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ABSTRACT

Cut Off from New Competition: Threat of Entry and Quality of Primary Care*

We study how the threat of entry affects service quantity and quality of general practitioners (GPs). We leverage Germany's needs-based primary care planning system, in which the likelihood of new GPs reduces by 20 percentage points when primary care coverage exceeds a cut-off. We compile novel data covering all German primary care regions and up to 30,000 GP-level observations from 2014 to 2019. Reduced threat of entry lowers patient satisfaction for incumbent GPs without nearby competitors but not in areas with competitors. We find no effects on working hours or quality measures at the regional level including hospitalizations and mortality.

JEL Classification: I11, I18, J44, J22, L10, L22, R23

Keywords: entry regulation, general practitioners, healthcare provision, threat of entry, regression discontinuity design

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1 Introduction

The provision of primary care is a cornerstone of sustainable healthcare systems (World Health Organization, 2023). To ensure equitable access, most countries regulate the distribution of general practitioners (GPs) by balancing market mechanisms and entry restrictions. Striking the right balance is crucial: entry restrictions should ensure that GP supply meets demand without stifling competition, which is key to maintaining high-quality care. As in other markets where firms compete over quality rather than prices, a lack of competition reduces the incentives of GPs to provide high-quality services (Gaynor and Town, 2011; Bloom et al., 2015; Eliason et al., 2019). Therefore, a major public policy challenge is to preserve competition among GPs while ensuring that regulations guarantee access to high-quality care. In many sectors, it is not just the presence of competition but also the mere threat of new market entrants that leads firms to change their behavior (Goolsbee and Syverson, 2008; Bergman and Rudholm, 2003). However, most studies focus on price effects, leaving us with a limited understanding of how the threat of entry affects non-price outcomes such as the quality of care (Prince and Simon, 2015; Clemens and Gottlieb, 2014). Disentangling the effect of the threat of new competition and of competition itself is difficult because the threat and actual competition are rarely observed separately. However, if the threat of new entrants alone influences the quality of care provided by GPs, evaluations of healthcare policies based solely on actual competition may be misleading.

In this paper, we explore how the threat of entry *alone* affects GPs' behavior and the health of their patients. We leverage a unique feature of the German needs-based planning system: regions that surpass a certain cut-off of primary care coverage are automatically blocked from new GP entry. This means that although regions just above and below the cut-off have the same GP-to-population ratio and thus similar levels of competition, incumbent GPs in regions with entry restrictions face a lower threat of new competing GPs setting up practices nearby. Drawing on a rich body of literature on healthcare competition (Gravelle et al., 2019), we hypothesize that this reduced threat leads GPs to be less responsive to patient needs because they face a reduced risk of losing them to new competitors.

We estimate a causal effect by exploiting the reduced threat of competition induced by the entry regulations using a regression discontinuity design (RDD). Essentially, this approach allows us to compare the quality and quantity of services provided by GP practices in regions that differ only in the probability of new GPs entering. To draw an in-depth picture of how entry restrictions change incumbent GPs' behavior, we compiled a novel and extensive dataset: the *Regional Health Panel*. For the first time, this new dataset offers a comprehensive view of relevant characteristics of the German needs-based planning system, seamlessly compiling data from multiple sources across all 1,394 German planning areas from 2014 to 2019. Given that planning areas are based on a non-standard, highly disaggregated geographic definition that frequently changes, we developed time-consistent crosswalks that allow us to integrate data at any regional level into our panel. Using these crosswalks, we enriched our dataset with municipality- and county-level data from the Federal Statistical Office, and practice-level data on approximately 30,000 individual practices from Germany's largest medical review website. To gain further insights into the distribution of doctors within planning areas, we combined geo-coded, practice-level information from the Yellow Pages and detailed spatial data from the 2011 census at the 100-meter grid level. This combination of datasets enables us to investigate in detail whether incumbent GPs react to a lower threat of competition by altering the quality or the quantity of their services. More broadly, we also investigate whether population health is impacted by analyzing whether patients substitute primary care with hospital care, and face impaired health, especially for diseases related to primary care.

Our analysis reveals that entry restrictions significantly reduce the threat of new competition without affecting current levels of competition among GPs or their demographic composition. Planning areas that are blocked to new GP entry have a 20 percentage points lower likelihood of new practitioners entering in the next year compared to similar open regions, while various measures of competition are unaffected. The threat of competition is particularly important for local monopolists—GPs without nearby competitors—who show a noticeable decline in service quality when their market is closed to new entrants. For them, the decline is reflected in lower patient satisfaction ratings, while for GPs in already competitive environments, entry restrictions have no discernible impact on service quality or quantity. At the regional level, our findings do not indicate substantial changes in overall hospitalizations or mortality rates, suggesting that, while entry restrictions affect the behavior and service quality of local monopolists, these effects do not necessarily translate to broader health outcomes.

Our paper mainly contributes to the economic literature on the impact of medical practice competition on healthcare quality. While existing research has explored how a changing population-to-practitioner ratio affects patient health, our study takes a unique approach by focusing on the threat of entry into the market for GP services. This focus is particularly relevant, because the sole threat of future competition has been shown to matter in other contexts, such as for airlines (Goolsbee and Syverson, 2008) and pharmaceuticals (Bergman and Rudholm, 2003). Bergman and Rudholm (2003) even find in their evaluation of the pharmaceutical market that the threat of future competition alone leads incumbents to lower the prices of their products to the same extent as they would if actual competition would take place. Counterintuitively, Prince and Simon (2015) find that quality outcomes such as on-time performance may deteriorate due to the threat of entry and suggest two reasons for this: aggressive cost-cutting and product differentiation. In our setting, incentives for product differentiation are limited because of volume caps, regressive payments, and graduated pricing in the German reimbursement system for GPs. Therefore, cost-cutting and reduced effort are more likely channels.

Existing studies on GP competition, as exemplified by Gravelle et al. (2019) and Dietrichson et al. (2016), have reported modest improvements in patient satisfaction and primary care quality with increased competition. For example, Gravelle et al. (2019) find a slight positive relationship between detailed spatial measures of family doctor competition in England and subjective quality measures. Similarly, Dietrichson et al. (2016) use a difference-in-differences strategy to assess how an increase in family doctor competition in Sweden affects healthcare quality. They find marginal improvements in subjective measures of primary care quality but no significant changes in avoidable hospitalizations or patient satisfaction regarding access to primary care. Both of these results are also in line with Santos et al. (2017), who show that doctor quality matters for patient choices, suggesting that competition based on quality is likely a significant factor in attracting patients. Moreover, earlier research, such as Pike (2010) and Schaumans (2015), which relied solely on cross-sectional variation, has also pointed to the impact of competition on healthcare quality. Unlike existing studies that focus primarily on actual competition levels, we demonstrate that the mere threat of entry can influence the behavior of GPs and lead to changes in service quality, even when the current competitive environment remains unchanged.

Our contribution extends to a broader literature on entry regulations in various contexts. While much of this research centers on occupational licensing (e.g. Kleiner and Soltas, 2023), a subset of studies specifically focuses on medical markets, which is more directly related to our work. For instance, Kugler and Sauer (2005) examine relicensing requirements for immigrant physicians, shedding light on the rents associated with a license and the impact of licensing requirements on service quality. Kugler and Sauer's findings reveal significant rents and reductions in service quality resulting from these requirements. Additionally, Deyo et al. (2023) demonstrate that a reform that reduced licensing barriers for physicians across the United States of America led to an increase in the number of states where individual physicians practice. Similarly, several studies have explored the effects of entry restrictions for pharmacies in different countries, highlighting how these restrictions may diminish competition (e.g., Schaumans and Verboven, 2008; Mocetti, 2016). For example, Mocetti (2016) and Pagano et al. (2022) both investigate a needs-based planning restriction that applies to Italian pharmacies. Specifically, Pagano et al. (2022) found negative health effects of the regulation, while Mocetti (2016) shows that the entry restriction increased the likelihood of pharmacists' children becoming pharmacists compared to the rest of the population. In contrast to the regulation we study, the entry restriction considered in these two papers directly reduces the availability of pharmacies rather than solely affecting the threat of entry.

In addition, our paper explores themes related to other works in health and labor economics, particularly on the quality of medical services and the labor supply of GPs. For example, we rely on established metrics from the literature on doctor quality that have been used to study how quality influences patient decisions (e.g., Leuven et al., 2013; Santos et al., 2017; Biørn and Godager, 2010). Moreover, our paper is also related to research on how regulatory measures influence labor decisions within the medical service industry. Although studies like Garthwaite (2012) observed reduced working hours due to changes in reimbursement schemes, and Broadway et al. (2017) and Kalb et al. (2018) found minimal or negative shifts in working hours and after-hours care in reaction to salary increases, our findings show no significant effect of entry regulation on practice opening hours.

The paper proceeds as follows: Section 2 provides an in-depth summary of the institutional setting of entry restrictions for general practitioners in Germany. Section 3 describes the data and methodology used in the analysis. Section 4 presents the results of the analysis. The conclusion in Section 5 draws together the key findings and their implications.

2 Institutional Background

2.1 Primary Care in Germany

Like in most other developed countries, general practitioners (GPs) play a crucial role in Germany's healthcare system (Blümel et al., 2020). They are the first point of contact for patients, offering health advice and primary care, including ongoing care for patients with chronic conditions. Although GPs do not act as gatekeepers, they are increasingly responsible for coordinating and referring patients to specialists and hospitals when necessary (Busse et al., 2017).

Needs-based Planning. Because of this central role, a stringent needs-based planning system aims to ensure an adequate distribution of GPs to meet the healthcare needs of the entire population.[1] Since its inception in 1977, needs-based planning has been carried out by joint regional committees of state associations of SHI-accredited doctors and statutory health insurers to avoid bias towards the objectives of either party. Rooted in the Law on the Further Development of Statutory Health Insurance, this system has undergone continual refinement over the years.[2] Its aim is to balance the medical services landscape effectively and to eliminate both over- and undersupply in healthcare provision.

[1] This needs-based planning system does not apply solely to primary care but also to secondary care. However, as we examine primary care, we further refer to the case of GPs when describing the planning procedure.

[2] A timeline for the legal changes in needs-based planning is provided in Table B.1 in the Appendix.

Table 1: Entry Regulation According to Needs-Based Planning

Step 1	Determine what type of planning region is used for the specific specialization		
	e.g., general practitioner needs are planned at the center area ('Mittelbereich') level		
Step 2	Determination of a TARGET level of care per physician group (ratios)		
	e.g., 1,740 inhabitants per general practitioner in a district		
Step 3	Determination of the actual level of care in the planning area		
	e.g., 317,417 inhabitants and 249 general practitioners = 1,274 inhabitants per general practitioner		
Step 4	Comparison of the ACTUAL and TARGET supply level as supply rate (coverage rate)		
	e.g., 1,274 compared to 1,740: $\frac{\text{TARGET}}{\text{ACTUAL}} = \frac{1{,}740}{1{,}274} = 137\%$		
Step 5	0% — 50% / 75%	50% / 75% – 110%	> 110%
	Undersupply	Regular supply	Over-supply
	Subsidized admission	Regular admission	Closed to entry
	e.g., because TARGET is 137% of ACTUAL, the region is closed to new entry		
If attractive regions are closed, doctors who want to set up their own practices have to move to less attractive regions.			

Notes: The table shows a five-step description to determine whether a planning region is closed to a certain type of doctor illustrated using the example of a general practitioner who wants to set up a practice in the city of Freiburg as of October 2018. Note that the target of 1,740 is locally adjusted, thus differing from the uniform target of 1,671. While the planning areas for primary care are center areas, general specialist care, specialized care, and extra-specialized care are planned at higher regional aggregates (between county and federal state level).

Target Coverage Rates. The primary metric for planning in this system is the regional coverage rate, which measures the ratio of GPs to the population against a set target. It is calculated by dividing the target population per GP by the actual number of individuals each GP serves. A coverage rate above 100% indicates a higher GP density than targeted, as it means there are fewer people per practitioner compared to the target level. If a planning area reaches a coverage rate of 110%, the area is automatically blocked to new GP entry, prohibiting any additional GPs from setting up their practices.[3] Blocked entry thus prevents both over- and undersupply by forcing GPs to settle in less attractive areas with a below-target coverage rate instead of attractive and more urban areas with a coverage rate that is too high according to the planning system. Table 1 presents

[3]Licensing committees can authorize GPs to settle in an entry-blocked planning area if there is a particular local need for care via special needs licenses. However, the issuing of such licenses is an exception and requires a detailed examination procedure and is therefore rare.

a description in five steps of how the coverage rate and the status (open to entry vs. blocked entry) are determined.

In 2013, a uniform national coverage rate target, adjusted based on the demographic composition of each planning area, was introduced. For GPs, that is, primary care, this target is set at 1,671 inhabitants per GP.[4]

International Comparisons of Coverage In Figure C.1 in the Appendix, we show that both the targeted and the actual population-to-GP ratio are quite similar to many European countries. This means that, although our sample is composed of planning areas with a high coverage rate—and thus competitive pressure—it is quite comparable to other higher-covered countries like the Netherlands, France, Spain, and especially Austria, for which the healthcare system is similar (see Appendix Table C.1).

Planning Areas and Their Definitions. Planning areas are not a classic administrative regional subdivision but represent the interlinking areas around a medium-sized center or a network of medium-sized centers defined by the German Federal Office for Building and Regional Planning (e.g., BBSR, or Bundesinstitut für Bau-, Stadt- und Raumforschung, 2012), which is called *center area* ('Mittelbereich'). Although the classification of center areas comes from the BBSR, state committees of the medical doctors' and health insurers' associations (KVs) have the possibility of adjusting the exact cuts. Thus, we use data on the actual regional definitions used for planning. Nevertheless, as almost 85% of the planning areas lie fully within official administrative counties (Kreise), we are confident that our results are not driven by endogenous adjustments. However, we keep the possibility of manipulation around the cut-off in mind and, therefore, test for bunching at the cut-off.

2.2 Implications for General Practitioners

Because of needs-based planning, GPs in Germany face restrictions in their choice of practice location. When a planning area is blocked to new entry, new GPs are not permitted to establish practices, and existing ones can only be transferred to a direct successor. Circumventing these restrictions is nearly impossible for GPs because compliance with needs-based planning is essential for billing patients under the statutory health insurance (SHI) system, which covers approximately 90% of the population. This entry restriction also has implications for incumbent GPs, given that no new competitors can enter their area.

[4]This target is based on West Germany's coverage rate after reunification in 1991 and has not been adjusted until 2019 when the target value was set to 1,609, and morbidity was additionally included in the local adjustment factors. For an overview of recent changes, see Lehmann and Uhlemann (2019).

Impact on Competition and GP Behavior. Regions just below and above the cut-off do not differ in terms of *competition* because they have a similar GP-to-population ratio. However, from the perspective of incumbent GPs, these regions differ in terms of the *threat of entry*, as additional competitors are unlikely to enter regions just above the cut-off. This reduced expectation of new entrants likely influences GP behavior depending on their competitive environment. For local monopolists—GPs without nearby competitors—entry restrictions mean they are likely to maintain their monopoly. As a result, patients may find it difficult to switch practices even with lower-quality services, allowing these monopolists to reduce effort without harming their business. In other words, reputation matters less for these local monopolists. This is arguably not the case for GPs with nearby competitors unless they are able to collude with their rivals.

SHI Reimbursement and Incentive Structures. The German SHI system's reimbursement model further exacerbates this effect heterogeneity in that it discourages physicians from extending services to increase profits (Kuhn and Ochsen, 2019). Unlike in a fee-for-service system, where even monopolists would increase service volume to maximize income, the SHI uses a points system under the Uniform Value Scale (Einheitlicher Bewertungsmaßstab, EBM), assigning point values to services instead of direct monetary payments (see Blümel et al., 2020, for an overview). Each physician is allocated a quarterly volume of services billable at a fixed rate per point. Exceeding this volume results in reduced compensation for additional services, as regional physician associations enforce budget caps on overall spending. As a result, even if GPs provide more services, their total reimbursement may not increase proportionally because services beyond the allocated volume are reimbursed at a lower rate, with only 2% of the total volume reserved for excess services. In this context, where incentives for additional services are already limited through volume caps, regressive payments, and graduated pricing, a reduced threat of new competitors arguably discourages local monopolist GPs from maintaining their level of effort, less with regard to the quantity (as they still have an incentive to provide a certain amount of care), but more to the quality of services (as their patients have no alternative for years to come).

2.3 Related Literature

Aligned with our argument, economic theory suggests that the impact of competition on the quality of healthcare services provided depends on market characteristics. Theoretically, the impact of a potential entry of a GP is ambiguous in a symmetric oligopoly (Dixit, 1979). Gal-Or (1983) shows that for uniform preferences, entry reduces average quality and increases aggregate output, although the effects are ambiguous for other types of preferences. This ambiguity is echoed in the empirical findings of studies like Eliason et al. (2019) and Clemens and Gottlieb (2014), which demonstrate that less competition resulting from acquisitions or lower pay can reduce quality through various mechanisms such as increasing drug doses, switching to more lucrative treatments, or adjusting service provision based on financial incentives.

Empirical Studies on Competition and Quality. Empirically, settings where prices are fixed or where price elasticity is low compared to quality elasticity tend to show positive effects of competition on service quality (Gaynor and Town, 2011; Dranove and Satterthwaite, 2000). Studies by Gravelle et al. (2019), Dietrichson et al. (2016), and Pike (2010) further suggest that competition is a significant driver of practice quality and higher patient satisfaction. These findings are supported by Santos et al. (2017), who highlight that quality measures significantly influence patient choices. Consistent with this literature, we argue that a reduction of the mere *threat* of new competition, similar to less actual competition, discourages (local monopolist) GPs in entry-restricted planning areas to enhance their efforts to satisfy patients. In attractive regions without restrictions to entry, GPs face the risk of patient switching should a new competitor emerge nearby. The importance of the threat of competition for incumbents' behaviour has also been highlighted in other industries, such as airlines and pharmaceuticals, where potential entry affects market behaviors significantly (Goolsbee and Syverson, 2008; Bergman and Rudholm, 2003).

