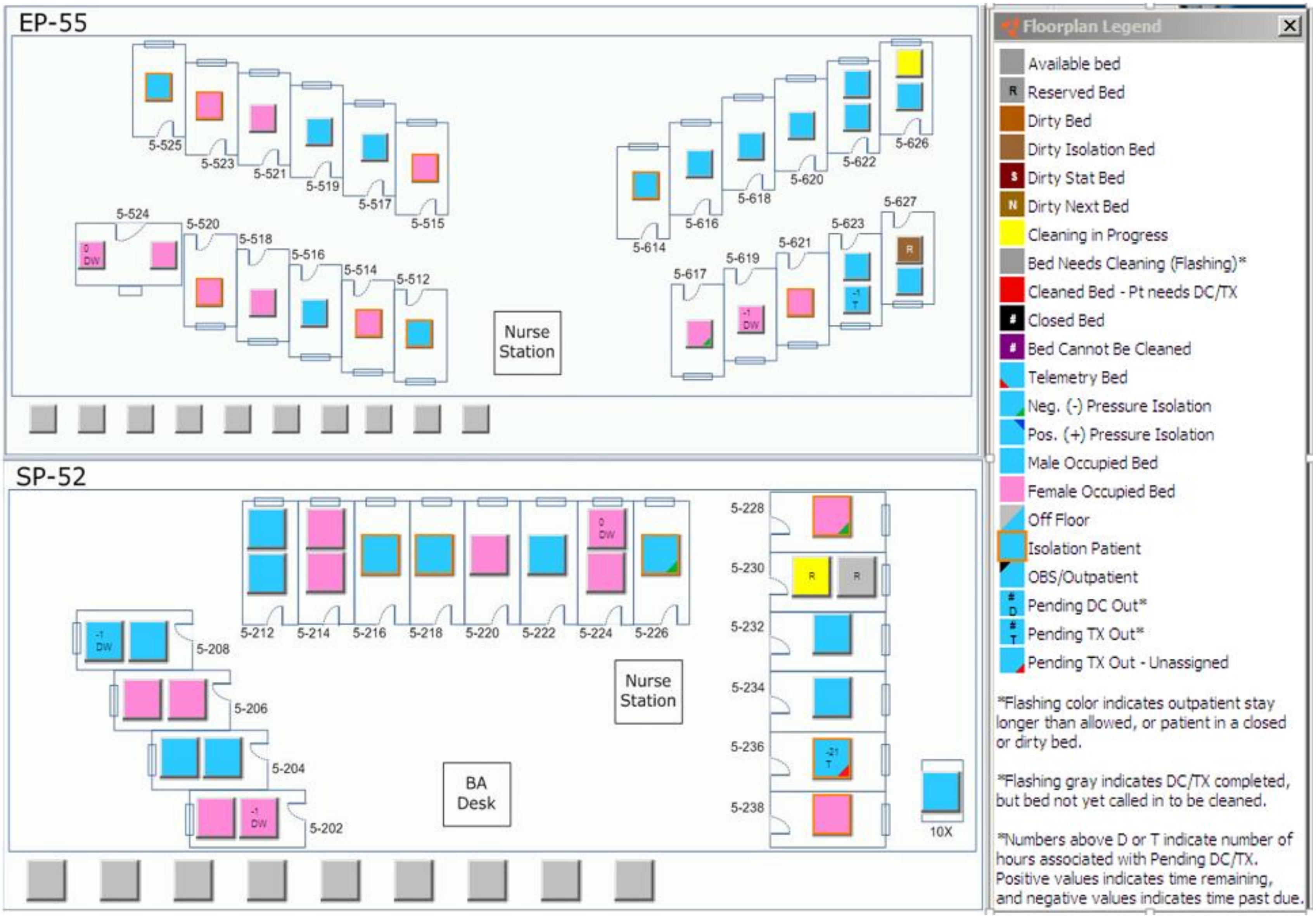

Table 1. Descriptive characteristics of the sample.

