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From dusk till dawn – Are nights a dangerous time for hospital admissions?

Corinna Hentschker*

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Abstract

This paper addresses the question whether patients have a higher risk of death if they are admitted to a hospital during the night rather than during the day. Since hospital resources and staffing are reduced at nights, both numerically and with regard to available expertise on site, there is a theoretical channel, explaining why night admissions might be more dangerous. However, since patients admitted during the night are special in terms of urgency and admission time, simple comparisons of patients admitted at night- and daytime may be misleading. To facilitate comparison, the empirical analysis compares patients who suffer from specific diseases considered as emergency conditions, i.e. upper gastrointestinal bleeding, or acute myocardial infarction and is based on regression adjusted propensity score matching as identification strategy. A full sample of all inpatients in Germany for the years 2005 to 2007 is used. Although the results show that patients admitted during the night have a higher risk of death, sensitivity analyses suggest, that this result is likely to be driven by unobserved patient heterogeneity.

KEYWORDS: hospital quality, mortality, regression adjusted propensity score matching

JEL: I11, I19

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1 Introduction

Hospital services are required 24 hours a day, 365 days a year. Nevertheless, it is not possible to maintain a constant number of employees throughout the whole day. Therefore, staffing levels are reduced at night. Since patient numbers decrease at night because elective cases are treated during the day, hospital work force reduction is an adaptation to this lower demand. However, during the night unexpected cases – in particular emergencies – may arrive with the same probability as during the day. These patients require the same adequate and often specialized care no matter the time of the day.

This paper addresses whether the mortality risk increases due to being admitted to a hospital at night. There are several possible reasons why patients admitted at different times of the day have different outcomes. First, overall staffing levels are lower at night. This includes specialized staff (Barba et al., 2006). Second, access to resources is reduced, e.g. to laboratory or radiology (Barba et al., 2006), which can diminish adequate treatment. Third, treatment mistakes may increase at night because of a disturbed biorhythm and a reduced concentration of the hospital staff (Kuhn, 2001). Prior studies have already focused on weekend admissions and some on night admissions. Both admission times belong to the ‘off-hour’, and the reasons for worse patient outcomes are similar since staffing levels are reduced and access to resources is limited during these times. In addition to weekends, the risk of medical errors can increase at night due to fatigue and sleep deprivation, which lead to more cognitive errors and decreases memory performance and coordination skills (Kahol et al., 2008; Kuhn, 2001). Consequently, it is necessary to investigate weekend and night effect separately.

Former studies on the ‘off-hour’ effect, i.e. on the weekend or on the night effect, range from single conditions like birth related diagnoses (e.g. Gould et al., 2003), stroke (e.g. Bray et al., 2014), upper gastrointestinal bleeding (e.g. Jairath et al., 2011), and heart attack (e.g. Becker, 2007) over to whole departments such as the intensive care unit (e.g. Barnett et al., 2002). The results are mixed. Some studies find a higher risk for patients admitted during ‘off-hours’ (e.g. Barba et al., 2006; Bell and Redelmeier, 2001; Becker, 2007; Kostis et al., 2007; Reeves et al., 2009). Others do not find any effect (e.g. Barnett et al., 2002; Berger et al., 2008; Gould et al., 2003; Magid et al., 2005). Some find an ‘off-hour’ effect

but conclude that this effect can be driven by unobserved patient heterogeneity, i.e. weekend patients and/or night patients are unobserved sicker which leads to an overestimation of the ‘off-hour’ effect (Barnett et al., 2002; Bray et al., 2014).

Most studies rely on logistic regressions to analyze the ‘off-hour’ effect. Doing so, they pay no attention to potential biased estimates resulting from unobserved patient heterogeneity. This is of special importance as many studies use administrative data without any clinical information. Patients admitted during the night are potentially sicker than patients admitted during daytime, which may remain unobserved. Therefore, it appears to be important to address the problem of unobserved heterogeneity.

An adequate consideration of unobserved patient heterogeneity and its effects on the result is one of the main goals of this paper. So far, two studies already try to account for unobserved heterogeneity. Becker (2007) finds that weekend hospitalization for heart attack patients lead to a 0.38 percentage point increase in 1-year mortality. However, by including hospital fixed effects he only controls for time-invariant differences in unobservable characteristics across hospitals. Unobserved heterogeneity within hospitals and over time may still drive the results. Schwierz et al. (2009) examine the weekend effect using German administrative data. They consider unobserved heterogeneity with a selection index¹ but they do not focus on specific diagnoses. The authors find that the coefficient of the selection index is not significant, i.e. they do not find any indications for unobserved heterogeneity. Although their results show that patients admitted on weekends have a higher mortality risk, the quantitative effect is small.

The main identification problem is that day and night patients are not directly comparable. Patients admitted at night are special in terms of urgency and admission time. Night patients have more severe and acute problems which cannot wait until the next day. By contrast, many elective patients are admitted during the day along with many acute patients. Hence, the main objective is to use statistical methods to make patients as similar as possible beforehand to ensure comparability. The only remaining difference between individuals should be the admission time. For this reason, I focus on specific emergency

¹The selection index measures the difference between the number of admissions each day and the number of expected admissions per day, which are assumed to be evenly distributed throughout the week.

conditions: upper gastrointestinal bleeding because of ulcers (UGIB) and acute myocardial infarction (AMI). I use a full-sample of all inpatients recorded for an administrative data set from Germany for the years 2005 to 2007 and apply propensity score matching methods in combination with regression adjustment to account for any observable differences. While administrative data offers the benefit that a full sample of the patient population is available, it is not ensured that every patient characteristic which influences outcome and admission time is observable. Yet this is the main assumption of propensity score matching. Therefore, I use two sensitivity analyses, which implement a potential binary confounder to assess the robustness of the treatment effect. My basic results show that night admissions lead to an increase in mortality. In the sensitivity analysis I find that it is very likely that unobserved heterogeneity can drive the results. Accounting for this unobserved heterogeneity can lead to insignificance of the night effect.

I contribute to the literature in the following ways: First, I use a full-sample of all inpatients in Germany and I am the first with an analysis of the night effect using German data. Second, I use a regression adjusted propensity score matching approach and include robustness checks to test whether unobserved heterogeneity influences the results. While some papers discuss potential unobserved patient heterogeneity, to the best of my knowledge, there is no paper trying to quantify its potential impact so far.

The remainder of this paper is organized as follows: Section 2 describes the data set and the main variables of interest. Section 3 presents the empirical strategy and explains the sensitivity analysis. Section 4 reports the results, and Section 5 concludes.

