

Ress, Vanessa; Wild, Eva-Maria

Article — Published Version

The impact of integrated care on health care utilization and costs in a socially deprived urban area in Germany: A difference-in-differences approach within an event-study framework

Health Economics

Provided in Cooperation with:

John Wiley & Sons

Suggested Citation: Ress, Vanessa; Wild, Eva-Maria (2023) : The impact of integrated care on health care utilization and costs in a socially deprived urban area in Germany: A difference-in-differences approach within an event-study framework, Health Economics, ISSN 1099-1050, Wiley, Hoboken, NJ, Vol. 33, Iss. 2, pp. 229-247, <https://doi.org/10.1002/hec.4771>

This Version is available at:

<https://hdl.handle.net/10419/288202>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



<http://creativecommons.org/licenses/by-nc-nd/4.0/>

The impact of integrated care on health care utilization and costs in a socially deprived urban area in Germany: A difference-in-differences approach within an event-study framework

Vanessa Röss^{1,2}  | Eva-Maria Wild^{1,2} 

¹Department of Health Care Management, University of Hamburg, Hamburg, Germany

²Hamburg Center for Health Economics (HCHE), Hamburg, Germany

Correspondence

Eva-Maria Wild, Hamburg Center for Health Economics, Universität Hamburg, Esplanade 36, Hamburg 20354, Germany. Email: eva.wild@uni-hamburg.de

Funding information

Innovation Fund of the German Federal Joint Committee, Grant/Award Number: NVF2_2016-042

Abstract

We investigated the impact of an integrated care initiative in a socially deprived urban area in Germany. Using administrative data, we empirically assessed the causal effect of its two sub-interventions, which differed by the extent to which their instruments targeted the supply and demand side of healthcare provision. We addressed confounding using propensity score matching via the Super Learner machine learning algorithm. For our baseline model, we used a two-way fixed-effects difference-in-differences approach to identify causal effects. We then employed difference-in-differences analyses within an event-study framework to explore the heterogeneity of treatment effects over time, allowing us to disentangle the effects of the sub-interventions and improve causal interpretation and generalizability. The initiative led to a significant increase in hospital and emergency admissions and non-hospital outpatient visits, as well as inpatient, non-hospital outpatient, and total costs. Increased utilization may indicate that the intervention improved access to care or identified unmet need.

KEYWORDS

difference-in-differences, evaluation, event study, health care utilization and costs, integrated care, socially deprived urban area

1 | INTRODUCTION

Social inequalities are reflected in worse health and lower life expectancy among people with lower socioeconomic status (Chetty et al., 2016; Hudomiet et al., 2021). The causes of this problem are multiple and complex; they are also intertwined and, in part, mutually exacerbating. One way to approach this from a health economic perspective is to examine whether the causative factors are located, broadly speaking, on the supply or demand side of health care services. For instance, on the demand side, factors such as language problems and low health literacy can lead to so-called misplaced demand (Berkman et al., 2011), such as the inappropriate use of emergency care and avoidable hospitalizations. On the supply side, deficits in health care provision, such as a lack of sufficient primary care infrastructure and social care in socially deprived areas, can not only lead to poor health outcomes but also worsen, or even cause, the problem of misplaced demand (Berkman et al., 2011; Schumacher

This is an open access article under the terms of the [Creative Commons Attribution-NonCommercial-NoDerivs](https://creativecommons.org/licenses/by-nc-nd/4.0/) License, which permits use and distribution in any medium, provided the original work is properly cited, the use is non-commercial and no modifications or adaptations are made.

© 2023 The Authors. Health Economics published by John Wiley & Sons Ltd.

et al., 2013). Misplaced demand, in turn, leads to inefficiencies in resource use and rising health care costs (Clancy, 2005; McCormack et al., 2017; Sundmacher et al., 2015).

These problems can only be addressed over the long term if the causative factors on both the demand and supply sides are taken into account (Saini et al., 2017). One solution that has received particular attention over the past two decades is the so-called integration of care. By fostering alignment and coordination across services including primary, community, hospital and tertiary care, as well as social care, education and housing, integrated care aims to reduce fragmentation in health care provision, directing demand to the appropriate places to prevent unnecessary hospitalizations, improve health outcomes and reduce costs (Hughes et al., 2020). Especially in socially deprived areas, patients often do not distinguish between social and medical problems when seeking help from medical providers (Cawston, 2011). Thus, the integration of medical and social care is needed to help ensure that patients' concerns are addressed adequately by providers with the appropriate competence and expertise (Valentijn et al., 2013).

Although population-based integrated care interventions tailored to the characteristics and needs of a population are considered to have substantial potential to improve care in such areas (Baxter et al., 2018; Valentijn et al., 2013), empirical evidence on their effects is sparse and characterized by methodological limitations such as relying purely on parametric methods and small numbers of observed characteristics to control for confounders. Previous findings on integrated care interventions are also limited in terms of their generalizability and transferability due to differences in the design of the interventions and the health care systems in which they were implemented. In particular, because the components of such interventions are often not clearly elucidated in the literature, the causal interpretation of the results is limited (Ouwens et al., 2005). This problem is particularly relevant in the context of integrated care, which frequently entails very complex interventions (themselves containing many sub-interventions). If an empirical model does not allow for disentangling the effect of these sub-interventions, it will capture only the overall effect and will fail to examine channels through which these may influence health care utilization and costs.

In the present study, we aimed to assess the impact of a large-scale integrated care initiative designed to improve health care in a socially deprived urban area in Germany. To do so, we empirically investigated the effects of the two sub-interventions that comprise the initiative on health care utilization and costs using administrative data. The two sub-interventions are (1) a cross-sectoral network of health, social and community care providers and (2) a community health advice and navigation service. We first investigated the two sub-interventions theoretically, identified the instruments in both and, based on previous evidence, explored their potential effects on health care utilization and costs. In our empirical model, we subsequently analyzed the effects of the two sub-interventions separately using a treatment and control group for each. To do so, we used a longitudinal data set (years 2015–2019) of insurance claims and applied an empirical methodology that allowed us to estimate the treatment effect on population-level health care utilization and costs. This comprised propensity score matching based on propensity scores estimated by the Super Learner machine learning algorithm (van der Laan et al., 2007) followed by difference-in-differences analyses within an event-study framework to compare changes for treated and control patients over time and to identify causal effects.

Our work adds to the literature in several ways. First, our approach allowed us to disentangle the effects of the sub-interventions and investigate the channels through which the overall initiative affects health care use and costs, thus making an innovative contribution to the causal interpretation of such results. Second, the use of an event-study framework allowed us to inspect the parallel trend assumption and deal with treatment effect heterogeneity by capturing the dynamic effects of the intervention over time. Third, we sought to address some of the methodological limitations of previous research on integrated care by employing the Super Learner algorithm, which does not rely on a parametric model and can use a wide range of measures as potential control variables. By matching intervention and control patients, we aimed to reduce bias due to confounding and make the groups comparable. Fourth, by studying an initiative targeted at a socially deprived area, we went beyond previous research on this setting, most of which focuses on correlations rather than causation.

Our results show that, for patients who had at least one visit with a physician involved in the cross-sector network of health, social and community care providers (i.e., the first sub-intervention), the integrated care initiative significantly increased the number of hospital admissions, emergency admissions and non-hospital outpatient visits, as well as inpatient, non-hospital outpatient and total costs. Patients who additionally used the community health advice and navigation service (i.e., the second sub-intervention) had a further increase in non-hospital outpatient visits and in non-hospital outpatient and total costs. All effects were more pronounced in the later quarters of our observation period. We did not observe statistically significant effects of the intervention on ambulatory-care-sensitive hospital admissions, hospital outpatient visits or hospital outpatient cost.

The rest of the paper is organized as follows. Section 2 briefly introduces the setting, the integrated care initiative under investigation, and the initiative's two sub-interventions. Section 3 summarizes prior evidence on integrated care initiatives in socially deprived areas and on the individual instruments employed in these initiatives. Section 4 describes the data and the propensity score matching approach. Section 5 presents the empirical strategy and Section 6 the results. Finally, Section 7 discusses the results and Section 8 concludes.

2 | INTEGRATED CARE INITIATIVE

The various sectors of the German health system are organized differently in terms of planning, financing, organization and governance, and the resulting fragmentation has been increasingly seen as a barrier to high-quality health care. Over the past two decades, pilot projects testing new integrated care interventions have aimed to overcome such barriers by improving coordination and cooperation among ambulatory physicians, hospitals and providers of social and community care. This trend toward the integration of care can be observed across mid-to-high-income nations, for example, in Patient-Centered Medical Homes and Accountable Care Organizations in the United States, Family Medicine Groups in Canada and Integrated Care Boards and associated initiatives in England (Alderwick et al., 2021; Barnes et al., 2014; David et al., 2018; Strumpf et al., 2017).

The present study was part of a larger research project evaluating one such pilot project, which was launched in Germany in 2017 in a deprived urban area in the city of Hamburg. The area has a population of about 110,000 people and is one of the poorest in Hamburg, with a mean income more than 40% below the city's average. It is characterized by a disproportionately high number of residents from socioeconomically deprived groups, including unemployed individuals, migrants and single parents.

To address the social gradient of health in this area, the project aims to reduce inequities in health caused by social circumstances, increase the health opportunities of the population, improve patient experience and satisfaction, and optimize the use of resources. To achieve this, the initiative employs two interrelated sub-interventions. The first of these is a **cross-sector network of health, social and community care providers**, which was established to provide patient-centered and efficient care. This sub-intervention focuses on the supply side, specifically targeting the providers of services and thus the supply of these services. A wide range of providers is involved, and cooperation agreements formalize the network. In addition to network meetings aiming to initiate and improve collaboration between providers, health professionals are offered training on a range of topics. The second sub-intervention is a **community health advice and navigation service** offering patients health advice and education by community health nurses in multiple languages. This sub-intervention targets both the supply and demand side of health care services, not only targeting providers and the supply of care, but also patients and their demand for services. In addition to one-on-one sessions, the service offers group interventions and support in finding and arranging appointments with local services and health care professionals through various channels, such as personal consultations, information events, flyers and hyperlinks on the service website. Individuals can book appointments with the service directly, or physicians or social care institutions can refer them to it by means of social prescribing. The cross-sector network and the community health advice and navigation service are intended to be in regular communication with each other, for example, through clinical case discussions and cross-sectoral coordination of individual patients' care. This approach aims to enable integrated care throughout the patient pathway. The sub-interventions, in turn, encompass multiple instruments, which are summarized in Figure 1. These instruments are intended to have a system-wide effect when used together, and thus interactive and multiplicative joint impact mechanisms are to be expected.