Defining and Measuring Quality in Primary Care. Quality in healthcare is multifaceted. To understand the effects of the threat of entry on quality, it is thus crucial to define quality and review empirical measures of quality in primary care. Generally, quality encompasses both subjective and objective factors that influence patient preferences, such as accessibility, waiting times, provider demeanor, and clinical outcomes. This broad perspective on quality underlines the importance of catering to diverse patient needs and preferences in a competitive environment, where GPs strive to enhance patient satisfaction and loyalty through various service attributes beyond just clinical care.

This is also in line with a broad literature that relies on more indirect quality metrics compared to ours. For example, Schaumans (2015) relies on prescriptions per GP as a quality metric and show that prescriptions are higher in more competitive settings. In a similar vein, referrals are employed as a quality metric, reflecting the competitive approach of attracting and retaining patients through prompt or improved referrals to specialists or hospitals to showcase responsiveness. For example, Godager et al. (2015) suggests that increased primary care competition has a limited positive effect on referrals to specialty care. However, hospitalizations can serve as a dual-faceted indicator. Hospitalizations not only hint at the underlying referral strategies employed by primary care providers but also stand as a critical measure of quality, reflecting the effects of inadequate care. In this context, Dietrichson et al. (2016) find that increased competition in primary care does not decrease hospitalizations for conditions related to primary care. To get a comprehensive overview of potential effects on quality, we combine both very direct subjective quality measures, data on hospitalizations, and data on mortality.

In the following section, we describe in detail how we combine fine-grained geographic data on planning and different quality measures with a regression discontinuity design to identify the causal effect of the threat of entry on general practitioner service quality.

3 Data and Empirical Strategy

3.1 The Regional Health Panel

To study the effects of needs-based planning, data on the location choice of GPs, patients' health outcomes, and the quality of services provided is needed at the level of the policy. Because this data has so far not been available, we have compiled a comprehensive data set, the *Regional Health Panel* (RHP), which contains rich information from multiple sources at various regional levels and forms a comprehensive basis for the analysis of the spatial distribution of healthcare in Germany.

Planning Areas. As described in Section 2, needs-based planning for GP care is done at the *center area* (Mittelbereich) level. These regional units, defined by the Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR), are smaller than governmental counties (Kreise) but larger than the around 11,000 municipalities (Gemeinden) in Germany. For our study, we focus on areas that consist of the same municipalities across different years. However, since the geographic boundaries of municipalities can also evolve, we needed to account for these changes in our analysis. Additionally, since state committees of medical doctors' and health insurers' associations (KVs) can adjust planning areas to meet local needs, we need to adjust for these deviations over time.[5] To overcome these different issues, we developed a technique to reliably identify constant planning areas in the face of these changes that we describe in section D.1 of the appendix.

Coverage Rates. Our main data source is the planning reports of the Federal Association of SHI-accredited Medical Doctors (Kassenärztliche Bundesvereinigung).[6] This data contains the detailed coverage rates (i.e., the ratio between the actual number of people

[5]Given the slight deviation of the definition of center area used for the German needs-based planning procedure from the official definition, we refer to the unit of observation (i.e., where planning occurs) as *planning areas* although it often coincides with the respective center area.

[6]The state associations of individual SHI-accredited medical doctors and the state associations of the statutory health insurances are jointly responsible for planning and send their final planning reports to the federal association every year.

per physician and the local target), with which we can determine whether a planning area is restricted to entry or not. We supplement this data with information from four different sources at different levels. The federal registers of medical doctors contain information on the composition of GPs at the county region ('Kreisregionen') level.[7] The regional database of the Federal Statistical Office and the INKAR database of the BBSR offer information at the municipality and county level. Furthermore, we use geo-coded information at the GP practice level extracted from the Yellow Pages and Jameda, the largest German doctor rating website.

Composition of GPs. We obtained detailed information on the demographic characteristics (age, gender), employment status (retired, practice owner, employed), and workload of GPs from the Federal Registers of Medical Doctors via the Federal Association of SHI-accredited Medical Doctors for each year and each of the 361 county regions. By analyzing this data, we can assess whether entry restrictions in planning areas lead to immediate changes in the GP composition, such as shifts in age distribution, variations in practice ownership versus employment, and changes in work patterns (e.g., from part-time to full-time employment).

Demand for Primary Care. The regional database of the Federal Statistical Office contains rich information regarding the local population, income taxes (to delineate richer and poorer regions), the local age and gender composition, and the number of people in need of long-term nursing care at the municipality level. Because these factors influence the demand for primary care, we use them as covariates. Furthermore, we use information on mortality (overall and by cause) at the municipality level and hospitalizations—which are only available for the years 2016 and 2017 and at the county level[8]—as outcome variables. This data allows us to evaluate whether behavioral changes by incumbent GPs resulting from entry restrictions increase hospital admissions as patients seek treatment elsewhere, or whether they are admitted to hospitals due to the reduced care quality and mortality. Examining mortality by cause of death enables us to distinguish between potentially preventable causes of death that could be averted through basic primary care in addition to overall mortality. This distinction provides us with a more comprehensive understanding of the potential effects on preventable deaths.[9]

[7]The basis for the definition is formed by the 401 German counties, with the difference that smaller independent cities with fewer than 100,000 inhabitants are combined with the counties assigned to them to form 361 county regions.

[8]To include relevant data that is only available at the county level, we use population weights to transfer the information from the county level to the planning areas. We are confident in the accuracy of this procedure, as 85% of regions fall clearly within the boundaries of an official administrative county.

[9]The detailed cause of death data is unfortunately missing for the entire state of Bavaria for our entire period of observation. Therefore, all our results on mortality by cause do not include information from Bavaria.

Quantity and Quality of Primary Care. To delve deeper into the implications of blocked entry on individual practitioner behavior (e.g., changes in opening hours) and the perceived service quality across regions, we created an extensive dataset by web-scraping Jameda, Germany's largest medical review platform. This dataset comprises patient ratings on various practice characteristics—such as waiting times, friendliness, and quality of advice—on a scale from one to five. As Avdic et al. (2019) emphasize, these subjective quality measures are vital in influencing patient choices and, along with our objective indicators, provide a more comprehensive evaluation of primary care providers by uncovering additional quality dimensions. Our data includes 207,486 individual patient ratings covering 31,505 of the 55,116 general practitioners in Germany. We aggregate these to roughly 129,643 year-average GP ratings. On average, the data contains ratings for 12,652 GPs in any given year. While it includes detailed yearly information on ratings for our entire observation period, the information on opening hours is only available for the year 2021. Furthermore, the dataset provides the exact geographic location for each practice and precise timestamps for every patient rating, allowing us to easily merge it with the information from the planning reports and the Yellow Pages (see Table 2 for an overview).

Table 2: Main Data Sources

Data	Unit	Observations	Years	Avg. observations per unit-year
Planning regions	regions	5,687	2014–2019	948
Jameda ratings	GPs	129,643	2014–2019	12,652
Yellow Pages	GPs	165,045	2014–2019	27,508
Jameda Opening hours	GPs	30,388	2021	30,388

Notes: The table presents an overview of data sets, including the lowest level of observation, the years of coverage, as well as the total and the average number of observations per year.

Access to Primary Care and Competition. Finally, we use the geographic coordinates of GP practices in Germany from six editions of the Yellow Pages.[10] We describe the detailed data preparation process from the raw Yellow Pages data in Appendix D.2. This unique dataset serves four pivotal purposes in our analysis.

First, we use the aggregated number of GP practices at the planning area level as an alternative outcome measure. This complements our main analysis using practices instead of practitioners by allowing us to examine how entry restrictions influence the formation of new GP practices and serve as a sensitivity analysis.[11]

[10]The data was generously provided by Dirk Engling. He also developed a specialized open-source tool to extract data from the yearly German Yellow Pages available on DVDs.

[11]Such an analysis is particularly important given that the official planning report data only contains the coverage rate instead of the actual number of GPs.

Secondly, we leverage this dataset in conjunction with the 100m grid of the 2011 Census population data to develop new metrics of access to primary care. To this end, we compute the distance to the nearest GP for each of the 3.1 million grid cells in Germany. We then aggregate these distances for each planning area and year to create a measure for the population-weighted distance to the nearest GP in kilometers.[12]

Thirdly, we also calculate the mean pairwise distances of GPs to examine the spatial distribution and proximity of GP practices within a region. This reflects a common approach in economic geography for mapping business clustering (McCann, 2001). This measure also serves as an indicator of overall regional competition, where shorter average distances between practices imply stronger local competition, consistent with Hotelling's (1929) principle of competitive overlap in customer bases or more modern circular city type models (Salop, 1979; Levaggi and Levaggi, 2024).

Lastly, we differentiated practices based on the number of competitors within a GP's local market. We rely on a commonly used typical walking distance of 1 km, which aligns well with the existing literature on patient and consumer behavior in urban settings.[13] We merge this information to the Jameda reviews based on practice names and addresses with a linking procedure outlined in appendix D.2. This allows us to analyze the effect of entry restrictions (i.e., a reduction in the threat of competition) separately for (i) local monopolists, who have no competitor within walking distance; and (ii) non-monopolists within the same planning region and year.

3.2 Descriptives

We provide key descriptive statistics of our data in Table 3. These statistics reveal a notable disparity in the distribution of general practitioners across planning areas, with an average of 55.5 GPs per area. This average masks the substantial variation indicated by the high standard deviation and the stark contrast between the smallest and largest numbers of GPs (ranging from 6 to 2478). The population data also reflects this diversity, ranging from Waldsassen (the smallest planning area with 9,790 inhabitants) to Berlin (the largest with 3,644,830 residents) against an average population of 86,556. Thus, planning areas show a wide range of variability in size and urban population density.

The data also shows that long-term care patients constitute an average of 4.3% of the population per area, with a median close to the mean, indicating a relatively stable distribution. The gender composition is fairly balanced, with an average of 51% female

[12]We map the number of GPs per 10,000 inhabitants and the population-weighted distance to the nearest GP for 2019 in Figure F.1 in the Appendix.

[13]While data on the typical search range for GPs in Germany is not readily available, Santos et al. (2017) found that for patients in the UK, the median distance to the nearest practice is 0.84 km (mean = 1.2 km) and the median distance to chosen practice is 1.48 km (mean = 1.88 km), which closely resembles our definition. Furthermore, our choice aligns with more general definitions of walking distance. For instance, Yang and Diez-Roux (2012) found that the median walking trip distance across all types of trips in the United States was about 0.7 miles (approximately 1.1 km), or a 10-15 minute walk.

residents. A small standard deviation suggests this balance is consistent across regions; however, the share of non-German citizens shows more variability, ranging from 0.4% to 26%, indicating differing demographic profiles in different planning areas. The population share of individuals over the age of 65 averages 21%, with a standard deviation of 2.6%, highlighting varying age demographics, which could influence healthcare needs and the distribution of general practitioners.

Table 3: Summary statistics for key variables in our sample

	Mean	SD	Min	Median	Max
Number of GPs	55.5	112.6	6	34	2478
Population	86,556	167,285	9,790	53,840	3,644,830
Competition between GPs					
People per GP	1583	215	753	1553	2761
Average number of competitors (1km)	2.67	2.00	0.08	2.25	19.17
Percentage of GPs with no competitor (1km)	26.76%	20.94%	0.00 %	25%	92.31%
Quantity and quality of services					
Overall quality rating	4.9	1.01	1	5	5
Opening hours	29.3	14.7	15	26	53
Health outcomes					
Hospitalization per 1000 inhabitants	252.12	33.42	164.8	248.0	358.8
Mortality per 1000 inhabitants	9.61	5.2	7.808	12.02	17.38
Controls					
Share long-term care patients	4.3%	1.2%	1.7%	4.2%	9.5%
Share of female residents	51.0%	0.7%	48.5%	51.0%	54.2%
Share of non-German citizens	5.6%	3.6%	0.4%	5.0%	26.0%
Share of residents over 65	21.0%	2.6%	14.5%	20.7%	34.2%
People per pharmacy	4167.9	1,124.8	677.8	4,035.6	22,690

Notes: The table presents summary statistics for the main variables in our sample. The units of observation are the planning areas observed from 2014 to 2019.

3.3 Identification Strategy

We apply a regression discontinuity design (RDD) to investigate the causal effects of the reduced threat of competition on the provision of medical services and health outcomes. This approach exploits the discontinuity at the 110% coverage rate cutoff, where planning areas are automatically blocked through regional entry restrictions. The RDD regression equation is characterized as

$$Y_{irt} = \alpha + \beta D_{rt} + \gamma_1 (X_{rt} - c) + \gamma_2 D_{rt}(X_{rt} - c) + \mathbf{Z}'_{rt}\delta + \epsilon_{irt} \tag{1}$$

where Y_{irt} denotes the outcome variable of interest for observation i in planning area r at time t.[14] D_{rt} is a treatment indicator equal to 1 if the coverage rate X_{rt} exceeds the threshold $c = 110\%$ and 0 otherwise. γ_1 and γ_2 are the coefficients of the slope of the running variable relative to the cutoff $(X_{rt} - c)$, which are allowed to differ on either side of the cutoff c. The coefficient of interest β captures the local average treatment effect of crossing the threshold (i.e., a lower threat of competition) on outcome Y_{irt}.

We apply kernel weighting using a triangular kernel, which gives more weight to observations closer to the threshold, and include observations only within the bandwidth $(|X_{rt} - c| \leq h)$, chosen based on the mean square error criterion around the cut-off, using the methods outlined by Calonico et al. (2014). In addition, $\mathbf{Z}'_{rt}$ controls for population density, income tax revenue, and age structure, in addition to physician-association- and year-fixed effects to account for potential confounding factors.

Standard errors are clustered at the treatment level (planning area) to correct for intra-group dependence. We report both conventional and robust estimates, which accommodate varying error distributions and allow for non-linearities at the cut-off. Robust estimates may differ from conventional ones because they use a bias-corrected approach, which adjusts the local fit around the cut-off, leading to potentially different point estimates that better capture the true treatment effect. This approach requires only relatively weak assumptions (see Lee and Lemieux, 2010) to identify local causal effects.[15]

Most importantly, units may not be able to manipulate their treatment status. Although there is legal leeway for the associations of the insurance providers and the state associations of SHI-accredited physicians to influence the local target, there is little possibility for them to admit GPs or for GPs to settle in closed regions (see Section 2 for a detailed discussion). Typically a region remains open to new GP entry until it reaches a coverage rate of just below 110%. If there is manipulation by local authorities, we would expect to see a clustering of regions just below the cut-off to allow room for maneuvering in local primary care. However, on average, the entry of a single new GP in regions just below the cut-off increases the coverage rate by approximately 3 percentage points, leading to an overshooting effect. Therefore, there should be some excess mass just to the right of the cut-off as a result of overshooting, regardless of manipulation.

To test whether we observe any signs of manipulation, we perform a density test of the running variable as suggested by Cattaneo et al. (2018). Figure F.2 in the Appendix presents density estimations of the test and a histogram of the running variable around the cut-off. The histogram shows that the expected excess mass is *above* the cut-off of

[14] The level of observation is either the patient, practice, or planning area.

[15] For the implementation of our approach, we rely on the `rdrobust` R packages provided by Calonico et al. (2022) and the `tidyverse` package ecosystem developed by Wickham et al. (2019).

a 110% coverage rate. We conclude that this is the result of overshooting and, thus, a feature of the policy, and not a sign of manipulation as, under manipulation, we would expect the bunching to occur right below the cut-off.

Nevertheless, as a robustness check, we restrict our sample to observations that are unlikely to be prone to manipulation by excluding units from our analysis that fall within a certain range around the cut-off (i.e., creating a so-called "donut hole"). We determine the size of this range based on the excess mass observed in the density test and exclude observations in a window of 1.5 percentage points around the cut-off coverage rate of 110%.[16] As Figure F.2 shows, this window is sufficiently large to ensure a continuous density around the cut-off.

Table 4: Test of Covariate Discontinuities

Covariate	**Mean (Germany)**	**Mean (Cut-off)**	**Point Estimate**	**Z-stat**	**P(|Z| > z)**	**95% Conf. Int.**
Population density (People per km^2)	360.30	415.88	-8.99	-0.27	0.79	[-75.48 ; 57.50]
Absolute population	86552	103161	-4130	-0.48	0.63	[-20975 ; 12715]
Income tax revenue per capita	3233.60	3272.32	20.09	0.26	0.80	[-132.85 ; 173.03]
Gross domestic product per capita	33077.50	33467.19	307.64	0.35	0.72	[-1391.36 ; 2006.64]
Share of people in need of nursing care	4.33%	4.30%	0.04%	0.71	0.48	[-0.07 %; 0.15%]
Population share of people over the age of 65	20.98	20.90	-0.08	-0.55	0.58	[-0.38 ; 0.21]
Population share of women	51.03%	51.08%	0.03%	0.51	0.61	[-0.07% ; 0.12%]
Share of foreign-born population	5.65%	5.85%	0.00	0.01	0.99	[-0.44% ; 0.44%]
People per of Pharmacy	4170.84	4103.49	119.64	1.56	0.12	[-30.28 ; 269.56]
Share of practices with a Jameda profile	47.12%	47.94%	-0.57%	-0.42	0.67	[-3.20% ; 2.06%]

Notes: This table presents the results of a test of covariate continuity around the cut-off using a regression discontinuity design. For each covariate, the mean value of the covariate over all of Germany and the mean in the bandwidth around the cut-off are shown. In addition, the point estimate of the covariate test—as well as the corresponding z-statistic, p-value, and lower and upper bound of the 95%-confidence interval— are displayed. Variables are included based on their importance for the demand for primary care. All specifications include year fixed effects and fixed effects for the state associations of individual SHI-accredited medical doctors.