2 Data

The following empirical analysis employs an administrative data set, which is a full sample of all inpatients in Germany for the years 2005 to 2007,² and includes information on the patient, e.g. age, sex, diagnoses and procedure codes, ZIP code of residence, and admission time. Hospital characteristics are also available, e.g. hospital identifier, ownership type and

²The administrative data of §21 KHEntgG was used as part of a cooperation agreement for the further development of the DRG-system from April, 1st 2011 between the RWI and the BKK Federal Association.

an indicator for university hospitals. I focus on patients who have either UGIB or AMI. Both conditions need a rapid treatment and have been used in ‘off-hour’ studies before. I only include patients who have one of the mentioned diagnoses coded as main diagnosis.³

UGIBs denote bleedings in the upper gastrointestinal tract. The main causes of these bleedings are gastric ulcers and duodenal ulcers. I restrict the sample to these two causes of the disease. The symptoms are vomiting of blood and a tarry stool. UGIBs are diagnosed with an endoscopy to detect the source of bleeding. With the endoscopy it is also possible to stop the bleeding. Additionally, medicaments are administered. If it is not possible to stop the bleeding, an operation is necessary (Biecker et al., 2008). For the identification of relevant patients in the data I use diagnoses and procedure codes of Wu et al. (2015) and Abougergi et al. (2014) and include only patients who get an endoscopy.

An AMI occurs if a blood clot blocks a coronary vessel and, hence, stops the blood flow to part of the heart. The symptoms can vary by person but the majority of patients experience chest pain, nausea and shortness of breath. Therapy is realized by revascularization or by medical management with a thrombolysis. Revascularization techniques comprise percutaneous transluminal coronary angioplasty (PTCA) or coronary artery bypass graft (CABG). The first is a minimally invasive procedure, the latter an open surgery. Because there is a selection of healthier patients into PTCA (Hentschker and Wübker, 2016), I only focus on patients with PTCA with the purpose of having only patients with the same treatment in the sample. Hence, I exclude patients treated with thrombolysis and who get a CABG. However, CABG is only executed for 5% of the patients. To specify AMI patients in the data I use diagnoses and procedure codes defined in the German inpatient quality indicators (Mansky et al., 2011). The exact codes for both diagnoses can be found in Table A1 in the Appendix.

I exclude patients with missing information on patient characteristics, patients younger than 19 years, and patients with an invalid ZIP code of residence. I also drop patients with discharge reason transfer or admission reason transfer. In the first case it is not possible to determine the outcome of the patient; in the second case it is not possible to obtain the admission time. I further exclude patients admitted on weekends. Weekend patients admitted on daytime are not comparable with patients admitted on the same time during the week

³The main diagnoses is defined as the main cause for the hospital stay.

as personnel and other resources are also reduced on Saturdays and Sundays. The weekend reflects therefore another ‘off-hour’ effect. To separate the pure night effect in comparison to “normal” daily routine in a hospital, I exclude weekend admissions. Furthermore, I delete patients who are treated in hospitals without night admissions. Hence, I reduce hospital heterogeneity, since hospitals with only daytime admissions may treat less severe patients or may be different in other respects.

I can further distinguish emergency admission and regular admissions in the data set. It is possible to exclude patients with regular admission status and to focus on emergencies only (e.g. Becker, 2007). I refrain from the exclusion of regular admissions as I can only distinguish administrative emergencies. In my data set, a patient is coded as emergency if he has reached the hospital without a doctor’s referral. This does not necessarily cover the medical emergency completely, where urgent help is needed as soon as possible. This paper focuses on conditions where it can be assumed that they are medical emergencies independent from their admission status. Additionally, a separate estimation with only emergency cases is executed in the robustness check.

My main variable of interest is admission at nighttime which is equal to 1 if the patient is admitted between 7 pm and 7 am, and 0 otherwise. Several variations of this definition are applied as robustness checks. Nighttime is a special time in a hospital since personnel reductions occur. During the night, assistant doctors from each field are on stand-by for emergency duties. They stay in the hospital, responding first to emergency admissions and attending to patients already admitted if they need a doctor. Concurrently, a senior doctor remains on call from home. If assistant doctors require help, they can call the senior doctor who will then come to the hospital and handle immediate treatment if necessary. By contrast, during the day doctors can ask other doctors about treatment options: the hospital is fully staffed. During the night, assistant doctors must make more often individual decisions. It may be a higher hurdle to call a senior doctor during the night than to consult him on-site during the day. A second issue may be that if an urgent treatment is required that can only be administered by a senior doctor on call, it takes time for the senior doctor to reach the hospital.

As dependent variable I use a binary variable which is equal to 1 if the patient died in hospital and 0 otherwise. Mortality is the most severe outcome and is often used in past studies (e.g. Abougergi et al., 2014; Bell and Redelmeier, 2001). Due to data limitations, I can only focus on in-hospital mortality, since I cannot track the patients after their hospital stay. Figure 1 and Figure 2 show the distribution of admission time and mortality for each diagnosis. There is a clear admission peak for both diagnoses between 9 am and 2 pm, going along with a dip in mortality rate during this time span. The dip is greater for UGIB than for AMI. On the one hand, this peak in admission time can be explained by the fact that during this time everybody is awake and the risk of disease may be higher than during nighttime. On the other hand, there may also be some less severe cases admitted to hospital. The number of admitted patients decreases during the night with the least number of patients admitted between midnight and 6 am. Table 1 summarizes the outcome variable by time of admission. The share of night admissions is 23% (UGIB) and 26% (AMI). The unadjusted mortality rate for UGIB patients is 4.9% at daytime and 6.5% at nighttime, i.e. patients admitted at night have a 1.6 percentage points (pp) higher unadjusted mortality rate. For AMI patients the unadjusted differences is smaller with 0.7 pp. Both differences are statistically significant.

Table 1: Descriptive statistics

	Mortality Sample		Mortality				Differ- ence	Share of night ad- missions	N
	Mean	SD	Day	Night					
			Mean	SD	Mean	SD			
	(1)	(2)	(3)	(4)	(5)	(6)	(5-3)		
UGIB	0.053	0.223	0.049	0.216	0.065	0.246	0.016***	0.233	62,922
AMI	0.058	0.234	0.056	0.230	0.063	0.244	0.007***	0.263	136,483

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

There are some different characteristics within each condition which can affect both admission time and outcome. I include these characteristics as covariates. For UGIB patients I control for different types of the ulcer. Additionally, I include indicators whether the patients get an operation and an indicator whether the ulcer is perforated. For AMI patients I include an indicator for different AMI types, i.e. whether the patients had an ST-elevated myocardial infarction (STEMI) or a Non-ST-elevated myocardial infarction (NSTEMI).

