HEDG
HEALTH, ECONOMETRICS AND DATA GROUP
THE UNIVERSITY of York

WP 16/29

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Corinna Hentschker & Ansgar Wübker

August 2016

http://www.york.ac.uk/economics/postgrad/herc/hedg/wps/

The impact of technology diffusion in health care markets – Evidence from heart attack treatment

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Abstract

Medical technological progress has been shown to be the main driver of health care costs. A key policy question is whether new treatment options are worth the additional costs. In this paper we assess the causal effect of percutaneous transluminal coronary angioplasty (PTCA), a major new heart attack treatment, on mortality. We use a full sample of administrative hospital data from Germany for the years 2005 to 2007. To account for non-random treatment assignment of PTCA, instrumental variable approaches are implemented that aim to randomize patients to different likelihoods of getting PTCA independent of heart attack severity. Instruments include differential distances to PTCA hospitals and regional PTCA rates. Our results suggest a 4.5 percentage point mortality reduction for patients who have access to this new treatment compared to patients receiving only conservative treatment. We relate mortality reduction to the additional costs for this treatment and conclude that this new treatment option is cost-effective in lowering mortality for AMI patients at reasonable cost-effectiveness thresholds.

KEYWORDS: acute myocardial infarction; instrumental variables; mortality

JEL: I11, I12, I18

*Both RWI – Leibniz Institute for Economic Research and Ruhr-University Bochum. – We thank Klaus Focke, Uwe Mehlhorn and Daniel Viehweg from the BKK Federal Association. Furthermore, we thank Thomas Bauer, Dörte Heger, Maryna Ivets, Martin Salm, and Hendrik Schmitz for valuable suggestions. Moreover, we are grateful for comments at the Spring Meeting of Young Economists (Ghent), the Tilburg Research Seminar and the Annual Workshop of the Econometrics Committee of the dggö (Essen). The administrative data of §21 KHEntgG was used as part of a cooperation agreement for the further development of the DRG-system from April, 1st 2011 between the RWI and the BKK Federal Association. – All correspondence to: Corinna Hentschker, RWI, Hohenzollernstr. 1-3, 45128 Essen, Germany, e-mail: corinna.hentschker@rwi-essen.de.

1 Introduction

Medical technological progress is widespread in health care and has been shown to be the main driver of health care costs (e.g. Newhouse, 1992; Cutler and McClellan, 2001; Okunade and Murthy, 2002). These advances often include implementing new treatment options. As a consequence, older treatments coexist with newer treatments for the same disease. New treatments are often more expensive but their additional benefits are often arguable. A key policy question is whether new treatment options are also more effective, i.e. lead to better outcomes, since health care resources are limited. An overall evaluation of technological progress is not possible but the single procedures can be assessed.

Acute myocardial infarction (AMI) is well suited for assessing the impact of technological progress of a single procedure, because treatment options for AMI can be clearly divided into "old" and "new" options. AMI occurs when a blood clot blocks a coronary vessel. AMI patients are treated either with thrombolytic drugs (i.e. the "old" treatment) to dissolve the blood clot or with revascularization techniques (i.e. the "new" treatment). Revascularization (REVAS) encompasses coronary artery bypass graft surgery (CABG) and percutaneous transluminal coronary angioplasty (PTCA).

Assessing new treatment options for AMI patients is of interest for several reasons. First, AMI belongs to the group of cardiovascular diseases which are the most common cause of death worldwide. AMI treatment has substantial welfare implications because AMI displays high mortality rates and treating it can substantially extend life. Second, assessing AMI patients allows us to focus on a large part of the health system, as AMI is one of the most common reasons for hospital admissions in Germany. The population is large enough to detect the impact of new treatment options on hospital mortality. Third, application of new AMI treatments displays strong regional differences and has expanded tremendously overall in recent years. Fourth, there is a lack of evidence on the effectiveness of new AMI treatment options. Although randomized controlled trials provide evidence for the effectiveness of REVAS (Stukel et al., 2007), it is not clear whether this effectiveness is practically realized, i.e. whether external validity exists.

This paper investigates whether new AMI treatment options reduce mortality compared to a conservative/old therapy. There are empirical challenges to this analysis: patients who

get new treatment options are not directly comparable to patients who get the old treatment. The first group is often younger and healthier, may have lower AMI severity and may differ in unobserved factors from patients who do not get the new treatment. Differences in outcomes among AMI patients who are treated differently may be attributable to unobserved factors, resulting in biased estimates of the effectiveness of alternative treatments (McClellan et al., 1994). In consequence, existing observational studies have used instrumental variable techniques to attempt to identify patients who are similar in terms of health status and other unobserved factors but who for some reason receive different AMI treatment.

McClellan et al. (1994) use the difference between the distance of the closest hospital offering new treatment options to the patient and the closest hospital treating AMI patients regardless of whether new treatments are available (differential distance) as instrument. The key identifying assumptions are that differential time affects the probability of receiving the treatment and is independent of the severity of the heart attack. The authors find a 5 percentage point reduction in mortality, but this reduction occurs already prior to the REVAS intervention which is reflected in the 1-day mortality. The authors therefore conclude that reduced mortality is not due to REVAS, but instead is attributable to high-volume hospitals that have better technology generally in addition to offering REVAS. Cutler (2007) uses the same instrument and Medicare data as McClellan et al. (1994). He has the advantage of being able to follow patients for up to 17 years, but only those AMI patients admitted in 1986-1988. He finds a one year additional life expectancy for REVAS patients at a cost of around $ 40,000 and concludes that REVAS is highly cost-effective.

We follow the instrumental variable (IV) approach introduced by McClellan et al. (1994) and use as instrument the differential time from a REVAS hospital to the closest hospital. In contrast to McClellan et al. (1994), who use Medicare data from 1987, we use (i) a full sample of all inpatients in Germany, and (ii) capture a more current time period from 2005 to 2007. In 1987 REVAS was rarely used on the first day of hospital admission. This has changed. It is now recommended to perform REVAS as soon as possible, i.e. within 12 hours of symptoms' onset or rather within 2 hours from the first medical contact (Steg et al., 2012). Moreover, it can be assumed that REVAS penetration rates have increased and standards have developed. Hence, the procedure in principle has improved which is not represented by 1987 data. In addition McClellan et al. (1994) could not detect whether the REVAS effect

comes from the procedure itself or from the higher case volume and, hence, specialization of the hospitals. We shed some light on this issue by using various robustness checks, like separate estimations for hospitals with lower case volumes.

Stukel et al. (2007) also measure the effect of REVAS on mortality with Medicare data from 1994/1995. They use an IV approach with the regional REVAS rate as instrument as well as propensity score matching (PSM). The authors argue that regional REVAS rates may serve as an effective instrumental variable, as prognostic factors for AMI mortality, such as mean AMI severity being similar between regions that have very different REVAS rates. They find a 50% reduction in mortality with PSM and a 16% reduction with IV. We also apply the IV strategy introduced by Stukel et al. (2007) as a robustness check and employ the huge variation in REVAS treatment within Germany.[1]

To preview our main results, we find in our basic specification a 4.5 pp reduction in mortality for patients receiving new treatment options. Our empirical results are robust with regard to the different instruments. We also find that the new treatment options are cost-effective at reasonable cost-effectiveness ratios. We conclude that the diffusion of new AMI treatment options in Germany may be worthwhile.

