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IMPRESSUM



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# Applying but not receiving: Longer working lives and institutionalized health investment*

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**Abstract**

Rising life expectancy and demographic change have increased the share of older workers, making their health and productivity central to aging societies. We study whether longer working lives translate into investments in work-related health before retirement. Exploiting a pension reform in Germany in a Regression Discontinuity Design, we show that women facing longer careers are more likely to apply for work-related rehabilitation, particularly those in poorer health or with weaker labor market attachment. Despite higher application and approval rates, this demand does not translate into higher rehabilitation completion. Together with intermediate outcomes, our findings are most consistent with capacity constraints in program delivery.

**Keywords:** Rehabilitation, Aging Societies, Health Investments, Pension Reform
**JEL classification:** H55, I12, J26

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# 1 Introduction

One of the most striking developments of the past century has been the substantial increase in human longevity. In the US, life expectancy at birth rose for women (men) from approximately 48 (46) years in 1900 to 80 (74) years in 2020; in Germany, from about 47 (44) to 83 (79) years over the same period (HMD, 2023). These gains have fundamentally altered the age structure of modern economies. In aging societies, now prevalent across most advanced economies, the productivity of older workers has become central to maintaining high levels of welfare. An important dimension of that productivity is health (Grossman, 1972): the ability of individuals to extend their working lives depends critically on their physical and psychological capacity to do so. Health is also a highly general form of human capital from which firms cannot fully appropriate the returns, so private investment is likely to fall short of the social optimum (Acemoglu & Pischke, 1998; Becker, 1962). This is one rationale for the large public programs that many countries maintain to restore and preserve the work capacity of older workers. Yet, empirical evidence on whether such institutionalized health investments respond to longer working lives is, to the best of our knowledge, non-existent.

This paper provides the first causal evidence on how longer working lives affect both the demand for and the realization of institutionalized health investments targeted at maintaining work capacity. We exploit the 1999 German pension reform that abolished the earliest retirement option for women at a sharp birth-cohort cutoff, and we follow the affected cohorts through the entire administrative process of publicly financed work-related rehabilitation — from the application, filed either by the individual or by hospital staff, through approval or rejection by a caseworker, to the start and the completion of the measure. Because each stage is governed by a different actor, this allows us to separate the behavioral response of individuals from the responses of physicians, of caseworkers, and of the providers who ultimately deliver the treatment. The distinction matters because each stage carries a different policy implication.

Germany is a particularly well-suited setting for this question. Its workforce is older than the EU average, with about 24% of workers aged 55–64 (Eurostat, 2024). Beyond that, three features recommend it: its institutions, its data, and a policy reform that generates exogenous variation in the length of working lives.

First, institutions. Germany has a long history of publicly provided health investments aimed at restoring the capacity to work. Institutionalized health investment takes various forms; we focus on work-related rehabilitation, that is, treatment with the stated purpose of keeping individuals fit for the labor market. Today, more than 1,000 rehabilitation institutions with more than 160,000 beds operate across the country, helping individuals recover their work capacity, often but not exclusively after accidents or serious illness.[1] The German pension insurance reports that medical rehabilitation raises the probability of returning to work by 15 to 20% among participants (Deutsche Rentenversicherung, 2025), and the medical literature documents positive health and employment effects across a range of diagnoses (Bethge et al., 2019, 2023; Brünger & Gellert, 2026; Elling et al., 2026; Karoff et al., 2007; Rick et al., 2017).

Second, data. We combine the universe of rehabilitation records of the German pension insurance with administrative data on individual pension accounts. For each woman we observe whether she applies for, starts, and completes a large-scale health program that is financed by the pension insurance and targeted

[1] The public provision of such health centers goes back to the public health reforms initiated by Bismarck and the German Empire in the late nineteenth and early twentieth centuries (Koppitz et al., 2005). Appendix Figure A1 shows an example from this period, the "Beelitzer Heilstätten", where individuals were sent to recover from tuberculosis so that they could return to work. More information on today's rehabilitation centers of the German pension insurance can be found here: https://meine-rehabilitation.de/pr-web/de

at improving work capacity and preventing early retirement, together with the medical diagnoses and the type of measure indicated in the application. Linking these records to complete biographical information on employment, earnings, unemployment and sick leave lets us characterize who responds: we can distinguish effects by diagnosis, by health history, and by prior labor supply. Crucially, every step of the administrative process is dated. We therefore observe not only whether a health investment took place, but at which point in the chain it failed to materialize.

Third, identification. An individual's working life rarely varies for exogenous reasons. In our setting, the variation comes from a pension reform that abolished the *pension for women*, the earliest retirement option available at age 60, for all women born after 1951. Statutory pension ages do not only change financial incentives; as documented by Seibold (2021) for Germany, they also define the legal framework and a strong social norm for the length of a working life. From the perspective of the individual, the reform therefore generates quasi-random variation in the expected duration of the working life, which we exploit in a regression discontinuity design (RDD) using the month of birth as the running variable. Two further features make the reform well suited to our question. The cutoff is sharp and the induced change is large, effectively raising the early retirement age from 60 to 63. And affected women were still in their forties when the reform was legislated, leaving many years over which an investment in work capacity could pay off — precisely the horizon over which forward-looking health investment should be visible.

Our first set of results concerns the behavior of individuals. The reform raises the probability of applying for medical rehabilitation by 0.5 percentage points, or about 17% relative to the pre-reform mean of 2.8%. Individual characteristics, including past sickness and employment histories, are well balanced across the cutoff, and the estimate is robust across RDD specifications, bandwidth choices, and placebo cutoffs. The response is stronger where a forward-looking interpretation predicts it should be: among women with a poorer health history, weaker past labor market attachment, and a prior rehabilitation measure — that is, among those closest to the health-capacity margin of labor supply. By contrast, we find no corresponding jump for the subset of measures initiated by hospital staff rather than by the patient. This both sharpens the interpretation of the individual response and speaks against a mechanical change in the underlying incidence of illness at the cutoff.

Our second set of results follows the same women through the remainder of the process. Approvals rise roughly one for one with applications: caseworkers convert the additional applications into additional approvals, and rejections do not increase. This is what one would expect from an administrative process bound by a legal framework that does not permit differentiation by remaining working life — but it also means that the additional demand survives the approval stage intact. Beyond that stage it disappears. We find no increase in measures started and none in measures completed, and no evidence that individuals withdraw once a measure has begun. Because all of these outcomes are estimated within the same RDD framework, we can locate the attrition precisely: it arises between approval and initiation, not at any earlier or later stage. This points to capacity constraints in program delivery. Rehabilitation places are scarce, there is a cap on the budget for rehabilitation measures, waiting lists are long even conditional on approval, and self-initiated applications receive lower priority than hospital-initiated cases, so an increase in approvals need not translate into an increase in treatment. Our study thus highlights a costly omission in policies for aging workforces: even when individuals anticipate longer working lives and act on that anticipation, systemic limits in program delivery can prevent the additional demand from becoming realized health investment.

The causal literature linking life expectancy to human capital investment is small and tied to particular settings. Oster et al. (2013) use variation in realized Huntington's disease risk among individuals with ex ante similar risks, and find responses consistent with human capital theory in college attendance and completion, in health outcomes, and in job training for individuals aged 17 to 35. We study a population two to three decades older, and an investment that is publicly provided rather than privately chosen.

A larger literature examines how pension reforms affect education and training (e.g. Brunello & Comi, 2015; Fürstenau et al., 2023) and labor market outcomes (e.g. Carta & De Philippis, 2023; Geyer & Welteke, 2021) before retirement, and generally finds evidence of forward-looking, intertemporal decision-making. To our knowledge, only two studies link pension reforms to health investment before retirement. Bertoni et al. (2018) show that a 2004 Italian reform postponing the minimum retirement age increased regular exercise, with positive implications for obesity and self-reported health satisfaction. Miller et al. (2025) study Chile's 1981 reform in a fuzzy regression kink design and find increases in preventive care. Both examine privately chosen preventive behavior measured in surveys. We study an institutionally provided investment whose explicit purpose is a return to work, observed in administrative records — which allows us to separate demand from delivery.

A separate strand studies health and healthcare utilization *after* retirement, with mixed findings (Barschkett et al., 2022; Bozio et al., 2021; Geyer et al., 2023; Hagen, 2018; Perdrix, 2022; Serrano-Alarcón et al., 2023); see Pilipiec et al. (2021) for an overview. We instead study health investment before retirement, and the role of public provision for this general form of human capital. Finally, work on rehabilitation in Germany has documented institutional barriers at the application margin, which lower the probability that individuals in need of rehabilitation apply at all (Telenga et al., 2026; Zimmer et al., 2022). Our results point to a further downstream barrier among applicants who were approved but did not receive treatment.

Section 2 describes the institutional setting. Sections 3 and 4 present the data and the empirical design. Section 5 reports the results, and Section 6 concludes.

# 2 Institutional background

The statutory public pension scheme forms the backbone of Germany's pension framework, encompassing about 90% of the labor force, excluding groups not subject to mandatory pension insurance, such as civil servants and most of the self-employed. This system comprises old-age pensions, invalidity pensions, survivor benefits, and rehabilitation measures. It operates on a pay-as-you-go basis, with benefits closely tied to contribution history. The pension system offers several avenues for early retirement, allowing individuals to claim benefits before the standard retirement age. In this study, we use policy variation related to the *pension for women*, which permits benefits to be drawn starting at age 60.[2]

## 2.1 Pension reform: The pension for women

With a pension reform implemented in 1999, the *pension for women* was abolished for women born after 1951. This effectively increased the Early Retirement Age (ERA) from 60 to 63 for affected women, thereby extending their working careers.[3] Women born before 1952 could still access the *pension for women* if they met certain requirements: (i) at least 15 years of contributions to pension insurance; and (ii) at least 10

[2] Other early retirement options include: (1) the *invalidity pension*; (2) the *pension after unemployment or old-age part-time work*; and (3) the *pension for the long-term insured*. For more details, see Geyer et al. (2020). For a general overview of the German pension system, refer to Boersch-Supan and Wilke (2004).

[3] The *pension after unemployment or old-age part-time work* was also discontinued simultaneously, but as the ERA for this type was already 63, it does not affect our study.

years of contributions after turning 40. The affected women from the cohort 1952 were 47 years old when the reform was introduced. Thus, there was a long anticipation period to prepare for a higher retirement age, including human capital and health investments (Fürstenau et al., 2023).

Studies by Geyer and Welteke (2021) and Geyer et al. (2020) examine the labor market impact of this pension reform using administrative data from public pension insurance accounts and survey data from the Microcensus. Their findings, which are central to our subsequent empirical analysis, show that the rise in the ERA significantly extended working life. Specifically, employment rates increased by about 15 percentage points, while the combined rise in inactivity and unemployment was roughly 12 percentage points. Moreover, Geyer and Welteke (2021) find no increase in disability pensions at the cutoff.

## 2.2 Institutional health investment

For our analysis, we focus on institutional health investment via rehabilitation programs financed by the German pension insurance, the largest provider of rehabilitation services.[4] The programs and services aim to sustain earning capacity and prevent early retirement. This includes preventive measures, medical rehabilitation, benefits for participation in working life, and other benefits to counteract or overcome the effects of an illness or a physical, mental, or emotional disability on the insured's ability to work (§9 of Social Code Book VI). Medical rehabilitation measures account for about 90% of all rehabilitation measures provided by the pension insurance.[5] Importantly, rehabilitation programs that are related to general health improvement without directly affecting employability are not covered by the pension insurance but by the health insurance. We do not include these measures in our analysis. Under the standard policy, workers are entitled to rehabilitation every four years. If early rehabilitation is necessary for medical reasons, an exception can be made according to Social Code Book V §40, but it requires detailed medical justification.

Medical rehabilitation is provided either as an inpatient stay in a dedicated rehabilitation facility or on an outpatient basis, with the large majority of measures delivered as inpatient treatment (79% in 2024, Rentenversicherung, 2025).[6] Most measures relate to diagnoses of the musculoskeletal system and connective tissue (MSC) (around 41% in 2024, Rentenversicherung, 2025). The second-largest diagnosis group consists of mental-health related diagnoses (around 18%), followed by cancer (around 14%). Across inpatient measures, MSC-related diagnoses account for around one-third of all measures, both for men and women. However, among women, the share of mental-health-related diagnoses is higher (25%) than for men (15%) for inpatient measures. Conversely, the share of measures related to cardiovascular diagnoses is higher for men (11%) than for women (3%) for inpatient measures. In contrast, looking at outpatient measures, MSC-related diagnoses account for around 73% of all measures for women, and for around 68% of all measures for men. The share of mental health-related diagnoses is higher for women (11%) than for men (6%) for outpatient measures; however, it is overall smaller than for inpatient measures. The average age for inpatient rehabilitation measures is 55 years, and 52 years for outpatient measures.

[4] The pension insurance provides more than half of all rehabilitation measures. The second-largest provider is health insurance. Other smaller providers include the accident insurance, the labor office, and the social assistance authorities.

[5] The remaining ∼10% are vocational rehabilitation measures (*Leistungen zur Teilhabe am Arbeitsleben*), such as retraining, workplace adaptations, and occupational therapy.

[6] The predominance of inpatient provision distinguishes the German system from most others. Work-related rehabilitation here is a multi-week residential stay in a dedicated facility rather than outpatient therapy; in many other health systems, inpatient rehabilitation is largely confined to post-acute care following stroke, trauma, or major surgery.

In terms of financing, the total expenditures for rehabilitation amounted to 8.7 billion euros in 2025 alone (Deutsche Rentenversicherung, 2026), about 2% of total pension expenditures or 0.2% of Germany's GDP. These expenditures are subject to a statutory cap. Under § 220 SGB VI, annual spending on rehabilitation is not determined by need but is indexed to the growth of gross wages and salaries per employee, and any overrun is automatically deducted from the budget two calendar years later. The cap became tight over the second half of our observation period (2004–2013): spending grew by 5.5% in 2008 and 6.3% in 2009, remained just below the statutory ceiling through 2011, and exceeded it by 13 million euros in 2012 (Bundesregierung, 2013). Pension insurance therefore cannot expand rehabilitation volumes in response to rising demand, even for eligible applicants whose applications are approved.[7]

A small portion of these costs is recovered through private co-payments to the public pension insurance that amount to 81 million euros, about 77 euros per treatment.[8] Besides the program itself, after six weeks of absence from work (including any preceding sick leave), individuals receive a wage replacement benefit ("Übergangsgeld"), paid by the pension insurance, which amounts to 68% of prior net earnings (75% with children in the household).