Furthermore, I control for other variables that may simultaneously influence admission time and outcome, such as age, gender, and admission reason. In addition, I use the Elix-

Figure 1: Distribution of admission time for UGIB

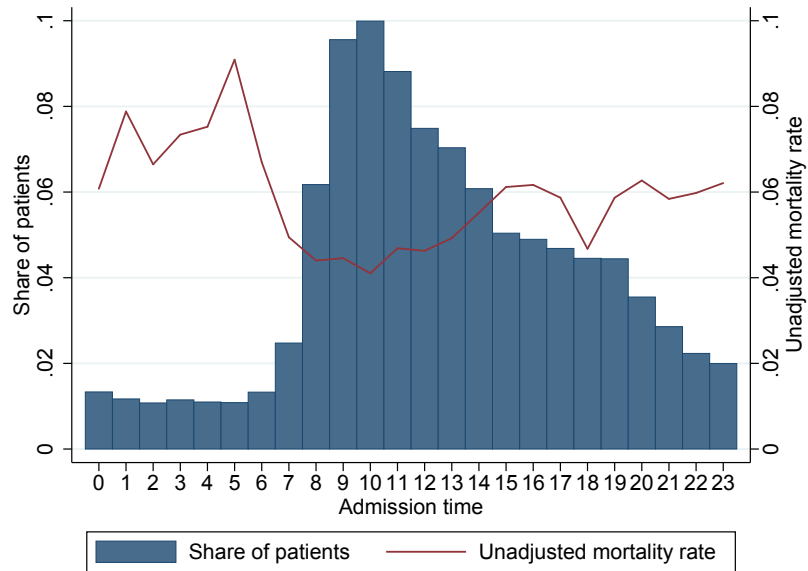
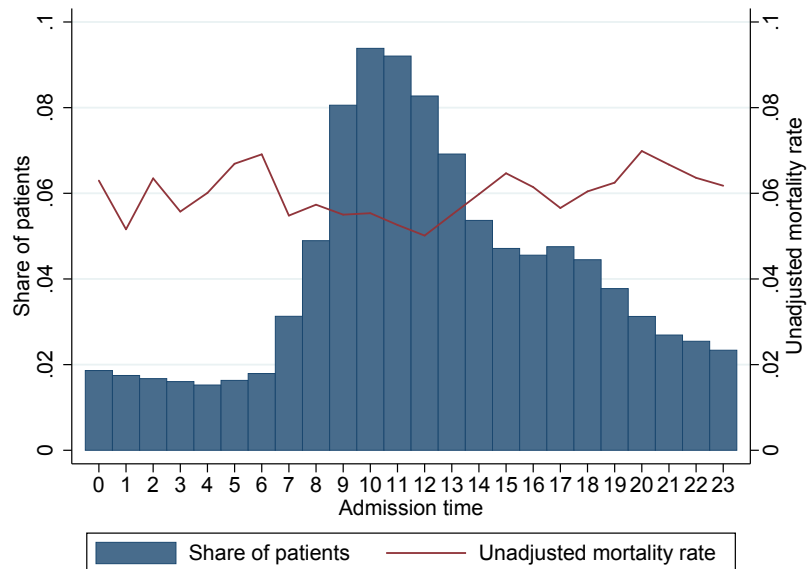


Figure 2: Distribution of admission time for AMI



hauser comorbidities for comorbidity risk adjustment (Elixhauser et al., 1998), i.e. diseases which affect the patient besides the main diagnosis. This adjustment comprises 30 comorbidity measures which are all specified as binary variables, e.g. hypertension, cardiac arrhythmia, renal failure, and diabetes. To capture regional variation, I define a variable “city” to control whether the patient lives in an urban or rural area. All patients living in counties with more than 150 inhabitants per square kilometer and patients living in cities with more than 100,000 inhabitants are defined as living in urban areas. All other patients are defined as living in rural areas. At the hospital level I control for ownership type with binary variables for public, not-for-profit or for-profit hospitals, case volume, and whether it is a university hospital. I add binary variables for each federal state to capture regional differences in emergency care.

3 Methods

To identify whether patients admitted at night have a higher risk of dying than those admitted during daytime, I apply regression adjusted propensity score matching (Rubin, 1979), a combination of matching and regression methods. I want to compare patients admitted at night with day admissions who should only differ in the admission time conditional on the control variables. I use the common notation of evaluation studies and assign the treatment status as $T = 1$ if the patient was admitted between 7 pm and 7 am (night admission), while $T = 0$ otherwise (day admission). As outcome (Y) I use mortality which is equal to 1 if the patient died in hospital and 0 otherwise.

I first estimate the propensity score, i.e. the probability that a patient is admitted during the night based on all conditioning variables (see Section 2), using a probit model. Patients with similar propensity scores in treatment and control group are possible matching partners. I use Epanechnikov kernel matching with a bandwidth of 0.03^4 and restrict the sample to the region of common support, i.e. treated observations with a propensity score below the minimum or above the maximum of the control group are excluded. One advantage of kernel matching is that all patients in the control group are included into the estimation but they are assigned with different weights which reduces the variance (Caliendo and Kopeinig, 2008). At the same time the matching bias can increase due to bad matches. I also use nearest-neighbor

⁴Different bandwidth choices ($BW = 0.01$ and $BW = 0.06$) do not change the results.

matching and radius matching with different calipers as robustness check but this does not change the results.

After the matching procedure I use the weights of the propensity score matching for the regression adjusted matching approach to compute the average treatment effect of the treated (ATT). This approach has also been applied by Marcus (2014) and Schmitz and Westphal (2015). It is a weighted regression of mortality on nighttime admission and all covariates used in the propensity score equation. The kernel weights of the propensity score matching are included as weights in the regression. There is a discussion of whether to use bootstrapped standard errors for the matching estimators (e.g. Caliendo and Kopeinig, 2008), but Marcus (2014) and Schmitz and Westphal (2015) show that bootstrapped standard errors only lead to slightly less conservative standard errors than standard errors from the regression. Hence, I refrain from using bootstrap methods and use clustered standard errors at the hospital level in the weighted regression. In a further regression, I add hospital fixed effects. These mainly capture fixed quality differences between hospitals which can also be correlated with the night admission variable. For example if more patients admitted at night are treated in good quality hospitals, the night effect will be underestimated without hospital fixed effects. It is also possible that fixed effects capture fixed differences in the level of patient sickness. For example if hospitals with a good reputation also treat sicker patients on average at night, it is not possible to determine the direction of the bias because the fixed quality and the fixed sickness bias run in opposite directions. The fixed effect regression can only be estimated for hospitals where at least one death occurred, i.e. variation is needed in the dependent variable within hospitals.

Sensitivity analysis

The matching approach is based on the conditional independence assumption (CIA), i.e. all variables which affect the treatment and the outcome must be observed. The CIA is also known as selection on observables or unconfoundedness assumption. It implies that if one has conditioned on all observed covariates there is no other (unobserved) variable which simultaneously influences night admission and mortality. The CIA does not hold if unobserved heterogeneity is an issue and, hence, estimation results will be biased. It is

an untestable assumption but some sensitivity analysis show how unobserved heterogeneity may influence the results. The main issue in my analysis is that I have administrative data without any medical and socioeconomic characteristics. The question arises whether unobserved characteristics may affect the results. In my case it is possible that I cannot fully observe sickness. If unobserved sicker patients, who inherently have also a higher mortality risk, are admitted relatively more often during the night, this will yield to an overestimation of the night coefficient.