We contribute to the literature in the following ways: We are the first to execute the analysis with German data. This is critical, because Germany is the country with the highest application of this new treatment worldwide (OECD, 2014) and evidence is needed to verify that higher utilization saves lives. Moreover, ethnic, geographic, and socioeconomic characteristics differ markedly between countries, and, hence, the effect of REVAS could also differ between countries. Second, we are the first who use comprehensive data from the unselected, complete hospital population of an industrialized nation to analyze the impact of new AMI treatment options. Third, existing literature uses data from 1995 and older; since that time REVAS techniques have likely improved and more patients are treated with REVAS. One exception is the study of Sanwald and Schober (2014) who use data from 2002 to 2011 but with a much smaller sample size and a different focus, namely on the effect of an admission to a hospital with a catheterization laboratories. Finally, we conduct cost-effectiveness exer-

[1]Sanwald and Schober (2014) examine the effect for patient's treatment at a PTCA hospital with an Austria dataset from 2002 to 2011. They find a 9.5 percentage point reduction in 3-year mortality for patients treated in a PTCA hospital.

cise that contributes to the literature analyzing whether technological change in heart attack treatment is worth it (e.g. Cutler and McClellan, 2001).

The remainder of this paper is organized as follows: Section 2 gives more insights into AMI treatment and the development of AMI rates and costs. Section 3 provides an overview of the data and descriptive statistics. The empirical approach is described in section 4, followed by the results in section 5. Section 6 concludes.

2 Background

AMI is an acute event characterized by an interruption of blood flow to a part of the heart due to the occlusion of arteries. The main goal of treatment is to limit immediate damage to the heart by restoring blood flow and providing the heart muscle with adequate oxygen as soon as possible. There are several options for treating AMI patients. One is medical management. Medical management often includes thrombolytic drugs, alongside with supportive care, in order to dissolve blood clots caused by AMI. An alternative to thrombolysis is using more intensive technological methods. Revascularization (REVAS) encompasses coronary artery bypass graft surgery (CABG) and percutaneous transluminal coronary angioplasty (PTCA). The main difference between CABG and PTCA is that PTCA is a minimally invasive procedure and CABG is an open surgery. Both methods developed in the late 1960s (CABG) and 1970s (PTCA) (Cutler and McClellan, 2001). CABG and PTCA are preceded by cardiac catheterization, a diagnostic procedure to identify the affected artery.

Cardiovascular diseases are the most frequent cause of death in Germany and other developed countries. Within this group AMI patients have a high share of deaths (Freisinger et al., 2014). In recent decades, however, a considerable reduction in AMI mortality rates can be observed in industrial countries (e.g. Smolina et al., 2012; Fox et al., 2007; Ford et al., 2007; Wübker, 2007).[2] Public health and medical literature attributes these improvements to a reduction of classical risk factors like smoking or hypertension or by better secondary prevention (e.g. long term drug therapy with statins, aspirin, etc.) (e.g. Fox et al., 2007; Ford et al., 2007; Wübker, 2007). However, improved AMI treatment like the expanded use of

[2]For example in 2002 over 69,000 people died from a heart attack in Germany; in 2013 the number of deaths decreased to nearly 55,000 people (6% of all deaths) (Statistisches Bundesamt, 2014).

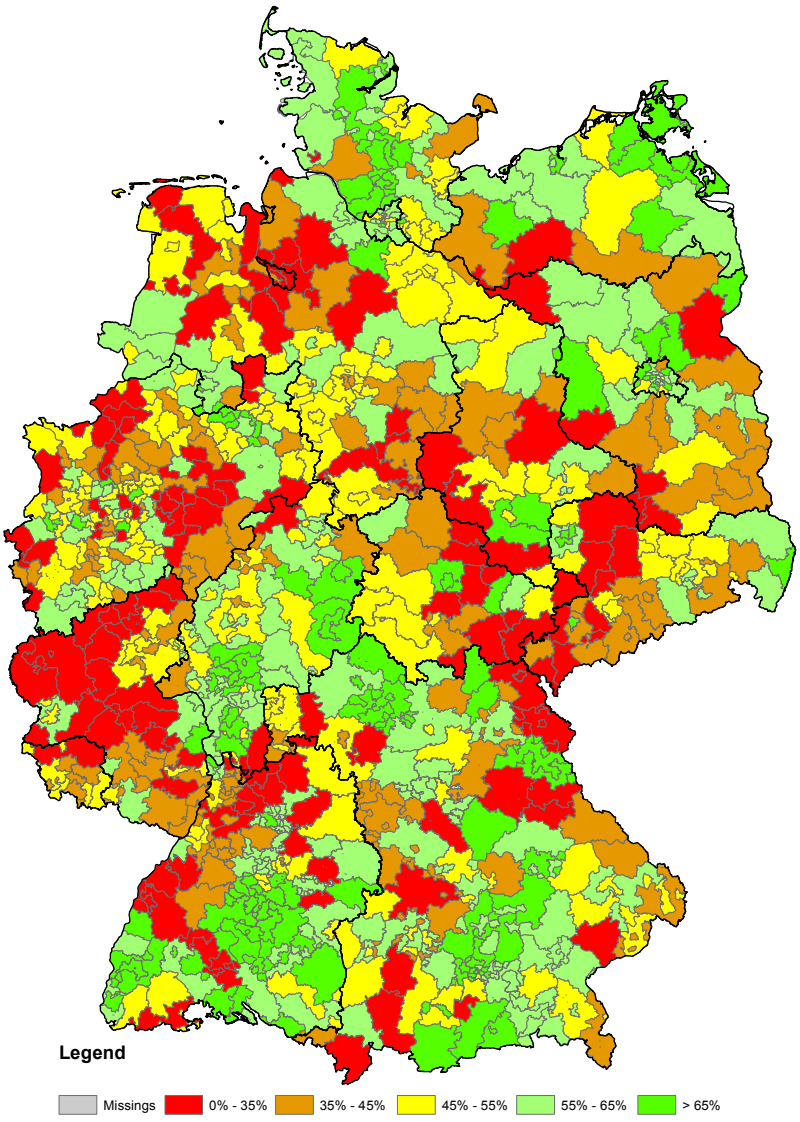
REVAS is considered as main cause for this development (Ford et al., 2007; Wübker, 2007). The advantage of REVAS over conservative AMI treatment has been documented in several clinical trials. In general, randomized controlled trials (RCTs) find that patients treated with REVAS have better outcomes than patients treated with thrombolytic drugs (Keeley et al., 2003). However, RCTs have been criticized because although they have high internal validity, they have shortcomings in external validity (Newhouse and McClellan, 1998). This is because RCTs are often executed under optimal conditions unachievable in the real world. Moreover, RCTs focus on narrow treatment comparisons and special patient populations, therefore their results are often insufficient to shape health policy (McClellan et al., 1994). With administrative data it is possible to detect the effect of REVAS on mortality in the whole population.