### 2.2.1 From Application to Completion

We summarize the timeline and application pathways for medical rehabilitation provided by the German pension insurance in Figure 1. There are two separate pathways through which an application for a rehabilitation measure can be initiated.[9] The first, Path A, is initiated by the individual outside a hospital setting. The application generally needs to be discussed with a physician and includes a medical assessment documenting a reduced or threatened ability to work.[10] The second route, Path B, is initiated directly by hospital staff during or immediately after a hospital stay (*Anschlussheilbehandlung*). In 2024, the share of rehabilitation measures following a hospital stay was 36% of all measures (Rentenversicherung, 2025). To examine how an extension of working life affects investment in work-related health we will primarily focus on applications initiated by individual workers. In an additional analysis, we also examine rehabilitation directly after the hospital stay in order to test if hospital staff take the working horizon of the patients into consideration when deciding about the work-related health investment.

Regardless of the source of the application, a caseworker of the pension insurance reviews the application and, if necessary, collects further medical documents before making a decision. About three-quarters of

[7] Since the 2014 reform (*RV-Leistungsverbesserungsgesetz*), the rehabilitation budget contains a demographic component: the cap on rehabilitation spending is indexed to changes in the share of the rehabilitation-intensive age group (45–67) in the working-age population (20–67). Because this share was still increasing, the reform initially expanded the budget.

[8] Co-payments are limited to between zero and 10 euros per day, depending on net income, for a maximum of 42 days.

[9] Some of the applications we classify as self-initiated arise in the context of disability pension claims. Under the principle of "rehabilitation before pension" (§ 9(1) SGB VI), rehabilitation takes precedence over a disability pension, and the pension insurance examines whether rehabilitation can avert a reduction in earning capacity before awarding one. Geyer and Welteke (2021) find no increase in disability pensions at the cutoff, so we do not expect this channel to contribute to the effect we estimate.

[10] One regional provider, the pension insurance institution in Westphalia, centralizes this step. At all other providers, insured persons ask their treating physician or occupational physician to prepare a medical report, which they submit together with the application.

applications are approved in the end, for instance, 74% in 2024 (Rentenversicherung, 2025).[11]

Once an application is approved, the individual must find a facility with available capacity. Allocations depend on the facility's specialization and the individual's regional preferences. Waiting times are long, particularly for applications initiated by the individual, since hospital-initiated cases are prioritized by providers (fast-track). On average, individuals wait about three months for a place, ranging from one to four months, depending on the medical diagnosis and the facility's region. In 2024, inpatient measures lasted 29 days on average, ranging from 23 to 24 days for orthopedic, rheumatological, and cardiological rehabilitation to 38 days for mental health diagnoses and 87 days for substance use disorders (Rentenversicherung, 2025). Longer stays are possible but must be justified by the facility. Measures vary by diagnosis and program type and may include physical, psychological, occupational, or nutritional therapy; stress management; information provision; further diagnostics; medication plans; and prevention and stabilization strategies and exercises.

Participation is therefore costly: weeks away from home and work on a dense therapy schedule, at reduced earnings, and with no further entitlement for four years. Rehabilitation is thus not plausibly consumed as leisure, and both applying and completing a measure are economically meaningful decisions.

Several reasons may prevent an application from leading to a completed measure: First, the caseworker may reject the application. Second, patients may drop out after starting treatment. Third, approved applicants can start only if capacity is available and the rehabilitation budget is not exhausted (see previous subsection).

# 3 Data and Descriptive Statistics

## 3.1 Datasets

The analysis combines two administrative data sets provided by the German public pension insurance. The first, the *Versicherungskontenstichprobe* (VSKT 2020), is a 2% random sample of all accounts held with the public pension insurance by persons aged 15–70 (Forschungsdatenzentrum der Rentenversicherung, 2020). It documents individual employment, earnings, unemployment and sick-leave histories, as well as retirement entry, at monthly frequency.

The second, the *Reha-Statistik-Datenbasis* (RSD 2024) covers the universe of medical and vocational rehabilitation measures provided by the German pension insurance between 2004 and 2021 (Forschungsdatenzentrum der Rentenversicherung, 2024). Each measure is recorded with the dates of application, approval, rejection, start, and completion. The daily precision allows us to follow the administrative process step by step and to measure the time elapsed between its stages.

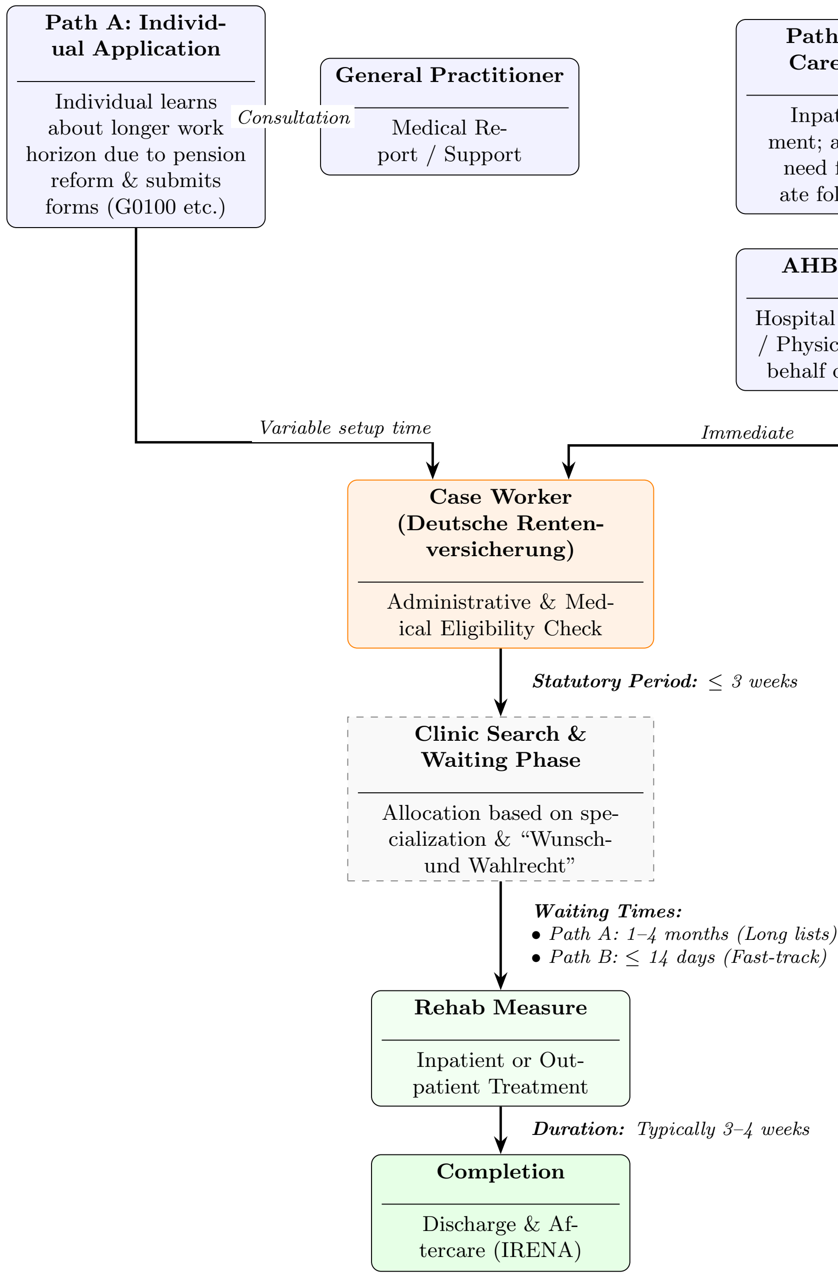
## 3.2 Sampling

We use the VSKT 2020, the most recent wave that still covers the birth cohorts around the reform cutoff. Cohorts 1950 to 1953 are observed in full, and the 2020 wave provides the longest employment histories and complete information on retirement entry for them.[12] We restrict the sample to women born in the years

[11] About 13% of all applications are rejected outright by pension insurance caseworkers, usually on medical grounds or on formal grounds, such as ineligibility arising from insufficient contribution periods or from a rehabilitation measure completed within the previous four years. A further 13% are forwarded to another rehabilitation provider that is formally responsible for the case.

[12] Individuals are included in the VSKT up to age 70. The 1950 cohort reaches that age in 2020, so later waves no longer cover it.

Figure 1: Vertical Timeline and Application Pathways for Medical Rehabilitation in Germany.




*Source*: Own visualization.
*Notes*: Figure shows the process of medical rehabilitation provided by the German pension insurance. Path A (on the left) shows initiation by the individual, Path B (on the right) imitation by a physician in a hospital. We focus on Path A, which is quantitatively about twice as important, to measure forward-looking individual behavior. Path B is used to study if hospital physicians show forward-looking behavior as supplementary evidence.

1950 to 1953, which allows us to use a bandwidth of up to 24 months in the regression discontinuity design (see Section 4). Furthermore, we include women from the year of their 54th birthday through the end of the calendar year in which they turn 60, that is, between 2004 and 2013.

In total, we obtain an individual-level panel dataset of 42,304 women born between 1950 and 1953. In addition to the rehabilitation information, the administrative data include important variables to study heterogeneous effects, among others, the entire employment history, including spells of unemployment and sick-leave periods.[13]

### 3.3 Measurement of Outcomes

To measure the work-related health investment of individuals, we focus on several outcome variables related to rehabilitation. As mentioned above, we can differentiate between applications for medical rehabilitation measures submitted from home and from the hospital (see Section 2). In addition, we have detailed information about the medical diagnoses that have been indicated in the rehabilitation application. This information is available on a somewhat aggregated level of medical diagnosis groups, which are defined according to the classification of the German public pension insurance (Rentenversicherung, 2025): Mental-health-related diagnoses, diagnoses related to the musculoskeletal system and connective tissue, cardiovascular diagnoses, cancer, metabolic or digestive diagnoses, and neurological diagnoses.[14] For each category, we define a binary outcome variable.[15] Thus, we can analyze whether a longer working horizon affects the work-related health investment in general and separately by medical diagnoses. We measure all outcome variables annually. In the analysis, we trace the entire process, including application approval and rejection, and the start and completion of approved applications. The outcome variables for approved and rejected applications are also binary.

### 3.4 Descriptive Analysis

We start by analyzing our data and main outcome variables descriptively. Table 1 displays the summary statistics for the main outcome variables of interest related to rehabilitation initiated from home (in total and by pre-reform and post-reform cohorts).[16] In our full sample, about 3% of women apply for medical rehabilitation from home each year. Most of these applications are approved (about 73 percent of all applications during the observation period across all observed birth cohorts which is consistent with aggregate statistics, see Section 2.2.1). The high approval rate reflects the fact that an application already requires a supporting physician's assessment. Differences in outcomes between the pre- and post-reform cohorts are small. Testing formally whether a longer working life affects institutional health investment requires a causal design.

[13]We measure health histories through registered sick-leave spells. Employers continue to pay wages for the first six weeks of an illness; only beyond that threshold does the health insurance take over with sickness benefits (*Krankengeld*), and only these longer spells are recorded in the pension insurance account. Our sick-leave indicators therefore capture spells of more than six weeks, and an individual coded as having no sick leave may still have experienced shorter absences. Since this censoring applies identically on both sides of the cutoff, it does not threaten identification, but it means our health-history measure identifies persistent rather than transitory health problems.

[14]In addition, we have information on the final medical diagnosis for all completed rehabilitation measures. Since focusing on these rehabilitation measures would restrict the analysis to measures that have been taken up and completed, we focus on the application diagnosis group in the main analysis.

[15]For each measure, we only include individuals with a rehabilitation due to the specific diagnosis and those without rehabilitation. We exclude observations with rehabilitation due to other diagnoses. This effectively results in a varying number of observations across diagnosis groups.

[16]Appendix Table A3 provides descriptive statistics for rehabilitation initiated from the hospital.

Table 1: Summary Statistics for Rehabilitation Initiated from Home

| Variable | 1950-1953 (full sample) | 1950-1951 (pre-reform) | 1952-1953 (post-reform) |
|---|---|---|---|
| Application | 0.030 | 0.028 | 0.031 |
| | (0.171) | (0.166) | (0.175) |
| Approved application | 0.023 | 0.021 | 0.024 |
| | (0.149) | (0.145) | (0.153) |
| Rejected application | 0.008 | 0.007 | 0.008 |
| | (0.088) | (0.085) | (0.090) |
| Begin | 0.022 | 0.021 | 0.022 |
| | (0.145) | (0.142) | (0.148) |
| Completion | 0.022 | 0.021 | 0.023 |
| | (0.145) | (0.142) | (0.148) |

*Source*: Forschungsdatenzentrum der Rentenversicherung, 2024, 2020, own calculations.
*Note*: The table shows means (standard deviations) of outcome variables of interest. $N = 293,637$ for the full sample of women born between 1950 and 1953 ($N = 145,076$ pre-reform; $N = 148,561$ post-reform) for the outcomes "application", "approved application", and "rejected application". $N = 293,733$ for the full sample ($N = 145,132$ pre-reform; $N = 148,601$ post-reform) for the outcome "begin". $N = 293,749$ for the full sample ($N = 145,142$ pre-reform; $N = 148,607$ post-reform) for the outcome "completion". We only include individuals with a rehabilitation application (begin / completion) and those without a rehabilitation application (begin / completion). We exclude measures where the application was submitted from the hospital (see Figure 1 for details). Cases where the application for and the beginning / completion of rehabilitation are recorded in different years, or applications without beginning / completing the measure, result in a varying number of observations across outcomes.

# 4 Empirical Method: Regression Discontinuity Design

To estimate the effect of an increase in working life on health investments we use a Regression Discontinuity Design (RDD) leveraging the 1999 pension reform. The reform leads to a sharp cut-off date for women born before and after December 31, 1951, which determines assignment to the treatment and control groups.

