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So Close Yet So Far? – Estimating the Relationship Between Distance and Hospital Utilization Using Road Closures

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So close yet so far? – Estimating the Relationship between Distance and Hospital Utilization using Road Closures*

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Abstract

Distance to healthcare services is a major influence on healthcare utilization. However, measuring its actual impact proves difficult because the location of healthcare facilities and place of residence are highly endogenous. This paper presents new exogenous variation to isolate this relationship: closures of German highways (*Autobahnen*). They are implemented using a fixed-effects model with administrative data from a large German health insurance company. Results indicate that the closures lead to significant changes in driving times and that inpatient utilization reacts with an elasticity of around -0.15%. This is much smaller than the overall correlation (-0.86%), but still of relevant size. Distance to a hospital is therefore, by itself, an important factor for its utilization, even if its impact is smaller than the overall correlation might suggest. Patients rather switch to different hospitals than forgo inpatient care or substitute it with primary care. Individuals living in rural areas or in areas with low purchasing power are the most sensitive to changes in driving times.

JEL Classification: I11, I14, I18, R41
Keywords: Healthcare utilization, Hospital accessibility, Distance to care, Driving time, Travel time, Highway closures

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1 Introduction

Inpatient care plays an important role in the German healthcare system. Germany has the second-highest number of hospital beds (relative to population) in the EU (Blümel et al., 2020). However, financing this capacity is becoming an increasing problem for the responsible state governments, resulting in a continuously decreasing number of hospitals (Augurzky et al., 2025b). On a local level, hospital closures are met with resentment. A major concern is reduced access to healthcare due to increased driving distance to the nearest hospital. While it is widely accepted that distance to a healthcare facility is an important factor associated with healthcare utilization (Kelly et al., 2016; Rana et al., 2022), it is unclear to what extent this relationship is causal.

Some insights can be derived from a large body of literature that focuses on the effects of hospital closures. They do seem to affect access to care, albeit to varying degrees. Buchmueller et al. (2006) finds that seniors experienced reduced access to care after hospital closures, whereas this result does not hold for the whole population. This might be explained by seniors' reduced mobility, which makes it more difficult for them to reach hospitals if they are farther away. For the case of Germany, Mensen (2022) shows that the increase in driving time after hospital closures is, on average, seven minutes. This increase is driven by a small group of individuals with large increases in driving times, whereas it is negligible for the majority of affected individuals. Still, hospitalizations decrease by 2 to 3 percentage points overall after closures. While hospital closures have a significant negative impact on emergency care (Avdic, 2016; Sriubaite, 2021; Ghislandi et al., 2025), they are less relevant for elective services. Travel distance itself does not seem to be an issue after maternity ward closures (Avdic et al., 2024). In line with this, Kollerup (2022) finds no adverse health effects of closures of breast cancer clinics, and the negative effects of closures found by Gujral and Basu (2019) are only observed for AMI patients but not for the general population. However, the conclusions that can be drawn from these studies for the impact of distance itself on hospital utilization are limited. Closures affect the regional healthcare market as a whole, and the remaining providers have to make up for the loss of capacity. For example, the results for maternity ward closures are driven by overcrowding and a shift to higher-quality clinics (Avdic et al., 2024). The latter is also observed for breast cancer surgery (Kollerup, 2022). The negative effects on AMI patients found by Avdic (2016) are only observed in the first year after the closure, after which the hospitals have adapted to the new situation. In line with this, Sriubaite (2021) suggests that efficiency increases in the remaining hospitals. Dong et al. (2024) focus specifically on the impact of hospital closures on remaining hospitals, observing increases in staffing levels and the number of provided services. Hospital closures are therefore most relevant for emergency care, whereas the changes in overall healthcare utilization are driven by changes in market structure and adaptations within the remaining hospitals.

A few studies use other forms of exogenous variation to investigate the impact of driving times. Bertoli and Grembi (2017) use variation in where traffic accidents occur, showing that a 5km increase in distance to a hospital leads to an increase in the fatality rate by 14%. Jena et al. (2017) show that increased driving times caused by marathons lead to an increase in AMI mortality by 13.3%. Both studies focus on emergency services, so it is unclear whether the results are applicable to healthcare utilization in general.

One major difference between emergency care and non-emergency care is who decides which hospital to seek care in and what factors this decision is based on. Outside of emergency care, this choice is, in most cases, made by patients. While distance does seem to be a major factor in their decision-making process (Smith et al., 2018), there is still ample evidence for hospital bypassing, especially for elective services such as cancer (Varkevisser and Van Der Geest, 2007; Mennicken et al., 2014; Versteeg et al., 2018; Balia et al., 2020).

While it is therefore clear that distance to a hospital is highly relevant for healthcare utilization and health outcomes in emergency settings, there is no evidence of the direct impact of driving time outside of emergency care, where decisions about healthcare utilization are made predominantly by patients themselves.

In this paper, I bridge this gap by introducing a new type of shock of distance: road closures. Specifically, I use closures of German highways (*Autobahnen*). They are unrelated to both patient and hospital characteristics and are highly observable to individuals making the decision to seek care, who potentially rely on these major roads as the fastest route to individual hospitals. In fact, while only 14% of ZIP-code hospital combinations are affected by road closures throughout the year of the analysis, the increase in driving time caused by the closures is on average 3.6 minutes – 16% of the average driving time. Compared to, for example, hospital closures, road closures have no significant long-term impact on regional hospital markets. So, while they are incorporated in the decision-making process of potential patients, they do not affect healthcare provision in hospitals. Notably, they can also be applied in non-emergency settings, where patients' decisions are an important channel for the impact of driving times. Results suggest that driving times do indeed affect healthcare utilization negatively, but in a more modest way than the overall correlation might suggest. This effect is driven by patients switching hospitals rather than forgoing care or using outpatient services as a substitute. Individuals in rural and poorer areas are more sensitive to changes in driving times.

The rest of the paper is structured as follows. Section 2 gives an overview of the German hospital market. Section 3 describes the different data sets that I use and how I calculate driving times. Section 4 briefly describes the estimation model. The results are presented in Section 5. Finally, Section 6 concludes.

