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Concentration of Hospital Capacities and Patients' Access to Care

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Anne Mensen[1]

Concentration of Hospital Capacities and Patients' Access to Care

Abstract

The concentration of hospital capacities often involves closures of smaller hospital sites. While advocates of hospital concentrations emphasize increased quality of care and cost savings, some people may feel their health care is at risk. In this paper, I analyze the effect of 18 recent hospital closures in Germany on patients' driving times and the probability to be hospitalized. Using an event study approach and rich patient-level data, I estimate the effect for individuals that are affected most by the closure, i.e., people for whom the hospital was the nearest one in their surroundings. My results show that the driving time to the nearest hospital increases slightly for the affected residents indicating that concentrations of hospital capacities do not severely jeopardize accessibility. Nevertheless, the probability to be admitted to a hospital decreases for residents who live in areas where a hospital closed, showing that the closure seems to affect patients' care.

JEL-Codes: I11, I12, I18, R41

Keywords: Hospital closures; access to health care; travel time; concentration process

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1 Introduction

Hospital closures are a largely debated and highly emotional topic in many industrialized countries. Advocates of closures emphasize potential improvements in care quality, e.g., through learning and specialization effects (Avdic et al. 2019a, Hentschker and Mennicken 2018), and the need of bundling capacities in times of skills shortages and aging population. At the same time, hospital closures are often accompanied by demonstrations or public petitions since the population fears insufficient care and longer distances to the hospital which might adversely impact emergency medical care. To shed light into this political debate, I analyze the effect of hospital closures in Germany on (i) patients' driving time to the nearest hospital and (ii) whether the closure changes the probability to be hospitalized.

Compared to other countries, Germany has a large hospital density and a high number of stationary cases given its population (Augurzky et al. 2021). In 2019, more than 19.4 million stationary cases were treated in 1,914 hospitals (Federal Statistical Office 2021) which is the highest number of cases per population that were treated in hospitals among OECD countries. In Germany, 252 patients per 1,000 inhabitants were discharged after having stayed at least one night in a hospital in 2019, while the OECD average is only 146 discharges per 1,000 inhabitants (OECD 2021). Since the German hospital market is largely decentralized and especially smaller hospitals suffer financial distress (Augurzky et al. 2021), it is often discussed about whether and how to concentrate hospital capacities. For instance, Albrecht et al. (2019) outline that the quality of care in Germany could be increased with only half as many hospitals.

In January 2016, the German legislature has set specific incentives to promote improvements in the German hospital market with the Hospital Structure Act (Krankenhausstrukturgesetz - KHSG). The intended goals are improvements in the hospital structure and better quality of care. A key element of the Hospital Structure Act is a structural fund that provides incentives to reach three main targets: (I) the reduction of overcapacities in the hospital sector, (II) the concentration of hospital sites and (III) the conversion of hospitals into non-acute local facilities or other needed disciplines. Since costs were partly covered by the structural fund and the federal states[2], it provided an exogenous incentive to restructure or close hospitals. In total, 34 hospitals closed as part of the fund (Deutscher Bundestag 2021).[3] In this study, I evaluate the effect of 18 hospital closures which were supported by the structural fund and closed from 2015 to 2018. I only analyze hospitals that closed until 2018 to have at least one period after the closure.

In my analysis, I focus on individuals that are affected most by the closure, i.e., residents for whom the closing hospital was the nearest hospital in their surroundings and who are therefore exposed to an increase in driving time. First, I show the extent to which patients' access to care is affected in terms of longer driving times.[4] Around 700,000 people must drive longer to the next hospital because their nearest hospital closed. The average increase in driving time is around 7 minutes. Although most people only experience small increases in their driving time, around 70,000 people are exposed to an increase of more than 20 minutes and, more importantly, for nearly 17,500 people the driving time increases to more than 30 minutes.[5] Second, I examine whether the closure affects the hospitalization rate, which serves as an indicator for patients' access to care. Using an event study design, I compare the probability to be admitted to the hospital between residents in affected regions, i.e., residents who are exposed to an increase in driving time, to residents in control regions, i.e., residents

[2] In some cases, the hospital owner also financed part of the costs, but they were not obliged to as long as the federal state financed 50% of the total costs.
[3] Some hospitals are still in operation but are going to close in the next years.
[4] The driving time is calculated from the center of each zip code area to the address of the nearest hospital.
[5] By law, a supply risk exists, if more than 5,000 people need more than 30 minutes to reach the closest hospital after a potential closure of one hospital. In that case, the hospital gets financial benefits to compensate for the structurally induced deficit of the hospital (Federal Joint Committee 2016, 2018).

who have constant driving times to the nearest hospital. My results show that the probability to be admitted to the hospital decreases by 2.1% and 3.2% in the first and second year after the closure for residents in affected regions. Moreover, my analysis shows that the effect is particularly striking for older people.

A lower probability to be admitted to the hospital does not have to be problematic itself if the residents are still treated sufficiently, e.g., in the ambulatory care sector. However, the answer to the question if and where these people are treated otherwise, goes beyond the scope of this paper. Nevertheless, my results show that concentration processes in the hospital sector have statistically relevant effects on the hospitalization rate for the population living in areas where the hospital closed. Thus, it must be guaranteed that the population gets sufficient other types of care, e.g., in the ambulatory care sector or in other hospitals around. This is especially relevant for people that are less mobile and for whom also small increases in the distance to the next hospital may pose problems.

In general, patients' choice of a hospital depends on various patient and provider characteristics (Victoor et al. 2012). Recent studies show that reputation is getting more important and that patients are willing to drive longer to a hospital if they expect better care quality (Avdic et al. 2019b, Pilny and Mennicken 2014, Varkevisser et al. 2012). Nevertheless, patients are very sensitive to travel times and usually choose a hospital in close distance to their place of residence (Smith et al. 2018). Gowrisankaran et al. (2015), for example, find that a five-minute increase in travel time to a hospital reduces demand in a range between 17% and 41% in the US. However, the fear to be exposed to longer distances after a closure is only partially justified for Germany: Previous studies that analyze the impact of hypothetical centralization processes only find minor effects on patients' driving time. For instance, Mennicken et al. (2014) show small increases in driving times for gynecology and obstetrics patients for different centralization scenarios in Germany. Furthermore, not all patients choose their nearest hospital. Versteeg et al. (2018) show that patients' actual driving time does not necessarily increase after a hospital closure since some patients bypass their nearest hospital already. This mitigates the effects of centralization processes. Taking this into account, a recent study by Aggarwal et al. (2020) reveals a socioeconomic gradient: Older and sicker patients and those with a lower socioeconomic status usually choose hospitals close to their residence. Thus, centralization processes may have different effects for different groups of patients.