More formally, in the empirical analysis, the standardized woman's month of birth is the running variable $M$ that determines treatment while $D$ is an indicator variable for women born after the cutoff December 31, 1951:

$$D_i = \begin{cases} 1, & \text{if} \quad M_i \geq c \\ 0, & \text{if} \quad M_i < c \end{cases} \tag{1}$$

Identification requires that the month of birth cannot be manipulated and that there is no selection into or out of treatment. In Section 5 we provide supporting evidence by analyzing the continuity of covariates across the cutoff and by moving the cutoff to hypothetical placebo dates. Moreover, as discussed in Geyer and Welteke (2021), no other relevant policy reform differently affected women born in 1951 and 1952.[17]

In the main specification, we implement the RDD in the following regression model:

$$Y_{it} = \alpha + \beta D_i + f_1(M_i - c) + D_i f_2(M_i - c) + X_{it}\delta + \epsilon_{it} \tag{2}$$

where $Y_{it}$ is the respective outcome. The woman's date of birth, $M_i$, is measured in months, and $c$ is the

[17] Note that in 2007, there was another pension reform, which shifted the normal retirement age for the 1952 cohort by an additional month compared with the 1951 cohort.

cutoff date for the ERA increase, January 1, 1952. The difference between a woman's birth month and the beginning of the ERA increase, $M_i - c$, gives the running variable. We account for further explanatory variables, $X_{it}$, including year fixed effects and socio-demographic as well as employment-related covariates.[18] $\epsilon_{it}$ captures the error term.

We estimate this specification using local linear regressions with triangular kernel functions and optimal bandwidths according to Calonico et al. (2014).[19] Moreover, we test for the robustness of our findings using various bandwidth choices. Robust standard errors are clustered by month of birth (the running variable).

# 5 Results

## 5.1 Balancing across the cutoff

Before presenting the main results, we provide evidence that there is no selection at the cutoff. Because the running variable is a birth date in the distant past, manipulation is not possible. We show that the group composition does not change at the cutoff. In Appendix Figure A2 we present regression results of the RDD specification for the relevant variables using different bandwidths. We find no systematic differences by number of children, employment history and sick leave. However, a persistent regional discontinuity remains between East and West Germany. This finding is consistent with Geyer and Welteke (2021) and likely reflects a change in the VSKT sampling procedure across birth cohorts. In the subsequent analysis, we show that this difference does not affect our results.

## 5.2 Effects on application for rehabilitation

### 5.2.1 Effects on applications filed by the individual

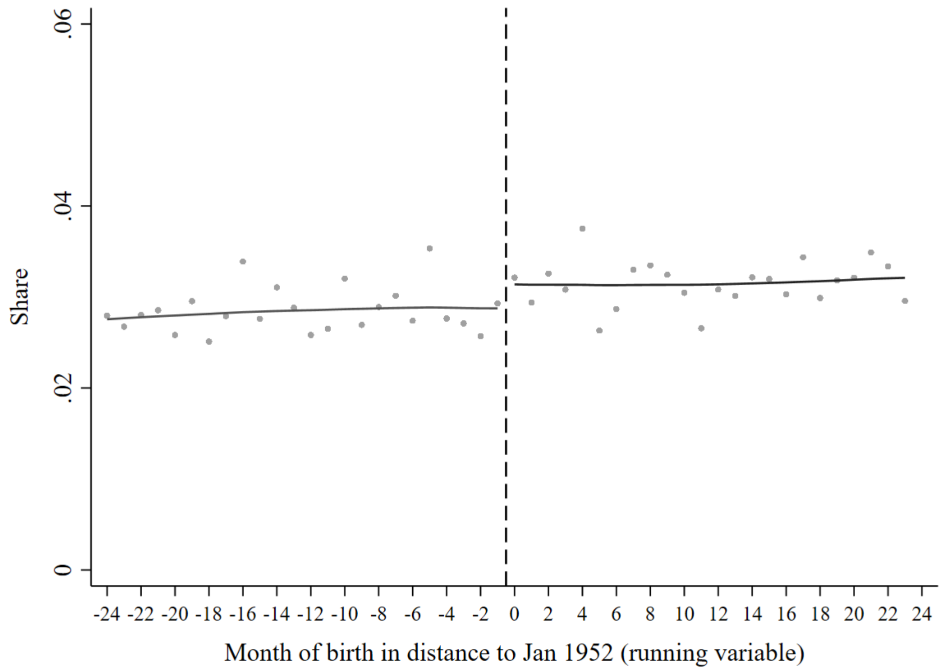
The graphical evidence in Figure 2 and the estimation results in Table 2 show that individuals are more likely to apply for work-related health investment when their retirement age increases. Figure 2 displays the application rate for medical rehabilitation initiated from home using monthly bins and additionally plots local linear regression lines (using a triangular kernel and a bandwidth of 24 months) on both sides of January 1952. The plots show that the share of individuals applying for medical rehabilitation from home slightly increases at the cutoff. In the following regression analysis, we test whether this discontinuity is statistically significant.

Irrespective of the specification (see Table 2), we find that the increase in the early retirement age significantly increases the probability of applying for medical rehabilitation. According to the main specification in Column 1, the probability increases by 0.478 percentage points, which amounts to a relative effect of around 17 percent compared to the pre-reform mean of around three percent. Restricting the sample to observations with non-missing values for the control variables (Column 2) slightly increases the estimated coefficient; however, when controlling for the covariates (Column 3), we estimate a coefficient very similar to that in the first column. We test the robustness of this finding against different bandwidth choices. In Appendix Figure A3 we show that the significant effect is robust to the choice of the bandwidth (varying between six and 24 months).

[18] Covariates include indicators for living in West Germany, having children, employment status and sick-leave history in the last five years.

[19] The optimal bandwidth varies between around six and nine months for most outcome specifications. If the optimal bandwidth according to Calonico et al. (2014) is below six months, we provide estimations with a bandwidth of twelve months in the main estimation table and test the robustness of our results using alternative bandwidth choices.

Figure 2: Local Linear Regression Plots for Application




*Source*: Forschungsdatenzentrum der Rentenversicherung, 2024, 2020, own calculations.
*Notes*: Scatter plots display mean outcome values using monthly bins. Local linear regression plots are based on triangular kernel functions with a bandwidth of 24 months.

We also test the robustness of this finding using a placebo cutoff date (January 1951) instead. We estimate a non-significant coefficient of -0.106 percentage points (p-value: 0.415), supporting the robustness of our estimated reform effect.

### 5.2.2 Heterogeneity by medical diagnosis

To better understand the positive application effects, we analyze heterogeneous effects for different medical diagnoses. For each medical rehabilitation application, we can observe the primary medical diagnosis indicated during the application process, which allows us to define diagnosis-specific applications as outcomes (see Section 3.3 for details). We summarize the estimated coefficients of interest in Figure 3, separated by diagnosis group. In addition, we provide detailed estimation results in Table A1 in Appendix A. With the exception of cardiovascular diagnoses, point estimates are all positive; however, they are not significant for every outcome. The estimates for applications associated with mental health-related and metabolic/digestion-related diagnoses are significant at the 10 percent level while the effect on the probability of applying for medical rehabilitation due to cancer is highly significant at the one percent level. The relative effect size is large for these diagnoses (about 41 to 79 percent) which reflects the small pre-treatment mean (0.001-0.004). The estimated differences for the diagnoses may reflect the nature of the diseases (i.e., requiring certain health investments in the observed age range) or a higher awareness among these patients of the relevance of health investments as human capital investments in the old-age work context.[20]

[20] Regarding cancer, it is important to highlight that our sample includes only cancer survivors, who might differ from the overall population of patients with a cancer diagnosis.

Table 2: RDD: Local Linear Regression Results, Application for Medical Rehabilitation

| | (1) | (2) | (3) |
|---|---|---|---|
| RDD estimate ($D_i$) | 0.00478** | 0.00590** | 0.00445** |
| | (0.00234) | (0.00289) | (0.00222) |
| *Relative estimate (in %)* | *17.1* | *17.4* | *13.1* |
| Observations | 293,637 | 248,852 | 248,852 |
| Pre-treatment mean | 0.028 | 0.034 | 0.034 |
| Year-FE | Yes | Yes | Yes |
| Socio-demographic controls | No | No | Yes |
| Employment controls | No | No | Yes |

*Source*: Forschungsdatenzentrum der Rentenversicherung, 2024, 2020, own calculations.

*Note*: Columns (1) to (3) show the RDD estimates (absolute and relative to the pre-treatment mean) for the outcome application for medical rehabilitation (indicator) from home. Thereby, we only include individuals with a rehabilitation application submitted from home and those without a rehabilitation application. We exclude observations with rehabilitation applications submitted from hospital. Column (1) captures the full sample and includes year dummies. Column (2) captures a sample for which none of the control variables are missing (restricted sample) and includes year dummies. Column (3) captures the restricted sample and additionally includes socio-demographic control variables as well as control variables that include information on employment status and history. Robust standard errors are clustered by month of birth (the running variable). Local linear regressions are based on triangular kernel functions using the Stata package "rdrobust" (Calonico et al., 2015). Optimal bandwidth according to Calonico et al. (2014). *** p<0.01, ** p<0.05, * p<0.1.

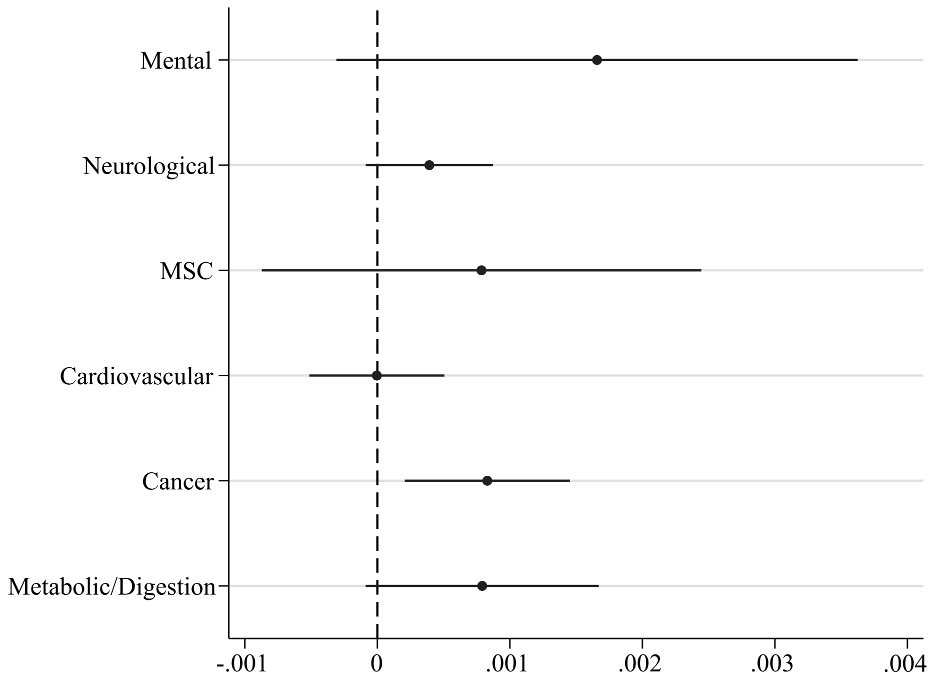
The findings for the different diagnoses are in general robust to the choice of the bandwidth (Figure A4 in Appendix A). If anything, we observe small changes in the estimated coefficients for specific diagnoses. While the estimated coefficient for cancer-related applications decreases with a larger bandwidth and becomes less significant, the estimated coefficients for applications related to mental health, metabolic-digestion, and cardiovascular diagnoses become more significant. This may be driven by an increase in estimation bias as the bandwidth increases.

### 5.2.3 Heterogeneity by employment history

In Figure 4 we summarize the heterogeneous effects for all applications by employment history. The detailed estimation results are presented in Appendix Table A2. While the effect is not statistically significant for the group of all employed individuals, we estimate a positive and statistically significant effect for the subgroup of employed individuals with a registered sick-leave spell in the last five years, that is, the main target group of the rehabilitation measure.[21] The relative effect size of around 17 percent is very similar to the baseline estimation result (Table 2). Looking at individuals with a sick leave spell in the last five years, regardless of employment status, the relative effect rises slightly to around 20 percent. For the group with the largest baseline mean of around 25 percent, i.e., individuals with a sick leave spell in the current year, we estimate a similar effect. Interestingly, additionally including individuals with an unemployment or care leave spell in the current year does not change the results. Finally, we find the largest relative estimate for the group of individuals with a past rehabilitation measure: A higher retirement age increases the probability

[21] Sick-leave spell refers to a sick leave of more than six weeks.

Figure 3: RDD: Local Linear Regression Results For Application by Diagnosis Group




*Source*: Forschungsdatenzentrum der Rentenversicherung, 2024, 2020, own calculations.
*Notes*: The plot shows the RDD estimates for the outcome application for medical rehabilitation from home (indicator variable), separated by the group of medical diagnoses indicated during the application process, where each coefficient refers to a separate regression outcome. All columns cover the full sample (for the respective subgroup) and include only year dummies. Robust standard errors are clustered by month of birth (running variable). Local linear regressions are based on triangular kernel functions. Optimal bandwidth according to Calonico et al. (2014).

of applying for medical rehabilitation by around 41 percent for this group. This effect may be driven by two channels: First, this group is more likely to have a long-lasting health issue and, therefore, has a higher incentive to react more strongly to an increase in the working horizon. Secondly, this group has experience with the bureaucratic process of applying for rehabilitation and therefore faces lower application costs when reapplying. Again, we show that the effects are robust to the choice of the bandwidth (Appendix Figure A5).

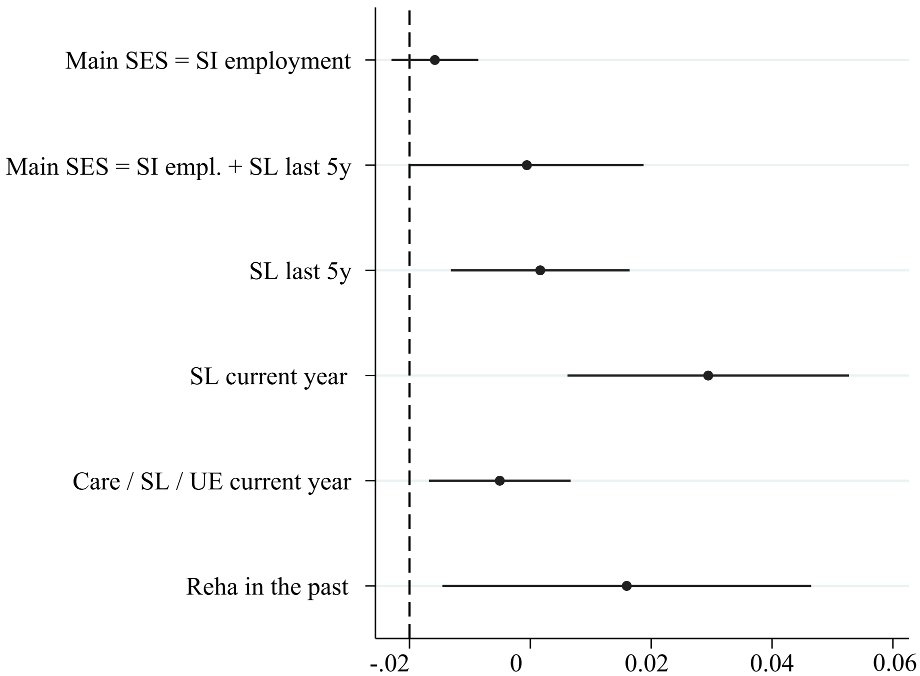
#### 5.2.4 Effects on applications filed by hospital staff

Our main analysis considers only applications initiated by the individual. We also estimate the reform effect on applications initiated by hospital staff during or immediately after an inpatient stay (Section 2.2.1); as for our main outcomes, the indicator is defined over the full sample rather than conditional on hospitalization. We estimate a small and statistically insignificant coefficient of 0.00057 (s.e. 0.00105) on a pre-reform mean of 0.009 (Appendix Table A4 and Figures A6–A7).

