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Abstract

Using high-quality administrative data from Upper Austria, we analyze the effect of hospital crowding on patients' short- and medium-term healthcare utilization and labor market outcomes. Focusing on acute inpatient diagnoses, we exploit idiosyncratic variation in daily diagnosis-related hospital occupancy rates to estimate the causal effect of hospital crowding. We find that higher crowding levels reduce hospital care intensity, as reflected in fewer medical services provided, lower hospital expenditures, and earlier discharges. Despite these changes, quality of care indicators, including readmissions and mortality, remain unaffected. However, no significant effects are observed either on inpatient and outpatient healthcare utilization in the short- and medium-term or on patients' labor market outcomes following initial hospitalization. These results suggest that crowding-induced differences in hospital care do not lead to changes in patients' health or economic situations over the medium term.

JEL Classification: I10, I12, I14, I31, J20.
Keywords: Hospital Crowding, Health Care Utilization, Labor Market.

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1 Introduction

The efficient organization of healthcare systems requires forward-looking capacity planning at various levels of service delivery. While predictable and unpredictable peaks in demand for health care services must be adequately managed, unused medical capacities generate economic costs. Demographic change, characterized by higher utilization of medical services among older populations, requires long-term capacity adjustments. Additionally, technological progress influences treatment options, particularly between inpatient and outpatient care. Even if health policy tries to respond to long-term trends in the organization of medical capacity, there are fluctuations in demand to which resources cannot be optimally adapted in the short term. This leads to the (economic) problem of maintaining sufficient capacity reserves to handle demand surges, such as those during a flu epidemic or, as highlighted by the Covid pandemic, to sustain functionality during exceptional situations. The allocation of capacities results in varying utilization levels, which not only have economic consequences but also affect the quality of care, and thus, patient health.

In this study, we examine how differences in hospital crowding affect health, health care utilization, and labor market outcomes. Using comprehensive high-quality individual-level data spanning from 2005 to 2018 from the Upper Austrian Health Register, we demonstrate the effects of higher or lower crowding rates on short- and medium-term health outcomes, such as length of stay, complication rates, or mortality, as well as the longer-term effects on outpatient healthcare utilization and labor market participation. We use the idiosyncratic changes in a hospital's daily diagnosis-related crowding rate in acute care as an exogenous variation for hospital crowding. We argue that conditional on diagnosis-related and hospital-specific month fixed effects as a predictor for hospital crowding, the remaining variation in hospital crowding can be expected to be uncorrelated with unobserved patient characteristics.[1]

We find that higher hospital crowding reduces the intensity of hospital care. A one-standard-deviation increase in hospital occupancy reduces the length of stay by 3.45 %, hospital expenditure by 2.37 %, number of hospital services provided by 1.42 %, expenditure per service by 1.38 %, and number of hospital departments visited by 0.98 %. Inpatient mortality and 30-day readmissions are not affected by hospital congestion, suggesting that the quality of care is not compromised. Additionally, hospitals admit fewer new patients when they are more crowded. Compared with the lowest level of occupancy, new admissions fall by up to 6 % when hospitals operate at full capacity.

Although high crowding in hospitals reduces the intensity of hospital care, it is uncertain whether fewer hospital services affect patients negatively in the medium-run. Therefore, we also consider outpatient utilization patterns following hospital discharge. Results indicate no

[1] We show that patient characteristics are uncorrelated with the unexpected variation in hospital crowding.

significant differences in expenditures on outpatient specialists, general practitioners, and drug prescriptions. Inpatient hospital expenditure in the following quarter also remains unaffected. These patterns are still persistent two years after discharge, suggesting that hospital congestion does not adversely affect patients' health in the short or medium term. Furthermore, labor market outcomes are also unaffected, with no differences in the number of days worked, sick leave usage, or wages two years after discharge. Similarly, retirement decisions, including total, early, or disability retirement days, also remain unchanged. Overall, congestion-related differences in hospital care do not seem to translate into changes in the health and economic situation of patients.

The existing literature on the causal effect of hospital crowding on patient outcomes focuses primarily on the inpatient setting and tends to find that higher crowding leads to shorter lengths of stay (Evans and Kim, 2006; Hoe, 2022; Schwierz et al., 2012; Sharma et al., 2008; Song et al., 2021), higher readmission rates (Evans and Kim, 2006; Hoe, 2022; Jiang and Pacheco, 2014), and higher (Gutierrez and Rubli, 2021; Singh and Venkataramani, 2022; Song et al., 2021) or unchanged (Evans and Kim, 2006; Hoe, 2022; Schwierz et al., 2012; Singh and Venkataramani, 2022) in-hospital mortality.[2] Similar to our study, most studies leverage pseudo-random variation in hospital admissions to identify the causal effect of hospital crowding.

Within the inpatient sector, several causal studies focus explicitly on childbirth in maternity wards (Bachner et al., 2024; Bensnes, 2024; Facchini, 2022; Freedman, 2016; Maibom et al., 2021; Marks and Choi, 2019). Most of these studies find that hospital crowding reduces treatment intensity with limited health impacts.[3] For Austria, Bachner et al. (2024) use – similar to our approach – idiosyncratic variation in hospital beds to identify causal effects of hospital overcrowding in Austrian maternity wards. A one-standard-deviation decrease in hospital bed occupancy increases the likelihood of cesarean delivery by 4 %, the length of stay by about 4.3 %, and the likelihood of readmission by 5.84 %. The authors conclude that mothers may benefit from higher levels of crowding because it is associated with less harmful overtreatment. Maibom et al. (2021) also use idiosyncratic variation in hospital crowding to identify causal effects on medical care and health outcomes in Danish maternity wards. They find that higher crowding leads to fewer procedures, shorter length of stay, and a lower likelihood of medically induced labor and pain relief, with only minor effects on maternal and child health within two years post-birth. Bensnes (2024) uses an instrumental variable approach in Norwegian maternity units, finding that crowding is associated with fewer interventions, fewer readmissions, and better birth outcomes, with health care use during the first three years after birth being minimally affected by hospital crowding.

[2] Other studies examine the effect of patient-to-nurse ratios (e.g., Cook et al., 2012; Harris et al., 2020; Raja, 2023) and hospital staff strikes (e.g., Costa, 2022; Stoye and Warner, 2023) on hospital and patient outcomes.

[3] In the context of childbirth, several studies examine the effects of maternity unit closures (e.g., Avdic et al., 2024) and policies (e.g., Andrew and Vera-Hernández, 2024) on patient outcomes.

In the context of emergency departments (EDs), crowding increases waiting times and reduces the volume and complexity of care (Turner et al., 2020). Francetic et al. (2024) show that ED crowding of low acuity patients has only minor spillover effects on the care of high acuity patients, with larger effects occurring only under severe crowding. Woodworth (2020) illustrates that a 10 % reduction in ED crowding reduces patients' 30-day mortality by 24 % and 6-month mortality by 17 %, while Turner et al. (2020) and Francetic et al. (2024) find no effect on 30-day mortality.[4] Martins and Filipe (2020) show that doctors discharge patients earlier and reduce the intensity of treatment as the length of queues in A&E departments increases. Sivey (2018) finds that longer waiting times reduce the treatment intensity of low acuity patients. Gruber et al. (2023) analyze a policy that incentivizes ED physicians to examine patients in less than four hours, finding reduced length of stay, lower mortality, and increased treatment intensity for these patients.

We contribute to the literature in three ways. First, while most previous studies focus only on the short-term direct effects of hospital crowding on patient outcomes, we extend these findings and address the question, of whether short-term reductions in hospital services are relevant for patient outcomes beyond the hospital stay by also studying the medium-term effects on patients' health outcomes outside the hospital.[5] We estimate the effect of hospital crowding one quarter and two years after discharge on both inpatient and outpatient health care utilization. Thus, we test whether differences in hospital use caused by crowding translate into longer-term differences in outpatient use. Second, we contribute by extending the analysis of hospital crowding to the medium-term labor market outcomes of patients. This is particularly interesting from an economic perspective, as it sheds light on whether crowding-induced differences in inpatient care translate into changes in patients' economic situation, such as labor market performance. To this end, we analyze, among other things, the employment, wage, and pension outcomes of patients two years post-discharge. Third, we analyze the effect of hospital crowding using a wide range of acute inpatient hospitalizations. Many previous studies analyze only a narrow range of inpatient hospitalizations, such as births in maternity wards (e.g., Bachner et al., 2024; Bensnes, 2024; Facchini, 2022; Freedman, 2016; Maibom et al., 2021; Marks and Choi, 2019) or trauma and orthopedic patients (Hoe, 2022).

The rest of the paper is structured as follows. Section 2 describes the data, institutional setting, and analysis sample. Section 3 outlines the empirical strategy and section 4 presents the results. Section 5 concludes the paper.

[4] There is also a large non-causal medical literature examining ED crowding. Bernstein et al. (2009), Hoot and Aronsky (2008), Morley et al. (2018), and Rasouli et al. (2019) provide literature reviews.

[5] Exceptions include Maibom et al. (2021) and Bensnes (2024), who also analyze longer-term health outcomes outside the hospital. However, both these studies focus on births in maternity wards, whereas we analyze a wider range of acute hospitalizations.

2 Data and institutional setting

2.1 Institutional setting

Austria operates a Bismarckian health care system with compulsory health insurance. Employees are automatically assigned to a health insurance provider based on the employer's type and location. Employees and their dependents, the unemployed, and retirees are insured by the Austrian Health Insurance Fund, which is organized at the federal level into nine regional health insurance funds. Insured persons have access to extensive public health services paid for by wage-based social security contributions from employers and employees, taxes at various federal levels, and low deductibles, such as a prescription fee of 6 € (2018).

Primary care doctors (general practitioners and pediatricians) and specialists offer outpatient care. Acting as gatekeepers, they refer patients to hospitals and specialists, prescribe drugs, and offer both preventive and acute medical services. Hospital care is offered by public and private not-for-profit hospitals, with services remunerated through a Diagnosis Related Groups system. This system categorizes hospital stays into case groups based on illness severity and the financial costs associated with the required diagnosis and medical treatment (Bachner et al., 2018).

The Austrian Healthcare Structure Plan (ÖSG 2023) establishes binding national guidelines for planning key healthcare areas in Austria, aiming to achieve uniform care quality. In addition to uniform quality criteria for inpatient care, this legal basis also includes the large-scale equipment plan. The detailed regional and structural planning of inpatient services is implemented at the provincial level by the regional hospital funds (Landesgesundheitsfonds in German). These funds are responsible for concrete regional care planning, including the allocation of inpatient bed capacities, considering Austria-wide planning benchmarks. Hospitals are required to maintain the allocated bed capacities for the agreed planning horizon. Depending on the current demand for hospital services, individual patients are confronted with varying crowding rates during their hospital stay.

2.2 Data sources

We combine two sources of administrative data at the individual level. Health data are provided by the Austrian Health Insurance Fund - Upper Austria (AHIF-UA), the primary statutory health insurer in the province of Upper Austria. It insures over one million private-sector employees and their dependents, representing about 80 % of the province's population.[6] Registry

[6] Upper Austria is the third largest of Austria's nine federal states. Its 1.5 million residents represent 16.7 % of Austria's population. Healthcare spending in 2018 was 4,135 € per capita, 6.5 % below the national average of 4,421 € (Hofmarcher and Singhuber, 2020).

data are available from 2005 to 2018 and include the number of sick days, detailed information on outpatient physician visits (general practitioners and specialists), drug prescriptions, and associated expenditures according to Anatomical Therapeutic Chemical classification system codes. Inpatient data include information on hospital admissions, including hospital days, expenditures, and admission diagnoses for each person according to the International Classification of Diseases (ICD-10).

We link the health register data to the Austrian Social Security Database (ASSD), a matched employer-employee dataset that provides individual-level information on the labor market histories for all Austrian workers from 1972 to 2022. The ASSD includes daily spells of labor market status, annual wages, and demographic characteristics such as age and sex (Zweimüller et al., 2009). Wages are top-coded because they are limited to the maximum social security contribution base. In addition to wages, we use the number of days of employment and several indicators of pension status, such as early retirement and disability pension, as medium-term outcome variables that could potentially be affected by hospital crowding.

2.3 Analysis sample

2.3.1 Sample construction

In our sample, we focus on acute hospital admissions based on a weekend classification method. This increases the credibility of our identification strategy, as hospitals could easily reschedule planned hospitalizations during periods of high occupancy, whereas acute illnesses occur unexpectedly and cannot be planned. In addition, we drop all birth- and pregnancy-related ICD-10 chapters and all patients aged under 15 years. Based on the universe of all hospitalizations in our dataset, we classify a hospital stay as acute if its ICD-3 digit code has a relatively high weekend admission rate. Planned hospital stays are exclusively scheduled from Monday to Friday. Therefore, diagnoses frequently treated on weekends indicate acute admissions. Specifically, we define a hospitalization based on the ICD-3 diagnosis as acute if the proportion of its admissions on Saturdays, Sundays, or holidays is above the 75^{th} percentile. This corresponds to a weekend admission rate of more than 20.7 %. In robustness analyses, we show how the results change for alternative definitions of acute hospital admissions and whether including non-acute hospital admissions creates selection problems (see section 4.3).

For each patient and ICD-10 chapter, we retain only the first acute hospital stay, implying that one patient may appear in the sample multiple times.[7] By restricting the sample to first hospitalizations, we exclude readmissions, simplifying the distinction between pre- and post-treatment periods. This also excludes the effect of earlier hospitalizations on subsequent

[7] Figure A.1 in the appendix illustrates the number of hospitalizations per patient in our analysis sample. Less than 30 % of patients experience an acute first hospitalization under more than one ICD-10 chapter.

admissions, allowing us to analyze the impact of hospital crowding on immediate and unanticipated cases.

Figure 1 shows the distribution of ICD chapters in our sample of first acute diagnoses. Injuries, poisonings, and other external causes are the most common diagnosis group at 25 %, followed by diseases of the respiratory, circulatory, and digestive systems as well as certain infectious and parasitic diseases. Symptoms and abnormal clinical and laboratory findings that cannot be classified elsewhere are also quantitatively important. Conversely, diagnoses such as cancer, metabolic diseases, skin diseases, and musculoskeletal diseases play a minor or no role, as might be expected. A detailed list of diagnoses on the 3-digit level is listed in Table A.1 in the appendix. Typical medical emergencies such as pneumonia, acute abdominal and chest pain, stroke and heart attack, and dizziness are among the most common diagnoses in the sample. Other frequent diagnoses include gastrointestinal inflammation, transient ischemic attacks, fractures, and mental disorders due to alcohol use. Figure 2 depicts the distribution of hospital stays across 22 hospitals in our sample. Two hospitals are larger than the others, which is reflected in their significantly higher relative shares of the total number of stays.

Figure A.2 in the appendix shows the distribution of hospitalizations over time in our analysis sample. The proportion of first diagnoses decreases over the years (panels (a) and (e)). This is mainly due to the fact that, for reasons of data availability, we can only use a few years for the first calendar years to check whether a hospital stay with the identical ICD-10 diagnosis group has already occurred.[8] Panels (b) and (d) document that the number of hospital admissions is higher in the winter months than in the rest of the year, while the distribution of acute first stays is almost equally distributed across the weekdays, with even lower uptake on Saturdays and Sundays than on other working days (panel (c)).

2.3.2 Measuring hospital crowding

Our data do not include information on the number of occupied beds in hospitals or hospital departments. Instead, we calculate hospital crowding as the ratio of patients treated per day to the maximum number of daily patients per year. For each hospital and ICD-10 chapter, the quotient of the number of patients per day divided by the maximum daily number of patients in that diagnosis group in the calendar year is calculated for each day. Each hospitalization is then assigned this quotient for the day before the admission day. Figure 3 shows the distribution of the hospital crowding rate and its development over admission time. Overall, the crowding rate density function is normally distributed with a mean and median of 0.58 and 0.593, respectively (panel (a)). Daily averages of the crowding share predominantly range between 0.4 and 0.7 (panel (b)). With values between 0.55 and 0.6, the crowding share is relatively constant over

[8] For example, if a patient records a stay with a certain ICD-10 coding in 2007, but already had such a stay in 2004, we cannot reflect this in the data and code the stay in 2007 as a first stay.

time, with both the number of patients treated per day and the annual maximum number of patients per day increasing between 2007 and 2018 (panel (c)). Finally, panel (d) shows a constant development in the percentiles of the crowding share distribution over time.

2.3.3 Descriptive statistics

Table 1 provides descriptive statistics for our sample. The average age of the patients is 56 years, with 53.1 % being female and 86 % holding Austrian citizenship. Hospital stays last, on average, 7 days and incur costs of approximately 3,600 €. The 30-day readmission rate is 2.6 %, while 6.4 % of patients require intensive care, and 8.7 % die within a year of discharge

In the year preceding hospitalization, patients spend an average of 531 € on outpatient medical care, 671 € on medication, and 2,800 € on inpatient care. On average, they spend just under nine days on sick leave. Considering the labor market performance of patients in the year before hospitalization, they earn approximately 10,000 €, 44.5 % are employed, 33.3 % work at least 270 days of the year, 44.1 % are retired, 31.9 % are in regular retirement, 3.4 % are in early retirement, and 9.2 % are in disability retirement.

Figure 4 displays the age distribution of patients at the time of hospitalization. The graph shows a relatively high proportion of adolescent patients, which decreases significantly until the age of 40. The proportion of patients increases again between the ages of 40 and 55 and from the age of 70.

3 Empirical strategy

3.1 Estimation

We estimate the following model:

$$y_{ihct} = \beta_0 + \beta_1 Crowding_{hct} + \theta \mathbf{X}_{ihct} + \eta_{hmd} + \epsilon_{ihct}, \tag{1}$$

where y_{ihct} is the outcome of patient i, admitted to hospital h with ICD-chapter diagnosis c, on day t. $Crowding_{hct}$ measures the crowding rate in hospital h, ICD-chapter diagnosis c, and day t. The crowding rate is measured one day before the patient is admitted to the hospital. $\mathbf{X}_{ihct}$ is a vector of controls including sex, five-year age group fixed effects, weekday fixed effects, and holiday (non-working) fixed effects. η_{hmd} represents fully interacted hospital (h), year-month (m), and 3-digit level ICD diagnosis (d) fixed effects. η_{hmd} contains 147,522 categories in the estimation sample. The sample size is 495,365 observations. The coefficient of interest is β_1, which captures the effect of hospital crowding share on outcomes. We estimate two different specifications. The first imposes a linear functional form between the hospital crowding share and the outcome variables, as shown in equation (1). As an alternative, we provide a semi-parametric variant where we use binary indicators for the p-th percentile of the hospital crowding distribution $Crowding^{p}_{hct}$.[9] The standard errors are clustered at the hospital $\times$ year level (208 clusters in the main sample).

