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SUPPLEMENT PAPER

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Spillover effects and other determinants of medical device uptake in the presence of a medical guideline: An analysis of drug-eluting stents in Germany and Italy

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Abstract

We investigated the role of spillover effects among hospitals in the diffusion of drug-eluting stents (DES) in Germany and Italy during a period in which the relevant medical guideline clearly recommended their use over bare-metal stents. We used administrative data of hospitalized patients treated with ST-elevation myocardial infarction from 2012 to 2016 to estimate spatial panel models allowing for global spillover effects. We used an inverse-distance weights matrix to capture the geographical proximity between neighboring hospitals and assigned a lower weight to more distant neighbors. For both countries, we found significant positive spatial autocorrelation in most years based on the global Moran's I test, and a significant, positive spatial lag parameter across model specifications, indicating positive spillover effects among neighboring hospitals. We found that private for-profit hospital ownership and hospital competition in Germany and the number of inpatient cases with circulatory system diseases in Italy were other significant determinants of DES adoption. Our results underline the importance of spillover effects among peers for the diffusion of medical devices even in the presence of a positive guideline recommendation. Policymakers might therefore consider promoting various forms of exchange and collaboration among medical staff and hospitals to ensure the appropriate use of medical technologies.

KEYWORDS
adaptation, diffusion, healthcare, hospital, international comparisons, medical devices, medical guidelines, spatial panel data analysis, spillover effects, technology

1 | INTRODUCTION

The rapid adoption of safe and effective medical technologies can improve patients' health outcomes and is positively correlated with gains in hospital productivity and overall welfare (Frankovic et al., 2020; Skinner & Staiger, 2015). Nevertheless, the literature has found the diffusion of most medical technologies to be slow and variation in their adoption among providers to be considerable, even in cases where their effectiveness and safety are widely acknowledged and evidence-based guidelines recommending their use are available (Frankovic et al., 2020; Skinner & Staiger, 2015). According to a study by Frankovic et al. (2020), the time span between the adoption of a new medical technology and its widespread use is about 9 years on average, resulting in an estimated 43% reduction in potential life-expectancy gains.

Research on technology diffusion and adherence to medical guidelines has identified several barriers that may explain the slow diffusion and high variation observed in the adoption of these technologies (Cabana et al., 1999; Pronovost, 2013; Skinner & Staiger, 2015). One of the most important barriers identified in the literature is a lack of knowledge, which is closely related to awareness about and familiarity with a medical technology or a guideline (Cabana et al., 1999; Skinner & Staiger, 2015). This finding is further supported by theoretical concepts of adoption mechanisms, such as the theoretical framework on knowledge, attitudes and behavior (e.g., Cabana et al., 1999) or the innovation-decision process described by Rogers (2003). In essence, both theories state that influencing individuals' knowledge is the basis for achieving a lasting effect on their attitudes and, ultimately, their behaviors – either with regard to the adoption of medical guidelines or new technologies.

Building on this literature, a growing number of studies are investigating the importance of so-called mimic behavior, or knowledge spillovers, between peers as an important channel for transmitting knowledge that can influence the diffusion of medical technologies (Barrenho et al., 2020; Barrenho et al., 2021; Chandra et al., 2014; Coleman et al., 1957; Huesch, 2011). These studies have shown that spillover effects among peers play an important role in the diffusion of medical technologies, such as the adoption of new pharmaceuticals (Coleman et al., 1957), keyhole surgery for colon cancer (Barrenho et al., 2020), laparoscopic colectomy (Barrenho et al., 2021), and the diffusion of drug-eluting stents (DES) (Chandra et al., 2014; Huesch, 2011). To date, however, the role of spillovers in situations in which medical guidelines already exist and make a clear recommendation in favor of a technology has not been considered (Tarricone et al., 2017). Indeed, Tarricone et al. (2017) asserted that addressing this research gap has become all the more important given the growing emphasis placed on evidence-based medicine, and evidence-based policymaking more generally, by regulators, professional societies and policymakers. Our study aims to help fill this gap by investigating the role of spillover effects among neighboring hospitals and other determinants of the use of drug-eluting stents (DES) in Germany and Italy from 2012, when the European Society of Cardiology first issued a recommendation (Class IIa, Level A) generally in favor of their use, through 2016.

The studies cited above applied various methods to investigate the role of spillovers and other determinants in the diffusion of medical technologies: Three (Barrenho et al., 2020, 2021; Coleman et al., 1957) used social network analysis to consider relationships among physicians, and two (Chandra et al., 2014; Huesch, 2011) used ordinary linear least squares (OLS) regressions. Of the two studies investigating the use of DES, Huesch (2011) conducted OLS regressions at the physician-level, considering measures of DES use by peers, and Chandra et al. (2014) conducted hospital-level OLS regressions, considering the rate of diffusion among hospitals in the hospital referral region (HRR). These studies do not, however, take into account exact measures of distance between their units of analysis. We suggest that even within defined analytical units, such as HRRs, the consideration of distance and distance decay between the units of analysis is important to explain the functioning of knowledge spillovers.

We used spatial econometric methods to investigate the role of spillovers and other determinants in the use of the stent technology recommended by the relevant medical guideline. To do so, we focused on geographical proximity based on the spatial connections between hospitals instead of individual relationships between physicians (social proximity), similar to Chandra et al. (2014). Geographical proximity is the standard type of proximity, which is most widely used in the literature (Knoben & Oerlemans, 2006; Marrocu et al., 2013). In addition to geographical proximity, other channels such as technological or social proximity can also be important for the diffusion of innovations and technologies (Knoben & Oerlemans, 2006; Marrocu et al., 2013). However, previous studies focusing on social proximity have shown that geographical proximity often reflects network effects. For example, a study by Barrenho et al. (2020) demonstrated that physicians' social networks are closely linked to geographic areas. This could be due to the fact that physician mobility is largely limited to the local region and that the majority of physicians do not change geographic regions during their careers (Goldacre et al., 2013). In addition, it seems likely that participation in medical training or physician network meetings, as well as intensive exchange with former study colleagues, also take place more frequently in spatial proximity to the workplace and physicians' place of residence as this involves less time and lower travel costs. Furthermore, our study does not explore differences in technological proximity. Instead, we held technological proximity constant, by only including hospitals in our study that treat patients diagnosed with ST-segment elevation myocardial infarction (STEMI) with stents. Therefore, all hospitals in our sample are homogenous in terms of technology, at least to some extent, as they all have at least a solid basic understanding of the technology. In addition, DES is not a complicated new technology that requires extensive training and the insertion of DES is no different from the insertion of other stent types. Therefore, we believe that for our analysis, geographical proximity is the most important venue of knowledge transfer and observational learning between hospitals, despite growing interconnectedness and digitalization.

Beyond examining spillover effects and other relevant determinants in this special context, we additionally contribute to the literature in two important ways. First, we investigate the diffusion of DES in a more mature/later phase of diffusion compared to the phases examined in most studies, which focus on the introduction and growth phase directly after market entry. From our point of view, the later phase of technology adoption deserves consideration because prior research has shown that the adoption and use of medical devices among physicians may differ according to the different stages of the product life span (Ex & Henschke, 2019; Hatz et al., 2017). In the case of DES, a long-term perspective on diffusion is especially interesting because the share of DES in the market has changed substantially over time. Second, In contrast to most studies, which – with few exceptions, such as Packer et al. (2006) – focus on the diffusion of medical technologies in individual countries, we investigate and compare the diffusion of DES from a cross-country perspective, that is, Germany and Italy. Investigating the diffusion of technology across jurisdictions is especially relevant given that the decision to adopt medical technologies and follow medical guidelines depends not only on physicians, but also other stakeholders, particularly hospital managers and administrators, hospital boards of directors, and hospital purchasing groups, as well as professional societies, regulators, and policymakers (Sorenson & Kanavos, 2011; Torbica & Cappellaro, 2010).

Our paper is structured as follows: In the first section, we provide some clinical background on the choice of DES over bare-metal stents (BMS) and compare the reimbursement and incentive structures for the use of DES in Germany and Italy. In the second section, we describe the spatial econometric methods we used, and we present the results of our analyses. Third, we discuss the results of our analyses by contrasting them with those in the literature and considering the institutional particularities of the countries under investigation. Finally, we consider the implications of our findings for policymakers and conclude.