The integrated care initiative was rolled out uniformly in the fourth quarter of 2017 across all relevant postal codes in the area in question. The target group of the initiative comprises all residents of the area and therefore follows a population-based rather than indication-based approach. All of the services offered as part of the initiative are free at point of use and are open to

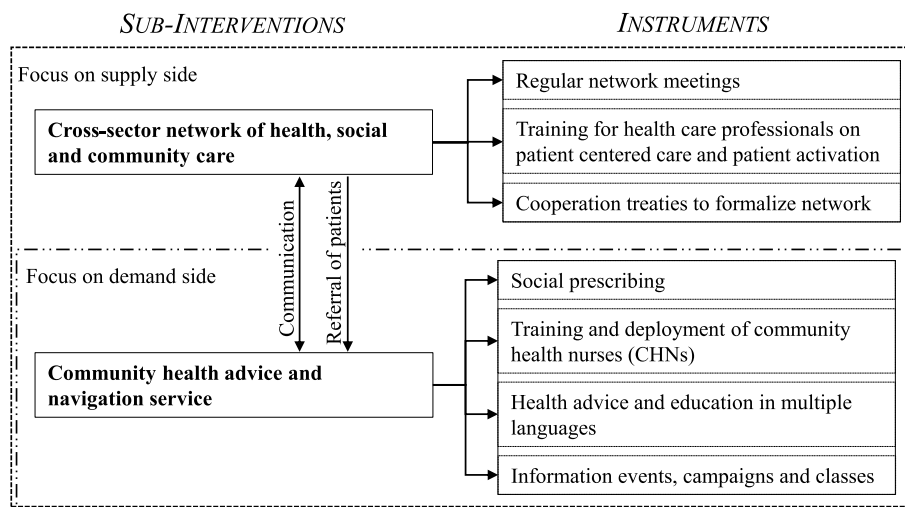


FIGURE 1 Overview of the integrated care initiative with its two sub-interventions and their instruments.

all residents of the target area. Individuals who wish to use any of the services have to enroll in the integrated care initiative as a whole. Doing so is voluntary and free of charge. Enrollment can take place either at the office of a physician involved in the network or at the community health advice and navigation center.

3 | LITERATURE REVIEW

3.1 | Evidence on effects of integrated care initiatives on health care utilization and costs in socially deprived areas

The results of earlier studies indicate that integrated care may improve the quality of and access to health care, but evidence with regard to costs and health outcomes remains inconsistent (Baxter et al., 2018; Damery et al., 2016; Hughes et al., 2020; Ouwens et al., 2005; Rocks et al., 2020). Moreover, very few studies of integrated care have focused exclusively on socially deprived areas, whose residents experience different circumstances (e.g., related to access to care or to language and cultural barriers) and may have different needs (e.g., multiple health and social care needs). This is unfortunate given that socially deprived populations may respond differently to such interventions. Goldzahl et al. (2022) assessed the effect of multi-disciplinary group meetings to discuss elderly high-risk patients in a socio-economically deprived area in England using longitudinal survey data and employing a triple difference-in-differences analysis after performing propensity score matching. The authors found that the intervention reduced the probability of primary care nurse visits and decreased the length of stay after emergency care admissions, but increased the use of planned hospital care, possibly due to the detection of unmet needs. Because primary care utilization was measured using survey data, however, their results should be interpreted with caution.

Berkowitz et al. (2018) examined a care coordination model with integrated behavioral health care provided in collaboration with community-based organizations in a deprived urban area in the United States. The authors observed a significant reduction in hospital care utilization and health care costs in the high-risk Medicaid subpopulation, which is considered to be affected the strongest by social determinants of health, and no significant effect on any outcome for the Medicare population. The authors used propensity score weighting and matching to create comparable intervention and control groups and employed a difference-in-differences analysis. However, the authors note that their selection of the control group may have biased the results, and only a small number of covariates was used for propensity score matching based on logistic regression.

Kringos et al. (2016) assessed the effect of a comprehensive integrated care intervention in a socially deprived neighborhood in the Netherlands on utilization patterns for general practice and hospital care. To do so, the authors compared the expected and actual health care utilization in the intervention and control groups over time. The authors found evidence that substituting primary care for hospital care was possible: analysis of utilization patterns showed an increase in the use of general practitioner (GP) services and a decrease in hospital use. The authors were unable to include utilization data for all providers or data on medication, however, and some of the confounders were aggregated at the district level.

3.2 | Evidence on effects of selected instruments employed by previous integrated care initiatives on health care utilization and costs

The field of integrated care is characterized by initiatives that use a wide range of instruments, limiting their comparability. In this section, we gather evidence from the current literature to elucidate, in an evidence-based manner, the mode of action of the instruments employed in our specific setting. It should be noted that the evidence we outline is not exhaustive, and other initiatives may use different instruments.

An instrument that might influence the *supply* of health care services in the initiative under investigation is the development of provider networks. These are often designed to promote greater professional collaboration and the exchange of knowledge, thus facilitating access to primary care and reducing the use of hospital services. In networks, providers are more strongly connected to one another, and the level of communication and coordination is higher, creating a positive working environment and fostering provider knowledge (Brown et al., 2016), which may result in a lower rate of physicians leaving their jobs or medicine altogether. On a smaller scale, access to primary care services can be improved by integrating providers and fostering teamwork within practices (Loussouarn et al., 2021). Thus, improving provider integration and job satisfaction can help lower the risk of shortages of professionals and ensure timely access to primary care, which in turn can reduce the number of emergency room visits and hospital admissions (Dolton & Pathania, 2016; Lippi Bruni et al., 2016).

Social and community care, patient-centered care and care coordination are instruments that could influence both the *supply* and *demand* of health care services in the integrated care initiative under investigation. Social and community care can improve

health care delivery and either reduce or increase health care costs and utilization depending on the degree of unmet needs in a given population. In one intervention in England, community health workers supported primary health care teams in a deprived urban area by addressing primarily social problems; this was associated with a reduction in the number of GP consultations and generally more appropriate use of primary care services (Abbott and Davidson, 2000). An earlier study of the same non-clinical community health advice and navigation service examined in the present investigation found that this easily accessible first point of contact might improve access to the health system, reduce unmet care needs and increase demand (Wild et al., 2022). In this separate study, which aimed to assess the effect of the integrated care initiative on the demand for GP visits, the role of the cross-sector network of providers was not considered. Moreover, the study included a more restrictive subset of the population compared to that in our analysis.

Community health workers are considered especially effective when they share ethnicity, language, socioeconomic status, and life experiences with the communities they serve (Hartzler et al., 2018). A literature review on the subject of partnerships in health and social care found that these were able to improve access to services in vulnerable communities and enable the development of new services to meet unmet needs, which could also lead to an increase in health care utilization and costs (Rummery, 2009). Another way to incorporate social and community services into health care provision is by social prescribing, which allows primary care professionals to send patients to social and community services (Bickerdike et al., 2017; Golubinski et al., 2020). A systematic review of social prescribing schemes in the United Kingdom showed decreases in health care utilization and improved patient outcomes, but evidence on costs was not clear (Bickerdike et al., 2017). In turn, patient-centered care, which implies that patient preferences are respected and patients are enabled to make informed decisions, has the potential to decrease health care utilization and costs. A systematic literature review on patient-centered care showed that increased patient satisfaction, patient activation and adherence can result in decreased acute care utilization and cost savings by preventing overuse and underuse of services while increasing the overall quality of care (Rathert et al., 2013). The effect of care coordination on health care utilization and costs remains unclear, with previous studies reporting varying findings. One study assessing a program for high-risk patients that included patient education and care coordination observed reductions in the use of hospital and emergency care (David et al., 2019), whereas a systematic review and meta-analysis on the effectiveness of case management in primary care for at-risk patients reported a significant increase in self-reported health and patient satisfaction, but no change in costs or utilization (Stokes et al., 2015). However, additional subgroup analyses indicated that effectiveness increased when case management was delivered by a multidisciplinary team or in an initially weak primary care setting, or when a social worker was involved (Stokes et al., 2015).

Lastly, an instrument that might influence the *demand* for health care services in the integrated care initiative under investigation is patient education. Educating and engaging patients and equipping them with the skills to manage their health can reduce health care costs and utilization. A scoping review of education interventions for patients with chronic illness found that patient education can reduce health care utilization and cut costs (Stenberg et al., 2018). A similar finding was reported in a study investigating a community-based intervention that provided chronic disease self-management support within peer-led group-based workshops and which reduced emergency room visits and hospitalizations and led to cost savings (Ahn et al., 2013). Additionally, individuals who are more actively engaged in their health care are less likely to visit the emergency department and have lower costs (Hibbard & Greene, 2013).

Based on this evidence, we expected that the integrated care initiative in Hamburg would lead to changes that affect both user and provider behavior, and therefore also health care utilization and costs. While previous evidence suggests that education, patient engagement, provider networks and patient-centeredness are likely to reduce health care utilization and costs, evidence on the effect of incorporating social and community care and care coordination on these outcomes is ambiguous. Although many factors seen as beneficial for a successful intervention are present in the integrated care initiative under investigation (e.g., an intervention targeted to the population's needs and involving community workers who share patients' languages and ethnicities), it remains unclear how the findings for similar interventions translate to the setting and intervention we consider. A decrease in health care utilization or a shift of inpatient activity to primary care as a result of more appropriate care is conceivable (Kringos et al., 2016), but so too is an increase in utilization due to the identification of previously unmet patient needs (Damery et al., 2016; Rummery, 2009).