In recent years REVAS has been increasingly used in Germany and in other developed countries. In Germany, the application of REVAS more than doubled between 1996 and 2004 (Schwierz and Wübker, 2010). About 48.1% of AMI patients were treated with PTCA methods in 2009 in Germany (Freisinger et al., 2014). Germany is first in the number of PTCAs per 100,000 inhabitants and second for CABG amongst OECD countries (Kumar and Schoenstein, 2013). At the same time, large regional variation occurs within Germany (Kumar and Schoenstein, 2013). Figure 1 illustrates that the share of PTCA procedures for AMI treatment is below 35% in some regions, for example in parts of west Rhineland-Palatinate or parts of Lower Saxony, but already above 65% in others, for example in east Hesse and parts of Baden-Württemberg. Variations in health care are analyzed in several publications (e.g. Skinner, 2012; Finkelstein et al., 2014). They find that these variations are caused by demand-side factors (e.g. patient characteristics) and supply-side factors (e.g. hospital market structure or provider beliefs).

AMI is of increasing economic importance. For example in Germany, €1.05 billion were spent on heart attack treatment in 2004, whereas by 2008 the total was €1.84 billion (GBE, 2015). Annual growth in real terms was about 8%. Increasing AMI costs cannot be explained by a rising number of heart attacks, because AMI overall incidence and AMI hospital incidence remained relatively constant in recent years (Freisinger et al., 2014). Similar trends of increasing heart attack spending have been observed in other developed countries, like

the US. Cutler and McClellan (2001) suggest that technological change, i.e. the extension of REVAS methods to more patients, is the main reason for the increasing costs.

Figure 1: Share of PTCA patients 2007



3 Data

We use a full sample of all hospital inpatients in Germany from 2005 to 2007. It is an administrative data set which must be generated by every hospital for insurance billing purposes and includes patient characteristics, e.g. age, sex, admission and discharge date, main and secondary diagnoses and procedure codes, and the ZIP code of the patient's residence. The data set also contains hospital characteristics, e.g. hospital identifier, ownership type, and

whether it is a university hospital. The hospital identifier allows us to add the address of the hospital from another data source. Because we only have patient resident ZIP codes, we geo-coded the hospital addresses and the centroids of the ZIP codes and calculate the distance for every ZIP code to the chosen hospital and to the surrounding hospitals.

We focus on patients with AMI. We use diagnosis and procedure codes from a German definition handbook for inpatient quality indicators (Mansky et al., 2011). We include patients who are coded with the main diagnosis of a ST-elevated myocardial infarction (STEMI, diagnosis codes I21.0–I21.2) or a Non-ST-elevated myocardial infarction (NSTEMI, diagnosis code I21.3). Patients with a subsequent MI or unspecified MI are not included. On the basis of the procedure codes we are able to determine the invasive treatment options, i.e. whether the patient received a PTCA or a CABG. In the final sample, we do not include patients with a CABG (N = 27,128). PTCA and CABG are both invasive treatments for the heart attack treatment but only 5% of the patients get a CABG. To determine the single effect of PTCA compared to medical treatment instead of the mixed effect of PTCA and CABG compared to medical treatment we exclude CABG patients.

Further exclusions are as follows: Patients under the age of 19 are excluded (N = 54). We delete patients with missing patient characteristics (N = 589) and patients with invalid ZIP codes (N = 6,816). We also exclude patients with a travel time exceeding 60 minutes to the chosen hospital (N = 15,488). It is unlikely that these patients had their heart attack at home but were on holiday, traveling etc. We exclude patients who have an ambulatory status and do not stay in the hospital (N = 1,408). We further remove patients who are coded with transfer as the reason for discharge (N = 126,455). This means that they were transferred to another hospital after their hospital stay. For the transferring hospital we cannot measure the outcome of the patient. We drop patients who are treated in hospitals with less than 10 cases (N = 1,719). We assume that these hospitals do not treat AMI patients and, therefore, do not belong in the sample. We end up with a sample of 406,281 patients treated in 1,292 hospitals.[3]

[3]Generally, we observe a unique identifier for hospitals in our data set but for some hospitals the identifier stands for two or more hospital locations. In this case, we checked which location offers AMI treatment at all and in case two or more locations offer AMI treatment, we assign the patients to the closest hospital location. With this procedure we end up with 30 more hospitals in the data set than without splitting the hospital locations. The results remain essentially the same.

The main variable of interest is PTCA which is specified as 1 if the patient received a PTCA and 0 if not. As outcome measure we use in-hospital mortality. We get the information from the variable discharge reason which can have the following main specifications: treatment ended regularly, discharge to another hospital[4], discharge to nursing home or rehab hospital. We recoded this variable as mortality which is 1 if patient died in hospital and 0 otherwise. In-hospital mortality of AMI patients is a widely used outcome parameter (e.g. Cutler, 2007; McClellan et al., 1994).

We define a PTCA hospital as a hospital which treats more than 10 patients with PTCA per year.[5] With this we are able to calculate distances from the patient's residence ZIP code to the closest hospital which treats AMI patients and the closest PTCA hospital. We calculate the difference of both variables which we use as an instrument (see Section 4).

The decision whether a patient receives a PTCA is not independent from other health characteristics which also influence the outcome. For this reason we control for further patient characteristics. We include age, sex, and admission reason. We include a binary variable whether the admission was on a weekend or holiday, and a binary variable whether the admission was at night. These variables should capture the effect of 'off-hour' admission because some literature has found that the mortality risk can increase during that time (e.g. Bell and Redelmeier, 2001). We use the Charlson Comorbidity Index (CCI)[6] to control for further comorbidities besides the AMI (Charlson et al., 1987). The higher the index number, the more ill the patient is besides the main diagnosis of AMI. Due to the different mortality rates of the two AMI types, we add a control variable for AMI type. We add a binary variable "city" which indicates whether patients live in an urban or rural area. We include also year dummies to capture any changes during the years. At the hospital level we control for ownership type (public, not-for-profit or for-profit), and university hospital.

We add federal state control variables to capture differences between federal states. We include purchasing power per inhabitant and the unemployment rate in every ZIP code of the year 2005 (Budde and Eilers, 2014; Microm, 2014; Microm, 2015a; Microm, 2015b; Microm,

[4]These patients are excluded.

[5]We also defined a PTCA hospital with 5, 24, and 48 cases per year. The results do not change.

[6]The CCI consists of 17 comorbidities which are coded as binary variables. Afterwards, they are weighted and summed up to an index. The first Charlson diagnosis is myocardial infarction. We set this diagnosis to "0" because all of our patients have it as main diagnosis.

2015c). These two variables capture socioeconomic differences between ZIP codes. Additionally, we include the minimum time to an AMI hospital to control for further structural differences between ZIP codes.

Table 1 shows descriptive statistics for the whole sample and the sample divided by the method of treatment, i.e. whether the patient receives a PTCA or not. 48% of all patients in our sample receive a PTCA. The average unadjusted mortality rate is 12.3%. It is 6.3% for patients who receive a PTCA and 17.9% for patients without. Patients are on average 70 years old. Patients who get a PTCA have an average age of 65 and, hence, they are nearly nine years younger than patients who do not get a PTCA. On average there are 8% of patients who have a CCI of 5 or higher. This share is much lower in the group of patients who get a PTCA (4.0%) compared to patients who do not get a PTCA (11.4%).

