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Christoph Schwierz, Boris Augurzky, Axel Focke, and Jürgen Wasem*

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Abstract

In times of peak demand hospitals may fail to deliver the high standard of treatment quality that they are able to offer their patients at regular times. To assess the magnitude of these effects, this study analyzes the effects of low staff-to-patients ratios on patient outcomes empirically. We use the variation of patient admissions over time as a proxy for varying staff level. Further, we control for within diagnosis unobservable variation in severity across days with as opposed to days without excess demand. We find that when this variation is ignored in the regression framework, the effect of demand on outcomes is biased upwards. The reason is that when demand is high more patients with a higher unobservable frailty are admitted to the hospitals. After having controlled for this selection of patients, excess demand does not negatively affect patient outcomes.

JEL Classification: I12; I18

Keywords: Hospital staffing, inpatient outcomes

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1. Introduction

Sufficient availability of personnel and infrastructural capacity may affect the quality of in-patient care in acute care hospitals. When demand is unexpectedly high, hospitals may be unable to provide the necessary number and quality of medical personnel and may lack sufficient diagnostic and surgical infrastructure. As a consequence, surgeries may be postponed, avoidable deaths may occur and health costs may increase due to increases in length of stay or the number of otherwise unnecessary readmissions. Such effects have important policy implications. If hospitals are unable to ensure the standards of quality of care in times of peak demand, this increases the benefits of policies ensuring adequate medical capacities, for instance laws requiring minimum staff-to-patient ratios established in California in 1999.

This paper examines the effects of variation in unexpected demand on patient outcomes in acute care German hospitals. These effects have been difficult to analyze empirically. First, most former studies focused on across-hospital comparisons. However, as hospitals widely differ in unobservable hospital and patient characteristics, observed links between demand and patient outcomes may be biased. Biases could result from unobservable hospital differences and/or an unobservable non-random selection of patients into hospitals. Second, even in within-hospital studies, where time-constant unobservable differences between hospitals can be neglected, it is still difficult to control for unobservable differences in patients' severity of illness due to e.g. non-random selection of patients into demand regimes.

Building upon Dobkin's (2003) approach we use a selection-index which captures differences in patients' unobservable severity of illness. It is calculated as the excess share of admissions per diagnosis on days with excess demand as compared to days without excess demand. The intuition is that hospitals experiencing excess demand may partially adapt demand to capacity constraints by selecting patients conditional on their (to us) unobservable risk factors. In particular, Dobkin shows that after correcting for non-random selection in favor of weekday admissions, excess mortality on weekends disappears. The explanation is that due to lower staffing on the weekend hospitals successfully shift low risk patients from weekends to weekdays, thereby increasing the unobservable risk pool of weekend admissions. Once this selection is corrected for, excess weekend mortality vanishes. We transfer Dobkin's approach finding that unexpectedly high levels of demand go along with an excess share of admissions in diagnoses with presumably higher risk factors in unobservable characteristics.

Our dataset is composed of administrative patient-level data of 72 German hospitals from the year 2004. It is the population of all patients treated by these hospitals and includes information of vital events (daily admission and discharge, patient emergency readmission and in-hospital death) and patient characteristics used as risk factors in the analysis. The sample allows for a detailed analysis of the effects of daily changes in demand on patient outcomes.

The empirical analysis basically consists of two stages. First, we construct measures of unexpected demand, unobservable patient selection and patient outcomes. Second, we estimate models explaining patient outcomes where outcomes depend on demand, unobservable patient selection, seasonal factors, as well as patient specific risk factors and unobservable hospital and department fixed-effects.

The paper is organized as follows. Section 2 reviews the literature that has investigated the effects of demand on patient outcomes within the separate frameworks of cross- and within-hospital studies. Section 3 presents the data, as well as the definitions of samples, patient outcomes, and the indices of unexpected demand and unobservable selection. Section 4 specifies the econometric models, while results are described in section 5. Section 6 concludes.

2. Literature review of the effect of demand on patient outcomes

Former studies on patient outcomes related to staffing were either based on across- or within-hospital comparisons. Across-hospital studies usually find positive effects of staff levels on patient outcomes (Aiken et al. 2002; Needleman et al. 2002). Their typical setup is to compare yearly averages of staff-to-patient ratios with average lengths of stay and 30 day mortality rates, after controlling for observable patient, staff and hospital characteristics. The main problems with this approach are measurement errors in staffing, fixed-differences across hospitals and (un-)observable differences in patients' severity of illness. Staffing is difficult to measure adequately, as it differs in functional (nurses, doctors, other staff members) and qualitative (levels of training, experience) aspects. It is difficult to adjust for fixed-differences in technology, as the diagnostic and therapeutic medical apparatus is large, rarely observable in total and its impact on patient outcomes specific.

Moreover and most importantly, patients' average characteristics differ widely between hospitals. This is due to (self-)selection of patient into hospitals and demographic and economic differences in average patient characteristics across regions. Patients self-select into hospitals according to differences in hospitals' reputation (Cutler et al. 2004) or levels of co-payments, whereas hospitals may deliberately choose patients on grounds of expected profitability (Resneck et al. 2004). Since good measures of patients' severity of illness are essential for accurate assessment of the quality of care (Silber et al. 1997) it is important to either control directly for this selection or to base this assessment on a relatively homogeneous sample of patients where selection issues are of minor importance.