To illustrate the variation we use to identify effects, we estimate a model similar to equation (1) with hospital crowding as the left-hand variable. This involves regressing $Crowding_{hct}$ on $\mathbf{X}_{ihct}$ and η_{hmd} and extracting predicted values and residuals. The distribution of the observed, predicted, and residual measures of hospital crowding are illustrated in Figure A.4 in the appendix. Plotting the means of the observed and predicted crowding proportions by hospital, ICD-chapter, and day shows the identifying variation in hospital crowding used in the analysis. Figure 5 illustrates one example of the largest hospital in our sample for digestive system diseases from 2015 to 2017. The difference between the predicted (black line) and observed (red line) crowding represents the idiosyncratic variation in hospital crowding and is assumed to be exogenous and unanticipated. Similar patterns are observed across other hospitals and diagnoses, as shown in Figure A.5 in the appendix. Hence, our empirical design exploits sufficient variation within and across hospitals as well as diagnosis, allowing us to identify a causal effect of hospital crowding on patient outcomes.

3.2 Identification

In our estimations, we flexibly control for hospital- and diagnosis-specific month fixed effects and exploit within-hospital and diagnosis-specific variation in hospital crowding shares to identify the causal effects. The underlying identifying assumption requires that unobserved within-hospital and diagnosis-specific month variation in patient characteristics is uncorrelated with within-hospital and diagnosis-specific month variation in crowding shares. This identification strategy would fail if hospitals systematically admitted certain types of patients in response to changes in hospital crowding. To support the credibility of our identification strategy, we offer the following line of argument regarding patient selection.

Patient selection: Table 2 presents results from estimating model (1) on health care use and sickness days one year before hospitalization. We find no significant effect of hospital crowding on patients' prior inpatient or outpatient health care use, including medication expenses and days of sickness. This is the first indication that the analyzed patients are not systematically selected according to their overall health status. This argument is supported by the results provided in Table 3 and Figure 6, which illustrate that both readmissions within 30 days and

[9] The distribution of hospital crowding for each decile used in the regressions is depicted in Figure A.3 in the appendix.

mortality remain unaffected by hospital crowding. These results imply that more severe cases may not be overrepresented when crowding is high. Therefore, we conclude that the effects of hospital utilization are not due to a systematic selection of certain patients, supporting the credibility of the chosen identification strategy.

In a closely related context, Bachner et al. (2024) show in their analysis of the effects of bed occupancy in (Upper) Austrian maternity wards on the probability of cesarean sections that hospitals do not adjust staffing levels according to capacity utilization. This allows the interpretation that the change in hospital crowding is exogenous from the hospitals' point of view and is not compensated by corresponding staffing adjustments on the part of hospital management.[10]

4 Results

In presenting and discussing the results, we first distinguish between the short- and medium-term effects of hospital crowding. The short-term effects relate to the immediate hospital stay, indicating how a change in hospital crowding affects the length of stay, intensity of care, quality indicators, and the number of newly admitted patients. In the medium term, we examine the effects of hospital crowding on both the use of health care services and the labor market in a time frame of one quarter to two years after the initial hospital stay. We also explore heterogeneous effects by sex and age and provide robustness checks using alternative definitions of acute hospitalization and comparisons between hospitals in and outside Linz.

4.1 Short-run effects

Table 3 presents the hospital outcomes during the initial hospital stay, based on the linear specification. Diagnosis-related hospital crowding has a significant negative impact on the length of stay, number of medical services, and amount of hospital spending, both overall and in terms of per service provided. However, the quantitative effects vary, with a one-standard-deviation increase in hospital crowding reducing the respective outcomes by between 0.98% (number of hospital departments affected) and 3.45 % (length of stay). The effects on readmissions, intensive care utilization, and mortality are either statistically insignificant or significant only at the 10 % level. These findings suggest that increased hospital crowding does not lead to a deterioration in the quality of care during the hospital stay.

Figure 7 shows the estimation results for health care utilization based on the semi-parametric specification. Length of stay decreases consistently over the entire distribution of hospital

[10] Duty rosters in hospitals in Upper Austria are typically determined on a long-term basis, depending on the day of the week, with no provision for short-term adjustments based on hospital capacity utilization.

crowding, reflecting a linear relationship. By contrast, the strongest reductions in the number of hospital services, spending, and the number of hospital departments involved occur within the first deciles of the crowding distribution. A further increase in hospital crowding towards capacity limits leads to only small additional reductions in these variables compared to the average crowding rate. The weak or insignificant effects of hospital crowding on readmissions, intensive care, and hospital mortality are confirmed in the semi-parametric specification shown in Figure 6.

Admission behavior In addition to the short-term crowding effects on the treatment intensity of hospitalized patients, a further step analyzes whether and to what extent a change in hospital capacity utilization affects the admission of new patients. Hospitals are expected to respond to higher crowding shares by reducing the number of new admissions. We aggregate the daily number of new admissions for each hospital and 3-digit ICD diagnosis and regress the number of new admissions on the hospital crowding measure, weekday, and holiday fixed effects, and fully interacting hospital, year-month, and 3-digit ICD diagnosis fixed effects. Only days with at least one admission and one diagnosis are included in the analysis.

Figure 8 illustrates the effect of hospital crowding on the number of new admissions at the hospital level in the semi-parametric variant, showing that the number of new admissions decreases as capacity utilization increases. While the reduction in new admissions is moderate (max. 3 %) up to the sixth decile of overcrowding, it becomes more pronounced, reaching a maximum of 6 % as hospitals approach full capacity.

To examine whether the reduction in admissions at full capacity reflects referrals to other nearby hospitals, we analyze admission behavior as a function of hospital location. Figure A.6 in the appendix shows the effect of hospital crowding on the number of new hospital admissions in and outside Linz.[11] For the hospitals located in Linz, we observe a significant decrease in new admissions with an increase in hospital crowding. For crowding rates in the sixth to tenth deciles, we observe significant decreases in the number of new admissions, ranging between 5 and 13 %. By contrast, we observe no significant or only minor adjustments in new admissions by peripheral hospitals in response to their crowding rates. Even at full capacity, these hospitals only reduce new admissions by 2.5 %.[12] The results suggest that hospitals in urban areas admit

[11] Out of 22 hospitals in our sample, 7 are located in the Upper Austrian capital Linz. The remaining hospitals are scattered across different towns in Upper Austria, with none having more than one hospital.

[12] Figure A.7 in the appendix shows the effect of hospital crowding on the number of new admissions over time and by hospital location. We analyze the response of hospital admissions to crowding after one, two, three, and four days. Panel (a) shows the effect for all hospitals, while panels (b) and (c) depict hospitals only in and outside Linz, respectively. The negative effect of crowding on the number of new admissions tends to decrease over time. While a high crowding rate (in the 8th or 9th decile) reduces the number of new admissions by approximately 4 % on the day after admission, the same effect is only 2 % four days later (panel a). The differences in new admissions as a function of the number of days since hospitalization are much more pronounced for Linz hospitals than for those in the surrounding area. The hospitals in Linz react quickly to increased capacity utilization by significantly reducing the number of admissions, while no significant effect is observed on new admissions four days later (panel b). Conversely, the differences in the effects of hospital

fewer patients when capacity is high and refer those who cannot be admitted to other nearby hospitals.[13]

Our short-term evidence suggests that increased hospital crowding reduces care intensity. As utilization increases, patients receive fewer individual medical services and are discharged earlier, leading to a significant reduction in hospital expenditure, while the quality of care—as measured by readmissions and mortality—remains unaffected. At the same time, hospitals in urban areas reduce new admissions as hospital capacity utilization increases.

Overall, our findings on the short-term effects of hospital crowding are consistent with those in the existing literature, confirming reduced treatment intensity. We find that a one-standard-deviation increase in crowding reduces the length of stay by 3.45 %, hospital expenditure by 2.37 %, and the number of services offered by 1.42 %. Our results are similar to, for example, Hoe (2022) and Bachner et al. (2024), who report a reduction in the length of stay by 1.4 % and 4.3 % respectively. In terms of treatment decisions, Hoe (2022) find a 0.3 % reduction in the number of procedures, while Bachner et al. (2024) find a 4 % reduction in the likelihood of having a cesarean section. In contrast to some other studies, we do not find statistically significant effects on hospital readmissions. We also find no significant effect on inpatient mortality, for which the evidence is mixed—some studies report no effects (Evans and Kim, 2006; Hoe, 2022; Schwierz et al., 2012; Singh and Venkataramani, 2022), whereas others confirm increased mortality (Gutierrez and Rubli, 2021; Singh and Venkataramani, 2022; Song et al., 2021) at higher hospital crowding rates.

4.2 Medium-run effects

Aligned with findings from other studies, we also find reductions in treatment intensity due to high hospital crowding. However, to comprehensively assess the impact of lower treatment intensity in hospitals, possible spillover effects after hospital discharge should also be considered to analyze how and to what extent fewer treatments possibly translate into worse medium-term outcomes. Therefore, in this section, we examine whether the decline in treatment intensity has medium-term implications for healthcare service demand and the labor market. Figure 9 illustrates the expenditure on healthcare utilization in the quarter following hospital discharge based on the semi-parametric specification. We find no significant effects of hospital crowding on expenditure on either pharmaceuticals (panel c) or outpatient and inpatient health care services (panels a, b, and d). The effects on the number of sick days are also consistently insignificant (see panel e). The lower treatment intensity during the first hospital stay does not

crowding on new admissions according to the number of days since admission are minimal in the peripheral hospitals (panel c).

[13] Section 4.3 examines whether the main results presented in Table 3 change when hospitals outside Linz are considered separately.

lead to higher medical treatment costs in the following quarter, suggesting patients' health does not deteriorate. The effects are confirmed when we extend the observation period. Figure 10 shows that even two years after the original hospitalization, there is no significant increase in healthcare expenditure due to higher hospital utilization.

Next, we examine whether the differences in hospital treatment caused by capacity utilization affect the ability of patients to work. Figure 11 depicts the labor market outcomes two years post-discharge in the semi-parametric specification. With a few exceptions, the coefficients are insignificant for all outcomes and deciles of capacity utilization. Moreover, the statistically significant point estimates are quantitatively negligible. Thus, there are no significant effects of differences in hospital crowding on the number of days worked and the number of days retired, or on real wages in the medium term.[14] These results also align with the previous analyses. Differences in treatment during hospitalization neither affect the medium-term use of health care services nor labor market participation. This again supports the hypothesis that differences in treatment during a stay in an Austrian hospital have no demonstrable impact on health status, and thus, on consequential labor supply behavior.[15]

4.3 Heterogeneity and Robustness

Heterogeneity: Figures 12, 13, and 14 illustrate the heterogeneity of the results by age, sex, and hospital location, respectively. Panels a–c show the estimation results for the length of hospital stays, number of medical services offered, and expenses during hospital stays, respectively. They show whether the impact of hospital crowding on these short-term variables, which are significant in the full sample, differs by sex, age group, or environment (urban or rural) of the hospital. For the medium-term effects, hospital expenditure one quarter and two years after the hospital stay (panels d and e, respectively) and employment effects also two years after the hospital stay (panel e) were selected.

The decline in both the length of stay and expenditure during hospital stays is similar for men and women, although the negative point estimates are slightly higher for men than for women (panels a and c in Figure 12, respectively). The reduction in the number of hospital services is only statistically significant for women (panel b). The point estimates for male patients are smaller and consistently insignificant. The medium-term and insignificant effects on hospital expenditure one quarter and two years after hospitalization show no gender differences, as do the effects on employment.

The results in Figure 13 show clear differences by age groups. The significant and negative

[14] Figure A.8 shows that the results are similar when considering extensive margin outcomes.

[15] Table A.2 in the appendix shows health care outcomes one quarter and two years post-discharge and labor market outcomes two years post-discharge in the linear specification. All coefficients are insignificant, thereby confirming the results of the semi-parametric specification.

effects of hospital occupancy on length of stay are most pronounced in the 30–60 age group. Compared to the youngest age group, the differences in the upper deciles of capacity utilization are more than half a day (panel a). A similar pattern is observed for hospital expenditure (panel c), with the middle age cohort showing the largest declines, ranging from 200 € to over 400 €. Conversely, the effects for the youngest group of patients remain insignificant. The number of services offered decreases only for the oldest age group and remains unchanged for the younger and middle cohorts (panel b). Overall, the patient group aged under 30 years shows no significant decline in treatment intensity due to increasing capacity utilization. The medium-term effects on the level of hospital expenditure and employment differ minimally between age groups and are mostly insignificant (panels d–e).[16]

To examine location effects, we split the sample and estimate the impact of hospital occupancy separately for hospitals in the Upper Austrian capital Linz, and in the periphery. The aim is to find out whether hospitals adjust their behavior differently in urban and rural areas due to their proximity to each other. As Figure 14 illustrates, the decline in treatment intensity is similar in urban and rural hospitals. We find a significant decrease in length of stays and short-term expenditure for inpatient stays for both hospital locations, with the negative effects for both variables being quantitatively larger for Linz hospitals (panels a and c). The differences in length of stays are up to 0.4 days and in costs up to 100 €. The opposite is true for the number of hospital treatments. An increase in hospital crowding only reduces the number of hospital treatments in the peripheral hospitals, while they remain unchanged in the Linz hospitals. All medium-term effects are identical and insignificant for both hospital locations.

Robustness: In our baseline specification, we define a hospitalization as acute if the weekend proportion of its corresponding ICD-10 diagnosis exceeds the 75^{th} percentile. To test robustness, alternative definitions of acute hospitalizations were considered, using thresholds above the 50^{th} and 90^{th} percentiles.[17] Figure A.9 in the appendix shows the results of this robustness check for selected outcomes.

The results for a weekend admission rate above the 75^{th} or 50^{th} percentile are very similar throughout. Both the point estimates and the significance levels are almost identical for the selected outcomes. At first glance, the specific definition of an acute hospital stay not playing a decisive role may appear surprising. However, the inclusion of fixed effects for (fully interacted) ICD diagnoses at the 3-digit level in all estimates effectively controls for the acute nature of admissions. Even the point estimates for a weekend admission rate above the 90^{th} percentile are comparable in magnitude to the results in the baseline specification, although with varying

[16] The short-term effects on expenditure per service and the number of hospital departments, which were also significant in the overall sample, do not differ by sex or age group. All other results not shown in the figures remain insignificant for men and women and patients of different ages, as in the full sample. Estimation results are available on request.

[17] Figure A.10 in the appendix compares the distribution of diagnoses for these alternative thresholds.

significance levels. As this variant contains very few diagnoses (see Figure A.10), the standard errors are large, leading to a comparatively higher number of insignificant estimates. In summary, the robustness checks confirm that the results are not sensitive to the specific threshold used to define acute hospitalization.

5 Conclusions

Using high-quality administrative data from Upper Austria, we analyzed the effect of hospital occupancy on patients' short- and medium-term health (expenditure) and labor market outcomes. Our findings revealed that the intensity of care in hospitals decreases as hospital occupancy increases, although this does not affect patient health adversely. Crowding does not affect readmissions, mortality, and health care use one quarter and two years after hospital discharge. Therefore, patients may not need to compensate for the lower intensity of care during their hospital stay to maintain a given level of health after discharge. We also found no effects on patients' labor market outcomes two years post-discharge.

Our results do not suggest that hospital patients are not receiving the care they need because of higher capacity utilization and the associated scarcity of resources in hospitals. Rather, the results suggest that, given a very high level of service provision in the inpatient sector, a slight reduction in service provision has no demonstrable effect on the health of patients. Austria has a health care system that is characterized by a high density of hospital beds and physicians by international standards, which may be at least partly explained by overtreatment. In 2014, Austria ranked third in the European Union in terms of beds-to-population ratio (5.84 acute care beds per capita) and second in terms of physician density (Bachner et al., 2018). This suggests that the standard level of available treatment capacity is relatively high. Therefore, increases in unpredictable demand for health care may be easier to manage than in other countries where bed density is not as high.

The finding that higher hospital occupancy rates reduce the intensity of inpatient care is consistent with that in other related studies. In contrast to most of these studies, we examine whether a (moderate) reduction in the intensity of inpatient treatment has longer-term consequences for the health and labor market participation of patients. We find that a reduction in hospital care does not negatively impact health and labor market outcomes, suggesting that Austrian hospitals can cope with unpredictable peaks in demand for health care without compromising patient well-being. In this context, this study is an important addition to the existing literature. A serious health economic evaluation of the effects of changes in hospital utilization must consider not only the immediate effects on treatment intensity but also the longer-term welfare effects. Most existing studies cannot analyze these medium- to long-term effects in detail. It is very likely that the short-term negative effects on the use of medical services overestimate the ultimately decisive medium- and long-term effects on patients' lives.

References

Andrew, Alison and Marcos Vera-Hernández (2024), 'Incentivizing Demand for Supply-Constrained Care: Institutional Birth in India', *The Review of Economics and Statistics* **106**(1), 102–118.

Avdic, Daniel, Petter Lundborg and Johan Vikström (2024), 'Does Health Care Consolidation Harm Patients? Evidence from Maternity Ward Closures', *American Economic Journal: Economic Policy* **16**(1), 160–89.

Bachner, Florian, Julia Bobek, Katharina Habimana, Joy Ladurner, Lena Lepuschütz Herwig, Ostermann, Lukas Rainer, Andrea E. Schmidt, Martin Zuba, Quentin Wilm and Juliane Winkelmann (2018), 'Austria: Health System Review', *Health Systems in Transition* **20**(3), 1–254.

Bachner, Florian, Martin Halla and Gerald J. Pruckner (2024), Do Empty Beds Cause Cesarean Deliveries?, IZA Discussion Papers, No 16981, Institute of Labor Economics (IZA), Bonn.