The second assumption necessary for obtaining valid causal estimates is that no systematic differences exist between planning areas near the cut-off, beyond what is observed in the coverage rate distribution. Overall, planning areas are very similar at the cut-off, as shown in Table 4. For example, in our data, Heidelberg and Darmstadt, two university cities with a strikingly similar economic structure, are affected differently by the entry restriction in 2019. While both boast similar population sizes (291,560 and 294,710), Heidelberg is blocked with a coverage rate of 110% whereas Darmstadt is open to entry with a coverage rate of 109%. Regression Discontinuity (RD) estimates in Table 4 using different regional characteristics as dependent variables confirm that there are no

[16] With a 1.5-percentage point band on both sides we naturally exclude any observations that are affected by the 3-percentage point overshooting effect.

significant discontinuities at the cut-off. Overall, regions near the cut-off appear slightly more urban with higher population density and absolute population than the German average. In other important dimensions, like the share of GPs with a Jameda profile or the share of inhabitants over 65, our sample does not differ from the German average. Additionally, the RD coefficients are very small relative to the respective averages within the bandwidth. The confidence intervals for these estimates are narrow and include zero, reinforcing the validity of this second assumption.

4 Results

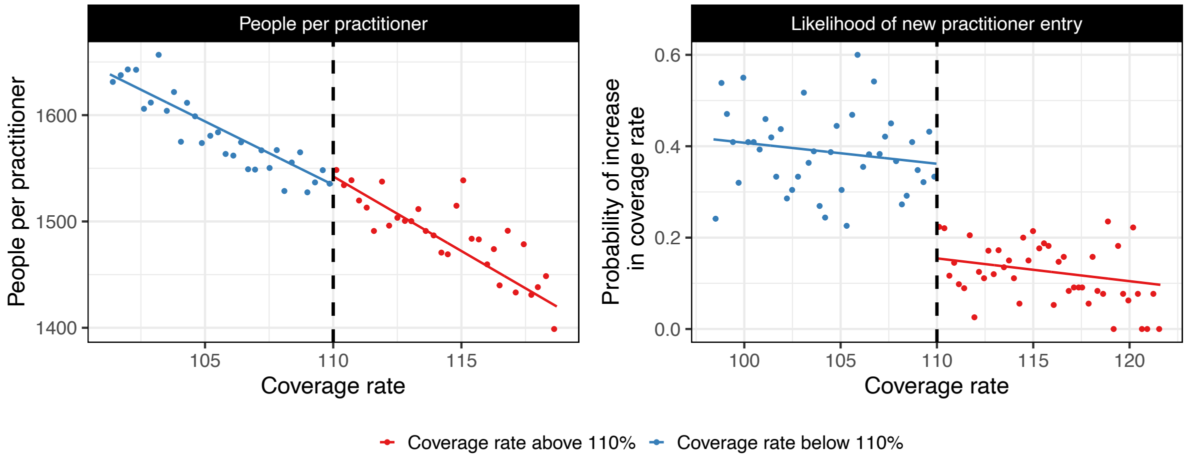
In this section, we present the results of our regression discontinuity analysis. First, we establish that entry restrictions significantly reduce the likelihood of new practices opening, thereby decreasing the *threat of entry*, while not affecting the level of *actual competition*. Next, we explore how this reduction in the threat of entry influences the local composition and the behavior of individual incumbent GPs. For the behavioral responses, we distinguish between GPs with no nearby competitors (local monopolists) and GPs with competitors (non-monopolists). While we do not expect behavioral responses from GPs in already competitive markets, entry restrictions shield local monopolists from competitors entering their market and enable them to lower the quality of services without the fear of losing market shares (see Section 2.2 for a detailed discussion). Finally, we assess how entry restrictions affect the health outcomes of local populations, potentially through changes in the behavior of incumbent GPs. Specifically, we investigate whether patients begin substituting primary care with hospital care and whether mortality rates increase, particularly for conditions commonly treated by general practitioners.

4.1 Entry Restrictions and the Threat of Entry

We start by examining how planning areas just below and above the cut-off of the 110% coverage rate differ in terms of (i) actual competition and (ii) the threat of competition. As argued before and captured in Figure 1, blocked entry does not affect the number of people per practitioner, our main measure of actual competition. However, it strongly diminishes the likelihood of new GPs entering, proxied by an increase in the coverage rate, which is our main measure of the threat of competition.

Competitive Pressure. Although the number of people per practitioner continuously shrinks along the coverage rate distribution, and thus the competitive pressure increases, there is no detectable jump at the cut-off (left panel). The point estimates for the number of people per practitioner show no economic and statistical significance, with an average of fewer than 8 people per GP (compared to mean values of 1,500 around the cut-off) and a p-value exceeding 0.20.

Figure 1: RD Estimates for People per Physician and Likelihood of Coverage Rate Increase



Panel A: People per practitioner				
Method	Point Estimate	z-Statistic	p-value	95% Confidence Interval
Conventional Estimate	7.9290	1.27	0.20	[-4.3095 ; 20.1674]
Robust	7.2672	1.02	0.31	[-6.7579 ; 21.2922]

Panel B: Likelihood of an increase in the coverage rate				
Method	Point Estimate	z-Statistic	p-value	95% Confidence Interval
Conventional Estimate	-0.2071	-6.64	0.00	[-0.2683 ; -0.1459]
Robust	-0.2052	-5.74	0.00	[-0.2752 ; -0.1351]

Notes: The figures show regression discontinuity plots for both the number of people per practitioner in a region (left panel) and the likelihood of an increase in the coverage level measured as the mean share of regions in which the coverage rate increases between t and $t+1$ (right panel). The blue line shows a linear fit left of the cut-off whereas the red line shows the fit right of the cut-off. Mean-square error optimal bandwidths are used for both panels. For the left panel, the bandwidth is 8.72 percentage points around the cut-off using $N = 2,155$ observations. For the right panel, the bandwidth is 11.63 percentage points around the cut-off using $N = 2,489$ observations. Both models control for population density, income tax revenue, and age structure, in addition to physician-association- and year-fixed effects. The precise estimates and the corresponding z-statistic, p-value, and confidence interval for both figures are presented in the table below.

This finding is insensitive to the choice of the outcome variable as we arrive at the same conclusion when using alternative measures of competition. Figure F.4 shows that neither the average distance from patients to their nearest GP nor the distance between

GPs changes at the cut-off.[17] This leads us to conclude that, around the cut-off, entry restrictions do not affect the access of patients to primary care and the level of competition.

Threat of Competition. This picture is markedly different for the likelihood of new practitioners entering (right panel). Incumbent GPs in planning areas above the cut-off face a 20 percentage points lower probability of additional competitors entering the market in the next year, compared to a baseline of roughly 40%.

This finding holds when using the probability of new practice openings obtained from the Yellow Pages as an alternative outcome. We find a decrease in the probability of new practice openings in the same order of magnitude (see Appendix Figure F.3 for a detailed analysis).[18]

Robustness. However, to ensure that these findings are robust and uniquely tied to the actual policy and thus, for instance, do not reflect other unobservable differences between planning areas above and below the cut-off, we perform a series of robustness checks.

First, to confirm that our results are uniquely tied to the actual policy cut-off, we apply placebo cut-offs at 100% and 120% of the coverage rate (as shown in Figure F.5 in the Appendix). Indeed, only at the 110% cut-off, where we expect the policy to impact the threat of competition, do we see such a discontinuity.

We also conduct a geographic placebo test in which we swap outcome variables of affected regions above the cut-off with those of their geographic neighbors below it (see Figure F.8 in the Appendix). This approach is designed to account for potential differences in spatially correlated unobserved variables. For example, blocked and open neighboring regions might differ in unobserved health-related behavior of their population and influence a part of the observed effect. In this case, the placebo estimates would reflect a similar effect. Reassuringly, this geographic placebo reveals no significant impact on the increase in coverage rate. Similarly, Figure F.9 shows that spatial spillovers to neighboring regions play no significant role, as the likelihood of entry does not increase in the closest open neighbor region when a planning region exceeds the cut-off.

We repeat the main analyses with a modified running variable, namely the number of GPs that are missing to exceed the 110% cut-off (see Figure F.6). The patterns observed are notably similar to our original analysis using the coverage rate directly.

Lastly, our results are highly robust across a wide range of bandwidth and specification choices, as well as to the exclusion of observations within a 1.5 percentage point window

[17] The average pairwise distance between GP locations within a region is a measure commonly used in economic geography. Based on Hotelling's model of spatial competition, this measure indicates competition intensity, with shorter distances suggesting higher competition due to firms being closer together and competing for the same customer base.

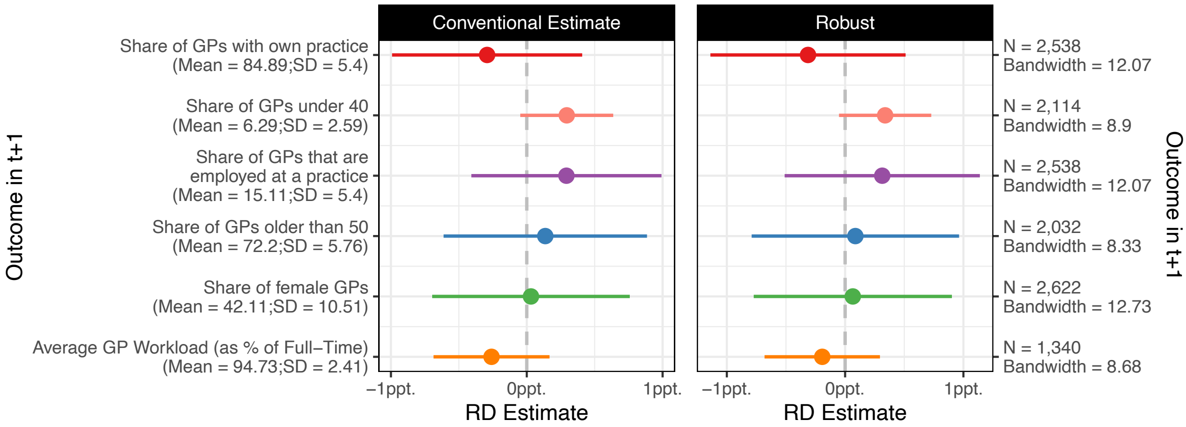
[18] For our main measure that is based on the probability of an increase of in the coverage rate, we also display the effect on the absolute change of the coverage rate in Figure F.7 in the Appendix.

around the cut-off. This robustness check, shown in Figure F.10 in the Appendix, reveals that the estimated coefficient remains nearly unchanged across almost all specifications.

4.2 Entry Restrictions and the Composition of GPs

Blocked entry for new, and potentially younger, practitioners can affect the composition of GPs in planning areas and therefore affect the quality of services provided. To test if this is the case, we look at variables reflecting both the demographic (e.g., age and gender) and the economic structure (e.g., ownership and retirement). However, Figure 2 indicates that crossing the cut-off has no immediate impact on the demographic or employment composition of GPs across regions.

Figure 2: Regional GP Composition Measures



Notes: The figure displays the estimated coefficients with their 95% confidence intervals from regression discontinuity designs examining the composition of GPs within regions. The outcomes analyzed include the average GP workload as a percentage of full-time, the share of female GPs, the share of GPs older than 50, the share of GPs employed at a practice, the share of GPs under 40, and the share of GPs owning their practice. All models control for population density, income tax revenue, and age structure, in addition to physician-association- and year-fixed effects. Standard errors are clustered by planning area. The means and standard deviations for each outcome are listed on the left axis. The right axis shows the bandwidths and the number of observations used in each regression discontinuity analysis.

All observed effects on composition measures are minimal, remaining below half a percentage point. Specifically, the average GP workload as a percentage of full-time employment remains stable at 94.73%, with no noticeable shifts detected at the policy cut-off. Similarly, the proportion of female GPs is unchanged at 42.11%. The percentage of GPs over 50, used as a proxy for retirement decisions, remains steady at 72.2%. This suggests that crossing the cut-off does not affect retirement timing decisions. Furthermore, the proportion of registered GPs employed at another practice, which stands at

15.11%, reflects minimal changes, indicating negligible effects on consolidation decisions and shifts between independent and group practice employment. Likewise, there is no observable difference in the share of GPs who own their practice, which remains at 84.89%. These findings indicate that entry restrictions do not immediately impact the broader labor market or demographic characteristics of GPs, such as retirement behavior, practice ownership, or employment type.

To see if these limited findings are due to the short time horizon, we employ a difference-in-difference strategy as an extensive robustness check. The analysis, which is described in detail in Appendix E, shows that, in the longer run, planning areas that are newly blocked for entrant GPs do not change substantially in terms of composition. Given the overall insignificant results for compositional changes in the characteristics of GPs, we can confidently rule out that these changes cause confounding variations in service quality or patient health. In the next step, we therefore consider whether, as expected, GPs react to the entry restrictions by changing their service supply behavior.

4.3 Behavioral Responses of Monopolists vs. Non-Monopolists

As shown, the planning system creates a discontinuity in the threat of entry without changing the competitive pressure or patients' access to medical services. This unique setting allows us to identify a causal link between the threat of entry and service quality of incumbent GPs.

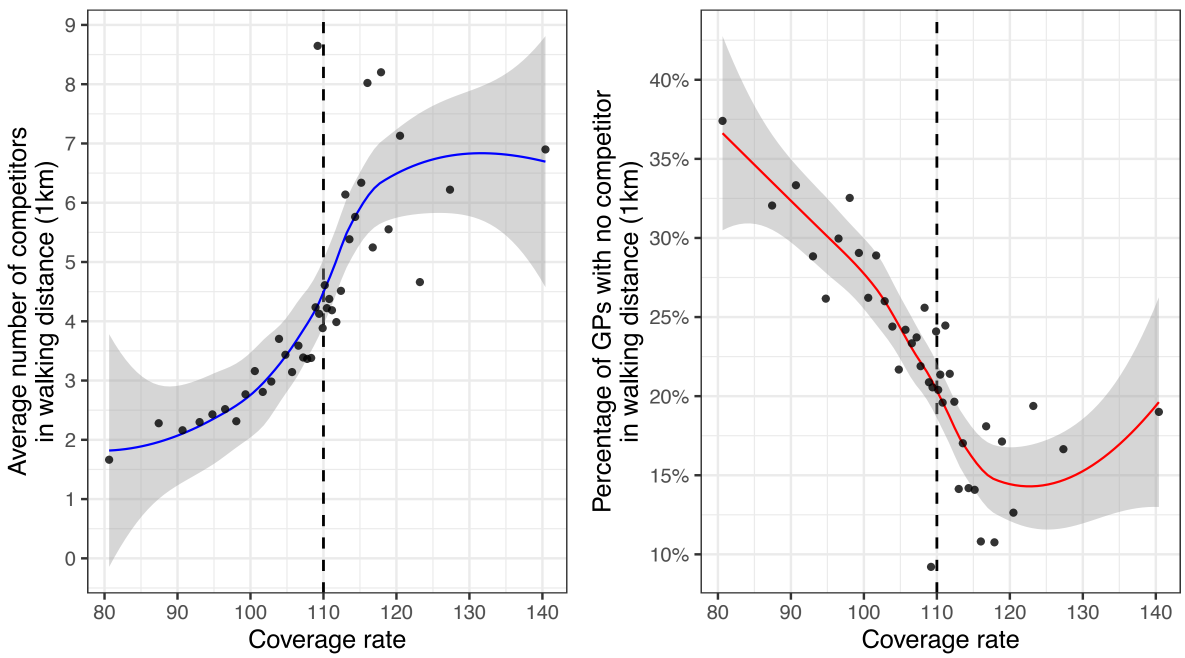
Unlike other countries with a fee-for-service model that incentivizes GPs to increase their service volume regardless of competitive dynamics, Germany operates under a different reimbursement framework. In Germany, GPs are assigned a fixed service volume per patient and any services provided beyond this allocation are compensated at a significantly reduced rate. This structure inherently limits the financial incentives for GPs to increase both the quantity and quality of services after a certain cut-off is reached. Additional efforts yield strongly diminishing returns (see Section 2 for details on the German reimbursement scheme).

Implications for monopolists vs. non-monopolists. Under these conditions, GPs' responses to entry restrictions depend on their competitive environment. If a planning area is blocked for new entrants, local monopolists can reduce the quality of services without fearing losing patients and, thus, a decrease in income, as the reimbursement scheme does not penalize lower service quality, and patients have limited alternatives to switch providers. In contrast, in a competitive local market, patients are not "locked in" but free to switch. Thus, the potential for these GPs to exploit the reduced threat of entry by lowering effort and service quality is limited.

To test whether the reduced threat of entry affects the behavior of GPs differently depending on whether they are local monopolists, we rely on a commonly used definition of walking distance (1 km) to define local monopolists as GPs having no competitors within that radius, which suits our urban context.

Figure 3 depicts the mean number of competitors (left panel) and the proportion of local monopolists within walking distance (right) across the coverage rate distribution. As shown before, the competitive pressure increases with the coverage rate and does not have a discontinuity at the cut-off. Around the cut-off, GPs have, on average, 4 to 5 competitors within walking distance. At the same time, the share of local monopolists decreases continuously to around 20% at the cut-off. For these 20% of GPs, entry restrictions effectively protect them from potential competition for several years, which we anticipate would result in reduced effort and, consequently, lower service quality.

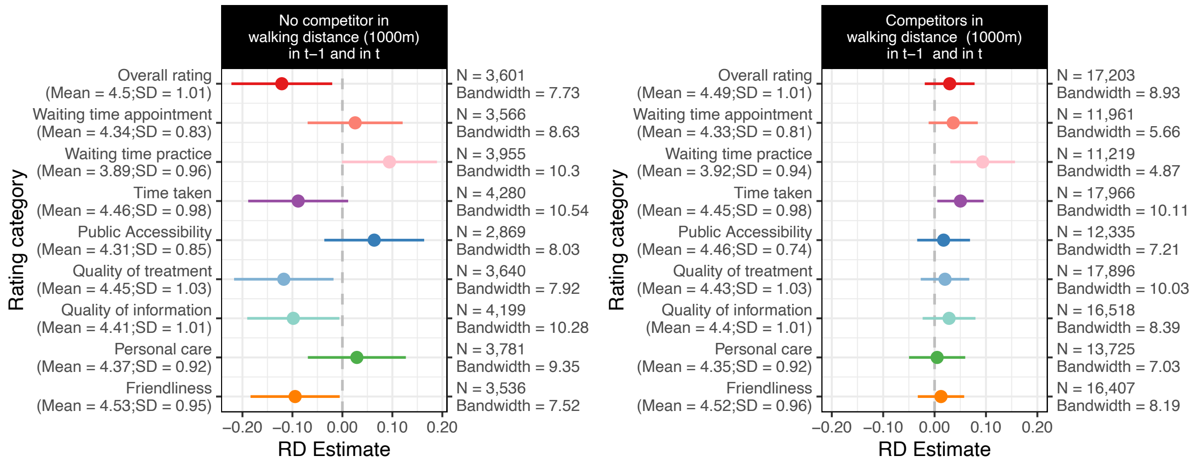
Figure 3: Competitors within Walking Distance by Coverage Rate



Notes: The figure shows binned scatter plots illustrating the local competitive environment of individual GPs based on regional coverage rates. The left panel displays the average number of competitors within a 1 km walking distance, while the right panel shows the percentage of GPs with no competitors within this range.