One way to attenuate the problem of heterogeneity across hospitals is to focus on within-hospital differences in outcomes. Within hospital studies have the advantage that time-constant unobservable differences in hospital characteristics can be neglected and that patients have fewer differences in observables within than across hospitals. These studies use the variation in patient volume over time as a proxy for variation in effective staff levels. Evans and Kim (2006) analyze the effects of short-term shocks in patient volume on the length of stay, in-hospital mortality and the probability of emergency readmissions. In more detail, they estimate whether an unexpectedly large influx of patients on Fridays and Saturdays negatively affects outcomes of patients admitted on Thursdays. Thursday admissions are prone to experience the largest variations in patient volume on Fridays as well as regular reductions in staff levels on Saturdays. As such, they are particularly susceptible to have lower effective staff levels during the first two days of their in-hospital stay. The authors only find few and largely negligible effects of patient volume on outcomes, concluding that hospitals are well equipped to deal with variation in patient volume over time.

There are two potential problems with this study. First, Evans and Kim measure patient volume on the level of hospitals. However, shocks in admissions may vary largely between clinical departments within a hospital. A peak in demand in an intensive care unit will most probably leave unaffected patients in gynecological departments. Moreover, the effects of demand on patient outcomes may be department specific, as the homogeneity in patient types and the process of providing care will typically be different among them (Harper et al. 2001). Finally, focusing on department level significantly increases the amount of variation in demand which can be used to study the desired effects. Therefore, in this study we compare the effects of demand on outcomes on department as opposed to hospital level.

Second, the authors do not control for patients' unobservable average severity of illness which may vary with the levels of demand. In theory, we would expect to find a positive correlation between excess demand and adverse patient outcomes. However, this effect may be biased if patients admitted on days with excess demand have different risk factors in both observable and/or unobservable patient characteristics than those admitted on days with a shortage of demand.

In another study Dobkin (2003) corrects for this selection problem. Dobkin compares patient outcomes between weekend and weekday admissions. On weekends staff levels are known to be lower than on weekdays. Methodologically, the problem arises that weekend admissions will probably be of higher risk for two reasons. First, hospitals may triage patients with no immediate need of treatment to Mondays. Second, patients may postpone admission until Monday if their medical condition allows for this behavior. Probably, this selection will only be partially captured by observable patient characteristics because the immediacy of the need of treatment is unobservable to the researcher. Dobkin therefore constructs a selection index based on excess admissions by diagnosis on weekdays as compared to weekends. He argues that without selection the proportion of admissions should be equal to the proportion of weekdays and weekend days, i.e. 5/7 and 2/7. Deviations from these proportions suggest a selection of patients which he finds to be associated positively with higher risk admissions on weekends. Once the selection index is added to he regression, the higher mortality for patients admitted on the weekend disappears. With his approach he questions the prominent results of Bell and Redelmeier (2001) who were among the first to state that outcomes of patient admitted on weekends are worse as compared to weekdays probably due to lower staffing. Our approach is similar, as we build a selection index comparing admissions per diagnosis on days with to days without excess demand.

3. Data, patient outcomes, samples, unexpected demand and unobservable selection

3.1 Data

The data are composed of administrative patient-level data from 423 departments within 72 German hospitals from the year 2004. The data set has a number of advantages. First, it is 100 percent comparable across hospitals because of legal requirements defining its data content. Second, since the data are used for billing purposes by health insurance companies, codification and measurement errors should be of minor importance. Third, it includes all in-patient cases of these hospitals and provides the day and initial department of admission and discharge as well as the occurrence and timing of within-hospital transfers between departments.[2] Given this detailed information, demand can be modeled accurately on department level. This is a distinct advantage over former studies, where demand was constrained to be

[2] A noteworthy limitation of the data set is that it does not allow linking patients across hospitals. Thus, any across hospital transfers are lost.

modelled on hospital level only. Fourth, the data provide several individual risk factors. Risk factors correct for the probability of the occurrence of an adverse health outcome. These include age, sex, 3-digit diagnosis related group (DRG), relative DRG weight, patient clinical complexity level (PCCL), occurrence of a surgery and minutes of artificial ventilation. The relative DRG weight determines the initial expected revenue of each case.[3] High weights go along with high reimbursement but also high costs due to time consuming and complex procedures. PCCL is a categorical variable with values ranging from one to four. A higher PCCL as well as the occurrence of a surgery and high durations of artificial ventilation are expected to reflect high degrees of severity of illness and thus also a high probability of the occurrence of an adverse health effect.[4] Finally, several standard patient outcomes described in the next subsection can be easily retrieved from the data.

As we are interested in a consistent data set we exclude observations which are likely to distort average effects of demand on patient outcomes. We exclude observations if the reason for admission is neither coded as normal nor as an emergency (e.g. removal of an organ or birth), if the discharge reason was other than regularly ended or death, or if there are missing values or wrongly coded variables of interest. Individuals below the age of 18 or above the age of 75 are excluded. The first group has a very low probability of adverse health outcomes and the second group can have high mortality rates due to many reasons not linked to the quality of care in a hospital. Moreover, due to coding rules we exclude all December admissions from our sample.[5] Additionally, we remove outliers defined by all observations below the 1st and above the 99th percentiles of the index of unexpected demand which will be defined below. Finally, we exclude all departments with less than 10 admissions per week. Those departments are too small to be regarded as separate medical units and typically experience a random volatility in patient volume.