4 Methods

To measure the effect of PTCA on mortality, we regress our binary outcome variable, y_{ih}, "death", which is 1 if patient i died in hospital h, on a binary variable, which indicates whether the patient received a PTCA (1) or not (0). We also control for further patient characteristics, x_{ih}, and hospital characteristics, k_{ih}. The specification is shown in equation (1). We estimate the equation on patient level. Standard errors are clustered at the hospital level.

$$y_{ih} = \alpha_0 + \beta_1 PTCA_{ih} + \boldsymbol{x'_{ih}}\boldsymbol{\beta_A} + \boldsymbol{k'_h}\boldsymbol{\beta_A} + \epsilon_{ih} \tag{1}$$

Our administrative data set has detailed information on patient characteristics. Nevertheless, socioeconomic characteristic and clinical parameters are missing. Hence, we cannot assume that we are able to control for all patient characteristics that are correlated with the decision whether a patient receives a PTCA or not. The reason for this is that patient groups with and without PTCA differ significantly, e.g. patients who receive PTCA are younger and healthier and therefore have a lower risk of death (see Table 1). The patient selection bias may occur not only in observable but also in unobservable characteristics which are captured in the error term. If unobserved healthier patients get the PTCA who inherently have also a lower mortality rate, this will lead to an overestimation of the PTCA effect in absolute terms.

Table 1: Descriptive statistics of AMI patients

	All Patients		Patients with PTCA		Patients w/o PTCA		Difference
	Mean	SD	Mean	SD	Mean	SD	
	(1)	(2)	(3)	(4)	(5)	(6)	(5)–(3)
Dependent variable							
Mortality	0.123	0.329	0.063	0.243	0.179	0.384	0.116***
Endogenous regressor							
PTCA	0.482	0.500	1.000	0.000	0.000	0.000	
Instrument							
Differential time	6.232	9.063	4.270	7.451	8.055	9.999	3.785***
Control variables							
Age	69.717	13.436	65.171	12.483	73.942	12.901	8.770***
Male	0.614	0.487	0.709	0.454	0.527	0.499	−0.182***
Admission reason: Emergency	0.639	0.480	0.657	0.475	0.621	0.485	−0.036***
Admission reason: Transfer	0.099	0.299	0.099	0.298	0.100	0.300	0.001
Non-ST-elevated MI	0.488	0.500	0.376	0.485	0.591	0.492	0.215***
CCI: 1-2	0.401	0.490	0.399	0.490	0.404	0.491	0.005***
CCI: 3-4	0.175	0.380	0.117	0.321	0.229	0.420	0.112***
CCI: ≥5	0.079	0.269	0.040	0.197	0.114	0.318	0.074***
Winter	0.339	0.473	0.333	0.471	0.344	0.475	0.011***
Weekend/holiday admission	0.245	0.430	0.233	0.423	0.256	0.437	0.023***
Night admission	0.248	0.432	0.241	0.428	0.254	0.436	0.013***
City	0.723	0.447	0.736	0.441	0.711	0.453	−0.025***
Year 2006	0.330	0.470	0.332	0.471	0.329	0.470	−0.004**
Year 2007	0.351	0.477	0.365	0.481	0.338	0.473	−0.026***
Ownership: not-for-profit	0.351	0.477	0.290	0.454	0.408	0.492	0.118***
Ownership: for-profit	0.144	0.351	0.161	0.367	0.128	0.334	−0.033***
University hospital	0.095	0.294	0.150	0.357	0.044	0.206	−0.106***
Minimum time to hospital	10.649	6.331	10.820	6.359	10.489	6.300	−0.331***
Purch. power per inhabitant	18.370	3.990	18.564	4.133	18.189	3.844	−0.375***
Unemployment rate	8.507	4.594	8.508	4.708	8.507	4.486	−0.002
Number of patients	406,281		195,705		210,576		

Notes: We control also for different federal states. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. CCI – Charlson Comorbidity Index.

To exclude problems with unobserved patient heterogeneity we use an instrumental variable (IV) approach. Therefore, we need an instrument which is highly correlated with the likelihood of receiving a PTCA but has no effect on mortality. We follow the work of McClellan et al. (1994) and Newhouse and McClellan (1998) who estimate the local average treatment effect of undergoing REVAS.[7] The authors showed that the differential distance between the nearest REVAS hospital and the nearest hospital was strongly correlated with the probability of getting a PTCA treatment but uncorrelated with observable indicators of quality. The differential distance has become a widely applied instrument to study different treatment effects in medical care (e.g. Gowrisankaran and Town, 1999; Khwaja et al., 2011).

[7]Cutler (2007) as well as Sanwald and Schober (2014) also followed the work of McClellan et al. (1994) and used the differential distance as instrument.

For example, Gowrisankaran and Town (1999) applied the differential distance between the nearest for-profit hospital and nearest hospital as an instrument for admission to a for-profit hospital in order to assess the quality of care for hospitals.

We use differential time as instrument and define differential time as the driving time to the closest PTCA hospital minus the driving time to the closest hospital which offers AMI treatment. For this instrument it does not matter which hospital the patient has chosen in reality. The differential time is 0 if the closest hospital is already a PTCA hospital and greater than 0 if the closest hospital offers no PTCA treatment option. Differential time must fulfill mainly two requirements to be a valid instrument. First, patients must not choose their place of residence based on the availability of hospital resources. This is not a testable criteria but the following Table 2 shows that the characteristics of patients who live close to a PTCA hospital and patients who live further away are balanced. This is also assumed for the unobservable characteristics. Second, the instrument must not be correlated with another (unobserved) variable which is also correlated with the outcome. For example, if PTCA hospitals are also better in the follow-up care of patients, the effect of PTCA is still overestimated in absolute terms (Cutler, 2007).

Figure 2 shows how differential distance varies within Germany and a descriptive statistic of our instrumental variable is shown in Table 2. Therefore we build two groups; the first group has a differential time of 0 and the second group has a differential time greater than 0. The instrument should divide the patients into two groups which should not differ in their patient characteristics but in the probability of receiving a PTCA. It is perceivable that the first group has a slightly lower unadjusted probability of death and has a higher share of patients who receive a PTCA (57.9% vs. 39.8%), i.e. patients who have as closest hospital a PTCA hospital have an 18 percentage points higher likelihood to receive a PTCA than patients who live further away. The minimum time to a hospital which treats AMI patients is still similar for both groups (10.5 and 10.8 minutes) but the minimum time to a PTCA hospital is much higher for the second group (22.4 minutes). Hence, it is obvious that the differential distance is a crucial factor whether the patient is treated in a PTCA hospital and receives a PTCA. The other patient characteristics are similar within the two groups. Due to the large sample size the differences between the patient characteristics are nearly all statistically significant but the magnitudes of the differences are rather small. One exception

is the distribution of urban and rural residence with a difference of more than 5%. This difference is rather caused by different hospital structures in rural and urban areas. The second exception is the different distribution of admission reason. On the one hand, this is a coding issue, because AMI patients are generally emergency cases and in our data set it is only possible to account for administrative emergencies[8]. On the other hand, patients with admission reason transfer are usually patients who are transferred to a PTCA hospital. Patients who have as closest hospital a PTCA hospital need no transfer into a PTCA hospital. We account for the differences in admission status and rural and urban areas by including the variables in the regression and execute separate regressions for each group in robustness checks.