However, the studies named so far analyze hypothetical centralization processes. Only very few papers examine how hospitals that already closed have affected patients' driving times, e.g., McCarthy et al. (2021) on rural US hospital closures and Buchmueller et al. (2006) on urban US hospital closures. Likewise, the evidence on hospital admission rates is very scarce and mainly based on US hospital closures. For instance, Joynt et al. (2015) find no significant increase in hospital admission rates. In contrast, a recent study by Caroll (2019) shows that hospital closures in rural areas lead to a decrease in hospital admissions by 5%. To the best of my knowledge, no study so far has analyzed the effect of real concentration processes in Germany on patients' driving times to the nearest hospital and their probability to be hospitalized. With this study, I can deliver a meaningful contribution to the literature by using data from Germany which is characterized by its large hospital density and has a high propensity for further adaptions of the hospital market in the near future (Augurzky et al. 2021).

The structure of this study is as follows. Section 2 describes the data sources that are used for the analysis and Section 3 outlines the empirical approach. Section 4 presents the results on driving time and hospitalization rates. Section 5 concludes.

2 Data

The analysis combines several data sources. First, I exploit a nationally representative sample of inpatient data from a large German health insurer which covers around 10% of the German population. The data include the main and secondary diagnoses, the date of admission and discharge, the patient's gender as well as age in years. Moreover, the data contains the place of resident for all insured people which enables me to calculate the probability to be hospitalized within a given time frame.

The second data set are Hospital Quality Reports (2016, 2017, 2018). The reports contain important hospital characteristics like the exact address, number of departments, number of beds and the number of cases for each hospital in Germany. In comparison to other official data sets, the quality reports are the only data that include all hospital sites without aggregating smaller hospitals sites to an upper level. This micro level is especially important because I use the address of each hospital to construct the driving time from each zip code area to the nearest hospital. Since the quality reports also include small specialist and day clinics, I limit the sample to hospitals that provide at least basic inpatient care. Specifically, I only include hospitals which have at least 20 beds and at least 100 inpatient cases per year. Furthermore, I exclude psychiatrics and special hospitals such as eye or pain clinics.

In total, I evaluate 18 hospital closures from 2015 to 2018 that closed as part of the structural fund. Seven of the hospitals were in public ownership, nine were private non-profit and two were private for-profit hospitals. Unfortunately, due to data restrictions, I cannot present detailed information on the specific hospitals.

Lastly, I use population data on the zip code level to calculate the number of people that live in affected regions and their increase in driving time to the nearest hospital (Deutsche Post

Direkt GmbH 2021, RWI microm 2020). In total, my sample consists of around 4.5 Mio. observations covering the years 2014 to 2019.

3 Estimation Strategy

Distance is a main driver of patients' hospital choice (Gowrisankaran et al. 2015, Smith et al. 2018). Therefore, I define individuals as affected by a closure if their nearest hospital has closed and they are forced to drive longer to the nearest hospital. Thus, I compare residents who are directly affected by the closure to residents who are not directly affected by the closure, i.e., their nearest hospital is still in operation. This approach is in line with the studies by Buchmueller et al. (2006) and Caroll (2019) who also define affected residents in relation to the change in distance to the nearest hospital. Thus, while affected residents figure an increase in driving time to their nearest hospital, residents in control regions have constant driving times. The control group covers all zip code areas of the district in which the hospital closed but where the driving time to the nearest hospital is not affected.[6] I calculate driving times from the center of each zip code area to the address of the hospital that has closed and all surrounding hospitals using the Open Source Routing Machine program (Luxen and Vetter 2011), based on OpenStreetMap road data (Haklay and Weber 2008), which contains nearly the complete German road network (Barrington-Leigh and Millard-Ball 2017).

In a first step, I examine the treatment intensity, i.e., how much longer treated individuals must drive to their next-nearest hospital. By doing so, I compare the driving time to the closing hospital and all other hospitals around. The change in driving time is given by the difference between the driving time to the hospital that closed and the next-nearest hospital.

[6] In cases where the next-nearest hospital is located in another district, the zip code areas of this neighboring district are also included in the control group.

In a second step, I analyze whether the closure affects the probability to be hospitalized. I use an event study design with event-time indicators that takes the following form:

$$y_{izt} = \alpha + \sum_{k=-3}^{2} \delta_k \, \mathbb{I}[t - E_z = k] + \lambda_t + \beta X_{izt} + \epsilon_{izt} \, , \qquad (1)$$

where y_{izt} is the probability of being admitted to the hospital at least once in year t for individual *i* living in zip code *z*, E_z is the year where zip code *z* is affected by the hospital closure and $\mathbb{I}[t - E_z = k]$ is an indicator for being k years from the treatment starting, λ_t are time fixed effects and X_{izt} are individual and zip-code level characteristics such as gender, age and the number of other hospitals, which provide at least basic inpatient care and are reached within 20 minutes driving time from the center of zip code *z*. Due to data restrictions, I cannot include zip code or district fixed effects. Nevertheless, the zip code areas that serve as control regions lie within the same (or neighboring) district and should thus be affected by almost similar regional characteristics.

I also estimate a classical difference-in-difference model which incorporates a single indicator for the post-closure period and takes the following form:

$$y_{izt} = \alpha + \gamma Affected\_region_z + \delta (Affected\ x\ Post)_{zt} + \beta X_{izt} + \lambda_t + \epsilon_{\mathrm{izt}} \, , \qquad (2)$$

where $Affected\_region_z$ is an indicator for zip code *z* which is equal to one if the zip code is affected by the hospital closure and $Affected\ x\ Post_{zt}$ is an indicator for the affected zip code *z* in the years after the closure. This approach checks for rather general differences between closing and control regions after the closure and may overcome problems of reduced power in the subsample analyses. Nevertheless, I refer to the event study design as my preferred specification as it visualizes potential dynamics of the effect of hospital closures directly.

To check whether the effects on the hospitalization rate are driven by specific types of admissions, I analyze ambulatory care sensitive and urgent conditions separately. Ambulatory care sensitive conditions (ACSC) are cases which could be avoided in hospitals given timely and effective ambulatory care. Different lists of ACSC have been developed in the literature, e.g., by Billings et al. (1993), Brown et al. (2001), Purdy et al. (2009). I use a list of conditions from Sundmacher et al. (2015) who selected the conditions based on a three round Delphi survey with forty physicians in Germany. The conditions are based on the patient's primary diagnoses and cover, for example, diabetes or bronchitis. In contrast, urgent conditions like an acute myocardial infarction must be treated immediately. A recent study by Krämer et al. (2019) assigns urgency levels to hospital diagnosis based on the patient's primary diagnosis. I classify hospital admissions as urgent conditions if their degree of urgency is above 80% based on the list provided by Krämer et al. (2019).

4 Results

4.1 Hospital closures and patients' driving time to the hospital

In total, I consider 18 hospitals that were closed from 2015 to 2018 as part of the Hospital Structure Fund (Table 1). Although the structural fund started just in the beginning of 2016, two hospitals already closed in the end of 2015. Six hospitals closed in 2017 and five hospitals closed in 2016 and 2018, respectively. More than 700,000 people are exposed to larger driving times to their nearest hospital due to the closures. The average increase in driving time to the next-nearest hospital is around 7 minutes. As mentioned above, I limit the sample of surrounding hospitals to hospitals which provide at least basic inpatient care to ensure that the next hospital is an adequate alternative.