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[3] The realized revenue is determined by the effective DRG weight which includes deductions/surcharges due to short/long stay patients, co-morbidities etc. Although available, the effective weight is endogenous to patient outcomes and therefore disregarded in the regression analysis. In contrast, the relative weight is only related to the initial diagnosis and exogenous to patient outcomes.

[4] PCCL is shown to be a strong predictor of in-hospital mortality when administrative hospital data is used (WIdO 2007).

[5] Coding rules require all patients admitted in year *t* and discharged in year *t + 1* to be included in the dataset in year t + 1. Only 2% of all patients have a length of stay above 1 month and 0.7% above 2 months. Therefore, by cutting off all admissions starting in December we observe almost all patients admitted before December 2004.

3.2 Patient outcomes

In general, causal factors behind the quality of care are difficult to identify or even to measure. In the first instance, quality is multidimensional and unobservable. Therefore, researchers study the variance of observable patient outcomes. Three measures of patient outcomes can be directly derived from the data: the length of stay, in-hospital mortality rates and unplanned readmissions. The third outcome is not directly recorded but can easily be constructed by linking subsequent stays of patients within a hospital. The advantages and shortcomings of these outcomes are discussed in the following.

One crude possibility to see whether there is a steering of admissions and discharges above of what may be expected from purely medical reasons, is considering the individual length of stay (LOS). If high unexpected demand meets capacity constraints in terms of personnel we expect lengths of stay to increase due to higher waiting times for (operative) treatment. They may also decrease if patients are dismissed faster in order to free up capacity. As an alternative to the crude length of stay we consider a diagnosis-adjusted LOS which is constructed as the percentage difference of the individual LOS to the hospital's average LOS within each 3-digit diagnosis. Positive (negative) percentages show that, on average, the patients stay longer (shorter) than the average patient in this diagnosis.

In-hospital mortality rates are a preferred measure of patient outcomes in many studies due to their availability, the negligible probability of mismeasurement and their generality as a viable adverse health effect for many medical conditions (Bell and Redelmeier 2001, Evans and Kim 2006, Vivian and Hamilton 2000, Cutler 1995). However, they are imperfect measures because patients may die after their discharge as an effect of insufficient quality of treatment or because of a premature discharge.[6] We use two measures of in-hospital mortality. Bell and Redelmeier (2001) show that the probability of dying in hospital decreases with the length of stay. For that reason, we first consider the 1-day mortality rate, which should be (if at all) as closely related as possible to immediate effects of shocks in demand. Second, however, we allow for longer term effects of shocks in demand by considering all in-hospital deaths.

[6] Cutler (1995) shows that in prospective payment systems there is some triage in the sense of an increase of in-hospital mortality rates versus a decrease of out-of-hospital deaths within one year after last discharge. Unfortunately, we are unable to identify out-of-hospital deaths due to a lack of data.

Our final measure is emergency readmissions. Studies have shown a negative link between readmission rates and the quality of the medical care process during hospital stay (Heggestad 2002; Weissman et al. 1999). We consider emergency readmissions up to 15 days after hospitalization. For this short spell the link between hospital's quality of treatment and the probability of readmission is strengthened relative to longer spells (Ashton and Wray 1997; Sibritt 1995).[7]

In contrast to Evans and Kim we consider emergency readmissions and we do not consider planned, elective readmissions. Elective readmissions cannot be interpreted as a sign of low quality of patients' treatment. Patients with planned readmission, e.g. those with regular dialysis treatment, will be readmitted independently of demand situations. Other planned readmissions could be postponed as a reaction to high demand without imposing any negative health effects. In contrast to elective (re)admissions, emergency admissions are unplanned. In Germany, every acute care hospital is required by law to admit all emergency cases unless it reaches its capacity limit.[8] Moreover, emergency patients by definition cannot easily select their day of admission.[9] As such, emergency (re)admissions are largely unplanned – both by patients and hospitals – and are therefore exogenous to hospitals' demand situation.

3.3 Samples

We are interested in measuring the effects of demand on patient outcomes. The effects of demand may, as outlined above, depend on the selection of patients. Due to more freedom in the admission of elective cases we expect selection to be stronger for elective than for emergency cases. If demand affects outcomes hospitals will more easily adapt their workload by selecting elective patients such that their outcomes should not be affected. In contrast, selection should be less of an issue for emergency cases. Thus, we use two separate samples: Elective and emergency admissions.

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[7] We can only identify readmissions at the same hospital possibly underestimating the true effect if there are readmissions across hospitals, which we necessarily fail to observe in our data.

[8] When reaching capacity limits a hospital can deny admitting further patients unless all other hospitals in a defined region have reached their limits, too. In this situation these hospitals have to admit patients even above their capacity.

[9] For less severe emergency cases this, however, may be untrue. Patients may deliberately postpone their admission until Mondays in order to avoid e.g. having to spend their weekend in a hospital.

In-hospital mortality is a rare event and irrelevant for many medical conditions. Following Evans and Kim we therefore construct one elective and one emergency high risk sample of patients with a higher susceptibility to adverse health outcomes. We do this in two steps. First, we identify patients whose primary three-digit-diagnosis belongs to one of the 100 most frequent causes of deaths in our data. Second, we choose from these subsamples patients with one of the 50 diseases with the highest mortality rates. The combination of the first and the second step avoids the inclusion of rare diseases with high mortality rates but few admissions. Patients not selected into the high-risk samples are gathered in low-risk samples. Thus, in total we have four samples: elective low-risk, elective high-risk, emergency low-risk and emergency high-risk.