As first sensitivity analysis I use the bounding approach of Rosenbaum (2002) which is for example applied by Caliendo et al. (2008) and Aakvik (2001). The initial point of their analysis is the idea that there are two identical individuals (i and j) in observable characteristics who only differ in the admission time. It is possible that these two individuals differ in their unobserved characteristics, for example in unobserved sickness characteristics. By introducing a hidden bias, the Rosenbaum bounds provide a measure on how large the bias must be in order to change the results. The probability of being admitted at night is given by

$$Pr(x_i) = Pr(T_i = 1 \mid x_i) = F(\beta x_i + \gamma u_i), \quad (1)$$

where x_i are the observed characteristics, u_i the unobserved characteristics, and γ is the effect of u_i on the probability to be admitted at night. Given that F is the logistic distribution function, the odds for individual i to be admitted at night are

$$\left(\frac{Pr(x_i)}{1-Pr(x_i)} \right) = \exp(\beta x_i + \gamma u_i). \quad (2)$$

The odds ratio for patients i and j is obtained by setting equation (2) in relation for both individuals (equation (3)). By assumption (due to the matching process) the individuals can only differ in u but not in x , i.e. x cancels:

$$\frac{\left(\frac{Pr(x_i)}{1-Pr(x_i)} \right)}{\left(\frac{Pr(x_j)}{1-Pr(x_j)} \right)} = \frac{Pr(x_i)(1-Pr(x_j))}{Pr(x_j)(1-Pr(x_i))} = \frac{\exp(\beta x_j + \gamma u_j)}{\exp(\beta x_i + \gamma u_i)} = \exp\{\gamma(u_i - u_j)\}. \quad (3)$$

By taking u as a binary variable, equation (3) can be rewritten as

$$\frac{1}{e^\gamma} \leq \frac{Pr(x_i)(1-Pr(x_j))}{Pr(x_j)(1-Pr(x_i))} \leq e^\gamma. \quad (4)$$

No selection bias occurs if u is not correlated with the probability of night admission ($\gamma = 0$). But if for example $e^\gamma = 2$, the individuals i and j are still similar in x but differ in their odds of night admission by the factor 2 or 100%. This would be a very large difference. With the Mantel and Haenszel test statistic it can be tested for which range of e^γ the results are stable by increasing values for e^γ ($1 \leq e^\gamma \leq 2$). The question is how large the unobserved differences between individuals are allowed to be without changing the results. The null hypothesis (H_0) is that there is over- or underestimation of the treatment effect. As long as H_0 can be rejected the results are not influenced by the hidden bias. It seems to be reasonable that only overestimation is an issue because there is a possible selection of unobserved sicker patients in night admissions. However, also the case of underestimation can be tested.

The second sensitivity analysis is suggested by Ichino et al. (2008). The authors introduce a synthetic binary confounder which was unobserved so far. If this confounder is included in the matching process, the CIA will hold and otherwise fail. I introduce a binary confounder S ‘sickness’ which is equal to 1 if patients are defined to be still sicker than others in addition to the already included covariates and 0 otherwise. This variable can be seen as a residual sickness which has not been accounted for so far. The sensitivity analysis shows how this confounder influences the results by including it in the matching process, i.e. pretending as if the confounder S is observable and use it as additional covariate. This results in a new ATT which is, by definition, unconfounded or rather robust to the inclusion of the confounder. By comparison with the basic ATT it is possible to show how the inclusion of the confounder changes the results. If the confounder does not alter the results, unobserved heterogeneity may be a negligible problem and the results can be interpreted as causal; otherwise the results are prone to be biased.

The distribution of the binary confounder S is specified by two parameters based on treatment status (night admission) and outcome (mortality) which leads to four different groups. With this, S is defined by the probability that $S = 1$ in each of the four groups:

$$p_{11} : Pr(S = 1 \mid T = 1, Y = 1),$$

$$p_{10} : Pr(S = 1 \mid T = 1, Y = 0),$$

$$p_{01} : Pr(S = 1 \mid T = 0, Y = 1),$$

$$p_{00} : Pr(S = 1 \mid T = 0, Y = 0).$$

Based on the chosen distribution of S , each patient receives a value for S . For example if $p_{11} = 0.4$, 40% of patients who are admitted at night ($T = 1$) and died ($Y = 1$) are randomly assigned with $S = 1$ and the others with $S = 0$. After the determination of S , S is included in the matching and regression process. This estimation is repeated 10 times⁵ to obtain a new estimate of the ATT. It is the average ATT over 10 iterations.

With the four groups it is possible to define the degree of influence of the confounder. The main issue in this analysis is the potential overestimation of the night effect. This occurs if the unobserved sicker patients are (i) mainly admitted during the night, which results in a positive *selection effect* ($p_{1.} - p_{0.} > 0$)⁶, and (ii) if sicker patients have a higher mortality (*outcome effect*), i.e. sickness is positively correlated with the outcome ($p_{01} - p_{00} > 0$)⁷. The outcome effect ($d = p_{01} - p_{00}$) measures the effect of the confounder on the control group, i.e. how the confounder (sickness) influences the outcome of patients admitted during the day. Larger values of d indicate that the share of sicker patients who are admitted during daytime is higher in the group of patients who died. For example if $d = 0.2$ the share of sicker patients ($S = 1$) is 20 pp higher in the group admitted during daytime and death ($T = 0, Y = 1$) than in the group admitted during daytime and survival ($T = 0, Y = 0$). The selection effect ($s = p_{1.} - p_{0.}$) measures the selection into treatment. The larger s the more selection into treatment occurs, i.e. sicker patients are more likely to be admitted at night. For example if

⁵There is no clear defined value how many iterations should be used in the sensitivity analysis. Ten repetitions are a quite low number but I checked for 10, 40, and 80 repetitions which only result in marginal differences of the estimated ATT and standard errors.

⁶ $p_{1.} - .$ stands for both outcomes, i.e. survived and died.

⁷This is also true for $p_{11} - p_{10} > 0$. But for the subsequent approach this term will be fixed following the approach of Ichino et al. (2008).

$s = 0.2$ the share of sicker patients at nighttime is 20 pp higher than at daytime. The higher d and s the more distortion of the ATT can occur.

The generated ATT gives a hint on the possible influence of S on the outcome. Overly strong influences of S might distort the results. However, too large influences of S seem unlikely because the available data set can already control for many observable confounding factors. There are two possibilities to determine the influence of S . The first possibility is to take the distributions from the conditioning variables for the distribution of S with the inherent assumption that S is at maximum as distorted as the observable variables in the data set (Ichino et al., 2008). The second possibility is to specify values for d and s in ascending order, i.e. the distortion and influence of S gets stronger by increasing the values for d and s . Ichino et al. (2008) call these ‘killer confounders’ because at a certain point the confounder will alter the results.

4 Results

Matching quality

The matching procedure has the goal to balance the distribution of covariates between treatment and control group, i.e. the differences of covariates should not be significant after the matching. Table 2 and Table 3 show the descriptive statistics before and after matching for UGIB and AMI, respectively. With the standardized bias it is possible to determine the size of the differences between treatment group and control group:

$$Standardized\ bias = \frac{100 \cdot (\bar{x}_t - \bar{x}_c)}{\sqrt{(\sigma_t^2 - \sigma_c^2)/2}},$$

where \bar{x} is the mean of treatment group t and control group c and σ^2 is the variance of the two groups (Caliendo and Kopeinig, 2008). After the matching, the standardized bias should not exceed values of 3% to 5% which indicates a good balancing (Caliendo and Kopeinig, 2008). In the current case this requirement is fulfilled. In most cases, the standardized bias is even lower than 1%. Before matching, patients admitted at night are younger, more

often administrative emergency cases and differ in some disease-specific parameters. After matching these differences disappear.