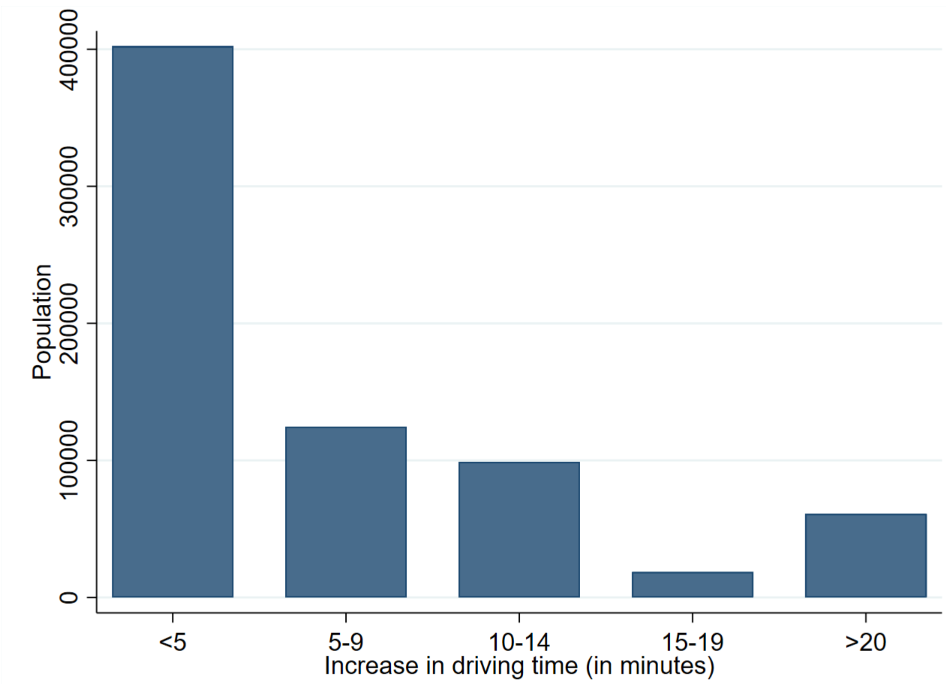
Table 1: Hospital closures and the surrounding population

	Closed hospitals	Affected regions	Population affected	Driving time (minutes) Pre-closure (mean (SD))	Post-closure (mean (SD))
2015	2	4	56,000	9.8 (4.9)	19.3 (6.7)
2016	5	33	90,000	13.3 (8.4)	18.2 (10.0)
2017	6	27	253,000	11.1 (5.0)	19.7 (5.2)
2018	5	17	306,000	17.5 (7.5)	25.2 (4.5)
N	18	81	705,000		

Notes: The affected regions are areas on the zip code level. A zip code area is characterized as an affected region if the driving time from the center of the zip code area to the nearest hospital increases due to the closure, i.e., the hospital that has closed was the nearest one for that zip code area. The population affected are rounded numbers from official population statistics in the closing regions (Deutsche Post Direkt GmbH 2021, RWI microm 2020).

Figure 1 shows that most people experience only small increases in their driving time (less than 5 minutes). Nevertheless, for nearly 70,000 people the increase in driving time to the nearest hospital amounts to more than 20 minutes after the closure. More importantly, for around 17,500 people the driving time to the nearest hospital increases to more than 30 minutes. In case of emergency, the population should reach a hospital in short distance to get treated immediately. By law, a supply risk exists, if more than 5,000 people need more than 30 minutes to reach the closest hospital after a potential closure of one hospital. In that case, the hospital gets financial benefits to compensate for the structurally induced deficit of the hospital (Federal Joint Committee 2016, 2018). However, this is not the case for the hospitals considered in this analysis.

Figure 1: Increase in driving time to the nearest hospital



Note: The figure shows the increase in driving time for the affected population, i.e., the people living in zip code-areas where the nearest hospital has closed. The population numbers give the count of people living in the affected zip code areas. The x-axis shows the increase in driving time that the affected population faces after the closure (Deutsche Post Direkt GmbH 2021, RWI microm 2020).

4.2 Descriptive Statistics

Table 2 shows descriptive statistics and compares relevant characteristics between affected and control regions. On average, residents living in closing regions are slightly younger and face a shorter driving time to the nearest hospital before the closures. The number of hospitals within 20 minutes driving time are slightly larger for the control regions. Thus, the people have a wider choice of hospitals in close distance compared to the people living in closing regions. The hospitalization rate of people living in closing regions (14.5%) is slightly smaller compared to the hospitalization rate in control regions (14.8%). Patients who are admitted to the hospital show similar characteristics regarding their hospital stay in both regions. For example, the comorbidity (Elixhauser) index and the length of stay are nearly identical.

Table 2: Descriptive Statistics for the pre-closing-period (year 2014)

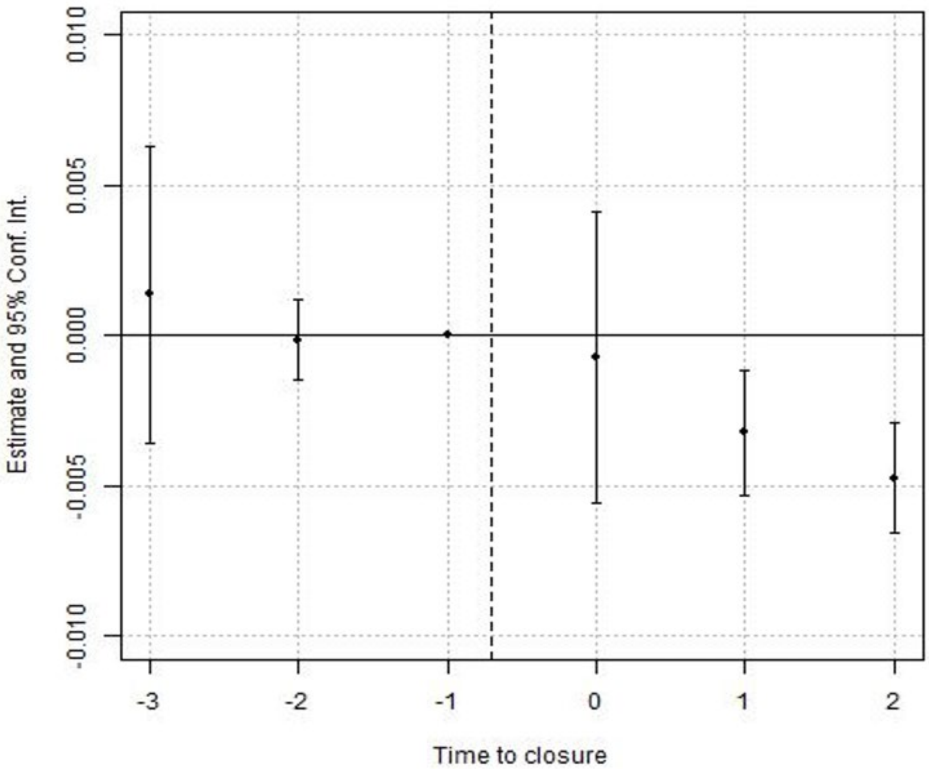
	Affected regions (Mean (SD))	**Control regions** (Mean (SD))
Age	45.2 (23.1)	45.9 (23.4)
Female	0.58 (0.49)	0.57 (0.50)
Driving time to the nearest hospital (minutes)	9.4 (5.9)	11.1 (6.9)
Other hospitals within 20 minutes	1.6 (2.6)	2.6 (3.1)
Hospitalization rates		
All cases	14.5% (35.2)	14.8% (35.6)
Ambulatory-care-sensitive cases	4.7% (2.1)	4.8% (2.1)
Urgent cases	1.4% (1.2)	1.4% (1.2)
Inpatient characteristics		
Elixhauser-Index	1.7 (1.8)	1.7 (1.8)
Length of stay (days)	8.1 (12.4)	8.2 (12.6)
Costs per case (euros)	3,894 (6,779)	3,834 (6,485)
N	62,937	604,252