2 Hospital care in Germany

Germany has one of the highest hospital densities in the EU, resulting in high availability of inpatient care (Blümel et al., 2020). However, a large share of these hospitals are located in urban areas, meaning that especially individuals from rural areas face longer driving times and are especially reliant on motor vehicles for transportation (Schröder et al., 2018). While there is no form of gatekeeping for ambulatory care, the patient pathway to inpatient care usually goes via referral by an outpatient physician. In this sense, utilization of hospital services is planned in advance and unlikely to be affected by changes in driving time. On the other hand, emergency services and after-hours care are provided to a large share by hospitals, which may lead to admission into inpatient care (Blümel et al., 2020). This more spontaneous pathway is potentially more sensitive to driving times. When seeking inpatient care, individuals face little copayments in the form of a small contribution of 10 EUR per day, which, together with the high hospital density, means that inpatient services are highly accessible. The downside is a high level of low-urgency demand for emergency services. 30% to 50% of patients in hospital emergency departments are low urgency (Scherer et al., 2017; von Stillfried et al., 2017), while convenience is stated as one of the main motives for these low-acuity visits (Schmiedhofer et al., 2016). A significant part of hospital utilization is therefore made up of low-urgency contacts, which might be the most sensitive to changes in driving times.

3 Data

My approach in this paper requires combining different data sources. In addition to information on the location and type of hospitals, I also use data on healthcare utilization, and – most importantly – road closures.

For healthcare utilization, I use administrative data from a large German health insurance company covering about 10.3% of the German population (Augurzky et al., 2025a). This data is aggregated on the ZIP-code hospital-day level. It contains the number of inpatient admissions of patients living in a ZIP-code area to individual hospitals for every day of the year 2024. I calculate the number of contacts per 1,000 insured persons per day by using the number of insured persons in each ZIP-code.

For the information on hospitals, I use the structured quality reports (*Strukturierte Qualitätsberichte*) of the German Federal Joint Committee. The data contains, among other things, the address of hospital locations and departments within the hospital. I geolocate the hospital address and restrict the sample to general hospitals, defined as having a department for internal medicine and a surgical ward.

The identification in this paper is based on the idea that individuals include the current driving time to a hospital in their decision-making process of whether to seek care or not. They are assumed to be aware of road closures and the resulting increase in driving time. This assumption is especially plausible for highway closures, since they are communicated in advance and, by affecting major roads, they potentially lead to major changes in driving time (Schuster et al., 2024). I use data on road closures provided by the *Autobahn GmbH des Bundes*, which is responsible for the administration of German highways. The data contains all closures of German highways for construction purposes in the year 2024, together with their duration and georeferenced location (N = 2,069). A map with the closures is provided in the Appendix in Figure A.1.

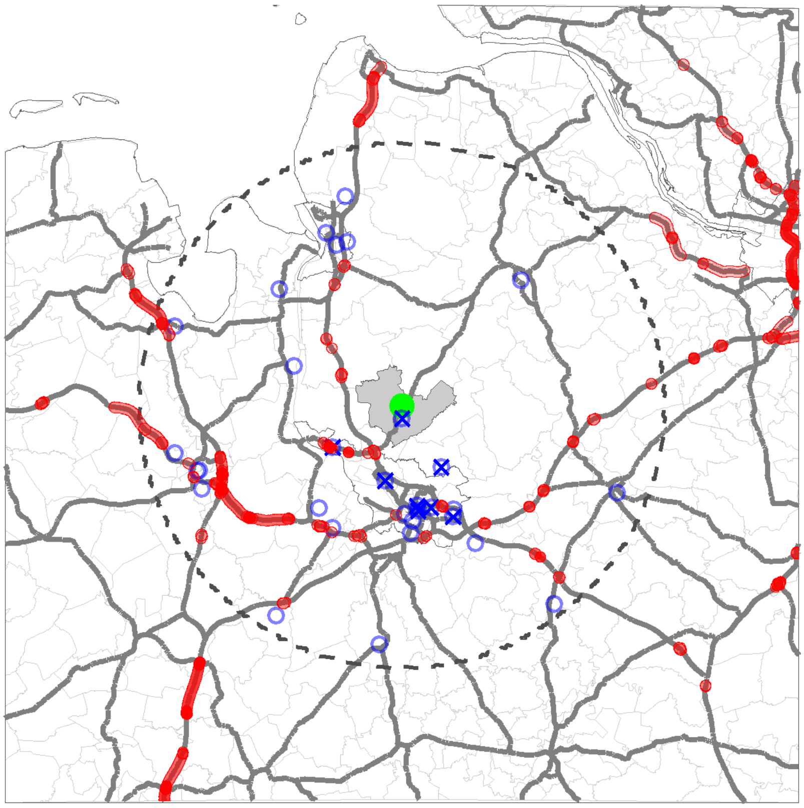
3.1 Calculation of Driving Time

With all these data, I am able to calculate day-specific driving times between hospitals and ZIP-code centroids. An example of this process is depicted in Figure 1.

First, the centroid of each ZIP-code area is determined. This is represented by the green dot in Figure 1. All distance calculations are based on the centroids. This is common in the literature, as it does not require individuals' addresses (which is highly sensitive information) and is computationally more feasible.

Second, all hospitals within a 50 km radius of the centroid are identified (the

Figure 1: Example of the calculation of driving times



Notes: Example for the ZIP-code 27711, marked by the gray area. The green dot represents the centroid of the area. The dashed line indicates a 50 km radius around the centroid. The blue circles represent all hospitals within a 50 km radius, of which the crossed circles are the five closest hospitals by driving time (irrespective of closures). The road closures are marked by the red areas.

blue circles in Figure 1). For these hospitals, the driving times without any road closures are calculated using a local *OpenStreetMap* (OSM) routing server, and the five hospitals with the shortest driving times are selected (marked by the crossed blue circles in Figure 1). Note that these hospitals are not necessarily the nearest hospitals by linear distance or driving distance. In particular, highways may allow for higher driving speeds and thus shorter driving times even if the driving distance is longer.