Table 1

Patient characteristics and outcomes by samples (Standard deviations in parentheses)

	Low-risk[1] elective	**High-risk[2] elective**	**Low-risk emergency**	**High-risk emergency**
Age	54.10 (15.38)	60.61 (11.59)	50.15 (16.94)	59.88 (12.66)
Clinical complexity level	1.18 (1.50)	2.31 (1.55)	1.41 (1.55)	2.71 (1.47)
Relative diagnosis weight	1.11 (0.98)	1.62 (2.99)	1.00 (0.99)	2.34 (3.89)
Share of men	0.47 (0.50)	0.58 (0.49)	0.50 (0.50)	0.61 (0.49)
Ventilation in min.	0.44 12.10)	16.16 (115.38)	0.75 (18.79)	34.98 (171.76)
Share of operative cases	0.46 (0.50)	0.14 (0.35)	0.29 (0.46)	0.18 (0.38)
Excess length of stay[3]	-0.0388 (0.59)	0.0549 (0.62)	0.0210 (0.41)	0.1067 (0.44)
Death within 1 day after admission	0.0005 (0.02)	0.0045 (0.07)	0.0021 (0.05)	0.0311 (0.17)
Death within hospital	0.0045 (0.07)	0.0533 (0.23)	0.0092 (0.10)	0.1118 (0.32)
Emergency readmission[4]	0.0060 (0.08)	0.0135 (0.12)	0.0154 (0.12)	0.0332 (0.18)
Observations	400,781	63,997	199,790	38,987

Notes: [1] Excluding high-risk admissions; [2] Selected from 50 diagnoses with the highest mortality rates within 100 diseases with the highest mortality counts; [3] Adjusted length of stay as deviation of the individual from the average length of stay by diagnosis and hospital; [4] Up to 15 days after discharge.

Table 1 shows that risk factors and outcomes differ on a wide array of indicators between the samples. On average, low-risk patients are younger, have lower clinical complexity levels and relative diagnosis weights, are less often men, have fewer minutes of artificial ventilation, and undergo more often operative procedures than the corresponding high-risk patients. They also have shorter excess length of stay, lower probabilities to die in hospital or being readmitted as emergency cases. The same is true when comparing low(high)-risk elective with low(high)-risk emergency samples except for age. Thus, risk increases and outcomes worsen when going from elective to emergency as well as from low- to high-risk samples.

3. 4 Demand

Hospitals experience cyclical and seasonal patterns of demand. Typically demand is lower on weekends, during public holidays, and during summer time. Because these demand patterns will be known to the hospital management staffing levels will most probably be adapted accordingly. As a consequence, foreseeable demand variation should leave quality of care unaffected. Cleansing demand from foreseeable demand variation is therefore essential in order to measure the impact of unexpected changes in demand on patient outcomes (Evans and Kim 2006). To this end, we run a regression of patient counts for department within hospital h on day t

We then predict daily expected patient counts based on the regression residuals. We then measure unexpected demand as the percentage difference between the predicted and the actual patient counts.

The results from the regression are depicted in Table 2. It shows the distribution of the variables of actual and unexpected demand. The variables are centered on 1. The values for actual demand depict the percentage difference between the yearly mean demand and daily demand. On 10% of all admission days actual demand is less than 42.8% of mean demand. On another 10% of all days actual demand is at least 173.0% above mean demand. Thus, hospitals have to deal with a high volatility in the daily number of patients. However, as visible in the index of unexpected demand a lot of this volatility is foreseeable.

Table 2
Descriptive statistics, the distribution of daily actual and unexpected demand

Demand	Mean	SD[1]	5th Perc.[2]	10th Perc.	25th Perc.	Median	75th Perc.	90th Perc.	95th Perc.
Actual	1.000	0.536	0.350	0.428	0.722	0.975	1.283	1.730	2.021
Unexpected[3]	1.004	0.176	0.727	0.800	0.905	1.005	1.100	1.199	1.274

Notes:[1] Standard deviation; [2] Percentile;[3] Percentage difference between the daily predicted and actual demand based on seasonal, cyclical, hospital and department fixed effects. Based on 135526 daily patient count observations within 423 departments in 72 hospitals;

Following the regression results, the measure of fit suggests that on average 90% of all variation in patient demand is explainable and, as we assume, foreseeable. The index of unexpected demand shows that on 20% of all days (10^{th} and 90^{th} percentile) admissions are 20% higher or lower than expected. In 10% of all days (5^{th} and 95^{th} percentile) actual demand deviates nearly 30% away from expected demand. Thus, although the volatility in demand is strongly leveled, it can still be considerable.

4. Models and estimation methods

4.1 Selection index

Excess demand may be negatively related to outcome. However, it may be composed of an excess share of high-risk patients in unobservable characteristics. These high-risk patients may suffer worse health outcomes because of unobservable characteristics and not because of too low staff-to-patient ratios in times of excess demand.