Notes: Affected regions are zip code areas where the driving time from the center of the zip code area to the nearest hospital increases due to a closure. The hospitalization rates show the percentage of people that are admitted to the hospital at least once during the year.

4.3 Event Study Results

This section illustrates how hospital closures affect the probability to be hospitalized. Figure 2 shows the estimated coefficients of interest from equation (1). They indicate the difference in the probability of being hospitalized between residents living in affected versus control regions for each period before and after the closure. The mean probability to be hospitalized in the baseline period $k = -1$ is 0.150 (which is comparable to survey data from Prütz and Rommel (2017)). Figure 2 shows that the probability to be hospitalized for residents that live in closing regions decreases after the closure. The effect is not statistically significant in the year of the closure ($k = 0$). This result is reasonable since the timing of the closure is not precisely incorporated in the model, i.e., the exact closing date can be anytime between the beginning and end of the year. However, for the first and the second year after the closure, I observe a statistically significant negative effect of 2.1% and 3.2%, respectively. As a back-of-the-envelope calculation, this translates into around 20,800 (31,200) inhabitants in Germany who are no longer treated in a hospital in the first (second) year since the 18 closures took place.[7]

Figure 2: Hospital closures and the probability to be hospitalized



Note: The figure shows the coefficients and 95 percent confidence interval of δ_k from regression equation (1). The coefficient for the year k = -1, which is the year prior to the closure is set to 0. The exact coefficients are report in Table A1. Standard errors are clustered on year level.

Next, I examine whether the decrease in hospitalization rates is driven by specific types of admissions. Specifically, it is of interest whether the decrease in admission rates is driven by urgent or non-urgent cases. Ambulatory care sensitive conditions are typically non-urgent. My results show that residents in closing regions are less likely to be admitted to the hospital with an ACSC after the closure. However, the difference between affected and control regions is

[7] Back-of-the-envelope calculation: My sample consists of around 650,000 people per year in closing and control regions. On average, 15% are admitted to the hospital at least once in the year prior to the closure, which are 97,240 people. In the first and second year after the closure, the hospitalization rate decreases by 2.1% and 3.2% translating into 95,160 (94,120) people who are admitted at least once a year to the hospital. Thus, 2,080 (3,120) people are no longer treated in a hospital. Since my sample covers around 10% of the German population, this translates into 20,800 (31,200) German inhabitants who are no longer treated in the hospital in the first (second) year after the closures.

not statistically significant (Figure A1). A similar pattern is observed for patients with an urgent condition[8] (Figure A2). The estimates for all variables included in equation (1) are shown in Table A1 in the Appendix.

In addition, I estimate a classic difference-in-difference model which incorporates a single past-treatment indicator. In comparison to the event study analysis which estimates a separate effect for each pre- and past-treatment period, the difference-in-difference model reduces noise in the smaller subsample analyses.[9] The result for the probability to be hospitalized with any cause is similar to the event study analysis. In contrast to the estimates of the event study, the probability to be hospitalized with an ACSC or urgent case is significantly lower after the closure (by 4% and 6%) in closing compared to control regions in the difference-in-difference estimation (Table A3). However, due to the small sample (especially for urgent cases) and the contrasting result in the event study, I do not want to overinterpret this effect.

Heterogenous effects

To get a deeper insight in the decrease in hospitalization rates, I analyze the probability to be hospitalized for different subsamples of residents. First, I examine whether the effect depends on the residents' possibility to choose other hospitals in their surroundings. If there are several other hospitals in close distance, it should be easier for residents to reach another hospital after the closure. Figure 3 shows the coefficients from the event study for residents that live in areas with (a) one or two other hospitals and (b) more than two other hospitals within 20 minutes driving time. Although both subsamples show a decrease in the probability to be

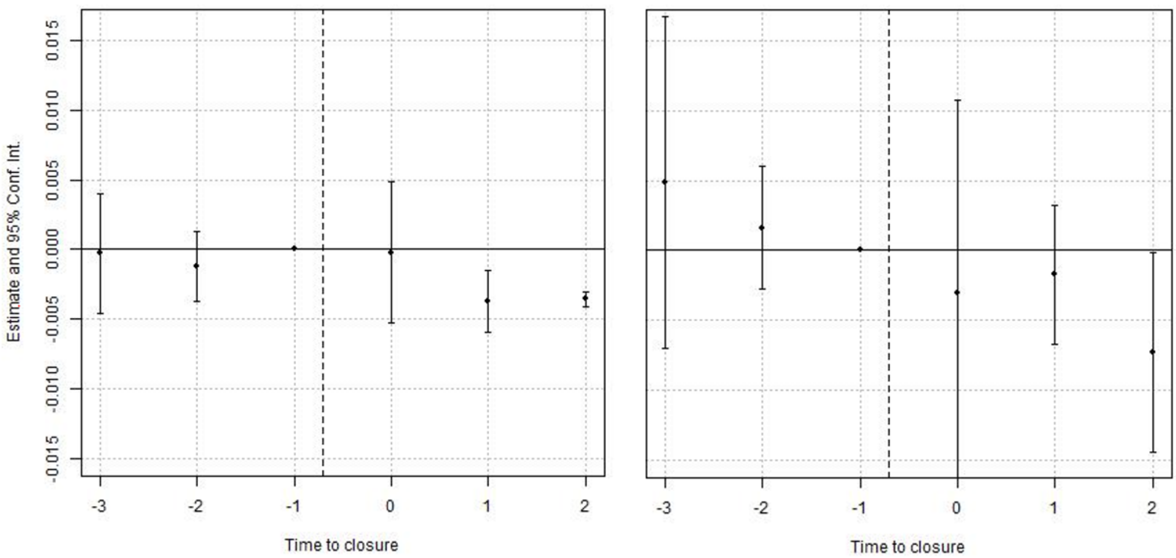
[8] I classify hospital admissions as urgent if their degree of urgency is above 80% Krämer et al. 2019.