Third, the driving times between the centroid and the five closest hospitals are calculated for every day of the year 2024, taking into account the road closures in place on that date. For this purpose, the local OSM routing server is set up with the road network of Germany. For every day, the nodes and relations representing the roads closed on that day are removed from the road network. The driving times are then calculated using the resulting road network.

Lastly, the driving times are merged with the administrative data. The result is a panel on the ZIP-code hospital day level containing driving time and hospital utilization.

3.2 Descriptives

Table 1 shows the descriptive statistics based on the ZIP-code hospital day level observations. Two samples are used. First, the sample *All*, in which all available data is used. Second, I use the subset of ZIP-code hospital combinations where driving time changes at any point during the year, called the *Any Change* sample. Only 14.2% of ZIP-code hospital combinations experience any change in driving time; these are depicted in Figure A.3 in the Appendix. There are on average 1,100 insured persons living in a ZIP-code area. The number of daily inpatient cases per 1,000 is 0.0737 for the complete sample and lower for the sample with any change in driving time (0.0474), although the difference is not statistically significant. The average driving time to the used hospitals is 22 minutes, or slightly more, 25 minutes, for the *Any Change* sample; however, this difference is not statistically significant. The corresponding driving distance is 20 km and 26 km, respectively. The change in driving time is about 4 seconds on average for the complete sample. However, as noted above, 85% of ZIP-code hospital combinations do not experience any change in driving time, which is why the change is much higher on average (30 seconds) for the *Any Change* sample. While this still seems small, this variable is highly skewed, with some ZIP-codes experiencing substantially larger changes. There is also substantial variation within ZIP-codes: only 14% of observations are affected by closures. To provide further insights into the variation the estimation relies on, I report the change in driving times excluding zeros, i.e., the mean change conditional on there being a change. On average, driving time increases by 3.6 minutes due to the closures. Compared to the average increase of seven minutes after hospital closures found by Mensen (2022), this is a relevant size. Two percent of the ZIP-code hospital-day observations are affected by a closure (*Any current closure*). As expected, this share is much higher for the *Any Change* sample (14%), of which 3.4 percentage points are closures that lead to an increase in driving time of more than 5 minutes. To investigate heterogeneities across ZIP-code areas, I use regional indicators from the INKAR database (BBSR, 2026). They are assigned to ZIP-codes based on the municipalities they belong to. The sample is then split based on the median of the respective indicator. A ZIP-code is classified as *Rural* if the population density lies below the median of 187.14 inhabitants/m^2; therefore, 50% of the sample are classified as rural. Access to general practitioners (GP) is defined based on the share of the population that lives less than 1,000 m away from a GP. ZIP-codes with a share above the median (69.61%) are classified as having good GP access. The median purchasing power per person is 29,433.76 EUR.

Table 1: Descriptive Statistics

	All		Any Change	
	Mean	SD	Mean	SD
Number of insurees	1,094	1,180	1,235	1,289
Total cases per 1,000	0.0737	0.5157	0.0474	0.3636
Driving time (min)	21.83	11.44	24.65	9.60
Driving distance (km)	20.01	12.41	26.29	12.59
Change in driving time (min)	0.0715	0.6908	0.5020	1.7711
Change in driving time excl. 0 (min)	3.5935	3.3682	3.5935	3.3682
Any current closure	0.0199	0.1396	0.1397	0.3467
Any current closure >5min	0.0048	0.0689	0.0335	0.1799
Rural	0.5012	0.5000	0.4576	0.4982
Good GP Access	0.4986	0.5000	0.5192	0.4996
High Purchasing Power	0.5014	0.5000	0.5096	0.4999
Number of Observations	13,587,384		1,933,944	
Number of ZIP Codes	7,646		2,674	
Number of Hospitals	1,418		719	
Number of ZIP X Hospitals	37,124		5,284	

Notes: Observations on the ZIP × Hospital × Day level. *All* = complete sample. *Any Change* = ZIP × Hospital combinations with any change in driving time throughout the year. *Change in driving time* = difference between current driving time and driving time without closures at the ZIP × Hospital level. *Change in driving time excl. 0* = Change in driving time excluding zeros. *Any current closure* = binary indicator if driving time differs from driving time without closures. *Any current closure > 5 min* = binary indicator if driving time is more than 5 min higher than driving time without closures. *Rural* = ZIP-codes in municipalities with population density below the median (187.14 inhabitants/m^2). *Good GP access* = ZIP-codes in municipalities with a share of the population living < 1,000 m away from a GP above the median (69.61%). *High purchasing power* = ZIP-codes in municipalities with purchasing power above the median (29,433.76 EUR).

4 Method

Given that there is exogenous variation in driving time within ZIP-code hospital combinations across the year, the main specification is a fixed-effects model that provides within-estimates of the effect of driving time on healthcare utilization:

$$Y_{zht} = \beta * DrivingTime_{zht} + \gamma_t + \delta_{hz} + \epsilon \tag{1}$$

With z indicating ZIP-code, h hospital, and t day. Thus Y_{zht} represents the number of daily cases for individuals living in a certain ZIP-code area in a given hospital per 1,000, γ_t are day fixed effects, δ_{hz} are ZIP-code hospital combination fixed effects, and ϵ is the error term. $DrivingTime_{zht}$ is the day-specific driving time between the ZIP-code and the hospital, and the coefficient of interest is β. It captures the effects of changes in driving time, accounting for the average number of cases in the ZIP-code hospital combination and the average number of cases on that day. Standard errors are clustered at the ZIP-code hospital combination level.

In order to make results more comparable, they are also presented as elasticities, indicating the change in cases in % for every 1% increase in driving time. They are calculated as:

$$Elasticity \approx \hat{\beta} * \frac{\overline{DrivingTime}}{\overline{Y}} \tag{2}$$

5 Results

Table 2 presents the main results. The first two columns show OLS estimates for both the complete sample and the *Any Change* sample. Overall, the negative correlation between distance and utilization as commonly found in the literature can be replicated. For the complete sample, an increase in driving time by one minute correlates with a reduction of 0.0023 inpatient cases per 1,000 per day, or an elasticity of -0.69%. When using the *Any Change* sample, this elasticity is around -0.86%. However, the Fixed-Effects model following Eq. 1 reveals that only a small part of this correlation can be attributed to driving time itself. An increase in driving time by 1 minute reduces utilization by 0.0003 cases per 1,000 per day in both samples. This translates into an elasticity of around -0.09% in the complete sample and -0.15% in the *Any Change* sample. Most of the correlation observed in the OLS estimates is therefore the result of hospital characteristics, ZIP-code characteristics, or the baseline level of utilization of hospitals by individuals living in a given ZIP-code.