Table 2: Descriptive statistics towards treatment status (UGIB)

	Treated		Controls		Mat. controls		Stand. bias	
	Mean	SD	Mean	SD	Mean	SD	Unmat.	Mat.
<i>Patient characteristics</i>								
Age	68.19	16.40	70.38	14.82	68.40	15.69	-14.02	-1.35
Male	0.57	0.50	0.53	0.50	0.57	0.50	7.90	0.51
Admission reason: Emergency	0.77	0.42	0.49	0.50	0.77	0.42	60.68	0.34
City	0.73	0.45	0.71	0.45	0.73	0.45	2.61	-0.24
Driving time to hospital (minutes)	16.64	28.78	16.03	24.86	16.74	28.82	2.30	-0.35
Duodenal ulcer (K26)	0.41	0.49	0.40	0.49	0.41	0.49	2.51	-0.55
Peptic ulcer (K27)	0.01	0.09	0.01	0.08	0.01	0.09	1.15	0.30
Peptic ulcer jejunum (K28)	0.01	0.12	0.02	0.13	0.01	0.12	-2.17	0.02
Perforation	0.02	0.16	0.02	0.14	0.02	0.15	3.92	0.24
Gastric surgery (5-449)	0.27	0.44	0.22	0.41	0.27	0.44	11.50	-0.41
Excision (5-452)	0.02	0.15	0.04	0.18	0.02	0.15	-7.48	0.27
Bowel surgery (5-469)	0.15	0.36	0.13	0.33	0.15	0.36	6.55	-0.51
<i>Comorbidities (selection)</i>								
Hypertension, uncomplicated	0.35	0.48	0.39	0.49	0.35	0.48	-8.38	-0.25
Fluid and electrolyte disorder	0.21	0.41	0.19	0.39	0.22	0.41	5.74	-0.93
Cardiac arrhythmias	0.18	0.38	0.19	0.39	0.18	0.38	-3.34	-0.58
Diabetes, uncomplicated	0.14	0.35	0.15	0.36	0.14	0.35	-2.27	-0.15
Renal failure	0.14	0.35	0.15	0.36	0.14	0.35	-3.33	-0.83
Congestive heart failure	0.14	0.34	0.15	0.35	0.14	0.35	-2.27	-0.45
Alcohol abuse	0.11	0.31	0.08	0.27	0.11	0.31	10.52	0.25
Liver disease	0.10	0.30	0.09	0.29	0.10	0.30	3.80	0.00
<i>Hospital characteristics</i>								
Ownership: not-for-profit	0.36	0.48	0.37	0.48	0.36	0.48	-1.80	0.06
Ownership: for-profit	0.13	0.34	0.13	0.34	0.13	0.34	0.11	-0.47
University hospital	0.05	0.23	0.04	0.19	0.05	0.23	7.39	-0.12
In case volume	3.89	0.51	3.94	0.47	3.90	0.45	-10.51	-1.41
Department gastroenterology	0.24	0.43	0.24	0.43	0.25	0.43	1.51	-0.32
Year 2006	0.33	0.47	0.33	0.47	0.33	0.47	1.55	0.32
Year 2007	0.33	0.47	0.34	0.47	0.33	0.47	-1.12	-0.31
N	14,670		48,252		48,251			

Note: Only comorbidities with a share of more than 10% shown.

Estimation results

Table 4 presents the results for the effect of night admission on mortality for both conditions. In the first column the results of the regression adjusted matching are shown. For both conditions mortality significantly increases by 0.71 pp and 0.53 pp for UGIB and AMI patients, respectively, if the patient is admitted at night compared to daytime admission. In a further regression I add hospital fixed effects which control for all (unobserved) hospital characteristics which are fixed over time, for example quality differences or fixed unobserved patient characteristics. To make the regressions comparable in observations, I execute the regression

Table 3: Descriptive statistics towards treatment status (AMI)

	Treated		Controls		Mat. controls		Stand. bias	
	Mean	SD	Mean	SD	Mean	SD	Unmat.	Mat.
<i>Patient characteristics</i>								
Age	63.99	12.75	65.50	12.27	64.15	12.44	-12.12	-1.30
Male	0.71	0.45	0.71	0.45	0.71	0.45	-0.04	-0.24
Admission reason: Emergency	0.85	0.35	0.63	0.48	0.85	0.35	52.56	-0.02
City	0.75	0.43	0.74	0.44	0.75	0.43	4.01	0.32
Non-ST-elevated MI	0.36	0.48	0.38	0.49	0.36	0.48	-3.05	1.05
<i>Comorbidities (selection)</i>								
Hypertension, uncomplicated	0.55	0.50	0.56	0.50	0.55	0.50	-1.95	-0.20
Congestive heart failure	0.29	0.45	0.27	0.44	0.28	0.45	2.98	0.44
Cardiac arrhythmias	0.22	0.42	0.21	0.41	0.22	0.41	2.52	0.06
Diabetes, uncomplicated	0.16	0.37	0.16	0.37	0.16	0.37	-0.64	0.06
Obesity	0.16	0.37	0.15	0.36	0.16	0.36	3.15	0.79
Renal failure	0.14	0.34	0.14	0.34	0.13	0.34	-0.17	0.22
Fluid and electrolyte disorder	0.13	0.34	0.11	0.31	0.12	0.33	6.67	1.72
Hypertension, complicated	0.11	0.31	0.11	0.31	0.11	0.31	0.55	0.24
<i>Hospital characteristics</i>								
Ownership: not-for-profit	0.28	0.45	0.30	0.46	0.28	0.45	-4.79	-0.46
Ownership: for-profit	0.15	0.36	0.16	0.36	0.15	0.36	-1.64	0.14
University hospital	0.16	0.36	0.14	0.34	0.16	0.36	5.95	0.16
ln case volume	5.54	0.68	5.54	0.68	5.54	0.67	-0.09	-0.18
Year 2006	0.34	0.47	0.34	0.47	0.34	0.47	0.18	0.07
Year 2007	0.36	0.48	0.36	0.48	0.36	0.48	0.65	0.06
N	35,905		100,578		100,578			

Note: Only comorbidities with a share of more than 10% shown.

only with patients who are also kept in the fixed regression estimation, i.e. all patients in hospitals where at least one death occurred (column 2). The coefficients do not strongly deviate from the regression with the full sample. In the fixed effect regression (column 3) the coefficients decrease but the differences to the baseline coefficients are rather small. I conclude that time-invariant differences between hospitals do not drive the results.