[9] The event study design is more flexible and shows the stepwise effects of the closure, but at the same time it is less precisely at estimating the probability to be hospitalized for specific causes since the number of observations gets much smaller in the sub-sample analysis.

hospitalized, the effect is only statistically significant for the sample with few other hospitals around. In contrast, the results from the difference-in-difference estimation depicts also significant effects for residents living in areas with more other hospitals around (Table A4). This finding suggests that the observed difference in the event study analysis between regions with more or less other hospitals are probably also related to the smaller sample of residents living in areas with more than two hospitals around and thus leading to less precise estimates for a single period.

Figure 3: Probability to be hospitalized and the number of other hospitals around

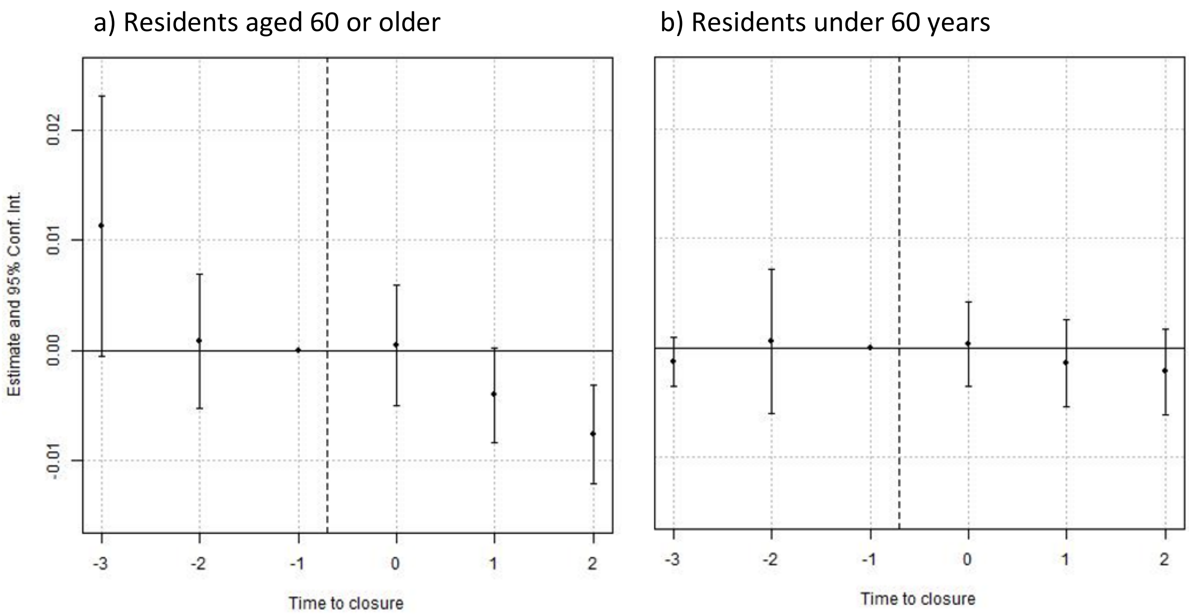
a) One or two other hospitals b) More than two other hospitals



Notes: The figures show the coefficients and 95% confidence interval of δ_k from regression equation (1) for two subsamples depending on the number of hospitals within 20 minutes driving time. The coefficient for the year k = -1, which is the year prior to the closure is set to 0. The exact coefficients are reported in Table A2. Standard errors are clustered on the year level.

Second, the effect may vary with the resident's age. Previous studies have shown that older individuals are more likely to be affected by hospital closures since they are less mobile and usually choose a hospital in close distance (Aggarwal et al. 2020, Versteeg et al. 2018). Figure 4 shows the coefficients from the event study for (a) residents aged 60 years or older and (b) residents aged younger than 60 years. In line with the hypothesis and the literature mentioned before, the effects are larger and only statistically significant for older residents. The probability to be admitted to the hospital is 3.2% lower in closing compared to control regions two years after the closure for individuals aged 60 years or older. In contrast, the effects for younger residents are small and insignificant. The estimated coefficients for all variables are shown in Table A2. The results from the difference-in-difference estimation are in line with the results from the event study design. The effect for residents under 60 years is smaller and only significant at the 10% level while the effect for older individuals is larger and highly significant (Table A4).

Figure 4: Probability to be hospitalized by residents' age



Notes: The figures show the coefficients and 95% confidence interval of δ_k from regression equation (1) for two subsamples depending on the residents' age. The coefficient for the year k = -1, which is the year prior to the closure is set to 0. The exact coefficients are reported in Table A2. Standard errors are clustered on the year level.

5 Conclusion and Discussion

This study analyzes the impact of hospital closures in Germany on patients' driving time and the probability to be admitted to the hospital. While previous studies focused mainly on hypothetical concentration processes (e.g., Hentschker and Mennicken (2015), Mennicken et al. (2014)), I analyze the effect of 18 hospital closures in Germany that took place from 2015 to 2018. Since Germany has a large hospital density and a considerable number of small and economically unprofitable hospitals, it is likely that further concentration processes will take place during the next years (Augurzky et al. 2021). Moreover, the structural fund, which induced the closures analyzed in this study, is already extended.

My results show that around 700,000 people must drive longer to the next hospital because their nearest hospital closed. Although most people experienced only a small increase in their driving time (7 minutes on average), around 70,000 people are exposed to an increase of more than 20 minutes. Using an event study design, I examine whether the closure also affects the probability to be admitted to the hospital. My results show a statistically significant decrease in the two years after the closure. Residents who are directly affected by the closure in terms of increased driving times to the nearest hospital are 2.1% and 3.2% less likely to be admitted to the hospital in the first and second year after the closure in comparison to residents in control regions. In line with a recent study by Caroll (2019), I find that the effect is particularly striking for older people.

Unfortunately, my results remain inconclusive regarding the type of patients (urgent versus non-urgent cases), who are no longer admitted to the hospital, which is probably related to the reduced sample size in the subsample analyses. On the one hand, a reduction in non-urgent admissions could hint to an efficient decrease in rather unnecessary stationary care. On the other hand, a decrease in urgent admissions would pose a severe problem. The study by Caroll (2019) suggests that the former is the case: the decrease in admission rates found in her study is mostly driven by non-urgent cases. However, her study also shows a 5% increase in mortality among patients with time-sensitive conditions. Likewise, Avdic (2016) showed that increased distance to the next hospital, caused by policy-induced emergency hospital closures in Sweden, decreases the probability to survive an acute myocardial infarction. Although this result is not directly transferable to Germany because Sweden is very sparsely populated and has a lower hospital density, it stresses the importance of immediate access to health care in case of an emergency. Relating to this, a recent study by Gujral and Basu (2019) shows that hospital closures in rural areas increase inpatient mortality by 8.7%, whereas urban closures have no measurable impact on mortality. At the same time, previous literature has shown that hospital closures can improve care quality by increasing case volume in the remaining hospitals, which in turn enhances patient outcomes through specialization and learning effects (Avdic et al. 2019a, Hentschker and Mennicken 2018). Thus, the overall effect of a closure depends on various circumstances and must be planned thoughtfully to ensure that the beneficial outweigh potential detrimental effects. In particular, it must be guaranteed that older and less mobile people are also able to reach adequate type of care.