Bensnes, Simon (2024), Time to Spare and Too Much Care? Congestion, Treatment and Health Outcomes in the Maternity Unit., Technical report, SSRN.

Bernstein, Steven L., Dominik Aronsky, Reena Duseja, Stephen Epstein, Dan Handel, Ula Hwang, Melissa McCarthy, K. John McConnell, Jesse M. Pines, Niels Rathlev, Robert Schafermeyer, Frank Zwemer, Michael Schull, Brent R. Asplin and Emergency Department Crowding Task Force Society for Academic Emergency Medicine (2009), 'The Effect of Emergency Department Crowding on Clinically Oriented Outcomes', *Academic Emergency Medicine* **16**(1), 1–10.

Cook, Andrew, Martin Gaynor, Melvin Stephens Jr and Lowell Taylor (2012), 'The Effect of a Hospital Nurse Staffing Mandate on Patient Health Outcomes: Evidence from California's Minimum Staffing Regulation', *Journal of Health Economics* **31**(2), 340–348.

Costa, Eduardo (2022), 'The Unintended Consequences of Hospital Strikes on Patient Outcomes Evidence from Multiple Strikes in the Portuguese National Health Service', *Health Economics* **31**(11), 2499–2511.

Evans, William N. and Beomsoo Kim (2006), 'Patient Outcomes When Hospitals Experience A Surge In Admissions', *Journal of Health Economics* **25**(2), 365–388.

Facchini, Gabriel (2022), 'Low Staffing in the Maternity Ward: Keep Calm and Call the Surgeon', *Journal of Economic Behavior & Organization* **197**, 370–394.

Francetic, Igor, Rachel Meacock, Luigi Siciliani and Matt Sutton (2024), Disorderly Queues: How Does Unexpected Demand Affect Queue Prioritisation in Emergency Care?, Technical report, HEDG, c/o Department of Economics, University of York.

Freedman, Seth (2016), 'Capacity and Utilization in Health Care: The Effect of Empty Beds on Neonatal Intensive Care Admission', *American Economic Journal: Economic Policy* **8**(2), 154–85.

Gruber, Jonathan, Thomas P. Hoe and George Stoye (2023), 'Saving Lives by Tying Hands: The Unexpected Effects of Constraining Health Care Providers', *The Review of Economics and Statistics* **105**(1), 1–19.

Gutierrez, Emilio and Adrian Rubli (2021), 'Shocks to Hospital Occupancy and Mortality: Evidence from the 2009 H1N1 Pandemic', *Management Science* **67**(9), 5943–5952.

Harris, Matthew C., Yinan Liu and Ian McCarthy (2020), 'Capacity Constraints and Time Allocation in Public Health Clinics', *Health Economics* **29**(3), 324–336.

Hoe, Thomas P. (2022), 'Does Hospital Crowding Matter? Evidence from Trauma and Orthopedics in England', *American Economic Journal: Economic Policy* **14**(2), 231–62.

Hofmarcher, Maria M. and Christopher Singhuber (2020), Leistungskraft regionaler Gesundheitssysteme in Zeiten von COVID-19. Ambulante Versorgung im Bundesländervergleich, Research Report, HealthSystemIntelligence, Vienna, August 2020.

Hoot, Nathan R. and Dominik Aronsky (2008), 'Systematic Review of Emergency Department Crowding: Causes, Effects, and Solutions', *Annals of Emergency Medicine* **52**(2), 126–136.

Jiang, Nan and Gail Pacheco (2014), 'Demand In New Zealand Hospitals: Expect The Unexpected?', *Applied Economics* **46**(36), 4475–4489.

Maibom, Jonas, Hans H. Sievertsen, Marianne Simonsen and Miriam Wüst (2021), 'Maternity Ward Crowding, Procedure Use, and Child Health', *Journal of Health Economics* **75**, 102399.

Marks, Mindy and Moonkyung Kate Choi (2019), 'Baby Boomlets and Baby Health: Hospital Crowdedness, Hospital Spending, and Infant Health', *American Journal of Health Economics* **5**(3), 376–406.

Martins, Bruno and Luís Filipe (2020), 'Doctors' Response to Queues: Evidence from a Portuguese Emergency Department', *Health Economics* **29**(2), 123–137.

Morley, Claire, Maria Unwin, Gregory M. Peterson, Jim Stankovich and Leigh Kinsman (2018), 'Emergency Department Crowding: A Systematic Review of Causes, Consequences and Solutions', *PLOS ONE* **13**(8), 1–42.

Raja, Chandni (2023), 'How do Hospitals Respond to Input Regulation? Evidence From The California Nurse Staffing Mandate', *Journal of Health Economics* **92**, 102826.

Rasouli, Hamid Reza, Ali Aliakbar Esfahani, Mohammad Nobakht, Mohsen Eskandari, Sardollah Mahmoodi, Hassan Goodarzi and Mohsen Abbasi Farajzadeh (2019), 'Outcomes of Crowding in Emergency Departments; A Systematic Review', *Archives of Academic Emergency Medicine* **7**(1), e52.

Schwierz, Christoph, Boris Augurzky, Axel Focke and Jürgen Wasem (2012), 'Demand, Selection and Patient Outcomes in German Acute Care Hospitals', *Health Economics* **21**(3), 209–221.

Sharma, Rajiv, Miron Stano and Renu Gehring (2008), 'Short-Term Fluctuations in Hospital Demand: Implications for Admission, Discharge, and Discriminatory Behavior', *The RAND Journal of Economics* **39**(2), 586–606.

Singh, Manasvini and Atheendar Venkataramani (2022), Rationing By Race, Working Paper 30380, National Bureau of Economic Research.

Sivey, Peter (2018), 'Should I Stay Or Should I Go? Hospital Emergency Department Waiting Times and Demand', *Health Economics* **27**(3), e30–e42.

Song, Jinglin, Chen Chen, Shaoyang Zhao, Leming Zhou and Hong Chen (2021), 'Trading Quality for Quantity? Evidence From Patient Level Data In China', *PLOS ONE* **16**(9), 1–18.

Stoye, George and Max Warner (2023), 'The Effects of Doctor Strikes on Patient Outcomes: Evidence from the English NHS', *Journal of Economic Behavior & Organization* **212**, 689–707.

Turner, Alex J., Laura Anselmi, Yiu-Shing Lau and Matt Sutton (2020), 'The Effects of Unexpected Changes in Demand on the Performance of Emergency Departments', *Health Economics* **29**(12), 1744–1763.

Woodworth, Lindsey (2020), 'Swamped: Emergency Department Crowding and Patient Mortality', *Journal of Health Economics* **70**, 102279.

Zweimüller, Josef, Rudolf Winter-Ebmer, Rafael Lalive, Andreas Kuhn, Jean-Philippe Wuellrich, Oliver Ruf and Simon Büchi (2009), The Austrian Social Security Database (ASSD), Working Paper 0903, The Austrian Center for Labor Economics and the Analysis of the Welfare State, University of Linz.

6 Figures (to be placed in the article)

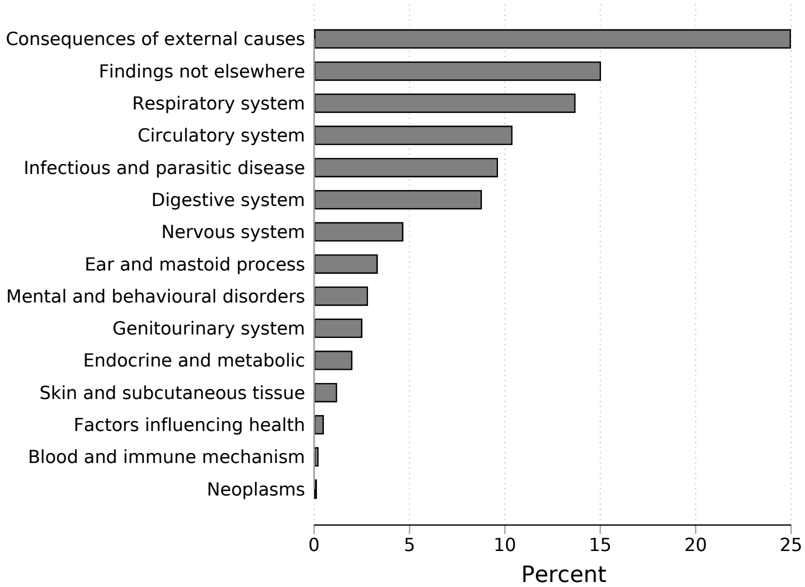


FIGURE 1 — Distribution of acute ICD-chapters in analysis sample

Note — The figure shows the distribution of ICD-chapter diagnoses in our main analysis sample. A more detailed discussion of the sample structure can be found in Section 2.3.

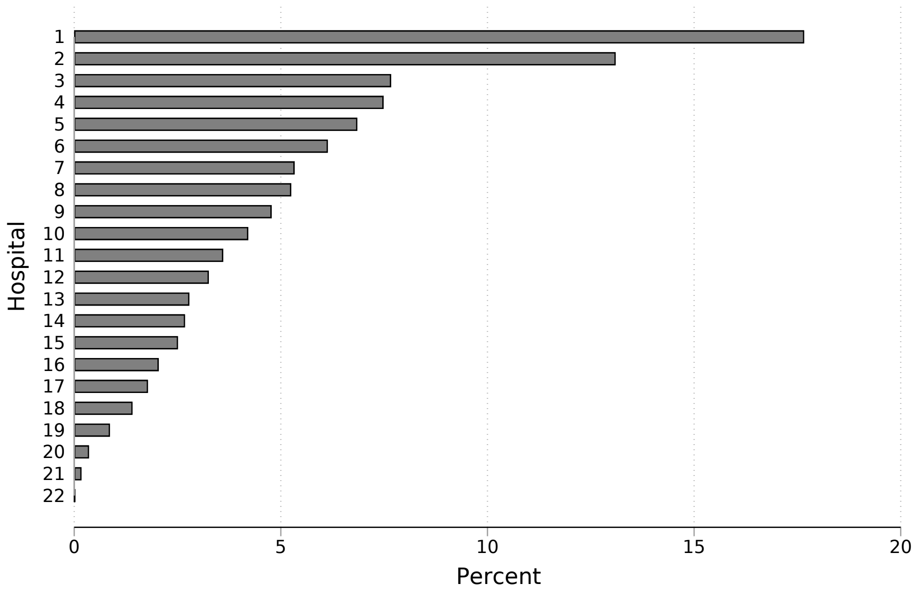


FIGURE 2 — Distribution of hospitals in analysis sample

Note — The figure shows the distribution of hospitals in our main analysis sample. A more detailed discussion of the sample structure can be found in Section 2.3.

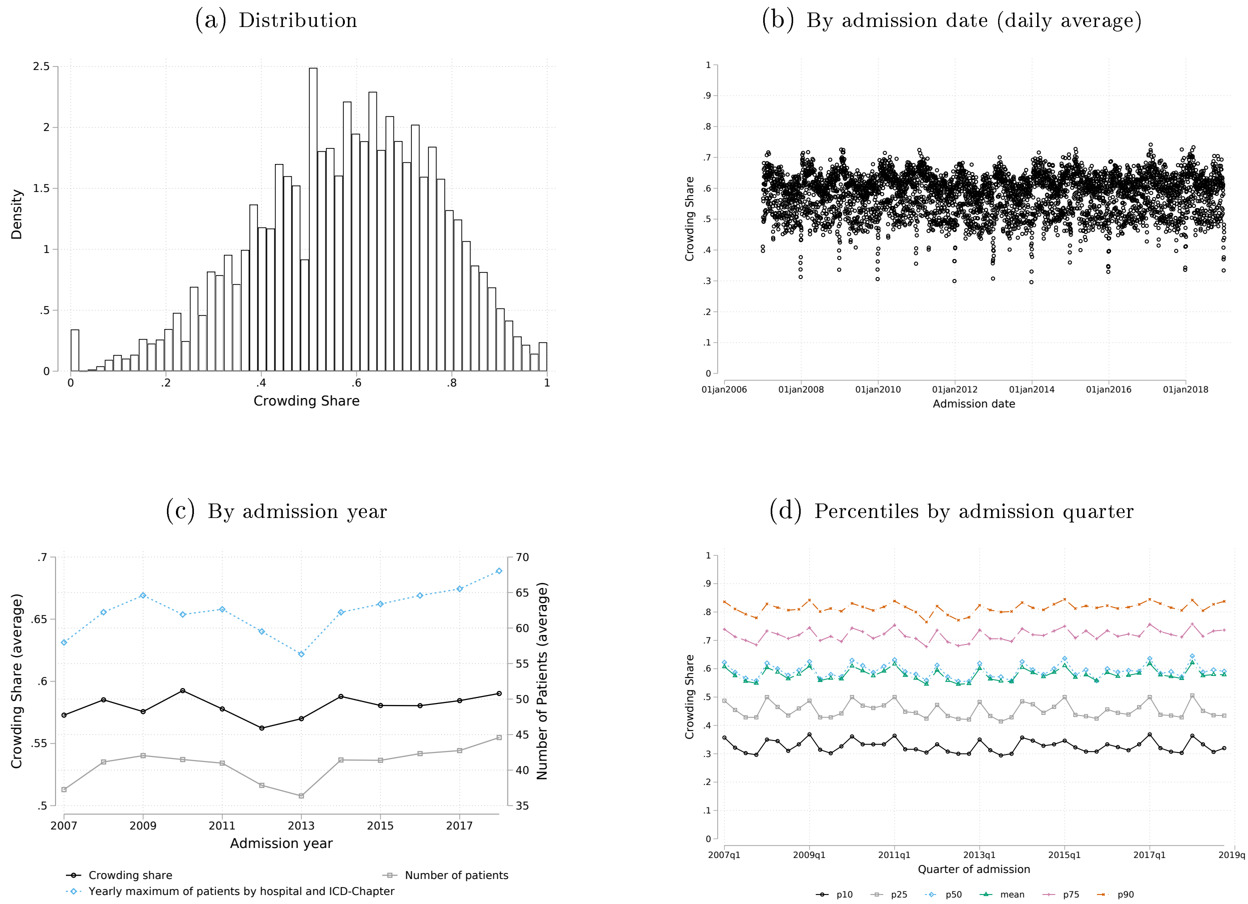


FIGURE 3 — Descriptives of hospital crowding measure

Note — This figure shows several descriptive properties of our hospital crowding measure. Panel (a) illustrates the distribution of the crowding measure. Panel (b) illustrates the daily average of the crowding measure by admission date. Panel (c) illustrates the average crowding measure, the number of patients, and the yearly maximum number of patients by hospital and ICD-chapter by admission year. Panel (d) illustrates different percentiles and the average hospital crowding measure by admission quarter. A more detailed discussion of the hospital crowding measure can be found in Section 2.3.2.

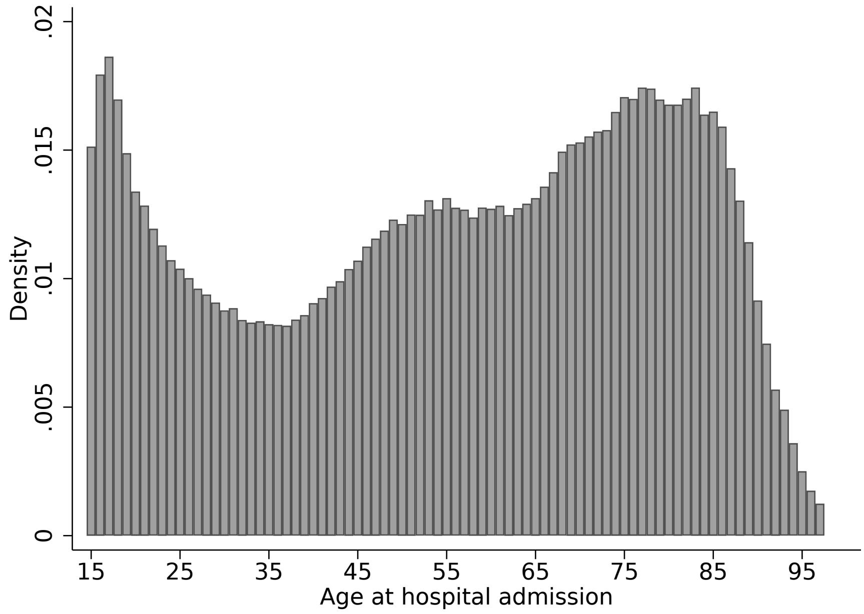


FIGURE 4 — Distribution of age at hospitalization in analysis sample

Note — The figure shows the age distribution at hospital admission in our main analysis sample. A more detailed discussion of the sample structure can be found in Section 2.3.

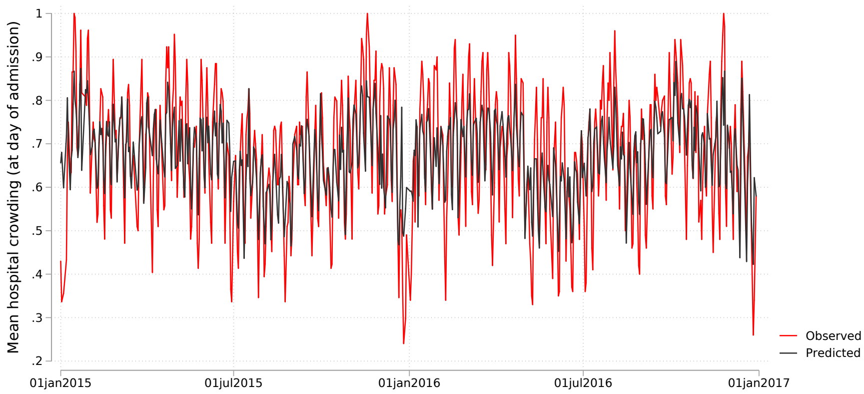


FIGURE 5 — Illustration of identifying variation for hospital 1 and diseases of the digestive system

Note — This figure illustrates an example of the identifying variation we use in our analysis for hospital 1 and admissions with a diagnosis in ICD-chapter 11 “Diseases of the digestive system." The black line shows average predicted hospital occupancy values while the red line denotes average observed hospital occupancy values. The difference between the black and red lines represents the idiosyncratic exogenous variation in hospital occupancy, which identifies the causal effects.