Variable	Obs	Mean	Std. Dev.	Min	Max
Patient Characteristics:					
Female	2643	0.527	0.499	0	1
Age	2643	59.790	19.471	18	102
Insurance type					
Private	2643	0.292	0.455	0	1
Medicaid	2643	0.223	0.416	0	1
Medicare	2643	0.456	0.498	0	1
None	2643	0.117	0.269	0	1
Type of admission					
Surgical	2643	0.224	0.417	0	1
Medical	2643	0.776	0.417	0	1
Prior hospitalization w/ 30 days	2643	0.128	0.334	0	1
Rothman Index:					
Admission	2643	80.774	13.356	15.3	99.6
Discharge	2643	81.942	12.970	9	99.3
Start of roommate spell, average	2643	80.787	13.111	18.733	99.600
End of roommate spell, average	2643	81.798	12.775	13.867	99.300
Other patient variables:					
Length of stay					
Untranformed, days	2643	2.972	2.992	1	66
Logged	2643	0.833	0.680	0	4.190
Re-transformed, days	2643	2.300		1	66
Total cost of hospitalization					
Untranformed, $2011	2643	9391.118	10557.380	0.006	185331.900
Logged	2643	8.807	0.824	-5.115996	12.130
Re-transformed, $2011	2643	6682.824		0.006	185331.242
High risk of mortality (dischage RI<60)	2643	0.100	0.300	0	1
Death during hospitalization	2643	0.000	0.019	0	1
Unplanned readmission w/ 30 days	2643	0.123	0.328	0	1
Average daily care activity	2637	14.228	6.314	4	50.364

Psychosocial assessment: effective coping					
Proportion of stay: agree	1577	0.761	0.377	0	1
Proportion of stay: agree, details noted	1577	0.147	0.298	0	1
Proportion of stay: disagree	1577	0.084	0.242	0	1
Roommate exposure variables:					
Proportion of stay in shared room	2643	0.978	0.030	0.9	1
Number of roommates	2643	1.845	1.319	1	30
Proportion of stay spent with a roommate	2643	0.716	0.305	0.033	1
Roommate characteristics					
Female	2643	0.530	0.494	0	1
Age	2643	61.663	16.144	18	101
Private insurance	2643	0.244	0.362	0	1
Medicaid	2643	0.220	0.345	0	1
Medicare	2643	0.511	0.429	0	1
Surgical admission	2643	0.124	0.303	0	1
Medical Admission	2643	0.695	0.443	0	1
AMI	2643	0.027	0.143	0	1
COPD	2643	0.011	0.088	0	1
CHF	2643	0.036	0.165	0	1
PNA	2643	0.026	0.136	0	1
Prior hospitalization w/ 30 days	2643	0.839	0.321	0	1
Rothman Index at start of spell	2643	74.110	14.046	19.1	98.95
Very low (<60)	2643	0.196	0.350	0	1
Low (60-72.4)	2643	0.198	0.343	0	1
Medium (72.5-81.4)	2643	0.197	0.333	0	1
High (81.5-88)	2643	0.202	0.336	0	1
Very High (>88)	2643	0.207	0.339	0	1

Table 2. Balancing tests, by gender.