References

Aggarwal, A., S. A. van der Geest, D. Lewis, J. van der Meulen and M. Varkevisser (2020), Simulating the impact of centralization of prostate cancer surgery services on travel burden and equity in the English National Health Service: A national population based model for health service re-design. *Cancer Medicine* 9 (12): 4175-4184.

Albrecht, M., S. Loos and K. Zich (2019), Zukunftsfähige Krankenhausversorgung: Simulation und Analyse einer Neustrukturierung der Krankenhausversorgung am Beispiel einer Versorgungsregion in Nordrhein-Westfalen: Bertelsmannstiftung.

Augurzky, B., S. Krolop, A. Pilny, C. M. Schmidt and C. Wuckel (2021), Krankenhaus Rating Report 2021: Mit Wucht in die Zukunft katapultiert. Heidelberg: medhochzwei.

Avdic, D. (2016), Improving efficiency or impairing access? Health care consolidation and quality of care: Evidence from emergency hospital closures in Sweden. *Journal of Health Economics* 48.

Avdic, D., P. Lundborg and J. Vikström (2019a), Estimating returns to hospital volume: Evidence from advanced cancer surgery. *Journal of Health Economics* 63: 81-99.

Avdic, D., G. Moscelli, A. Pilny and I. Sriubaite (2019b), Subjective and objective quality and choice of hospital: Evidence from maternal care services in Germany. *Journal of Health Economics* 68: 102229.

Barrington-Leigh, C. and A. Millard-Ball (2017), The world's user-generated road map is more than 80% complete. *PLOS ONE* 12 (8): e0180698.

Billings, J., L. Zeitel, J. Lukomnik, T. S. Carey, A. E. Blank and L. Newman (1993), Impact of socioeconomic status on hospital use in New York City. *Health Affairs* 12 (1): 162-173.

Brown, A. D., M. J. Goldacre, N. Hicks, J. T. Rourke, R. Y. McMurtry, J. D. Brown and G. M. Anderson (2001), Hospitalization for ambulatory care-sensitive conditions: a method for comparative access and quality studies using routinely collected statistics. *Canadian journal of public health* 92 (2): 155-159.

Buchmueller, T. C., M. Jacobson and C. Wold (2006), How far to the hospital? The effect of hospital closures on access to care. *Journal of Health Economics* 25 (4): 740-761.

Caroll, C. (2019), Impeding Access or Promoting Efficiency? Effects of Rural Hospital Closure on the Cost and Quality of Care. Working Paper.

Deutsche Post Direkt GmbH (2021), Postleitzahlengebiete Deutschland. Dataset.

Deutscher Bundestag (Ed.) (2021), Bericht über den durch die Förderung nach dem Krankenhausstrukturfonds bewirkten Strukturwandel. Internet: https://dserver.bundestag.de/btd/20/002/2000225.pdf (accessed on December, 06, 2021).

Federal Joint Committee (2016), Beschluss des Gemeinsamen Bundesausschusses über die Erstfassung der Regelungen für die Vereinbarung von Sicherstellungszuschlägen gemäß § 136c Absatz 3 des Fünften Buches Sozialgesetzbuch (SGB V).

Federal Joint Committee (2018), Beschluss des Gemeinsamen Bundesausschusses über die Änderung der Regelungen für die Vereinbarung von Sicherstellungszuschlägen gemäß § 136c Absatz 3 des Fünften Buches Sozialgesetzbuch (SGB V).

Federal Statistical Office (Ed.) (2021), Krankenhäuser: Einrichtungen, Betten und Patientenbewegung. Internet: https://www.destatis.de/DE/Themen/Gesellschaft-Umwelt/Gesundheit/Krankenhaeuser/Tabellen/gd-krankenhaeuser-jahre.html (accessed on 18 December, 2021).

Gowrisankaran, G., A. Nevo and R. Town (2015), Mergers When Prices Are Negotiated: Evidence from the Hospital Industry. *American Economic Review* 105 (1): 172-203.

Gujral, K. and A. Basu (2019), Impact of Rural and Urban Hospital Closures on Inpatient Mortality. NBER Working paper Series. Working Paper No. 26182.

Haklay, M. and P. Weber (2008), OpenStreetMap: User-Generated Street Maps. *IEEE Pervasive Computing* 7 (4): 12-18.

Hentschker, C. and R. Mennicken (2015), The volume-outcome relationship and minimum volume standards - Empirical evidence for Germany. *Health Economics* 24 (6): 644-658.

Hentschker, C. and R. Mennicken (2018), The Volume-Outcome Relationship Revisited: Practice Indeed Makes Perfect. *Health Services Research* 53 (1): 15-34.

Hospital Quality Reports (2016), Structured Hospital Quality Reports (§ 137 Abs. 3 Satz 1 Nr. 4 SGB V).

Hospital Quality Reports (2017), Structured Hospital Quality Reports (§ 137 Abs. 3 Satz 1 Nr. 4 SGB V).

Hospital Quality Reports (2018), Structured Hospital Quality Reports (§ 137 Abs. 3 Satz 1 Nr. 4 SGB V).

Joynt, K. E., P. Chatterjee, E. J. Orav and A. K. Jha (2015), Hospital closures had no measurable impact on local hospitalization rates or mortality rates, 2003-11. *Health Affairs* 34 (5): 765-772.

Krämer, J., J. Schreyögg and R. Busse (2019), Classification of hospital admissions into emergency and elective care: a machine learning approach. *Health Care Management Science* 22 (1): 85-105.

Luxen, D. and C. Vetter (2011), Real-time routing with OpenStreetMap data. *Proceedings of the 19th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*: 513–516.

McCarthy, S., D. Moore, W. A. Smedley, B. M. Crowley, S. W. Stephens, R. L. Griffin, L. C. Tanner and J. O. Jansen (2021), Impact of Rural Hospital Closures on Health-Care Access. *Journal of Surgical Research* 258: 170-178.

Mennicken, R., I. W. Kolodziej, B. Augurzky and R. Kreienberg (2014), Concentration of gynaecology and obstetrics in Germany: is comprehensive access at stake? *Health Policy* 118 (3): 396-406.

OECD (2021), Health at a Glance 2021: OECD Indicators, OECD Publishing, Paris, https://doi.org/10.1787/ae3016b9-en.

Pilny, A. and R. Mennicken (2014), Does Hospital Reputation Influence the Choice of Hospital? *Ruhr Economic Papers 516*.

Prütz, F. and A. Rommel (2017), Inanspruchnahme von Krankenhausbehandlungen in Deutschland. *Journal of Health Monitoring* 2 (4): 95-100.

Purdy, S., T. Griffin, C. Salisbury and D. Sharp (2009), Ambulatory care sensitive conditions: terminology and disease coding need to be more specific to aid policy makers and clinicians. *Public Health* 123 (2): 169-173.

RWI microm (2020), RWI-GEO-GRID: Socio-economic data on grid level- Scientific Use File (wave 9). RWI-GEO-GRID. Version: 1. RWI – Leibniz Institute for Economic Research. Dataset.