4 | DATA

4.1 | Data sources and key variables

We used administrative data from three participating statutory health insurers covering the period from January 1, 2015 to December 31, 2019. The data contained exhaustive information on inpatient and outpatient costs, health care utilization,

prescriptions, nursing care and demographics for 556,911 residents throughout Hamburg who were continuously insured with one of the three insurers. We considered data from the first quarter of the year 2015 to the third quarter of 2017 to be pre-treatment and data from the fourth quarter of 2017 to the fourth quarter of 2019 to be post-treatment as the integrated care initiative was rolled out in the fourth quarter of 2017.

In line with related research (Ding et al., 2021; Strumpf et al., 2017), we measured health care utilization and costs in a multidimensional manner using a set of dependent variables. To measure *health care utilization*, we considered the number of: hospital admissions overall, admissions for ambulatory-care-sensitive conditions (ACSCs) (Sundmacher et al., 2015), emergency admissions (Krämer et al., 2019), non-hospital outpatient visits, and hospital outpatient visits. We classified an admission as being for an ACSC if the primary diagnosis was among the 22 core ACSC groups proposed for the German context by Sundmacher et al. (2015). Similarly, we classified an admission as an emergency admission if the primary diagnosis could be categorized as urgent based on the model developed by Krämer et al. (2019). Non-hospital outpatient visits in Germany encompass both office-based primary care and office-based specialist care. To measure *health care costs*, we considered inpatient, non-hospital outpatient, hospital outpatient and total costs per patient in euros from the insurer perspective. All measures were per person per quarter/year. The exact definitions of these outcome variables are reported in Appendix A1.

4.2 | Construction and description of the analysis samples

Using postal codes, we identified 49,959 individuals aged 18 or above who lived in the intervention's socially deprived target area. The effects of the individual instruments cannot be considered in isolation from each other, and we refrained from an analysis at the instrument level in our study. The focus of our empirical analysis was therefore on the two sub-interventions, which can be clearly distinguished from one another in their mode of action and their characteristics. To assess the effect of the cross-sector network of health, social and community care providers (i.e., the first sub-intervention), we identified a subset of 38,360 individuals who had at least one non-hospital outpatient visit in the post-treatment period and did not use the community health advice and navigation service. Our outcome measure comprising the number of non-hospital outpatient visits included the index visit among these. The index visit was the visit we used to determine whether a patient belonged to the intervention or the control group. 16,199 of these individuals had at least one non-hospital outpatient visit with a physician involved in the cross-sector network. These observations formed the first intervention group (IG_1). The observations of the remaining individuals, who had no visits with a physician involved in the network formed the control group (CG_1). Additionally, to assess the impact of the community health advice and navigation service (i.e., the second sub-intervention), we identified 1029 individuals from the target area who had at least one non-hospital outpatient visit with a physician involved in the cross-sector network and also used the community health advice and navigation service at least once during the observation period (IG_2). We then compared them to the individuals who had at least one non-hospital outpatient visit with a physician involved in the cross-sector network and did not use the health advice and navigation service (i.e., $IG_1 = CG_2$). See Figure 2 for an overview of the intervention and control group definitions and group sizes.

Individuals in the target area can choose their physicians freely and probably do so without considering whether the physicians are involved in the cross-sector network. In contrast, physicians self-select into this sub-intervention. As a consequence,

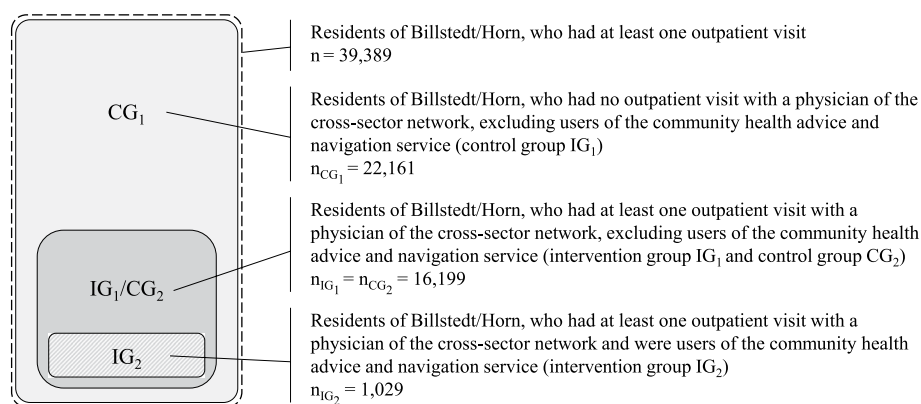


FIGURE 2 Definitions of intervention and control groups. We used negative binomial models for utilization and generalized linear models (GLM) for costs, and report the marginal effects for the difference-in-differences (DiD) estimates. Utilization was measured as the number of admissions/visits per person per quarter and cost was measured in euros per person per quarter.

individuals' choice of physicians may be guided by correlated features, and we therefore cannot assume that they were randomly assigned to this sub-intervention. For the second sub-intervention (i.e., the community health advice and navigation service), the self-selection of patients into the treatment leads to treated and untreated patients not being comparable. To address these issues, we first performed matching to make the treatment and control groups comparable and control for selection bias. Because the issue remains that physicians who are involved in the cross-sector network and those who are not involved would not treat the same patient similarly even in the absence of the intervention, we performed difference-in-differences analysis based on the matched patient groups.

For matching, we used a propensity score method based on radius matching. For this approach, all control observations within a given radius around an intervention observation are used to construct its match. This helps avoid bad matches by automatically imposing the common support condition, and it reduces variance by using more than one observation to construct the matches (Caliendo & Kopeinig, 2008). Following Baser (2006), we chose a radius size equal to one-fourth of the standard error of the propensity score, resulting in a radius size of 0.0003 for the matching of IG₁ and a radius size of 0.0001 for the matching of IG₂. Although control observations with too much weight should be trimmed to avoid them dominating the estimator and its variance (Huber et al., 2013), this was not necessary in our case because the large number of comparable control observations meant that the weights did not exceed a relative value of 0.15%. We performed the matching procedures using the *psmatch2* command in Stata MP 15.1.

We used all of the information available in the administrative data set to adjust for individuals' health status and underlying confounders. Although the propensity score would ideally include all variables that influence both treatment selection and outcome (Caliendo & Kopeinig, 2008), there is no a priori knowledge about which variables satisfied this condition. Table 1 provides an overview of the 6466 variables we used to estimate the propensity score. For each individual, we included diagnosis data in the propensity score model as variables that captured the frequency with which each three-digit International

TABLE 1 Variables used for propensity score estimation.

Group	Variables	Number of variables
Characteristics of insured individuals	Gender, age, occupational group, ...	7
Health care programs	Participation in integrated care program	1
	Participation in one of six disease management programs	6
Work incapacity	Number of days	1
	Cost	1
Inpatient	Frequency of diagnoses (3-digit ICD codes)	1611
	Frequency of procedures and diagnostics (4-digit OPS codes)	1569
	Days in hospital	1
	Number of hospital admissions	1
	Number of emergency admissions	1
	Number of admissions due to ambulatory-care-sensitive conditions	1
	Cost	1
Outpatient	Frequency of diagnoses (3-digit ICD codes)	1691
	Frequency of procedures and diagnostics (4-digit OPS codes)	806
	Number of non-hospital outpatient visits	1
	Number of hospital outpatient visits	1
	Non-hospital outpatient cost	1
	Hospital outpatient cost	1
Medication	Frequency of medication prescriptions (5-digit ATC codes)	756
	Cost	1
Nursing care	Days of nursing care per nursing level	5
	Cost	1
	Total cost	1

Note: All variables were calculated based on data from the first quarter of 2015 to the third quarter of 2017.

Abbreviations: ATC, Anatomical Therapeutic Chemical Classification System; ICD, International Classification of Diseases; OPS, Operationen- und Prozedurenschlüssel, German Operation and Procedure Classification System.

Classification of Diseases (ICD) code was coded for that individual from the first quarter of 2015 to the third quarter of 2017 for the inpatient and again separately for the outpatient setting. We followed the same procedure to capture the frequency with which four-digit Operationen- und Prozedurenschlüssel, German Operation and Procedure Classification System (OPS) codes and five-digit Anatomical Therapeutic Chemical Classification System (ATC) codes were used. If a code was not used at all across the population, adjustment was neither possible nor necessary, and we dropped the variable. As a result, the number of ICD and OPS codes differs between the inpatient and outpatient settings.

To estimate the propensity score, we used the Super Learner (van der Laan et al., 2007), a weighted ensemble of multiple base learners that can include both parametric (i.e., regression) and non-parametric (i.e., random forest) approaches, thus minimizing the reliance on parametric modeling assumptions. The weights of the base learners are computed by minimizing a specified loss function using V-fold cross-validation (van der Laan et al., 2007). The Super Learner performs at least as well as the best base learner included in the ensemble (van der Laan et al., 2007). While logistic regression remains the standard approach for estimating the propensity score, Super Learner estimates can reduce bias and improve covariate balance in case of model misspecification (Pirracchio et al., 2015). We ran the computations using the *SuperLearner* package (Polley et al., 2021) in R version 4.0.0. We included the following five algorithms as base learners: mean, generalized linear model with penalized maximum likelihood (*glmnet* function) (Friedman et al., 2010), random forest (*ranger* function) (Wright & Ziegler, 2017), gradient boosting (*xgboost* function) (Chen et al., 2015), and classification and regression trees (*rpart* function) (Breiman et al., 2017). All functions were used with the default parameters. We used 10-fold cross-validation, minimizing non-negative least squares normalized to one to estimate the base learner weights (van der Laan et al., 2007).

The common support assumption is central to propensity score matching (Rosenbaum & Rubin, 1983) and was assessed graphically by examining whether the propensity scores of the intervention and the control groups overlapped, which was indeed the case (see Appendix A2 for the propensity score distributions). By using radius matching, we restricted our analysis by definition to observations that were within the common support region.

Table 2 shows descriptive characteristics for age, gender and the measures used as outcomes before and after matching on the propensity score. Almost all differences between the intervention and control groups were statistically significant before the propensity score procedure. For both IG₁ and IG₂, the matching procedure decreased mean health care utilization and costs compared to the values beforehand, whereas the means increased in the corresponding control groups. For some variables, the means were significantly higher in the control group than in the intervention group after matching. These differences were, however, no reason for concern because we subsequently applied a difference-in-differences approach to the matched data, allowing us to eliminate the remaining differences between the groups.