2 | CLINICAL BACKGROUND

In our study, we focus on patients treated in the hospital with a STEMI, a more severe form of acute myocardial infarction (AMI). Most STEMI patients are treated with primary percutaneous transluminal coronary angioplasty (PTCA), which usually involves the placement of coronary stents, such as BMS or DES to ensure that the arteries remain open and to reduce the risk of target vessel revascularization (Zhu et al., 2001). In contrast to BMS, DES are coated with an anti-proliferative drug, which is released over time and inhibits cell growth in the vessel around the stent (Chitkara & Pujara, 2010).

Investigating variation in the use of DES compared to BMS is interesting because the scientific evidence and expert opinion on these technologies have changed substantially over time. After market entry in the early 2000s, DES were considered superior to BMS and adopted quickly in the US and several European countries, such as Denmark, the Netherlands, Norway, Spain, Switzerland, Sweden, and the United Kingdom (Epstein et al., 2012; Packer et al., 2006). This is also true of Italy, where DES procedures comprised about 38% of all PTCA procedures between 2003 and 2007, rising from 30% in 2004 to more than 40% in 2005 and more than 50% in 2006 (Cappellaro et al., 2011). In contrast, in Germany, the initial diffusion of DES was modest, with DES procedures comprising 15.5% of stent procedures among AMI patients between 2004 and 2005 (Bäumler et al., 2012).

Around 2005, the overall trend toward DES use reversed due to the increased incidence of reported sub-acute stent thrombosis and higher long-term mortality rates among patients treated with DES (Chitkara & Pujara, 2010). From 2008 onwards, however, a resumption in the use of DES can be observed and is related to the development of an improved second generation of DES (Epstein et al., 2012). More recent evidence suggests that contemporary DES are generally preferred over BMS due to a lower risk of restenosis (Bønaa et al., 2016; Stettler et al., 2007). In addition, there is evidence that even though the purchasing costs for DES are higher, their long-term outcomes make them more cost-effective than BMS (Cheng et al., 2019).

These findings are also reflected in international guidelines on the treatment of patients with a STEMI diagnosis. In 2012, the European Society of Cardiology (ESC) issued a Class IIa, Level A recommendation stating that DES should generally be preferred over BMS unless there are certain contraindications (Steg et al., 2012).

The ESC guideline recommendations were translated and adopted by the national cardiac societies in Germany (Deutsche Gesellschaft für Kardiologie – Herz- & Kreislaufforschung e.V., 2012) and Italy and are consistent with other important international guidelines, such as the guideline of the American College of Cardiology/American Heart Association (Kushner et al., 2009). In more recent ESC guidelines, published in 2014 (Kolh et al., 2014) and 2017 (Neumann et al., 2019), the recommendation was strengthened further by making it a Class Ia recommendation, in which the use of BMS is generally no longer recommended.

3 | DIFFERENCES IN REIMBURSEMENT FOR CORONARY STENTS

The German and Italian healthcare systems have been described and analyzed in detail in a series of country-based reports (see Blümel et al. (2021) for the German health system and Poscia et al. (2018) for the Italian health system). In the following, we describe only the main aspects of the two systems that are of specific relevance to our study, focusing on payment, incentive structures, and procurement for the different types of coronary stent technologies.

The first similarity between Germany and Italy is that they are two of the largest medical device markets in Europe[1] (MedTech Europe, 2020). The second similarity is that they both generally use diagnosis-related groups (DRGs) to determine payments for inpatient care on a case-fee basis, which in principle covers the costs for the use of medical devices (Schreyögg et al., 2009). Nevertheless, both countries enable additional payments for certain costly medical devices and for new treatments that are considered innovative (Sorenson & Kanavos, 2011).

In Germany, the cost of BMS is reimbursed through the DRG payment, whereas the cost of DES has been covered since 2009 by fixed (i.e., not negotiable) supplementary payments whose amount is pre-determined and is the same throughout Germany (Henschke et al., 2010). The supplementary payment for DES has decreased over time along with a continuous decline in procurement costs. Whereas in 2012 the insertion of one DES (ZE101.01) led to a payment of €384.58, the amount had decreased to €119.83 in 2016 (Reimbursement Institute, 2021). The fact that supplementary payments are employed to reimburse hospitals in Germany for using DES can be expected to act as an incentive to use them instead of BMS (Ex & Henschke, 2019).

In Italy, even though reimbursement for the cost of medical devices is determined nationally, regions may deviate from the national payment scheme and base their decisions on self-developed fee schedules and their own assessments (Cavalieri et al., 2013). The payment is based on national or regional DRGs. Since the adoption of the latest update to the classification system (v. 24 of Medicare's DRG system) in Italy in 2009, there have been three specific DRGs (DRG 556, 557, 558) for coronary stent insertion: One for BMS and two for DES (with and without major cardiac complications). In 2013, the reference values for the DRGs were set at the national level, ranging from a baseline of €4747 for ordinary hospitalization for BMS to €6436 and €8128 for interventions with DES, respectively with and without major cardiac complications (i.e., AMI) (Ministero della Salute, 2020). However, also due to the fact that there have been no further updates at the national level since 2013, the actual amount of reimbursement for this DRG differed substantially among regions across time.

4 | METHODS

4.1 | Data

Our analysis is based on the administrative data of patients with a primary or secondary diagnosis of STEMI, who were (1) discharged from a hospital between January 1, 2012 and December 31, 2016 and (2) underwent either a BMS or DES procedure during their hospital stay. Table A1 (in the Appendix) shows the diagnosis and procedure codes used to select the patient sample in Germany and Italy.

The German dataset was compiled from three different data sources. The patient-level hospital discharge data were obtained from an administrative database containing a comprehensive sample of all German hospitals (G-DRG data according to § 21 KHEntgG). The patient-level data were aggregated at the hospital-level and, via a unique hospital identifier (Institutionskennzeichen) for the main hospital sites, joined with hospital characteristics and geographic locations from the mandatory, publicly available structured quality reports (Strukturierte Qualitätsberichte, SQB) reported by all German hospitals that provide healthcare to patients with statutory health insurance (based on § 137 SGB V).[2] Lastly, we used administrative data on indicators for spatial and urban development (INKAR) from the Federal Institute for Research on Building, Urban Affairs, and Spatial Development (BBSR) to obtain data on characteristics at the regional (NUTS-3)[3] level. The variable for the number of general practitioners (GPs) per 100000 population, which we will refer to as GP density, was retrieved from the Central Institute for Statutory Health Insurance in the Federal Republic of Germany (Zi) for the years 2012 and 2013, and from the National Association of Statutory Health Insurance Physicians (KBV) for 2014 through 2016. The regional characteristics were merged with the hospital-level data based on the location (i.e., NUTS-3 codes) of the hospitals. The final balanced sample for Germany consisted of 2605 observations from 521 hospitals and 307 NUTS-3 regions.[4]

For Italy, the dataset was compiled in a similar manner to that used for Germany. The patient-level data were retrieved from the hospital discharge database (Schede di Dimissione Ospedaliera—SDO) hosted by the Italian Ministry of Health. The database contains data on all admissions to public and private hospitals that are financed by the regional Italian National Health Service (NHS) ("private convenzionati"). Information on hospital characteristics and hospital addresses were either already included in the SDO dataset or obtained from publicly available data from the Italian Ministry of Health. Using the hospital addresses, we retrieved latitude and longitude coordinates for each Italian hospital in our dataset using the Open Geocoding API from MapQuest.[5] Information on regional characteristics at the NUTS-3 level were drawn from the National Statistical Institute (Istituto Nazionale di Statistica—ISTAT), the Ministry of Finance, Eurostat and the Ministry of the Interior (Ministero dell'Interno). The variable share of population with an academic degree could only be retrieved for 1 year and had to be imputed for the other years.