Table 4: The effect of night admission on mortality

	Basic	Basic 2	Basic 2 + FE
	(1)	(2)	(3)
UGIB			
Admission betw. 7 pm and 7 am	0.0071*** (0.0023)	0.0076*** (0.0025)	0.0062*** (0.0019)
N	62,921	59,578	59,578
N (hospital clusters)	910	783	
AMI			
Admission betw. 7 pm and 7 am	0.0053*** (0.0015)	0.0054*** (0.0015)	0.0051*** (0.0012)
N	136,483	135,284	135,284
N (hospital clusters)	438	405	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; standard errors clustered at the hospital level except for column (3); ATTs of the regression adjusted matching approach are reported; (1) shows the ATT for the basic specification, (2) only include patients in hospitals where at least one patient died, (3) hospital fixed effects (FE) are added to the basic specification (i.e. hospitals without any deaths are omitted).

A 0.71 pp higher mortality for UGIB patients admitted at night corresponds to on average 35 additional deaths per year in Germany which occur only because of a night admission.⁸ This is a small effect in absolute terms. The overall picture changes if a relative basis is used. The mean mortality rate for UGIB patients admitted during the day is 4.9%. This results in an adjusted mortality rate of 5.6% for patients admitted at night. Hence, the 35 additional deaths relate to 3.3% of all deaths but account for 12.6% of all deaths at night. This is similar for AMI. The higher mortality for AMI patients admitted at night of 0.53 pp corresponds to on average 63 additional deaths per year.⁹ The mean mortality rate of AMI

⁸62,922 patients were admitted to hospital because of an UGIB between 2005 and 2007 of whom 14,670 patients were admitted at night. Hence, 104 additional deaths within 3 years occurred at night due to the higher risk of mortality of 0.07 pp ($0.0071 \cdot 14,670$).

⁹136,483 patients were admitted because of an AMI between 2005 and 2007 of whom 35,905 were admitted at night. Due to the excess mortality of 0.53 pp at night, 190 additional deaths occur within 3 years ($0.0053 \cdot 35,905$).

patients is 5.6% in the day time. The corresponding adjusted mortality rate is 6.1%. Hence, 63 additional deaths relate to 3.3% of all deaths and to 8.6% of all deaths at night.

Table 5 shows the estimation results for night admissions for different subgroups. At first, I exclude patients who are admitted on Friday night. These patients rather count to the weekend effect but the results also stay robust without these patients. There is the possibility that hospitals with different case volumes differ in care provision at night. For this reason, I build three case volume categories for each condition and run separate regressions. For AMI patients, the night effect disappears in small hospitals. This is a rather counterintuitive result. For UGIB there is no clear tendency; the night effect for patients treated in medium-sized hospitals disappears and is only significant at the 10%-level for patients treated in hospitals with a low or high case volume. Hence, I cannot detect any clear correlation between case volume and night admissions. University hospitals are maximum-care providers and might have more resources available at night. This may be the reason that there is no significant night effect observable in these hospitals in both conditions. I also execute separate regressions for patients with different admission statuses. This is done by keeping in mind the restrictions mentioned in the data section. It is striking that in all conditions the night effect decreases if only (administrative) emergency cases are considered. These coefficients reflect lower bounds of the night effect. At night nearly all patients are coded as emergencies. In the day some of these patients would be coded as non-emergencies. These patients can be considered as less severe cases because they can see a doctor beforehand. This is not obvious at night, i.e. all are coded as emergency cases. If I consider now only patients with emergency admission, I drop the less severe cases in the day. With this, the differences between night and day gets smaller.

The classification of day- and nighttime admission is arbitrary. Therefore, Table 6 shows different classifications for night admissions. The results stay robust. Interestingly, the night effect appears already after 4 pm. At least for UGIB, the effect is driven by patients admitted between 7 pm and 7 am. Patients admitted between 4 pm and 7 pm have no higher risk of death compared with patients admitted between 7 am and 4 pm. For AMI patients this is not the case. One explanation of the effect may be that in many hospitals the regular working hours of the doctors end at 4 pm and the stand-by duty begins, i.e. personnel and other resources are reduced.

Table 5: The effect of night admission on mortality by subgroups

	UGIB			AMI		
	Coeff.	S.E.	N	Coeff.	S.E.	N
Admission without Friday night	0.0068***	0.0025	61,175	0.0053***	0.0016	132,722
Case volume: low	0.0099**	0.0045	13,841	0.0026	0.0032	32,155
Case volume: middle	0.0047	0.0030	34,903	0.0051**	0.0020	66,473
Case volume: high	0.0101*	0.0053	14,171	0.0071**	0.0029	37,852
University hospital	0.0041	0.0103	2,648	0.0070	0.0047	19,315
No university hospital	0.0072***	0.0024	60,264	0.0047***	0.0016	117,163
Emergency admission	0.0059**	0.0027	34,868	0.0036**	0.0017	94,065

Notes: The table shows the effect of night admission on mortality for different subgroups for UGIB and AMI. Each cell represents a separate ATT. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; standard errors clustered at the hospital level; different case volume thresholds for the two conditions: AMI (low: ≤ 100 ; middle: > 100 and ≤ 200 ; high: > 200), UGIB (low: ≤ 25 ; middle: > 25 and ≤ 50 ; high: > 50).

Table 6: The effect of night admission on mortality for different definitions of night admission

	UGIB			AMI		
	Coeff.	S.E.	N	Coeff.	S.E.	N
Admission between 7 pm and 7 am	0.0071***	0.0023	62,921	0.0053***	0.0015	136,483
Admission between 8 pm and 6 am	0.0074***	0.0026	62,920	0.0041**	0.0016	136,483
Admission between 9 pm and 6 am	0.0080***	0.0027	62,922	0.0031*	0.0018	136,482
Admission between 4 pm and 7 am	0.0048**	0.0021	62,919	0.0046***	0.0013	136,483

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; standard errors clustered at the hospital level; ATTs of the regression adjusted matching approach are reported for different night definitions. Variation of the sample size due to the common support assumption.

Sensitivity analysis

The night coefficient may still be biased if unobserved variables are simultaneously correlated with night admission and outcome. Sensitivity analyses show how the estimation results react to the introduction of a confounder and, hence, assess the credibility of the CIA. As a first sensitivity analysis I use Rosenbaum bounds. I am interested in the question whether the night coefficient might be overestimated due to unobserved characteristics. Based on the Mantel and Haenszel test statistic I find a critical value for UGIB patients of $e^\gamma = 1.25$. If two individuals which are identical in observables differ by more than 25% in unobservables, the night effect will no longer be significant. For AMI patients the critical value is $e^\gamma = 1.1$. The night effect will disappear if the patients differ by more than 10% in unobservable characteristics. The null hypothesis that the night effect is underestimated can always be rejected which indicates that there is no problem with underestimation. The bounds are no proof that unobserved heterogeneity exists (Becker and Caliendo, 2007), but they give a first indication how large the influence of unobserved heterogeneity must be to alter the results. In my case the UGIB results seem to be more robust to unobserved heterogeneity than the AMI results.