5 | EMPIRICAL FRAMEWORK

For our baseline model, we used a 2×2 (two groups, two periods) difference-in-differences (DiD) approach with two-way fixed effects to estimate the average effect of the intervention on health care utilization and costs. The DiD specification took the form:

$$Y_{it} = \alpha + \beta \text{Group}_i * \text{Post}_t + \alpha_g + \alpha_t + \varepsilon_{it},$$

where Y_{it} denoted the outcome for individual i in period t , and Group_i and Post_t were binary variables indicating the treatment group and the post-treatment period, α_g was group fixed effects, α_t was year-by-quarter fixed effects and ε_{it} was the additive time-varying error term. The interaction of the binary variables for post-treatment and intervention group $\text{Group}_i * \text{Post}_t$ is our primary variable of interest and equals one if an observation is in the intervention group and from the post-treatment period. Therefore β captures the effect of the intervention. We considered correlation within individuals over time and adjusted standard errors for individual-level clustering.

Cost and utilization data are typically non-negative and characterized by many zero values and skewness (Manning & Mullahy, 2001). In our data, the measures had non-negative values, the proportion of zeros was especially high for hospital admissions due to ACSCs (92.3%) and for emergency admissions (90.7%), and the distributions were right-skewed with long tails. To account for the distribution of our data, we used generalized linear models (GLM) with a gamma family and log link for the analysis of cost measures. For the analysis of utilization measures, we used negative binomial regression.

In our main model, we used a DiD approach within an event-study framework to estimate the effects of the intervention over time. The event-study DiD has two chief advantages over the baseline model. First, the estimation of pre-treatment intervention effects makes it possible to inspect the parallel trend assumption, which states that, in the absence of treatment, the outcome of

T A B L E 2 Baseline characteristics for age, gender, and the measures used as outcomes before and after matching.

Variables	Matching of IG ₁			Matching of IG ₂						
	Unmatched		Matched	Unmatched		Matched				
	IG ₁	CG ₁	IG ₁	Mean (SD)	CG ₁	IG ₂	Mean (SD)	CG ₂	IG ₂	Mean (SD)
Age	53.44 (19.01)	49.79 (19.01)	52.79 (18.97)	52.95 (19.01)	53.44 (14.94)	55.54 (15.18)	53.44 (19.01)	55.59 (15.18)	56.13 (17.94)	
Male	0.45 (0.50)	0.48 (0.50)	0.45 (0.50)	0.46 (0.50)	0.45 (0.46)	0.32 (0.47)	0.45 (0.50)	0.32 (0.47)	0.37 (0.48)	
Number of hospital admissions (per person per year)	0.33 (0.60)	0.26 (0.54)	0.31 (0.59)	0.33 (0.61)	0.45 (0.64)	0.43 (0.61)	0.33 (0.60)	0.43 (0.61)	0.45 (0.72)	
Number of emergency admissions (per person per year)	0.11 (0.36)	0.11 (0.38)	0.10 (0.35)	0.11 (0.35)	0.11 (0.37)	0.12 (0.35)	0.11 (0.36)	0.12 (0.35)	0.16 (0.45)	
Number of ambulatory-care-sensitive admissions (per person per year)	0.10 (0.34)	0.10 (0.38)	0.09 (0.33)	0.10 (0.34)	0.14 (0.37)	0.13 (0.36)	0.10 (0.34)	0.13 (0.36)	0.15 (0.44)	
Number of non-hospital outpatient visits (per person per year)	15.82 (13.34)	12.06 (13.43)	15.07 (12.94)	15.38 (13.52)	21.98 (16.02)	20.84 (15.04)	15.82 (13.34)	20.84 (15.04)	20.27 (15.85)	
Number of hospital outpatient visits (per person per year)	0.11 (0.43)	0.08 (0.35)	0.10 (0.42)	0.10 (0.42)	0.19 (0.59)	0.18 (0.58)	0.11 (0.43)	0.18 (0.58)	0.15 (0.52)	
Inpatient costs (£ per person per year)	1012.15 (8080.70)	781.34 (1857.14)	980.56 (8261.60)	1130.01 (4858.49)	1205.52 (2583.5)	1163.69 (2584.00)	1012.15 (8080.70)	1163.69 (2584.00)	1345.69 (3456.41)	
Non-hospital outpatient costs (£ per person per year)	757.53 (1124.87)	578.61 (1173.40)	720.00 (1127.49)	752.88 (1280.96)	1116.48 (1400.39)	1059.06 (1394.53)	757.53 (1124.87)	1059.06 (1394.53)	1029.45 (1637.84)	
Hospital outpatient costs (£ per person per year)	29.67 (131.27)	23.31 (139.12)	28.69 (129.05)	30.26 (151.89)	59.10 (205.85)	56.96 (206.01)	29.67 (131.27)	56.96 (206.01)	45.14 (168.65)	
Total costs (£ per person per year)	2971.84 (10,727.41)	2290.73 (6836.91)	2832.84 (10,898.70)	3023.927 (7370.02)	3430.82 (4452.96)	3281.10 (4410.11)	2971.84 (10,727.41)	3281.10 (4410.11)	3971.75 (7286.01)	
N	16,199	22,161	15,352	18,915	1029	961	16,199	16,199	13,088	

Note: Due to the large number of variables used to estimate the propensity score, other variables are omitted from the table. All of the variables shown except for inpatient costs in the matching of IG₂ were significantly different at $p \leq 0.05$ before matching. Underlined numbers were significantly different at $p \leq 0.05$ after matching.

interest in the intervention and control groups would have followed a similar trend over time. Second, the event-study DiD is able to deal with treatment effect heterogeneity and captures the dynamic effects of the intervention over time. The following equation was estimated:

$$Y_{it} = \alpha + \sum_{\substack{v=-10 \\ v \neq 0}}^9 \beta_v \text{Group}_i * \text{Time}_v + \alpha_g + \alpha_t + \varepsilon_{it}$$

where Y_{it} , Group_i , α_g and α_t were defined in the same way as above. The indicator variables Time_v indicate the relative quarter-by-year of an observation to last quarter-by-year before the implementation of the intervention in the fourth quarter of 2017. Our parameters of interest are β_v , which capture the temporal effects of the intervention by comparing the difference in outcomes between intervention and control groups to such a difference in the reference quarter-by-year (third quarter of year 2017). As above, standard errors were clustered at the individual level and we estimated GLM with a gamma family and log link for cost measures and negative binomial regression for utilization measures.

6 | RESULTS

Table 2 presents summary statistics for the measures of health care utilization and cost, as well as for age and gender, in the intervention and control groups at baseline. In the matched sample 1, the mean age was around 53 years and about 45% of the observations were from men. On average, individuals who used the community health advice and navigation service (IG₂) were older and more likely to be female than individuals who did not use the service (CG₂). Baseline utilization of health care services was higher on average in IG₂ than in IG₁, and the same applies to costs.

6.1 | Results of the 2 × 2 DiD analyses

In Table 3 we present the 2 × 2 DiD estimates as incremental effects (i.e., average marginal effects for the binary independent variables) to facilitate interpretation. The DiD estimates represent the average treatment effect per person per quarter. The results indicate that for patients who had at least one visit with a provider involved in the cross-sector network of health, social and community care providers (IG₁), both health care utilization and costs increased, compared to patients who had no visit with a provider in the network (CG₁). The number of overall hospital admissions increased by 0.016 admissions per person per quarter and the number of emergency admissions by 0.005 admissions per person per quarter. These represent increases

TABLE 3 Estimated intervention effect on health care utilization and cost based on 2 × 2 DiD analyses.

	IG ₁ versus CG ₁			IG ₂ versus CG ₂		
	DiD marginal effect estimate	SE	p-value	DiD marginal effect estimate	SE	p-value
Utilization						
Hospital admissions	0.016***	0.003	<0.001	0.022**	0.008	0.005
Emergency admissions	0.005**	0.002	0.006	0.009*	0.004	0.040
Ambulatory-care-sensitive admissions	0.003	0.002	0.085	0.007	0.004	0.070
Non-hospital outpatient visits	0.506***	0.047	<0.001	0.906***	0.113	<0.001
Hospital outpatient visits	0.007**	0.002	0.002	0.014*	0.007	0.046
Costs						
Inpatient	67.588**	24.404	0.006	30.587	42.582	0.473
Non-hospital outpatient	23.012***	5.720	<0.001	49.307***	13.220	<0.001
Hospital outpatient	2.532**	0.829	0.002	2.151	2.278	0.345
Total	146.346***	33.845	<0.001	118.821	73.153	0.104

Note: DiD, difference-in-differences; SE, (cluster-robust) standard errors. We used negative binomial models for utilization and generalized linear models for costs, and report the marginal effects for the DiD estimates. Utilization was measured as the number of admissions/visits per person per quarter and cost was measured in euros per person per quarter.

*p-value <0.05; **p-value <0.01; ***p-value <0.001.

of 21% and 20%, respectively, compared to pre-intervention levels. In contrast, we found no statistically significant effect on the number of admissions for ambulatory-care-sensitive conditions. The number of outpatient visits increased by 0.506 visits per person per quarter for non-hospital outpatient visits (+13%) and 0.007 visits per person per quarter for hospital outpatient visits (+28%). We observed statistically significant increases per person per quarter for all cost measures in the IG₁ group, with inpatient costs increasing by €67,888 (+28%), non-hospital outpatient costs by €23,012 (+13%), hospital outpatient costs by €2532 (+35%) and total costs by €146,346 (+21%). For individuals who used the community health advice and navigation service (IG₂), the number of hospital admissions increased by 0.022 admissions (+21%), emergency admissions increased by 0.009 admissions (+30%), non-hospital outpatient visits by 0.906 visits (+17%) and hospital outpatient visits by 0.014 visits (+31%), all per patient per quarter. Regarding the cost measures, only non-hospital outpatient costs increased significantly, by €49,307 per patient per quarter, representing a 19% increase compared to pre-intervention levels.