In the Italian dataset, we excluded 25 observations from five hospitals based on the island of Sardinia because we assumed that the mechanisms for spillovers between hospitals on a more remote island and hospitals on the mainland might be different (e.g., hospitals on an island might have limited contact with hospitals on the mainland, and the ease and availability of ferry connections might play a greater role than geographical distances). The final balanced panel dataset for Italy consisted of 1445 observations from 289 hospitals and 86 NUTS-3 regions.[6]

4.2 | Dependent variable

The formula for calculating the dependent variable is as follows:

$$y_{it} = \log\left(\left(1 - \frac{\mathrm{DES}_{it}}{\mathrm{DES}_{it} + \mathrm{BMS}_{it}}\right) + 0.01\right)$$

where y_{it} is a vector that includes the values of the dependent variable of hospital i at time t, DES_{it} denotes the number of patients with a primary or secondary diagnosis of STEMI in a hospital i at time t, who received at least one DES, and BMS_{it} is the number of patients with a primary or secondary diagnosis of STEMI in a hospital i at time t, who received at least one stent (either BMS or DES). Because the dependent variable was negatively skewed in both the Italian and the German datasets, we applied a reflected log transformation ($Y = \log((1 - Y) + 0.01)$) to better approximate a normal distribution.

4.3 | Independent variables of interest

First, we included several hospital characteristics in our analysis, such as number of full-inpatient cases as a proxy for hospital size, number of full-inpatient cases with a disease of the circulatory system (i.e., at least one diagnosis of chapter 9 in ICD-10-GM in the German context or chapter 7 in ICD-9-CM in the Italian context) to measure a hospital's experience in treating cardiovascular diseases, and hospital competition measured with the Herfindahl-Hirschman Index (HHI) based on ICD chapter 9 (ICD-10-GM)/ICD chapter 7 (ICD-9-CM) as a measure of market concentration and specialization within a hospital's market area in the relevant medical discipline.[7] These variables could be potential determinants of DES use based on existing literature. Previous studies have demonstrated that DES use is lower at low-volume hospitals (Chandra et al., 2014; Rao et al., 2006). Hospital size has also shown to be positively correlated with the diffusion of DES (Chandra et al., 2014). In addition, competition has been shown to be positively correlated with the diffusion of DES in some studies (Karaca-Mandic et al., 2017), albeit not in others (e.g., Chandra et al., 2014). Furthermore, we included dummies for private for-profit hospital ownership status and university hospital status. While most studies find consistent positive correlations between university hospital status and DES use (Chandra et al., 2014; Grilli et al., 2007), the results on the effect of for-profit hospital ownership on the use of DES are contradictory. Whereas Chandra et al. (2014) found that for-profit hospitals were less likely to adopt DES, Grilli et al. (2007) and Bäumler (2013) found that, on average, private for-profit hospitals used DES more frequently compared to public hospitals.

Second, we included variables for the characteristics of the NUTS-3 regions in which the hospitals were located,[8] that is, GP density, population density (inhabitants/km^2), life expectancy,[9] unemployment rate, regional income[10] in purchasing power parity (PPP), and share of population with an academic degree.[11] Existing studies suggest that these variables could also be relevant determinants of DES use. For example, it has been shown, that DES use is lower at rural hospitals (Rao et al., 2006) and higher in hospitals located in neighborhoods with higher income (Yong et al., 2014). In addition, studies focusing on the diffusion of other medical technologies in the field of interventional cardiology indicate that GP density (Groeneveld et al., 2020) and the level of education in a region are positively correlated with the use of these technologies (Groeneveld et al., 2020; Torbica et al., 2017).

4.4 | Control variables

We controlled for differences in patient characteristics aggregated at the hospital-level, such as mean age, share of female patients, average number of Elixhauser comorbidities (Elixhauser et al., 1998)[12] and share of patients with STEMI as their main diagnosis. Patient characteristics, such as comorbidities may influence the choice of DES over BMS, as the preference for DES depends on the patient's ability to undergo extended dual antiplatelet therapy (DAPT) for at least 3 months, whereas for BMS this is required for 1 month only (Colombo et al., 2017). Furthermore, existing studies suggest that patient characteristics, such as age and gender influence DES use (Chandra et al., 2014; Krone et al., 2010; Rao et al., 2006; Ting et al., 2008).

Following the argumentation of Keele et al. (2020) and Hünermund and Louw (2020) we do not interpret the coefficients of our control variables and only show them in the Appendix (Tables A3 and A4).

4.5 | Estimation strategy

We expected spatial dependence in our data because studies on DES diffusion in the United States have shown that spillovers among nearby hospitals play an important role in the use of DES (Chandra et al., 2014). In the case of spatial dependence – which can occur in the dependent variable, explanatory variables, and error term – ordinary least squared (OLS) regression will be biased (Anselin, 2013; LeSage & Pace, 2009). Besides the advantage of obtaining unbiased effect estimates, most spatial econometric models also allow for empirically assessing the magnitude and significance of spillover effects, which was of interest for our research question (Elhorst & Vega, 2013). We therefore decided to test first for spatial dependence in our data, and to apply a spatial econometric model if it was present.

In order to test for spatial dependence, a spatial weight matrix is required that describes the geographic associations between the units of analyses, in our case hospitals that perform stent procedures in patients with a STEMI diagnosis. In line with the recent literature examining spillover effects among hospitals (Baltagi & Yen, 2014; Longo et al., 2017), we used an inverse-distance weights matrix W for our main model specification because this matrix captures the geographical proximity between neighboring hospitals more accurately than a binary weight matrix, as it assigns a lower weight to more distant neighbors:

$$W = w_{ij} = \begin{cases} 0 \text{ if } i = j \\ \dfrac{1}{d_{ij}} \text{ if } d_{ij} \leq b \text{ and } i \neq j \\ 0 \text{ if } d_{ij} > b \text{ and } i \neq j \end{cases}$$

where w_{ij} are the spatial weights for each hospital pair, b is the distance band, which was set to 51.55 km for Germany and 73.24 km for Italy (corresponding to the largest minimum distance between a hospital and its closest neighboring hospital in each country),[13] and d_{ij} is the great-circle distance between two hospitals i and j. The great circle distance was calculated based on the latitude and longitude coordinates of the main hospital sites by using the haversine formula.[14] In addition, we normalized the spatial weights matrix, which means that each row of the matrix sums up to 1 (see Anselin & Bera, 1998).

For creating and storing the spatial weight matrices, we used the Stata commands *spmat* (Drukker et al., 2013) and *spatwmat* (Belotti et al., 2017).

The connections of hospitals expressed in the spatial weight matrices are illustrated in Figure 1. In the Italian weight matrix, a hospital has 15.47 neighbors on average, and the maximum number of neighbors is 44, whereas in the German weight matrix, a hospital has 17.77 neighbors on average, and the maximum number of neighbors is 62.

The spatial literature generally distinguishes between *global* and *local* spillover scenarios depending on how far-reaching the spillover effects are and whether they involve feedback effects (Anselin, 2003; LeSage, 2014). In line with studies taking into account spatial interactions among hospitals (Baltagi et al., 2018; Longo et al., 2017), we assumed that the spillover effects we were investigating are global, which means that spillovers were not restricted to a specific region or radius. Although we expected to observe stronger and more immediate spillovers within a closer radius, we assumed that