Table 2: Main Results

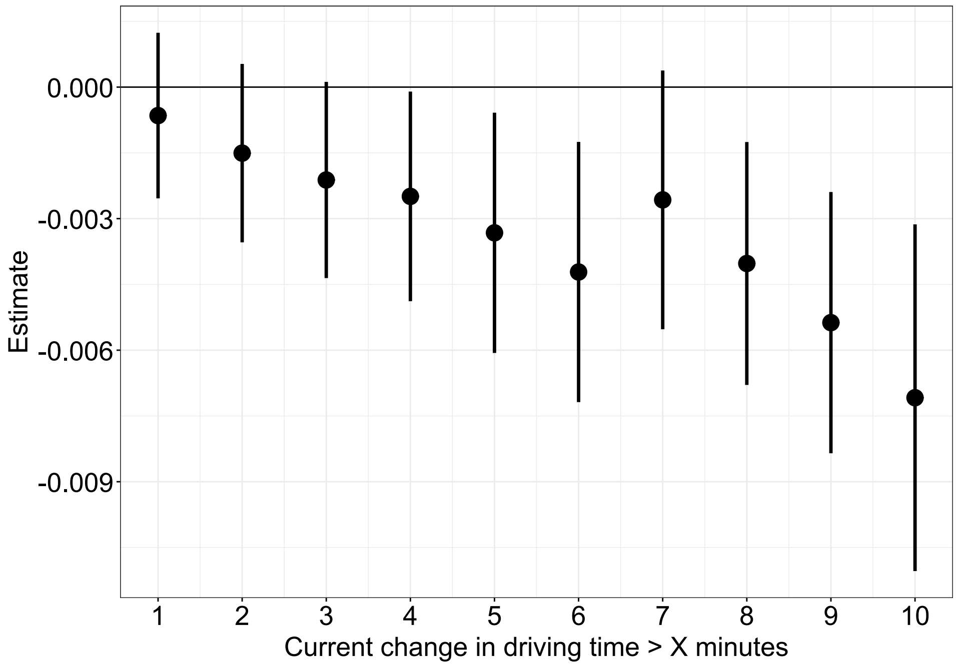
	OLS		FE	
	All	Any Change	All	Any Change
Outcome: Cases per 1000				
Driving time (min)	-0.0023^{***}	-0.0017^{***}	-0.0003^{**}	-0.0003^{**}
SE	0.0001	0.0001	0.0001	0.0001
Day FE			X	X
Hospital × ZIP FE			X	X
Num Obs	$13,587,384$	$1,933,944$	$13,587,384$	$1,933,944$
Mean Cases	0.0737	0.0474	0.0737	0.0474
Mean Driving Time	21.8346	24.6524	21.8346	24.6524
Elasticity	-0.6883	-0.8584	-0.0911	-0.1461

Note: Elasticities calculated according to Eq. 2. * P<0.1, ** P<0.05, *** P<0.01.

The main results are based on any change in driving time. However, one would expect that larger changes in driving time have a stronger impact than smaller ones. Figure 2 investigates this dose-response relationship. For this, the driving time in Eq. 1 is replaced by a binary indicator of whether the current driving time is more than X minutes longer than the driving time without closures. The figure clearly shows that the reduction in inpatient cases is indeed larger for larger increases in driving time, showing a roughly linear relationship.

I therefore observe a reduction in the demand for individual hospitals. The question is now whether this translates into an overall reduction in healthcare utilization. Table 3 shows estimates using the share of cases, total inpatient cases, and GP cases as outcomes in the fixed-effects model. The total number of cases is the number of all daily inpatient or GP cases in the ZIP-code area (compared to the main results, which are based on cases in a specific hospital). The share of inpatient cases is the share of daily cases in a ZIP-code area that are treated in the hospital at hand. The results show that the share of cases is reduced, while the total number of inpatient cases is unaffected. This indicates that patients rather switch hospitals than reduce their overall demand for inpatient services. I also do

Figure 2: Dose Response Relationship



Notes: Based on Equation 1, but replacing driving time with a binary indicator that takes value 1 if the current change in driving time is larger than X minutes. Lines represent 95% confidence intervals. Based on the complete sample.

not observe spillovers to GP care.

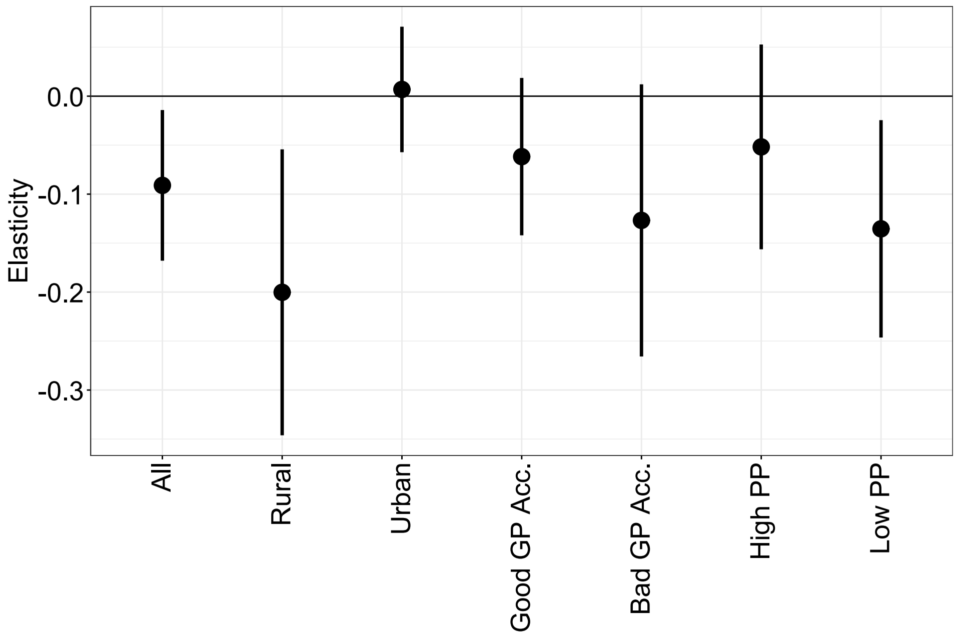
Table 3: Regression Results overall health care utilization