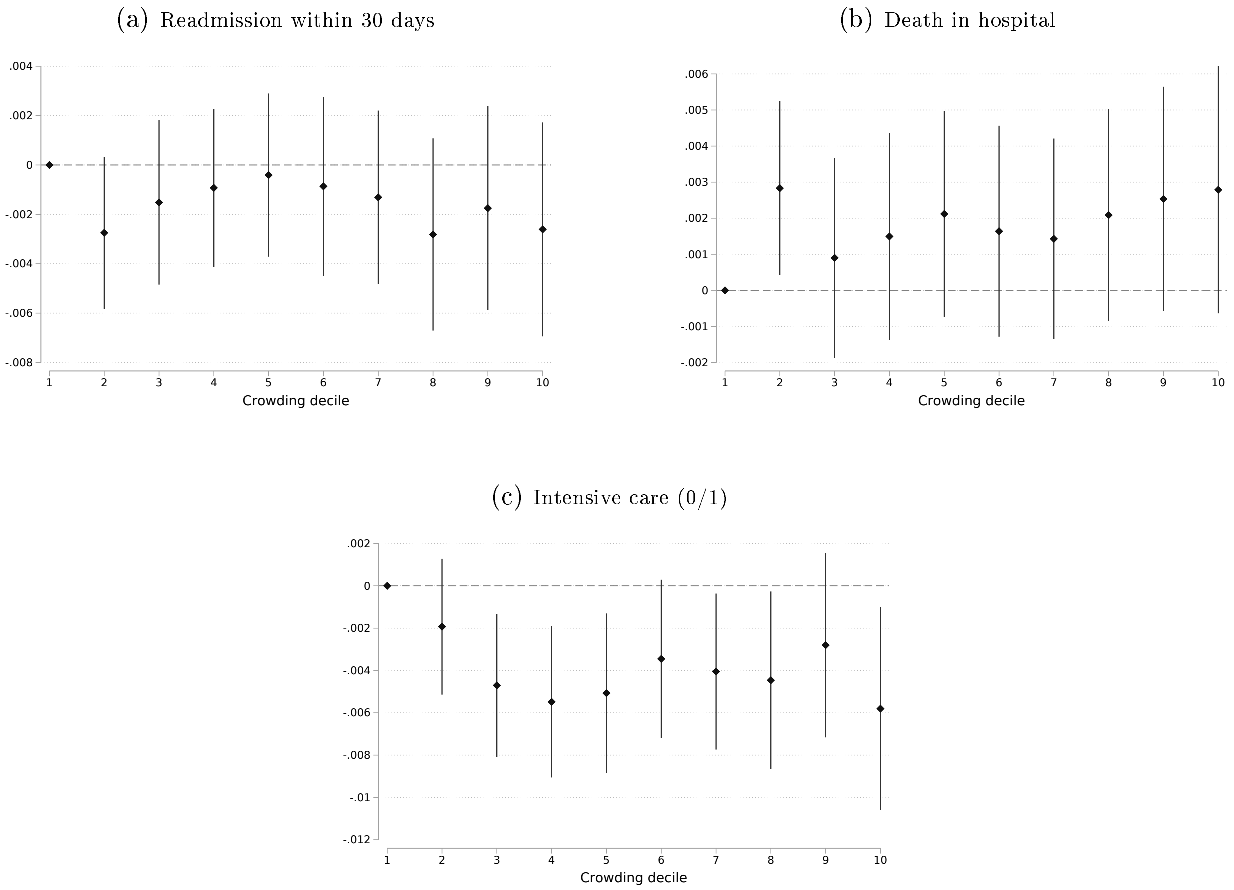


FIGURE 6 — Hospitalization quality measures of initial hospital stay

Note — This figure shows the estimated coefficients along with the corresponding 95 percent confidence intervals for the effect of hospital occupancy on various outcomes measuring hospital quality during the initial hospital stay. The coefficients are estimated using Equation (1) in the semi-parametric variant. Standard errors are clustered at the hospital $\times$ year level.

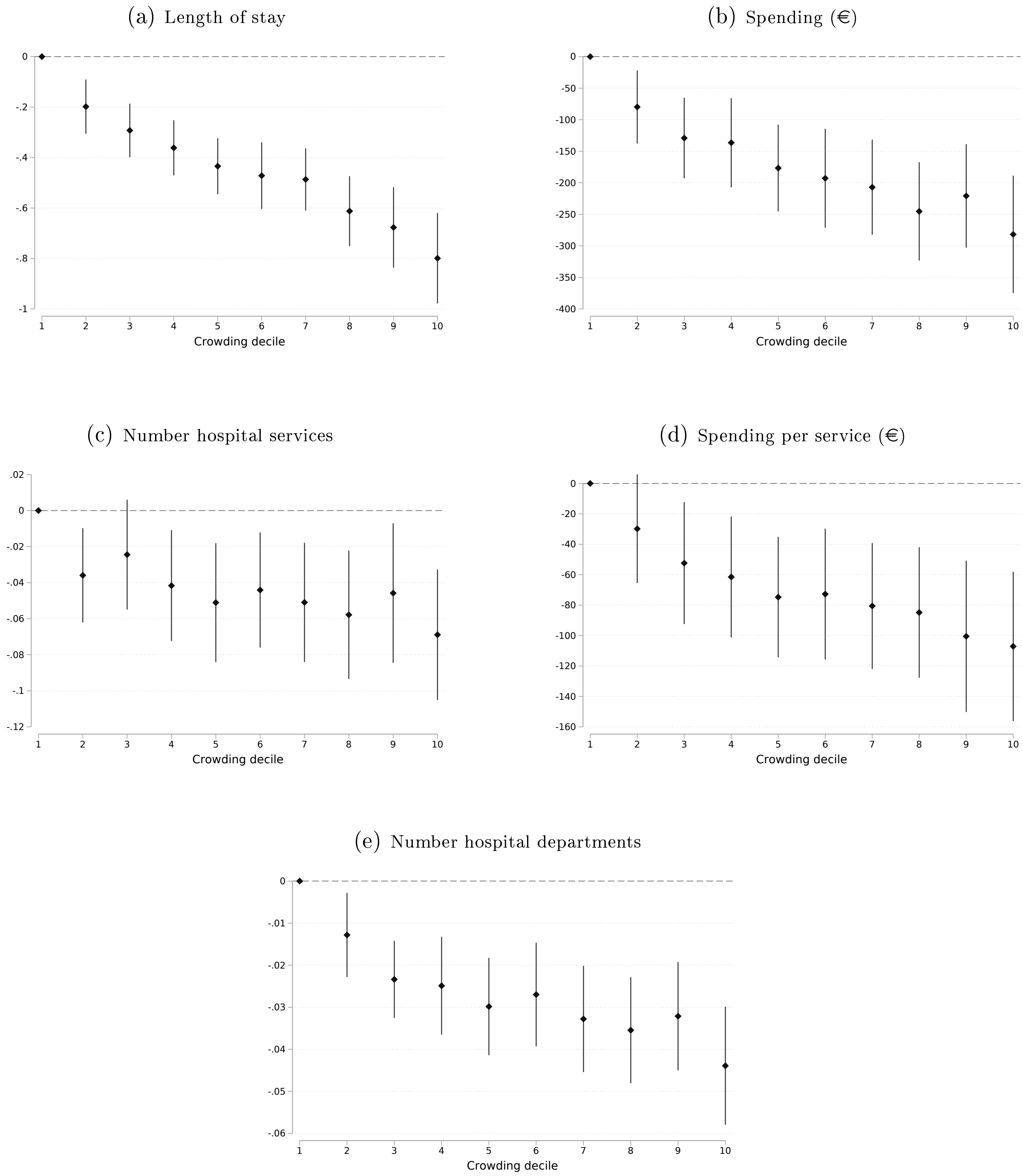


FIGURE 7 — Utilization during initial hospital stay

Note — This figure shows the estimated coefficients along with the corresponding 95 percent confidence intervals for the effect of hospital occupancy on various outcomes of the patient's initial hospital stay. The coefficients are estimated with Equation (1) in the semi-parametric variant. Standard errors are clustered at the hospital $\times$ year level.

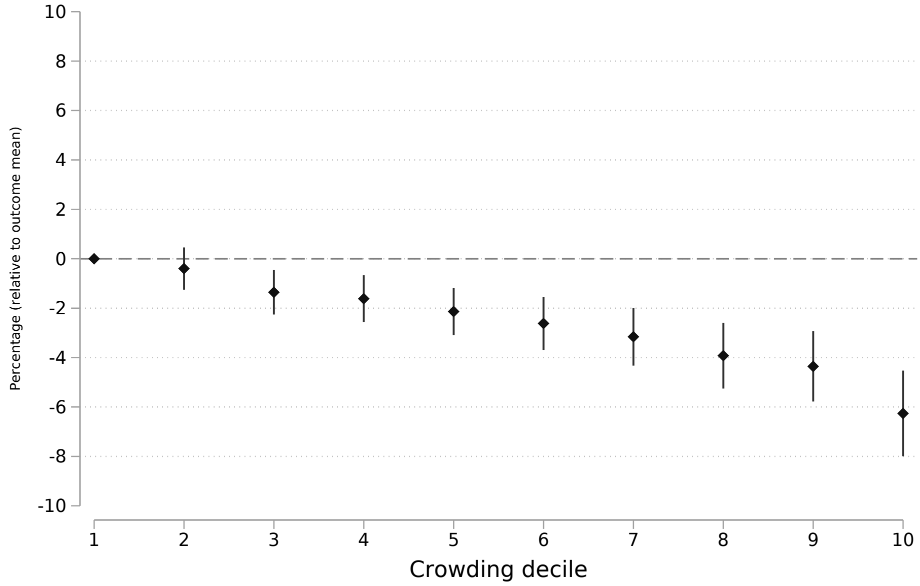
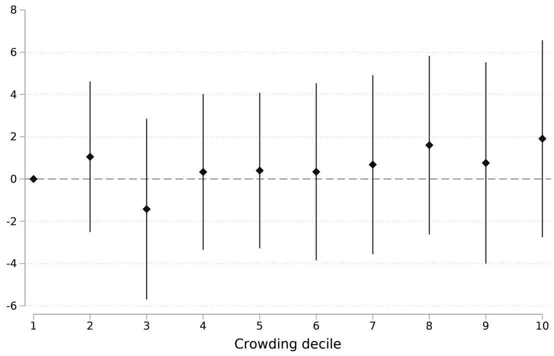


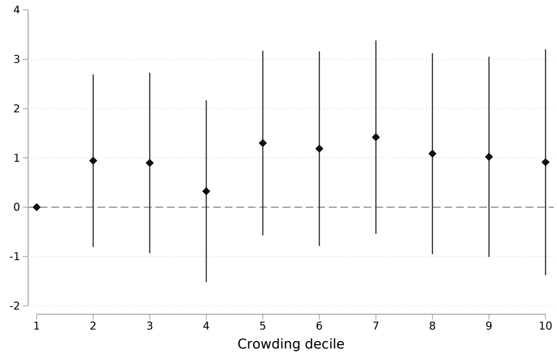
Figure 8 — Effect of hospital crowding on number of new admissions

Note — This figure shows the estimated coefficients along with the corresponding 95 percent confidence intervals for the effect of hospital occupancy on the number of new admissions as a percentage of the overall outcome mean. For this, we aggregate our main estimation sample to provide us with the daily number of new admissions for each hospital and ICD diagnosis at the 3-digit level. Only days with at least one hospital admission and a given diagnosis are included in the analysis. We then regress the number of new admissions on the hospital crowding measure, day-of-week and holiday fixed effects, and fully interacted hospital, year-month, and ICD diagnosis at the 3-digit level fixed effects. Standard errors are clustered at the hospital $\times$ year level.

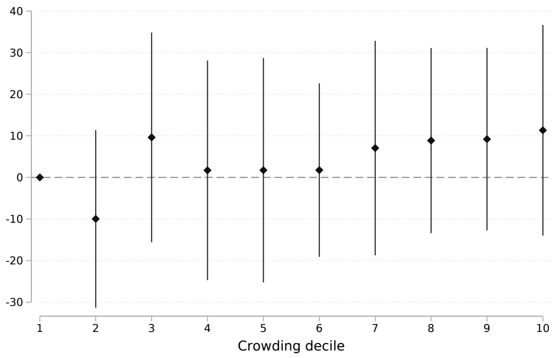
(a) Outpatient specialists (€)



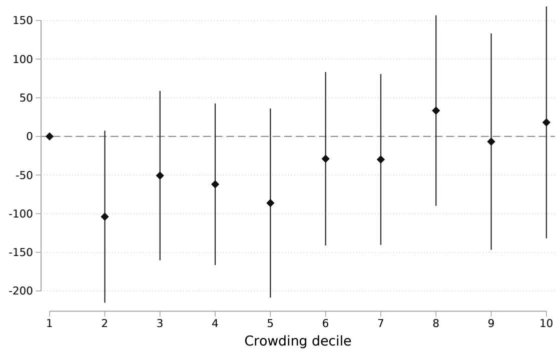
(b) General practitioner (€)



(c) Drugs (€)



(d) Hospital spending (€)



(e) Sick leave days

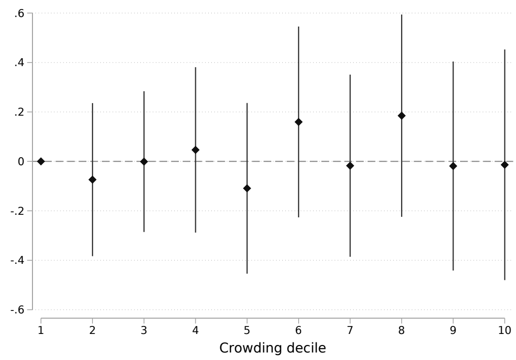


Figure 9 — Short-term healthcare use

Note — This figure shows the estimated coefficients along with the corresponding 95 percent confidence intervals for the effect of hospital occupancy on various outcomes measuring patients' short-term healthcare use one quarter after hospital discharge. The coefficients are estimated with Equation (1) in the semi-parametric variant. Standard errors are clustered at the hospital $\times$ year level.

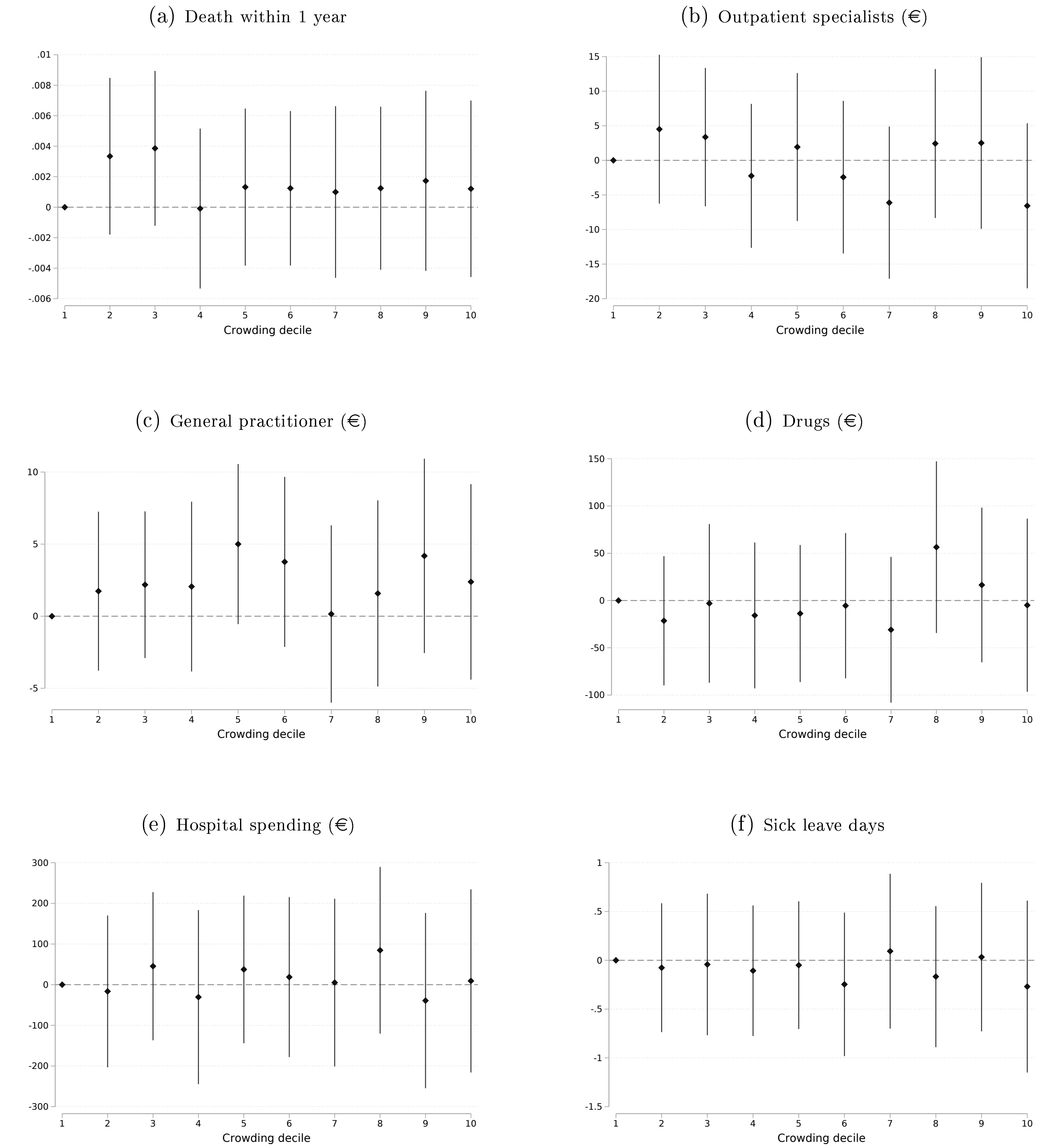


FIGURE 10 — Medium-term healthcare use

Note — This figure shows the estimated coefficients along with the corresponding 95 percent confidence intervals for the effect of hospital occupancy on various outcomes measuring patients' medium-term healthcare use two years after hospital discharge. The coefficients are estimated with Equation (1) in the semi-parametric variant. Standard errors are clustered at the hospital × year level.