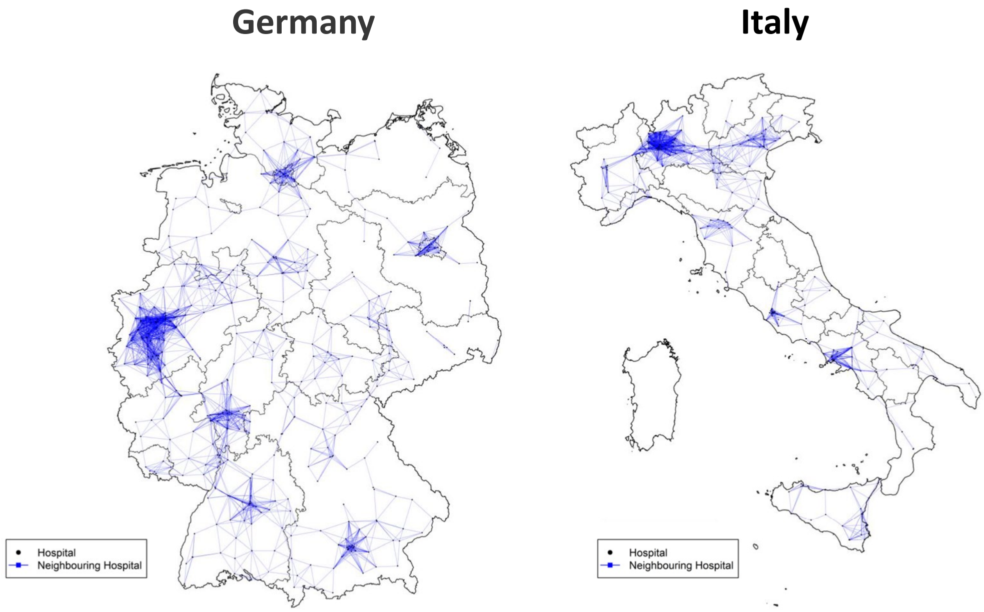

FIGURE 1 Illustration of spatial weight matrices for Germany and Italy. *Source*: Authors' own representation based on German and Italian hospital coordinates. Software used to create the plots: R Version 4.0.2 (R Foundation for Statistical Computing, Vienna, Austria) [Colour figure can be viewed at wileyonlinelibrary.com]

the effects would probably also affect the use of DES by hospitals outside of this radius, also leading to endogenous feedback effects.

We therefore measured the degree of spatial autocorrelation in the outcome variable using the global Moran's I test:

$$I = \frac{N}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij} \left(y_i - \overline{y}\right)\left(y_j - \overline{y}\right)}{\sum_i \left(y_i - \overline{y}\right)^2} \tag{1}$$

where N denotes the number of hospitals, w_{ij} is the weight of hospital i and neighboring hospital j, y_i denotes the value of the dependent variable in hospital i, $\overline{y}$ is the mean of the value of the dependent variable, and y_j is the value in hospital j. A significant Moran's I statistic indicates that there is significant autocorrelation among the values of hospitals that are located close to each other.[15]

In the event of significant spatial autocorrelation in our outcome variable, we followed the suggestion of LeSage and Pace (2009) and started by estimating a Spatial Durbin Model (SDM), which includes a spatial lag of the dependent variable and spatially lagged explanatory variables. In doing so, the model takes into account that not only the dependent variable is spatially autocorrelated, but also the explanatory variables could be correlated among neighboring hospitals.

$$y_{it} = \rho W y_{it} + \text{PatHosp}_{it}\beta_1 + \text{Reg}_{it}\beta_2 + W\,\text{PatHosp}_{it}\theta + u_{it} \tag{2}$$

where y_{it} is a vector that includes the values of the dependent variable in hospital i at time t, ρ is the spatial autoregressive coefficient and measures the spillover effects in the dependent variable, and W denotes the $N \times N$ spatial weight matrix, whose diagonal elements are zero and whose off diagonal elements indicate the weighted average geographical proximity between hospital pairs. We standardized the spatial weight matrix by dividing each entry by the total for that row. We obtained the geographical proximity between hospitals by calculating the inverse of the distance between the point latitudes and longitudes of the hospitals. Furthermore, PatHosp_{it} denotes a matrix of aggregated patient and hospital characteristics of hospital i at time t, Reg_{it} is a matrix of the characteristics of the region in which hospital i is located at time t, and u_{it} is a vector of spatially uncorrelated error component disturbances. Although we started with the SDM, we also estimated two additional spatial panel models: the Spatial Autoregressive Model (SAR) and the Spatial Error Model (SEM).

The SAR is a simplified form of the SDM because it includes only a spatial lag of the dependent variable:

$$y_{it} = \rho W y_{it} + \text{PatHosp}_{it}\beta_1 + \text{Reg}_{it}\beta_2 + u_{it} \tag{3}$$

The SEM, on the other hand, includes only a spatial parameter in the error term:

$$y_{it} = \text{PatHosp}_{it}\beta_1 + \text{Reg}_{it}\beta_2 + u_{it} \text{ with } u_{it} = \lambda W u_{it} + \varepsilon_{it} \tag{4}$$

To determine the most appropriate spatial model specification, we first used a likelihood-ratio test to compare the SDM with the SAR, as suggested by Elhorst (2010) and Elhorst (2014). If we could not reject the first null hypothesis, stating that the SDM can be simplified to the SAR, we used a likelihood-ratio test again but to test the second null hypothesis that it can be simplified to the SEM.

As our baseline model we estimated a model with fixed effects for years, which includes all relevant explanatory and control variables. In addition to the baseline model with fixed effects for years, we also estimated a two-way fixed effects and a random-effects within-between (REWB)[16] model as a sensitivity analysis to ensure that our estimates were unbiased and not affected by unobserved hospital characteristics that we could not account for.

When interpreting the results of our spatial regression models, we followed the reasoning of LeSage and Pace (2009), who, instead of interpreting the point estimates of the coefficients, propose distinguishing between *direct* effects, *indirect* effects, and *total* effects because a change in the unit of an explanatory variable of hospital i may not only have a *direct* effect on the outcomes of hospital i but can also have an *indirect* effect on the outcomes of hospital j. The *total* effect comprises the *direct* and *indirect* effects.

We conducted our analyses using Stata Version 13.1 (StataCorp LP, College Station, Texas). The spatial panel models and the estimations of *direct, indirect,* and *total* effects were performed with the *xsmle* command (Belotti et al., 2017).

5 | RESULTS

5.1 | Descriptive statistics

The diffusion of DES use in patients with a STEMI diagnosis in Germany and Italy over time is illustrated in Figure 2. During the observation period from 2012 through 2016, a clear shift can be observed in the use of BMS to DES for the treatment of patients with a STEMI diagnosis in both countries. Beginning with large variation in stent choices among hospitals in 2012, the behaviors in Germany and Italy converged significantly over time, with almost all of the hospitals in both countries clearly preferring DES over BMS for the treatment of STEMI patients by 2016. Furthermore, Figure 2 shows that, in 2012, the level of DES use was higher in Germany (Mean: 65.09%) than in Italy (Mean: 52.25%). This finding is interesting considering, in particular, that DES use during the phase of initial diffusion was much higher in Italy than in Germany, as mentioned in the clinical background chapter above.

In the Appendix, we further illustrate the differences in DES use in Germany and Italy across geographic areas (Figure A1). Table A2 in the Appendix gives the summary statistics of our data for the years 2012 through 2016. The description of Table A2 can also be found in the Appendix.

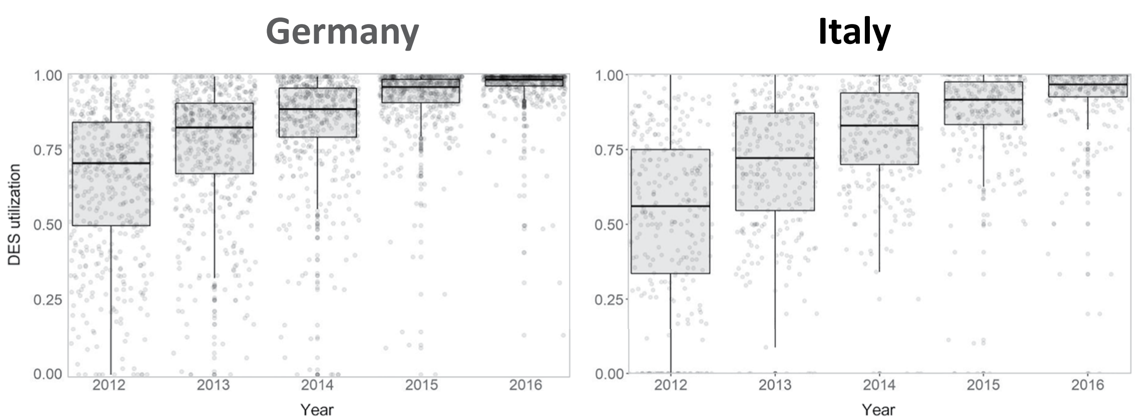

FIGURE 2 The diffusion of DES use for patients with a STEMI diagnosis in Germany and Italy. *Source*: Authors' own representation based on hospital discharge data in Germany (§ 21 KHEntgG) and Italy (SDO). Software used to create the plots: R Version 4.0.2 (R Foundation for Statistical Computing, Vienna, Austria)

5.2 | Spatial interdependencies

Table 1 reports the results of the global Moran's I test, measuring spatial autocorrelation in the outcome variable (DES use rate) for both samples. For Germany, the Moran's I coefficients were positive and significant in each of the 5 years of the observation period. This finding suggests significant spatial autocorrelation in the German sample and indicates that neighboring hospitals were more likely to have similar rates of DES use. For Italy, the Moran's I coefficient was positive and significant in three of the 5 years of the observation period. This indicates a similarity between neighboring hospitals with regard to DES use in the years 2012, 2013, and 2015. Overall, we came to the conclusion that, because we found significant spatial autocorrelation in both countries in most years of our observation period, we should take account of this spatial dependency in our regression analyses to avoid biased coefficients.