### 5.3 Effects on completion of medical rehabilitation

In contrast to the finding that individuals respond to an increase in working life, Figure 5 and Table 3 show that the increase in the application does not lead to a significant increase in the completion of rehabilitation

Figure 4: RDD: Local Linear Regression Results for Application by Subgroups

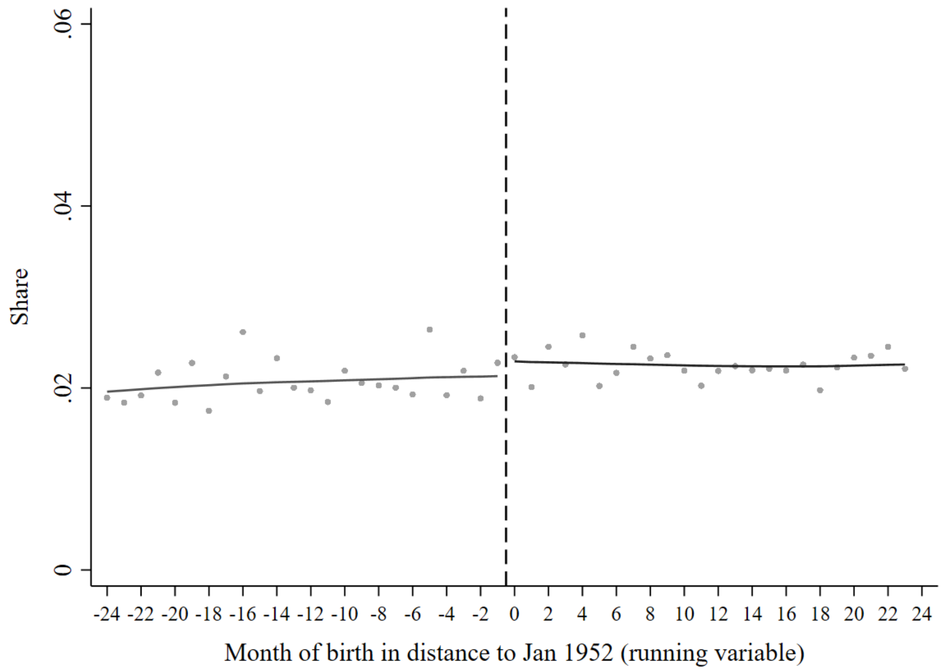



*Source*: Forschungsdatenzentrum der Rentenversicherung, 2024, 2020, own calculations.
*Notes*: The plot shows the RDD estimates for the outcome application for medical rehabilitation from home (indicator), where each column shows the estimation result for a separate subgroup of individuals. All columns cover the full sample (for the respective subgroup) and include only year dummies. "Main SES = SI employment" includes individuals for whom the main socioeconomic status is socially insured employment, meaning that for the majority of the respective year, the individual has been employed in a job with social security contributions. "SL last 5y" ("SL current year") refers to individuals with a long-term sick leave spell, i.e., of more than six weeks, within the last five years (within the current year). "Care / SL / UE current year" refers to individuals with a registered long-term care, sick-leave or unemployment spell in the current year. "Reha in the past" includes individuals who already completed a rehabilitation measure within the observation period. Robust standard errors are clustered by month of birth (running variable). Local linear regressions are based on triangular kernel functions. Optimal bandwidth according to Calonico et al. (2014).

measures. Specifically, discontinuity of completed rehabilitation at the cutoff is barely visible (Figure 5). The regression analysis confirms this null effect (Table 3) across all three specifications: the point estimate is about one third of the effect on applications and is never statistically significant. This result is robust for different choices of the estimation bandwidth (Appendix Figure A8).

We also conduct heterogeneity analyses for completions. We find that the estimates remain statistically insignificant for nearly all diagnoses and subgroups. In Figure 6 we present the results for the main specification, while Appendix Table A5 shows detailed estimation results, and Appendix Figure A9 the corresponding robustness checks for different bandwidths. In the main specification, we find a significant effect only for measures related to cancer. However, the robustness checks for the cancer outcome show that this result strongly depends on the choice of the bandwidth. Thus, we cannot conclude that the completion of rehabilitation measures has increased due to the reform. In Figure 7, Appendix Table A6, and Appendix Figure A10, we also provide evidence that this null effect is present for all sub-groups, independent of the employment and

Figure 5: Local Linear Regression Plots for Completion




*Source*: Source: Forschungsdatenzentrum der Rentenversicherung, 2024, 2020, own calculations.
*Notes*: Scatter plots display mean outcome values using monthly bins. Local linear regression plots are based on triangular kernel functions with a bandwidth of 24 months.

health history.

## 5.4 Mechanisms: Effects on approval, rejection, and beginning of medical rehabilitation

To better understand the differential effects for applications and completions and to identify potential mechanisms for this difference, we first focus on the approval and rejection of applications. Panel A of Figure 8 plots the share of approved applications over the month of birth, while Panel B plots the share of rejected applications.[22] We find a small jump in the share of approved applications at the cutoff, while the share of rejected applications remains unchanged.

The graphical evidence is supported by regression results, which are displayed in Columns 1 and 2 in Table 4.[23] Column 1 of Table 4 shows that the reform had a positive effect on the probability of applying for rehabilitation with subsequent approval. The relative effect size of around 17 percent is similar to the main finding for the probability of applications in Table 2 and robust across different bandwidth choices (Figure A11, Panel A). In contrast, the probability of applying for rehabilitation and then being rejected remains unchanged at the cut-off (Column 2). We estimate a small positive coefficient; however, the estimate is never

[22]Due to endogeneity issues, we do not restrict the sample to applications. Instead, we estimate the effect on the probability of applying for rehabilitation with subsequent approval across the whole sample.

[23]The table shows the results for specifications with year fixed effects only. Specifications in which we additionally control for socio-demographic and employment covariates yield similar results.

Table 3: RDD: Local Linear Regression Results, Completion of Medical Rehabilitation

| | (1) | (2) | (3) |
|---|---|---|---|
| RDD estimate ($D_i$) | 0.00151 | 0.00291 | 0.00132 |
| | (0.00208) | (0.00258) | (0.00201) |
| *Relative estimate (in %)* | *7.2* | *12.1* | *5.5* |
| Observations | 293,749 | 248,950 | 248,950 |
| Pre-treatment mean | 0.021 | 0.024 | 0.024 |
| Year-FE | Yes | Yes | Yes |
| Socio-demographic controls | No | No | Yes |
| Employment controls | No | No | Yes |

*Source*: Forschungsdatenzentrum der Rentenversicherung, 2024, 2020, own calculations.

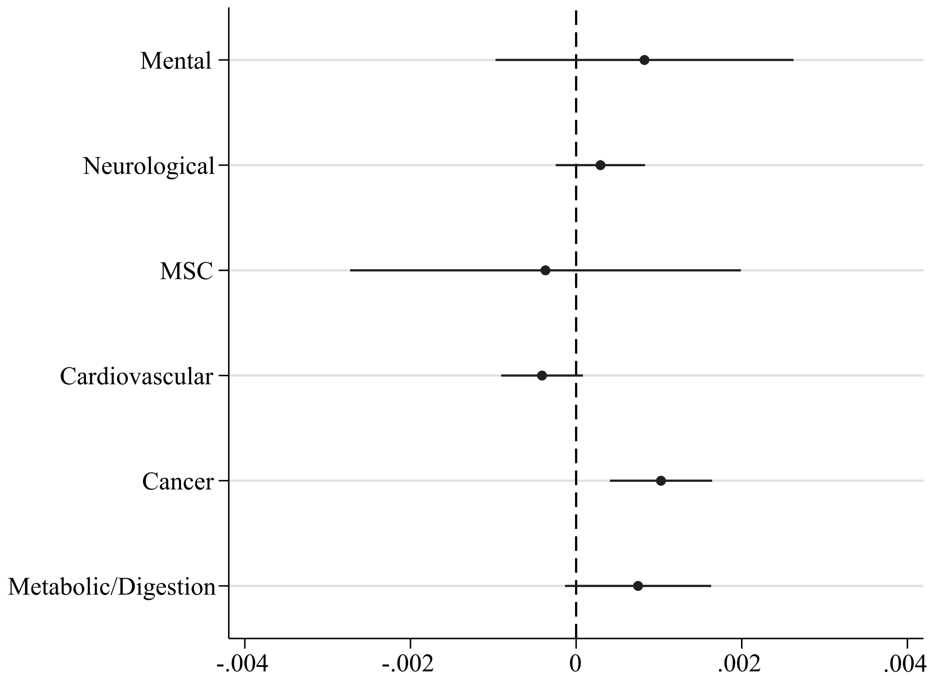
*Note*: Columns (1) to (3) show the RDD estimates (absolute and relative to the pre-treatment mean) for the outcome completion of medical rehabilitation (indicator). Thereby, we only include individuals with a completed rehabilitation (if the application was submitted from home) and those without a completed rehabilitation. We exclude measures where the application was not submitted from home. Cases where application for and completion of rehabilitation are recorded in different years, or applications without completions, by construction, result in a different number of observations than in Table 2. Column (1) captures the full sample and includes year dummies. Column (2) captures a sample for which none of the control variables are missing (restricted sample) and includes year dummies. Column (3) captures the restricted sample and additionally includes socio-demographic control variables as well as control variables that include information on employment status and history. Robust standard errors are clustered by month of birth (the running variable). Local linear regressions are based on triangular kernel functions using the Stata package "rdrobust" (Calonico et al., 2015). Optimal bandwidth according to Calonico et al. (2014). *** p<0.01, ** p<0.05, * p<0.1.

statistically significant irrespective of the bandwidths (Figure A11, Panel B). This null effect implies that the caseworkers base their decisions on formal criteria and do not differentiate based on the applicant's longer working life. While this result might be reassuring from an administrative point of view, it suggests that the administration process does not internalize the economic incentive induced by a longer working life — otherwise we should see a negative effect on rejections.

As for all applications, the effect on approved applications is driven primarily by individuals with sick leave in the current year or in the last five years, and by individuals with a past rehabilitation measure (Table A7). For rejections, we do not find a significant effect for groups with current or past sick leave; however, we estimate a positive effect for individuals with a past rehabilitation measure and for individuals with sick leave, unemployment, or a care spell in the current year (Table A8). The rejections of individuals with prior rehabilitation measures are likely driven by cases in which the individual participated in a rehabilitation measure within the last four years.[24] The positive effect on rejections within the other group likely stems from individuals in unemployment (the group of caregivers is comparatively small), who are rejected for formal reasons or whose prospects of rehabilitation success are deemed insufficient. Overall, this analysis shows that the differential effect for applications and completions cannot be explained by a systematic change in the administrative process resulting in more rejections.

[24]Institutional regulations typically require rehabilitation to be conducted only every four years, see Section 2 for details.

Figure 6: RDD: Local Linear Regression Results for Completion by Diagnosis Group



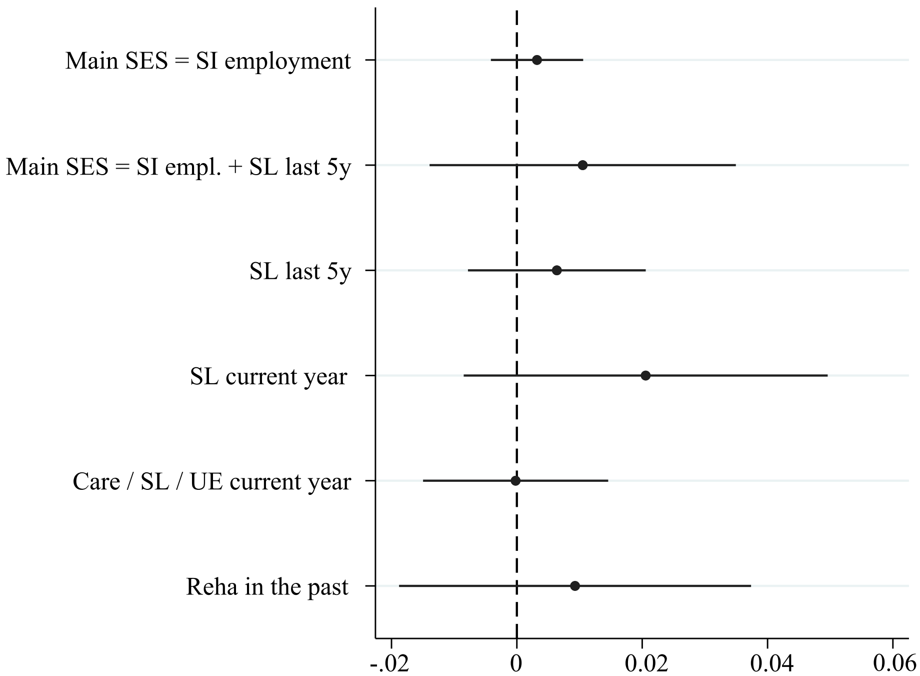

*Source*: Forschungsdatenzentrum der Rentenversicherung, 2024, 2020, own calculations.
*Notes*: The plot shows the RDD estimates for the outcome completion of medical rehabilitation from home (indicator variable), separated by the group of medical diagnoses indicated during the application process, where each coefficient refers to a separate regression outcome. All columns cover the full sample (for the respective subgroup) and include only year dummies. Standard errors are clustered by month of birth (running variable) and are robust. Local linear regressions are based on triangular kernel functions. Optimal bandwidth according to Calonico et al. (2014).