Outcome:	Share of Inpatient Cases	Total Inpatient Cases	Total GP Cases
Driving time (min)	-0.0001 **	0.0002	-0.0034
SE	0.0001	0.0007	0.0056
Day FE	X	X	X
Hospital X ZIP FE	X	X	X
Num Obs	13,587,384	13,587,384	13,587,384
Mean Outcome	0.0454	0.5928	19.9687
Mean Driving Time	21.8346	21.8346	21.8346
Elasticity	-0.0609	0.0088	-0.0038

Note: Elasticities calculated according to Eq. 2. * P<0.1, ** P<0.05, *** P<0.01.

Next, I investigate heterogeneities across ZIP-codes, based on the median splits presented in Table 1. The results are presented in Figure 3. Rural areas seem to be more sensitive to changes in driving times. This is understandable because individuals living in these areas may rely on highways to reach the nearest hospital more often. There is no difference based on GP access. This may be explained by the fact that the analysis at hand is based on inpatient cases. Individuals with worse GP access are potentially more likely to visit hospitals via emergency departments or after-hours services. However, these types of contacts are probably treated as outpatient cases. Regions with lower purchasing power seem to be more affected by changes in driving times. This is unlikely to be due to lower purchasing power being correlated with higher rurality, as the correlation between the two factors is only 0.19. Increased driving times therefore disproportionately affect individuals in rural and poorer areas, which are already experiencing lower accessibility of care.

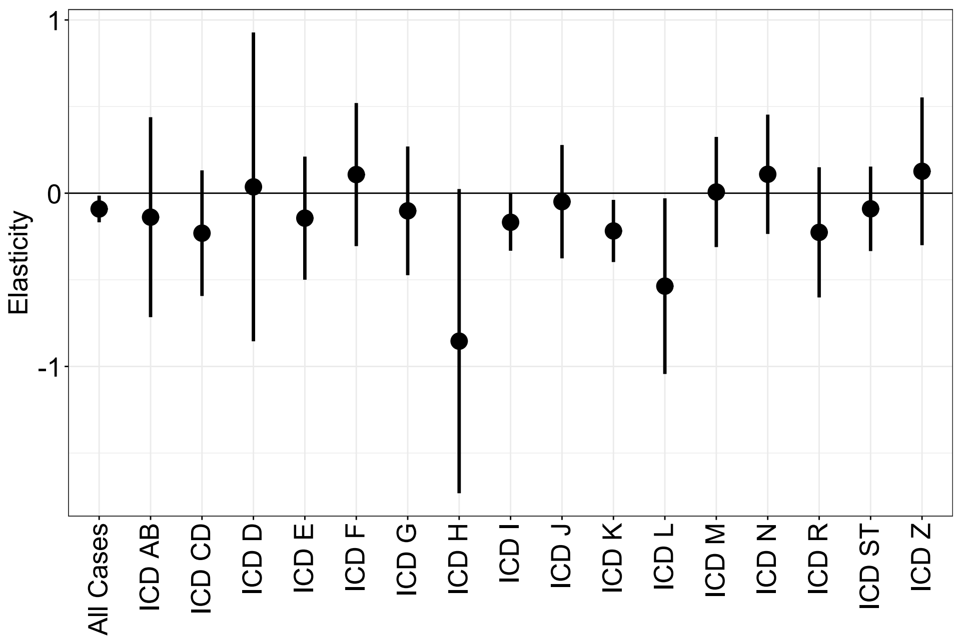
Figure 3: Heterogeneity



Notes: The figure presents the respective elasticities in % according to Eq. 2. Lines represent 95% confidence intervals. *All* = complete sample. *Rural* = ZIP-codes in municipalities with population density below the median (187.14 inhabitants/m^2), $N = 6,805,770$. *Urban* = ZIP-codes in municipalities with population density above the median, $N = 6,772,830$. *Good GP Acc.* = ZIP-codes in municipalities with GP accessibility above the median (69.61% of the population lives less than 1,000 m away from a GP), $N = 6,760,020$. *Bad GP Acc.* = ZIP-codes in municipalities with GP accessibility below the median, $N = 6,797,352$. *High PP* = ZIP-codes with purchasing power per person above the median (29,433.76 EUR), $N = 6,773,928$. *Low PP* = ZIP-codes with purchasing power per person below the median, $N = 6,736,962$.

So far, I have used all inpatient cases. However, it is reasonable to assume that some conditions are more sensitive to driving times than others. For this reason, I estimate the fixed-effects model for the complete sample using cases per ICD chapter as outcomes, again as daily cases per 1,000.[1] The resulting elasticities are presented in Figure 4. While most individual estimates are negative, only those for ICD chapters I (Diseases of the cardio-vascular system), K (Diseases of the digestive system), and L (Diseases of the skin) are significantly different from zero. The estimate for chapter H (Diseases of the ear and mastoid process) is the largest in absolute terms, but only statistically significant at the 10% level. Chapters K, L, and H potentially include less severe conditions, which may explain the higher sensitivity to changes in driving times. Chapter I is the most common among the inpatient cases (see Table B.1 in the Appendix). While it includes severe conditions such as heart attacks (I21) or strokes (I63 and I64), it also includes common chronic conditions such as hypertension (I10 to I15). The observed sensitivity might therefore be driven by less severe conditions within this chapter.

Figure 4: Elasticity by ICD-Chapter



Notes: The figure presents the respective elasticities in % according to Eq. 2. Lines represent 95% confidence intervals. *All Cases* = all inpatient cases; the main estimate. *ICD ...* = number of cases of the respective ICD chapter according to the ICD-10-GM classification, used as the outcome variable in the model in Eq. 1 for the complete sample.