5.3 | Panel regressions

Table 2 reports the results of the spatial panel specifications and an ordinary least squared (OLS) regression with year fixed effects with DES use as the dependent variable. All standard errors are robust and clustered by hospital. The spatial autoregressive coefficient ρ (rho) was significant and positive across all spatial panel specifications for Germany and Italy. This finding supports our assessment of the appropriateness of a spatial model compared to a non-spatial model for both countries. In addition, the significant and positive ρ indicates that, on average, a given hospital had a higher rate of DES use if the neighboring hospitals had high rates of DES use.

When examining DES use in the specifications with year fixed effects, aside from the autoregressive coefficient, few of our explanatory variables were significantly correlated with DES use in Germany or Italy. In the German context the explanatory variable with a statistically significant ($p < 0.01$) coefficient across all model specifications was private for-profit hospital ownership. In addition, the spatial lag of hospital competition (measured by the HHI) was significantly correlated ($p < 0.01$) with DES use in the SDM specification. In the Italian context the number of cases with a circulatory system disease (diagnosis of ICD chapter 7) was at least weakly statistically significant (ranging from $p < 0.1$ to $p < 0.05$) across model specifications. In the OLS specification, a statistically significant correlation ($p < 0.05$) was also found between the number of GPs in the hospital region and DES use, however, this was no longer present once controlled for spatial spillover effects. Furthermore, the spatial lag of the number of full-inpatient cases was significantly correlated ($p < 0.05$) with DES use in the SDM specification. The directions of the estimates were similar between the different model specifications, except for the estimate of the spatial lag of the number of cases with a circulatory system disease (diagnosis of ICD chapter 7) in the SDM specification.

The estimates shown in Table 2, however, do not represent the most precise estimates for the spatial models because they do not take into account any spillover and feedback effects between hospitals. For a more detailed interpretation of the effects of the control variables, we rely on Table 3, which presents the marginal effect estimates decomposed into *direct*, *indirect*, and *total* effects for the most appropriate spatial model specification.

For both Germany and Italy, the most appropriate model was the SDM because in both cases we could reject the first null hypothesis that the SDM can be simplified to the SAR model. Table 3 shows the main coefficient estimates of the SDM specification with year fixed effects, the coefficient estimates of the spatially lagged aggregated hospital characteristics, and the marginal effects of the explanatory variables decomposed into *direct*, *indirect*, and *total* effects.

Factor variables were excluded from Table 3 because the marginal effects could not be computed for these variables (for further explanation, see Belotti et al. (2017)). Therefore, to interpret the statistically significant ($p < 0.01$) negative correlation

TABLE 1 Moran's I spatial autocorrelation coefficient for Germany and Italy by year

	Germany	Italy
Year	**W = Hospital radius**	**W = Hospital radius**
2012	0.142***	0.184***
2013	0.158***	0.058**
2014	0.153**	0.008
2015	0.140***	0.076**
2016	0.121***	−0.005

Significance levels: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Source: Authors' own representation based on German and Italian datasets for years 2012–2016.

TABLE 2 Estimates of different panel data models for DES use with fixed effects for years

DES use (reflected log-transformed)	Germany W = Hospital radius OLS	SEM	SAR	SDM Main	SDM Wx	Italy W = Hospital radius OLS	SEM	SAR	SDM Main	SDM Wx
Hospital characteristics										
Full-inpatient cases[a]	−0.000	−0.000	−0.000	−0.000	−0.002	−0.002	−0.002	−0.001	−0.001	0.028**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)	(0.014)
Cases with diseases of the circulatory system[a,b]	0.006	0.021	0.018	0.020	−0.038	0.072*	0.092**	0.085*	0.073	−0.251**
	(0.037)	(0.044)	(0.045)	(0.045)	(0.096)	(0.040)	(0.046)	(0.045)	(0.048)	(0.113)
Hospital competition (HHI)	0.286	0.180	0.187	−0.417	1.219***	0.078	0.013	0.038	−0.233	0.473
	(0.229)	(0.262)	(0.231)	(0.297)	(0.420)	(0.284)	(0.294)	(0.277)	(0.453)	(0.638)
Hospital ownership: Private for-profit	−0.249***	−0.219***	−0.229***	−0.225***	−0.249	−0.148	−0.160	−0.151	−0.129	0.317
	(0.087)	(0.084)	(0.084)	(0.085)	(0.195)	(0.126)	(0.123)	(0.124)	(0.130)	(0.247)
University hospital status	−0.031	−0.049	−0.045	−0.067	0.217	−0.221	−0.216	−0.245	−0.253	−0.513
	(0.125)	(0.126)	(0.123)	(0.123)	(0.294)	(0.226)	(0.211)	(0.212)	(0.220)	(0.434)
Regional characteristics										
Number of GPs in the hospital region	0.001	0.003	0.002	0.001		−0.024**	−0.008	−0.009	−0.013	
	(0.002)	(0.002)	(0.002)	(0.002)		(0.011)	(0.012)	(0.011)	(0.012)	
Population density[a]	−0.090	−0.068	−0.070	−0.064		0.013	0.014	0.002	−0.040	
	(0.058)	(0.065)	(0.056)	(0.058)		(0.131)	(0.131)	(0.126)	(0.129)	
Life expectancy	−0.076	−0.078	−0.088	−0.077		0.016	−0.029	−0.019	−0.028	
	(0.055)	(0.071)	(0.061)	(0.062)		(0.078)	(0.079)	(0.074)	(0.075)	
Unemployment rate	0.017	0.019	0.010	0.019		0.011	0.003	0.007	0.014	
	(0.019)	(0.022)	(0.020)	(0.019)		(0.016)	(0.016)	(0.016)	(0.017)	
Income (in PPP)[a,c]	−0.133	−0.076	−0.067	−0.067		0.237	0.702	0.672	0.680	
	(0.114)	(0.120)	(0.106)	(0.113)		(0.620)	(0.629)	(0.595)	(0.610)	
% Population with an academic degree	0.011	0.006	0.008	0.010		0.034	0.015	0.016	0.028	
	(0.010)	(0.012)	(0.011)	(0.011)		(0.022)	(0.023)	(0.022)	(0.022)	
Spatial autoregressive coefficient (ρ)			0.264***	0.239***						
			(0.035)	(0.034)						

TABLE 2 (Continued)

DES use (reflected log-transformed)	Germany W = Hospital radius OLS	SEM	SAR	SDM Main	SDM Wx	Italy W = Hospital radius OLS	SEM	SAR	SDM Main	SDM Wx
Spatial error parameter (λ)		0.256***					0.134***	0.115***	0.120***	
		(0.039)					(0.046)	(0.044)	(0.044)	
Spatial lags for hospital characteristics	No	No	No	Yes		No	No	No	Yes	
Year fixed effects	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes	
Control variables	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes	
R-squared (within)	0.642	0.015	0.009	0.013		0.520	0.038	0.064	0.080	
R-squared (between)	0.053	0.063	0.077	0.102		0.062	0.082	0.079	0.109	
R-squared (overall)	0.429	0.030	0.033	0.044		0.354	0.014	0.010	0.016	
Log-likelihood value		−3696	−3690	−3675			−2170	−2171	−2160	
Number of observations	2605	2605	2605	2605		1445	1445	1445	1445	
Number of groups	521	521	521	521		289	289	289	289	

Note: Cluster-robust standard errors in parentheses.