6.2 | Results of the event-study DiD analyses

The estimates of the DiD analyses within the event-study framework decompose the 2×2 DiD effects and capture the temporal effects of the intervention over time (estimates are presented in Appendix A3 and visualized in Figures 3 and 4). It is important to note that all effects are relative to the last quarter-by-year before the implementation of the intervention. Most coefficients for the pre-intervention quarters were statistically non-significant for both intervention groups, supporting the parallel trend assumption. The significant coefficients in the pre-period were for hospital admissions, hospital outpatient visits and the cost measures for IG₁ and for non-hospital outpatient visits for both IG₁ and IG₂. Although only a few coefficients were significantly different from zero, they are nevertheless grounds for caution when interpreting the results (additional analyses are presented in Section 6.3).

The significant coefficients for the post-intervention quarters suggest that, controlling for time trends common among intervention and control groups, the intervention increased the number of hospital admissions, emergency admissions, non-hospital outpatient visits, inpatient costs, non-hospital outpatient costs, and total costs for intervention group IG₁, with more prominent effects being seen in the later quarters. For intervention group IG₂, we observed increases in non-hospital outpatient visits and costs, as well as in total costs, with stronger effects again being seen in later quarters. By identifying patients who had at least one visit with a physician in the cross-sector network but did not consult the community health advice and navigation service and using them as a control group (IG₁, CG₂) we were able to assess the effect of the community health advice and navigation service independently from the effect of the cross-sector network. When interpreting these results, it is important to keep in mind that the effects are independent and need to be added together for patients who were reached by both sub-interventions. By design, we observed coefficients similar to those in the 2×2 DiD analyses. However, compared to the 2×2 DiD approach, far fewer data were used to calculate the coefficient for the treatment effect in each quarter, leading to less precise estimates with larger confidence intervals.

6.3 | Sensitivity analyses

We conducted a series of robustness checks to ensure the reliability of our results, see Appendix A4. We took into account that we analyzed multiple outcomes and adjusted our 2×2 DiD analyses for multiple hypothesis testing using the Romano-Wolf method (Romano & Wolf, 2016). This method controls for the family-wise error rate, that is, the probability of at least one type I error (rejection of true null hypothesis), within a family of outcomes at the desired significance level α . To do so, the Romano-Wolf method employs a step-down procedure and implicitly accounts for the dependence structure of the hypotheses by bootstrapping. We grouped variables measuring health care costs and variables measuring health care utilization into families and calculated adjusted p -values using the Stata command *rwolf* (Clarke et al., 2020). The DiD estimates were, by definition, not altered by this approach, and for IG₁ all increases in utilization and costs remained significant. For IG₂, the increases in hospital admissions, emergency admissions, non-hospital outpatient visits and non-hospital outpatient costs remained significant.

Our results were also robust to different specifications of the matching procedure and the propensity score. First, to check the robustness of our results to changes in the matching radius chosen for the main specification, we performed radius matching with the propensity score estimated by the Super Learner but varying the radius. The results were robust with regard to effect size, direction and significance in both the 2×2 DiD and the event-study DiD analyses. Second, to check the robustness of the results to the choice of variables used for matching and the use of the Super Learner, we estimated the propensity score with a logit regression on Elixhauser groups (Elixhauser et al., 1998) instead of ICD, OPS and ATC codes. The effects on most outcomes were very similar to those in the main specifications with regard to size, direction and significance. However, the

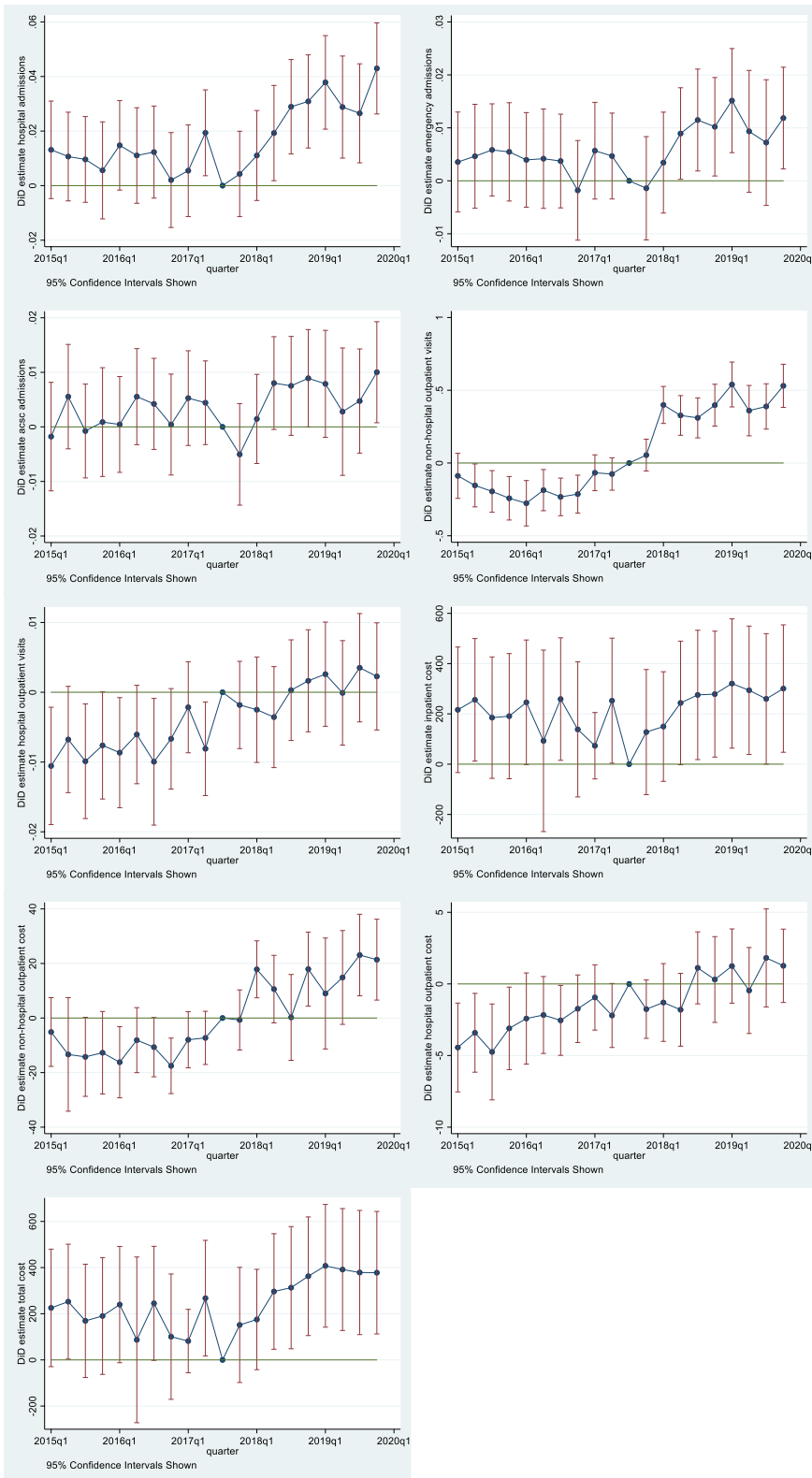
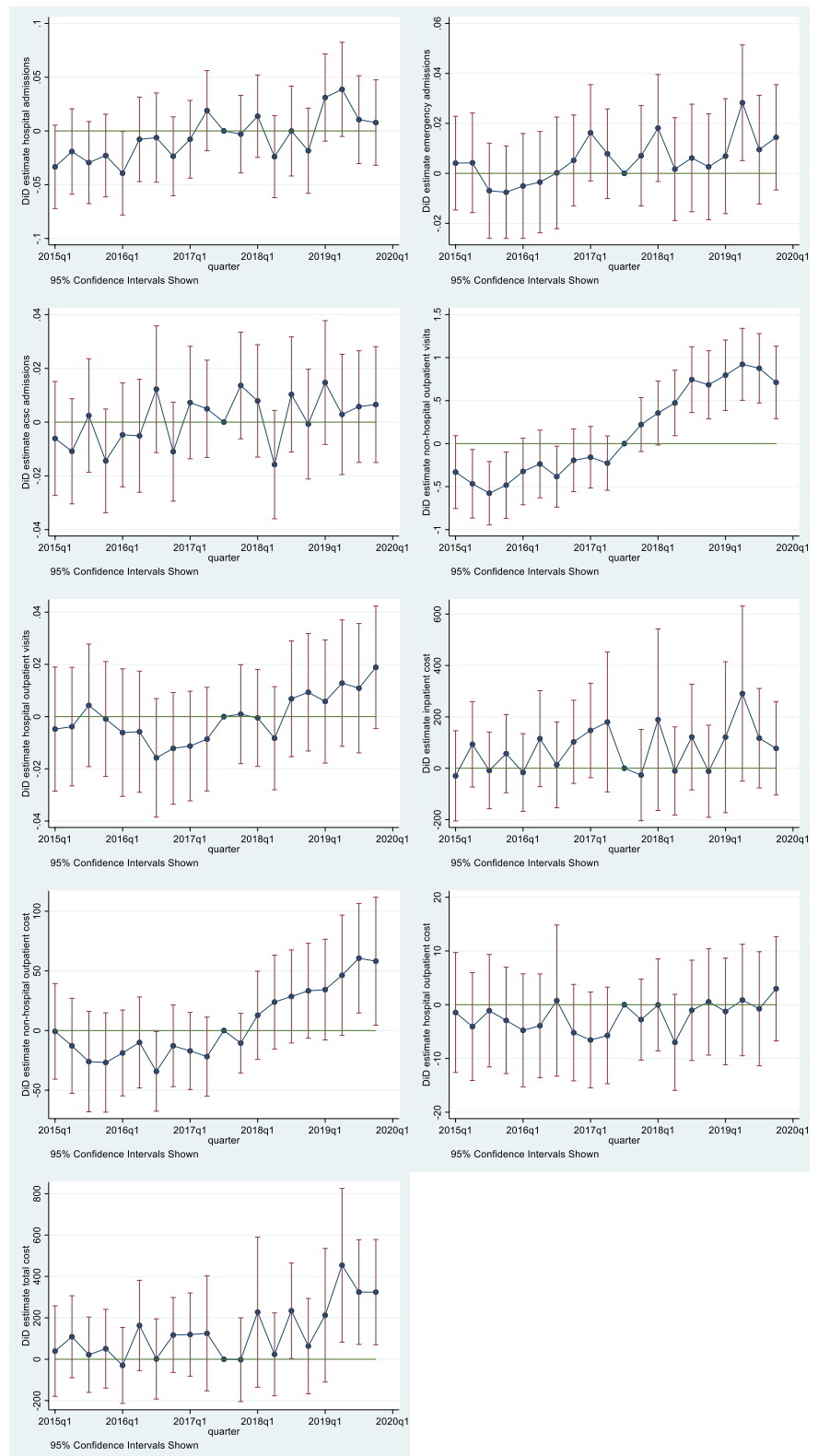