Individual-Level Results. Figure 4 illustrates the respective RD estimates on Jameda ratings for both groups. The left side depicts ratings for persistent local monopolists, while the right side focuses on ratings for practices that consistently faced competition. For persistent local monopolists, we observe lower overall quality ratings, particularly in areas such as information quality, treatment quality, time spent per patient, and friendliness. However, waiting times—and consequently the number of patients treated—appear unchanged. The observed effects correspond to approximately 10% of the standard deviation in ratings, suggesting slightly inferior services for local monopolists without the threat of new competitors. In contrast, these effects are not observed in practices that have consistently faced competition. This gives us confidence that the threat of entry matters for the behavior of GPs, but only for those for which blocked entry means that their local monopoly remains unchallenged in the future. Henceforth, local monopolists provide lower-quality services.

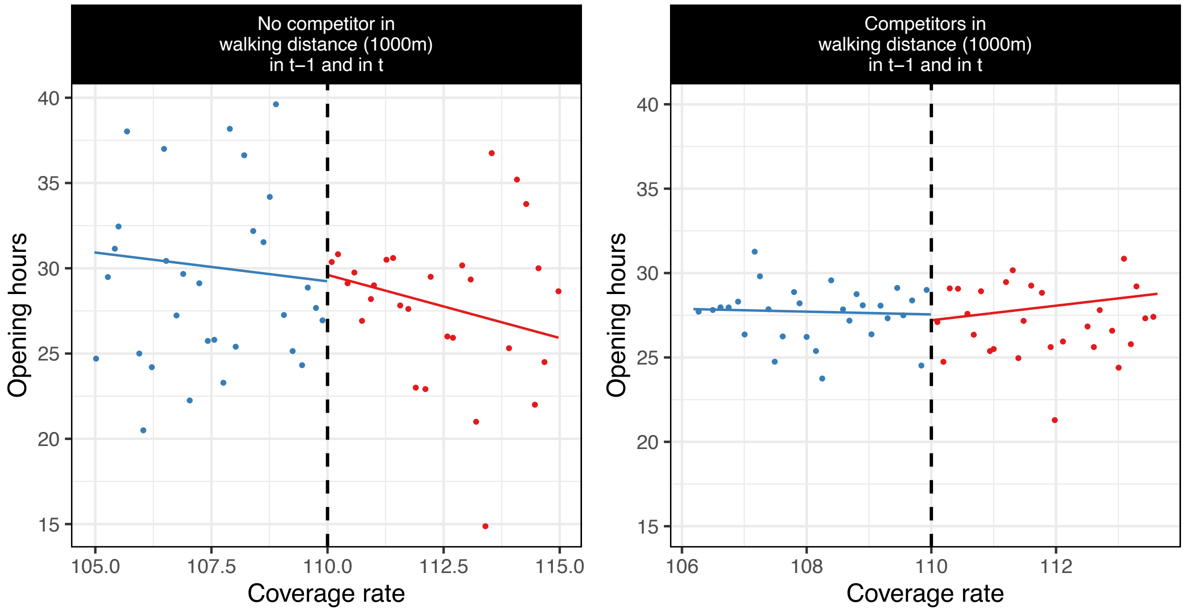
Figure 4: Jameda Ratings for Local Monopolists within Walking Distance



Notes: The figure presents the estimated coefficients along with their 95% confidence intervals from multiple regression discontinuity designs, focusing on subjective patient ratings. All models incorporate controls for population density, income tax revenue, and age structure, and include fixed effects for physician-association and year. Given that the estimations are conducted at the individual physician level while the treatment is administered at the regional level, standard errors are clustered by planning region. The left panel displays estimates for GPs without competitors within a 1,000-meter walking distance both before and after blocked entry, whereas the right panel shows estimates for GPs with competitors throughout. The rating categories, along with their means and standard deviations, are listed on the left axis. The right axis provides information on the bandwidths and the number of observations used in each regression discontinuity analysis.

As an additional placebo check, we compare *persistent local monopolists* —GPs who remained without competitors both before and after entry was blocked in their planning area— with "unlucky" *former local monopolists* in Appendix Figure F.12. These "unlucky" former local monopolists, previously the sole practitioners in their area, now face competition within their area that is blocked to entry. This competition arises primarily from movements within the existing practitioners (relocations) or through special licensing exceptions rather than new, external entries into the market. This comparison highlights that unlucky former local monopolists, who unexpectedly face new competition, do not show the same reduction in service quality as persistent monopolists.

Figure 5: RD Estimates for Opening Hours by Competitive Environment



Panel A: GP Opening Hours of local monopolists within walking distance

Method	Point Estimate	z-Statistic	p-value	95% Confidence Interval
Conventional Estimate	0.33	0.33	0.74	[-1.60 ; 2.25]
Robust	0.89	0.82	0.41	[-1.25 ; 3.03]

Panel B: GP Opening Hours of local non-monopolists within walking distance

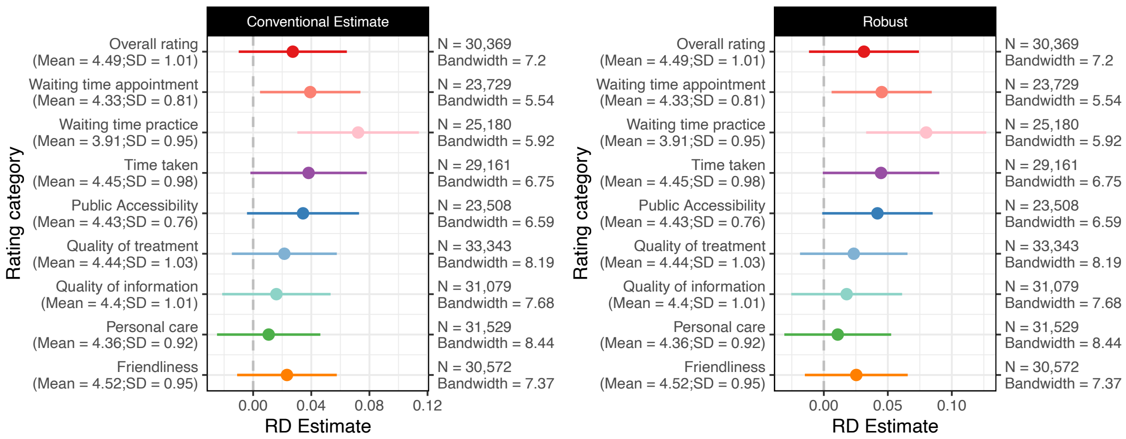
Method	Point Estimate	z-Statistic	p-value	95% Confidence Interval
Conventional Estimate	-0.35	-1.05	0.29	[-1.01 ; 0.30]
Robust	-0.45	-1.11	0.27	[-1.24 ; 0.35]

Notes: The figure presents regression discontinuity plots for the opening hours of GPs (General Practitioners) by competitive environment within walking distance (1,000m). Panel A shows the results for local monopolists, while Panel B depicts the results for local non-monopolists. The blue line represents a linear fit to the left of the cut-off, and the red line represents the fit to the right. A mean-square error optimal bandwidth is used for the estimation in both panels. For Panel A, the bandwidth is 5.089 around the cut-off, with $N = 2,257$ observations used in the estimation, and for Panel B, the bandwidth is 3.859 with $N = 14,104$ observations. The table below the plots reports the respective RD estimation results.

To investigate the impact of the threat of entry on the quantity of services beyond rating for (e.g., waiting times), we explore the actual opening hours, measured in 2020, of GPs who operate as local monopolists within walking distance, compared to those who face competition throughout. Figure 5 presents the regression discontinuity estimates for both groups. The effects only amount to a third of an hour compared to a baseline of roughly 30 hours in both groups. This suggests that GPs who do not have to fear nearby competitors do not adjust their opening hours or the quantity of services they provide in response to entry restrictions.

Aggregate-Level Results. Next, we are interested in the aggregate effects at the planning area level. Figure 6 shows the overall RD estimates on the subjective perception of individual GPs using patients' online ratings. Both for the overall practice rating and across all rating sub-categories, we do not find any meaningful effect of blocked entry. The estimates are accurate and almost negligibly small, with all 95% confidence intervals spanning less than a tenth of a standard deviation around zero. To assess the effect of entry restrictions on the quantity of services, we look at both a subjective measure (perceived waiting times) as well as an objective measure (practice opening hours). As for the individual-level results and unlike the effects on quality, we do not expect practitioners to react by either increasing or decreasing the number of services given the German SHI reimbursement scheme. For waiting time ratings, we find an economically small positive increase of at most 0.06 points on a 5-point Likert scale.

Figure 6: Coefficient Plot for RD Estimates on Practice Ratings



Notes: The figure plots the estimated coefficients and the respective 95% confidence intervals across multiple regression discontinuity designs for subjective patient ratings. All models control for population density, income tax revenue, and age structure, in addition to physician-association- and year-fixed effects. Since the estimation is at the individual physician level, but the treatment is at the regional level, we cluster by planning region. The left plot shows conventional estimates, while the right panel shows bias-corrected robust estimates. The rating categories, as well as their means and standard deviations, are on the left axis. Moreover, the right axis displays bandwidths and observation numbers of the RDs.

Next, we look at the overall impact of entry restrictions on GP opening hours in Figure F.11 in the Appendix. The effect detected is very small—a mere 1.5 ($= 0.0258 \times 60$) minutes relative to a baseline of 29 hours, suggesting no substantial change. This conclusion is reinforced by a tight confidence interval, which is only half an hour above and below zero, underscoring the negligible effect of entry restrictions on service quantity. This result is also in line with the disaggregated results reported in Figure 5 that showed no change for either monopolists or non-monopolists.

These small and insignificant aggregate effects are not surprising given that local monopolists, which is the only group for which we suspect and observe substantial changes in behavior, make up only 20% of all GPs at the cut-off. However, this does not mean that the population is not affected in terms of their health given patients of monopolists face now lower service quality over years to come and are "locked in". Therefore, we investigate the possible health implications in the following.

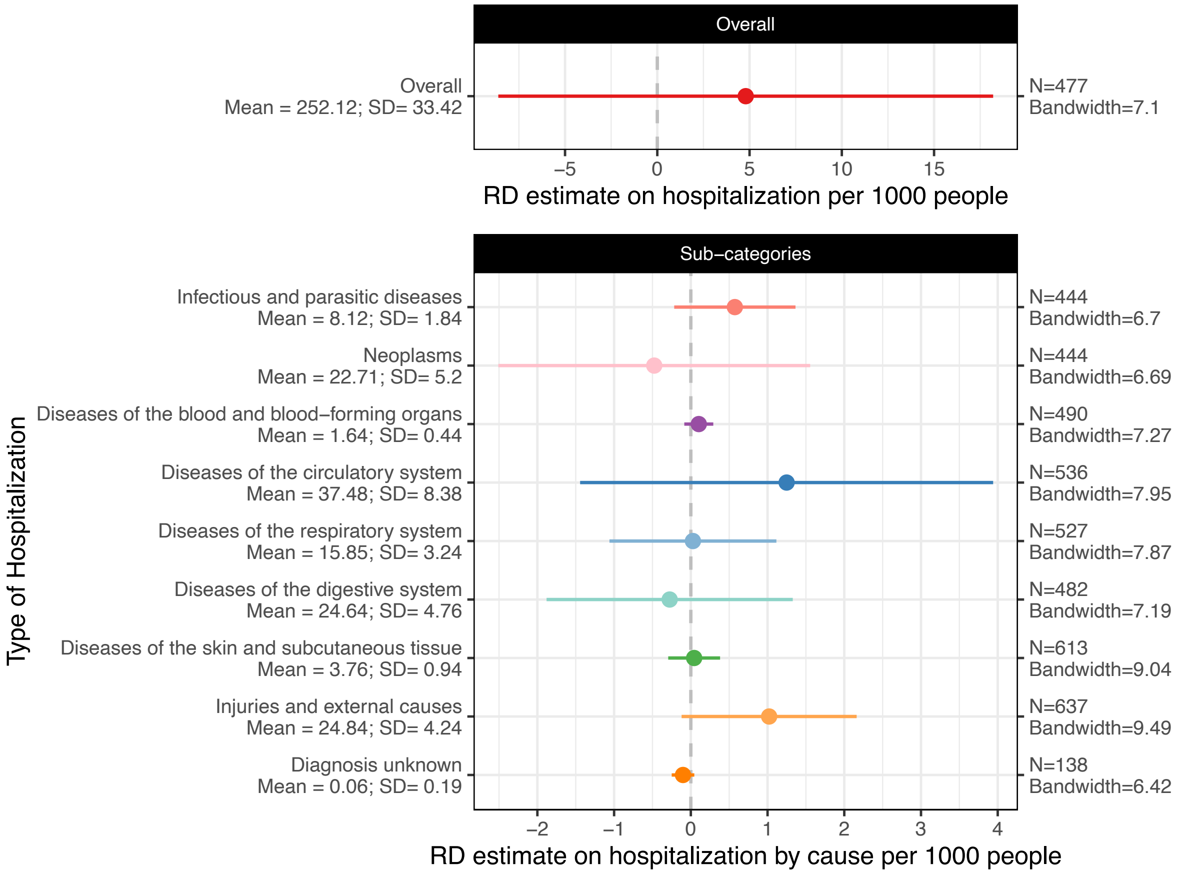
4.4 Consequences for Population Health

While our analysis of individual GPs' behavior highlights that entry restrictions mainly affect local monopolists, it remains to be seen whether these restrictions have wider regional effects on patients' behavior and their health.

Substitution of Primary Care by Hospitals. As part of our exploration of the broader regional implications of entry restrictions, we examine whether there is a shift from primary care provided by GPs to hospital care. Even though GPs do not act as gatekeepers, they play a crucial role by referring patients to specialists only if needed and helping to prevent unnecessary hospital admissions (see Table C for a comparison across countries). Given that entry restrictions reduce the quality of services provided by local monopolist GPs, it might also increase hospital admissions for conditions typically managed within primary care settings—either voluntarily as patients seek treatment elsewhere, or involuntarily as patients are admitted to hospitals as they lack adequate treatment.

As in Dietrichson et al. (2016), we investigate whether there is an increase in hospitalizations in regions where new entry is blocked. Additionally, our rich administrative data at the regional level allows us to differentiate the reasons for hospital admissions to see whether hospital admissions are especially pronounced for conditions typically managed or screened by GPs. However, our analysis reveals no significant increase in overall hospitalizations or in admissions for conditions commonly handled by GPs, as shown in Figure 7.

Figure 7: Coefficient Plot for RD Estimates on Hospitalizations

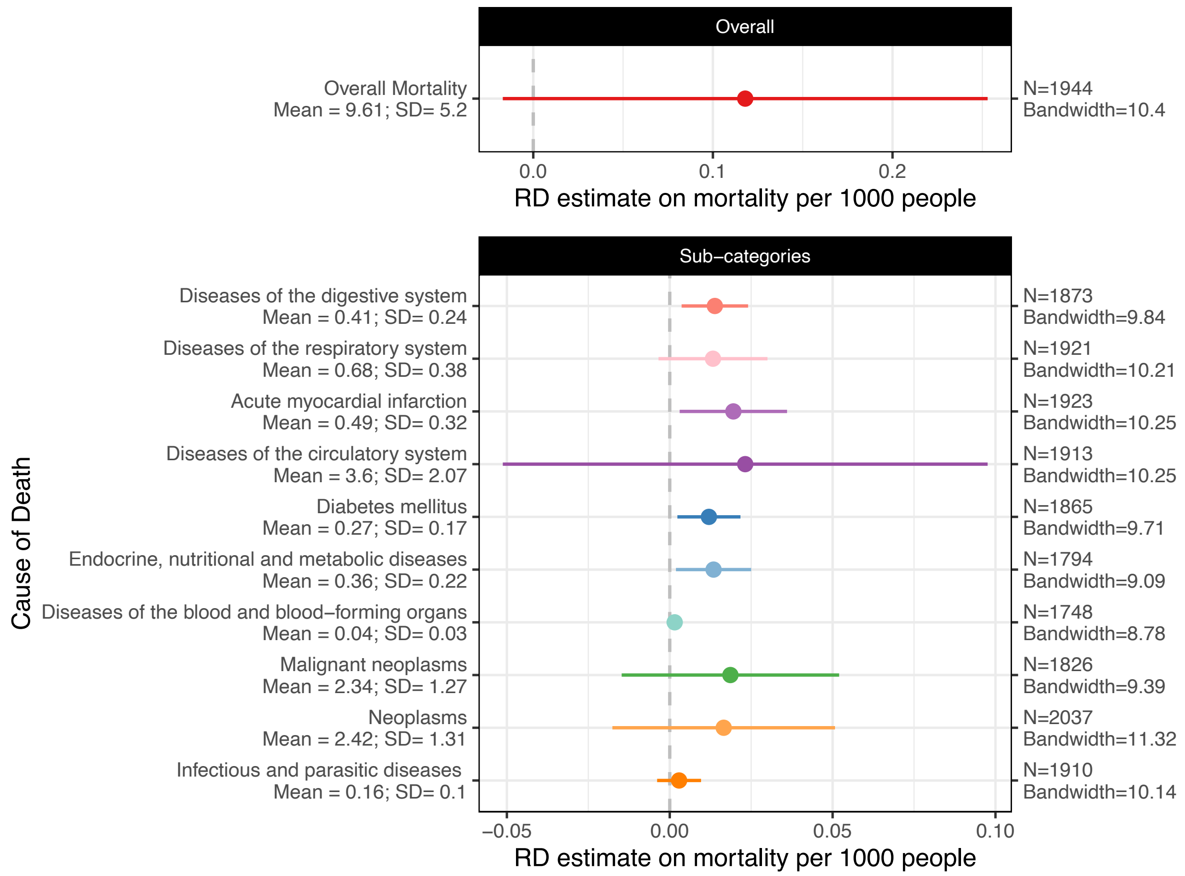


Notes: The figure plots the bias-corrected robustly estimated coefficients and the respective 95% confidence intervals of multiple regression discontinuity designs for hospital admissions by different International Classification of Diseases (ICD) diagnoses. All models control for population density, income tax revenue, and age structure, in addition to physician-association- and year-fixed effects. Standard errors are clustered by planning area. The separate diagnoses as well as the population means and standard deviations of these variables, are shown on the left axis. Moreover, the right axis displays bandwidths and observation numbers of the RDs.