Smith, H., C. Currie, P. Chaiwuttisak and A. Kyprianou (2018), Patient choice modelling: how do patients choose their hospitals? *Health Care Management Science* 21 (2): 259-268.

Sundmacher, L., D. Fischbach, W. Schuettig, C. Naumann, U. Augustin and C. Faisst (2015), Which hospitalisations are ambulatory care-sensitive, to what degree, and how could the rates be reduced? Results of a group consensus study in Germany. *Health Policy* 119 (11): 1415-1423.

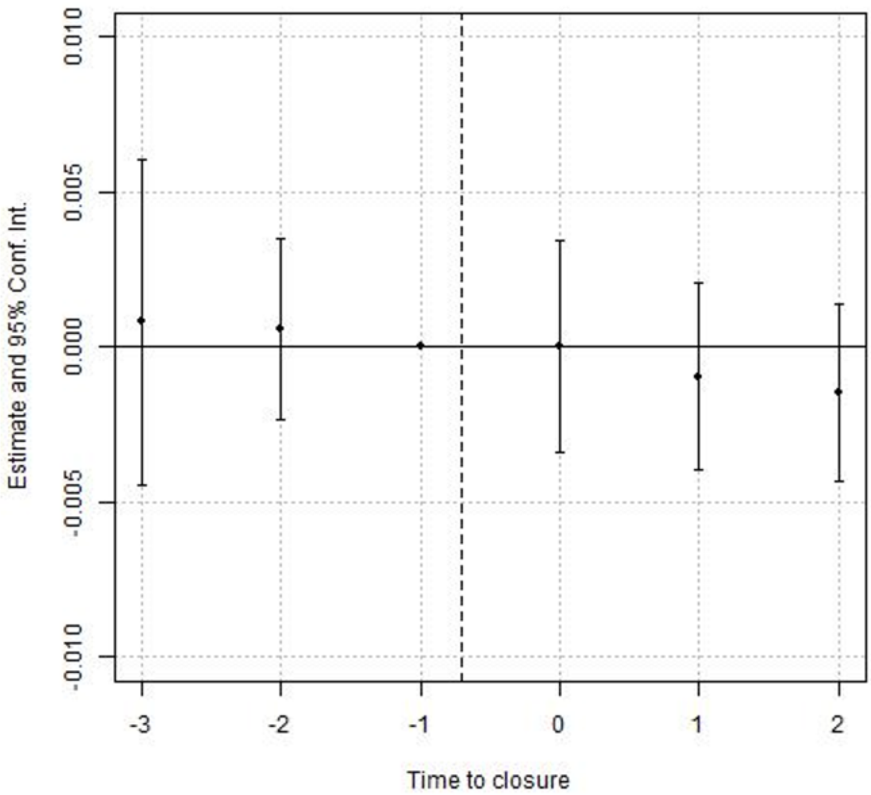
Varkevisser, M., S. A. v. d. Geest and F. T. Schut (2012), Do patients choose hospitals with high quality ratings? Empirical evidence from the market for angioplasty in the Netherlands. *Journal of Health Economics* 31 (2): 371-378.

Versteeg, S. E., V. K. Y. Ho, S. Siesling and M. Varkevisser (2018), Centralisation of cancer surgery and the impact on patients' travel burden. *Health Policy* 122 (9): 1028-1034.

Victoor, A., D. M. J. Delnoij, R. D. Friele and J. J. Rademakers (2012), Determinants of patient choice of healthcare providers: a scoping review. *BMC Health Services Research* 12 (1): 272.

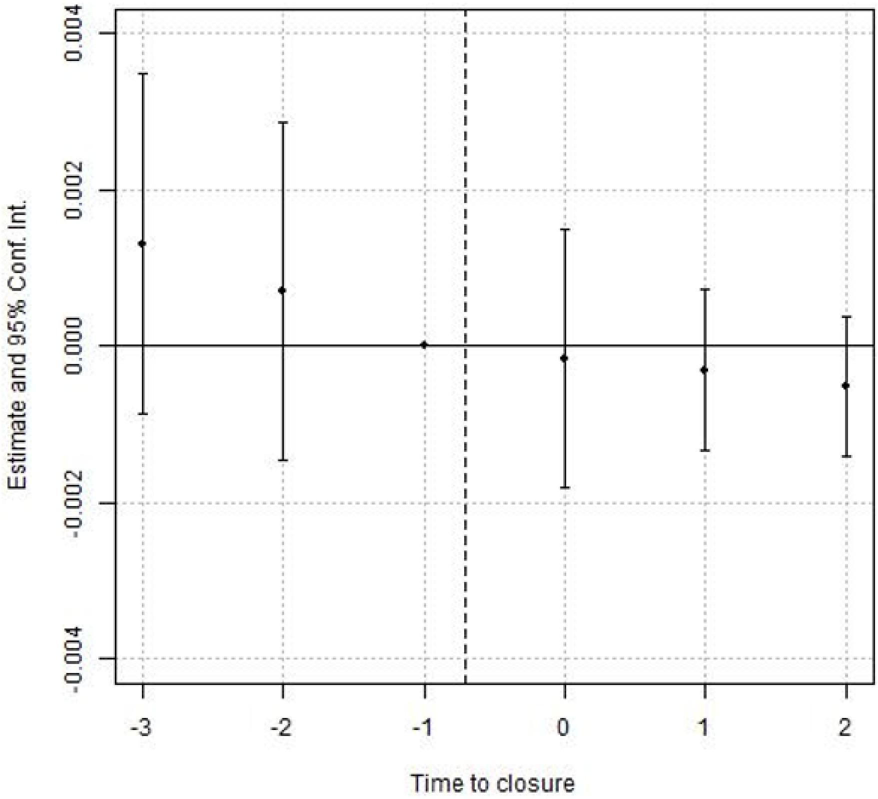
6 Appendix

Figure A1: Hospital closures and the probability to be hospitalized with an ACSC



Notes: The figure shows the coefficients and 95% confidence interval of δ_k from regression equation (1), but for ambulatory-care-sensitive conditions only. The coefficient for the year k = -1, which is the year prior to the closure is set to 0. The exact coefficients are reported in Table A1. Standard errors are clustered on year level.

Figure A2: Hospital closures and the probability to be hospitalized with an urgent case



Notes: The figure shows the coefficients and 95% confidence interval of δ_k from regression equation (1), but for urgent conditions only. The coefficient for the year k = -1, which is the year prior to the closure is set to 0. The exact coefficients are reported in Table A1. Standard errors are clustered on year level.