FIGURE 3 Event-study difference-in-differences (DiD) estimates for estimated intervention effect on health care utilization and costs for intervention group IG_1 versus CG_1 . We used negative binomial models for utilization and generalized linear models (GLM) for costs, and report the marginal effects for the DiD estimates. Utilization was measured as the number of admissions/visits per person per quarter and cost was measured in euros per person per quarter. [Colour figure can be viewed at wileyonlinelibrary.com]

effect on emergency visits for both IG_1 and IG_2 and inpatient costs for IG_1 was smaller and not statistically significant in the 2×2 DiD analyses. Third, we checked the robustness of the results by using entropy balancing (Hainmueller, 2012) instead of matching to achieve covariate balance. As before, we used a restricted set of variables with Elixhauser groups instead of ICD, OPS and ATC codes. The results of these analyses were robust with regard to effect size, direction and significance for most outcomes except emergency visits for both IG_1 and IG_2 and inpatient costs for IG_1 , which were again smaller and not significant in the 2×2 DiD analyses.

FIGURE 4 Event-study difference-in-differences (DiD) estimates for estimated intervention effect on health care utilization and costs for intervention group IG_2 versus CG_2 . We used negative binomial models for utilization and generalized linear models (GLM) for costs, and report the marginal effects for the DiD estimates. Utilization was measured as the number of admissions/visits per person per quarter and cost was measured in euros per person per quarter. [Colour figure can be viewed at wileyonlinelibrary.com]



We assessed the robustness of our event-study DiD analyses to potential violations of the parallel trend assumption by using the framework introduced by Rambachan and Roth (2023). This framework imposes restrictions on the magnitude of post-treatment deviations from the pre-treatment differences. Examining Figures 3 and 4 raised concerns regarding the violation of the parallel trend assumption due to long-term trends evolving smoothly over time. To address this, we incorporated smoothness restrictions by imposing a limitation on the extent to which post-treatment violations of parallel trends can deviate from a linear extrapolation of the pre-trend. For IG_1 , we found that the results pertaining to the utilization of health care services

were robust when assuming linear deviations from the parallel trend but not for non-linear deviations. Similarly, the results pertaining to costs were robust under the assumption of non-linear deviations from the parallel trend. For IG_2 , we observed that the results pertaining to non-hospital outpatient visits were robust only for linear violations of the parallel trend assumption, whereas those for non-hospital outpatient costs were robust for non-linear violations. For total cost, the results were robust neither for linear nor for non-linear violations of the parallel trend assumption.

We tested the robustness of our results for the effects of the community health advice and navigation service to the choice of intervention group. To do so, we changed the inclusion criterion for both intervention and control groups to patients who were not affected by the cross-sector network. Hence, the intervention group comprised all residents of the target area who did not have any non-hospital outpatient visits with a physician involved in the cross-sector network but who used the community health advice and navigation service at least once during the observation period (IG_3 ; $n = 240$). The control group comprised all residents of the target area who did not have any visits with a physician involved in the cross-sector network and who did not use the community health advice and navigation service ($CG_1 = CG_3$). For the 2×2 DiD analyses, all effects were in the same direction as those in the analyses that used IG_2 . The effect sizes, however, were larger compared to those observed for IG_2 for the number of emergency admissions and smaller for the number of non-hospital outpatient visits. Overall, due to the smaller sample size, fewer effects were significant with the exception of the number of hospital outpatient visits and hospital outpatient costs, both of which increased significantly for IG_3 . In the event-study DiD analyses, the quarterly effects for the number of non-hospital outpatient visits for IG_3 were very similar to those of IG_2 , but the effects were not statistically significant and the pre-trends less clear. For non-hospital outpatient costs, we observed no effect in the event-study DiD analyses for IG_3 , whereas there was a significant increase in total costs for IG_3 , which was slightly larger compared to the effect observed in the analyses for IG_2 .

7 | DISCUSSION

The aim of the present study was to assess the impact of a large-scale integrated care initiative designed to improve health care in a socially deprived urban area in Germany. We empirically investigated the effects of the two sub-interventions that comprise the initiative on health care utilization and costs using administrative data. A lack of sufficient health care services and inadequate targeting of care to the needs of the population are frequent problems in such areas (Berkman et al., 2011; Schumacher et al., 2013; Valentijn et al., 2013), resulting in poorer access to health care (Kontopantelis et al., 2010), overburdened providers (West et al., 2018), and unmet health and social care needs in the population (Goldzahl et al., 2022). With our analyses, we were able to disentangle the effects of the two sub-interventions and, in doing so, improve the causal interpretation and generalizability of the results. For the effect of the cross-sector network of health, social and community care providers, we found an increase in the number of hospital admissions, emergency admissions, and non-hospital outpatient visits, as well as in inpatient, non-hospital outpatient, and total costs. These effects were likely driven by changes on the supply side of health care services given that the main instruments in this sub-intervention are provider cooperation, network meetings and provider training. Our findings are in part reflected in previous studies. Goldzahl et al. (2022), for example, also observed increased utilization of some health care services due to multidisciplinary groups addressing the unmet needs of their patients. In our study, for patients additionally reached by the initiative's other sub-intervention—the community health advice and navigation service—we observed increases in the number of non-hospital outpatient visits and costs, as well as in total costs. These effects were probably driven by changes on both the demand and the supply sides of health care services because the main instruments of this sub-intervention involve social and community care, and patient education. Increases in health care utilization and costs have also been observed in previous studies that have assessed partnerships in health and social care (e.g., Rummery, 2009), whereas other studies have found reductions health care use (e.g., Abbott & Davidson, 2000). Importantly, both sub-interventions had similar but also additive effects. This means that patients who were reached by both sub-interventions had larger increases in costs and utilization compared to patients who were reached only by one.

The utilization of health care services is one possible measure of access to care, and earlier studies have interpreted increases in the utilization of outpatient care (and concomitant decreases in the utilization of inpatient care) as improved access to outpatient services (Andersen, 1995; Gulliford et al., 2002). Another measure of access to outpatient care based on utilization is hospitalization rates for ambulatory-care-sensitive conditions (Sundmacher et al., 2015). Especially in socially deprived areas, where people have poorer access to care compared to residents of more affluent areas, assessing whether an intervention improves access to care is important. Our results in this regard were mixed: whereas the number of outpatient visits increased in the intervention groups, suggesting improved access, the number of hospital admissions, especially those for ACSCs, failed to decrease. From our data, however, we were unable to determine whether the integrated care initiative or its two

sub-interventions actually addressed unmet need because it was not possible to determine which individuals needed medical services before the intervention and subsequently were able to gain access to appropriate care because of it.

To verify our results and enrich their interpretation, we discussed our findings with staff from the community health advice and navigation service, as well as with physicians from the cross-sector network, using short interviews. The staff reported that many users of the service (a) had medical problems, but did not know about their condition, (b) did not think a physician visit was necessary and waited until their condition worsened and they needed emergency care, or (c) did not use their physician's referrals to specialists. This suggests that there were shortcomings on the demand side of health care provision, such as misplaced demand and insufficient use of medical services, and that the users of the service were indeed in need of health and/or social care before the intervention. From the perspective of the staff at the health advice and navigation service, the main reasons for this were language barriers, inadequate knowledge of their conditions and the importance of treatment, and psychosocial factors such as a lack of trust in physicians. At the same time, the staff pointed out that there was a shortage of nearby specialists and that general practitioners were overburdened, indicating problems on the supply side as well. This was also reported by the physicians in the cross-sector network. In summary, our discussions with staff suggest that the initiative did indeed improve access to care for individuals who needed services before the initiative was implemented.

In contrast to many previous studies assessing integrated care in socially deprived areas (e.g., Berkowitz et al., 2018; Kringos et al., 2016), we did not find a decrease in hospital utilization, but rather an increase that we could attribute to the cross-sector network of health, social and community care providers. One possible explanation for this finding could be a change in the types of cases admitted to hospitals. However, additional analyses could not confirm this with our data. Examining the most frequent diagnoses over time, we observed no clear trends aside from the length of stay being shorter for the intervention group in the post-treatment period. It is also conceivable that the cross-sector network of providers improved access to care and, in doing so, identified unmet needs that resulted in hospital admissions (Baxter et al., 2018; Goldzahl et al., 2022). A third possible explanation for the increase in hospital admissions might be overburdened general practitioners and the shortage of nearby specialists described by the staff of the community health advice and navigation service, possibly leading to a redirection of patients to the hospital. Assuming that the integrated care initiative identified unmet medical needs, this explanation is quite plausible and was also confirmed in the interviews with physicians, who reported already being overburdened by their workload at the beginning of the initiative. This would have made it difficult for them to meet additional demand, leading to patients being redirected to the inpatient sector.

This being said, the integrated care initiative we investigated aims to address the problem of unmet needs. Therefore, the effects seen during our observation period may only be of a short-term nature. Over the long term, the impact of the initiative could change if the accumulated unmet needs are successfully addressed. Indeed, in the DiD analyses of the event studies, we observed heterogeneity in the treatment effect, which may suggest that the effect is changing over time.