VARIABLES	Unconditional Females N=1,392 (2,707 obs)	Unconditional Males N=1,251 (2,170 obs)	Conditional Females N=1,392 (2,707 obs)	Conditional Males N=1,251 (2,170 obs)
RI at admission	0.0878***	0.115***	-0.00683	-0.00535
	(8.92e-06)	(2.79e-08)	(0.723)	(0.795)
Age	0.140***	0.177***	0.0152	-0.0194
	(0.0241)	(0.0254)	(0.0158)	(0.0182)
Insurance type:				
Private	0.0700***	0.0148	-0.0171	-0.00170
	(0.0258)	(0.0272)	(0.0177)	(0.0219)
Medicaid	0.0546**	0.0415	-0.0147	0.0107
	(0.0248)	(0.0253)	(0.0181)	(0.0198)
Medicare	0.0870***	0.0634**	-0.0152	-0.00918
	(0.0234)	(0.0254)	(0.0174)	(0.0226)
Prior hospitalization	-0.00682	0.000224	-0.00718	-0.00219
	(0.0221)	(0.0230)	(0.0168)	(0.0197)
Type of admission: Surgical	0.481***	0.440***		
	(0.0369)	(0.0360)		
Select primary diagnoses:				
Dysrhythmia	0.125**	0.225***		
	0.0492	0.0482		
Skin infection	(0.0384)	(0.0391)		
	(0.0495)	(0.0507)		
Coronary atherosclerosis	-0.0339***	0.0566		
	(0.00492)	(0.0394)		
Congestive heart failure	0.307***	0.173***		
	(0.107)	(0.0609)		
Acute myocardial infarction	-0.00825	0.0269		
	(0.0122)	(0.0316)		
Pneumonia	0.210***	0.0976**		
	(0.0763)	(0.0446)		

Conditional on type of admission (med/surg) and primary diagnosis and room fixed effects. Observations are weighted with standardized roommate exposure weights; standard errors are adjusted for clustering at the patient level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3. Roommate effects on clinical condition, by gender.

	Females, N=1,392				Males N=1,251			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	RI, t=1	ΔRI	RI, t=1	ΔRI	RI, t=1	ΔRI	RI, t=1	ΔRI
Roommate's RI, t=0:								
RI	0.0261**	0.0255**			-0.0137	-0.0108		
	(0.0117)	(0.0128)			(0.0125)	(0.0140)		
Low RI (60-72.4)			0.813	0.517			-1.281**	-1.159*
			(0.601)	(0.644)			(0.611)	(0.676)
Medium RI (72.5-81.4)			0.481	0.873			-0.931	-0.758
			(0.607)	(0.664)			(0.597)	(0.640)
High RI (81.5-88)			1.180**	1.395**			-0.846	-0.644
			(0.588)	(0.656)			(0.581)	(0.654)
Very High RI (>88)			1.347**	1.317**			-0.676	-0.604
			(0.569)	(0.619)			(0.609)	(0.690)
Patient characteristics:								
RI, start of spell	0.700***		0.699***		0.716***		0.716***	
	(0.0223)		(0.0222)		(0.0264)		(0.0263)	
Age	-0.0609***	-0.00915	-0.0601***	-0.00917	-0.0512***	0.0144	-0.0538***	0.0120
	(0.0155)	(0.0166)	(0.0155)	(0.0166)	(0.0162)	(0.0173)	(0.0164)	(0.0175)
Insurance: Medicare	-2.143***	-1.200*	-2.155***	-1.192*	-1.823***	-1.469***	-1.794***	-1.439**
	(0.580)	(0.642)	(0.581)	(0.641)	(0.501)	(0.559)	(0.502)	(0.561)
Insurance: Medicaid	-1.401***	-0.649	-1.387***	-0.634	-0.899*	0.00354	-0.898*	0.00336
	(0.507)	(0.592)	(0.508)	(0.592)	(0.502)	(0.543)	(0.502)	(0.541)
Insurance: other	0.337	0.665	0.370	0.700	0.810	0.662	0.775	0.627
	(0.511)	(0.576)	(0.513)	(0.578)	(0.548)	(0.602)	(0.549)	(0.603)
Prior hospitalization	-0.784	-0.399	-0.734	-0.394	-1.441**	-0.623	-1.390**	-0.572
	(0.633)	(0.652)	(0.633)	(0.650)	(0.621)	(0.657)	(0.618)	(0.656)
Type of admission: surg	1.087	2.400**	1.115	2.405**	0.170	0.521	0.231	0.581
	(0.901)	(1.028)	(0.904)	(1.031)	(0.865)	(0.936)	(0.871)	(0.950)
Proportion stay alone	-0.634***	-0.191	-0.641***	-0.195	0.0378	0.172	0.0106	0.148
	(0.215)	(0.214)	(0.215)	(0.214)	(0.201)	(0.222)	(0.199)	(0.223)
Observations	2,707	2,707	2,707	2,707	2,170	2,170	2,170	2,170
R-squared	0.761	0.751	0.762	0.751	0.770	0.762	0.771	0.763