The measured effect on overall hospitalizations is just 5 hospitalizations compared to a baseline of 252, with narrow confidence bands around zero. The analysis of subcategories shows that the effect sizes are uniformly small, resulting in precise null effects across different conditions. This consistency across all categories, from injuries to chronic diseases, suggests that the shift from primary care to hospital admissions is not significant enough to become evident in the data.

It is important to note, however, that the absence of detectable effects on hospitalizations at the regional level does not rule out the possibility of an impact at a more granular level. For instance, patients of the 20% of GPs who operate as local monopolists and thus provide lower service quality in planning areas with blocked entry could experience higher rates of hospitalization. Unfortunately, due to data limitations, we cannot disaggregate hospital admissions data to this level of detail to test for such specific effects. Therefore, while the broader regional analysis suggests no substantial shifts from primary to hospital care, there may still be undetected effects among subgroups of patients more directly impacted by entry restrictions.

Figure 8: Coefficient Plot for RD Estimates on Mortality by Cause



Notes: The figure plots the bias-corrected robustly estimated coefficients and the respective 95% confidence intervals of multiple regression discontinuity designs for deaths per 1,000 residents by cause. All models control for population density, income tax revenue, and age structure, in addition to physician-association- and year-fixed effects. The separate causes as well as the population means and standard deviations of these variables, are shown on the left axis. Moreover, the right axis displays bandwidths and observation numbers of the RDs.

Regional Cause-Specific Mortality Considering that our findings show no significant changes in the ratio of people per practitioner, no variation in current competition, and no altered (regional) hospital admission behavior, it is unlikely that any effect on regional mortality outcomes can be detected. To confirm this, we examine regional mortality rates. Figure 8 shows the estimated regression discontinuity coefficients and confidence intervals for overall regional mortality and cause-specific mortality rates. Diseases particularly in the focus of the regular health check-ups and thus of our analysis are oncological diseases (e.g., neoplasms), endocrine diseases (e.g., diabetes mellitus), and cardiovascular diseases (e.g., myocardial infarction). Aligned with our expectations, our analysis reveals no significant rise in overall mortality in regions with blocked entry. Furthermore, while we observe statistically significant effects on certain cause-specific mortality rates, such as metabolic diseases in general and diabetes mellitus in particular, these increases are modest and, at most, amount to a tenth of a standard deviation. This minimal magnitude suggests that there are no substantial differences in mortality.

5 Conclusion

In this paper, we investigate how entry restrictions affect the quantity and quality of medical services provided by incumbent general practitioners (GPs) by shielding them from new competitors. In Germany, regions are automatically blocked from new entry once they exceed a locally adjusted but nationally set GP-to-population rate. Applying a regression discontinuity design (RDD) to a novel data collection at the most fine-grained geographic level of planning, we can investigate whether the reduced threat of entry affects incumbent GPs' behavior and, ultimately, patients' outcomes.

Our analysis shows that entry restrictions significantly reduce the likelihood of new GPs settling in planning regions by 20 percentage points, thus strongly diminishing the threat of entry for incumbent GPs. Measures such as the GP-to-population ratio and other indicators of actual competition, like patient access to GPs and spatial competition are not affected. The same is true for the quantity of service provision in measures such as working hours. On the contrary, the reduced threat of new competitors opening a practice in proximity affects the quality of services provided by local monopolists (i.e., GPs without nearby competitors). Unlike GPs in a competitive environment, local monopolists have lower incentives to provide high-quality services once they know that no competition can be established, resulting in patients having limited alternatives.

This finding goes beyond previous studies, which detect a positive effect of GP *competition* on patient satisfaction and practice quality: our results show that the *threat of competition* can improve service quality. However, as only around 20% of GPs are local monopolists, our findings do not translate into regional-level aggregate effects on healthcare quality or access. This finding emphasizes the need to differentiate between potential competition and its realization in healthcare markets.

Furthermore, our findings extend to a broader discussion on the unintended consequences of entry regulations. From the perspective of policymakers, these restrictions are aimed at promoting equal access to medical services between over and undersupplied regions. Similar to previous research on licensing for GPs and entry restrictions for pharmacists, our study demonstrates that entry restrictions in primary care markets have adverse effects because they reduce the service quality of local monopolist GPs. Although these quality effects do not translate into aggregate health effects at the cutoff, they might be well present in a more rural or segregated market where patients are more reliant on a single primary care provider (i.e., the share of local monopolists is higher). Thus, we believe it is crucial for policymakers to not only ensure access to medical services in undersupplied regions but also increase the (threat of) competition for GPs.

Additionally, we introduce the *Regional Health Panel*, a novel dataset featuring detailed administrative data on planning targets and actual practitioner density, along with a broad array of objective regional health outcome measures covering all 1,394 German planning areas between 2014 and 2019. We link this data to a new collection of individual practitioner information from Jameda and the Yellow Pages, covering yearly outcomes of more than 30,000 GPs over the full period. This comprehensive dataset opens up new avenues for research on regional differences in the provision of primary care.

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Appendix

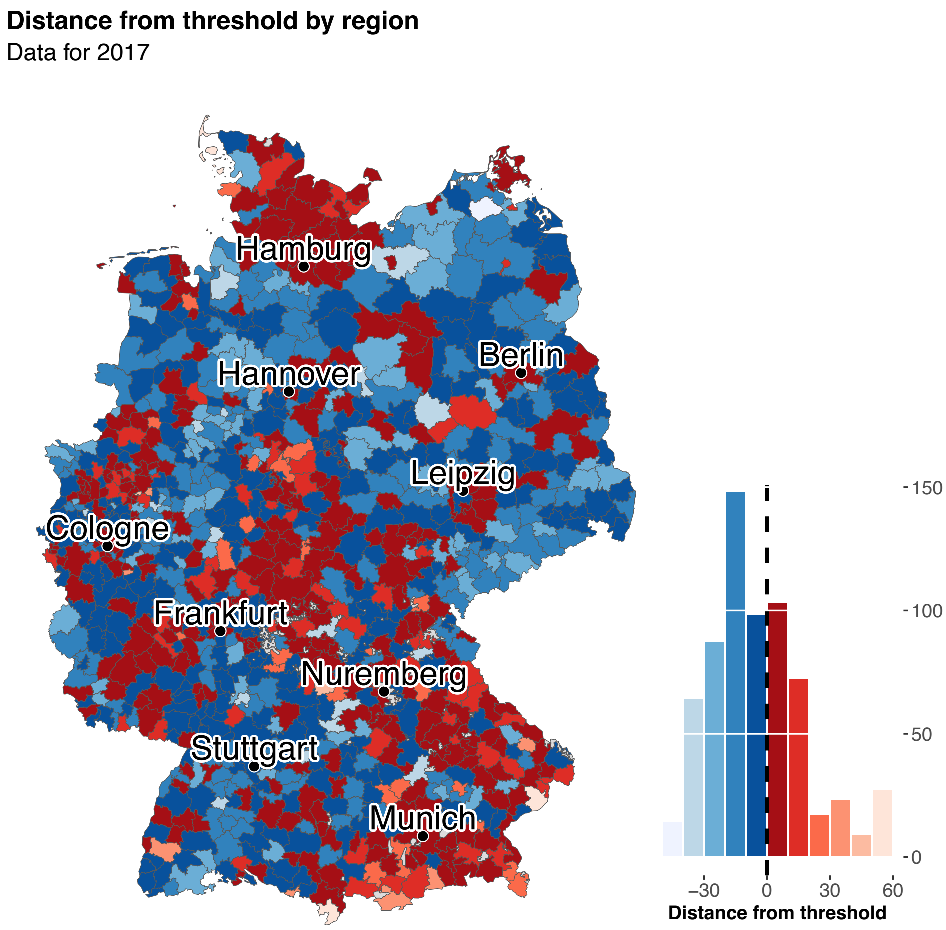
A Key Variable Definitions

Table A.1: Definition of Key Variables

Variable	Definition	Unit
Coverage rate	Regional target population per GP divided by the actual regional population per GP	Ratio
Remaining GPs until cut-off	Absolute number of GPs needed to reach 110% coverage rate cut-off	#
Threat of competition		
Likelihood of coverage rate increase	Indicator for coverage$_{t+1}$ >coverage in$_t$, else 0	Dummy Variable
Likelihood of new GP	Indicator of an increase in the number of GPs between t and $t+1$ in the Yellow Pages	Dummy Variable
Competition between GPs		
Service accessibility	People per practitioner	Ratio
Spatial proximity	Mean pairwise distances of GPs	km
Competitors nearby	Average competitors in walking distance (1km)	#
Local monopolists	GPs with no competitor in walking distance (1km)	Share
Composition of GP markets		
Self-employed	Share of GPs with own practice in region	Share
Employment	Share of GPs employed at practice in region	Share
Young age	Share of GPs under 40 in region	Share
Old age	Share of GPs older than 50 in region	Share
Female	Share of female GPs in region	Share
Part-time	Average GP Workload (as % of Full-time) in region	Share
Quantity of services		
Opening hours	Opening hours per week	hours per week
Public accessibility	Mean rating by GP	5-point Likert scale
Waiting times	Mean rating by GP	5-point Likert scale
Quality of services		
Time taken	Mean rating by GP	5-point Likert scale
Quality of treatment	Mean rating by GP	5-point Likert scale
Quality of information	Mean rating by GP	5-point Likert scale
Personal care	Mean rating by GP	5-point Likert scale
Friendliness	Mean rating by GP	5-point Likert scale
Health outcomes		
Hospital admissions	Hospital admissions by different diagnoses	Cases per 1,000
Mortality	Causes of death	Deaths per 1,000

Notes: # denotes number.

Figure A.1: Map of Distance from the Cut-off in 2017



Notes: The map illustrates the average distance of 2017 mid-level areas from the needs-based planning cut-off of 110% of the local target value. The color scheme distinguishes (open) regions below the cut-off in blue and (blocked) regions above it in red. The saturation of the color corresponds to the distance of each region from the 110% cut-off.

The key policy variable—the coverage rate—also exhibits a strong variability. However, even though variability is high along all these variables, the regions we typically compare in our regression discontinuity approach are very similar. Figure A.1 shows a map of all planning areas available in 2017 and their coverage rates. Typically the regions right below the target (darkest shade of blue) and right above the target (darkest shade of red) are rather urban. Thus, the comparison in this paper is mostly within similar urban regions, for instance between Darmstadt (population: 294,710; 109% coverage rate) and Heidelberg (population: 291,560; 110% coverage rate).

B Institutional overview

Table B.1: Timeline of the Needs-Based Planning System in Germany

Time	Event
1914	Berlin Agreement: 1,350 insured persons per physician as the minimum standard for statutory health insurance (SHI). At the same time, individual restrictions of health insurance funds on the number of licensed physicians
1932	Admission regulations: Limitation of admission based on ratio of 600 SHI members per physician per licensing district
1960	German Federal Constitutional Court: Restrictions on registration contradict freedom of profession (Art. 12 GG)
1977	Health insurance law: Health insurers draw up demand plans and, in the event of undersupply in a district, they can block adjacent districts
1986	Needs-Based Planning law: Physician group-specific ratios on the level of the and determination of overprovision at 150%. In the event of overprovision, optional regulation for the blocking of the area
1993	Health structure law
2010	Introduction of demographic factor: 2 groups (age $<$65 and $>$65)
2012	Regional and local specific factors can be considered at the state level
2019	Replacement of demographic factor by morbidity factor: 8 groups by age and gender ($<$20; 20-45; 45 to $<$75; $\geq$75 and female/male); increase of min. consultation hours from 20 to 25 per week

Notes: The table shows the timeline of the Needs-Based Planning System in Germany, which was introduced to regulate the provision of physicians in statutory health insurance. The system has undergone several changes over the years, including the introduction of group-specific ratios and demographic and morbidity factors

C Comparison to Other Countries

We compare key features of demand planning systems in several countries.

Table C.1: Comparison of Medical Training and Healthcare Systems in Different Countries

Country	**Germany**	**Austria**	**Sweden**	**Netherlands**	**England**
Planning of medical training	No	No	Yes	Yes	Yes
Planning of number of physicians	Yes	Yes	No	No	Yes
Coverage vs. Gatekeeper system	Coverage	Coverage	Gatekeeper	Gatekeeper	Gatekeeper
Inhabitants per GP	1,387	1,316	1,613	1,112	1,562
Main location for specialized services in outpatient care	in medical practices	in medical practices	in the hospital	in the hospital	in the hospital

Notes: The table shows features of comparable health systems in European countries. Following Kleinke et al. (2019), the features refer to England as an example for the UK. We follow Kleinke et al. (2019) and classify countries in a coverage or gate-keeper system. In a gatekeeper system, an appointment with a specialist can be made only on the basis of a referral from a general practitioner. Inhabitants per GP are taken from Eurostat for 2019, except for England which is from a reference in Kleinke et al. (2019) and refers to 2012.

Planning of medical training. The number of doctors in the Netherlands is regulated by the state via training and further education capacities. The future demand for and supply of doctors is modeled on the basis of data and expert assessments, and the training and further education capacities are adjusted accordingly. Training and further training capacities are also controlled in England. In Germany, the number of places for medical studies is controlled at the state level. There is no central or federal control of specialist training.

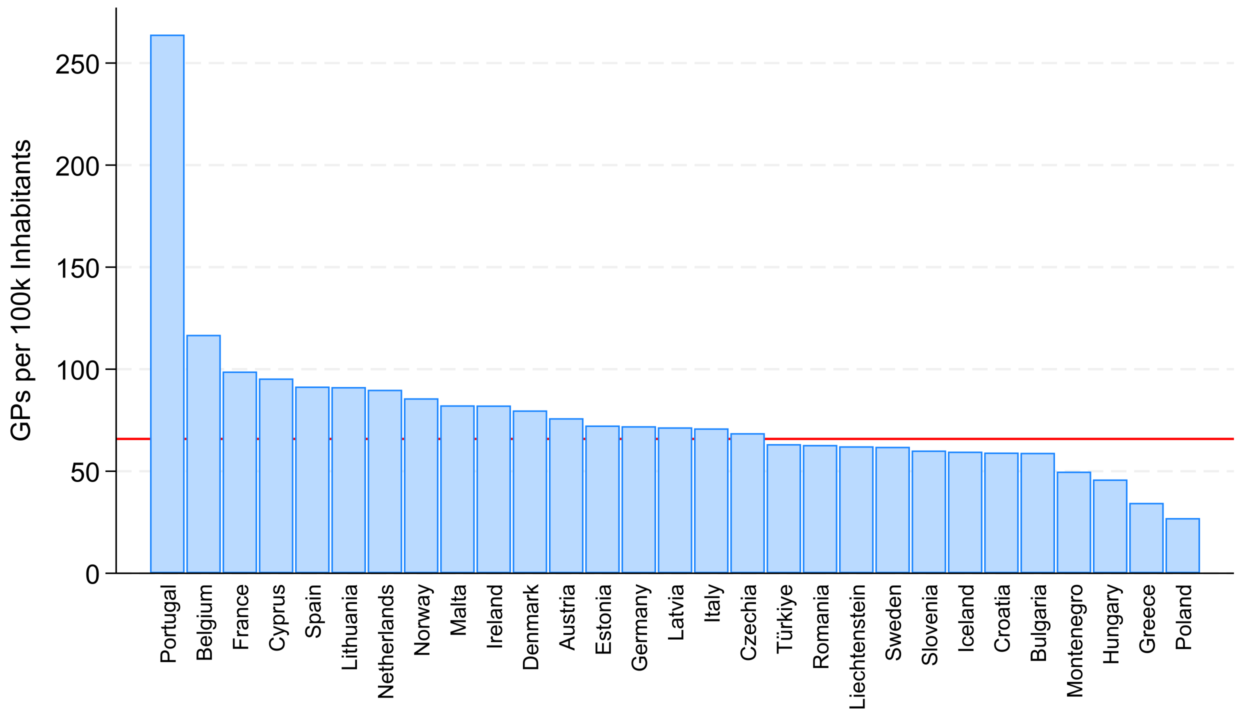
Planning of the number of physicians. The systems of demand planning for England, the Netherlands, and Sweden differ fundamentally from the system in Germany. In England and Sweden, the planning of the number of doctors takes place at the regional level. The number of doctors is determined via individual contracts with the service providers. In the Netherlands, doctors are free to set up their own practices. The spatial distribution of GPs is not planned but determined by market conditions.

Coverage vs. Gatekeeper system. An important difference is whether a country uses coverage rates or a gatekeeper system to steer demand for medical services. In a gatekeeper system, an appointment with a specialist can be made only on the basis of a referral from a general practitioner.

Main location for specialized services. In England, the Netherlands, and Sweden, outpatient care is organized in primary and secondary areas. In England, the Netherlands, and Sweden, nurses are actively involved in outpatient care. Primary care is provided by GPs in cooperation with non-physician healthcare professionals. Secondary care (specialist care) is provided by outpatient doctors at hospitals. Since specialist care is provided to patients in hospitals, there is no double specialist structure in these countries, as is the case in Germany and Austria.

