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# FUNDAMENTALLY REFORMING THE DI SYSTEM: EVIDENCE FROM GERMAN NOTCH COHORTS Bjoern Fischer Johannes Micha Geyer Nicolas R. Ziebarth Working Paper 30812 http://www.nber.org/papers/w30812

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Fundamentally Reforming the DI System: Evidence from German Notch Cohorts Bjoern Fischer, Johannes Micha Geyer, and Nicolas R. Ziebarth NBER Working Paper No. 30812 December 2022, Revised January 2024 JEL No. H53,H55,I10,I14,I18,J14,J21,J26

## **ABSTRACT**

This paper studies a 2001 reform that abolished public occupational disability insurance (ODI) for German cohorts born after 1960. The first part shows a causal reduction in overall DI inflows by more than 30% in the long-run. The second part studies interaction effects with the private individual risk-rated ODI market. Representative data provide little evidence for significant overall increases in private ODI take-up. A general equilibrium model featuring the social safety net, asymmetric information and administrative costs explain weak private-public market interactions as well as stylized facts about take-up such as gradients by income and health. It also simulates policies.

Bjoern Fischer ZEW Mannheim bjoern.fischer@zew.de

Johannes Micha Geyer Deutsches Institut für Wirtschaftsforschung Mohrenstraße 58 10117 Berlin Germany jgeyer@diw.de Nicolas R. Ziebarth ZEW Mannheim D-68161, Mannheim Germany and ZEW Mannheim nicolas.ziebarth@zew.de

## 1 Introduction

For decades, the question of how to design "optimal" social insurance systems has been at the core of economic research (Chetty and Saez, 2010; Chetty and Finkelstein, 2013; Luttmer and Samwick, 2018; Goodman-Bacon, 2018; Cabral and Cullen, 2019). While countries around the world have organized their social insurance and safety net systems differently, three integral strands exist in every OECD (2010) country: unemployment insurance (Lalive et al., 2015; Hendren, 2017), Workers' Compensation (Powell and Seabury, 2018) and public disability insurance (Koning and Lindeboom, 2015). What's more, their design and structure are similar across countries. Consequently, experiences from one OECD country might hold important lessons for others (Burkhauser et al., 2016).

As a result of rising public disability insurance (DI) rates and spending, economists have analyzed the implications for labor supply, earnings, beneficiaries' health and well-being, multigenerational "welfare" cultures as well as household income, consumption and poverty (Dahl et al., 2014; Deshpande, 2016; Autor et al., 2019; Ruh and Staubli, 2019; Gelber et al., 2023). Using quasi-random case worker assignment, studies inside and outside the United States conclude that employment rates among marginally rejected applicants are 10 to 30 percentage points higher compared to marginally accepted applicants (Bound, 1989; Chen and Van der Klaauw, 2008; von Wachter et al., 2011; Maestas et al., 2013; French and Song, 2014; Kostøl and Mogstad, 2014; Koning et al., 2022).

Further, the generosity of the public DI system, the barriers to applying, and the stringency of the health screening process are major determinants of the inflow of cases (Autor and Duggan, 2003; De Jong et al., 2011; Deshpande and Li, 2019). For example, using a sufficient statistics welfare framework and two Austrian reforms, Haller et al. (2023) show that tighter DI eligibility rules produce higher fiscal cost savings and lower insurance losses compared to benefit cuts. In the context of the Dutch DI system, Borghans et al. (2014) find that for each euro of reduced DI benefits,  $\in 0.30$  are offset by increases in other social insurance programs.

Finally, as receiving DI benefits is usually an absorbing state, reform debates often surround the question of how to prevent DI take-up in the first place. For example, Burkhauser and Daly (2012) propose experience-rated premiums to incentivize worker accommodations after health shocks. Using Dutch administrative data, Koning and van Lent (2022) provide evidence that incentivized insurers and employers can indeed lower caseloads through workplace accommodation. Other U.S. policy reform proposals also target a better employer accommodation and suggest partial disability coverage to achieve that goal (Autor and Duggan, 2010; Maestas, 2019).