Table 2: Descriptive statistics of instrumental variable

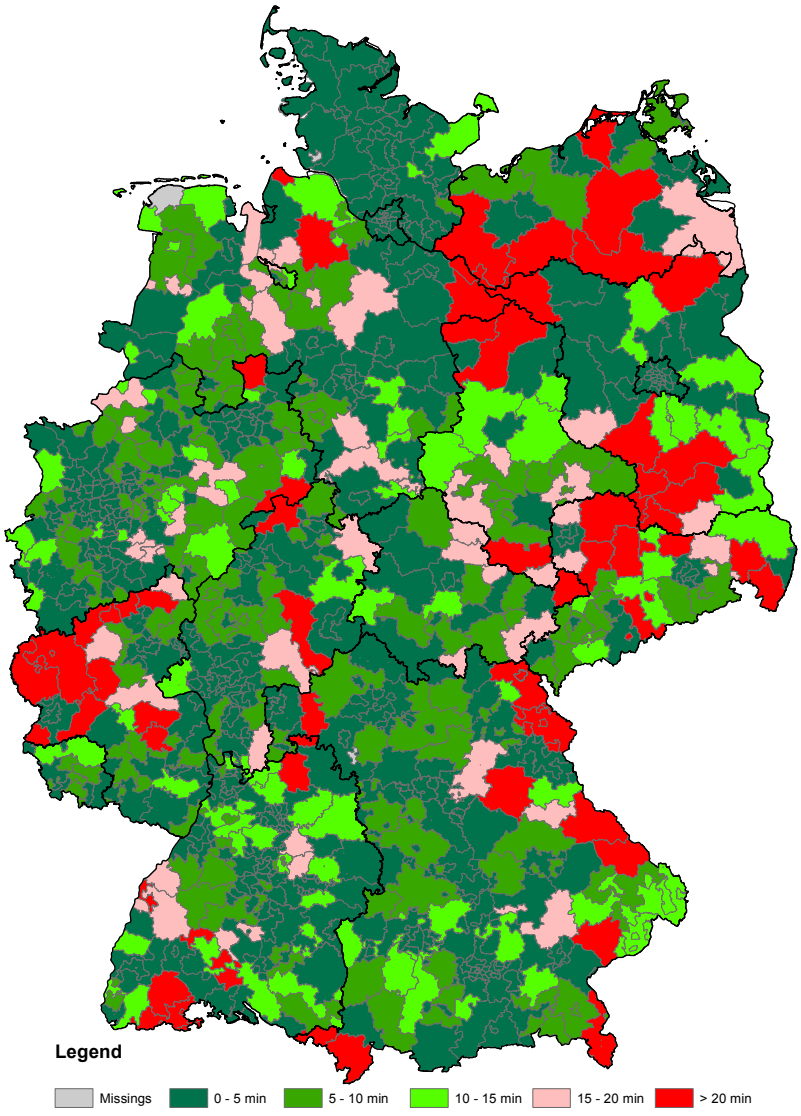
Differential time	**0 min**		**> 0 min**		**Difference**
	Mean	**SD**	**Mean**	**SD**	
Mortality	0.119	0.324	0.126	0.332	0.007***
PTCA	0.579	0.494	0.398	0.489	−0.181***
Differential time	0.000	0.000	11.578	9.524	11.578***
Age	69.587	13.470	69.828	13.406	0.241***
Male	0.618	0.486	0.612	0.487	−0.006***
Admission reason: Emergency	0.695	0.460	0.590	0.492	−0.105***
Admission reason: Transfer	0.054	0.227	0.138	0.345	0.083***
Non-ST-elevated MI	0.487	0.500	0.489	0.500	0.002
CCI: 1-2	0.399	0.490	0.404	0.491	0.005***
CCI: 3-4	0.174	0.380	0.175	0.380	0.001
CCI: ≥5	0.077	0.266	0.080	0.272	0.004***
Winter	0.339	0.473	0.338	0.473	−0.001
Weekend/holiday admission	0.252	0.434	0.240	0.427	−0.013***
Night admission	0.261	0.439	0.237	0.425	−0.024***
City	0.757	0.429	0.695	0.461	−0.062***
Year 2006	0.336	0.472	0.326	0.469	−0.010***
Year 2007	0.368	0.482	0.337	0.473	−0.031***
Ownership: not-for-profit	0.323	0.468	0.375	0.484	0.053***
Ownership: for-profit	0.141	0.348	0.146	0.353	0.004***
University hospital	0.094	0.291	0.097	0.295	0.003***
Minimum time to hospital	10.456	6.152	10.815	6.475	0.359***
Purchasing power per inhabitant	18.988	4.279	17.840	3.642	−1.148***
Unemployment rate	8.781	4.750	8.273	4.442	−0.508***
Number of patients	187,596		218,685		

Notes: We control also for different federal states. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. CCI – Charlson Comorbidity Index.

We apply the IV regression in the established two-step procedure. In the first-stage equation (equation (2)), we regress our endogenous variable PTCA on all covariates and our

[8]In our data set all patients are coded as emergencies if they reached the hospital without a doctor's referral. This is not comparable to a medical emergency.

Figure 2: Differential time 2007



instrument differential time (DT). In the second-stage equation (equation (3)), we use the fitted values of PTCA from equation (2) to estimate the causal effect of PTCA on mortality.

$$PCTA_{ih} = \pi_0 + \boldsymbol{x'_{ih}}\boldsymbol{\pi_1} + \boldsymbol{k'_h}\boldsymbol{\pi_2} + \gamma_2 DT_{ih} + \nu_{ih} \tag{2}$$

$$y_{ih} = \alpha_0 + \beta_2 \widehat{PTCA}_{ih} + \boldsymbol{x'_{ih}}\boldsymbol{\beta_B} + \boldsymbol{k'_h}\boldsymbol{\beta_B} + \epsilon_{ih} \tag{3}$$

With IV regression we only measure a local average treatment effect (LATE). In our case it is the effect for patients who receive a PTCA because they live close to a PTCA hospital but would not get a PTCA if they lived further away (compliers).

5 Results

Regression coefficients of the linear probability model (LPM) are shown in Table 3.[9] In a bivariate regression of PTCA on mortality (model (1)) we find an 11.7 percentage point (pp) reduction in mortality for PTCA patients compared to patients with a conservative therapy. If we add further patient and hospital characteristics the effect slightly decreases to 10.2 pp (model (4)). Because of unobserved patient characteristics the OLS coefficients are biased and, hence, we turn to our IV results. Our instrument differential time highly correlates with our endogenous variable PTCA. The first-stage F-statistic is 353 if we use the model with all covariates (model (8)). We further can reject the null hypothesis of the Durbin-Wu-Hausman test that volume is exogenous ($p < 0.01$). Hence, we conclude that IV regression is necessary and we have a strong instrument.