Table A1: Event study results on the probability to be hospitalized

	Probability to be hospitalized with		
	Any condition	Ambulatory care sensitive conditions	Urgent conditions
	(1)	(2)	(3)
Time to event x affected areas			
Three years to closure	-0. 0014	-0. 0008	-0. 0013
	(0.0025)	(0.0027)	(0.0011)
Two years to closure	-0.0001	0.0006	0.0007
	(0.0007)	(0.0015)	(0.0011)
Closing year	-0.0007	0.0000	-0.0002
	(0.0025)	(0.0017)	(0.0008)
One year after closure	-0.0032*	-0.0010	-0.0003
	(0.0011)	(0.0015)	(0.0005)
Two years after closure	-0.0048**	-0.0015	-0.0005
	(0.0009)	(0.0014)	(0.0005)
Female	0.0028***	-0.0048***	-0.0041***
	(0.0003)	(0.0001)	(0.0001)
Age	0.0028***	0.0012***	0.0007***
	(0.0000)	(0.0000)	(0.0000)
Other hospitals around	0.0001	0.0000215	0.0002***
	(0.0001)	(0.0001)	(0.0000)
Year fixed effects	Yes	Yes	Yes
Observations	4,568,206	4,568,206	4,568,206
Average probability to be hospitalized in t= -1	0.1496	0.0484	0.0150

Notes: Affected areas are zip code areas where the driving time from the center of the zip code area to the nearest hospital increases due to a closure. The outcome variable is the probability to be admitted to any hospital at least once during a year with (1) any condition, (2) ACSC or (3) urgent conditions. The coefficient for the year prior to the closure (k = -1) is set to 0. The variable "other hospitals around" is a continuous variable indicating the number of other hospitals that provide at least basic inpatient care and which are reached within 20 minutes driving time from the individuals place of resident. Standard errors are clustered on year level. *p<0.1**p<0.05***p<0.01.

Table A2: Event study results on the probability to be hospitalized – Heterogenous effects

	Probability to be hospitalized and the number of hospitals around		Probability to be hospitalized and residents' age	
	One or two	Three or more	60 or older	Younger than 60
	(1)	(2)	(3)	(4)
Time to event x affected areas				
Three years to closure	-0.0003	0.0049	0.0112	-0.0013
	(0.0022)	(0.0060)	(0.0060)	(0.0011)
Two years to closure	-0.0012	0.0016	0.0008	0.0006
	(0.0013)	(0.0022)	(0.0031)	(0.0034)
Closing year	-0.0002	-0.0031	0.0004	0.0003
	(0.0026)	(0.0070)	(0.0028)	(0.0020)
One year after closure	-0.0037*	-0.0017	-0.0041	-0.0014
	(0.0011)	(0.0025)	(0.0022)	(0.0020)
Two years after closure	-0.0036***	-0.0073	-0.0077*	-0.0022
	(0.0003)	(0.0036)	(0.0023)	(0.0020)
Female	0.0018***	0.0045***	-0.0355***	0.0228***
	(0.0003)	(0.0005)	(0.0009)	(0.0004)
Age	0.0027***	0.0030***	0.0087***	0.0008***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Other hospitals around	-0.0014*	0.0008**	0.0001	-0.0005**
	(0.0004)	(0.0001)	(0.0002)	(0.0001)
Year fixed effects	Yes	Yes	Yes	Yes
Observations	2,919,103	1,649,103	1,517,790	3,050,416
Average probability to be hospitalized in t= -1	0.1483	0.1528	0.2441	0.1032

Notes: Affected areas are zip code areas where the driving time from the center of the zip code area to the nearest hospital increases due to a closure. The outcome variable is the probability to be admitted to any hospital at least once during a year with any condition. In column (1) and (2), the sample is split by the number of hospitals that are reachable within 20 minutes driving time and which provide at least basic inpatient care. In column (3) and (4), the sample is split by the resident's age. The coefficient for the year prior to the closure (k = -1) is set to 0. Standard errors are clustered on year level. *p<0.1**p<0.05***p<0.01.

Table A3: Difference-in-difference results on the probability to be hospitalized

	Probability to be hospitalized with		
	Any condition	Ambulatory care sensitive conditions sensitive conditions	Urgent conditions
	(1)	(2)	(3)
Affected area	0.0003	0.0006	0.0005**
	(0.0007)	(0.0004)	(0.0002)
Affected x Past Closure	-0.0042***	-0.0017**	-0.0009**
	(0.0012)	(0.0007)	(0.0004)
Female	0.0028***	-0.0048***	-0.0041***
	(0.0003)	(0.0002)	(0.0001)
Age	0.0028***	0.0012***	0.0007***
	(0.00001)	(0.000004)	(0.000002)
Other hospitals around	0.0001*	0.00002	0.0002***
	(0.0001)	(0.00003)	(0.00002)
Year fixed effects	Yes	Yes	Yes
Observations	4,568,206	4,568,206	4,568,206
Average probability to be hospitalized in t= -1	0.1496	0.0484	0.0150

Note: Affected areas are zip code areas where the driving time from the center of the zip code area to the nearest hospital increases due to a closure. Past Closure is an indicator for the time periods after the closure (*k*=0,1,2). The outcome variable is the probability to be admitted to any hospital at least once during a year with (1) any condition, (2) ACSC or (3) urgent conditions. The coefficient for the year prior to the closure (k = -1) is set to 0. The variable "other hospitals around" is a continuous variable indicating the number of other hospitals that provide at least basic inpatient care and which are reached within 20 minutes driving time from the individuals place of resident. Standard errors are clustered on year level. *p<0.1**p<0.05***p<0.01.

Table A4: Difference-in-difference results on the probability to be hospitalized – Heterogenous effects

	Probability to be hospitalized and the number of hospitals around		Probability to be hospitalized and residents' age	
	One or two	Three or more	60 or older	Younger than 60
	(1)	(2)	(3)	(4)
Affected area	-0.0005	0.0017	0.0027^{*}	0.0006
	(0.0008)	(0.0014)	(0.0015)	(0.0007)
Affected x Past Closure	-0.0031^{**}	-0.0063^{***}	-0.0084^{***}	-0.0024^{*}
	(0.0014)	(0.0024)	(0.0026)	(0.0013)
Female	0.0018^{***}	0.0045^{***}	-0.0355^{***}	0.0228^{***}
	(0.0004)	(0.0006)	(0.0007)	(0.0004)
Age	0.0027^{***}	0.0030^{***}	0.0087^{***}	0.0008^{***}
	(0.00001)	(0.00001)	(0.00004)	(0.00001)
Other hospitals around	-0.0014^{***}	0.0008^{***}	0.0001	-0.0005^{***}
	(0.0003)	(0.0001)	(0.0001)	(0.0001)
Year fixed effects	Yes	Yes	Yes	Yes
Observations	2,919,103	1,649,103	1,517,790	3,050,416
Average probability to be hospitalized in t= -1	0.1483	0.1528	0.2441	0.1032

Notes: Affected areas are zip code areas where the driving time from the center of the zip code area to the nearest hospital increases due to a closure. Past Closure is an indicator for the time periods after the closure (*k*=0,1,2). The outcome variable is the probability to be admitted to any hospital at least once during a year with any condition. In column (1) and (2), the sample is split by the number of hospitals that are reachable within 20 minutes driving time and which provide at least basic inpatient care. In column (3) and (4), the sample is split by the resident's age. Standard errors are clustered on year level. *p<0.1**p<0.05***p<0.01.