Our study has a number of important limitations that must be considered when interpreting its results, but which additionally offer avenues for future research. First, we had no data on the costs of the integrated care initiative, limiting the informative value of our analyses regarding its cost-effectiveness. Moreover, our analyses were based on administrative data, so it was not possible to measure access to care directly, or to assess the initiative's impact on dimensions like patient satisfaction. Further research could therefore focus on long-term effects by investigating longer observation periods, considering the costs of the intervention, and evaluating soft outcomes based on survey data or qualitative approaches. Second, including variables in a propensity score model that are associated with treatment selection but not the outcome leads to balanced samples but may reduce the number of matched pairs that are found, in addition to increasing variance and, to a smaller degree, bias (Austin et al., 2007). At the same time, omitting variables that are simultaneously related to treatment and outcome may increase bias substantially (Austin et al., 2007). While the Super Learner allowed us to avoid (a) parametric assumptions and (b) using all of the available variables, we cannot know which variables were actually used to estimate the propensity score. As a result, we have no information about the variables on which the intervention and control groups were matched. Third, our event-study DiD and sensitivity analyses indicate that the assumption of parallel trends may not hold and is not robustly supported for all outcomes, particularly for outpatient outcomes in both intervention groups and total costs in IG₂. As a result, the findings related to these outcomes should be interpreted with caution because they may underestimate or overestimate the intervention effects. A fourth limitation relates to the transferability and generalizability of our results. Due to the setting, we were only able to compare the effect on residents who received the intervention to residents of the same socially deprived area who did not receive it. Using a comparative multi-case research design to compare residents in such areas who receive an intervention of this nature to people in more affluent areas who also received the intervention would make it possible to study whether and how the intervention effect varies depending on the target population. Lastly, while we defined the key instruments of the initiative and how we expected them to affect health care costs and utilization, we do not know whether the changes we observed were driven from the supply or demand side and cannot disentangle the effects of the individual instruments used in each of the initiative's

two sub-interventions. To overcome this limitation concerning the transferability of our results, further research is needed to assess the system-wide multiplicative effects of single instruments, like social prescribing or network meetings.

8 | CONCLUSION

In this study, we evaluated the impact of an integrated care initiative on health care utilization and costs in a socially deprived urban area. By targeting both the supply and demand sides of health care services and offering low-barrier integrated care, the initiative aims to improve the health opportunities of this population, as well as patient experience and satisfaction, and the use of available resources. We overcame the methodological limitations of the previous literature by using the Super Learner approach to estimate the propensity score while avoiding parametric assumptions and including a large set of variables. We performed propensity score matching for the intervention and control groups to address selection on observables and then used 2×2 and event-study difference-in-differences analyses to estimate the intervention effects on health care utilization and costs, accounting for the distribution of our data. By elucidating the key instruments of the intervention, we aimed to improve the causal interpretation of results.

We found that the integrated care initiative significantly increased the number of hospital admissions, emergency admissions and non-hospital outpatient visits, as well as inpatient, non-hospital outpatient and total costs for patients who had at least one visit with a physician involved in the cross-sector network of health, social and community care providers. The effects were more pronounced in later quarters for all outcomes. Patients who additionally used the community health advice and navigation service had a further increase in non-hospital outpatient visits, as well as non-hospital outpatient and total costs.

Increases in health care utilization may indicate that the initiative improved access to care and reduced unmet needs. A longer time horizon of three to five years could lead to more meaningful and reliable results.

ACKNOWLEDGMENTS

This work was supported by the Innovation Fund of the German Federal Joint Committee, P.O. Box 12 06 06, Berlin, Germany [NVF2_2016-042].

Open Access funding enabled and organized by Projekt DEAL.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data are owned by the German statutory health insurers DAK, BARMER and AOK-RH. To fulfill the legal requirements to obtain the data, researchers must obtain permission for a specific research question from the German Federal (Social) Insurance Office.

ORCID

Vanessa Ress  <https://orcid.org/0000-0003-2989-8638>

Eva-Maria Wild  <https://orcid.org/0000-0001-7243-5984>

REFERENCES

- Abbott, S., & Davidson, L. (2000). Easing the burden on primary care in deprived urban areas: A service model. *Primary Health Care Research & Development*, 1(4), 201–206. <https://doi.org/10.1191/146342300127205>
- Ahn, S., Basu, R., Smith, M. L., Jiang, L., Lorig, K., Whitelaw, N., & Ory, M. G. (2013). The impact of chronic disease self-management programs: Healthcare savings through a community-based intervention. *BMC Public Health*, 13(1), 1141. <https://doi.org/10.1186/1471-2458-13-1141>
- Alderwick, H., Gardner, T., & Mays, N. (2021). England's new health and care bill. *BMJ*, 374, n1767. <https://doi.org/10.1136/bmj.n1767>
- Andersen, R. M. (1995). Revisiting the behavioral model and access to medical care: Does it matter? *Journal of Health and Social Behavior*, 36, 1. <https://doi.org/10.2307/2137284>
- Austin, P. C., Grootendorst, P., & Anderson, G. M. (2007). A comparison of the ability of different propensity score models to balance measured variables between treated and untreated subjects: A Monte Carlo study. *Statistics in Medicine*, 26(4), 734–753. <https://doi.org/10.1002/sim.2580>
- Barnes, A. J., Unruh, L., Chukmaitov, A., & van Ginneken, E. (2014). Accountable care organizations in the USA: Types, developments and challenges. *Health Policy*, 118, 1–7. <https://doi.org/10.1016/j.healthpol.2014.07.019>
- Baser, O. (2006). Too much ado about propensity score models? Comparing methods of propensity score matching. *Value in Health: The Journal of the International Society for Pharmacoeconomics and Outcomes Research*, 9(6), 377–385. <https://doi.org/10.1111/j.1524-4733.2006.00130.x>

- Baxter, S., Johnson, M., Chambers, D., Sutton, A., Goyder, E., & Booth, A. (2018). The effects of integrated care: A systematic review of UK and international evidence. *BMC Health Services Research*, 18(1), 350. <https://doi.org/10.1186/s12913-018-3161-3>
- Berkman, N. D., Sheridan, S. L., Donahue, K. E., Halpern, D. J., & Crotty, K. (2011). Low health literacy and health outcomes: An updated systematic review. *Annals of Internal Medicine*, 155(2), 97–107. <https://doi.org/10.7326/0003-4819-155-2-201107190-00005>
- Berkowitz, S. A., Parashuram, S., Rowan, K., Andon, L., Bass, E. B., Bellantoni, M., Brotman, D. J., Deuschendorf, A., Dunbar, L., Durso, S. C., Everett, A., Giuriceo, K. D., Hebert, L., Hickman, D., Hough, D. E., Howell, E. E., Huang, X., Lepley, D., Leung, C., ... Brown, P. M. C. (2018). Association of a care coordination model with health care costs and utilization: The Johns Hopkins community health partnership (J-CHiP). *JAMA Network Open*, 1(7), e184273. <https://doi.org/10.1001/jamanetworkopen.2018.4273>
- Bickerdike, L., Booth, A., Wilson, P. M., Farley, K., & Wright, K. (2017). Social prescribing: Less rhetoric and more reality. A systematic review of the evidence. *BMJ Open*, 7(4), e013384. <https://doi.org/10.1136/bmjopen-2016-013384>
- Breiman, L., Friedman, J., Olshen, R. A., & Stone, C. J. (2017). *Classification and regression trees*. Routledge.
- Brown, B. B., Patel, C., McInnes, E., Mays, N., Young, J., & Haines, M. (2016). The effectiveness of clinical networks in improving quality of care and patient outcomes: A systematic review of quantitative and qualitative studies. *BMC Health Services Research*, 16(1), 360. <https://doi.org/10.1186/s12913-016-1615-z>
- Caliendo, M., & Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys*, 22(1), 31–72. <https://doi.org/10.1111/j.1467-6419.2007.00527.x>
- Cawston, P. (2011). Social prescribing in very deprived areas. *British Journal of General Practice*, 61(586), 350. <https://doi.org/10.3399/bjgp11X572517>
- Chen, T., He, T., Benesty, M., Khotilovich, V., Tang, Y., Cho, H., & Chen, K. (2015). Xgboost: Extreme gradient boosting. *R Package Version 0.4-2*, 1, 1–4.
- Chetty, R., Stepner, M., Abraham, S., Lin, S., Scuderi, B., Turner, N., Bergeron, A., & Cutler, D. (2016). The association between income and life expectancy in the United States, 2001–2014. *JAMA*, 315(16), 1750–1766. <https://doi.org/10.1001/jama.2016.4226>
- Clancy, C. M. (2005). The persistent challenge of avoidable hospitalizations. *Health Services Research*, 40(4), 953–956. <https://doi.org/10.1111/j.1475-6773.2005.00442.x>
- Clarke, D., Romano, J. P., & Wolf, M. (2020). The Romano–Wolf multiple-hypothesis correction in Stata. *STATA Journal*, 20(4), 812–843. <https://doi.org/10.1177/1536867X20976314>
- Damery, S., Flanagan, S., & Combes, G. (2016). Does integrated care reduce hospital activity for patients with chronic diseases? An umbrella review of systematic reviews. *BMJ Open*, 6(11), e011952. <https://doi.org/10.1136/bmjopen-2016-011952>
- David, G., Saynisch, P. A., & Smith-McLallen, A. (2018). The economics of patient-centered care. *Journal of Health Economics*, 59, 60–77. <https://doi.org/10.1016/j.jhealeco.2018.02.012>
- David, G., Smith-McLallen, A., & Ukert, B. (2019). The effect of predictive analytics-driven interventions on healthcare utilization. *Journal of Health Economics*, 64, 68–79. <https://doi.org/10.1016/j.jhealeco.2019.02.002>
- Ding, H., Chen, Y., Yu, M., Zhong, J., Hu, R., Chen, X., Wang, C., Xie, K., & Eggleston, K. (2021). The effects of chronic disease management in primary health care: Evidence from rural China. *Journal of Health Economics*, 80, 102539. <https://doi.org/10.1016/j.jhealeco.2021.102539>
- Dolton, P., & Pathania, V. (2016). Can increased primary care access reduce demand for emergency care? Evidence from England's 7-day GP opening. *Journal of Health Economics*, 49, 193–208. <https://doi.org/10.1016/j.jhealeco.2016.05.002>
- Elixhauser, A., Steiner, C., Harris, D. R., & Coffey, R. M. (1998). Comorbidity measures for use with administrative data. *Medical Care*, 36(1), 8–27. <https://doi.org/10.1097/00005650-199801000-00004>
- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization paths for generalized linear models via coordinate descent. *Journal of Statistical Software*, 33, 1–22. <https://doi.org/10.18637/jss.v033.i01>
- Goldzahl, L., Stokes, J., & Sutton, M. (2022). The effects of multi-disciplinary integrated care on healthcare utilization: Evidence from a natural experiment in the UK. *Health Economics*, 31(10), 2142–2169. <https://doi.org/10.1002/hec.4561>
- Golubinski, V., Wild, E.-M., Winter, V., & Schreyögg, J. (2020). Once is rarely enough: Can social prescribing facilitate adherence to non-clinical community and voluntary sector health services? Empirical evidence from Germany. *BMC Public Health*, 20(1), 1827. <https://doi.org/10.1186/s12889-020-09927-4>
- Gulliford, M., Figueroa-Munoz, J., Morgan, M., Hughes, D., Gibson, B., Beech, R., & Hudson, M. (2002). What does 'access to health care' mean? *Journal of Health Services Research & Policy*, 7(3), 186–188. <https://doi.org/10.1258/135581902760082517>
- Hainmueller, J. (2012). Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies. *Political Analysis*, 20(1), 25–46. <https://doi.org/10.1093/pan/mpr025>
- Hartzler, A. L., Tuzzio, L., Hsu, C., & Wagner, E. H. (2018). Roles and functions of community health workers in primary care. *The Annals of Family Medicine*, 16(3), 240–245. <https://doi.org/10.1370/afm.2208>
- Hibbard, J. H., & Greene, J. (2013). What the evidence shows about patient activation: Better health outcomes and care experiences; fewer data on costs. *Health Affairs*, 32(2), 207–214. <https://doi.org/10.1377/hlthaff.2012.1061>
- Huber, M., Lechner, M., & Wunsch, C. (2013). The performance of estimators based on the propensity score. *Journal of Econometrics*, 175, 1–21. <https://doi.org/10.1016/j.jeconom.2012.11.006>
- Hudomiet, P., Hurd, M. D., & Rohwedder, S. (2021). Forecasting mortality inequalities in the U.S. based on trends in midlife health. *Journal of Health Economics*, 80, 102540. <https://doi.org/10.1016/j.jhealeco.2021.102540>
- Hughes, G., Shaw, S. E., & Greenhalgh, T. (2020). Rethinking integrated care: A systematic hermeneutic review of the literature on integrated care strategies and concepts. *The Milbank Quarterly*, 98(2), 446–492. <https://doi.org/10.1111/1468-0009.12459>