Finally, I test what results alternative specifications would yield, which are presented in Table 4. The first column shows the results when applying the main spe-

[1]Descriptive statistics are provided in Table B.1 in the Appendix.

cification to the subsample of ZIP-code hospital combinations that experience a change in driving time of more than five minutes at any point during the year. The point estimate is basically the same as for both samples in Table 2, but because the mean number of cases is smaller, the elasticity is higher at -0.25%. In the second column, I use an alternative model specification by including ZIP-code fixed effects and hospital fixed effects separately. While the point estimate – and, as a result, the elasticity – is much larger in absolute terms, this alternative specification does not compare changes in driving time within ZIP-code hospital combinations. Instead, the estimate captures the effects of changes in driving time, accounting for the average number of cases in the ZIP-code area, the average number of cases in the hospital, and the average number of cases on that day. It therefore does not account for the fact that patients from ZIP codes are generally treated more often in certain hospitals than in others, so the results need to be interpreted as evidence that patients use closer hospitals more often. This crucial effect is accounted for by the ZIP-code hospital fixed effects in the main specification. The last specification uses the five most used hospitals per ZIP code instead of the five closest ones. At first, it seems problematic that no effects are found in this alternative specification. However, the overlap of ZIP-code hospital combinations between this sample and the main sample is around 50%. The difference is made up of hospitals that are among the most preferred ones by patients but that are not among the closest ones. Put differently, this sample includes hospitals that are preferred not because they are close, but for other factors. Since driving time is less relevant for choosing these hospitals, one would expect patients to be less sensitive to changes in driving times, which is indeed what I find.

While the results overall reveal that driving times do in fact have a small direct impact on the use of inpatient services, some limitations need to be pointed out. First, defining the place of residence as the centroid of the ZIP-code naturally reduces precision. However, this is common practice in the literature, as it is simply infeasible to calculate the exact driving times based on addresses. It is unclear in which direction this potentially biases results, as this depends on whether the actual increase in travel times for individuals is larger or smaller than the increase for the centroid. Second, I do not consider the impact of traffic on driving time. This is on purpose, as the increase in driving time caused by the detour is much easier for individuals to anticipate than the increase caused by traffic, which can vary significantly across the day. However, in most cases accounting for traffic would mean that the increases in driving times are probably larger, so I am therefore potentially overestimating the impact. Third, I have no information on the mode of transportation used to get to the hospital, which unfortunately includes ambulances. However, this information is not available. Relatedly, I cannot identify outpatient services provided in hospitals – including emergency department visits

Table 4: Alternative Specifications

	FE Any Change >5min	No FE Interaction	Most used Hospitals
Driving time (min)	-0.0003 **	-0.0068 ***	-0.0001
SE	0.0001	0.0003	0.0002
Day FE	X	X	X
Hospital FE		X	
ZIP FE		X	
Hospital X ZIP FE	X		X
Num Obs	$648,918$	$13,587,384$	$12,066,288$
Mean Cases	0.0315	0.0737	0.1022
Mean Driving Time	27.4587	21.8346	25.6311
Elasticity	-0.2491	-2.0052	-0.0274

Note: Elasticities are calculated according to Eq. 2. *FE Any Change > 5 min* = sample of ZIP-code $\times$ hospitals combinations that experience a change in driving time greater than 5 minutes throughout the year. *No FE interaction* = complete sample; instead of including ZIP-code $\times$ hospital fixed effects, this specification includes ZIP-code fixed effects and hospital fixed effects separately. *Most used Hospitals* = sample where, for each ZIP-code, the five most used hospitals are included instead of the five closest hospitals. * P<0.1, ** P<0.05, *** P<0.01.

– in the data. These types of services are potentially more sensitive to changes in driving time, and one would therefore expect larger estimates than those shown. Lastly, I have no information on whether the inpatient case was planned. However, while unplanned hospital stays may decrease in response to longer driving times, planned hospital stays are either unaffected or also decrease. The overall decrease I observe is therefore mostly driven by unplanned stays.

While these limitations might seem severe, they mostly mean that I cannot investigate the types of healthcare services that are most sensitive to changes in driving time. Or, put differently, I use services that should be relatively insensitive, but I am still able to show that driving time has an impact. Adding to this, Germany not only has an extensive road infrastructure, but also a high hospital density. Driving times are generally quite short, and even closing major roads only increases them by a few minutes. Despite this, I am still able to provide evidence for their impact on healthcare utilization.

6 Conclusion

In this paper, I use road closures as a new source of exogenous variation to estimate the relationship between distance and hospital utilization. I find that driving time to a hospital is, by itself, a determinant of healthcare utilization, but to a much smaller degree than the overall correlation might suggest. While a 1% increase in driving time is correlated with an up to 0.86% reduction in inpatient cases, this value is only 0.15% when accounting for patient and hospital characteristics. There is a clear, linear dose-response relationship: larger increases in driving times lead to larger decreases in hospital utilization. This decrease is driven rather by switching to other hospitals than by foregoing inpatient services or substituting them with outpatient services. Individuals in rural areas and poorer areas are more sensitive to changes in driving times. There is only some indication that less severe cases are more sensitive to changes in driving times. This can be explained by the fact that individuals have limited information about the severity of their condition when making the decision to seek care.

In general, my estimates are quite small. Relating this to the previous literature indicates that the large effects of hospital closures are not the result of increased driving times, but of changes in the overall market structure and adaptations within hospitals. This is a crucial insight given the current debate about Germany's high hospital density. Driving times therefore play only a minor role in patient decision-making overall, so other metrics such as quality should play a more dominant role in hospital planning. Still, it needs to be kept in mind that individuals in rural and poorer areas are disproportionately affected by increased driving times.

Overall, my contribution is twofold. First, I provide a new source of exogenous variation for estimating the impact of driving times, which can also be applied in settings outside of healthcare. Second, I contribute to the sparse evidence on the immediate relationship between driving times and healthcare utilization.