All models control for primary diagnosis and room fixed effects. Observations are weighted with standardized roommate exposure weights; standard errors are adjusted for clustering at the patient level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4A. Roommate effects on cost, length of stay, and readmission, females N=1,392.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Cost		Length of stay		Unplanned readmission	
Roommate's RI, start of spell:						
RI	-0.000188		-0.00130		0.984**	
	(0.000896)		(0.000921)		(0.00691)	
Low RI (60-72.4)		0.0168		0.0356		0.765
		(0.0430)		(0.0455)		(0.227)
Medium RI (72.5-81.4)		-0.0341		-0.0331		0.469**
		(0.0431)		(0.0430)		(0.169)
High RI (81.5-88)		-0.00882		-0.0250		0.571*
		(0.0434)		(0.0438)		(0.185)
Very High RI (>88)		0.0129		-0.0452		0.438**
		(0.0434)		(0.0435)		(0.160)
Patient characteristics:						
RI, start of spell	-0.0115***	-0.0117***	-0.0127***	-0.0129***	0.975**	0.974**
	(0.00156)	(0.00155)	(0.00161)	(0.00161)	(0.0109)	(0.0108)
Age	-0.00114	-0.00109	0.000863	0.000935	0.987	0.987
	(0.00130)	(0.00130)	(0.00136)	(0.00136)	(0.0112)	(0.0112)
Insurance: Medicare	0.0847	0.0827	0.146***	0.145***	2.160*	2.129*
	(0.0552)	(0.0552)	(0.0527)	(0.0526)	(0.932)	(0.921)
Insurance: Medicaid	0.0393	0.0384	0.0931*	0.0938*	1.234	1.198
	(0.0496)	(0.0497)	(0.0481)	(0.0481)	(0.484)	(0.465)
Insurance: other	0.0122	0.0134	0.0504	0.0502	1.019	1.029
	(0.0384)	(0.0386)	(0.0394)	(0.0395)	(0.342)	(0.348)
Prior hospitalization	-0.0377	-0.0347	0.0820	0.0814		
	(0.0504)	(0.0505)	(0.0553)	(0.0552)		
Type of admission: surg	0.604***	0.607***	0.185**	0.187**	1.468	1.570
	(0.0914)	(0.0917)	(0.0876)	(0.0878)	(0.942)	(1.005)
Proportion stay alone	0.0375*	0.0368*	0.0691***	0.0691***	1.077	1.084
	(0.0202)	(0.0202)	(0.0204)	(0.0205)	(0.145)	(0.145)
Observations	2,707	2,707	2,707	2,707	2,331	2,331
R-squared	0.502	0.502	0.370	0.371		