Finally, we test whether the null effect for completions is related to dropouts from the rehabilitation measures or to missing initiations. Panel C of Figure 8 plots the share of individuals beginning a medical rehabilitation measure, which hardly changes at the cut-off date. The formal test using the regression is presented in Column 3 of Table 4. We find no statistically significant effect on the probability of starting rehabilitation. Moreover, the relative effect size of 7.6 percent is almost identical to the relative effect size for completion (7.2 percent) and robust across different bandwidth choices (Figure A11, Panel C). Heterogeneity analyses confirm this picture for different subgroups (Table A9).

To summarize, we find positive effects on the probability of applying for medical rehabilitation and on the probability that the application is approved, but no significant effects on rejections, the probability of starting rehabilitation, or the probability of completing it. Thus, we can rule out that the discrepancy between applications and completions is driven by caseworkers rejecting a larger share of applications or by individuals dropping out after beginning rehabilitation. Instead, our findings suggest that caseworkers largely follow the existing administrative process and legal framework, simply translating the increase in applications into a corresponding increase in approvals rather than strategically prioritizing individuals with longer remaining working lives. This administrative behavior, however, cannot explain why higher approval rates do not translate into more completed rehabilitation measures.

Instead, our results point to capacity constraints in rehabilitation delivery. The absence of an effect already

Figure 7: RDD: Local Linear Regression Results for Completion by Subgroups



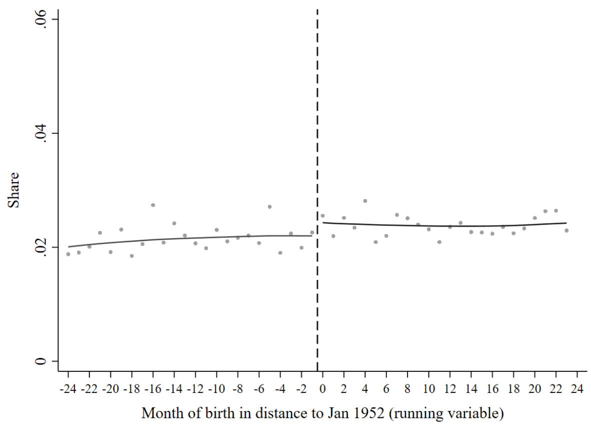

*Source*: Forschungsdatenzentrum der Rentenversicherung, 2024, 2020, own calculations.
*Notes*: The plot shows the RDD estimates for the outcome completion of medical rehabilitation from home (indicator), where each column shows the estimation result for a separate subgroup of individuals. All columns cover the full sample (for the respective subgroup) and include only year dummies. "Main SES = SI employment" includes individuals for whom the main socioeconomic status is socially insured employment, meaning that for the majority of the respective year, the individual has been employed in a job with social security contributions. "SL last 5y" ("SL current year") refers to individuals with a long-term sick leave spell, i.e., of more than six weeks, within the last five years (within the current year). "Care / SL / UE current year" refers to individuals with a registered long-term care, sick-leave or unemployment spell in the current year. "Reha in the past" includes individuals who already completed a rehabilitation measure within the observation period. Standard errors are clustered by month of birth (running variable) and are robust. Local linear regressions are based on triangular kernel functions. Optimal bandwidth according to Calonico et al. (2014).

on rehabilitation starts indicates that the additional approved applicants largely did not enter treatment. Two institutional features explain why approvals can rise without treatments following. First, the two stages are governed by different constraints. Caseworkers decide case by case within a legal framework that does not permit differentiation by remaining working life, so an increase in eligible applications translates one for one into an increase in approvals. The pension insurance as an organization, however, cannot expand the volume of rehabilitation it delivers: annual expenditure is capped by law (§ 220 SGB VI) and indexed to wage growth rather than to need (Section 2). Approvals are determined individually and are not capped, yes treatments are capped in the aggregate. Additional approved applicants therefore join a queue rather than enter treatment. Second, within that queue, the applications we study are precisely those that lose: self-initiated cases receive lower priority than hospital-initiated ones, so the marginal applicant induced by the reform is also the applicant least likely to be served.

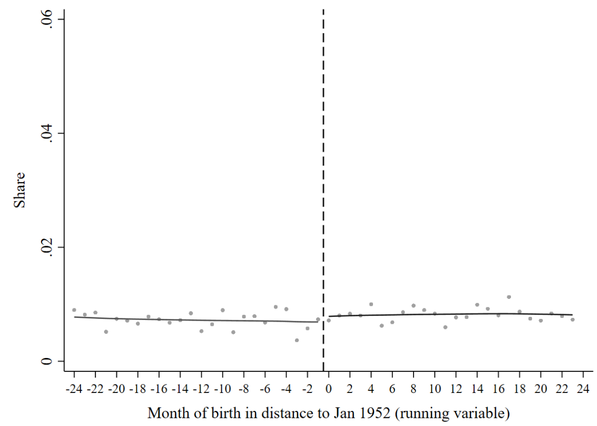
The expenditure cap applies to both cohorts in any given calendar year and therefore does not generate the discontinuity itself. What it generates is the inelasticity of supply. The reform shifts demand at the cutoff,

Figure 8: Local Linear Regression Plots: Mechanisms

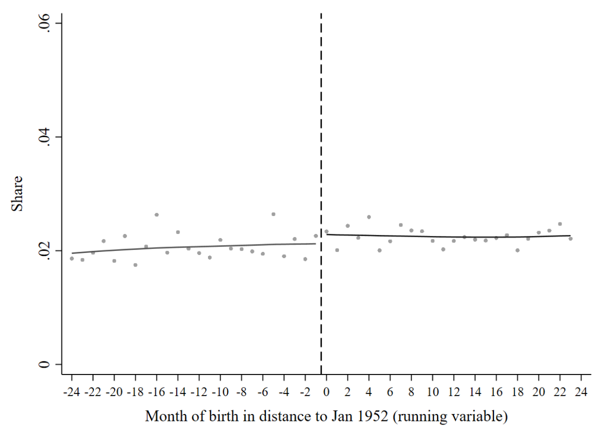
(a) Panel A: Approved applications




(b) Panel B: Rejected applications




(c) Panel C: Begin




*Source*: Forschungsdatenzentrum der Rentenversicherung, 2024, 2020, own calculations.
*Notes*: Scatter plots display mean outcome values using monthly bins. Local linear regression plots are based on triangular kernel functions with a bandwidth of 24 months.

while the quantity of rehabilitation the system may deliver is fixed by statute, so the additional demand is absorbed by the queue rather than by additional treatment.

Table 4: RDD: Local Linear Regression Results, Mechanism Outcomes

| | **Approved appl.** | **Rejected appl.** | **Begin** |
|---|---|---|---|
| | (1) | (2) | (3) |
| RDD estimate ($D_i$) | 0.00348** | 0.00168 | 0.00160 |
| | (0.00165) | (0.00136) | (0.00205) |
| *Relative estimate (in %)* | *16.6* | *24.0* | *7.6* |
| Observations | 293,637 | 293,637 | 293,733 |
| Pre-treatment mean | 0.021 | 0.007 | 0.021 |
| Year-FE | Yes | Yes | Yes |

[1] *Source*: Forschungsdatenzentrum der Rentenversicherung, 2024, 2020, own calculations.
[2] *Note*: Column (1) shows the RDD estimates (absolute and relative to the pre-treatment mean) for the outcome approved application (indicator), column (2) shows the RDD estimates for the outcome rejected application (indicator) and column (3) shows the RDD estimates for the outcome beginning of medical rehabilitation (indicator), where each column shows the estimation result for a separate outcome. We only include individuals with a rehabilitation application (begin) and those without a rehabilitation application (begin). We exclude measures where the application was not submitted from home. Cases where the application for and the beginning of rehabilitation are recorded in different years, or applications without beginning the measure, result in a varying number of observations across columns. All columns cover the full sample and include only year dummies. Standard errors are clustered by month of birth (the running variable) and are robust. Local linear regressions are based on triangular kernel functions using the Stata package "rdrobust" (Calonico et al., 2015). Optimal bandwidth according to Calonico et al. (2014). *** p<0.01, ** p<0.05, * p<0.1.

# 6 Conclusion

This paper examines whether a longer expected working life causally affects investments in work-related health before retirement. Exploiting a German pension reform that abolished the earliest retirement option for women and using the resulting sharp birth-cohort discontinuity, we identify the effect of an exogenous increase in the expected working horizon on medical rehabilitation behavior.

Our findings suggest the following pattern. Individuals exposed to the reform become more likely to apply for medical rehabilitation, particularly when applications are initiated by the individuals themselves, among those with poorer health histories, and for diagnoses where rehabilitation is likely to improve future work capacity. These results are consistent with forward-looking behavior predicted by human capital models: individuals respond to longer expected careers by increasing investments in their health.

However, we find no corresponding increase in participation. Across a wide range of specifications, bandwidths, diagnoses, and individual characteristics, we find no increase in completed rehabilitation measures. We further show that this result is driven neither by higher rejection rates nor by individuals dropping out after rehabilitation begins. Instead, the evidence points to capacity constraints in program delivery. This constraint is statutory rather than physical: annual expenditure on rehabilitation is capped and indexed to the growth of gross wages, not to the number of insured in rehabilitation-intensive ages or to the demand generated by later retirement. Reforms that extend working lives therefore raise the demand for work-related health investment through one part of the pension system, while another part of the same system is legally prevented from meeting it.

Taken together, our results suggest that individuals respond to pension reforms in the predicted direction by increasing investments in their work capacity. However, institutional capacity constraints prevent these additional investments from translating into actual rehabilitation. This finding highlights that extending working lives is not only a question of retirement incentives but also of healthcare capacity. Without sufficient rehabilitation resources, policies aimed at lengthening careers may leave part of the potential productivity and health gains untapped.

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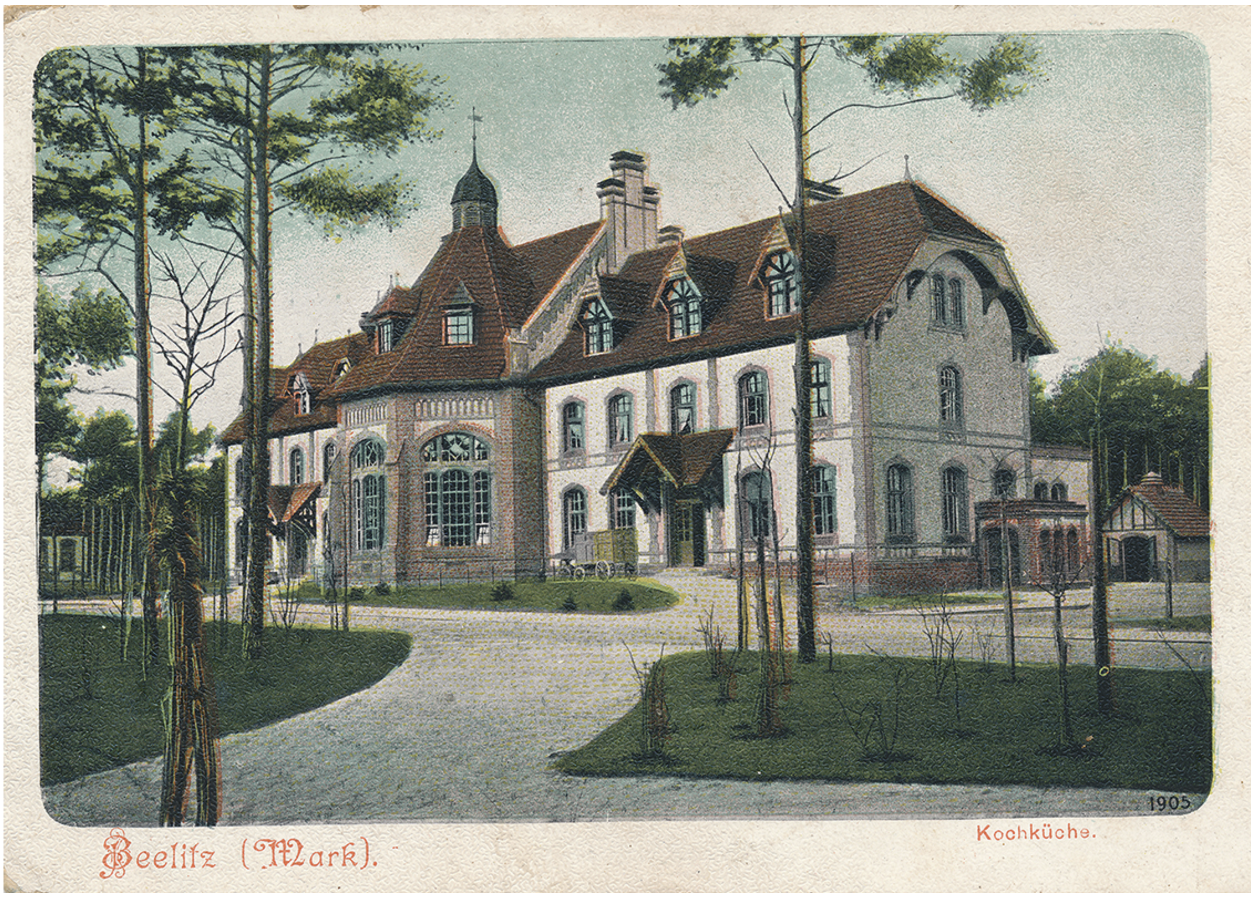
# Appendices

## A Additional Figures and Tables

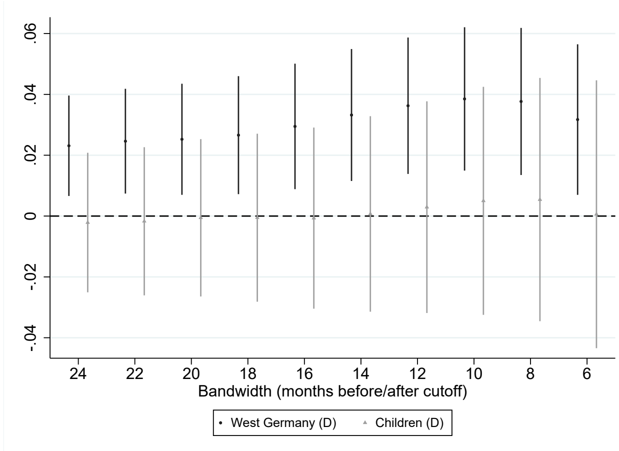
Figure A1: The Beelitz rehabilitation center in 1905



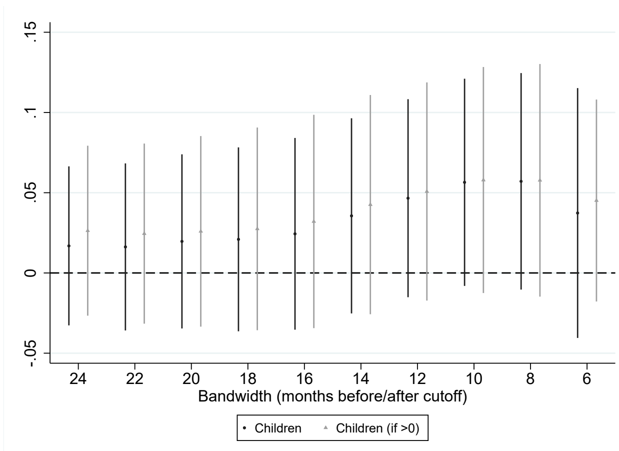

*Source*: Baum & Zeit, https://baumundzeit.de/geschichte/ [last access 19.03.2026]
*Notes*: This is a 1905-postcard of one of the buildings from the "Beelitzer Heilstätten" that focused on rehabilitation and return to work after lung diseases for workers from the Berlin factories. This is an early example of a publicly funded rehabilitation center with an capacity of 1200 beds, the remains of which can be visited as a tourist site. Today, over 1,000 such rehabilitation centers exist, with about 160,000 beds, spread all over Germany, and specialized into the rehabilitation of workers.