The second sensitivity analysis of Ichino et al. (2008) has the advantage that it estimates a new ATT which accounts for potential unobserved heterogeneity in form of a binary confounder S . The CIA only holds if the confounder S is included in the matching process in addition to the other covariates. It is possible to observe the influence of S directly by comparing the basic ATT and the new ATT including S . First, I use distributions of S similar to the distributions of my conditioning variables. Table 7 and Table 8 show the distribution of confounder S , which is included into the matching process, and the corresponding ATT for UGIB and AMI, respectively. For both conditions, most of the data set confounders show an outcome effect that is below 0.2, in most cases even below 0.1. The same is observable for the selection effect, which is mainly below 0.1. One exception is the conditioning variable emergency. Both, outcome and selection effect are positive and lead to an insignificant ATT if a variable similar to emergency would be unobserved. For all other confounders the size of

the ATT is similar to the basic estimate without including the confounder. The ATTs also stay significant.¹⁰

As described in Section 3, only confounders that have a positive outcome and selection effect (d and s) matter. To determine the distribution of S (p_{11} , p_{10} , p_{01} , p_{00}) with the resulting outcome and selection effect, I fix two parameters. I set $Pr(S = 1) = 0.4$ and $p_{11} - p_{10} = 0$. The former characterizes the share of ‘sicker’ patients in the whole data set. By setting the required values for d and s , p_{01} and p_{00} can be calculated.¹¹ Table 9 and Table 10 show ATTs if the influence of d and s is increasing. In each row d is fixed and in each column s is fixed. It is obvious that even with small outcome and selection effects, the ATT rapidly becomes zero or even negative. The negative effect would lead to the conclusion that patients will have an even better outcome if they are admitted at night. However, I only test the hypothesis that the night effect is overestimated but not underestimated. Hence, the results should not be over-interpreted. The crucial point is that already with outcome and selection effect of 0.1 the night effect significantly decreases and disappears already for outcome and selection effects of 0.2. These are sobering results in terms of the influence of unobserved heterogeneity, but keeping in mind that no medical and socioeconomic characteristics are available, my conditioning variables might not be sufficient to capture all characteristics influencing both night admission and mortality. Another explanation for this result is that the ‘killer confounders’ are working mechanically, i.e. the ATT becomes insignificant at a certain point. For rather small treatment effects this can occur at an early stage because the method is quite severe against small ATTs (Origo, 2009). Hence, the results have to be seen in the overall context.

¹⁰However, the significance is not so important in this case. The focus should be on the comparison of the point estimates (Nannicini, 2007).

¹¹For a detailed methodological approach, see Ichino et al. (2008).

Table 7: Effect of possible data set confounders (UGIB)

	Distribution of $S = 1$				d	s	ATT	S.E.
	P11	P10	P01	P00				
No confounder	0.00	0.00	0.00	0.00	0.00	0.00	0.0070	0.0023
Neutral confounder	0.50	0.50	0.50	0.50	0.00	0.00	0.0070	0.0023
Confounder (S) similar to:								
<i>Patient characteristics</i>								
Age	0.76	0.52	0.80	0.59	0.22	-0.06	0.0096	0.0023
Male	0.50	0.57	0.48	0.53	-0.06	0.04	0.0075	0.0023
Admission reason: Emergency	0.79	0.77	0.59	0.48	0.11	0.28	0.0007	0.0027
City	0.71	0.73	0.71	0.71	-0.01	0.01	0.0070	0.0023
Duodenal ulcer (K26)	0.53	0.40	0.54	0.39	0.15	0.01	0.0067	0.0023
Peptic ulcer (K27)	0.00	0.01	0.01	0.01	0.00	0.00	0.0070	0.0023
Peptic ulcer jejunum (K28)	0.01	0.01	0.01	0.02	-0.01	0.00	0.0069	0.0023
Perforation	0.10	0.02	0.08	0.02	0.07	0.01	0.0060	0.0023
Gastric surgery (5-449)	0.35	0.26	0.31	0.21	0.10	0.05	0.0055	0.0024
Excision (5-452)	0.01	0.02	0.01	0.04	-0.03	-0.01	0.0064	0.0023
Bowel surgery (5-469)	0.28	0.14	0.28	0.12	0.16	0.02	0.0055	0.0024
<i>Comorbidities (selection)</i>								
Congestive heart failure	0.32	0.12	0.34	0.14	0.20	-0.01	0.0079	0.0023
Cardiac arrhythmias	0.27	0.17	0.32	0.18	0.14	-0.01	0.0077	0.0023
Hypertension, uncomplicated	0.25	0.36	0.28	0.40	-0.12	-0.04	0.0061	0.0023
Diabetes, uncomplicated	0.16	0.14	0.16	0.15	0.01	-0.01	0.0070	0.0023
Renal failure	0.22	0.14	0.27	0.15	0.12	-0.01	0.0075	0.0023
Fluid and electrolyte disorder	0.35	0.20	0.38	0.18	0.19	0.02	0.0056	0.0023
<i>Hospital characteristics</i>								
Ownership: not-for-profit	0.38	0.36	0.36	0.37	-0.01	-0.01	0.0070	0.0023
Ownership: for-profit	0.14	0.13	0.14	0.13	0.01	0.00	0.0070	0.0023
University hospital	0.05	0.05	0.04	0.04	0.00	0.02	0.0069	0.0023
Department gastroenterology	0.21	0.25	0.22	0.24	-0.02	0.01	0.0070	0.0023

Notes: Table shows the influence of confounder U on the ATT. The distribution of U is specified based on the distribution of the conditioning variables in the data set. Age is transformed into a binary variable with the threshold at the median.

Table 8: Effect of possible data set confounders (AMI)

	Distribution of $S = 1$				d	s	ATT	S.E.
	P11	P10	P01	P00				
No confounder	0.00	0.00	0.00	0.00	0.00	0.00	0.0049	0.0015
Neutral confounder	0.50	0.50	0.50	0.50	0.00	0.00	0.0049	0.0015
Confounder (S) similar to: <i>Patient characteristics</i>								
Age	0.74	0.47	0.75	0.53	0.22	-0.06	0.0074	0.0015
Male	0.62	0.72	0.62	0.72	-0.10	0.00	0.0049	0.0015
Admission reason: Emergency	0.86	0.85	0.72	0.63	0.09	0.22	0.0004	0.0016
City	0.76	0.75	0.74	0.73	0.00	0.02	0.0049	0.0015
Non-ST-elevated MI	0.16	0.38	0.17	0.39	-0.22	-0.01	0.0042	0.0015
<i>Comorbidities (selection)</i>								
Congestive heart failure	0.48	0.27	0.43	0.26	0.17	0.01	0.0043	0.0015
Cardiac arrhythmias	0.45	0.21	0.43	0.20	0.23	0.01	0.0042	0.0015
Hypertension, uncomplicated	0.34	0.56	0.35	0.57	-0.23	-0.01	0.0045	0.0015
Hypertension, complicated	0.08	0.11	0.07	0.11	-0.04	0.00	0.0049	0.0015
Diabetes, uncomplicated	0.18	0.16	0.17	0.16	0.00	0.00	0.0049	0.0015
Renal failure	0.22	0.13	0.22	0.13	0.09	0.00	0.0049	0.0015
Obesity	0.10	0.16	0.09	0.15	-0.06	0.01	0.0051	0.0015
Fluid and electrolyte disorder	0.26	0.12	0.23	0.10	0.13	0.02	0.0033	0.0015
<i>Hospital characteristics</i>								
Ownership: not-for-profit	0.27	0.28	0.28	0.30	-0.02	-0.02	0.0048	0.0015
Ownership: for-profit	0.15	0.15	0.17	0.16	0.01	-0.01	0.0049	0.0015
University hospital	0.19	0.15	0.17	0.13	0.03	0.02	0.0046	0.0015

Notes: Table shows the influence of confounder U on the ATT. The distribution of U is specified based on the distribution of the conditioning variables in the data set. Age is transformed into a binary variable with the threshold at the median.