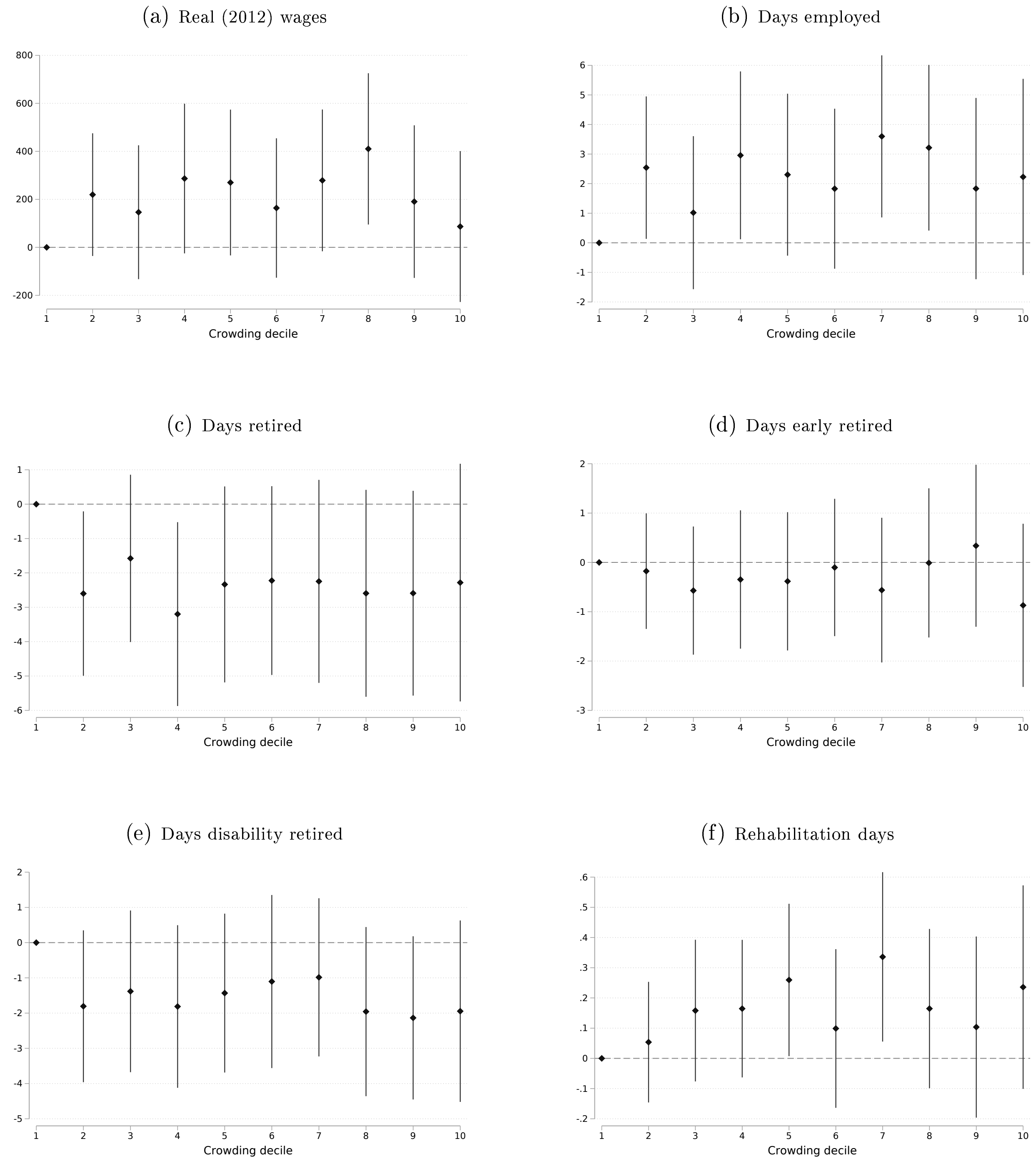


Figure 11 — Medium-term labor market outcomes

Note — This figure shows the estimated coefficients along with the corresponding 95 percent confidence intervals for the effect of hospital occupancy on various outcomes measuring patients' medium-term labor market performance two years after hospital discharge. The coefficients are estimated with Equation (1) in the semi-parametric variant. Standard errors are clustered at the hospital $\times$ year level.

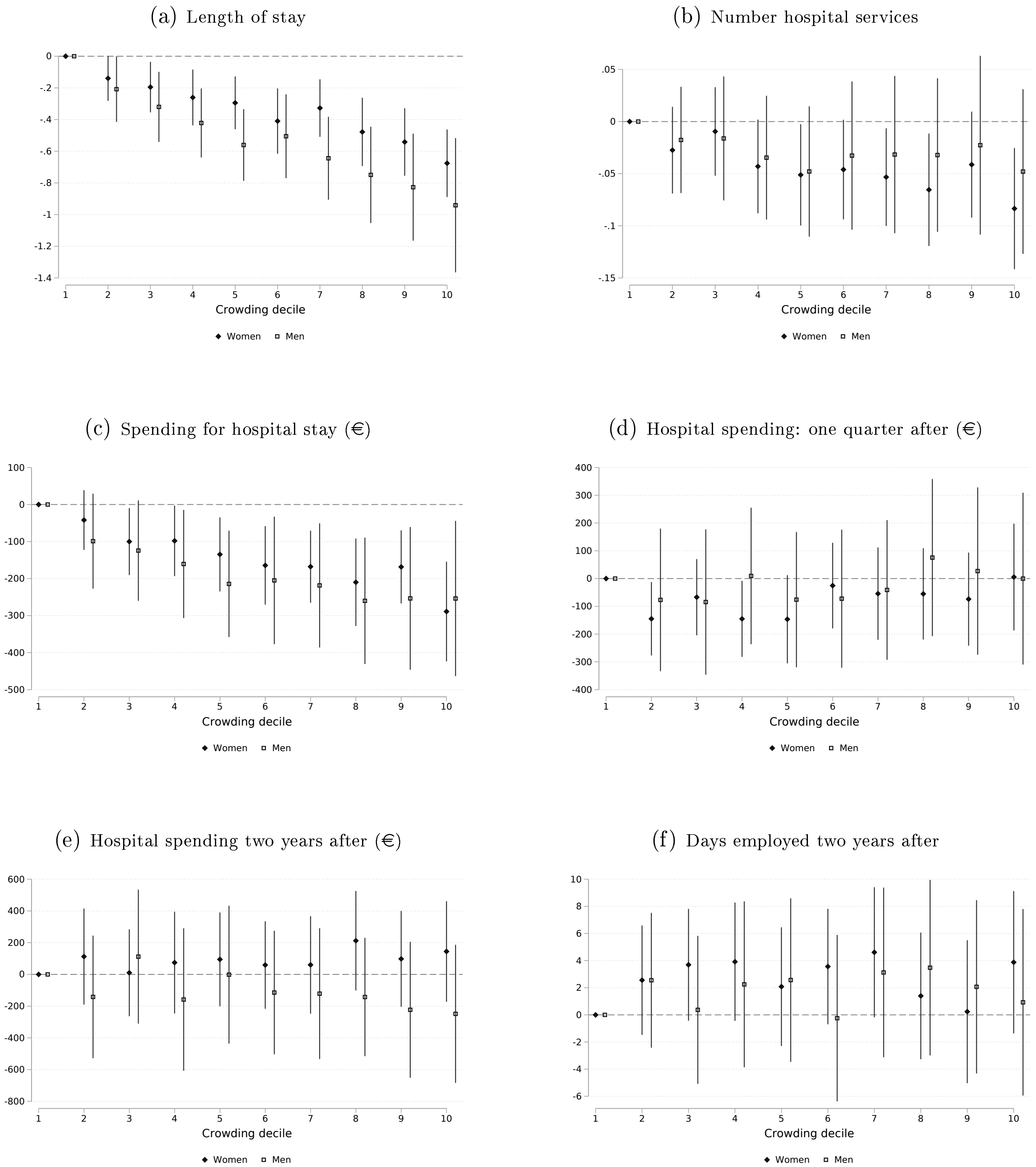


Figure 12 — Heterogeneity by sex (some selected outcomes)

Note — This figure shows the estimated coefficients along with the corresponding 95 percent confidence intervals for the effect of hospital occupancy on selected outcomes by patient's sex. The coefficients are estimated using Equation (1) in the semi-parametric variant. Standard errors are clustered at the hospital $\times$ year level.

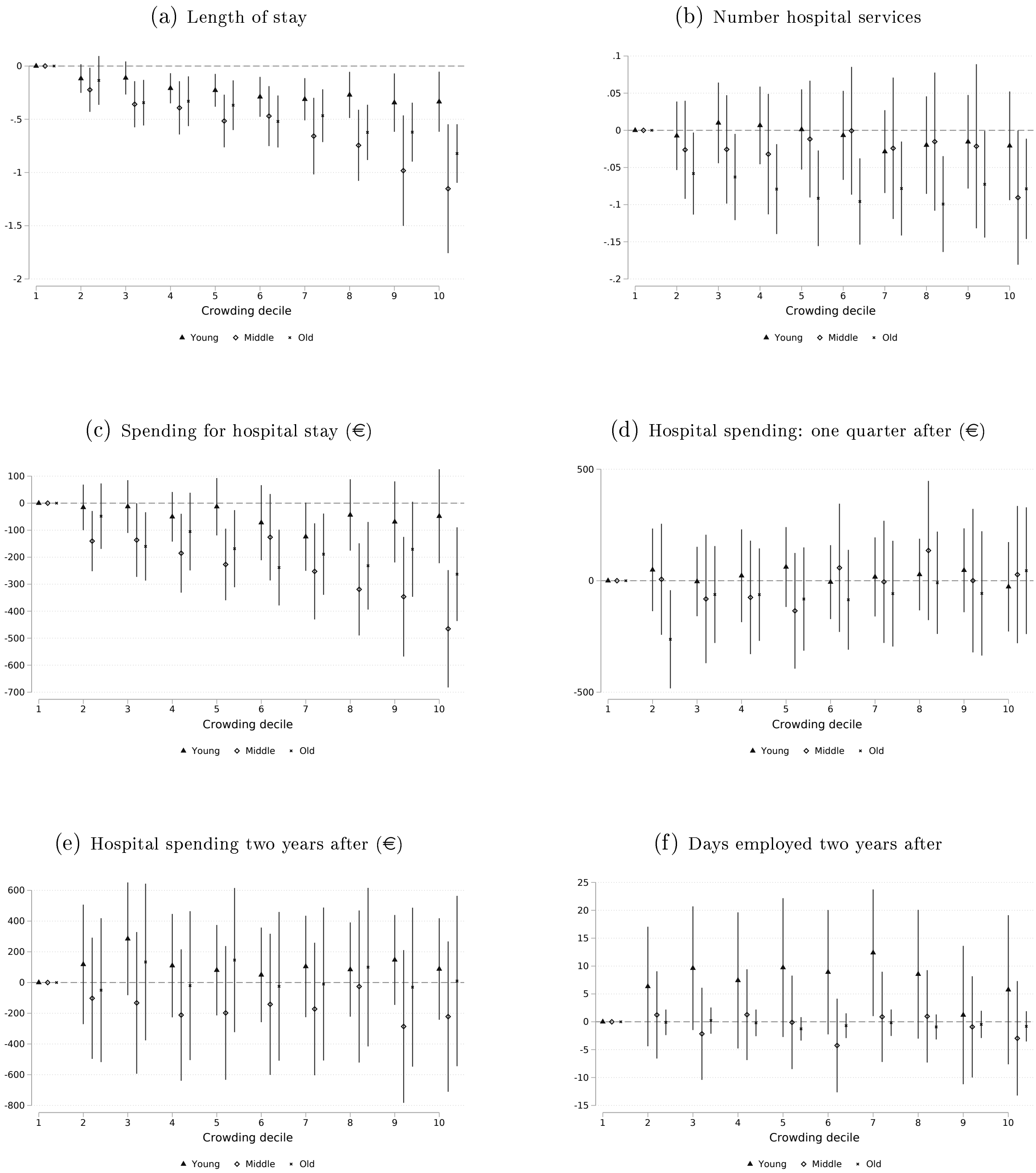
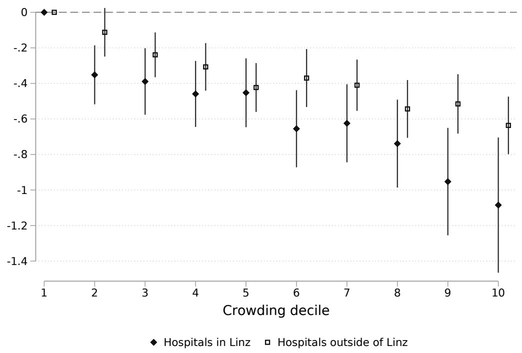


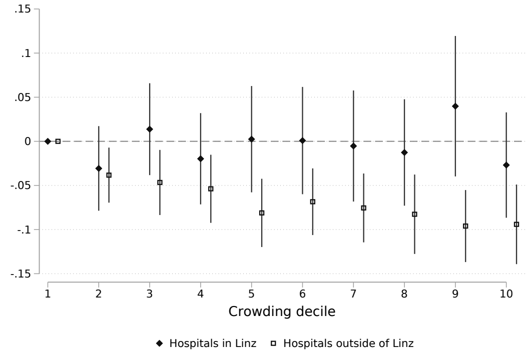
FIGURE 13 — Heterogeneity by age (some selected outcomes)

Note — This figure displays the estimated coefficients along with the corresponding 95 percent confidence intervals for the effect of hospital occupancy on selected outcomes by patient's age. Individuals aged 30 years or below at the time of hospitalization are defined as young, those between 31 and 60 years as middle, and those aged 60 years and above as old. The coefficients are estimated using Equation (1) in the semi-parametric variant. Standard errors are clustered at the hospital × year level.

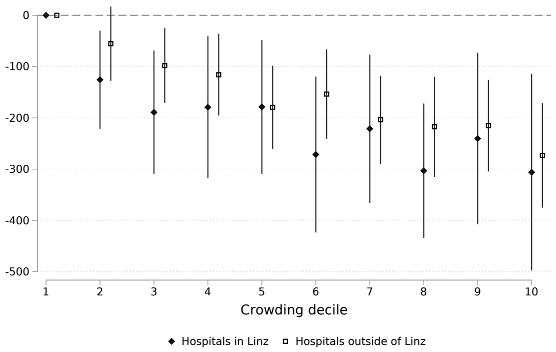
(a) Length of stay



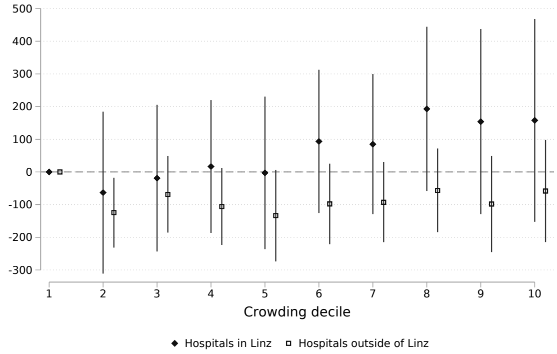
(b) Number hospital services



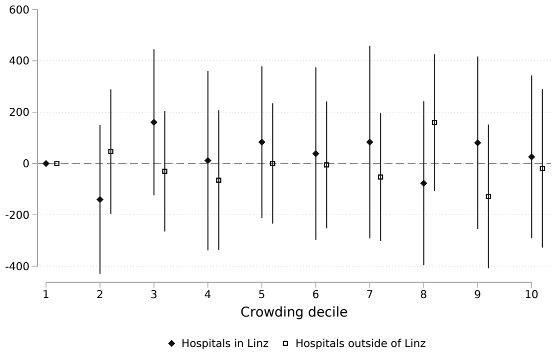
(c) Spending for hospital stay (€)



(d) Hospital spending: one quarter after (€)



(e) Hospital spending two years after (€)



(f) Days employed two years after

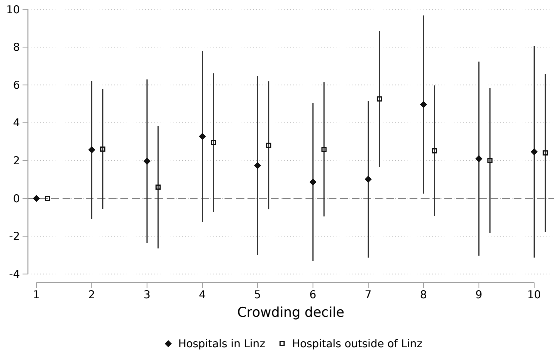


FIGURE 14 — Heterogeneity by hospital location (some selected outcomes)

Note — This figure shows the estimated coefficients along with the corresponding 95 percent confidence intervals for the effect of hospital occupancy on selected outcomes by hospital location. We illustrate the effects on patients admitted to hospitals located in Linz (the capital of Upper Austria) and outside Linz. The coefficients are estimated using Equation (1) in the semi-parametric variant. Standard errors are clustered at the hospital $\times$ year level.