Figure A2: RDD Balancing: Local Linear Regression Results for Covariates, Bandwidth Variation

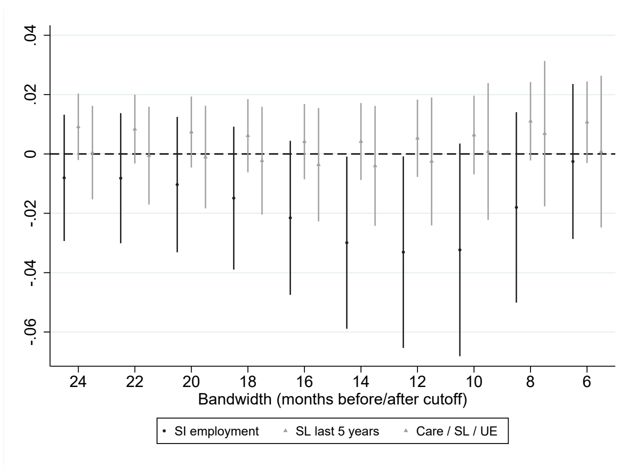
(a) Panel A: Socio-demographics I




(b) Panel B: Socio-demographics II

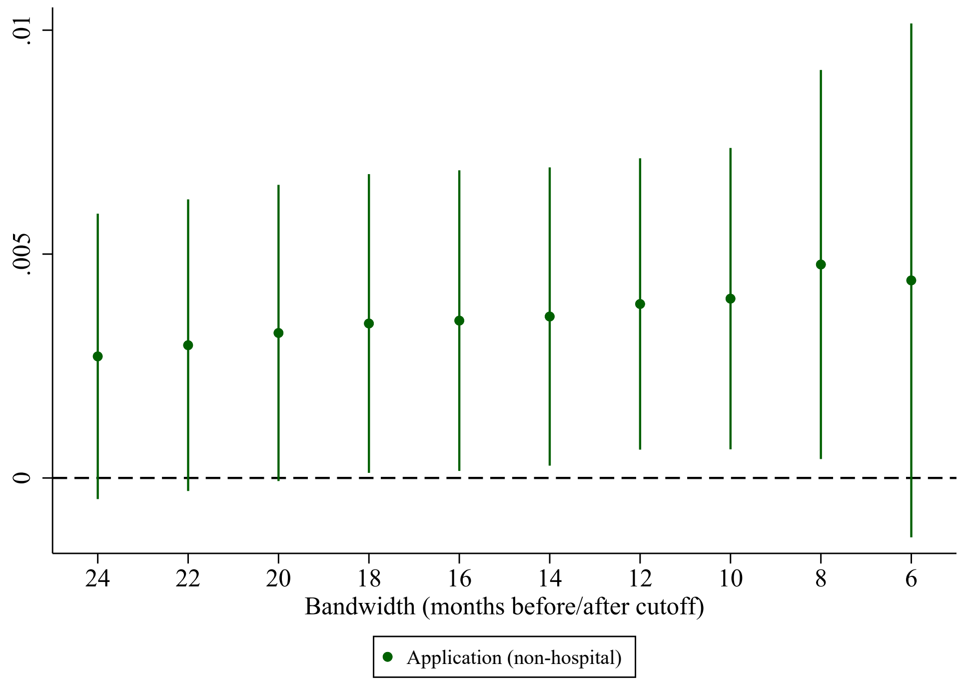



(c) Panel C: Employment



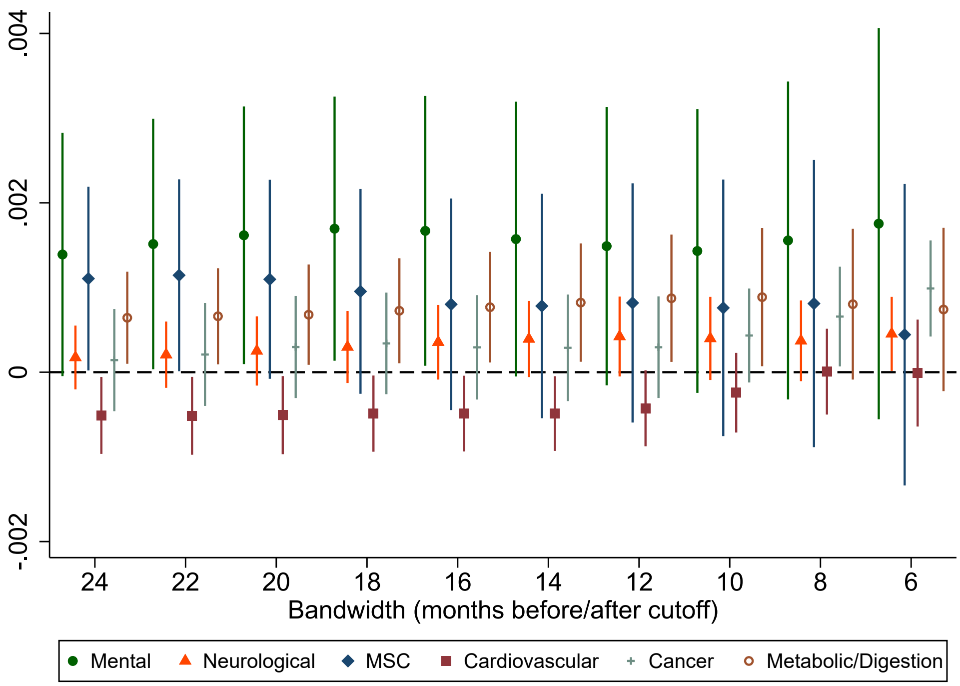

*Source*: Forschungsdatenzentrum der Rentenversicherung, 2024, 2020, own calculations.
*Notes*: The plot shows the RDD estimates for different covariates. Estimations include only year dummies. Standard errors are clustered by month of birth (running variable) and are robust. Local linear regressions are based on triangular kernel functions.

Figure A3: RDD: Local Linear Regression Results for Application, Bandwidth Variation



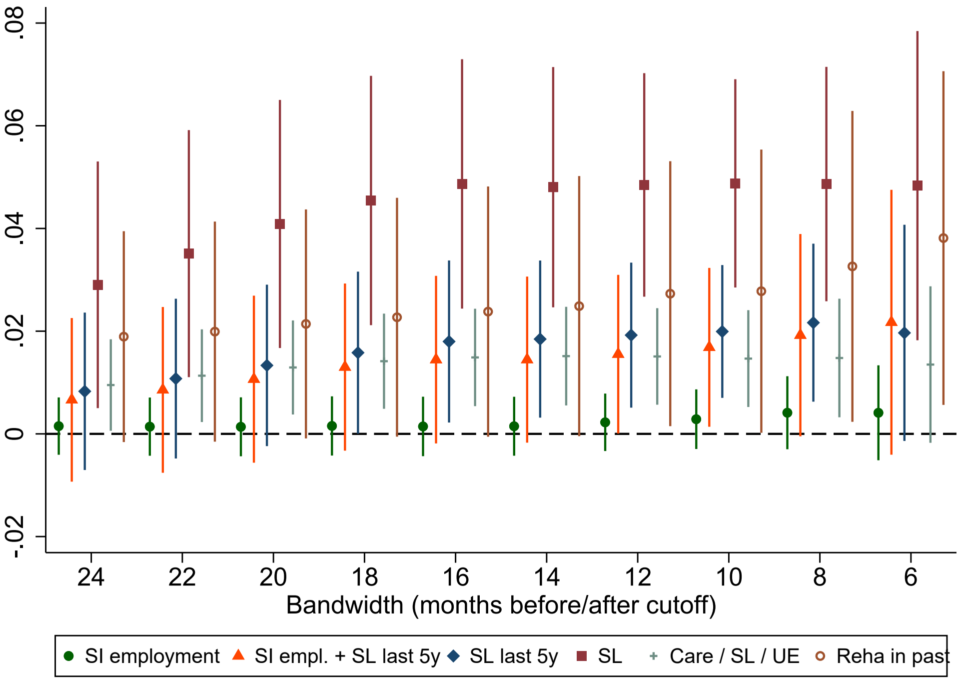

*Source*: Forschungsdatenzentrum der Rentenversicherung, 2024, 2020, own calculations.
*Notes*: The plot shows the RDD estimates for the outcome application for medical rehabilitation from home (indicator), where each coefficient shows the estimation result for a different bandwidth. Estimations include only year dummies. Standard errors are clustered by month of birth (running variable) and are robust. Local linear regressions are based on triangular kernel functions.

Figure A4: RDD: Local Linear Regression Results for Application, by Diagnosis Outcome, Bandwidth Variation



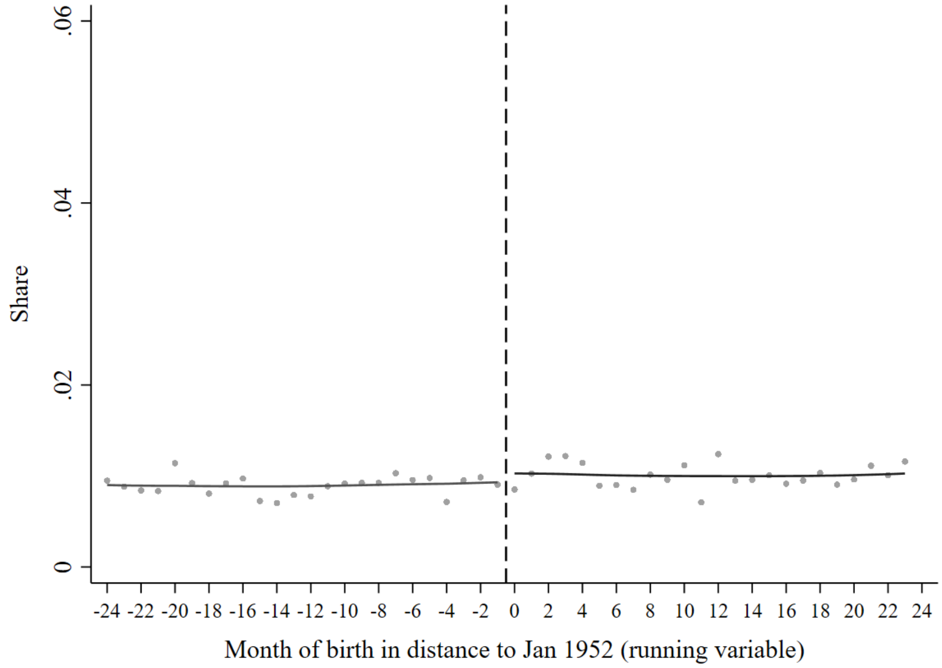

*Source*: Forschungsdatenzentrum der Rentenversicherung, 2024, 2020, own calculations.
*Notes*: The plot shows the RDD estimates for the outcome application for medical rehabilitation from home (indicator), where each coefficient shows the estimation result for a different bandwidth. Estimations include only year dummies. Standard errors are clustered by month of birth (running variable) and are robust. Local linear regressions are based on triangular kernel functions.

Figure A5: RDD: Local Linear Regression Results for Application, by Subgroup, Bandwidth Variation



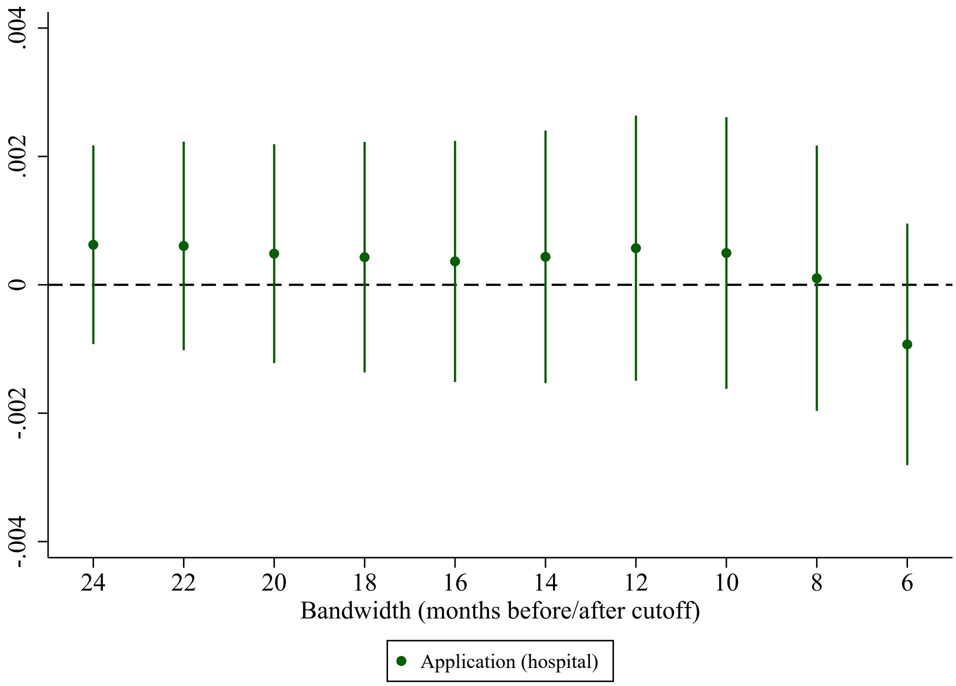

*Source*: Forschungsdatenzentrum der Rentenversicherung, 2024, 2020, own calculations.
*Notes*: The plot shows the RDD estimates for the outcome application for medical rehabilitation from home (indicator), where each coefficient shows the estimation result for a different bandwidth. Estimations include only year dummies. "Main SES = SI employment" includes individuals for whom the main socioeconomic status is socially insured employment, meaning that for the majority of the respective year, the individual has been employed in a job with social security contributions. "SL last 5y" ("SL current year") refers to individuals with a long-term sick leave spell, i.e., of more than six weeks, within the last five years (within the current year). "Care / SL / UE current year" refers to individuals with a registered long-term care, sick-leave or unemployment spell in the current year. "Reha in the past" includes individuals who already completed a rehabilitation measure within the observation period. Standard errors are clustered by month of birth (running variable) and are robust. Local linear regressions are based on triangular kernel functions.