Abbreviations: GP, General Practitioner; HHI, Herfindahl-Hirschman Index; OLS, Ordinary Least Squares; PPP, Purchasing Power Parity; SAR, Spatial Autoregressive Model; SDM, Spatial Durbin Model; SEM, Spatial Error Model.

[a]Variables are measured in 1000s.

[b]Germany: Full-inpatient cases with a diagnosis from ICD chapter 9 (ICD-10-GM); Italy: Full-inpatient cases with a diagnosis from ICD chapter 7 (ICD-9-CM).

[c]Germany: Median income of full-time employees subject to social insurance contributions; Italy: Mean income.

Significance levels: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Source: Authors' own representation based on German and Italian datasets for years 2012–2016.

TABLE 3 Coefficient estimates and direct, indirect, and total effects of SDM with year fixed effects for DES use

	Germany					Italy				
	W = Hospital radius					W = Hospital radius				
			SDM					SDM		
DES use (reflected log-transformed)	Main	Wx	Direct	Indirect	Total	Main	Wx	Direct	Indirect	Total
Hospital characteristics										
Full-inpatient cases[a]	0.001	0.000	0.001	0.001	0.002	−0.001	0.018	−0.001	0.019	0.018
	(0.002)	(0.006)	(0.003)	(0.008)	(0.009)	(0.006)	(0.012)	(0.006)	(0.014)	(0.016)
Cases with a circulatory system disease[a,b]	0.005	−0.009	0.003	−0.017	−0.014	0.061	−0.232**	0.057	−0.245*	−0.188
	(0.039)	(0.088)	(0.040)	(0.120)	(0.139)	(0.047)	(0.116)	(0.046)	(0.132)	(0.150)
Hospital competition (HHI)	−0.428	1.173***	−0.367	1.372***	1.005**	−0.236	0.495	−0.225	0.525	0.300
	(0.301)	(0.428)	(0.285)	(0.514)	(0.448)	(0.439)	(0.606)	(0.446)	(0.658)	(0.458)
Regional characteristics										
GP density	0.000		0.000	0.000	0.001	−0.006		−0.006	−0.001	−0.007
	(0.002)		(0.002)	(0.001)	(0.003)	(0.011)		(0.011)	(0.002)	(0.013)
Population density[a]	−0.067		−0.068	−0.021	−0.089	−0.009		0.001	−0.002	−0.000
	(0.059)		(0.056)	(0.018)	(0.074)	(0.124)		(0.122)	(0.019)	(0.140)
Life expectancy	−0.081		−0.082	−0.026	−0.108	−0.021		−0.018	−0.002	−0.020
	(0.062)		(0.064)	(0.021)	(0.085)	(0.075)		(0.074)	(0.012)	(0.086)
Unemployment rate	0.014		0.014	0.004	0.019	0.006		0.005	0.001	0.006
	(0.019)		(0.020)	(0.006)	(0.026)	(0.016)		(0.015)	(0.002)	(0.018)
Income (in PPP)[a,c]	−0.009		−0.010	−0.003	−0.013	0.769		0.735	0.114	0.849
	(0.113)		(0.115)	(0.038)	(0.152)	(0.629)		(0.614)	(0.112)	(0.715)
% Population with an academic degree	0.009		0.009	0.003	0.012	0.018		0.017	0.003	0.020
	(0.011)		(0.011)	(0.004)	(0.015)	(0.022)		(0.021)	(0.003)	(0.024)

TABLE 3 (Continued)

	Germany					Italy				
	W = Hospital radius					W = Hospital radius				
			SDM					SDM		
DES use (reflected log-transformed)	**Main**	**Wx**	**Direct**	**Indirect**	**Total**	**Main**	**Wx**	**Direct**	**Indirect**	**Total**
Spatial autoregressive coefficient (ρ)	0.251***					0.133***				
	(0.034)					(0.044)				
Spatial lags for hospital characteristics	Yes					Yes				
Year fixed effects	Yes					Yes				
Control variables	Yes					Yes				
R-squared (within)	0.005					0.099				
R-squared (between)	0.081					0.093				
R-squared (overall)	0.033					0.009				
Log-likelihood value	−3689					−2167				
Number of observations	2605					1445				
Number of groups	521					289				

Note: Cluster-robust standard errors in parentheses. The direct, indirect and total effects could not be computed for the factor variables hospital ownership and university hospital status (for further explanations, see Belotti et al. (2017)).

Abbreviations: GP, General Practitioner; HHI, Herfindahl-Hirschman Index; PPP, Purchasing Power Parity; SDM, Spatial Durbin Model.

[a]Variables are measured in 1000s.

[b]Germany: Full-inpatient cases with a diagnosis from ICD chapter 9 (ICD-10-GM); Italy: Full-inpatient cases with a diagnosis from ICD chapter 7 (ICD-9-CM).

[c]Germany: Median income of full-time employees subject to social insurance contributions; Italy: Mean income.

Significance levels: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Source: Authors' own representation based on German and Italian datasets for years 2012–2016.

between private for-profit hospital ownership and DES use in Germany we rely on the imprecise estimates from Table 2. When interpreting this effect, it is important to consider that the outcome variable was reflected and log-transformed. Therefore, the negative correlation between private for-profit hospital ownership and DES use needs to be interpreted in the opposite sense – that is, private hospitals have a 20.15% higher use of DES compared to public hospitals.

In addition, we found statistically significant and positive *indirect* ($p < 0.01$) and *total* ($p < 0.05$) effects for hospital competition (as measured by the HHI) on DES use in the German context (see Table 3). The *total* effect is mainly composed of the *indirect* effect. When interpreting this effect, it is again important to mention that the outcome variable was reflected and log-transformed – that is, a one percentage point increase in HHI, implying lower competition, in a hospital i is on average correlated with a 3.94% lower DES use in neighboring hospitals.

Regarding the variation between hospitals in Italy, we found a weakly significant ($p < 0.1$) negative *indirect* effect for the number of inpatient cases with a circulatory system disease on DES use suggesting that a higher number of inpatient cases with a circulatory system disease in a hospital i is correlated with a higher DES use in neighboring hospitals. An increase of inpatient cases with a circulatory system disease by 1000 is correlated with an average increase of 21.73% in DES use rates in neighboring hospitals.

6 | SENSITIVITY ANALYSES

We conducted several sensitivity analyses to ensure the robustness of our estimates. While the estimates from the German analyses remained quite robust across a range of sensitivity analyses, the estimates from the Italian analyses were somewhat less robust in terms of the statistical significance of the estimates.

First, in addition to the model with fixed effects for years, we estimated a two-way fixed effects (see Appendix Table A5) and a REWB SDM (see Appendix Table A6) to ensure the accuracy of our estimates. For both, the two-way fixed effects and the REWB specification, we excluded the time-invariant variables and the regional characteristics. For both countries and across specifications, the spatial autoregressive coefficient ρ (rho) remained significant and positive. Only the magnitude of the autoregressive coefficient ρ (rho) changed slightly compared to the baseline model. As expected, the coefficients for the between predictors of the REWB model were relatively similar to those estimated in the baseline model. The estimates for the independent variables in the two-way fixed effects and the within predictors of the SDM are not comparable to the estimates from the baseline model because they estimate variation within hospitals.

Second, we restricted our sample to hospitals that conducted (DES or BMS) stent procedures in at least 50 STEMI patients in each of the years under consideration to investigate whether hospital similarity has an impact on our outcomes (see Appendix Table A7). This reduced the German sample to 2060 observations and 412 hospitals and the Italian sample to 1020 observations and 204 hospitals. The results remained fairly robust for Germany. The spatial autoregressive coefficient ρ (rho) remained positive and significant, but decreased in magnitude. In the Italian context, the spatial autoregressive coefficient ρ (rho) remained positive but not statistically significant. In addition, the effect estimates and the significance levels for the explanatory variables changed to some extent for both countries. In particular, the effects of private for-profit hospital ownership in Germany and cases with a circulatory system disease in Italy maintained the same direction but were no longer statistically significant.