The IV coefficients are smaller in absolute terms than the OLS coefficients. Even though the coefficients are not directly comparable because they measure different treatment effects (ATT vs. LATE), the reduction in absolute terms is in line with the basic idea that unobserved patient characteristics may influence the PTCA treatment decision. If (unobserved) healthier patients get a PTCA the PTCA coefficient will decrease in an IV specification. In the bivariate specification, we find a 4.5 pp reduction in mortality for PTCA patients (model (5)). After adding the covariates, the effect of PTCA on mortality stays constant by 4.5 pp (model (8)).

[9] The complete regression results are shown in the Appendix in Table A1.

Table 3: Regression results (instrument: differential time)

	LPM			
	(1)	(2)	(3)	(4)
PTCA	−0.1165***	−0.0983***	−0.1023***	−0.1019***
	(0.0023)	(0.0025)	(0.0023)	(0.0023)
Patient characteristics	No	Yes	Yes	Yes
Hospital characteristics	No	No	Yes	Yes
Socioeconomic/structural indicators	No	No	No	Yes
Federal state indicators	No	No	No	Yes
R-squared	0.031	0.091	0.092	0.093
Number of patients	406,281	406,281	406,281	406,281
Number of hospitals	1,292	1,292	1,292	1,292

	IV			
	(5)	(6)	(7)	(8)
PTCA	−0.0454***	−0.0486***	−0.0504***	−0.0451***
	(0.0100)	(0.0088)	(0.0089)	(0.0098)
Patient characteristics	No	Yes	Yes	Yes
Hospital characteristics	No	No	Yes	Yes
Socioeconomic/structural indicators	No	No	No	Yes
Federal state indicators	No	No	No	Yes
R-squared	0.020	0.086	0.087	0.087
First-stage F-statistic	210.0809	281.6580	349.7454	352.8525
Test for endogeneity (p-value)	0.0000	0.0000	0.0000	0.0000
Number of patients	406,281	406,281	406,281	406,281
Number of hospitals	1,292	1,292	1,292	1,292

Notes: Clustered standard errors (at the hospital level) in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In a robustness check we also use a similar instrument to Stukel et al. (2007). We specify the instrument as the share of PTCA patients in a 4-digit ZIP code area. Regional PTCA rates may serve as an effective instrumental variable, as prognostic factors for AMI mortality, such as mean AMI severity, and are similar between regions that have very different PTCA rates. The causal effect of PTCA in this IV specification is a 4.8 pp reduction in mortality in the full model (Table 4, model (4)). This is a 0.3 pp higher reduction than the effect obtained when using differential time as instrument. There is no statistically significant difference between the two effects. This is investigated with a tentative test in order to check whether the confidence intervals overlap.

To get more specific insights in the PTCA effectiveness, we split the sample into different subgroups (Table 5). In Table 5 every regression includes all covariates of the full model of Table 3. Due to different availability of rescue services and PTCA possibilities in urban

Table 4: Regressions results (instrument: share of PTCA patients)

	IV			
	(1)	(2)	(3)	(4)
PTCA	-0.0575^{***}	-0.0570^{***}	-0.0606^{***}	-0.0480^{***}
	(0.0056)	(0.0058)	(0.0061)	(0.0058)
Patient characteristics	No	Yes	Yes	Yes
Hospital characteristics	No	No	Yes	Yes
Socioeconomic/structural indicators	No	No	No	Yes
Federal state indicators	No	No	No	Yes
R-squared	0.023	0.088	0.088	0.087
First-stage F-statistic	1,305.7594	1,349.4760	1,165.1244	1,498.7146
Test for endogeneity (p-value)	0.0000	0.0000	0.0000	0.0000
Number of patients	406,281	406,281	406,281	406,281
Number of hospitals	1,292	1,292	1,292	1,292

Notes: Clustered standard errors (at the hospital level) in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

and rural areas, we specify different regressions for these regions, in order to rule out the possibility that the PTCA effect is only driven by PTCA hospitals in cities. Patients living in rural areas benefit even more from a PTCA than patients living in urban areas. This can be due to the effect that the differential time differs between urban and rural areas and has a higher variance in rural areas. In our sample we have patients with different admission statuses, namely regular admissions, emergencies and transfers from other hospitals. As outlined in Section 3 we can only distinguish administrative emergencies but no medical emergencies. Nevertheless, we specified a regression only with coded emergency cases. The PTCA effect increases in absolute terms. For patients with admission reason transfer it is not possible to calculate the real value for the instrument because the patients have been in another hospital before. In a robustness check we exclude these patients from the sample. The PTCA effect increases also in this case. For both regressions on the admission status the conclusions drawn from the main results remain the same. For the effectiveness of PTCA it does not matter whether the patient has been admitted at day or night time – the coefficients of PTCA for day and night are nearly identical. At night it is more likely that the patient is at home when the heart attack occurs. As the coefficients are comparable, we think we do not have a problem during the day with a measurement error of the instrument. The advantage of PTCA is greater for patients over the age of 65. The reason for this is that younger patients may have less severe heart attacks and the benefit of PTCA is less important. A clear different effect is identified for different AMI types. Patients with a ST-elevated myocardial

infarction benefit much more from a PTCA than patients with a Non-ST-elevated myocardial infarction.

Former literature (e.g. McClellan et al., 1994) could not detect whether the PTCA effect comes from the procedure itself or whether it is for example hospital's case volume or hospital's specialization. We want to shed some light on this issue. Figure 3 shows the distribution of hospital case volume for all hospitals and separately for hospitals with and without PTCA possibility. It is obvious that PTCA hospitals treat much more patients in general, i.e. there are only a few hospitals above 250 cases per year which do not offer PTCA treatment. This is one reason why the effect of PTCA and case volume are difficult to separate. We want to check whether the PTCA effect also exists in hospitals with lower case volumes. We specify a regression for patients treated in hospitals with less than 400 cases up to a case volume with less than 150 cases. The effect of PTCA decreases if the hospitals with the highest case volume are excluded from the sample but they have still large relevance. For hospitals with a case volume below 150 cases, the PTCA effect becomes insignificant. Taken together, it can therefore be concluded that the PTCA effect is not only driven by hospitals with the highest case volume.