Figure C.1 provides an overview of the number of GPs per 100,000 inhabitants across European countries and highlights the German cut-off in red. The coverage target in Germany, and thus also the window we are focusing on in our RDD, is relatively close to the European average.

Figure C.1: General Practitioner Density across European Countries in 2019



Notes: The blue bars reflect the number of GPs per 100,000 inhabitants across major European countries for the year 2019, obtained from Eurostat. The line in red indicates the German national target of 1,671 inhabitants per GP or around 60 GPs per 100,000 inhabitants, i.e. a coverage of 100%.

D Data preparation and linkage

D.1 Planning region crosswalk

We build a three-step method to accurately link planning region definition across multiple years: First, we established a population-consistent walkover for municipal codes (AGS) between all consecutive pairs of years in our sample period, ensuring accurate tracking of demographic shifts across changing municipality boundaries. By combining this walkover with the definitions of planning areas — where each planning area is defined by the municipalities it contains in a given year — we created accurate lists of municipality codes of planning areas that can be consistently tracked across time. Second, using these municipality lists, we merged the planning areas that contained the same municipalities across different years. Here, the complete lists of municipalities in each planning area served as the merge key, allowing us to link old and new planning area codes across time. Through the iterative application of this approach, we achieved a population-consistent transition of planning area codes across years. The final step involves generating unique identifiers for time-consistent regional units. All results remain virtually the same if we only use the smaller subset of planning areas that are strictly identical to counties.

D.2 Preparation of the Yellow Pages Data

To construct a panel of GPs we rely on raw binary data from German Yellow Pages CDs, kindly provided by Dirk Engling. We focus on the general practitioner (Hausärzte) directories from 2009 to 2020 and use a command line tool by Engling (`telefonbuch`) to extract the raw data. A key challenge in building a panel from these annual directories is the variation in entry formats across the years. For instance, a practitioner's name might appear with an initial one year (e.g., J. Müller) and as a full name with a title in another year (e.g., Dr. Med. Jan Müller). To transform these annual snapshots into a longitudinal panel, we rely on `MatchMaker` a novel R package that implements an index-based fuzzy record linkage approach suggested by Doherr (2023).

To improve matching efficiency and accuracy, we create stable geographic units for blocked search of entries, despite changes in German county (Kreis) boundaries during the study period. We use geocoordinates for each address, joining them spatially with 2016 county definitions to assign consistent county identifiers across all years. This approach divides the data into geographically consistent units, reducing computational work and preventing false matches between entries in distant locations.

As a first step in the linkage process, the names and addresses in each entry in a base and target year are normalized (i.e., special characters are transcribed, and the entries are converted to uppercase) and split into individual word tokens. We build a frequency-based dictionary from the base year tokens, determining each token's identification potential in the target table. Common phrases like "Dr. Med." have low identification potential, while unique names have maximum potential. We calculate the relative identification potential for each token within entries in the base and target tables, using weights of 70% for name tokens and 30% for address tokens. This allows us to evaluate which entries share the most identification potential. Matches exceeding a 70% similarity cut-off are retained, with the highest-scoring candidate selected as the final match. For example, when linking entries from the Yellow Pages for the county of Mannheim from 2013 to 2014, the approach sums the relative identification potential for all matching tokens for an entry in 2013 to get a list of search candidates in 2014. To handle duplicate entries in the raw Yellow Pages data, we apply the same strategy, using a

90% identical identification potential criterion to spot duplicates. We first remove duplicates in each year-county cell, then find matches for consecutive years in each county. After matching all year pairs, we create consistent panel IDs for practices across all available years, letting us define time-constant names and IDs for each matched practice. We account for practices that may temporarily drop out of the Yellow Pages by searching for duplicates in the time-constant practice list and merging IDs where needed. Finally, we fill in observations between a practice's first and last appearance to generate consistent records with realistic entries and exits. Taken together, we can link 98% of the records in the Yellow Pages across time. Comparisons with a manually linked version for one county (Mannheim) suggest that the matching quality is as good as manual linkage by a research assistant.

This comprehensive approach enables us to construct a robust panel dataset that tracks individual practitioners over time, accounting for practice relocations, (slight) name changes, and data entry variations across years.

E Difference-in-Differences (DiD)

In this section, we introduce a multi-period difference-in-difference (DiD) approach as a sensitivity analysis to complement the main analysis based on the regression discontinuity design (RDD). As in the main analysis, we use the data from the *Regional Health Panel* at the planning area level for the years 2014 to 2019, thus a rather short time horizon. However, the DiD approach gives us the advantage of studying the duration and persistence of the treatment's effects, providing insights into whether the limited short-term impacts on the composition observed in Section 4.2 become more pronounced in the long run.

Estimation. In our case, the treatment (i.e., crossing the cut-off and thus blocked entry for new GPs) not only is staggered but also has a non-absorbing state. This means that planning areas can switch both in and out of treatment over the period of observation. Therefore, we use the empirical approach described in de Chaisemartin and D'Haultfœuille (2024).[19] The estimator introduced there is both heterogeneity-robust, meaning prone against problems arising from the staggered adoption of treatment[20], as well as usable when treatment is non-absorbing. First, we assign a treatment $D_{p,t} = 1$ for planning areas p where the coverage rate exceeds 110% and entry is thus blocked. Then, we estimate the coefficient of crossing the cut-off of 110% in a given year t by regressing the outcomes of interest Y on $D_{p,t}$ while controlling for planning area and year fixed effects. Because of our rather short panel, we restrict the periods used to assess the leads and lags (i.e., the evolution of coefficients over time, to 2 and 3 years). Other than in our main analysis, where we can compare all planning areas within a bandwidth around the cut-off, here we restrict ourselves to planning areas that cross the cut-off conditional on not crossing it at least 2 years prior. Further, we cluster standard errors at the planning area

[19]We use the Stata package `did_multiplegt_dyn` for the empirical analysis.

[20]See, for example, de Chaisemartin and D'Haultfœuille (2020) or Goodman-Bacon (2021) for a detailed description of problems arising as a result of heterogeneity in treatment timing.

level.[21]

Compositional Effects. Firstly, we show in Table E.1, using the DiD approach described above, that the opening and closing events are rather persistent over time: in more than 60% of all cases, the planning area remains blocked to entry for at least 3 years. This means that blocked entry is neither a strongly absorbing state nor is treatment status turning "on" and "off" frequently. Further, Table E.1 shows that changes in the size or population of planning areas are rarely the reasons for crossing the 110% coverage cut-off. This means that planning areas cross the cut-off, and thus face entry restrictions, mainly through an inflow of GPs. The inflow increases the coverage on average by 4 percentage points—from a coverage rate level of 106%—but returns to pre-closing levels after 3 years.

The DiD analysis also shows that crossing the cut-off has no immediate impact on the demographic (Table E.2) or employment (Table E.3) composition of GPs, both in the short and long run. All coefficients displayed are both economically and significantly insignificant with the exception of the share of GPs being employed instead of owning a practice themselves rising by 0.4 percentage points. This is well in line with our main results from the RDD and could point towards an increase in GPs. Thus, the crossing of the cut-off is driven by hirings, especially in medical care centers (MVZs), as column 3 in Table E.3 shows. However, the shifts are economically very small, leading us to conclude that the economic and employment composition is largely unaffected by entry restrictions.

Health Effects. Finally, we also look at patients' health outcomes. As with the composition, it is likely that the effects of reduced service quality by GPs with local monopolies are only detectable in the long run. However, Table E.4 confirms the results from our main analysis by showing that entry restrictions do not affect the number of deaths and life expectancy neither in the long nor short run.

[21]Using planning areas that changed treatment status only once as the treatment group or restricting the control group to never-treated planning areas leaves the results unchanged. Results are available upon request.

Table E.1: DiD Results Describing the Treatment

	Share closed	Area	Population	Coverage rate
Effect in t+1	100.00	0.01	32.88	4.03***
	(.)	(0.01)	(94.85)	(0.25)
Effect in t+2	68.45***	0.07	338.40	1.71***
	(2.21)	(0.05)	(239.91)	(0.35)
Effect in t+3	63.18***	0.00	814.75*	0.12
	(2.72)	(0.06)	(491.61)	(0.44)
Mean of Y	39.90	376.81	86555.63	106.29
SD of Y	48.97	282.86	167284.78	13.58
p-value placebo	1.00	0.46	0.60	0.64
Observations	4144	4144	4144	3971
Switchers	1037	1037	1037	888

Notes: This table reports the results of a multi-period difference-in-differences (DiD) estimation with staggered adoption and non-absorbing treatment status following de Chaisemartin and D'Haultfœuille (2024). The coefficients displayed show the difference in the outcome Y in a given year $t + g \in \{1, 2, 3\}$ as a result of crossing the cut-off of the 110% coverage rate relative to the year prior to the event year t. Outcome variables are an indicator of whether a planning area is closed for new entrants, thus reflecting the share of closed planning areas, the size (in square km), the population, and the coverage rate. All variables are described in detail in Section 3. Standard errors are heterogeneity robust and clustered at the planning area level. Below the coefficients, the mean and standard deviation of the outcome variable, a p-value of an F-test that all placebos are jointly equal to zero, and the number of observations—overall and of the treatment group ("switchers")—are displayed.

Table E.2: DiD Results for Demographic Composition

	Female	Below 40	Above 50	Mean age
Effect in t+1	0.13	-0.15	0.14	-0.02
	(0.08)	(0.10)	(0.14)	(0.02)
Effect in t+2	0.29**	0.01	-0.19	-0.06
	(0.15)	(0.16)	(0.22)	(0.04)
Effect in t+3	0.34	-0.08	-0.39	-0.03
	(0.22)	(0.21)	(0.31)	(0.06)
Mean of Y	42.11	6.29	72.20	55.30
SD of Y	10.51	2.59	5.76	1.35
p-value placebo	0.42	0.86	0.11	0.88
Observations	4144	4144	4144	4144
Switchers	1037	1037	1037	1037

Notes: This table reports the results of a multi-period difference-in-differences (DiD) estimation with staggered adoption and non-absorbing treatment status following de Chaisemartin and D'Haultfœuille (2024). The coefficients displayed show the difference in the outcome Y in a given year $t+g \in \{1,2,3\}$ as a result of crossing the threshold of the 110% coverage rate relative to the year prior to the event year t. Outcome variables are the share of female GPs, of GPs below 40 and over 50, and the mean age of GPs. All variables are described in detail in Section 3). Standard errors are heterogeneity robust and clustered at the planning area level. Below the coefficients, the mean and standard deviation of the outcome variable, a p-value of an F-test that all placebos are jointly equal to zero, and the number of observations—overall and of the treatment group ("switchers")—are displayed.

Table E.3: DiD Results for Economic Composition

	Share employed	In practices	In MVZs
Effect in t+1	0.18*	0.08	0.10
	(0.11)	(0.08)	(0.09)
Effect in t+2	0.42**	0.18	0.25*
	(0.18)	(0.12)	(0.15)
Effect in t+3	0.40	0.24	0.16
	(0.25)	(0.17)	(0.20)
Mean of Y	15.11	3.65	11.46
SD of Y	5.40	3.84	4.66
p-value placebo	0.20	0.72	0.25
Observations	4144	4144	4144
Switchers	1037	1037	1037

Notes: This table reports the results of a multi-period difference-in-differences (DiD) estimation with staggered adoption and non-absorbing treatment status following de Chaisemartin and D'Haultfœuille (2024). The coefficients displayed show the difference in the outcome Y in a given year $t + g \in \{1, 2, 3\}$ as a result of crossing the cut-off of the 110% coverage rate relative to the year prior to the event year t. Outcome variables are the share of GPs employed (contrary to owning an own practice), and of GPs employed in a practice or medical care center (MVZ). All variables are described in detail in Section 3. Standard errors are heterogeneity robust and clustered at the planning area level. Below the coefficients, the mean and standard deviation of the outcome variable, a p-value of an F-test that all placebos are jointly equal to zero, and the number of observations—overall and of the treatment group ("switchers")—are displayed.

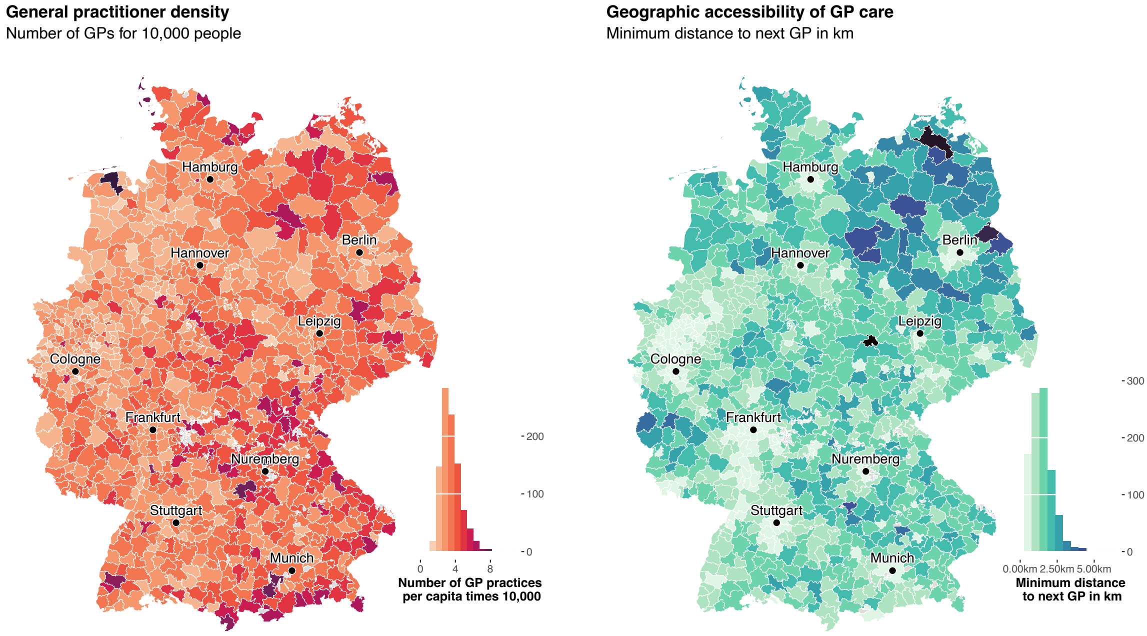
Table E.4: DiD Results for Health Outcomes

	Deaths	Life expectancy	Rem. life exp.
Effect in t+1	-7.59*	0.01	0.01
	(4.38)	(0.01)	(0.01)
Effect in t+2	-5.42	-0.00	0.01
	(4.06)	(0.01)	(0.01)
Effect in t+3	-6.69	-0.02	0.01
	(7.11)	(0.02)	(0.01)
Mean of Y	970.26	80.89	23.27
SD of Y	1614.76	0.88	0.56
p-value placebo	0.89	0.12	0.17
Observations	4144	4126	4126
Switchers	1037	1034	1034

Notes: This table reports the results of a multi-period difference-in-differences (DiD) estimation with staggered adoption and non-absorbing treatment status following de Chaisemartin and D'Haultfœuille (2024). The coefficients displayed show the difference in the outcome Y in a given year $t+g \in \{1,2,3\}$ as a result of a crossing of the cut-off of the 110% coverage rate relative to the year prior to the event year t. Outcome variables are the number of death cases, the life expectancy (for newborns), and the remaining life expectancy at age 60. All variables are described in detail in Section 3. Standard errors are heterogeneity robust and clustered at the planning area level. Below the coefficients, the mean and standard deviation of the outcome variable, a p-value of an F-test that all placebos are jointly equal to zero, and the number of observations—overall and of the treatment group ("switchers")—are displayed.