It is for instance possible that patients are heterogeneous with respect to the immediacy of the need of treatment, which is unobservable to the researcher. In order to control for this heterogeneity,we build upon Dobkin's (2003) approach. Dobkin assumes that, regardless of the day of the week, for each illness the same number of patients should be admitted to hospitals if patients are not selected by severity. To test this hypothesis he constructs a selection index. This index is measured as the within-diagnosis difference between the number of admissions on each day of the week and an evenly distributed number of admissions throughout the week. We use conceptually a similar identification strategy. While Dobkin (2003) compares selection between weekends and weekdays, our comparison is between days *with* excess demand as opposed to days *without* excess demand.

For each illness we measure how much higher or lower admissions in each diagnosis during days with excess demand are than we would expect if all patients were admitted at random. This variable is supposed to measure the bias introduced by within diagnosis unobservable variation in severity across the week. As an explanation consider the following example.

Let us assume that within a given diagnosis excess demand leads to a higher probability to die within hospital. Now, if patients admitted on days with excess demand are the same in their unobservable risk factors as patients admitted on days without excess demand, then there is no unobservable variation in severity by the level of demand. Consequently, if all observable risk factors are taken account of, the estimated effect of excess demand on the probability to die within the hospital will be unbiased. However, if for a given diagnosis excess demand is composed of a systematically higher share of patients, which have a higher unobservable risk to die within hospital, then the effect of excess demand on mortality will be biased upwards. This is, because it comprises of the true effect of demand and the effect of variation in unobservable severity of illness by the level of demand. Thus, introducing a control for unobservable selection should reduce the potential bias in the estimate of excess demand on adverse health outcomes.

We measure the selection of illness *j* in department *d* of hospital *h*, s_{jdh}, as follows. First, for each department, we measure the number of days with excess demand, d_{dh}^{E}, the number of days with a shortage of demand, d_{dh}^{S}, and calculate their ratio $r_{dh} = d_{dh}^{E} / \left(d_{dh}^{E} + d_{dh}^{S}\right)$. r_{dh} is the expected share of admissions on days with excess demand. It is equivalent to Dobkin's (2003) proportion of expected admissions on weekends, which equals 2/7. Second, for each illness *j* within each department *d* of hospital *h* we calculate the number of admissions on days with excess demand, d_{jdh}^{E}, and the number of admissions on days without excess demand, d_{jdh}^{S}, arriving at the ratios $r_{jdh} = d_{jdh}^{E} / \left(d_{jdh}^{E} + d_{jdh}^{S}\right)$. If there is no selection, then $r_{dh} = r_{jdh}$ for each *j* within the same department. If the difference $s_{jdh} = r_{jdh} - r_{dh} > 0$, then there are excess admissions in illness *j* on days with excess demand and a shortage of admissions on days without excess demand and vice versa.

Table 3 outlines the distribution of the values of all s_{jdh}. In 10 percent of all cases there are 7.2 percent fewer admissions per diagnosis on days with excess demand as opposed to days without excess demand, than what would we expect, if there was no variation of admissions by diagnosis across demand. In another 10 percent of cases there are 29.8 percent more admissions per diagnosis than in case of an equal distribution of admissions by diagnosis across demand. Thus, diagnoses are obviously not evenly distributed across days with as opposed to days without excess demand, such that unobservable selection may drive health outcomes of patients.

Table 3
Descriptive statistics, distribution of the selection index

	Mean	SD[1]	10th Perc.[2]	25th Perc.	Median	75th Perc.	90th Perc.
Selection index[3]	0.010	0.128	-0.072	-0.026	0.011	0.060	0.298

Notes: [1] Standard deviation; [2] Percentile; [3]Admission ratios calculated as the difference between the expected number of admissions by department and diagnosis on days with as opposed to days without excess demand.

4.2 Models and estimation methods

The aim of our model is to single out the impact of unexpected demand variation and selection on unobservables on the probability of occurrence of adverse health outcomes. To this aim and in contrast with most previous literature we employ a within-department model controlling for unobservable hospital and department fixed effects. For patient *i* with illness *j* in department *d* of hospital *h* at admission day *t* let Y_{ijdht} be the outcome. We assume that:

$$Y_{ijdht} = \lambda D_{dht} + \mu s_{jdh} + \beta X_i + \gamma T_i + u_h + v_d + w_{ijdht.}$$

The main variable of interest D_{dht} is the excess demand at admission day *t* in department *d* of hospital *h*. The variable s_{jdh} is the selection index capturing within diagnosis unobservable variation in severity across demand. X_i are patients' characteristics: Sex, dummies for patients aged 30 to 39, 40 to 49, 50 to 59, 60 to 69 and 70 to 75 and interactions between sex and age groups, the relative DRG weight, dummies for patient clinical complexity level, whether a DRG was operative, the number of secondary diagnoses and the minutes of artificial ventilation. T_i is a vector of dummies denoting weekdays (Monday to Sunday) and months (January to November) of admission, and whether admission took place on a public holiday. Finally, u_h is a hospital fixed-effect, v_d is a department fixed-effect, and w_{ijdht} is a random error.

In a first estimate of equation (1) we drop the selection index and add it in a second estimate. This way we can assess the magnitude of unobservable selection that is driving the impact of demand on outcomes. We also experiment with a few additional specifications of the demand variable. First, there may be a lag between demand and its impact on outcomes. In this case one would employ a measure of lagged demand on outcomes. As a lag we use the mean value of unexpected demand from two days before admission of a patient on her outcome.[10] Second, in all models we additionally employ a non-linear specification of the demand variable in nine categories of the

[10] We also constructed lagged demand as demand one, two and three days before admission as well as mean demand from three and two days before admission with no apparent differences in the results from those presented here.

form: “Less then -20%”, …, “-10 to -5%”, “-5 to 5%”, “5 to 10%”, …, “More than 20%”.