7 Tables (to be placed in the article)

Table 1 — Descriptive statistics

	Mean	Median	SD	Min	Max	N
	(1)	(2)	(3)	(4)	(5)	(6)
Hospital Stay						
Crowding share	0.580	0.593	0.190	0.00	1.00	495,365
Length of stay	6.851	5.000	7.464	1.00	189.00	495,365
Hospital spending	3,568.204	2,264.310	4,839.353	16.90	76,589.89	495,365
Hospital spending per service	2,193.242	1,788.710	1,735.730	5.53	42,850.92	304,669
Total number of services	1.457	1.000	1.964	0.00	18.00	495,365
Total number of departments	1.256	1.000	0.658	1.00	6.00	495,190
Readmission within 30 days (ICD-3)	0.026	0.000	0.160	0.00	1.00	495,365
Patient died in hospital	0.023	0.000	0.149	0.00	1.00	495,365
Death within 1 year after hospital discharge	0.087	0.000	0.282	0.00	1.00	495,350
Patient has points for intenive care	0.064	0.000	0.244	0.00	1.00	495,365
Patient Characteristics						
Female	0.531	1.000	0.499	0.00	1.00	495,365
Age of patient at hospital admission	56.025	59.000	23.154	15.00	97.00	495,365
Year of birth of patient	1,956.118	1,953.000	23.220	1,910.00	2,003.00	495,365
Austrian citizenship (2022)	0.861	1.000	0.346	0.00	1.00	495,365
Patient lives in urban area	0.250	0.000	0.433	0.00	1.00	495,365
Healthcare (1 year before admission)						
Outpatient medical care	531.455	358.310	637.652	0.00	38,158.46	474,197
Outpatient specialists	278.436	145.600	413.205	0.00	25,407.82	474,197
Drugs	671.210	148.100	3,631.697	0.00	1,010,214.72	474,197
Hospital days	5.024	0.000	13.504	0.00	343.00	474,197
Hospital spending	2,769.930	0.000	9,143.155	0.00	576,568.92	474,197
Sick leave days	8.824	0.000	28.798	0.00	366.00	474,197
General practitioner	189.683	130.612	240.065	0.00	37,848.24	474,197
Labor Market (1 year before admission)						
Real (2012) wages	9,937.813	0.000	16,276.212	0.00	64,727.51	458,698
Employed days (overall)	133.559	0.000	165.825	0.00	366.00	458,698
P(Employed)	0.445	0.000	0.497	0.00	1.00	458,698
P(Employed >= 270 days)	0.333	0.000	0.471	0.00	1.00	458,698
Retired days (overall)	158.516	0.000	180.166	0.00	366.00	458,698
P(Retired)	0.441	0.000	0.497	0.00	1.00	458,698
Regular retired days	114.991	0.000	169.020	0.00	366.00	458,698
P(Regular retired)	0.319	0.000	0.466	0.00	1.00	458,698
Early retired days	10.575	0.000	59.326	0.00	366.00	458,698
P(Early retired)	0.034	0.000	0.182	0.00	1.00	458,698
Disability pension days	32.855	0.000	103.970	0.00	366.00	458,698
P(Disability retired)	0.092	0.000	0.289	0.00	1.00	458,698
Sick leave days	3.146	0.000	20.668	0.00	366.00	458,698
Rehabilitation days	0.235	0.000	8.129	0.00	366.00	458,698

Note — The table presents descriptive statistics for hospital stay, patient characteristics, patients' healthcare utilization one year before hospital admission, and patients' labor market outcomes one year before hospital admission for the main analysis sample. A more detailed discussion of the sample structure can be found in Section 2.3. Columns (1)—(6) present the mean, median, standard deviation, minimum value, maximum value, and number of observations, respectively.

Table 2 — Healthcare utilization one year before hospital admission

	(1) Coefficient	(2) Significance	(3) Standard Error	(4) Crowding ↑ 1 SD	(5) in %	(6) Outcome Mean	(7) N
Outpatient medical care (€)							
Hospital crowding	-4.034		13.703	-0.765	-0.14	531.455	474,197
Outpatient specialists (€)							
Hospital crowding	4.277		7.791	0.811	0.29	278.436	474,197
General practitioner (€)							
Hospital crowding	-3.473		4.023	-0.659	-0.35	189.683	474,197
Drugs (€)							
Hospital crowding	61.654		69.694	11.695	1.74	671.210	474,197
Hospital days							
Hospital crowding	0.163		0.227	0.031	0.62	5.024	474,197
Hospital spending (€)							
Hospital crowding	165.934		160.409	31.477	1.14	2,769.930	474,197
Sick leave days							
Hospital crowding	-0.458		0.499	-0.087	-0.99	8.824	474,197

Note — The table reports the estimated coefficients for the effect of hospital occupancy on various outcomes measuring patients' healthcare utilization one year before hospital admission. The coefficients are estimated using Equation (1). Column (1) shows the coefficient of interest β_1, which captures the effect of hospital crowding on outcomes. We additionally control for sex, five-year age group fixed effects, day-of-week fixed effects, holiday fixed effects, and fully interacted hospital, year-month, ICD diagnosis at the 3-digit level fixed effects. Column (2) shows the significance level: * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$. Column (3) shows the standard error clustered at the hospital×year level. Column (4) shows the effect of a one-standard-deviation increase in hospital crowding. Column (5) shows the effect of (4) in percent relative to the outcome mean. Column (6) shows the mean of the outcome variable and Column (7) shows the number of observations.

Table 3 — Hospital outcomes of initial stay

	(1) Coefficient	(2) Significance	(3) Standard Error	(4) Crowding ↑ 1 SD	(5) in %	(6) Outcome Mean	(7) N
Length of stay							
Hospital crowding	-1.244	***	0.120	-0.236	-3.45	6.851	495,365
Spending (€)							
Hospital crowding	-446.547	***	66.542	-84.736	-2.37	3,568.204	495,365
Number hospital services							
Hospital crowding	-0.109	***	0.028	-0.021	-1.42	1.457	495,365
Spending per service (€)							
Hospital crowding	-161.703	***	35.967	-30.358	-1.38	2,193.242	304,669
Number hospital departments							
Hospital crowding	-0.065	***	0.010	-0.012	-0.98	1.256	495,190
Readmission within 30 days							
Hospital crowding	-0.005	*	0.003	-0.001	-3.66	0.026	495,365
Death in hospital							
Hospital crowding	0.004		0.002	0.001	2.95	0.023	495,365
Intensive care (0/1)							
Hospital crowding	-0.006	*	0.003	-0.001	-1.80	0.064	495,365

Note — The table reports the estimated coefficients for the effect of hospital occupancy on various outcomes of the patient's initial hospital stay. The coefficients are estimated using Equation (1). Column (1) shows the coefficient of interest β_1, which captures the effect of hospital crowding on outcomes. We additionally control for sex, five-year age group fixed effects, day-of-week fixed effects, holiday fixed effects, and fully interacted hospital, year-month, ICD diagnosis at the 3-digit level fixed effects. Column (2) shows the significance level: * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$. Column (3) shows the standard error clustered at the hospital×year level. Column (4) shows the effect of a one-standard-deviation increase in hospital crowding. Column (5) shows the effect of (4) in percent relative to the outcome mean. Column (6) shows the mean of the outcome variable and Column (7) shows the number of observations.

Web Appendix

This Web Appendix provides additional material discussed in the unpublished manuscript “Hospital Crowding and Patient Outcomes” by Wolfgang Frimmel, Felix Glaser, and Gerald J. Pruckner.

A Additional Figures and Tables

A.1 Additional Figures

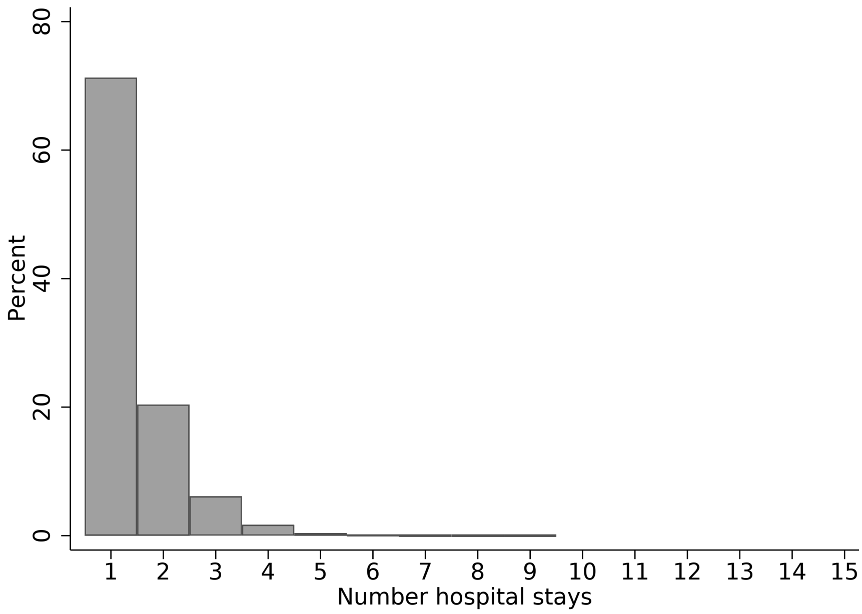


FIGURE A.1 — Distribution of the number of hospital admissions per patient in the sample (different ICD-chapters)

Note — The figure shows the distribution of hospital admissions per patient in our main analysis sample. A patient can be in the sample more than once, but only with different ICD-chapter diagnoses. A more detailed discussion of the sample structure can be found in Section 2.3.

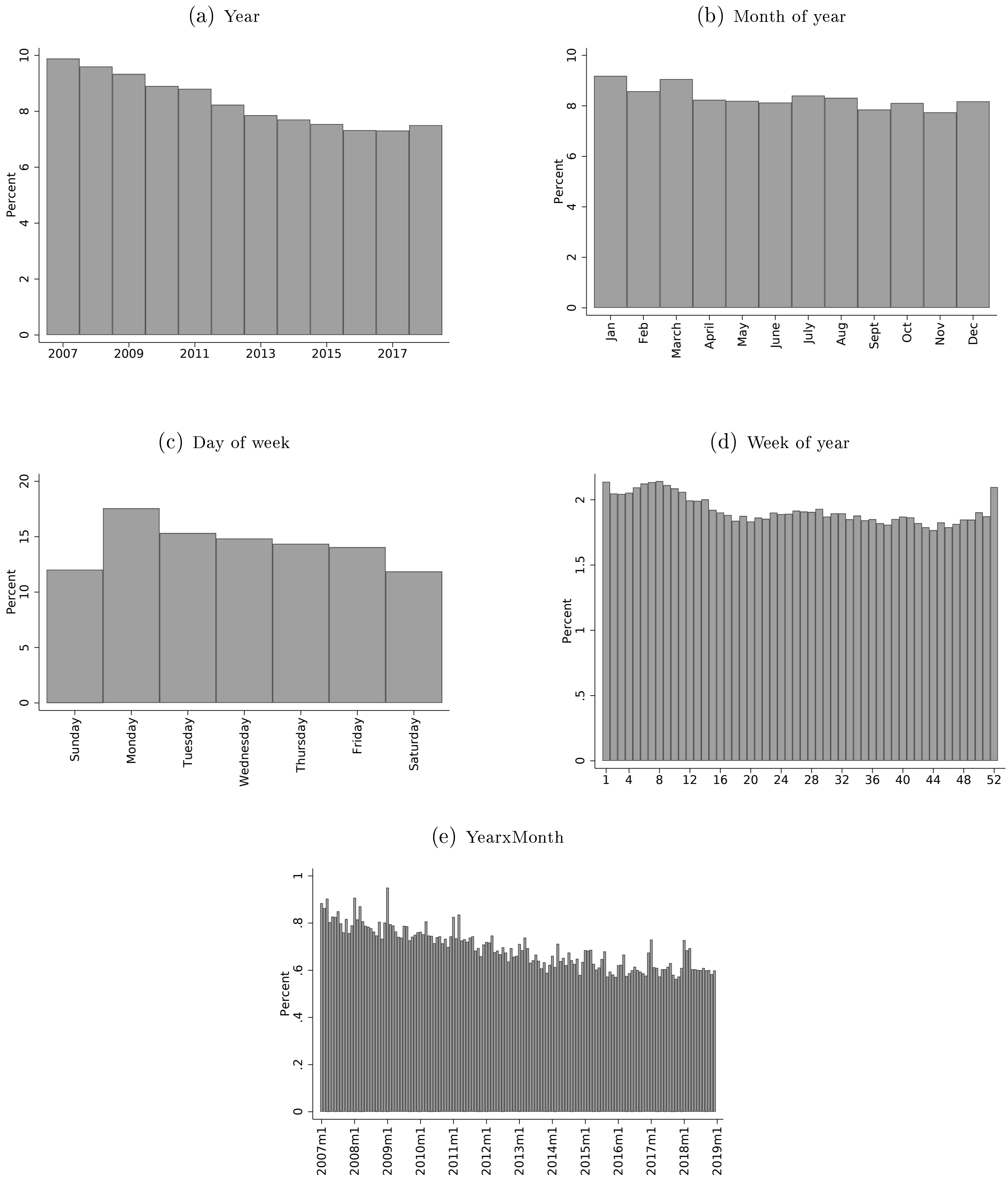


Figure A.2 — Distribution of hospital stays by admission time

Note — The figure shows the distribution of hospital admissions over time in our main analysis sample. Panel (a) shows the years. Panel (b) shows the month of the year. Panel (c) shows the day of the week, panel (d) the week of the year, and panel (e) the year-month. A more detailed discussion of the sample structure can be found in Section 2.3.

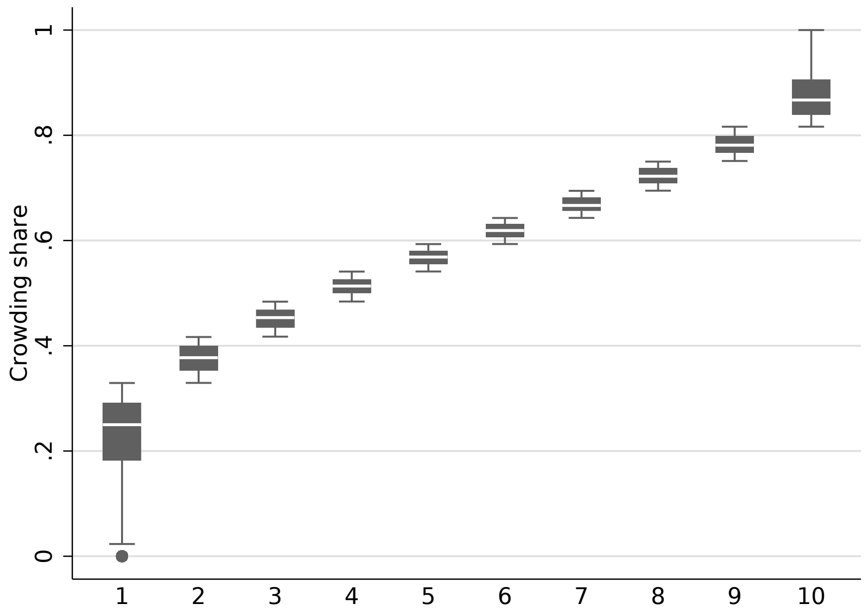


Figure A.3 — Distribution of hospital crowding for each decile

Note — This figure shows the distributions (box plots) of the hospital occupancy share for each decile used in the regression analysis. A more detailed discussion of the hospital crowding measure can be found in Section 2.3.2.

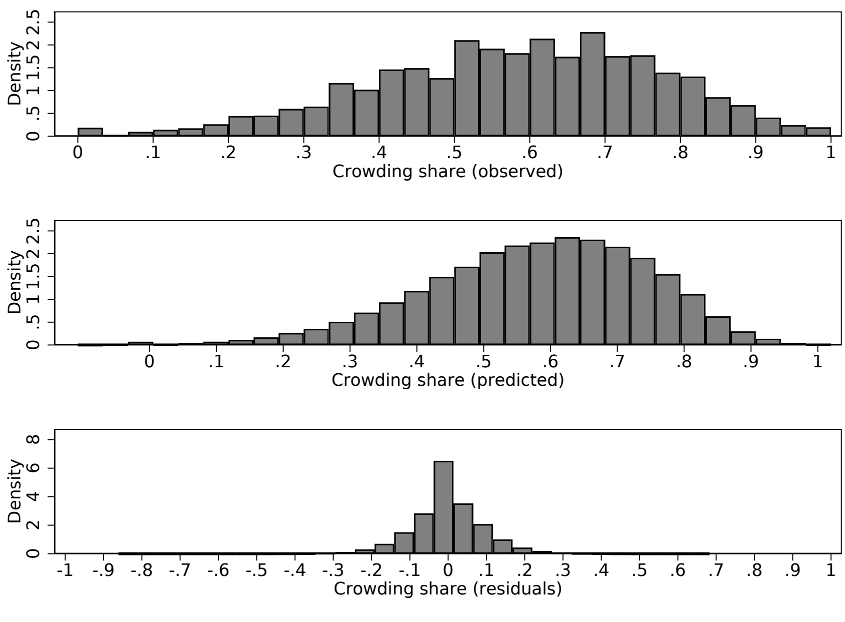


Figure A.4 — Distribution of observed, predicted, and residual hospital crowding measure

Note — This figure shows the distribution of the observed, predicted, and residual crowding shares to illustrate the variation used to identify effects. To achieve this, we estimate a model similar to equation (1) with hospital crowding as the left-hand variable. Specifically, we regress $Crowding_{hct}$ on $\mathbf{X}$ and η_{hmd}.