Table 9: Effect of confounders with positive outcome and selection effect (UGIB)

		Selection effect (s)					
		s = 0.1	s = 0.2	s = 0.3	s = 0.4	s = 0.5	s = 0.6
Outcome effect (d)	d = 0.1	0.0051 (0.0024)	0.0030 (0.0025)	0.0008 (0.0026)	-0.0015 (0.003)	-0.0061 (0.0032)	-0.0090 (0.0038)
	d = 0.2	0.0045 (0.0024)	-0.0002 (0.0025)	-0.0051 (0.0027)	-0.0103 (0.003)	-0.0163 (0.0033)	-0.0234 (0.004)
	d = 0.3	0.0013 (0.0025)	-0.0021 (0.0025)	-0.0097 (0.0028)	-0.0166 (0.0032)	-0.0256 (0.0032)	-0.0335 (0.0042)
	d = 0.4	-0.0033 (0.0025)	-0.0124 (0.0027)	-0.0222 (0.003)	-0.0279 (0.0031)	-0.0334 (0.0032)	-0.0452 (0.0037)
	d = 0.5	-0.0040 (0.0025)	-0.0149 (0.0028)	-0.0275 (0.003)	-0.0403 (0.0034)	-0.0541 (0.0036)	-0.0695 (0.004)
	d = 0.6	-0.0027 (0.0025)	-0.0165 (0.0027)	-0.0303 (0.0031)	-0.0454 (0.0033)	-0.0618 (0.0042)	-0.0788 (0.0045)

Notes: Table shows simulated ATTs for different outcome and selection effects (standard errors in parentheses).

Table 10: Effect of confounders with positive outcome and selection effect (AMI)

		Selection effect (s)					
		s = 0.1	s = 0.2	s = 0.3	s = 0.4	s = 0.5	s = 0.6
Outcome effect (d)	d = 0.1	0.0033 (0.0015)	0.0011 (0.0016)	−0.0009 (0.0017)	−0.0036 (0.0018)	−0.0089 (0.0022)	−0.0135 (0.0027)
	d = 0.2	−0.0015 (0.0016)	−0.0056 (0.0017)	−0.0102 (0.0019)	−0.0158 (0.0021)	−0.0207 (0.0022)	−0.0265 (0.0027)
	d = 0.3	−0.0028 (0.0016)	−0.0095 (0.0017)	−0.0157 (0.0019)	−0.0237 (0.002)	−0.0315 (0.0022)	−0.0400 (0.0027)
	d = 0.4	−0.0039 (0.0016)	−0.0117 (0.0018)	−0.0205 (0.0019)	−0.0299 (0.0022)	−0.0403 (0.0024)	−0.0513 (0.0026)
	d = 0.5	−0.0036 (0.0016)	−0.0136 (0.0017)	−0.0243 (0.002)	−0.0354 (0.0021)	−0.0469 (0.0023)	−0.0600 (0.0027)
	d = 0.6	−0.0026 (0.0016)	−0.0144 (0.0017)	−0.0270 (0.0019)	−0.0535 (0.0026)	−0.0686 (0.0027)	−0.0856 (0.003)

Notes: Table shows simulated ATTs for different outcome and selection effects (standard errors in parentheses).

5 Conclusion

This paper addresses the question whether patients admitted to a hospital at night have a higher mortality risk than patients admitted during the day. The analysis is based on a full-sample of all inpatients in Germany for the years 2005 to 2007 and focuses on patients with upper gastrointestinal bleeding and acute myocardial infarction because they are emergency conditions. Applying a regression adjusted propensity score matching approach, the basic results show a 0.71 pp and 0.53 pp increase in mortality for UGIB and AMI patients, respectively. In absolute numbers the effects seem to be small with 35 and 63 additional deaths per year in the whole population because of a night admission. However, in relative numbers this accounts for 3.3% of all deaths in each condition, which is already a sizable effect. Nevertheless, the estimates can only be seen as an upper bound of the night effect. Both sensitivity analyses show that the results are sensitive to unobserved patient heterogeneity. Since the night effect disappears already for small selection and outcome effects, it is possible that patients admitted at night are unobserved sicker which drives the effect.

However, the magnitude of unobserved heterogeneity is unknown. Both, the night effect – ignoring any unobserved factors – and the potential for a higher share of high risk patients at night highlight the importance of having enough personnel and resources available for night admissions. To find the causal effect of night on mortality, it might be necessary to

use other data in addition to administrative data. If the night effect is still significant, one possibility would be to improve access to resources and increase the availability of personnel. However, this increase must be in due proportion to the growing costs. Considering the lower case volume at night, it might not be reasonable to increase the resources in all hospitals. Hence, a second possibility would be the centralization of nighttime health care. Since there are mainly emergencies at night, reaching the hospital in an adequate time frame must be guaranteed.

Although the results of this study are not clearly verified, the matching approach can take into account observable heterogeneity and the sensitivity analyses show how large the problems resulting from unobserved heterogeneity can be. Previous studies with similar data sets only qualitatively – not quantitatively – mention the problem of unobserved heterogeneity (e.g. Barba et al., 2006; Bell and Redelmeier, 2001). In contrast to Schwierz et al. (2009), I find that omitted variables can influence the results in administrative data.

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A Appendix

Table A1: Diagnosis and procedure codes for UGIB and AMI

Condition	Incl./Excl.	Diagnosis Codes	Procedure Codes
UGIB	Incl.	K25.0; K25.2; K25.4; K25.6; K26.0; K26.2; K26.4; K26.6; K27.0; K27.2; K27.4; K27.6; K28.0; K28.2; K28.4; K28.6	1-630.*; 1-631; 1-632; 1-635; 1-636.*; 1-638.*; 1-63a; 1-63b
	Excl.	C*	
AMI	Incl.	I21.0; I21.1; I21.2; I21.3; I21.4	8-837.*

Notes: The included diagnosis code is related to the coded main diagnosis. The exclusion restriction for the diagnosis code is related to the secondary diagnosis. A patient is only included in the sample if additionally to the diagnosis code a procedure code is coded. “*” stands for all possible subcategories.