All models control for primary diagnosis and room fixed effects. Observations are weighted with standardized roommate exposure weights; standard errors are adjusted for clustering at the patient level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4B. Roommate effects on other outcomes, males N=1,251.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Cost		Length of stay		Unplanned readmission	
Roommate's RI, start of spell:						
RI	-0.00170		-0.00279***		1.002	
	(0.00143)		(0.00103)		(0.00819)	
Low RI (60-72.4)		0.112		0.0533		1.698
		(0.0694)		(0.0500)		(0.577)
Medium RI (72.5-81.4)		0.136*		-0.0617		0.651
		(0.0784)		(0.0499)		(0.261)
High RI (81.5-88)		-0.0394		-0.0853*		0.667
		(0.0687)		(0.0502)		(0.262)
Very High RI (>88)		0.0126		-0.101**		2.013*
		(0.0781)		(0.0490)		(0.752)
Patient characteristics:						
RI, start of spell	-0.0130***	-0.0129***	-0.0164***	-0.0164***	0.968**	0.967**
	(0.00238)	(0.00237)	(0.00176)	(0.00175)	(0.0127)	(0.0130)
Age	-0.000707	-0.000302	-0.000637	-0.000413	1.016	1.016
	(0.00173)	(0.00170)	(0.00144)	(0.00144)	(0.0107)	(0.0109)
Insurance: Medicare	-0.0562	-0.0609	0.0431	0.0406	0.789	0.832
	(0.0624)	(0.0620)	(0.0473)	(0.0473)	(0.318)	(0.339)
Insurance: Medicaid	-0.0902	-0.0846	-0.0501	-0.0486	0.897	1.006
	(0.0565)	(0.0563)	(0.0522)	(0.0520)	(0.343)	(0.388)
Insurance: other	0.0980	0.101*	-0.0315	-0.0269	0.713	0.794
	(0.0606)	(0.0604)	(0.0474)	(0.0473)	(0.251)	(0.279)
Prior hospitalization	-0.161	-0.170	0.131**	0.127**		
	(0.131)	(0.132)	(0.0610)	(0.0613)		
Type of admission: surg	0.303**	0.298**	0.362***	0.357***	0.605	0.590
	(0.136)	(0.136)	(0.0983)	(0.0990)	(0.388)	(0.373)
Proportion stay alone	0.0410	0.0427*	0.0439**	0.0474**	1.150	1.164
	(0.0260)	(0.0258)	(0.0199)	(0.0199)	(0.174)	(0.176)
Observations	2,170	2,170	2,170	2,170	1,869	1,869
R-squared	0.388	0.392	0.435	0.438		

All models control for primary diagnosis and room fixed effects. Observations are weighted with standardized roommate exposure weights; standard errors are adjusted for clustering at the patient level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5. Roommate effects on amount of daily care activity, by gender.

	Females, N=1,392		Males N=1,251	
	(1)	(2)	(5)	(6)
Rommate's RI, start of spell:				
RI	-0.0504***		-0.0239*	
	(0.0114)		(0.0144)	
Low RI (60-72.4)		-0.456		-0.0924
		(0.511)		(0.679)
Medium RI (72.5-81.4)		-1.139**		-0.466
		(0.493)		(0.682)
High Ri (81.5-88)		-1.910***		-0.729
		(0.511)		(0.658)
Very High RI (>88)		-1.765***		-0.779
		(0.529)		(0.712)
Patient characteristics:				
RI, start of spell	0.0188	0.0167	0.0199	0.0200
	(0.0129)	(0.0131)	(0.0182)	(0.0182)
Age	0.0138	0.0140	0.0106	0.0112
	(0.0117)	(0.0117)	(0.0159)	(0.0160)
Insurance: Medicare	-0.348	-0.360	0.251	0.246
	(0.492)	(0.495)	(0.558)	(0.561)
Insurance: Medicaid	0.365	0.338	-0.628	-0.604
	(0.504)	(0.503)	(0.502)	(0.503)
Insurance: other	-0.204	-0.224	-0.00870	0.00232
	(0.499)	(0.502)	(0.566)	(0.569)
Prior hospitalization	0.678	0.625	1.254*	1.239*
	(0.505)	(0.503)	(0.672)	(0.672)
Type of admission: surg	0.0191	0.0870	-1.920	-1.874
	(0.962)	(0.964)	(1.907)	(1.921)
Proportion stay alone	0.651***	0.647***	0.367	0.377*
	(0.198)	(0.198)	(0.226)	(0.227)
Observations	2,673	2,673	2,128	2,128
R-squared	0.269	0.267	0.256	0.255

All models control for primary diagnosis and room fixed effects. Observations are weighted with standardized roommate exposure weights; standard errors are adjusted for clustering at the patient level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1