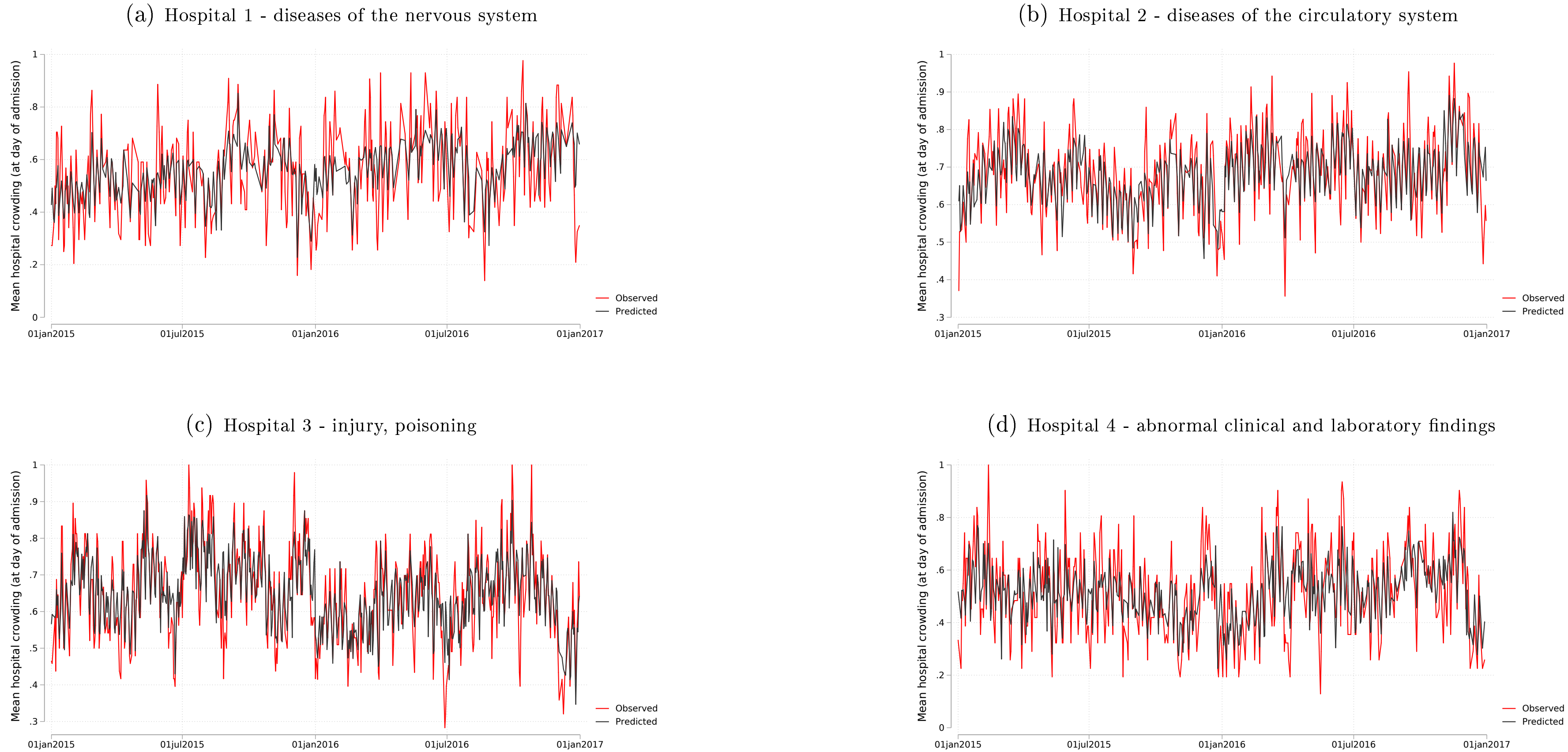


FIGURE A.5 — Illustration of identifying variation: further examples

Note — This figure illustrates more examples of the identifying variation we use in our analysis for different hospitals and admission diagnoses. The black lines denote average predicted hospital occupancy values while the red lines show average observed hospital occupancy values. The difference between the black and red lines represents the idiosyncratic exogenous variation in hospital occupancy, which identifies the causal effects.

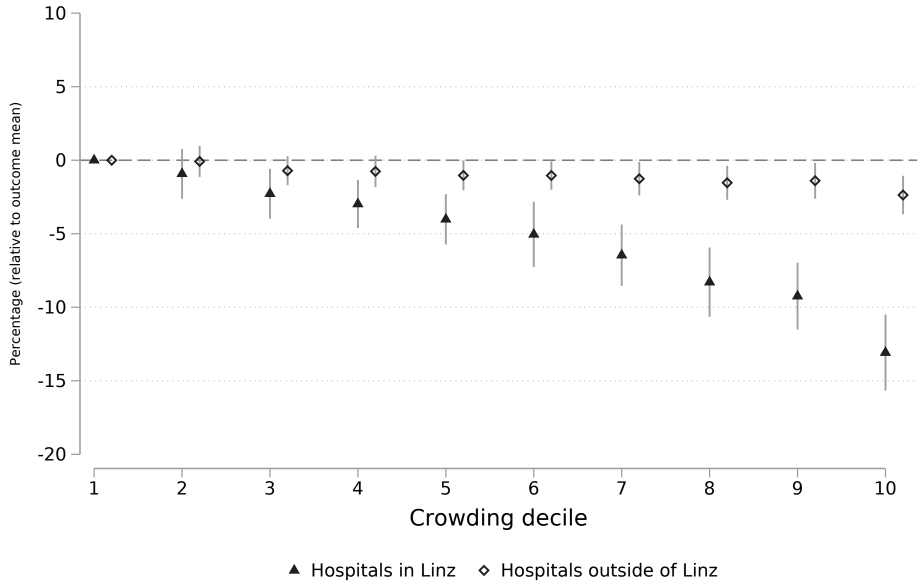
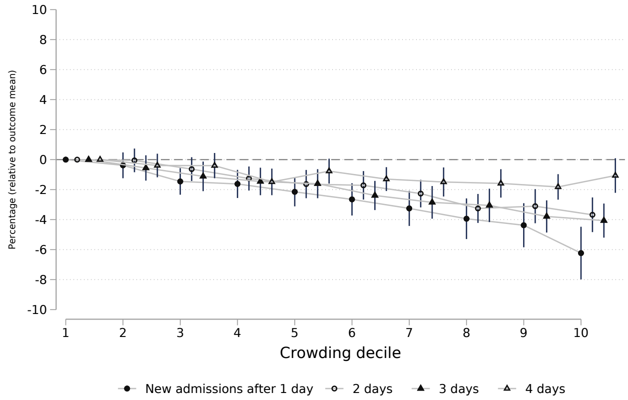


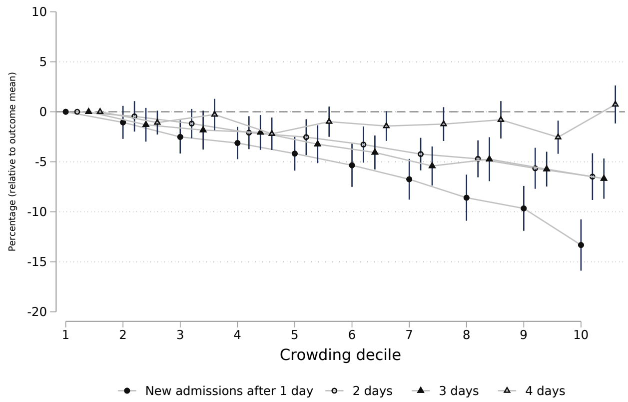
FIGURE A.6 — Effect of hospital crowding on the number of new admissions by hospital location

Note — This figure shows the estimated coefficients along with the corresponding 95 percent confidence intervals for the effect of hospital occupancy on the number of new admissions as a percentage of the overall outcome mean by hospital location. We show the effects on hospitals located in Linz (the capital of Upper Austria) and outside Linz. For this, we aggregate our main estimation sample to provide us with the daily number of new admissions for each hospital and ICD diagnosis at the 3-digit level. Only days with at least one hospital admission and a given diagnosis are included in the analysis. We then regress the number of new admissions on the hospital crowding measure, day-of-week and holiday fixed effects, and fully interacted hospital, year-month, and ICD diagnosis at the 3-digit level fixed effects. Standard errors are clustered at the hospital $\times$ year level.

(a) All hospitals



(b) Hospitals in Linz



(c) Hospitals outside of Linz

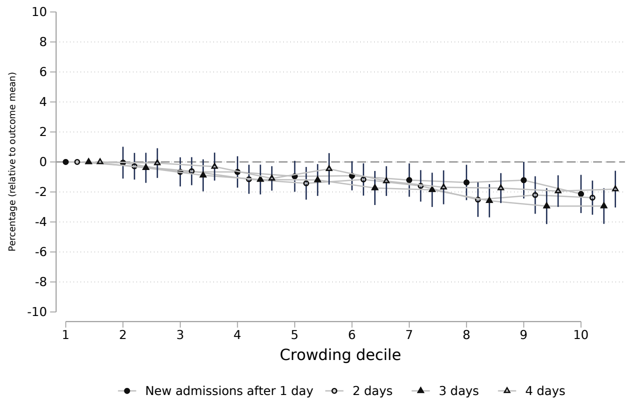


Figure A.7 — Effect of hospital crowding on number of new admissions over time

Note — This figure shows the estimated coefficients along with the corresponding 95 percent confidence intervals for the effect of hospital occupancy on the number of new admissions as a percentage of the overall outcome mean over time. We show the effects on all hospitals (panel a), hospitals located in Linz (panel b), and outside Linz (panel c). For this, we aggregate our main estimation sample to provide us with the daily number of new admissions for each hospital and ICD diagnosis at the 3-digit level. Only days with at least one hospital admission and a given diagnosis are included in the analysis. We then regress the number of new admissions on the hospital crowding measure, day-of-week, and holiday fixed effects, and fully interacted hospital, year-month, and ICD diagnosis at the 3-digit level fixed effects. Standard errors are clustered at the hospital × year level.

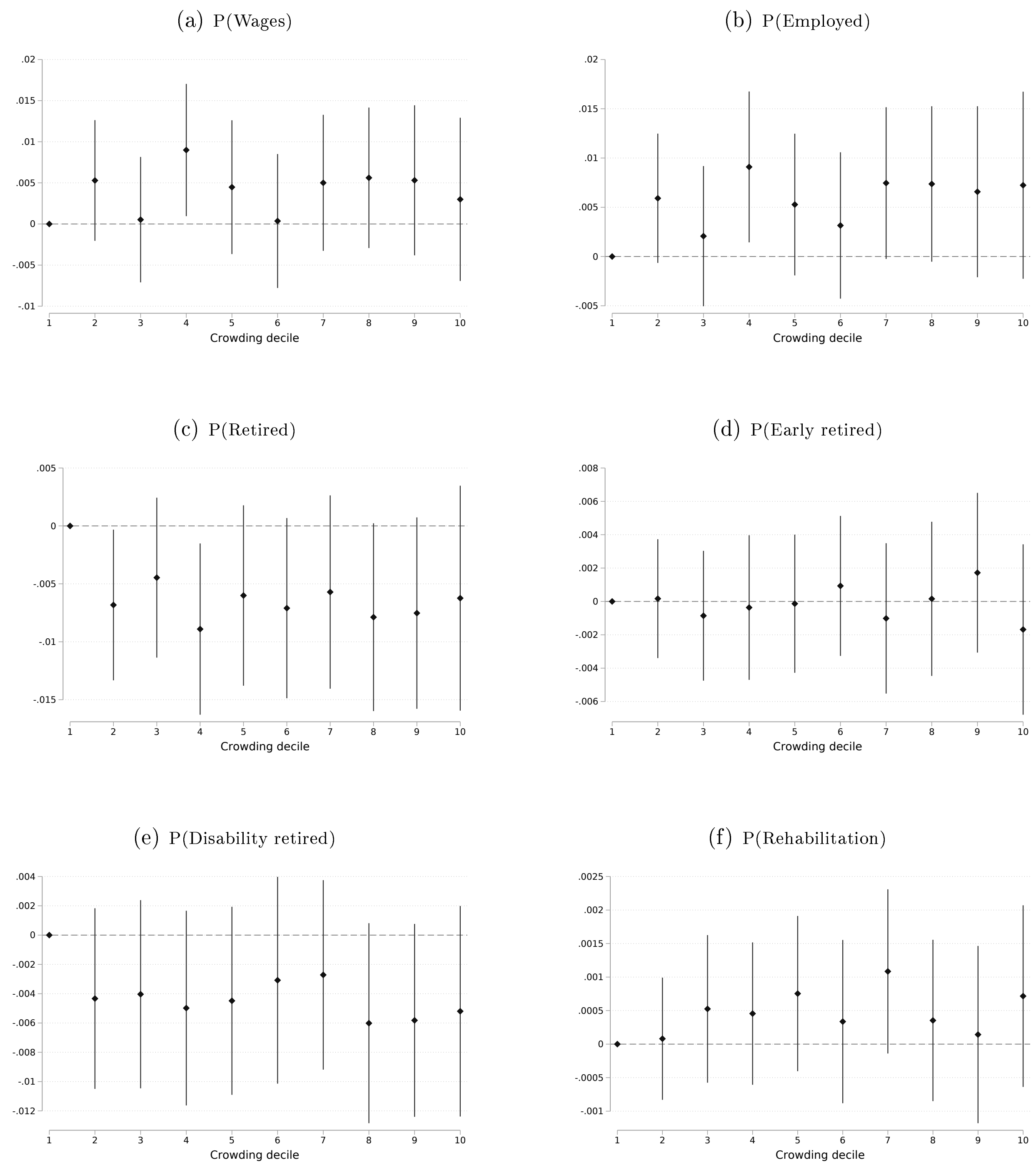


FIGURE A.8 — Extensive margin: medium-term labor market outcomes

Note — This figure shows the estimated coefficients along with the corresponding 95 percent confidence intervals for the effect of hospital occupancy on various outcomes measuring patients' medium-term labor market performance two years after hospital discharge on the extensive margin. The coefficients are estimated using Equation (1) in the semi-parametric variant. Standard errors are clustered at the hospital $\times$ year level.

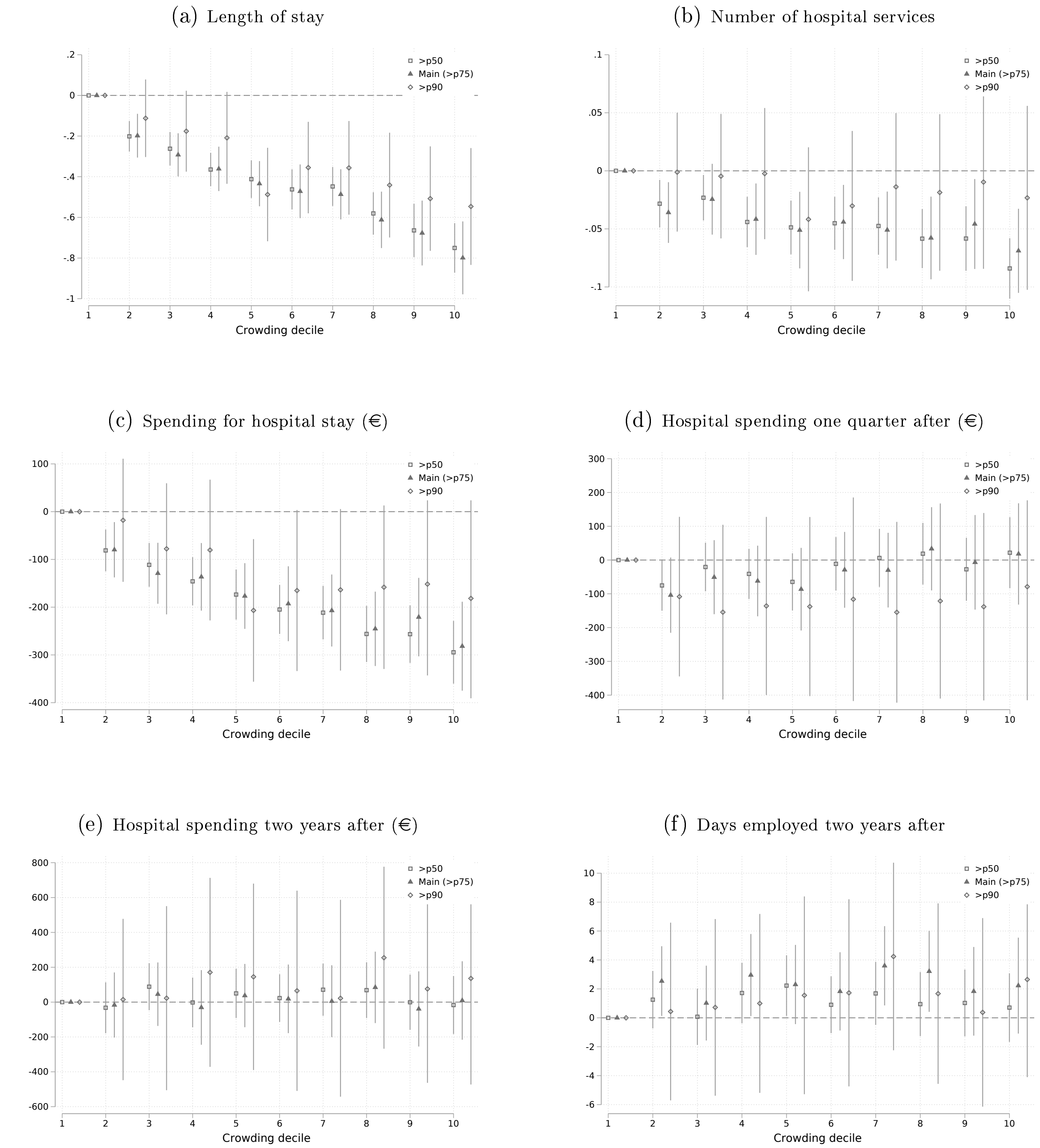
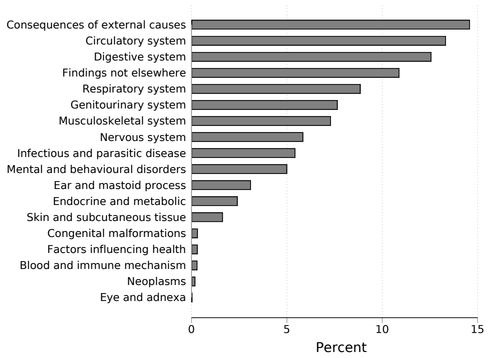


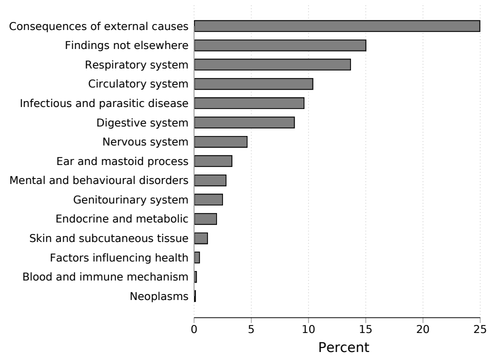
FIGURE A.9 — Different definitions of acute hospital admissions (some selected outcomes)

Note — This figure shows the estimated coefficients along with the corresponding 95 percent confidence intervals for the effect of hospital occupancy on selected outcomes for different acute admission sample definitions. Specifically, we compare samples of ICD-3 diagnoses with weekend admission rates above the 50^{th}, 75^{th}, and 90^{th} percentiles. A more detailed discussion of the sample structure can be found in Section 2.3. The coefficients are estimated using Equation (1) in the semi-parametric variant. Standard errors are clustered at the hospital $\times$ year level.