For the outcome “excess length of stay” we estimate OLS models with robust standard errors. For “in-hospital mortality” and “emergency readmissions” we estimate probit models, where the occurrence of an adverse health outcome is specified as 1 and 0 otherwise. We exclude all patients who die in a hospital when using emergency readmissions as the outcome. Estimations are done separately for each of the four outcomes, four samples, four specifications of the demand variable and the two models. In total this adds up to 128 model specifications, which should give a detailed account of the effects of demand on patient outcomes.

5. Results

In the following we focus on the impact of unexpected demand and unobservable selection on adverse health outcomes. We do not depict results of the other covariates in order to save space.[11] The estimates for the outcomes of “excess length of stay” and “emergency readmission” are presented in Table 4.

First consider “excess length of stay” in the first specification of the model, i.e. excluding the correction term for unobservable selection. We find statistically significant negative effects of demand within the samples of low-risk and high-risk elective admissions. These negative effects show that in times of peak demand elective patients are dismissed earlier than expected, probably in order to free up capacities. On the contrary, the effect is positive and statistically significant within the high-risk emergency sample. This suggests that when demand is high emergency patients stay longer in hospital. This may be due to longer waiting times for adequate treatment. Thus, possibly there is a trade-off between lengths of stay of elective and emergency patients, when capacity is close to its limits.

Now consider the second specification after inclusion of the selection index. The magnitude of the coefficients of excess demand decreases in comparison to the first specification of the model, i.e. excess demand has now a smaller impact on length of stay. Moreover, in all samples the coefficient of

[11] Overall we find that patients who are male, older, have more minutes of artificial ventilation, a higher clinical complexity level, a lower relative diagnosis weight and those not treated operatively have significantly higher excess length of stay and higher probabilities of in-hospital death or being readmitted as an emergency. Moreover, we find significant differences across individual diagnoses, departments, hospitals and days and month of admission. Results are available from the authors upon request.

the selection index is positive and highly statistically significant. This shows that within diagnosis unobservable variation in severity positively contributes to the excess length of stay on days with excess as opposed to days without excess demand. This indicates that patients admitted on days with excess demand have systematically higher unobservable risk characteristics than patients admitted on days without excess demand.

When considering emergency readmissions (lower panel in Table 4), we do not find any statistically significant effects of demand. This does not change after inclusion of the selection term into the model, although for the samples of low-risk and high-risk emergency admissions the coefficients of the selection indices are highly statistically significant and positive.

Table 5 depicts the results for in-hospital mortality. In all but one specifications demand is not significantly related to the probability of in-hospital mortality. This is contrary to the effects of the selection index, which is positive and in all but one case highly statistically significant. Only within the high-risk emergency sample a surge in unexpected demand significantly raises the probability of dying within the first day of admission. However, the effect disappears after inclusion of the selection index.

To better understand the workings of demand and unobservable selection on patient outcomes, we present simulation results of the expected patient outcomes for the range of values of the indices of unexpected demand and unobservable selection. To this end, we set each of the indices at a given percentile and, using simulated parameters values, we generate the mean expected value of a patient outcome, as well as the 95 percent confidence interval at each percentile of the respective index.[12] We then draw 1,000 simulations of the estimated model parameters from their asymptotic sampling distribution. To generate the expected outcomes all variables other then the indices used are set at their mean values.

First, consider the outcome of excess length of stay. Figure 1 presents the simulated expected values and the 95 percent confidence interval of this outcome for the range of values of the selection index. The positive slopes show that within the whole range of values of the selection index excess length of stay rises. The rise is steeper near the boundaries. Also the shape of the confidence interval illustrates that the degree of uncertainty regarding the simulated length of stay is small across the whole range of the selection index. Table 4

[12] We use CLARIFY, a STATA add-on, for this purpose (Tomz et al. (2003), King et al. (2000)).

Impact of demand and unobservable selection on the length of stay and the probability of an emergency readmission

	Elective admissions				Emergency admissions			
	Low-risk[1]		High-risk[2]		Low-risk		High-risk	
	(1)[3]	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**
	Outcome: Excess length of stay[4]							
Unexpected demand	-.032711***	-.015980***	-0.066781*	-0.030518*	0.018691	0.014222	0.069199**	0.03704**
	(-2.77)	(-3.04)	(-1.77)	(-1.87)	(1.47)	(1.12)	(2.49)	(2.42)
Selection index	-	.352715***	-	0.3196973***	-	0.2938585***	-	0.118479***
	-	(20.20)	-	(10.27)	-	(18.87)	-	(4.04)
R^2	0.0794	0.0820	0.0657	0.0675	0.1091	0.1121	0.1036	0.1040
	Outcome: Probability of an emergency readmission[5]							
Unexpected demand	0.023316	0.023796	-0.08515	-0.085018	0.08001	0.0823886	0.0715026	0.071981
	(0.46)	(0.47)	(-0.88)	(-0.87)	(1.51)	(1.55)	(-0.51)	(-0.52)
Selection index	-	-0.031827	-	-0.039082	-	0.1119707*	-	0.1528789**
	-	(-0.49)	-	(-0.30)	-	(1.83)	-	(1.97)
R^2	0.1665	0.1665	0.1446	0.1446	0.2298	0.2299	0.3999	0.4000