Third, we excluded 2014 and 2015 from the sample because DES use in those years was already more widespread in both countries than in previous years. The estimates remained quite robust for both countries (see Appendix Table A8). The spatial autoregressive coefficient ρ (rho) remained positive and significant. The effect estimates for the explanatory variables and the significance levels were mostly comparable to the main model for both countries.

Fourth, we conducted a sensitivity analysis excluding all hospitals from our sample that did not use any DES at all in at least 1 year of the observation period (see Appendix Table A9). This reduced the German sample to 2515 observations from 503 hospitals and the Italian sample to 1235 observations from 247 hospitals. In the German sample, the estimates remained mostly stable. The spatial autoregressive coefficient ρ (rho) remained positive and significant, but decreased in magnitude. In the Italian sample the spatial autoregressive coefficient ρ (rho) remained positive but not significant. The effect estimates and the significance levels for the explanatory variables changed slightly.

Fifth, we reduced the analysis to hospitals that have a high specialization in cardiology, to examine whether they have a role as opinion leaders (see Appendix Table A10). We operationalized specialization as the number of cases treated with a disease of the circulatory system (ICD-10-GM chapter 9 (Germany)/ICD-9-CM chapter 7 (Italy)) as a proportion of the total number of cases treated in the hospital. Hospitals with values above the median were considered specialized hospitals. The spatial autoregressive coefficient ρ (rho) remained positive and significant in the German context, but decreased in magnitude. In the Italian context, the spatial autoregressive coefficient ρ (rho) became negative and not statistically significant. In addition, the effect estimates for the explanatory variables and the significance levels changed quite substantially for both countries.

Sixth, we tested multiple weight matrices, applying different distance bands for the hospital radius to both samples (see Tables A11, A12, and A13). In the German context, the spatial autoregressive coefficient ρ (rho) remained positive and significant and the effect estimates of the explanatory variables also remained quite stable when applying bands of 30, 50, or 80 km. However, for Italy, the spatial autoregressive coefficient ρ (rho) only remained positive and statistically significant (at a 5% significance level) when applying a band of 80 km. When a distance band of 50 km was applied, the spatial autoregressive coefficient ρ (rho) remained weakly significant (at a 10% significance level). At a distance band of 30 km it became insignificant. In addition, the effect estimates for the explanatory variables changed quite considerably in the Italian context at the different distance bands.

Finally, we included a regional (NUTS-3) fixed-effect for the Italian sample to capture potential unobserved variation in profitability of stents across regions in Italy (see Appendix Table A14). In this sensitivity analysis, the spatial autoregressive coefficient ρ (rho) was no longer significant, and the coefficients of the explanatory variables that were previously significantly correlated with DES use were no longer significant either.

7 | DISCUSSION

This study represents an extensive analysis of the diffusion of DES among hospitals in Germany and Italy. It expands the existing literature in several important ways: (1) to our knowledge, it is the first study to investigate the role of spillover effects among hospitals in close geographical proximity, and thus the uptake of a medical technology in the presence of a medical guideline clearly recommending its use; (2) it is one of few studies to analyze the long-term diffusion of medical devices at a later stage of the product lifespan; and (3) it contributes to the hitherto sparse literature on comparative analyses of the diffusion of medical devices across countries.

Our results suggest the existence of spillover effects among neighboring hospitals in the case of DES in Germany and Italy in the years 2012 through 2016. However, the spillover effects in Italy were less pronounced and not robust across all sensitivity analyses. One reason for this could be the different reimbursement of the cost of DES between NUTS-3 regions in Italy. Because Italian hospitals are exposed to different incentive structures when located in different regions, there may be less knowledge exchange between them, even if they are not located far from each other. This assumption is further supported by the disappearance of significant spillover effects between hospitals in the sensitivity analysis for Italy, where we included fixed effects for NUTS-3 regions. Another reason could be that physicians, who believed in the technology very early on and preferred first-generation DES to BMS, and then were proven wrong due to the new findings on the negative long-term effects, could be more reluctant to use second-generation DES and less receptive to hearing from other physicians about its benefits. As a consequence, the peer influence could be less strong, as physicians' previous bad experiences may be predominant here. Because the diffusion of first-generation DES right after market entry was faster and more extensive in Italy than in Germany, the possibly more restrained adoption of second-generation DES may apply more to Italian physicians.

In addition, the results of the sensitivity analyses show that the spillover effects are smaller (in Germany) or non-significant (in Italy) if the sample is reduced to specialized hospitals or to hospitals with a higher volume of stent procedures. This could indicate that knowledge spillovers primarily occur between specialized and nonspecialized hospitals, which would emphasize the importance of opinion leaders. In addition, the spillover effects become smaller (in Germany) or non-significant (in Italy) at a lower radius (30 km). This may suggest that it is not necessarily the closest hospitals that are most important for knowledge exchange, but rather the more specialized hospitals in the surrounding area that act as opinion leaders.

Aside from the spatial autoregressive coefficient ρ (rho), some of the explanatory variables included in our main analysis showed a significant correlation with DES use in the German and Italian contexts. The effect estimates must be interpreted with caution, however, as they did not remain stable across all sensitivity analyses. In particular, in the sensitivity analyses in which we focused on specialized hospitals or on hospitals that conducted (DES or BMS) stent procedures in at least 50 STEMI patients each year, some of the determinants were no longer statistically significant.

In Germany, the explanatory variables that were significantly correlated with the use of DES in our main analysis were private for-profit hospital ownership and hospital competition. Specifically, we found that private hospitals on average have a 20.15% higher use of DES compared to public hospitals. Similar results have also been found in other studies (Bäumler, 2013; Grilli et al., 2007) which, however, focus on the period after market entry of DES. Bäumler (2013) found that between 2004 and 2006, patients in Germany were over 50% more likely to receive DES if they were treated in a private hospital compared to a public hospital. The differences between private and public hospitals in terms of DES use in Germany appear to have persisted but decreased between 2004 through 2006 and 2012 through 2016. The rationale Bäumler (2013) gave for these differences in DES use was that private hospitals may be more effective at negotiating purchasing prices for DES, are smaller and more dynamic, and therefore may adjust treatment pathways more quickly, and potentially use new technologies to strategically position themselves in the competition for patients. These reasons could still apply, although in this study we consider a later observation period and the differences found are now less pronounced.

In addition, we found that an increase in a hospital's market concentration (indicating lower competition for this hospital and higher competition for neighboring hospitals) was significantly correlated with lower DES use in neighboring hospitals in Germany. This finding seems counterintuitive at first, as previous studies that did not consider spillover effects have shown that competition is positively associated with DES use (Karaca-Mandic et al., 2017). However, the significant *indirect* effect we found could be explained by the fact that hospitals may be less likely to specialize in an area if there is another hospital that is already highly specialized and has a high market concentration in this area.

In the Italian context, the only explanatory variable weakly correlated with the use of DES in our main analysis was the number of full-inpatient cases with a disease of the circulatory system (diagnosis of ICD chapter 7). This implies that a higher number of inpatient cases with a circulatory system disease in a hospital is weakly correlated with a higher DES use in neighboring hospitals. An explanation for this could be an exchange of knowledge between experienced and less experienced hospitals. An increase of inpatient cases with a circulatory system disease could lead to higher specialization of hospitals in this area and an increased use of DES, including potential knowledge spillovers to hospitals located nearby.

In contrast to other studies, we found no significant correlations between other hospital characteristics, such as university/teaching hospital status or hospital size (overall case volume), and the use of DES in our main analysis. Moreover, we also found no significant correlations between regional characteristics and DES use in our baseline model, although some studies have also reported significant effects here. An explanation for this could be that, in contrast to our study, most of the existing studies have focused on the use of DES in previous periods directly after market entry, which may also explain different results. For example, it is possible that the differences in DES use during this later observation period are more likely to be found between hospitals than between regions. In addition, other studies that have found significant correlations between hospital size or volume and DES use, such as that by Chandra et al. (2014), have operationalized these variables in a way that differs slightly from the approach taken in our study (i.e., the authors used hospital beds instead of number of full-inpatient cases as a proxy for hospital size and cumulative stent volume instead of number of patients treated with a disease of the circulatory system[17] to account for hospital volume in the relevant medical specialty). Furthermore, we found no significant correlations between any of the regional characteristics and DES use in our baseline model.