(a) >p50



(b) Main (>p75)



(c) >p90

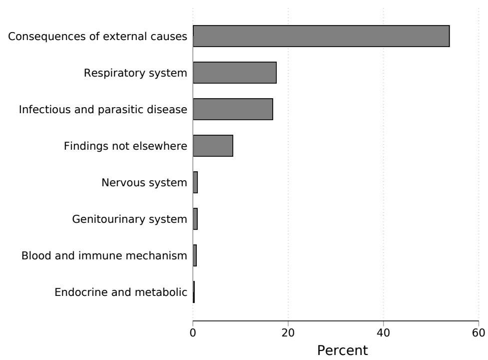


FIGURE A.10 — Distribution of diagnoses by varying the definition of acute admissions

Note — The figure shows the distribution of ICD-chapter diagnoses for different acute admission sample definitions. We compare samples of ICD-3 diagnoses with weekend admission rates above the 50^{th}, 75^{th}, and 90^{th} percentiles. A more detailed discussion of the sample structure can be found in Section 2.3.

A.2 Additional Tables

Table A.1 — Distribution of acute ICD-3-digit diagnoses in the analysis sample

ICD-3-digit	Name	ICD-Chapter	Number of admissions	Percent
J18	Pneumonia, organism unspecified	Respiratory system	22407	4.523
I10	Essential (primary) hypertension	Circulatory system	17021	3.436
R10	Abdominal and pelvic pain	Findings not elsewhere classified	16450	3.321
R55	Syncope and collapse	Findings not elsewhere classified	15006	3.029
A09	Other gastroenteritis and colitis of infectious and unspecified origin	Certain infectious and parasitic diseases	14202	2.867
H81	Disorders of vestibular function	Ear and mastoid process	13597	2.745
R07	Pain in throat and chest	Findings not elsewhere classified	13269	2.679
S06	Intracranial injury	Consequences of external causes	12258	2.475
I63	Cerebral infarction	Circulatory system	12066	2.436
F10	Mental and behavioural disorders due to use of alcohol	Mental and behavioural disorders	11190	2.259
K35	Acute appendicitis	Digestive system	11057	2.232
G45	Transient cerebral ischaemic attacks and related syndromes	Nervous system	10772	2.175
K52	Other noninfective gastroenteritis and colitis	Digestive system	10600	2.14
S72	Fracture of femur	Consequences of external causes	10357	2.091
R42	Dizziness and giddiness	Findings not elsewhere classified	9979	2.014
I21	Acute myocardial infarction	Circulatory system	9041	1.825
S82	Fracture of lower leg, including ankle	Consequences of external causes	8715	1.759
A46	Erysipelas	Certain infectious and parasitic diseases	8679	1.752
J44	Other chronic obstructive pulmonary disease	Respiratory system	8053	1.626
T81	Complications of procedures, not elsewhere classified	Consequences of external causes	7946	1.604
G40	Epilepsy	Nervous system	7467	1.507
S32	Fracture of lumbar spine and pelvis	Consequences of external causes	6940	1.401
S52	Fracture of forearm	Consequences of external causes	6407	1.293
S22	Fracture of rib(s), sternum and thoracic spine	Consequences of external causes	6014	1.214
S02	Fracture of skull and facial bones	Consequences of external causes	5965	1.204
S00	Superficial injury of head	Consequences of external causes	5891	1.189
A41	Other sepsis	Certain infectious and parasitic diseases	5445	1.099
S42	Fracture of shoulder and upper arm	Consequences of external causes	5419	1.094
J15	Bacterial pneumonia, not elsewhere classified	Respiratory system	5022	1.014
T78	Adverse effects, not elsewhere classified	Consequences of external causes	5011	1.012
B99	Other infectious disease	Certain infectious and parasitic diseases	4936	.996
N17	Acute renal failure	Genitourinary system	4629	.934
J20	Acute bronchitis	Respiratory system	4623	.933
K56	Paralytic ileus and intestinal obstruction without hernia	Digestive system	4447	.898
K92	Other diseases of digestive system	Digestive system	4315	.871
J06	Acute upper respiratory infections of multiple and unspecified sites	Respiratory system	4308	.87
E86	Volume depletion	Endocrine, nutritional and metabolic diseases	4276	.863
R04	Haemorrhage from respiratory passages	Findings not elsewhere classified	4174	.843
N10	Acute tubulo-interstitial nephritis	Genitourinary system	3933	.794
E87	Other disorders of fluid, electrolyte and acid-base balance	Endocrine, nutritional and metabolic diseases	3839	.775
J03	Acute tonsillitis	Respiratory system	3696	.746
I95	Hypotension	Circulatory system	3642	.735
A04	Other bacterial intestinal infections	Certain infectious and parasitic diseases	3374	.681
B02	Zoster [herpes zoster]	Certain infectious and parasitic diseases	3127	.631

Table A.1 — Distribution of acute ICD-3-digit diagnoses in analysis sample (*Continued*)

ICD-3-digit	Name	ICD-Chapter	Number of admissions	Percent
I47	Paroxysmal tachycardia	Circulatory system	3117	.629
R00	Abnormalities of heart beat	Findings not elsewhere classified	2884	.582
K85	Acute pancreatitis	Digestive system	2838	.573
T51	Toxic effect of alcohol	Consequences of external causes	2750	.555
K81	Cholecystitis	Digestive system	2746	.554
S01	Open wound of head	Consequences of external causes	2589	.523
R50	Fever of other and unknown origin	Findings not elsewhere classified	2497	.504
G51	Facial nerve disorders	Nervous system	2393	.483
L50	Urticaria	Skin and subcutaneous tissue	2308	.466
L03	Cellulitis	Skin and subcutaneous tissue	2246	.453
J36	Peritonsillar abscess	Respiratory system	2224	.449
S30	Superficial injury of abdomen, lower back and pelvis	Consequences of external causes	2219	.448
T79	Certain early complications of trauma, not elsewhere classified	Consequences of external causes	2181	.44
J45	Asthma	Respiratory system	2168	.438
K01	Embedded and impacted teeth	Digestive system	2161	.436
A08	Viral and other specified intestinal infections	Certain infectious and parasitic diseases	2133	.431
J40	Bronchitis, not specified as acute or chronic	Respiratory system	2092	.422
S43	Dislocation, sprain and strain of joints and ligaments of shoulder girdle	Consequences of external causes	2035	.411
R11	Nausea and vomiting	Findings not elsewhere classified	2026	.409
J22	Unspecified acute lower respiratory infection	Respiratory system	1891	.382
R31	Unspecified haematuria	Findings not elsewhere classified	1887	.381
S20	Superficial injury of thorax	Consequences of external causes	1871	.378
I61	Intracerebral haemorrhage	Circulatory system	1857	.375
T63	Toxic effect of contact with venomous animals	Consequences of external causes	1769	.357
S92	Fracture of foot, except ankle	Consequences of external causes	1759	.355
I64	Stroke, not specified as haemorrhage or infarction	Circulatory system	1711	.345
K37	Unspecified appendicitis	Digestive system	1681	.339
J69	Pneumonitis due to solids and liquids	Respiratory system	1646	.332
T50	Poisoning by diuretics and other and unspecified drugs, medicaments and biological substances	Consequences of external causes	1569	.317
T14	Injury of unspecified body region	Consequences of external causes	1538	.31
S66	Injury of muscle and tendon at wrist and hand level	Consequences of external causes	1510	.305
N45	Orchitis and epididymitis	Genitourinary system	1497	.302
G35	Multiple sclerosis	Nervous system	1495	.302
J01	Acute sinusitis	Respiratory system	1490	.301
Z34	Supervision of normal pregnancy	Factors influencing health status	1463	.295
S13	Dislocation, sprain and strain of joints and ligaments at neck level	Consequences of external causes	1458	.294
S70	Superficial injury of hip and thigh	Consequences of external causes	1451	.293
N23	Unspecified renal colic	Genitourinary system	1421	.287
K12	Stomatitis and related lesions	Digestive system	1372	.277
H66	Suppurative and unspecified otitis media	Ear and mastoid process	1370	.277
S86	Injury of muscle and tendon at lower leg level	Consequences of external causes	1336	.27
S61	Open wound of wrist and hand	Consequences of external causes	1305	.263
S80	Superficial injury of lower leg	Consequences of external causes	1244	.251

Table A.1 — Distribution of acute ICD-3-digit diagnoses in analysis sample (*Continued*)

ICD-3-digit	Name	ICD-Chapter	Number of admissions	Percent
B27	Infectious mononucleosis	Certain infectious and parasitic diseases	1219	.246
R54	Senility	Findings not elsewhere classified	1208	.244
J10	Influenza due to other identified influenza virus	Respiratory system	1204	.243
A49	Bacterial infection of unspecified site	Certain infectious and parasitic diseases	1190	.24
F23	Acute and transient psychotic disorders	Mental and behavioural disorders	1166	.235
D68	Other coagulation defects	Blood and blood-forming organs and immune mechanism	1161	.234
K11	Diseases of salivary glands	Digestive system	1134	.229
J96	Respiratory failure, not elsewhere classified	Respiratory system	1047	.211
Z04	Examination and observation for other reasons	Factors influencing health status	1046	.211
R57	Shock, not elsewhere classified	Findings not elsewhere classified	959	.194
S81	Open wound of lower leg	Consequences of external causes	953	.192
S27	Injury of other and unspecified intrathoracic organs	Consequences of external causes	953	.192
S09	Other and unspecified injuries of head	Consequences of external causes	943	.19
R56	Convulsions, not elsewhere classified	Findings not elsewhere classified	935	.189
K55	Vascular disorders of intestine	Digestive system	932	.188
S05	Injury of eye and orbit	Consequences of external causes	906	.183
R41	Other symptoms and signs involving cognitive functions and awareness	Findings not elsewhere classified	905	.183
S93	Dislocation, sprain and strain of joints and ligaments at ankle and at foot level	Consequences of external causes	872	.176
E65	Localized adiposity	Endocrine, nutritional and metabolic diseases	859	.173
T90	Sequelae of injuries of head	Consequences of external causes	849	.171
F19	Mental and behavioural disorders due to multiple drug use and use of other psychoactive substances	Mental and behavioural disorders	846	.171
A48	Other bacterial diseases, not elsewhere classified	Certain infectious and parasitic diseases	838	.169
J11	Influenza, virus not identified	Respiratory system	805	.163
I60	Subarachnoid haemorrhage	Circulatory system	796	.161
H83	Other diseases of inner ear	Ear and mastoid process	790	.159
B34	Viral infection of unspecified site	Certain infectious and parasitic diseases	761	.154
H60	Otitis externa	Ear and mastoid process	738	.149
T18	Foreign body in alimentary tract	Consequences of external causes	733	.148
R73	Elevated blood glucose level	Findings not elsewhere classified	723	.146
D11	Benign neoplasm of major salivary glands	Neoplasms	711	.144
R40	Somnolence, stupor and coma	Findings not elsewhere classified	695	.14
R09	Other symptoms and signs involving the circulatory and respiratory systems	Findings not elsewhere classified	691	.139
J81	Pulmonary oedema	Respiratory system	683	.138
J41	Simple and mucopurulent chronic bronchitis	Respiratory system	676	.136
S12	Fracture of neck	Consequences of external causes	674	.136
T00	Superficial injuries involving multiple body regions	Consequences of external causes	638	.129
N12	Tubulo-interstitial nephritis, not specified as acute or chronic	Genitourinary system	630	.127
S51	Open wound of forearm	Consequences of external causes	620	.125
J04	Acute laryngitis and tracheitis	Respiratory system	615	.124
F48	Other neurotic disorders	Mental and behavioural disorders	610	.123
J02	Acute pharyngitis	Respiratory system	603	.122
G41	Status epilepticus	Nervous system	584	.118

Table A.1 — Distribution of acute ICD-3-digit diagnoses in analysis sample (*Continued*)

ICD-3-digit	Name	ICD-Chapter	Number of admissions	Percent
L27	Dermatitis due to substances taken internally	Skin and subcutaneous tissue	567	.114
S39	Other and unspecified injuries of abdomen, lower back and pelvis	Consequences of external causes	563	.114
S76	Injury of muscle and tendon at hip and thigh level	Consequences of external causes	557	.112
A02	Other salmonella infections	Certain infectious and parasitic diseases	541	.109
I24	Other acute ischaemic heart diseases	Circulatory system	531	.107
E16	Other disorders of pancreatic internal secretion	Endocrine, nutritional and metabolic diseases	523	.106
T75	Effects of other external causes	Consequences of external causes	514	.104
S36	Injury of intra-abdominal organs	Consequences of external causes	505	.102
I46	Cardiac arrest	Circulatory system	501	.101
B00	Herpesviral [Herpes simplex] infections	Certain infectious and parasitic diseases	489	.099
J13	Pneumonia due to Streptococcus pneumoniae	Respiratory system	473	.095
L08	Other local infections of skin and subcutaneous tissue	Skin and subcutaneous tissue	472	.095
J39	Other diseases of upper respiratory tract	Respiratory system	465	.094
S40	Superficial injury of shoulder and upper arm	Consequences of external causes	458	.092
G03	Meningitis due to other and unspecified causes	Nervous system	434	.088
E41	Nutritional marasmus	Endocrine, nutritional and metabolic diseases	423	.085
J91	Pleural effusion in conditions classified elsewhere	Respiratory system	413	.083
N44	Torsion of testis	Genitourinary system	392	.079
L23	Allergic contact dermatitis	Skin and subcutaneous tissue	380	.077
S64	Injury of nerves at wrist and hand level	Consequences of external causes	378	.076
S50	Superficial injury of forearm	Consequences of external causes	355	.072
S91	Open wound of ankle and foot	Consequences of external causes	353	.071
I45	Other conduction disorders	Circulatory system	351	.071
T59	Toxic effect of other gases, fumes and vapours	Consequences of external causes	349	.07
A40	Streptococcal sepsis	Certain infectious and parasitic diseases	343	.069
S60	Superficial injury of wrist and hand	Consequences of external causes	335	.068
A87	Viral meningitis	Certain infectious and parasitic diseases	330	.067
I99	Other and unspecified disorders of circulatory system	Circulatory system	326	.066
J09	Influenza due to certain identified influenza virus	Respiratory system	316	.064
S37	Injury of urinary and pelvic organs	Consequences of external causes	316	.064
S53	Dislocation, sprain and strain of joints and ligaments of elbow	Consequences of external causes	314	.063
T17	Foreign body in respiratory tract	Consequences of external causes	313	.063
I40	Acute myocarditis	Circulatory system	300	.061
J00	Acute nasopharyngitis [common cold]	Respiratory system	296	.06
S31	Open wound of abdomen, lower back and pelvis	Consequences of external causes	291	.059
T65	Toxic effect of other and unspecified substances	Consequences of external causes	288	.058
J42	Unspecified chronic bronchitis	Respiratory system	280	.057
S90	Superficial injury of ankle and foot	Consequences of external causes	263	.053
K72	Hepatic failure, not elsewhere classified	Digestive system	256	.052
I30	Acute pericarditis	Circulatory system	252	.051
R68	Other general symptoms and signs	Findings not elsewhere classified	192	.039
F61	Mixed and other personality disorders	Mental and behavioural disorders	183	.037
J12	Viral pneumonia, not elsewhere classified	Respiratory system	157	.032
B08	Other viral infections characterized by skin and mucous membrane lesions, not elsewhere classified	Certain infectious and parasitic diseases	135	.027

Table A.1 — Distribution of acute ICD-3-digit diagnoses in analysis sample (*Continued*)

ICD-3-digit	Name	ICD-Chapter	Number of admissions	Percent
J21	Acute bronchiolitis	Respiratory system	128	.026
J05	Acute obstructive laryngitis [croup] and epiglottitis	Respiratory system	100	.02

Note — The table shows the distribution of ICD-3-digit diagnoses in our main analysis sample. A more detailed discussion of the sample structure can be found in Section 2.3.

Table A.2 — Medium-run outcomes

	(1) Coefficient	(2) Significance	(3) Standard Error	(4) Crowding ↑ 1 SD	(5) in %	(6) Outcome Mean	(7) N
Healthcare (1 quarter after)							
Outpatient specialists (€)							
Hospital crowding	2.517		3.642	0.478	0.61	78.973	453,722
General practitioner (€)							
Hospital crowding	0.856		1.627	0.163	0.26	61.569	453,722
Drugs (€)							
Hospital crowding	27.536		19.164	5.232	2.33	224.805	453,722
Hospital spending (€)							
Hospital crowding	120.840		99.746	22.960	1.69	1,356.309	453,722
Sick leave days							
Hospital crowding	-0.103		0.320	-0.019	-0.34	5.741	453,722
Healtcare (2 years after)							
Death within 1 year							
Hospital crowding	0.000		0.004	0.000	0.08	0.087	495,350
Outpatient specialists (€)							
Hospital crowding	-7.370		8.952	-1.400	-0.45	308.113	421,847
General practitioner (€)							
Hospital crowding	1.440		4.797	0.274	0.13	214.974	421,847
Drugs (€)							
Hospital crowding	55.191		66.074	10.488	1.37	766.087	421,847
Hospital spending (€)							
Hospital crowding	20.213		173.318	3.841	0.13	3,039.708	421,847
Sick leave days							
Hospital crowding	-0.231		0.632	-0.044	-0.46	9.545	421,847
Labor market (2 years after)							
Real (2012) wages							
Hospital crowding	121.382		226.397	23.059	0.22	10,581.896	422,661
Days employed							
Hospital crowding	2.675		2.296	0.508	0.37	138.562	422,661
Days retired							
Hospital crowding	-2.774		2.453	-0.527	-0.36	145.328	422,661
Days early retired							
Hospital crowding	-0.266		1.164	-0.051	-0.53	9.469	422,661
Days disability retired							
Hospital crowding	-1.944		1.681	-0.369	-1.39	26.547	422,661
Rehabilitation days							
Hospital crowding	0.276		0.234	0.052	10.78	0.486	422,661

Note — The table reports the estimated coefficients for the effect of hospital occupancy on patients' medium-run outcomes. The coefficients are estimated using Equation (1). Column (1) shows the coefficient of interest β_1, which captures the effect of hospital crowding on outcomes. We additionally control for sex, five-year age group fixed effects, day-of-week fixed effects, holiday fixed effects, and fully interacted hospital, year-month, ICD diagnosis at the 3-digit level fixed effects. Column (2) shows the significance level: * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$. Column (3) shows the standard error clustered at the hospital×year level. Column (4) shows the effect of a one-standard-deviation increase in hospital crowding. Column (5) shows the effect of (4) in percent relative to the outcome mean. Column (6) shows the mean of the outcome variable and Column (7) shows the number of observations.