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Appendix

A Additional Figures

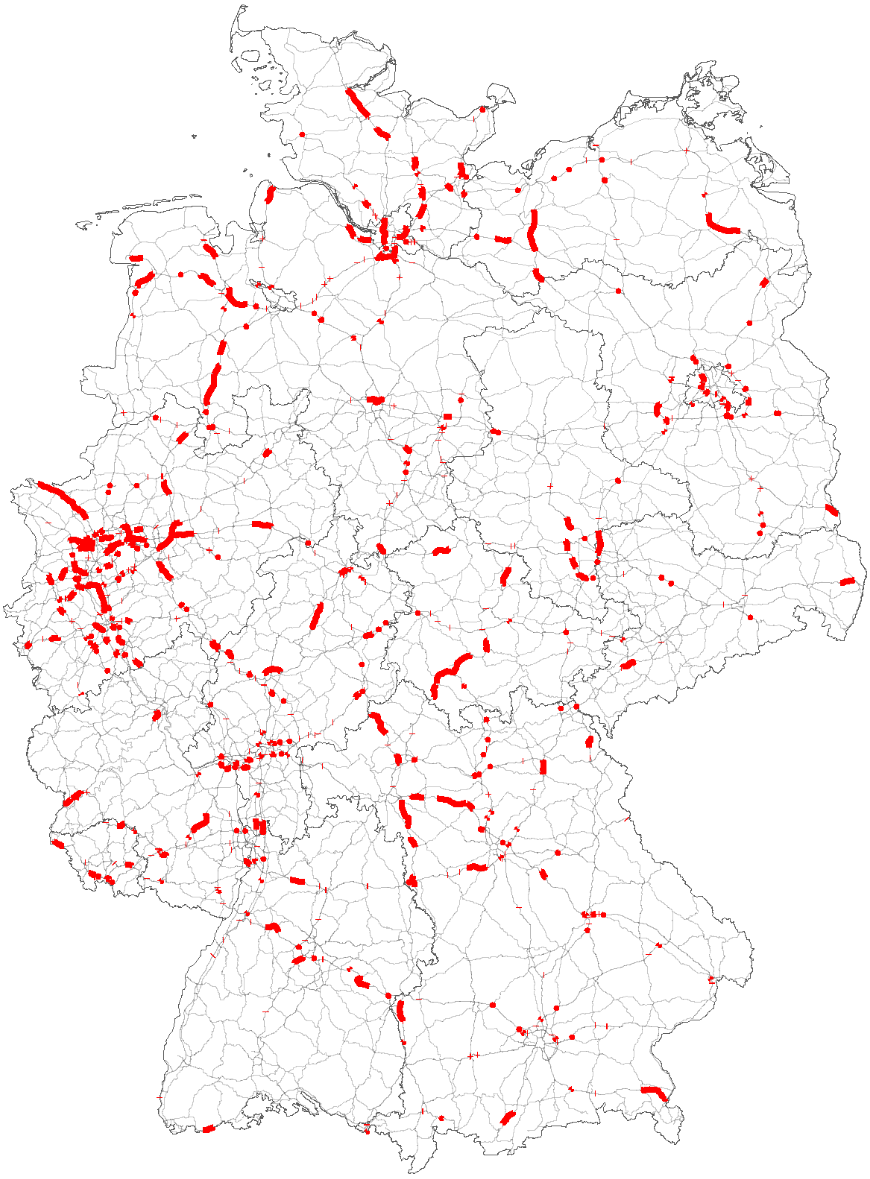

Figure A.1: Closures on Autobahnen (Red)