- Kontopantelis, E., Roland, M., & Reeves, D. (2010). Patient experience of access to primary care: Identification of predictors in a national patient survey. *BMC Family Practice*, 11(1), 61. <https://doi.org/10.1186/1471-2296-11-61>
- Krämer, J., Schreyögg, J., & Busse, R. (2019). Classification of hospital admissions into emergency and elective care: A machine learning approach. *Health Care Management Science*, 22(1), 85–105. <https://doi.org/10.1007/s10729-017-9423-5>
- Kringos, D. S., van den Broeke, J. R., van der Lee, A. P. M., Plochg, T., & Stronks, K. (2016). How does an integrated primary care approach for patients in deprived neighbourhoods impact utilization patterns? An explorative study. *BMC Public Health*, 16(1), 545. <https://doi.org/10.1186/s12889-016-3246-z>
- Lippi Bruni, M., Mammi, I., & Ugolini, C. (2016). Does the extension of primary care practice opening hours reduce the use of emergency services? *Journal of Health Economics*, 50, 144–155. <https://doi.org/10.1016/j.jhealeco.2016.09.011>
- Loussouarn, C., Franc, C., Videau, Y., & Mousquès, J. (2021). Can general practitioners Be more productive? The impact of teamwork and cooperation with nurses on GP activities. *Health Economics*, 30(3), 680–698. <https://doi.org/10.1002/hec.4214>
- Manning, W. G., & Mullahy, J. (2001). Estimating log models: To transform or not to transform? *Journal of Health Economics*, 20(4), 461–494. [https://doi.org/10.1016/S0167-6296\(01\)00086-8](https://doi.org/10.1016/S0167-6296(01)00086-8)
- McCormack, L. A., Jones, S. G., & Coulter, S. L. (2017). Demographic factors influencing nonurgent emergency department utilization among a Medicaid population. *Health Care Management Science*, 20(3), 395–402. <https://doi.org/10.1007/s10729-016-9360-8>
- Ouwens, M., Wollersheim, H., Hermens, R., Hulscher, M., & Grol, R. (2005). Integrated care programmes for chronically ill patients: A review of systematic reviews. *International Journal for Quality in Health Care*, 17(2), 141–146. <https://doi.org/10.1093/intqhc/mzi016>
- Pirracchio, R., Petersen, M. L., & van der Laan, M. (2015). Improving propensity score estimators' robustness to model misspecification using super learner. *American Journal of Epidemiology*, 181(2), 108–119. <https://doi.org/10.1093/aje/kwu253>
- Polley, E., LeDell, E., Kennedy, C., & van der Laan, M. (2021). Super learner: Super learner prediction. Retrieved from <https://cran.r-project.org/web/packages/SuperLearner/index.html>
- Rambachan, A., & Roth, J. (2023). A more credible approach to parallel trends. *The Review of Economic Studies*, 90(5), 2555–2591. <https://doi.org/10.1093/restud/rdad018>
- Rathert, C., Wyrwich, M. D., & Boren, S. A. (2013). Patient-centered care and outcomes: A systematic review of the literature. *Medical Care Research and Review*, 70(4), 351–379. <https://doi.org/10.1177/1077558712465774>
- Rocks, S., Berntson, D., Gil-Salmerón, A., Kadu, M., Ehrenberg, N., Stein, V., & Tsiachristas, A. (2020). Cost and effects of integrated care: A systematic literature review and meta-analysis. *The European Journal of Health Economics*, 21(8), 1211–1221. <https://doi.org/10.1007/s10198-020-01217-5>
- Romano, J. P., & Wolf, M. (2016). Efficient computation of adjusted p-values for resampling-based stepdown multiple testing. *Statistics & Probability Letters*, 113, 38–40. <https://doi.org/10.1016/j.spl.2016.02.012>
- Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1), 41–55. <https://doi.org/10.1093/biomet/70.1.41>
- Rummery, K. (2009). Healthy partnerships, healthy citizens? An international review of partnerships in health and social care and patient/user outcomes. *Social Science & Medicine*, 69(12), 1797–1804. <https://doi.org/10.1016/j.socscimed.2009.09.004>
- Saini, V., Garcia-Armesto, S., Klemperer, D., Paris, V., Elshaug, A. G., Brownlee, S., Ioannidis, J. P. A., & Fisher, E. S. (2017). Drivers of poor medical care. *The Lancet*, 390(10090), 178–190. [https://doi.org/10.1016/S0140-6736\(16\)30947-3](https://doi.org/10.1016/S0140-6736(16)30947-3)
- Schumacher, J. R., Hall, A. G., Davis, T. C., Arnold, C. L., Bennett, R. D., Wolf, M. S., & Carden, D. L. (2013). Potentially preventable use of emergency services: The role of low health literacy. *Medical Care*, 51(8), 654–658. <https://doi.org/10.1097/mlr.0b013e3182992c5a>
- Stenberg, U., Vågan, A., Flink, M., Lynggaard, V., Fredriksen, K., Westermann, K. F., & Gallefoss, F. (2018). Health economic evaluations of patient education interventions a scoping review of the literature. *Patient Education and Counseling*, 101(6), 1006–1035. <https://doi.org/10.1016/j.pec.2018.01.006>
- Stokes, J., Panagioti, M., Alam, R., Checkland, K., Cheraghi-Sohi, S., & Bower, P. (2015). Effectiveness of case management for 'at risk' patients in primary care: A systematic review and meta-analysis. *PLoS One*, 10(7), e0132340. <https://doi.org/10.1371/journal.pone.0132340>
- Strumpf, E., Ammi, M., Diop, M., Fiset-Laniel, J., & Tousignant, P. (2017). The impact of team-based primary care on health care services utilization and costs: Quebec's family medicine groups. *Journal of Health Economics*, 55, 76–94. <https://doi.org/10.1016/j.jhealeco.2017.06.009>
- Sundmacher, L., Fischbach, D., Schuettig, W., Naumann, C., Augustin, U., & Faisst, C. (2015). Which hospitalisations are ambulatory care-sensitive, to what degree, and how could the rates be reduced? Results of a group consensus study in Germany. *Health Policy*, 119(11), 1415–1423. <https://doi.org/10.1016/j.healthpol.2015.08.007>
- Valentijn, P. P., Schepman, S. M., Opheij, W., & Bruijnzeels, M. A. (2013). Understanding integrated care: A comprehensive conceptual framework based on the integrative functions of primary care. *International Journal of Integrated Care*, 13(1), e010. <https://doi.org/10.5334/ijic.886>
- van der Laan, M. J., Polley, E. C., & Hubbard, A. E. (2007). Super learner. *Statistical Applications in Genetics and Molecular Biology*, 6(1), Article25. <https://doi.org/10.2202/1544-6115.1309>
- West, C. P., Dyrbye, L. N., & Shanafelt, T. D. (2018). Physician burnout: Contributors, consequences and solutions. *Journal of Internal Medicine*, 283(6), 516–529. <https://doi.org/10.1111/joim.12752>
- Wild, E.-M., Winter, V., Röss, V., & Golubinski, V. (2022). What is the impact of introducing a non-clinical community health advice and navigation service on the demand for primary care in socially deprived areas? Evidence from an observational panel study with difference-in-differences design. *BMJ Open*, 12(10), e061964. <https://doi.org/10.1136/bmjopen-2022-061964>
- Wright, M. N., & Ziegler, A. (2017). Ranger: A fast implementation of random forests for high dimensional data in C++ and R. *Journal of Statistical Software*, 77(1). <https://doi.org/10.18637/jss.v077.i01>

SUPPORTING INFORMATION

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

How to cite this article: Ress, V., & Wild, E.-M. (2024). The impact of integrated care on health care utilization and costs in a socially deprived urban area in Germany: A difference-in-differences approach within an event-study frameworks. *Health Economics*, 33(2), 229–247. <https://doi.org/10.1002/hec.4771>