Our overall finding of spillover effects among neighboring hospitals in the case of DES is in line with a previous study, by Chandra et al. (2014), which finds spillover effects between hospitals in the diffusion of DES in the US after market entry (2002–2005). Our key finding is that spillover effects among hospitals using DES in close geographical proximity continue to play an important role for DES use even after (a) a positive recommendation has been made for a specific technology in the relevant medical guideline and (b) an increasing amount of robust scientific evidence in favor of their use has become available. This implies that technology adoption behaviors are not influenced solely by guidelines or scientific publications. This result could further indicate that guidelines cannot replace informal communication channels or observational learning among peers. These explanations are consistent with the results of qualitative studies suggesting that medical guidelines and scientific evidence are not necessarily decisive for physicians' treatment decisions (Cutler et al., 2019) and, indeed, may not be the main drivers of the adoption of medical devices (Hatz et al., 2017).

8 | LIMITATIONS

While this study offers valuable insights into the importance of spillover effects among hospitals and other relevant determinants in the diffusion of medical technologies, it nevertheless has some limitations that must be acknowledged. First, we did not have any information on physician characteristics within hospitals, hospital corporations that may set corporation-specific guidelines, or collaborations between hospitals operating as purchasing groups in our data. Studies have shown that physician characteristics such as gender and training play an important role in DES adoption (Karaca-Mandic et al., 2017). In addition, other recent studies have shown that physician networks play a major role in the diffusion of medical technologies, such as keyhole surgery for colon cancer (Barrenho et al., 2020) and laparoscopic colectomy (Barrenho et al., 2021). Furthermore, institutional cooperation between hospitals operating as a group could lead to the development of similar clinical policies among neighboring hospitals. Disentangling the exact mechanisms of the spillovers between physicians and hospitals would be important for future research. Future research could also consider training structures in the region and publication activities of the respective hospitals on the technology of interest, which could more accurately depict regional knowledge processes and the technological proximity between hospitals.

Second, we use the general term *spillover effects*, which may include different types of spillovers, such as knowledge spillovers (meaning that physicians or hospital managers and administrators exchange knowledge through informal communication) and so-called "mimic behavior" or observational learning (Chandra et al., 2014; Vogt et al., 2014). Our analysis is unable to distinguish between these.

Third, we rely on administrative data at the patient level and self-reported data by the hospitals at the hospital level from different diagnosis (ICD-9-CM and ICD-10-GM) and procedure coding systems and from different data sources for Germany and Italy. This resulted in two datasets with sometimes slightly diverging definitions for the variables included in our models. However, because we made efforts to harmonize the data, estimated separate regressions for both countries, and did not compare effect sizes for the coefficient estimates between countries, these differences should not influence our results.

Fourth, we focus our investigation only on one specific medical technology, which hardly differs in application from the alternative technology and is therefore not very complex. Consequently, we cannot make any statements on whether the results can be transferred to other medical fields, especially if the complexity of the products differs.

9 | CONCLUSION

In this study, we investigated the role of spillover effects among neighboring hospitals and other relevant determinants of technology diffusion in the uptake of a medical device that was clearly recommended in the relevant medical guideline. More specifically, our analysis focused on the diffusion of drug-eluting stents (DES) in Germany and Italy in the presence of a Class IIa recommendation by the European Society of Cardiology in favor of using this technology. We found clear spatial clustering of similarly behaving hospitals with regard to DES use in Germany, suggesting the existence of spillover effects, for example, through knowledge transfers or mimic behavior. In Italy, we also found spatial clustering of similarly behaving hospitals with regard to DES use. However, the results in Italy were less pronounced and not robust across all sensitivity analyses.

From a policy perspective, our findings suggest that regular communication and exchange between providers play an important role in the diffusion of medical devices above and beyond the publication of medical guidelines and scientific evidence. Policymakers could use this as an argument for developing and promoting various forms of exchange among hospital staff and hospitals, as well as cooperation within hospital groups to ensure the appropriate use of medical technologies. One idea, for example, could be to promote regular exchange programs between hospitals, sending physicians to other hospitals. Through these programs, better inter-hospital networks could be established, and physicians could learn about new treatment methods and possibly adopt them for their own patients. In particular, an exchange program between highly specialized and less specialized hospitals could be beneficial.

Future research is needed to extend our findings and investigate the type of spillover effects between neighboring hospitals and their role in the diffusion of other medical devices. It would be particularly interesting to study medical devices with technologies of varying complexity, as the results could change depending on the level of complexity. Furthermore, it would be interesting to compare how the role of peer effects changes as the body of scientific opinions and evidence on the benefits of medical devices and guidelines themselves change over time, particularly over a longer period. In addition, the channels and types of spillover effects could be investigated further, for example, by disentangling physician spillovers from hospital spillovers, or further examining the role of physician networks, and cooperation within hospital groups, as well as assessing the impact of physical or digital formats of knowledge exchange.

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CONFLICT OF INTEREST

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DATA AVAILABILITY STATEMENT

Research data are not shared.

ETHICS STATEMENT

Ethical approval for compliance with terms of use and ethical standards was obtained by the Economic and Social Sciences Research Laboratory (WiSo Forschungslabor) of the Universität Hamburg on April 26, 2018.

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ENDNOTES

[1] In 2018, the medical device market in Germany accounted for the largest share (27.1%) of the medical device market in Europe as a whole, while the medical device market in Italy, with a share of 10.1%, ranked as the fourth largest.

[2] Approximately 90% of residents in Germany are insured through the statutory health insurance system (Blümel et al., 2021).

[3] The NUTS classification (Nomenclature of territorial units for statistics) provides a consistent territorial division of the EU to enable comparability of regional statistics between countries of the EU. The category NUTS-3 refers to the third level and thus the lowest aggregation level of territorial units available (e.g., in Germany this level corresponds to counties).

[4] The sample does not include all hospitals and NUTS-3 regions in Germany that provide healthcare to patients with statutory health insurance, because we only included hospitals, which treated patients with a STEMI diagnosis with stents during the observation period.

[5] For more information, see: https://developer.mapquest.com/documentation/open/geocoding-api/

[6] The sample does not include all hospitals and NUTS-3 regions in Italy because we only included hospitals, which treated patients with a STEMI diagnosis with stents during the observation period.

[7] We calculated the HHI based on hospital discharge data within a catchment area with a 30 km radius (Longo et al., 2017; Bloom, Propper, Seiler, & van Reenen, 2015).

[8] Because our study focuses on patients with an emergency condition, we expect the characteristics of the regions in which the hospitals are located to be highly congruent with the regions in which the patients reside.

[9] Life expectancy is measured as the average life expectancy of a newborn baby in years.

[10] In the German dataset, the average regional income is measured as the median income of full-time employees subject to social insurance contributions, whereas in the Italian dataset it is measured as mean income.

[11] The definition of academic degree corresponds to the levels 6–8 of the International Standard Classification of Education (ISCED) 2011 (UNESCO Institute for Statistics, 2012).

[12] We use the Elixhauser comorbidity measures because these have shown to be superior to the Charlson measure for patients with AMI in Europe (Gutacker, Bloor, & Cookson, 2015). We constructed the Elixhauser comorbidities using the ICD-9 codes for Italy and the ICD-10 codes for Germany based on the classification by Quan et al. (2005). The total number of Elixhauser comorbidities is a comorbidity measure that is commonly used in the literature (see e.g., Gutacker, Bloor, Cookson, Garcia-Armesto, & Bernal-Delgado, 2015).

[13] With this data-driven approach for choosing the cut-off, we ensure that, in both countries, each hospital is assigned at least one neighbor.

[14] To calculate the distances between hospital pairs based on the haversine formula, we used the *vincenty* command (Nichols, 2003) in Stata.

[15] We used the user-written Stata command *spatgsa* (Pisati, 2012) to estimate the global Moran's I statistic.

[16] The REWB model is also known as the "Mundlak" or the "hybrid" model (Dieleman & Templin, 2014).

[17] This includes all patients with at least one diagnosis of ICD chapter 9 in ICD-10-GM or ICD chapter 7 in ICD-9-CM.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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