Notes:

1 Excluding high-risk admissions;
2 Selected from 50 diagnoses with the highest mortality rates within 100 diseases with the highest mortality counts;
3 Model without (1) and model with selection index (2)
4 OLS estimation results, t-values in parentheses;
5 Marginal effects from probit models, t-values in parentheses; Patients who died in hospital are excluded from these models;
On patient level independent variables include age in the age categories 30-39, 40-49, 50-59, 60-69, 70-75, sex, interactions between age and sex, minutes of artificial ventilation, the clinical complexity level, average diagnosis weight, dummy for an operation and an emergency admission (except within the emergency sample) and three-digit main diagnosis. Moreover, we control for hospital and departmental fixed-effects, dummies for the month, day and the week of admission of a patient as well as for admission on a public holiday; ***, **, * significant at 1%, 5% and 10% level respectively.

Table 5

Impact of demand and unobservable selection on the probability of in-hospital death

	Elective admissions				**Emergency admissions**			
	Low-risk		**High-risk**		**Low-risk**		**High-risk**	
	(1)	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**
	Outcome: Death within the first day of admission							
Unexpected demand	0.000020	0.000010	-0.109436	-0.118975	0.000204	0.000221	0.001372**	-0.002416
	(1.02)	(0.94)	(-0.54)	(-0.65)	(0.69)	(0.76)	(2.37)	(-1.01)
Selection index	-	.356884**	-	0.255482	-	0.468872***	-	0.265852***
	-	(2.07)	-	(1.32)	-	(4.05)	-	(3.78)
R^2	0.4441	0.4456	0.4528	0.4533	0.4315	0.4344	0.4670	0.4971
	Outcome: Death within hospital stay							
Unexpected demand	-0.064415	-0.073215	0.000540	0.000285	0.000009	0.000014	-0.014499	-0.020289
	(-0.95)	(-1.08)	(0.35)	(0.31)	(0.02)	(0.04)	(-0.25)	(-0.34)
Selection index	-	0.296994***	-	0.114098**	-	0.001543***	-	0.190225***
	-	(5.56)	-	(2.11)	-	(5.25)	-	(3.66)
R^2	0.2752	0.2768	0.2493	0.2494	0.2583	0.2597	0.1909	0.1568

Notes: Marginal effects from probit models, t-values in parentheses; See also Table 4; ***, **, * significant at 1%, 5% and 10% level respectively.

Figure 1. Simulation results for the expected excess length of stay by percentiles of the selection index

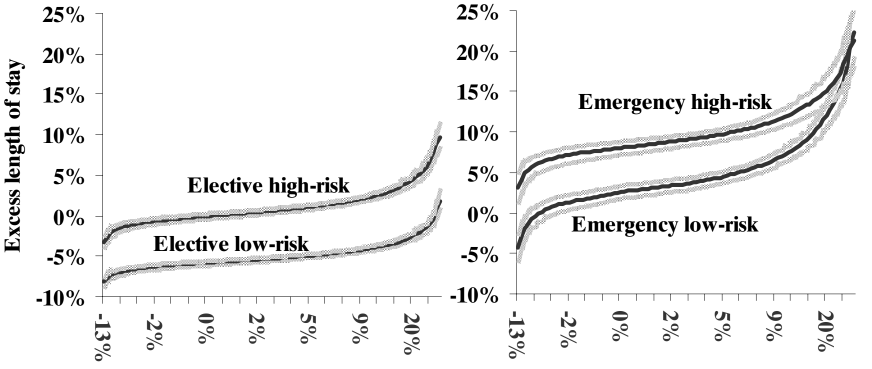
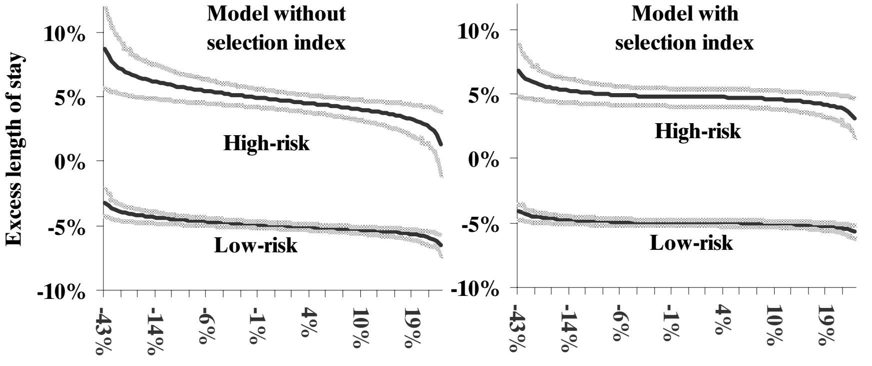


Figure 2. Simulation results for the expected excess length of stay of elective admissions by percentiles of the demand index



Grey lines show 95-percent confidence intervals

Figure 3. Simulation results for the expected excess length of stay of emergency admissions by percentiles of the demand index