Figure A6: Local Linear Regression Plots for Application for Rehabilitation Initiated from Hospital



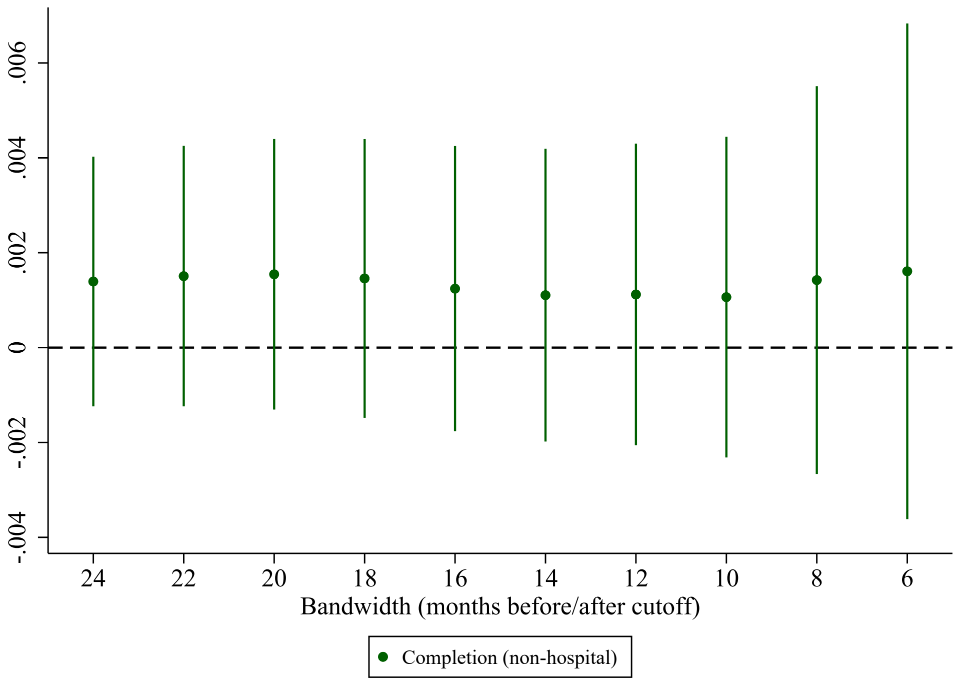

*Source*: Source: Forschungsdatenzentrum der Rentenversicherung, 2024, 2020, own calculations.
*Notes*: Scatter plots display mean outcome values using monthly bins. Local linear regression plots are based on triangular kernel functions with a bandwidth of 24 months.

Figure A7: Local Linear Regression Results for Application for Rehabilitation Initiated from Hospital, Bandwidth Variation



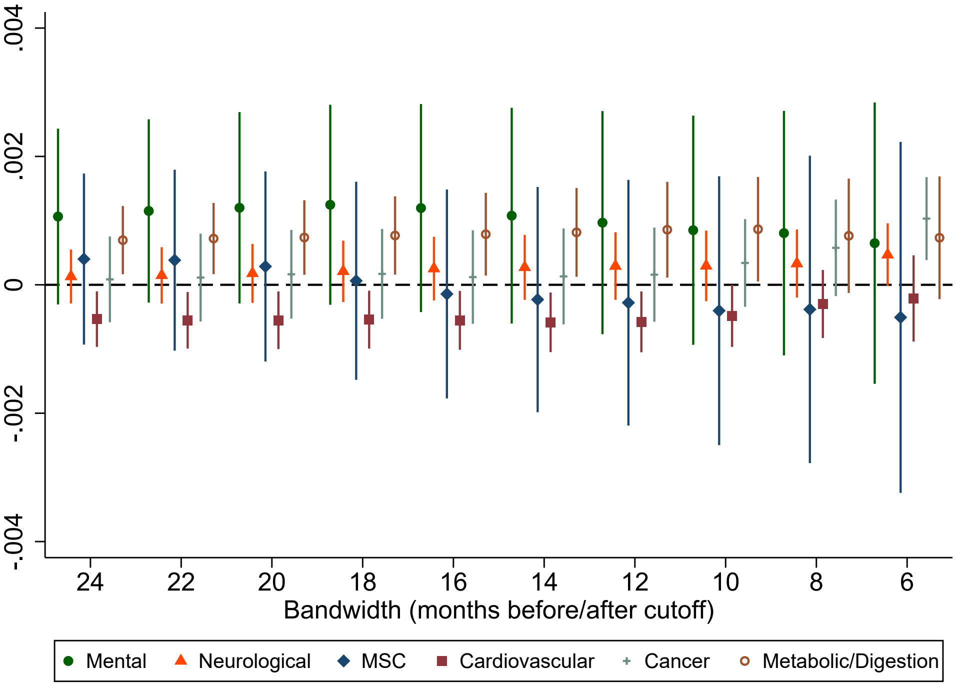

*Source*: Source: Forschungsdatenzentrum der Rentenversicherung, 2024, 2020, own calculations.
*Notes*: Scatter plots display mean outcome values using monthly bins. Local linear regression plots are based on triangular kernel functions with a bandwidth of 24 months.

Figure A8: RDD: Local Linear Regression Results for Completion, Bandwidth Variation



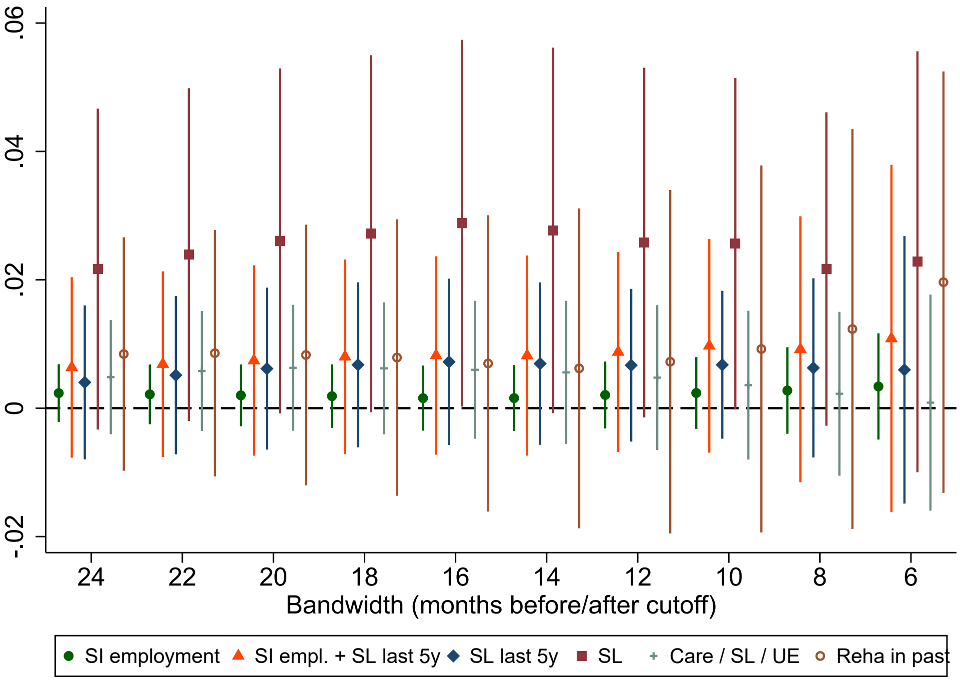

*Source*: Forschungsdatenzentrum der Rentenversicherung, 2024, 2020, own calculations.
*Notes*: The plot shows the RDD estimates for the outcome completion of medical rehabilitation from home (indicator), where each coefficient shows the estimation result for a different bandwidth. Estimations include only year dummies. Standard errors are clustered by month of birth (running variable) and are robust. Local linear regressions are based on triangular kernel functions.

Figure A9: RDD: Local Linear Regression Results for Completion, by Diagnosis Outcome, Bandwidth Variation




*Source*: Forschungsdatenzentrum der Rentenversicherung, 2024, 2020, own calculations.
*Notes*: The plot shows the RDD estimates for the outcome completion of medical rehabilitation from home (indicator), where each coefficient shows the estimation result for a different bandwidth. Estimations include only year dummies. Standard errors are clustered by month of birth (running variable) and are robust. Local linear regressions are based on triangular kernel functions.

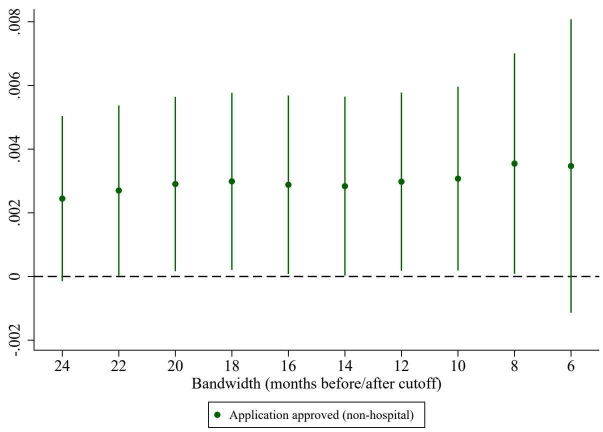
Figure A10: RDD: Local Linear Regression Results for Completion, by Subgroup, Bandwidth Variation



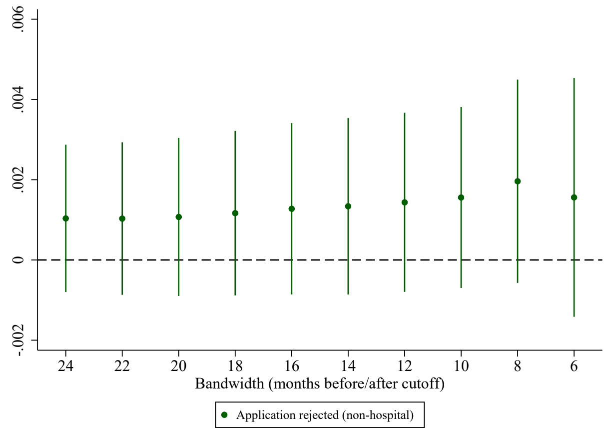

*Source*: Forschungsdatenzentrum der Rentenversicherung, 2024, 2020, own calculations.
*Notes*: The plot shows the RDD estimates for the outcome completion of medical rehabilitation from home (indicator), where each coefficient shows the estimation result for a different bandwidth. Estimations include only year dummies. "Main SES = SI employment" includes individuals for whom the main socioeconomic status is socially insured employment, meaning that for the majority of the respective year, the individual has been employed in a job with social security contributions. "SL last 5y" ("SL current year") refers to individuals with a long-term sick leave spell, i.e., of more than six weeks, within the last five years (within the current year). "Care / SL / UE current year" refers to individuals with a registered long-term care, sick-leave or unemployment spell in the current year. "Reha in the past" includes individuals who already completed a rehabilitation measure within the observation period. Standard errors are clustered by month of birth (running variable) and are robust. Local linear regressions are based on triangular kernel functions.

Figure A11: RDD: Local Linear Regression Results for Mechanisms, Bandwidth Variation

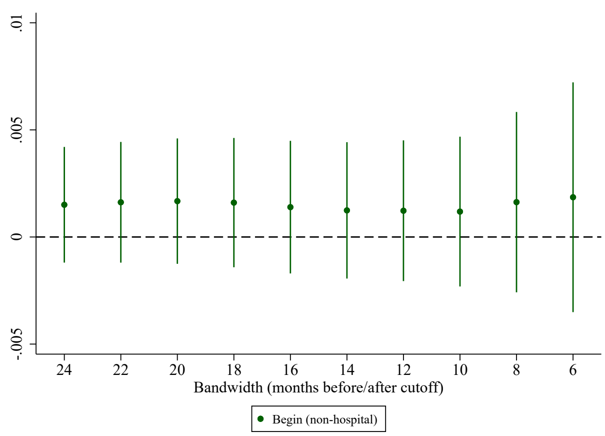
(a) Panel A: Approved application




(b) Panel B: Rejected application




(c) Panel C: Begin




*Source*: Forschungsdatenzentrum der Rentenversicherung, 2024, 2020, own calculations.
*Notes*: The plot shows the RDD estimates for the outcomes (A) approved application for medical rehabilitation from home (indicator) and (B) rejected application for medical rehabilitation from home (indicator), where each coefficient shows the estimation result for a different bandwidth. Estimations include only year dummies. Standard errors are clustered by month of birth (running variable) and are robust. Local linear regressions are based on triangular kernel functions.

Table A1: RDD: Local Linear Regression Results, Application by Diagnosis

| | **Mental** | **Neuro** | **MSC** | **Cardio** | **Cancer** | **Met/Dig** |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| RDD estimate ($D_i$) | 0.00166* | 0.000393 | 0.000786 | -0.000004 | 0.000830*** | 0.000791* |
| | (0.00100) | (0.000245) | (0.000846) | (0.000260) | (0.000318) | (0.000449) |
| *Relative estimate (in %)* | *41.5* | *39.3* | *6.6* | *-0.4* | *41.5* | *79.1* |
| Observations | 286,277 | 284,964 | 288,318 | 285,108 | 285,490 | 285,033 |
| Pre-treatment mean | 0.004 | 0.001 | 0.012 | 0.001 | 0.002 | 0.001 |
| Year-FE | Yes | Yes | Yes | Yes | Yes | Yes |

[1] *Source*: Forschungsdatenzentrum der Rentenversicherung, 2024, 2020, own calculations.
[2] *Note*: Columns (1) to (6) show the RDD estimates (absolute and relative to the pre-treatment mean) for the outcome application for medical rehabilitation (indicator), where the outcome is separated by diagnosis category and each column shows the estimation result for a separate diagnosis category outcome. For each diagnosis category, we define a binary outcome variable. Thereby, we only include individuals with a rehabilitation application due to the respective diagnosis category and those without a rehabilitation application. We exclude observations with rehabilitation applications due to other diagnoses. This effectively results in a varying number of observations across diagnosis categories (columns). All estimations include year dummies. Standard errors are clustered by month of birth (the running variable) and are robust. Local linear regressions are based on triangular kernel functions. Optimal bandwidth according to Calonico et al. (2014). *** p<0.01, ** p<0.05, * p<0.1.