Figure 3: Distribution of case volume

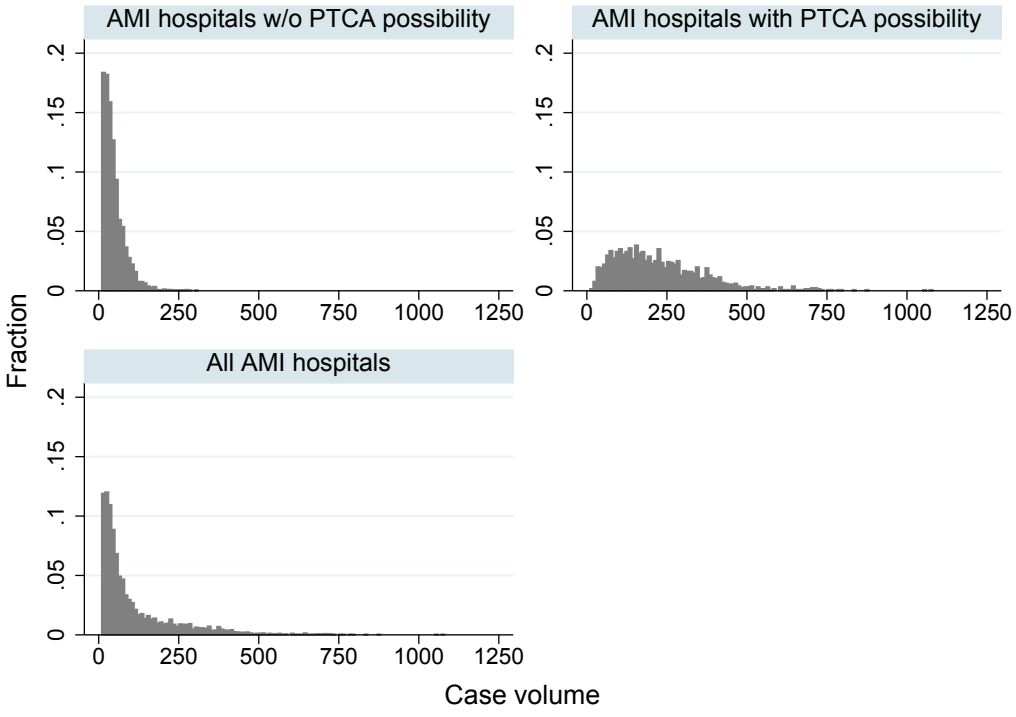


Table 5: Robustness regressions for different subgroups

	OLS		IV					
	Coefficient	**S.E.**	**Coefficient**	**S.E.**	**First-stage F-statistic**	**Test for endogen. (p-value)**	**Number of patients**	**Number of hospitals**
Basic model	-0.1019^{***}	0.0023	-0.0451^{***}	0.0098	352.8525	0.0000	406,281	1,292
Regional area								
Rural area	-0.0990^{***}	0.0038	-0.0766^{***}	0.0169	200.4305	0.1828	112,440	799
Urban area	-0.1035^{***}	0.0026	-0.0213^{**}	0.0108	211.8138	0.0000	293,841	1,137
Admission status								
Emergency	-0.1284^{***}	0.0027	-0.0581^{***}	0.0106	569.8578	0.0000	259,399	1,256
w/o Transfers	-0.1152^{***}	0.0023	-0.0534^{***}	0.0092	545.7250	0.0000	365,961	1,286
Admission time								
Day time	-0.0980^{***}	0.0023	-0.0458^{***}	0.0103	295.7826	0.0000	305,450	1,292
Night time	-0.1166^{***}	0.0032	-0.0464^{***}	0.0141	523.5723	0.0000	100,831	1,261
Age								
Age $<$ 65 years	-0.0563^{***}	0.0022	-0.0206^{***}	0.0071	261.6932	0.0000	129,471	1,254
Age $\geq$ 65 years	-0.1158^{***}	0.0027	-0.0541^{***}	0.0134	378.9362	0.0000	276,810	1,292
AMI type								
Non-ST-elevated MI	-0.0592^{***}	0.0018	-0.0219^{*}	0.0127	291.3082	0.0045	198,174	1,290
ST-elevated MI	-0.1440^{***}	0.0036	-0.0576^{***}	0.0115	349.6927	0.0000	208,107	1,292
Case volume								
Case volume $<$ 400 cases	-0.1031^{***}	0.0024	-0.0387^{***}	0.0092	519.7764	0.0000	332,583	1,261
Case volume $<$ 350 cases	-0.1022^{***}	0.0025	-0.0380^{***}	0.0091	591.0795	0.0000	301,457	1,239
Case volume $<$ 300 cases	-0.1006^{***}	0.0026	-0.0359^{***}	0.0093	611.0190	0.0000	265,729	1,208
Case volume $<$ 250 cases	-0.0981^{***}	0.0028	-0.0390^{***}	0.0094	642.9564	0.0000	225,682	1,168
Case volume $<$ 200 cases	-0.0955^{***}	0.0033	-0.0278^{***}	0.0105	561.8094	0.0000	186,862	1,109
Case volume $<$ 150 cases	-0.0970^{***}	0.0038	-0.0131	0.0146	363.3696	0.0000	146,892	1,038
Placebo regression			-0.1353	0.2925	6.7857	0.9090	406,281	1,292

Notes: Clustered standard errors (at the hospital level) used; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions are estimated with all covariates of the full standard regression model.

As another robustness check we follow Bound et al. (1995) and do a placebo regression. Therefore, we randomly assign our instrument values to the patients. Hence, the instrument should have no explanatory power for the endogenous variable. Our first-stage F-statistic reduces below one and the results do change completely. We find further evidence that our original instrument has explanatory power and can be used as instrument for PTCA.

We find a 4.5 pp reduction in mortality for patients treated with PTCA. This is a sizable effect. Nevertheless the additional PTCA costs must be in an appropriate proportion to these benefits. Due to the limited resources in the health system it is necessary to spend money only for treatments which have an adequate cost-benefit ratio. Therefore, we calculate the minimum number of years which a patient must live in perfect health in order to make PTCA cost-effective. We have 195,705 patients who get a PTCA in our sample during 2005 and 2007. 8,826 deaths are avoided through this intervention. PTCA costs are €1,600 above the costs of conservative treatment, i.e. €315 million for all PTCA patients within that period.[10] For the calculation a value of a quality adjusted life year (QALY) has to be assigned. The thresholds are between US$ 50,000 to US$ 100,000 (approx. €35,700 to €71,400[11]) in the USA and between £ 20,000 to £ 30,000 (approx. €28,500 to €42,800) in the UK (Ryen and Svensson, 2015). The total benefit of the PTCA results from the multiplication of the number of avoided deaths, the value of a QALY and the additional number of years lived. The benefit must be higher than the additional costs. Therefore, we calculate the minimum number of years lived in perfect health to make PTCA cost-effective and set the PTCA benefit equal to the additional PTCA costs. The PTCA patients must therefore live at minimum 0.5 to 1.2 additional years in perfect health so that PTCA is cost-effective. Cutler (2007) finds that PTCA patients have a 1.1 years additional life expectancy. We therefore think that PTCA is also a cost-effective intervention.

[10] For 2007, we have accounting data for the AMI patients available. We take the weighted average for patients with and without PTCA which results in €1,600 additional costs for PTCA. This is 1.4 times higher than treatment without PTCA and comparable with the study of Soekhlal et al. (2013) in the Netherlands.

[11] We use exchange rates of the year 2007, i.e. for the US $ 1.4 per euro and for the UK £ 0.7 per euro.

6 Conclusion

Technological improvements account for the bulk of health care cost increases over time (Cutler and McClellan, 2001). These improvements usually include new treatment options. As a consequence, older treatments coexist with more expensive newer treatments for the same disease. A key policy question is whether these new treatments lead to better outcomes than older, less expensive treatments since health care resources are limited.