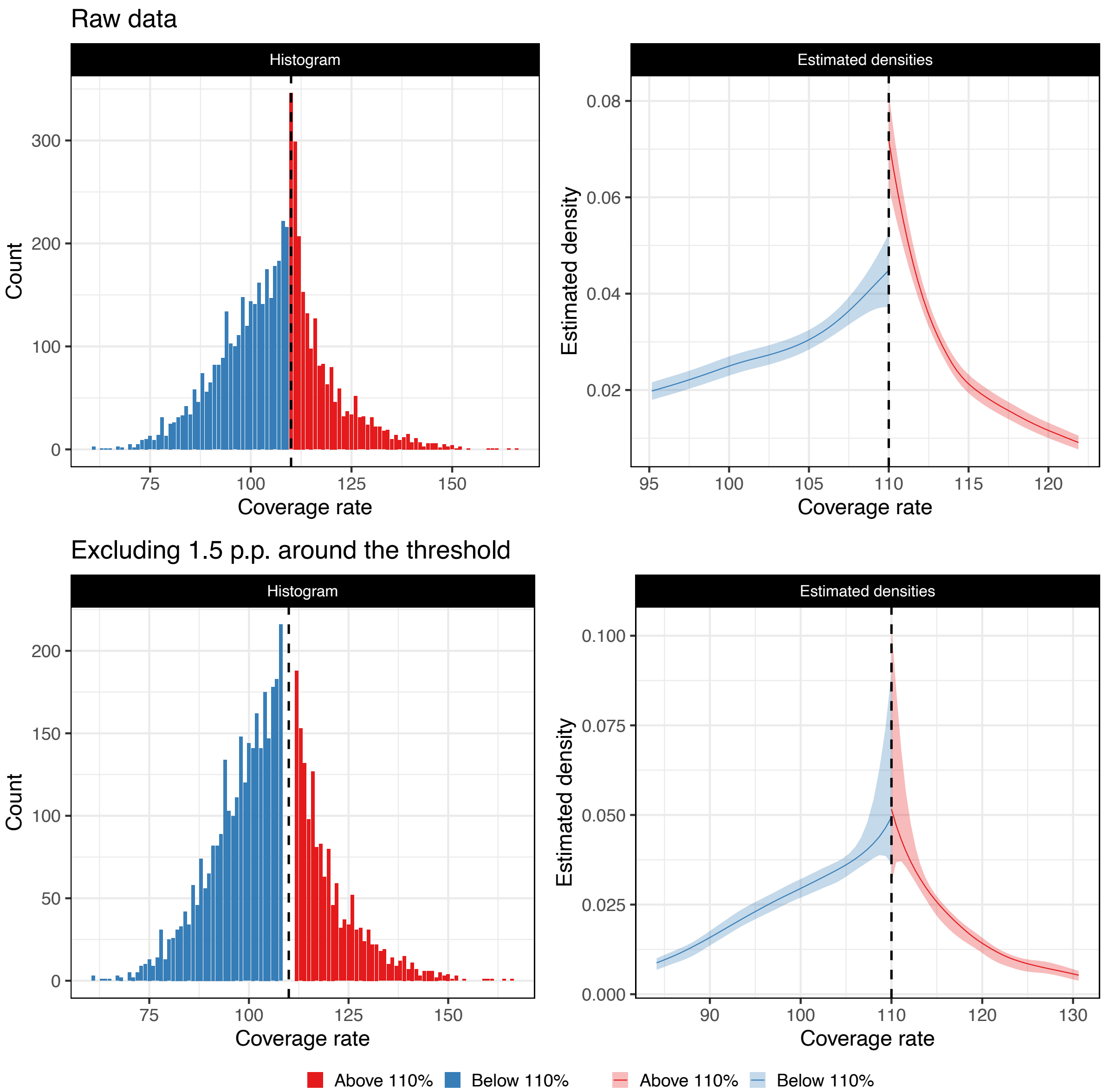
F Additional figures and tables

Figure F.1: Maps of Regional Accessibility and Competition Measures



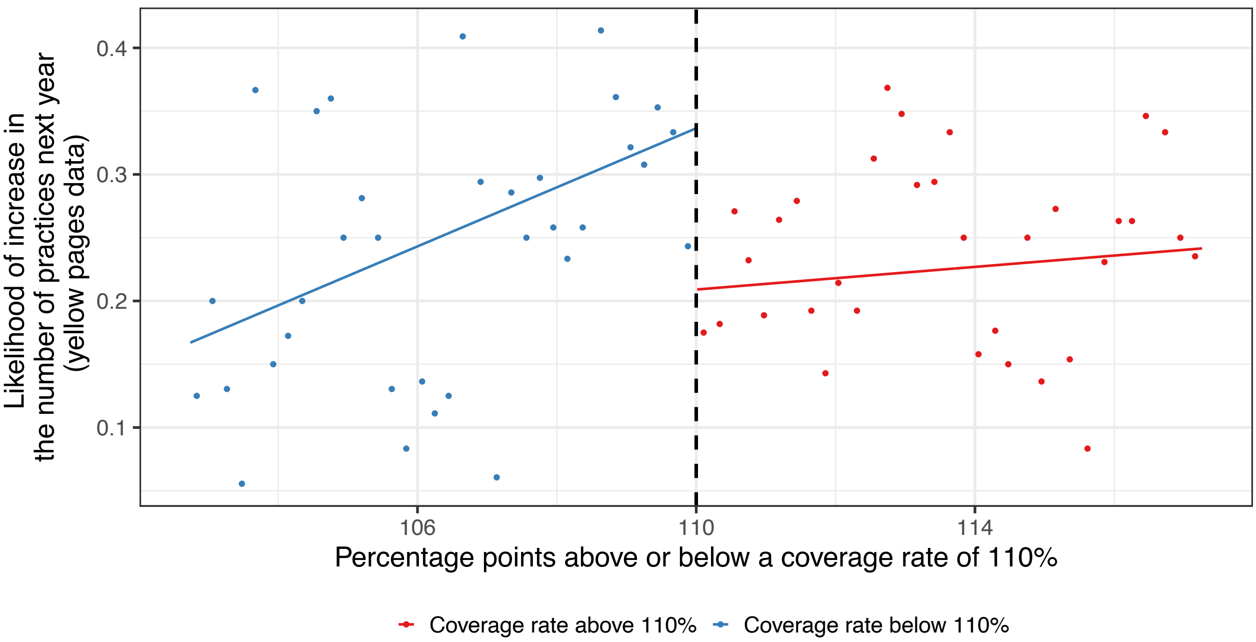
Notes: The figure shows two maps for variables generated from our Yellow Pages data. Both maps are for planning areas in 2019. The left panel shows a map of the number of GPs per 10,000 people, while the right panel plots the population-weighted distance to the nearest GP.

Figure F.2: Density Test of the Running Variable



Notes: The figure shows two visualizations of the typical density test for manipulation, for both the complete raw data (top) and a sub-sample (bottom) where observations within a 1.5 percentage point band around the cut-off were excluded. The histogram for the running variable of the RDD (the coverage rate) is in the left panels and estimated densities right and left of the cut-off of a 110% coverage rate are in the right panels.

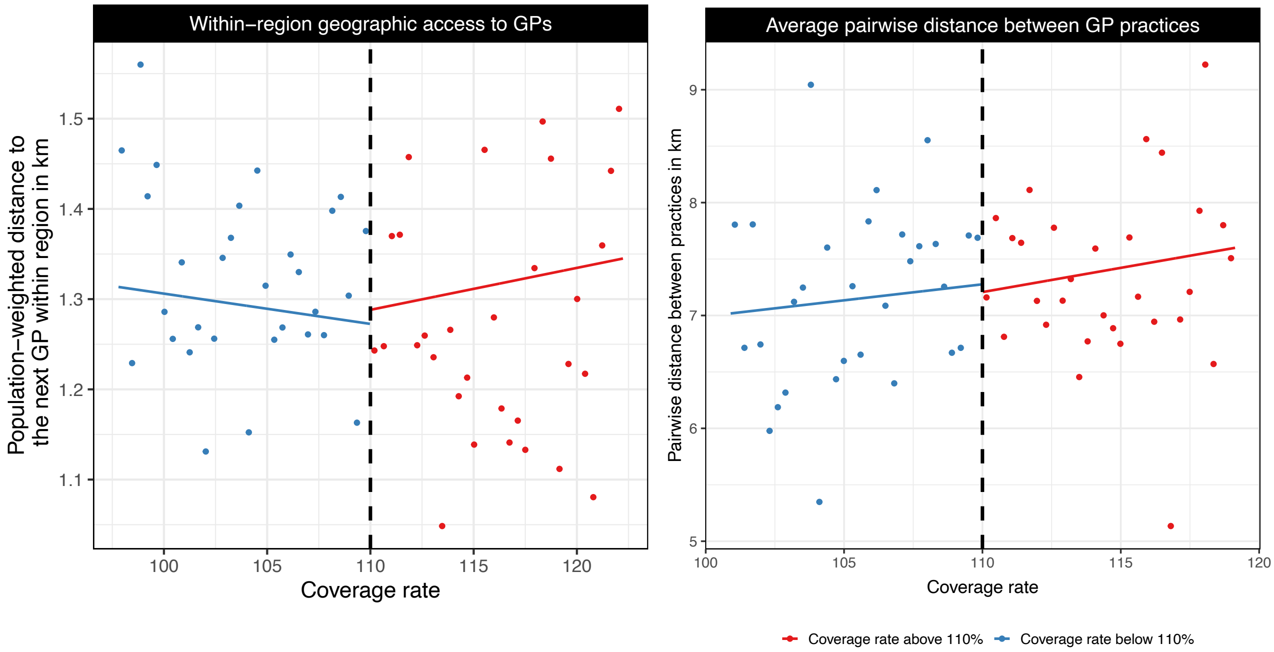
Figure F.3: RD Plot for Likelihood of New Practice Opening (Yellow Pages)



Method	Point Estimate	z-Statistic	p-value	95% Confidence Interval
Conventional Estimate	-0.1274	-3.36	0.00	[-0.2017 ; -0.0532]
Robust	-0.1412	-3.30	0.00	[-0.2250 ; -0.0573]

Notes: RD plot for the likelihood of a new practice opening based on Yellow Pages data. The horizontal axis is the coverage rate in percentage points, and the vertical axis plots the likelihood of a practice opening in the next year. Observations are binned in evenly spaced bins to the left and right of the cut-off. The blue line shows a linear fit left of the cut-off whereas the red line shows the fit right of the cut-off. The table below the plot reports the results of the RD estimation, including controls for population density, income tax revenue, and age structure, in addition to physician-association- and year-fixed effects. The estimated optimal bandwidth used is 7.26 percentage points around the cut-off. In total $N = 1,863$ observations are used for the plot and estimates.

Figure F.4: RD Estimates for Spatial Access and Competition Measures



Panel A: Population-weighted minimum distance to next GP within regions

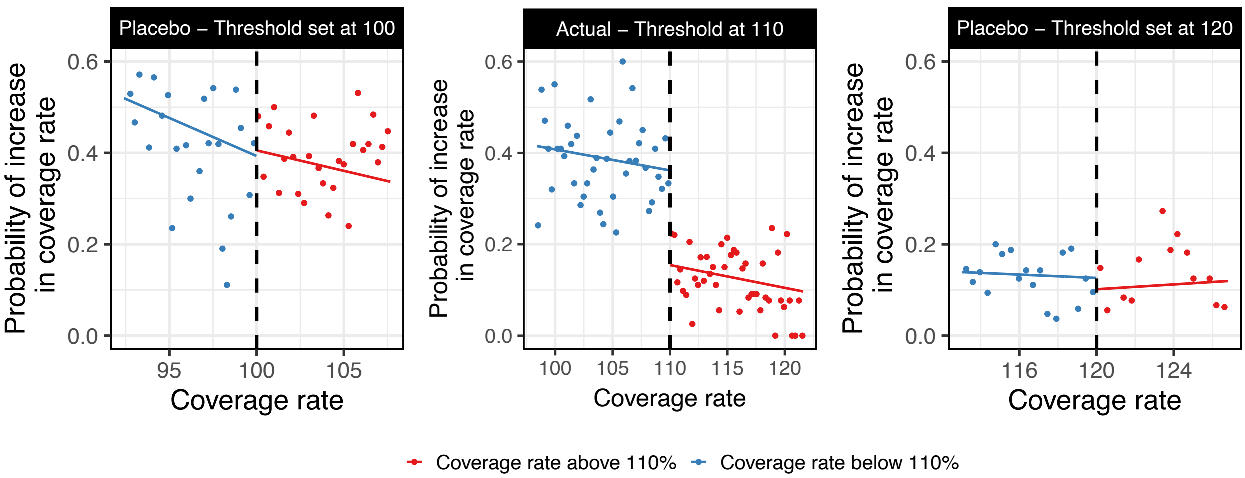
Method	Point Estimate	z-Statistic	p-value	95% Confidence Interval
Conventional Estimate	0.0157	0.5117896	0.6087983	[-0.0443 ; 0.0757]
Robust	0.0116	0.3310931	0.7405742	[-0.0570 ; 0.0802]

Panel B: Average pairwise distance between GP practices

Method	Point Estimate	z-Statistic	p-value	95% Confidence Interval
Conventional Estimate	-0.0664	-0.3198212	0.7491039	[-0.4736 ; 0.3408]
Robust	-0.1132	-0.4694196	0.6387697	[-0.5859 ; 0.3595]

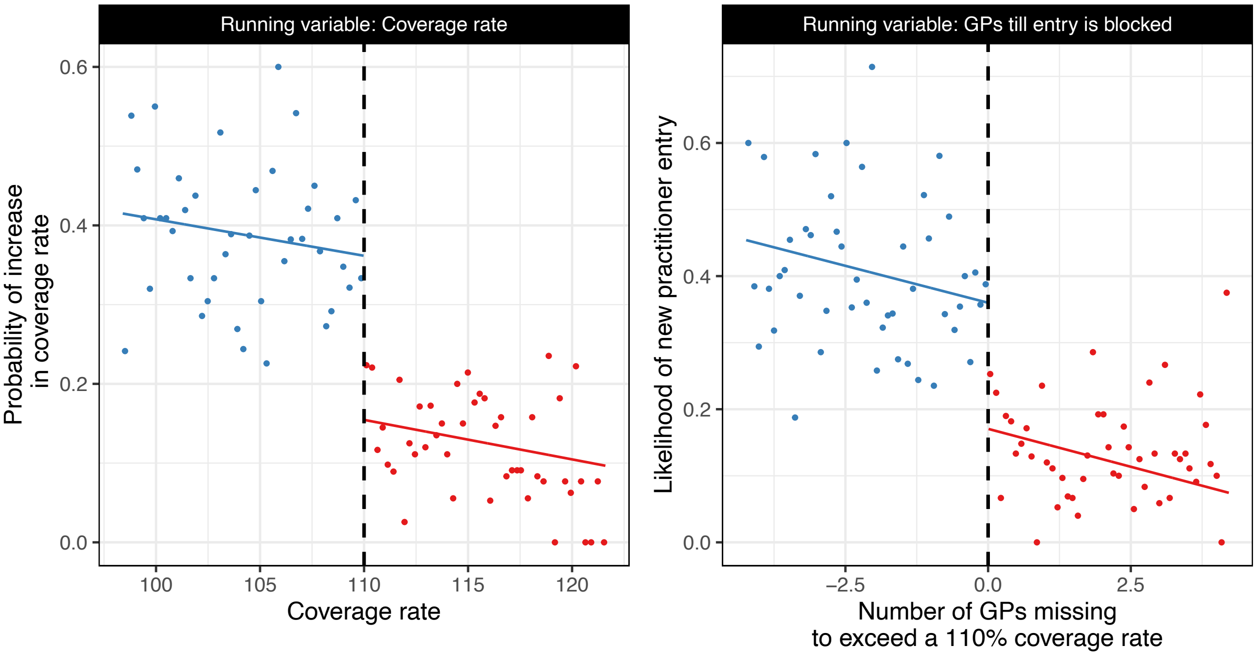
Notes: The figure presents regression discontinuity (RD) estimates for measures of spatial access and competition among general practitioner (GP) practices. Panel A (left) displays the population-weighted minimum distance to the nearest GP within regions, while Panel B shows the average pairwise distance between GP practices. The blue line represents the linear fit to the left of the cut-off, and the red line represents the fit to the right of the cut-off. Mean-square error optimal bandwidths are used for both panels. For Panel A, the bandwidth is 12.238 around the cut-off using $N = 3,962$ observations. For Panel B, the bandwidth is 9.193 around the cut-off using $N = 3,962$ observations. Both models include controls for population density, income tax per capita, age structure, and fixed effects for physician association and year.

Figure F.5: RD Plots for Placebo Cut-offs



Notes: The three panels of the figure plot regression discontinuity designs for two placebo cut-offs set at 100% (left panel) and 120% (right panel) of the coverage rate and the actual 110% cut-off (middle panel). Observations are always binned in evenly spaced bins to the left and right of the cut-offs. The blue line shows a linear fit left of the respective cut-off whereas the red line shows the fit right of the cut-off.

Figure F.6: Alternative Running Variable



Panel A: Coverage rate as running variable

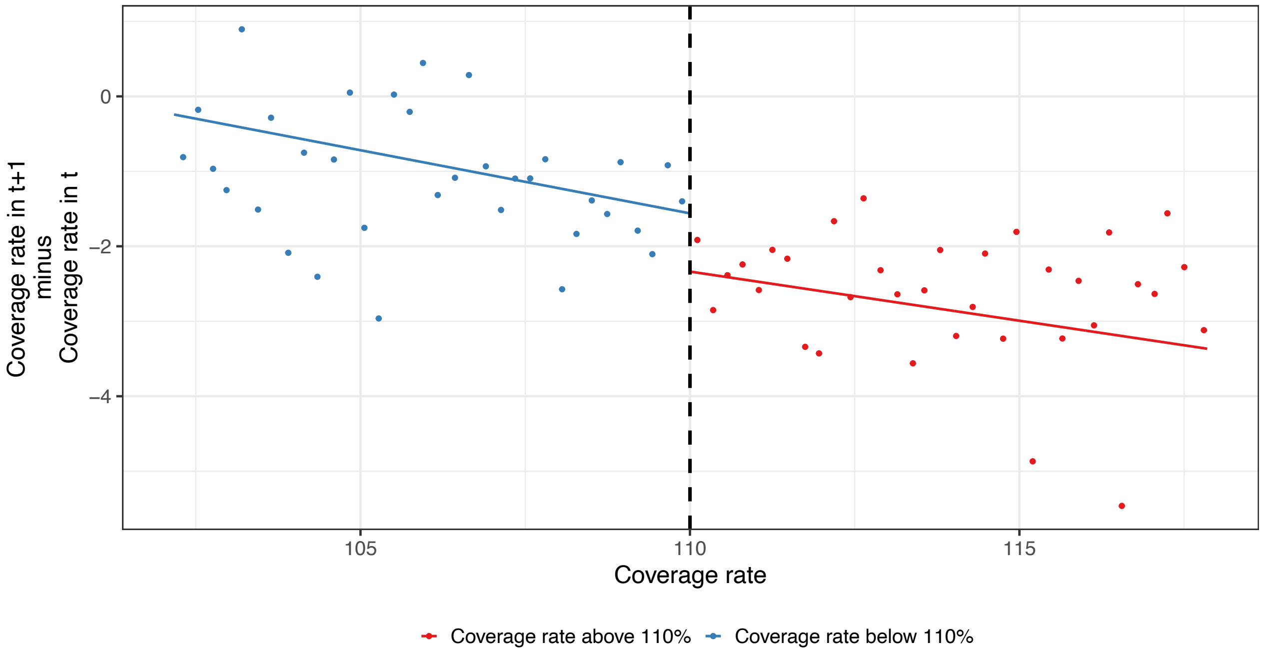
Method	Point Estimate	z-Statistic	p-value	95% Confidence Interval
Conventional Estimate	-0.2071	-6.64	0.00	[-0.2683 ; -0.1459]
Robust	-0.2052	-5.74	0.00	[-0.2752 ; -0.1351]

Panel B: GPs needed to exceed cut-off as running variable

Method	Point Estimate	z-Statistic	p-value	95% Confidence Interval
Conventional Estimate	-0.1896	-6.45	0.00	[-0.2472 ; -0.1320]
Robust	-0.1842	-5.66	0.00	[-0.2480 ; -0.1204]

Notes: The figures show regression discontinuity plots for the likelihood of an increase in the coverage rate for two different running variables, the coverage rate (Panel A) and the number of GPs until blocked entry (Panel B). The table below the plot reports the results of the RD estimations, including controls for population density, income tax revenue, and age structure, in addition to physician-association- and year-fixed effects. For the left panel, the bandwidth is 11.63 percentage points around the cut-off using $N = 2,489$ observations. For the right panel, the bandwidth is 9.08 percentage points around the cut-off using $N = 2,750$ observations.