Table A2: RDD: Local Linear Regression Results, Application by Subgroups

| | **SI empl.** | **SI empl. + SL last 5y** | **SL last 5y** | **SL** | **Care / SL / UE** | **Reha in past** |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| RDD estimate ($D_i$) | 0.00420 | 0.0194** | 0.0216*** | 0.0494*** | 0.0149** | 0.0360** |
| | (0.00366) | (0.00985) | (0.00755) | (0.0119) | (0.00599) | (0.0156) |
| *Relative estimate (in %)* | *9.1* | *16.9* | *19.8* | *19.5* | *18.6* | *41.9* |
| Observations | 128,736 | 30,424 | 43,810 | 13,403 | 53,168 | 35,364 |
| Pre-treatment mean | 0.046 | 0.115 | 0.109 | 0.254 | 0.080 | 0.086 |
| Year-FE | Yes | Yes | Yes | Yes | Yes | Yes |

[1] *Source*: Forschungsdatenzentrum der Rentenversicherung, 2024, 2020, own calculations.
[2] *Note*: Columns (1) to (6) show the RDD estimates (absolute and relative to the pre-treatment mean) for the outcome application for medical rehabilitation (indicator), each column shows the estimation result for a separate subgroup of individuals. All columns cover the full sample (for the respective subgroup) and include only year dummies. "Main SES = SI employment" includes individuals for whom the main socioeconomic status is socially insured employment, meaning that for the majority of the respective year, the individual has been employed in a job with social security contributions. "SL last 5y" ("SL current year") refers to individuals with a long-term sick leave spell, i.e., of more than six weeks, within the last five years (within the current year). "Care / SL / UE current year" refers to individuals with a registered long-term care, sick-leave or unemployment spell in the current year. "Reha in the past" includes individuals who already completed a rehabilitation measure within the observation period. Standard errors are clustered by month of birth (the running variable) and are robust. Local linear regressions are based on triangular kernel functions. Optimal bandwidth according to Calonico et al. (2014). *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Summary Statistics for Rehabilitation Initiated from Hospital

| Variable | 1950-1953 | 1950-1951 (Pre-Reform) | 1952-1953 (Post-Reform) |
|---|---|---|---|
| Application | 0.010 | 0.009 | 0.010 |
| | (0.097) | (0.094) | (0.100) |

*Source*: Forschungsdatenzentrum der Rentenversicherung, 2024, 2020, own calculations.
*Note*: The table shows means (standard deviations) of outcome variables of interest. $N = 287,565$ for the full sample of women born between 1950 and 1953 ($N = 142,219$ pre-reform; $N = 145,346$ post-reform). We only include individuals with a rehabilitation application and those without a rehabilitation application. We exclude observations with rehabilitation applications submitted from home (see Figure 1 for details), leading to a different number of observations than in Table 1.

Table A4: RDD: Local Linear Regression Results, Application for Medical Rehabilitation Initiated from Hospital

| | (1) | (2) | (3) |
|---|---|---|---|
| RDD estimate ($D_i$) | 0.000571 | 0.000569 | 0.000423 |
| | (0.00105) | (0.00122) | (0.00142) |
| *Relative estimate (in %)* | *6.3* | *5.2* | *3.9* |
| Observations | 287,565 | 243,009 | 243,009 |
| Pre-treatment mean | 0.009 | 0.011 | 0.011 |
| Year-FE | Yes | Yes | Yes |
| Socio-demographic controls | No | No | Yes |
| Employment controls | No | No | Yes |

[1] *Source*: Forschungsdatenzentrum der Rentenversicherung, 2024, 2020, own calculations.
[2] *Note*: The table shows the RDD estimates (absolute and relative to the pre-treatment mean) for the outcome application for medical rehabilitation (indicator) from the hospital. Thereby, we only include individuals with a rehabilitation application submitted from hospital and those without rehabilitation. We exclude observations with rehabilitation applications submitted from home, leading to a different number of observations than in Table 2. Standard errors are clustered by month of birth (the running variable) and are robust. Local linear regressions are based on triangular kernel functions. Since the optimal bandwidth according to Calonico et al. (2014) is below six months, we provide estimations with a bandwidth of twelve months and test the robustness of our results using alternative bandwidth choices in Figure A7. *** p<0.01, ** p<0.05, * p<0.1.

Table A5: RDD: Local Linear Regression Results, Completion by Diagnosis

| | **Mental** | **Neuro** | **MSC** | **Cardio** | **Cancer** | **Met/Dig** |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| RDD estimate ($D_i$) | 0.000825 | 0.000294 | -0.000370 | -0.000412 | 0.00102*** | 0.000748* |
| | (0.000918) | (0.000275) | (0.00120) | (0.000252) | (0.000315) | (0.000450) |
| *Relative estimate (in %)* | *20.6* | *29.4* | *-3.4* | *-41.2* | *51.0* | *74.8* |
| Observations | 288,759 | 287,526 | 290,762 | 287,667 | 288,012 | 287,598 |
| Pre-treatment mean | 0.004 | 0.001 | 0.011 | 0.001 | 0.002 | 0.001 |
| Year-FE | Yes | Yes | Yes | Yes | Yes | Yes |

[1] *Source*: Forschungsdatenzentrum der Rentenversicherung, 2024, 2020, own calculations.
[2] *Note*: Columns (1) to (6) show the RDD estimates (absolute and relative to the pre-treatment mean) for the outcome completion of medical rehabilitation (indicator), where the outcome is separated by diagnosis category and each column shows the estimation result for a separate diagnosis category outcome. For each diagnosis category, we define a binary outcome variable. Thereby, we only include individuals with a completed rehabilitation due to the respective diagnosis category and those without rehabilitation. We exclude observations with rehabilitation due to other diagnoses. This effectively results in a varying number of observations across diagnosis categories (columns). All estimations include year dummies. Standard errors are clustered by month of birth (the running variable) and are robust. Local linear regressions are based on triangular kernel functions. Optimal bandwidth according to Calonico et al. (2014). *** p<0.01, ** p<0.05, * p<0.1.

Table A6: RDD: Local Linear Regression Results, Completion by Subgroups

| | **SI empl.** | **SI empl. + SL last 5y** | **SL last 5y** | **SL** | **Care SL / UE** | **Reha in past** |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| RDD estimate ($D_i$) | 0.00322 | 0.0105 | 0.00638 | 0.0206 | -0.000197 | 0.00929 |
| | (0.00375) | (0.0125) | (0.00724) | (0.0148) | (0.00754) | (0.0143) |
| *Relative estimate (in %)* | *9.5* | *11.8* | *7.4* | *9.3* | *-0.3* | *10.2* |
| Observations | 128,736 | 30,393 | 43,779 | 13,331 | 53,139 | 35,302 |
| Pre-treatment mean | 0.034 | 0.089 | 0.086 | 0.221 | 0.063 | 0.091 |
| Year-FE | Yes | Yes | Yes | Yes | Yes | Yes |

[1] *Source*: Forschungsdatenzentrum der Rentenversicherung, 2024, 2020, own calculations.
[2] *Note*: Columns (1) to (6) show the RDD estimates (absolute and relative to the pre-treatment mean) for the outcome completion of medical rehabilitation (indicator), each column shows the estimation result for a separate subgroup of individuals. All columns cover the full sample (for the respective subgroup) and include only year dummies. "Main SES = SI employment" includes individuals for whom the main socioeconomic status is socially insured employment, meaning that for the majority of the respective year, the individual has been employed in a job with social security contributions. "SL last 5y" ("SL current year") refers to individuals with a long-term sick leave spell, i.e., of more than six weeks, within the last five years (within the current year). "Care / SL / UE current year" refers to individuals with a registered long-term care, sick-leave or unemployment spell in the current year. "Reha in the past" includes individuals who already completed a rehabilitation measure within the observation period. Standard errors are clustered by month of birth (the running variable) and are robust. Local linear regressions are based on triangular kernel functions. Optimal bandwidth according to Calonico et al. (2014). *** p<0.01, ** p<0.05, * p<0.1.

Table A7: RDD: Local Linear Regression Results, Approved Application by Subgroups

| | **SI empl.** | **SI empl. + SL last 5y** | **SL last 5y** | **SL** | **Care SL / UE** | **Reha in past** |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| RDD estimate ($D_i$) | 0.00370* | 0.0149** | 0.0146* | 0.0363*** | 0.00459 | 0.0304** |
| | (0.00221) | (0.00753) | (0.00860) | (0.0133) | (0.00727) | (0.0141) |
| *Relative estimate (in %)* | *10.0* | *15.5* | *16.8* | *16.7* | *7.2* | *49.9* |
| Observations | 128,736 | 30,424 | 43,810 | 13,403 | 53,168 | 35,364 |
| Pre-treatment mean | 0.037 | 0.096 | 0.087 | 0.217 | 0.064 | 0.061 |
| Year-FE | Yes | Yes | Yes | Yes | Yes | Yes |

[1] *Source*: Forschungsdatenzentrum der Rentenversicherung, 2024, 2020, own calculations.
[2] *Note*: Columns (1) to (7) show the RDD estimates (absolute and relative to the pre-treatment mean) for the outcome approved application of medical rehabilitation (indicator), each column shows the estimation result for a separate subgroup of individuals. All columns cover the full sample (for the respective subgroup) and include only year dummies. "Main SES = SI employment" includes individuals for whom the main socioeconomic status is socially insured employment, meaning that for the majority of the respective year, the individual has been employed in a job with social security contributions. "SL last 5y" ("SL current year") refers to individuals with a long-term sick leave spell, i.e., of more than six weeks, within the last five years (within the current year). "Care / SL / UE current year" refers to individuals with a registered long-term care, sick-leave or unemployment spell in the current year. "Reha in the past" includes individuals who already completed a rehabilitation measure within the observation period. Standard errors are clustered by month of birth (the running variable) and are robust. Local linear regressions are based on triangular kernel functions. Optimal bandwidth according to Calonico et al. (2014). *** p<0.01, ** p<0.05, * p<0.1.

Table A8: RDD: Local Linear Regression Results, Rejected Application by Subgroups

| | **SI empl.** | **SI empl. + SL last 5y** | **SL last 5y** | **SL** | **Care SL / UE** | **Reha in past** |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| RDD estimate ($D_i$) | 0.00191 | 0.00812 | 0.00441 | 0.00692 | 0.00866** | 0.00755*** |
| | (0.00256) | (0.00544) | (0.00373) | (0.00856) | (0.00348) | (0.00291) |
| *Relative estimate (in %)* | *17.4* | *33.8* | *17.6* | *14.1* | *45.6* | *28.0* |
| Observations | 128,736 | 30,424 | 43,810 | 13,403 | 53,168 | 35,364 |
| Pre-treatment mean | 0.011 | 0.024 | 0.025 | 0.049 | 0.019 | 0.027 |
| Year-FE | Yes | Yes | Yes | Yes | Yes | Yes |

[1] *Source*: Forschungsdatenzentrum der Rentenversicherung, 2024, 2020, own calculations.
[2] *Note*: Columns (1) to (7) show the RDD estimates (absolute and relative to the pre-treatment mean) for the outcome rejected application of medical rehabilitation (indicator), each column shows the estimation result for a separate subgroup of individuals. All columns cover the full sample (for the respective subgroup) and include only year dummies. "Main SES = SI employment" includes individuals for whom the main socioeconomic status is socially insured employment, meaning that for the majority of the respective year, the individual has been employed in a job with social security contributions. "SL last 5y" ("SL current year") refers to individuals with a long-term sick leave spell, i.e., of more than six weeks, within the last five years (within the current year). "Care / SL / UE current year" refers to individuals with a registered long-term care, sick-leave or unemployment spell in the current year. "Reha in the past" includes individuals who already completed a rehabilitation measure within the observation period. Standard errors are clustered by month of birth (the running variable) and are robust. Local linear regressions are based on triangular kernel functions. Optimal bandwidth according to Calonico et al. (2014). *** p<0.01, ** p<0.05, * p<0.1.

Table A9: RDD: Local Linear Regression Results, Begin by Subgroups

| | **SI empl.** | **SI empl. + SL last 5y** | **SL last 5y** | **SL** | **Care SL / UE** | **Reha in past** |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| RDD estimate ($D_i$) | 0.00379 | 0.00864 | 0.00578 | 0.0176 | -0.000926 | 0.0139 |
| | (0.00340) | (0.0115) | (0.00850) | (0.0196) | (0.00879) | (0.0150) |
| *Relative estimate (in %)* | *11.1* | *9.6* | *6.7* | *8.0* | *-1.5* | *16.2* |
| Observations | 128,726 | 30,398 | 43,789 | 13,350 | 53,150 | 35,352 |
| Pre-treatment mean | 0.034 | 0.090 | 0.086 | 0.219 | 0.063 | 0.086 |
| Year-FE | Yes | Yes | Yes | Yes | Yes | Yes |

[1] *Source*: Forschungsdatenzentrum der Rentenversicherung, 2024, 2020, own calculations.
[2] *Note*: Columns (1) to (7) show the RDD estimates (absolute and relative to the pre-treatment mean) for the outcome beginning of medical rehabilitation (indicator), each column shows the estimation result for a separate subgroup of individuals. All columns cover the full sample (for the respective subgroup) and include only year dummies. "Main SES = SI employment" includes individuals for whom the main socioeconomic status is socially insured employment, meaning that for the majority of the respective year, the individual has been employed in a job with social security contributions. "SL last 5y" ("SL current year") refers to individuals with a long-term sick leave spell, i.e., of more than six weeks, within the last five years (within the current year). "Care / SL / UE current year" refers to individuals with a registered long-term care, sick-leave or unemployment spell in the current year. "Reha in the past" includes individuals who already completed a rehabilitation measure within the observation period. Standard errors are clustered by month of birth (the running variable) and are robust. Local linear regressions are based on triangular kernel functions. Optimal bandwidth according to Calonico et al. (2014). *** p<0.01, ** p<0.05, * p<0.1.