This paper investigates whether the use of new treatments (i.e. PTCA) for AMI leads to a reduction in mortality compared to a conservative/old therapy. We use administrative hospital data of a full sample of all inpatients in Germany from 2005 to 2007. Due to problems with unobserved patient heterogeneity we use an instrumental variable approach. As an instrument we use in our basic specification the differential time of the closest hospital to the patient offering new treatment options and the closest hospital treating AMI patients regardless of whether new treatment techniques are available. We find a 4.5 pp reduction in mortality for patients receiving new treatment compared to old treatment. Our estimations measure the treatment effect on the marginal population. We measure the effect for AMI patients who receive a PTCA because they live relatively close to a PTCA hospital but who would not have get a PTCA if they lived further away. These estimates on the marginal returns to care are the important once because they give the effect for people who would be affected by a policy decision (Almond et al., 2010).

In a robustness check, we apply another IV specification and measure the treatment effect of an alternative marginal population, defined as patients who get a PTCA in regions with higher rates but not with lower PTCA rates. The regional IV predicts a wide range of PTCA rates, as the share of PTCA procedures for AMI treatment is below 35% in some regions and above 65% in others. For this IV approach we find in the most conservative specification a 4.8 pp reduction in mortality for patients who were treated with PTCA compared to conservative therapy which is a similar effect as in our main specification.

A further robustness check indicates that the PTCA effect stays similar for day and night time admissions. New treatment options are more beneficial for patients with ST-elevated MI compared to patients with Non-ST-elevated MI and for patients older than 65 years compared to younger patients. The PTCA effect is not a specific effect in urban areas; in fact, it has a

stronger effect in rural areas. For smaller hospitals the PTCA effect disappears. In a placebo regression we show that the instrument has explanatory power.

It cannot be completely ruled out that that the PTCA effect still can be include other effects which are better within PTCA hospitals and lead to a better outcome, e.g. the follow-up care of patients. The effect of PTCA would then decrease. Nevertheless, our robustness checks indicate that the procedure itself substantially contributes to the treatment outcome.

What policy conclusions can be drawn from our results? To answer this question, we have to admit, that our IV estimates reflect the marginal population and need a careful interpretation as discussed above. Notwithstanding this constraint, our results suggest the diffusion of new AMI treatment options in Germany may be worthwhile. Applying simple back-of-the-envelope calculations, we find that PTCA is cost-effective at reasonable cost-effectiveness thresholds, if the patients live for a minimum of 0.5 to 1.2 years in perfect health after the PTCA.

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A Appendix

Table A1: Regression results (instrument: differential time)

	LPM				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PTCA	−0.1165***	−0.0983***	−0.1023***	−0.1019***	−0.0454***	−0.0486***	−0.0504***	−0.0451***
	(0.0023)	(0.0025)	(0.0023)	(0.0023)	(0.0100)	(0.0088)	(0.0089)	(0.0098)
Age		0.0044***	0.0045***	0.0045***		0.0049***	0.0049***	0.0049***
		(0.0001)	(0.0001)	(0.0001)		(0.0001)	(0.0001)	(0.0001)
Male		0.0010	0.0008	0.0012		−0.0036**	−0.0037***	−0.0037**
		(0.0012)	(0.0012)	(0.0012)		(0.0015)	(0.0014)	(0.0015)
Admission reason: Emergency		0.0220***	0.0205***	0.0200***		0.0207***	0.0199***	0.0197***
		(0.0018)	(0.0018)	(0.0018)		(0.0018)	(0.0018)	(0.0018)
Admission reason: Transfer		−0.0052	−0.0084*	−0.0100**		−0.0048	−0.0064	−0.0079*
		(0.0047)	(0.0044)	(0.0044)		(0.0043)	(0.0042)	(0.0041)
Non-ST-elevated MI		−0.1216***	−0.1225***	−0.1224***		−0.1142***	−0.1147***	−0.1138***
		(0.0018)	(0.0018)	(0.0018)		(0.0022)	(0.0023)	(0.0023)
CCI: 1-2		0.0058***	0.0051***	0.0047***		0.0089***	0.0085***	0.0084***
		(0.0017)	(0.0017)	(0.0017)		(0.0018)	(0.0018)	(0.0018)
CCI: 3-4		0.0230***	0.0221***	0.0216***		0.0305***	0.0301***	0.0304***
		(0.0026)	(0.0026)	(0.0026)		(0.0029)	(0.0030)	(0.0030)
CCI: ≥5		0.0476***	0.0465***	0.0457***		0.0586***	0.0581***	0.0584***
		(0.0036)	(0.0035)	(0.0034)		(0.0041)	(0.0041)	(0.0042)
Winter		0.0027**	0.0027**	0.0027**		0.0032***	0.0032***	0.0032***
		(0.0011)	(0.0011)	(0.0011)		(0.0011)	(0.0011)	(0.0011)
Weekend/holiday admission		0.0135***	0.0134***	0.0136***		0.0154***	0.0154***	0.0156***
		(0.0012)	(0.0012)	(0.0012)		(0.0013)	(0.0013)	(0.0013)
Night admission		0.0062***	0.0059***	0.0060***		0.0074***	0.0072***	0.0074***
		(0.0013)	(0.0013)	(0.0013)		(0.0013)	(0.0013)	(0.0013)
City		−0.0000	0.0001	0.0026		−0.0014	−0.0015	0.0011
		(0.0025)	(0.0025)	(0.0026)		(0.0024)	(0.0024)	(0.0025)
Year 2006		0.0050***	0.0053***	0.0054***		0.0033**	0.0035**	0.0034**
		(0.0014)	(0.0014)	(0.0014)		(0.0014)	(0.0014)	(0.0014)
Year 2007		0.0111***	0.0115***	0.0116***		0.0082***	0.0084***	0.0081***
		(0.0015)	(0.0015)	(0.0015)		(0.0015)	(0.0015)	(0.0016)

Continued on the next page.

	LPM				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ownership: not-for-profit			−0.0074***	−0.0110***			−0.0033	−0.0080***
			(0.0026)	(0.0027)			(0.0026)	(0.0026)
Ownership: for-profit			0.0013	−0.0015			−0.0015	−0.0045
			(0.0037)	(0.0038)			(0.0037)	(0.0038)
University hospital			0.0276***	0.0261***			0.0150***	0.0123**
			(0.0049)	(0.0047)			(0.0052)	(0.0049)
Minimum time to hospital				0.0002				−0.0001
				(0.0001)				(0.0001)
Purchasing power per inhabitant				−0.0000				−0.0006**
				(0.0003)				(0.0003)
Unemployment rate				0.0009***				0.0006**
				(0.0003)				(0.0003)
Constant	0.1793***	−0.1156***	−0.1130***	−0.1185***	0.1451***	−0.1700***	−0.1687***	−0.1648***
	(0.0021)	(0.0056)	(0.0059)	(0.0098)	(0.0051)	(0.0106)	(0.0109)	(0.0126)
Federal state indicators	No	No	No	Yes	No	No	No	Yes
R-squared	0.031	0.091	0.092	0.093	0.020	0.086	0.087	0.087
First-stage F-statistic					210.0809	281.6580	349.7454	352.8525
Test for endogeneity (p-value)					0.0000	0.0000	0.0000	0.0000
Number of patients	406,281	406,281	406,281	406,281	406,281	406,281	406,281	406,281
Number of hospitals	1,292	1,292	1,292	1,292	1,292	1,292	1,292	1,292

Notes: Clustered standard errors (at the hospital level) in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. CCI – Charlson Comorbidity Index.