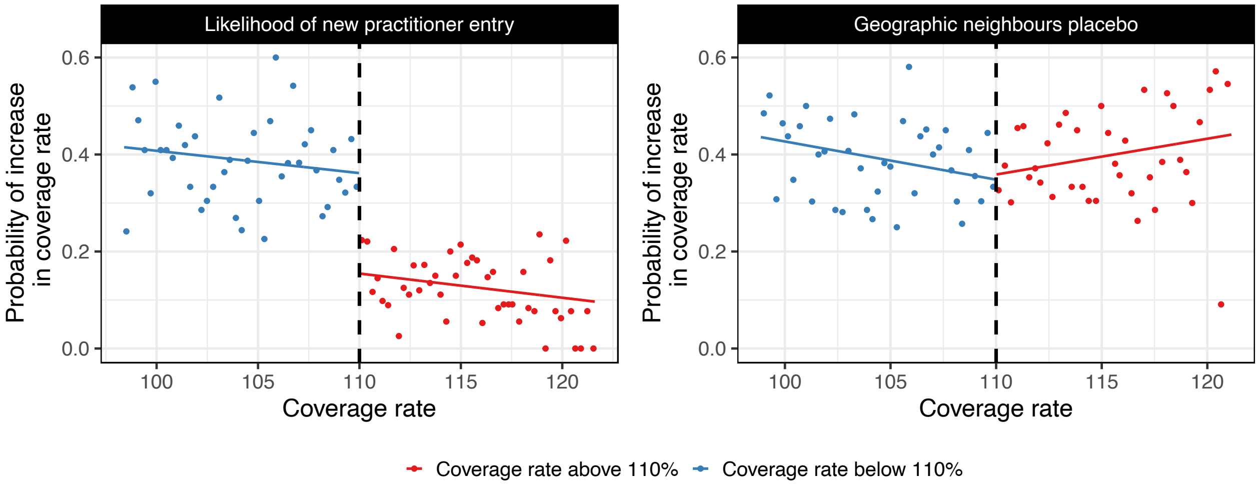
Figure F.7: RD Plot for the Change in the Coverage Rate



Method	Point Estimate	z-Statistic	p-value	95% Confidence Interval
Conventional Estimate	-0.7777	-2.90	0.0036	[-1.3027 ; -0.2526]
Robust	-0.6794	-2.31	0.0207	[-1.2549 ; -0.1039]

Notes: This figure shows the regression discontinuity plot for the absolute change in the coverage rate between t and $t+1$. The blue line shows a linear fit left of the cut-off whereas the red line shows the fit to the right. Mean-square error optimal bandwidths are used for both panels. The table below the plot reports the results of the respective RD estimation, including controls for population density, income tax revenue, and age structure, in addition to physician-association- and year-fixed effects. The estimated optimal bandwidth used is 7.88 percentage points around the cut-off. In total $N = 1,942$ observations are used for the plot and estimates.

Figure F.8: Geographic Neighbours Placebo Exercise

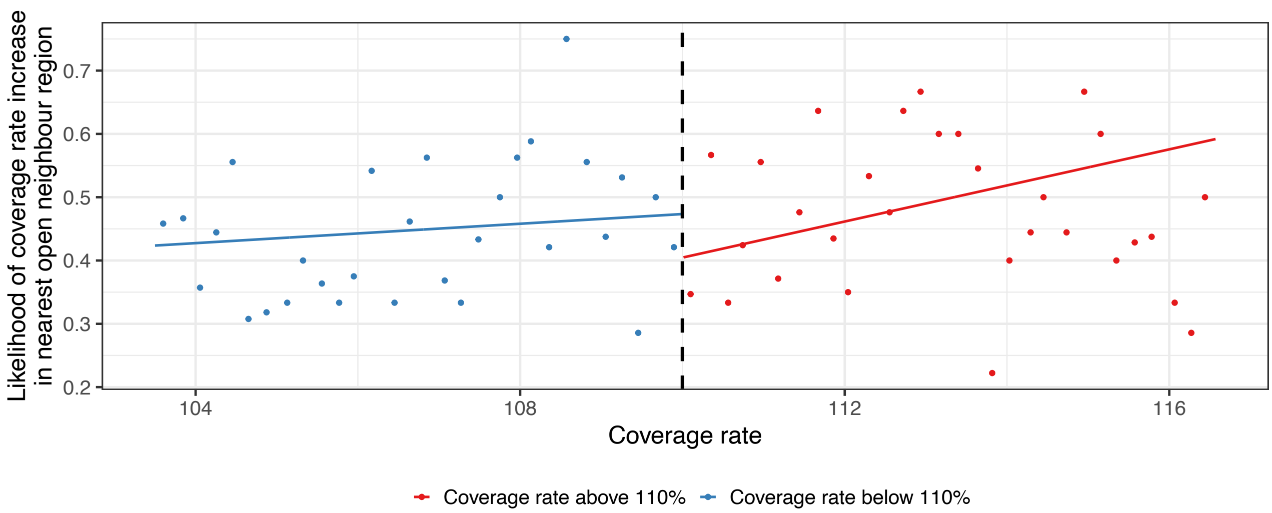


Panel A: Likelihood of an increase in coverage rate (Actual)				
Method	Point Estimate	z-Statistic	p-value	95% Confidence Interval
Conventional Estimate	-0.2071	-6.64	0.00	[-0.2683 ; -0.1459]
Robust	-0.2052	-5.74	0.00	[-0.2752 ; -0.1351]

Panel B: Likelihood of an increase in coverage rate (Geographic Placebo)				
Method	Point Estimate	z-Statistic	p-value	95% Confidence Interval
Conventional Estimate	0.0105	0.31	0.76	[-0.0567 ; 0.0778]
Robust	0.0069	0.17	0.86	[-0.0703 ; 0.0840]

Notes: The figures show regression discontinuity plots both for the actual likelihood of an increase in the coverage rate and a geographic placebo, where the outcome of a geographic neighbor region below the cut-off was swapped against the outcome of a randomly chosen region above the cut-off. The table below the plot reports the results of the RD estimations, including controls for population density, income tax revenue, and age structure, in addition to physician-association- and year-fixed effects. For the left panel, the bandwidth is 11.63 percentage points around the cut-off using $N = 2,489$ observations. For the right panel, the bandwidth is 11.16 percentage points around the cut-off using $N = 2,306$ observations.

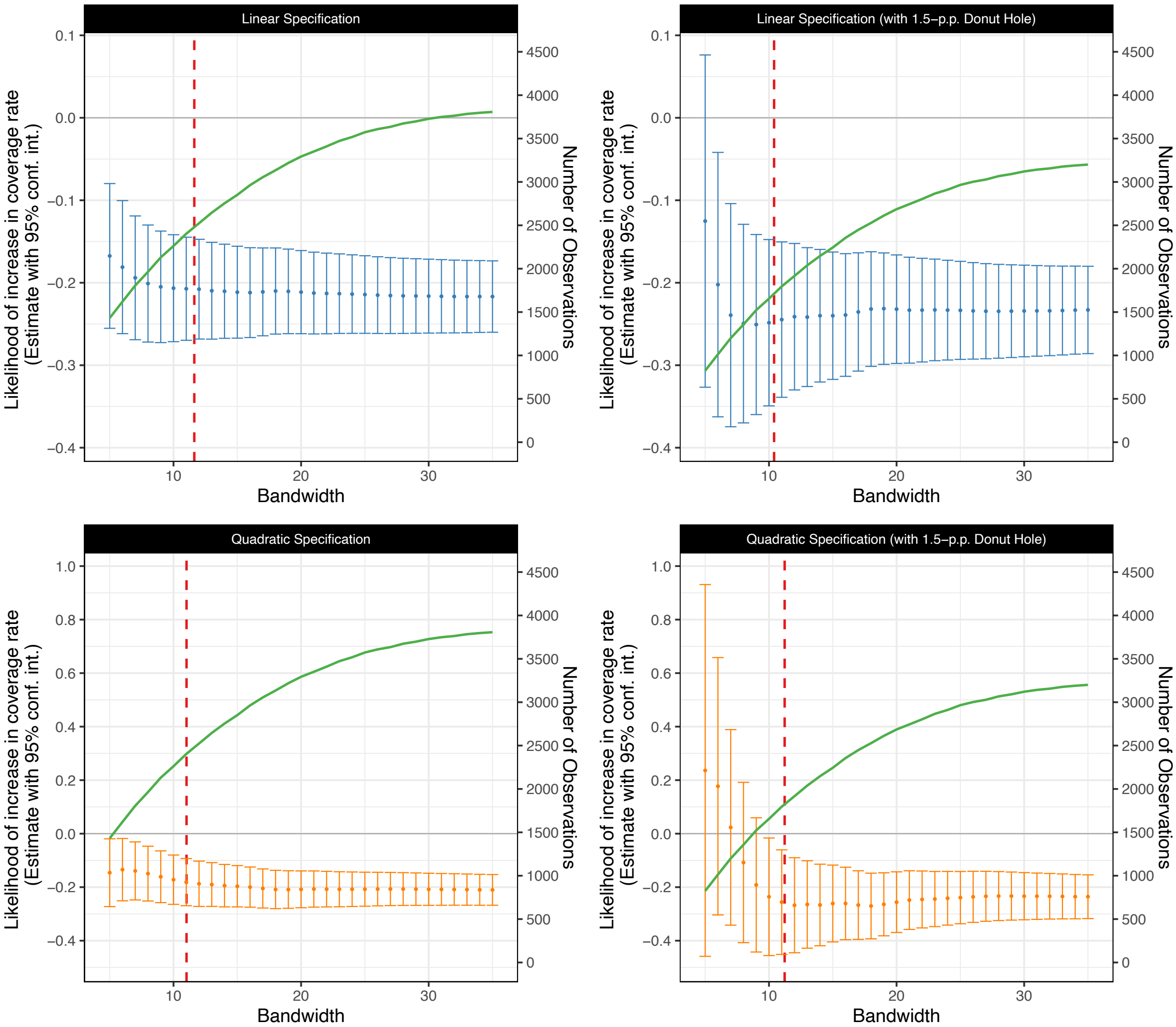
Figure F.9: RD Plot for Entry into Nearest Open Neighbour Region



Coverage rate increase in nearest open neighbour region				
Method	Point Estimate	z-Statistic	p-value	95% Confidence Interval
Conventional Estimate	-0.0687	-1.21	0.22	[-0.1796 ; 0.0422]
Robust	-0.0848	-1.31	0.19	[-0.2113 ; 0.0418]

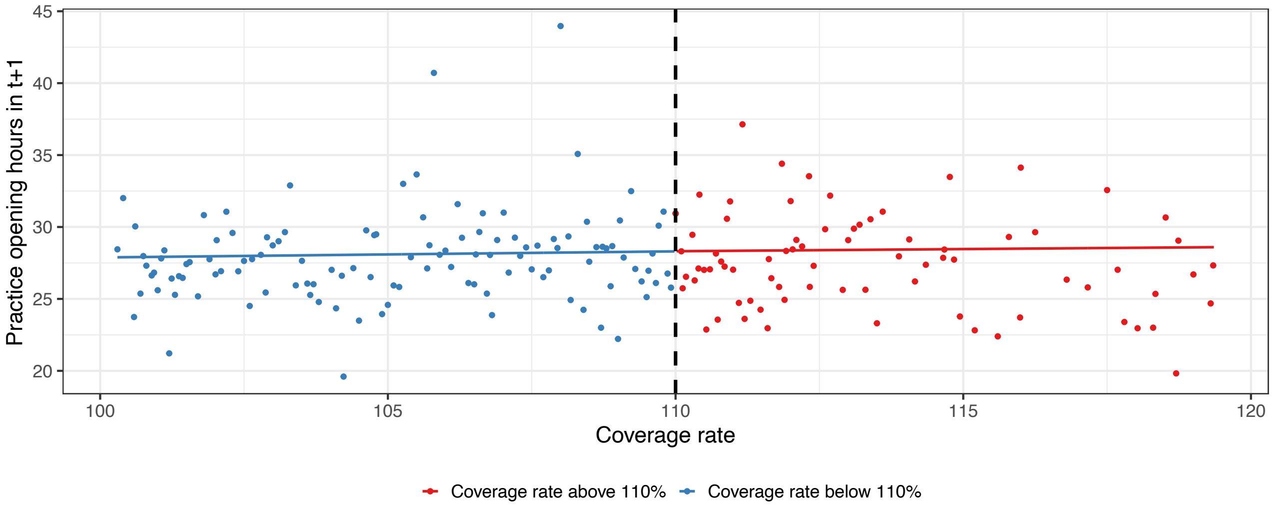
Notes: This figure shows the regression discontinuity plot for the likelihood that the coverage rate in the nearest open neighbor region increases. The blue line shows a linear fit left of the cut-off whereas the red line shows the fit to the right. A mean-square error optimal bandwidth of 11.44 percentage points around the cut-off is used for the estimation. The table below the plot reports the results of the respective RD estimation, including controls for population density, income tax revenue, the age structure and the number of neighbours. In total $N = 2,383$ observations are used for the plot and estimates.

Figure F.10: Robustness Analysis for the Likelihood of New Entry



Notes: The figure plots the bias-corrected robust estimated coefficients and the respective 95% confidence intervals of multiple regression discontinuity designs for the likelihood of an increase in the local coverage rate. Each confidence interval is from a different specification using a different bandwidth between 5 and 35 percentage points. The mean-square error optimal bandwidth for all specifications is marked by a red dashed line. We consider standard RD specifications in the left panels and specifications that exclude 1.5 percentage points around the cut-off in the right panels ("donut hole" design). The upper panels (blue) show linear specifications, while the lower panels (yellow) show quadratic specifications. All models control for population density, income tax revenue, and age structure, in addition to physician-association- and year-fixed effects. Moreover, we include the number of used sample sizes for each estimation in green and show the respective observation number on the second vertical axis on the right.

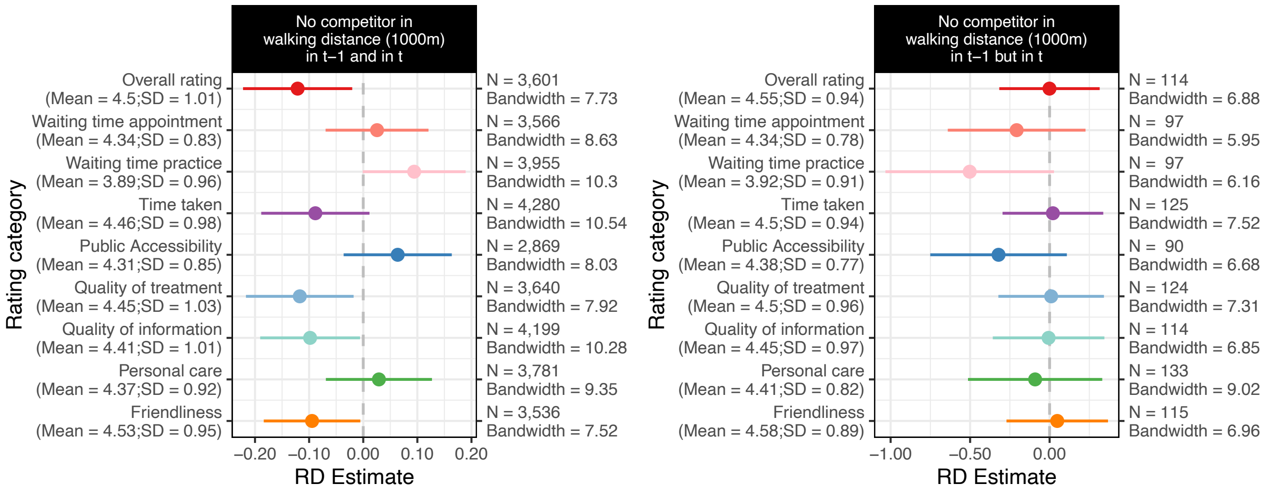
Figure F.11: RD Estimates for Individual GP Opening Hours



Practice opening hours				
Method	Point Estimate	z-Statistic	p-value	95% Confidence Interval
Conventional Estimate	0.0258	0.01	0.93	[-0.4801 ; 0.5316]
Robust	0.0500	0.17	0.86	[-0.5222 ; 0.6223]

Notes: This figure shows the regression discontinuity plot for the individual opening hours of practices. The blue line shows a linear fit left of the cut-off whereas the red line shows the fit to the right. A mean-square error optimal bandwidth of 9.74 percentage points around the cut-off is used for the estimation. The table below the plot reports the results of the respective RD estimation, including controls for population density, income tax revenue, and age structure. In total $N = 14,542$ observations are used for the plot and estimates.

Figure F.12: Jameda Ratings for Local Monopolists and Unlucky Former Monopolists



Notes: The figure illustrates the estimated coefficients and their 95% confidence intervals from multiple regression discontinuity designs focused on subjective patient ratings. The models account for population density, income tax revenue, and age structure, and include fixed effects for physician-association and year. Given that the estimations occur at the individual physician level while the treatment is applied at the regional level, standard errors are clustered by planning region. The left panel shows the estimates for "persistent local monopolists" (GPs with no competitors within a 1,000-meter walking distance both before and after the entry restriction), while the right panel presents estimates for "unlucky former local monopolists" (GPs who gained a new competitor even though the market was blocked to entry and despite being sole practitioners within walking distance previously). The rating categories, along with their means and standard deviations, are listed on the left axis, while the right axis provides details on the bandwidths and the number of observations used in each regression discontinuity analysis.