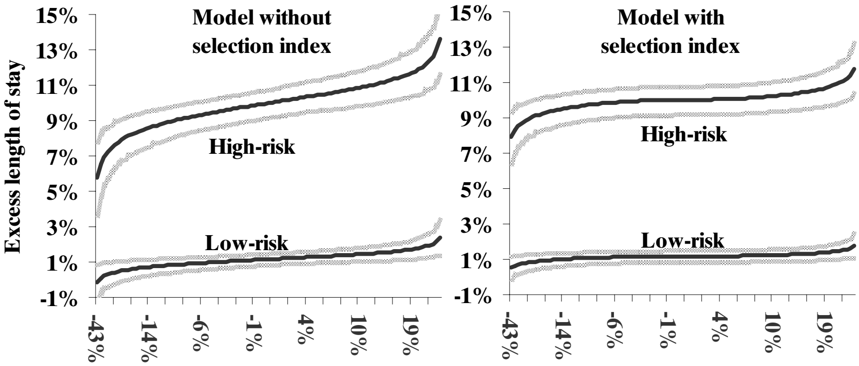
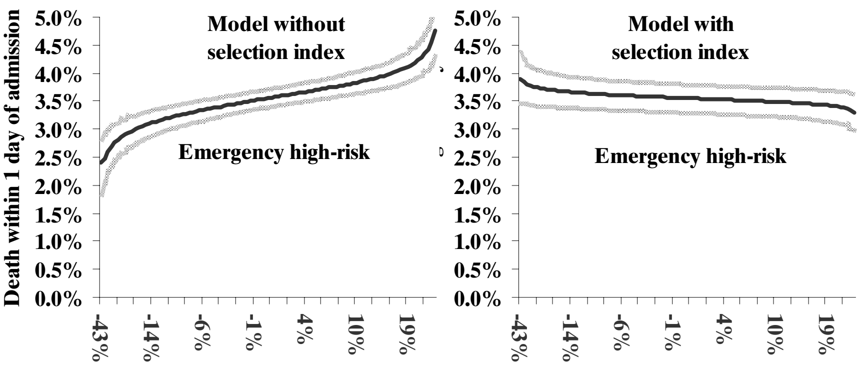


Figure 4. Simulation results for the one day mortality of high-risk emergency admissions by percentiles of the demand index



Grey lines show 95-percent confidence intervals

In Table 4 we have shown that after inclusion of the selection index the impact of excess demand on length of stay decreases. This effect is graphed in Figure 2 for the elective samples and in Figure 3 for the emergency samples. The left panels in Figures 2 and 3 result from estimates of model (1), i.e. excluding the selection term from the regression. Consistent with the regression results, increases in excess demand decrease the length of stay of elective patients, whereas they increase the length of stay of emergency patients. The results of model (2), i.e. regressions with the selection term, are depicted in the right panels in Figures 2 and 3. Here the slopes of the curves are flatter as compared to the corresponding left panel graphs. Visibly, the inclusion of the selection index in the models corrects decreases the impact of demand on length of stay.

Finally, consider the statistically significant impact of demand on the one day mortality within the emergency high risk sample within model (1) as in Table 5. Figure 4 (left panel) presents the positive impact of demand on this outcome, when unobservable selection is ignored. This impact vanishes after inclusion of the selection term (right panel). The slope of the curve is turned slightly negative and statistically insignificant.

As mentioned in section 4 we also experimented with the impact of lagged demand as well as with non-linear specifications of demand on outcomes. Considering lagged demand we did not find any statistically significant results. Thus, we conclude that levels of demand from the two days before admission do not impact on the outcomes of patients admitted two days later. As far as the non-linear specification of the demand variable is concerned, we could not find any systematic gradient of increasing risk of adverse health outcomes with higher levels of unexpected demand. For the sake of brevity, we thus do not present those results in more detail.

6. Conclusion

In this paper, we have examined the effects of demand on patient outcomes in acute care German hospitals. Typically, demand will only be partially foreseeable. Naturally, an unexpected surge in demand may negatively affect the quality of care and thus patient outcomes, such as in-hospital mortality. The main message of this analysis is that hospitals are well prepared to deal with this volatility, as by and large it does not negatively affect patient outcomes.

We used around 700 000 patient-level observations from 432 departments within 72 German acute care hospitals, exploiting detailed data on patients' severity of illness and patient outcomes. By focusing on within-hospital differences we followed the more recent development in the literature to avoid potentially unfair comparisons across hospitals, because of unobservable hospital differences. We added to this framework by disaggregating demand on the level of within-hospital departments, thus being able to exploit more variation in demand.

Intuitively, high levels of demand may be negatively related to outcome. However, excess demand may be composed of an excess share of high-risk patients in unobservable characteristics, who suffer worse health outcomes because of their high-risk factors. The intuition may be that in times of peak demand only patients most needy of an immediate treatment are admitted to hospitals. Those, who can wait, are probably triaged to days when capacities are freed up. Thus, excess demand may not be the reason for worse outcomes but the high-risk factors of patients admitted during times of excess demand. Our results show that this may be indeed the case. We have found a higher impact of demand on the lengths of stay of patients, when unobservable selection of patients was not controlled for in the regressions. In the case of high-risk emergency patients the positive link between demand and one day mortality was turned statistically insignificant after inclusion of the selection term into the model. Thus, this study confirms Dobkin's (2003) results that even in within-hospital studies unobservable selection can be an important problem.

Our results are also largely in line with the results from Evans and Kim (2006). They find only few and modest effects of demand on patient outcomes. Together the evidence suggests that overall hospitals are well prepared to deal with variation in unexpected demand and that laws imposing minimum staff-to-patient ratios may be unnecessary for the installment of adequate levels of quality of care in acute care hospitals.

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