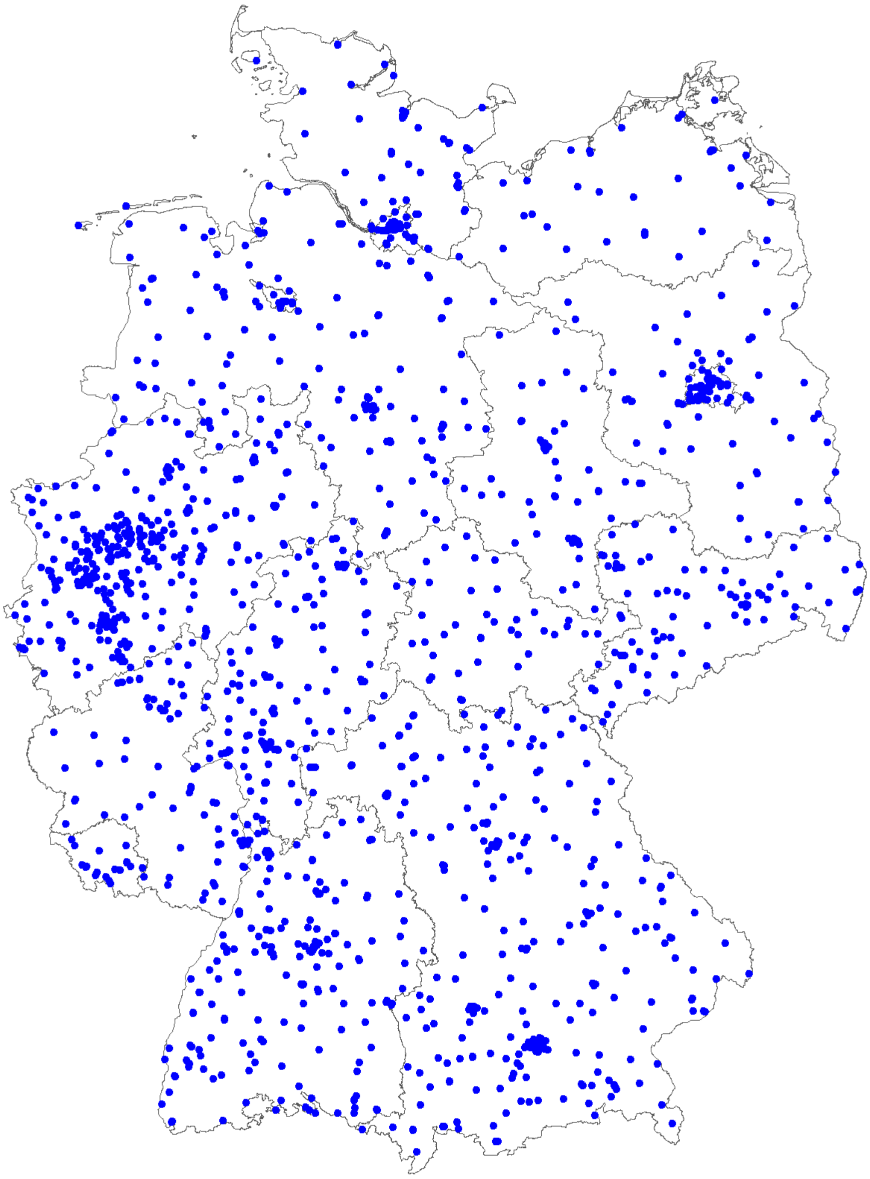

Figure A.2: Hospitals Providing Inpatient Services

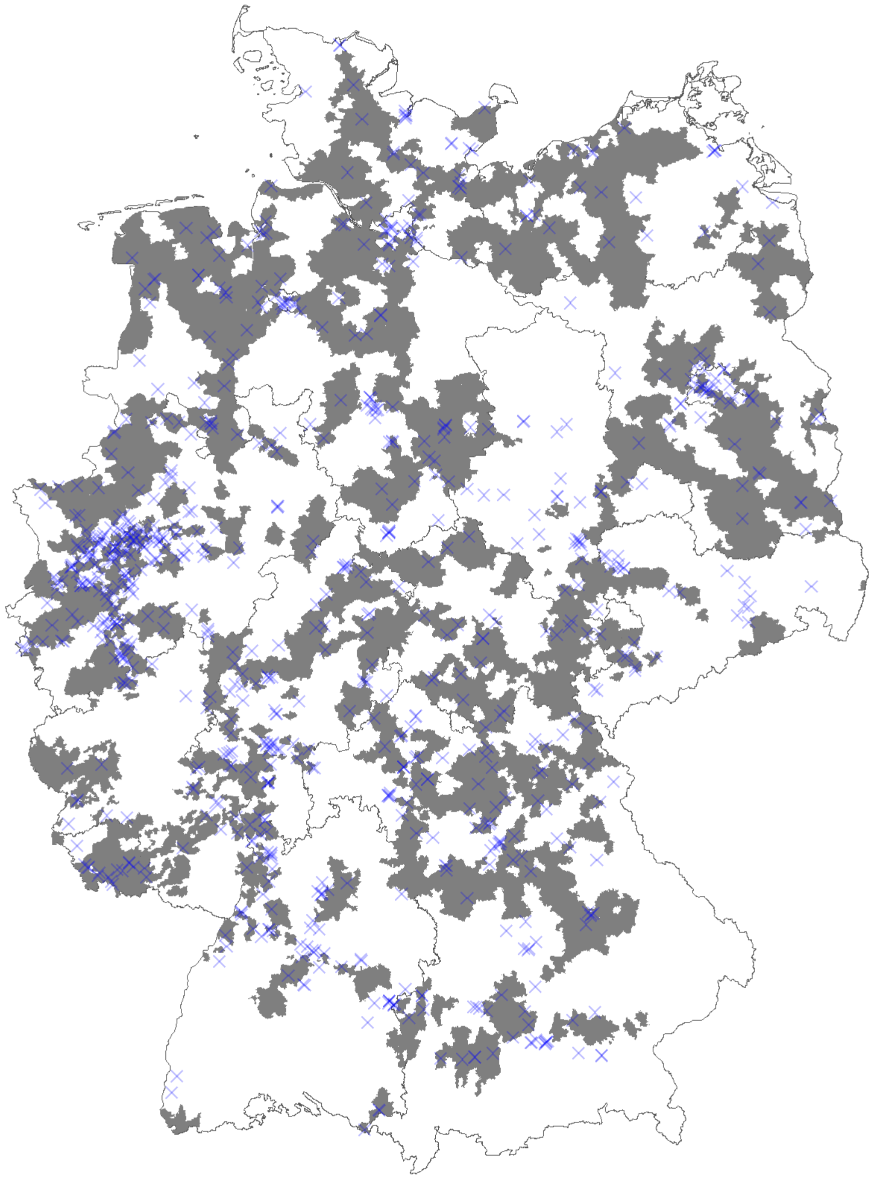

Figure A.3: ZIP codes (grey areas) and General Hospitals (blue crosses) Used in the Final Sample

B Additional Tables

Table B.1: Descriptive Statistics Inpatient

	All		Any Change	
	Mean	SD	Mean	SD
Total cases per 1,000	0.0737	0.5157	0.0474	0.3636
Elective cases per 1,000	0.0294	0.3254	0.0193	0.2325
Acute cases per 1,000	0.0219	0.2805	0.0123	0.1826
Cases of ICD AB per 1,000	0.0021	0.0842	0.0013	0.0647
Cases of ICD CD per 1,000	0.0053	0.1387	0.0044	0.1071
Cases of ICD D per 1,000	0.0005	0.0397	0.0003	0.0262
Cases of ICD E per 1,000	0.0019	0.0763	0.0011	0.0538
Cases of ICD F per 1,000	0.0031	0.0988	0.0023	0.0801
Cases of ICD G per 1,000	0.0024	0.0893	0.0017	0.0680
Cases of ICD H per 1,000	0.0011	0.0533	0.0011	0.0514
Cases of ICD I per 1,000	0.0108	0.1947	0.0066	0.1319
Cases of ICD J per 1,000	0.0044	0.1289	0.0026	0.0798
Cases of ICD K per 1,000	0.0079	0.1836	0.0045	0.1161
Cases of ICD L per 1,000	0.0009	0.0526	0.0005	0.0325
Cases of ICD M per 1,000	0.0054	0.1327	0.0036	0.0980
Cases of ICD N per 1,000	0.0039	0.1108	0.0026	0.0805
Cases of ICD R per 1,000	0.0032	0.1038	0.0018	0.0727
Cases of ICD ST per 1,000	0.0074	0.1591	0.0041	0.1095
Cases of ICD Z per 1,000	0.0020	0.0967	0.0013	0.0617
Number of Observations	13,587,384		1,933,944	
Number of ZIP Codes	7,646		2,674	
Number of Hospitals	1,418		719	
Number of ZIP X Hospitals	37,124		5,284	