In this paper, we study a fundamental reform to the German public DI system. It became effective in 2001 and cut an entire category of insurance benefits for younger cohorts. We first study how the reform affected public DI inflows in the short and long-run. Then, we study how the reform interacted with the individual private market for disability insurance. Studying interaction effects between public and private insurance is a key area of research in economics. Interaction effects allow researchers to infer how individuals value insurance (Cabral and Cullen, 2019), or to analyze the potential for private markets to substitute for reduced government provision of benefits. In fact, several U.S. reform proposals explicitly point toward the fundamental DI reforms in Germany and the Netherlands, arguing that the private market could compensate for reduced public DI generosity (Autor and Duggan, 2010; Fremstad and Vallas, 2013; Winship, 2015; Burkhauser and Daly, 2022). Whether and how private markets can substitute for reductions in public DI provision is, however, an unresolved question. This paper provides empirical evidence on how the private German DI market responded to the 2001 reform. It uses an economic general equilibrium framework to analyze the response as a function of market regulation, the social safety net, asymmetric information and administrative costs.

For the United States, rich research analyzes selection and crowd-out effects between Medicaid (means-tested, state-level health insurance) and *private health insurance* markets (cf. Cutler and Gruber, 1996; Card and Shore-Sheppard, 2004; Clemens, 2015). The relevance of Medicaid the only public insurance that covers long-term care expenses—for *private long-term care insurance* markets has also attracted economists' attention. Similar to disability insurance, the private market for long-term care insurance is fairly small despite a high risk in old age (Sloan and Norton, 1997; Brown and Finkelstein, 2008; Braun et al., 2019). For Canada, Stepner (2021) finds that employer-provided short-term disability insurance, also called *long-term sick leave* or medical leave (cf. Ziebarth, 2013; Pichler and Ziebarth, 2020), has positive spillover effects on public DI caseloads.

Ours is one of the first papers to study interaction effects between a federal entitlement disability insurance program and individual (long-term) *private disability insurance*. While some published papers have described characteristics of the private German DI market (Soika, 2018; McVicar et al., 2022), very few published economic papers study private markets for long-term (as opposed to short-term) disability insurance, with Autor et al. (2014) and Cabral and Cullen (2019) being notable exceptions in the context of U.S. group insurance. Autor et al. (2014) study determinants of private DI take-up and Cabral and Cullen (2019) use group pricing variation to

assess the value of public DI.<sup>1</sup>

We study a DI reform in the context of the German welfare state, which is known to be generous but whose public DI system became significantly less generous over time, see McVicar et al. (2022) for an overview of the major reforms since the 1970s. The 2001 reform studied in this paper substantially reduced the generosity of the public DI system for those born after 1960. Effective 2001, those cohorts lost access to the second strand of the German public DI system: "Occupational Disability Insurance" (ODI), or also called "Own Occupation Disability Insurance." ODI insures the lifecycle risk to become work disabled in the previous occupation (or a comparable occupation in terms of income and social standing). Thus, ODI can be thought of as a supplemental insurance that tops up the basic first public DI strand: "Work Disability Insurance (WDI)." WDI insures the risk to become work disabled in in any job. Besides Börsch-Supan et al. (2022) and McVicar et al. (2022), we are not aware of published economic research that has assessed this reform. Börsch-Supan et al. (2022) find that the 2001 reform has not systematically improved target quality. McVicar et al. (2022) use time series data to show that private ODI take-up increased substantially already pre-reform. In a concurrent working paper, using data from a single private insurer Seibold et al. (2022) find modest increases in private ODI sales and a low "observed willingness-to-pay of many individuals." They argue that distributional concerns and potentially biased perceptions by workers would imply that the 2001 reform was welfare-decreasing.

Using 1995-2018 administrative data from the German Statutory Pension Insurance (SPI) and difference-in-differences (DD) models, the first part of this paper shows that the 2001 reform significantly reduced the overall inflow of new DI recipients by more than 30% in the long-run. The decrease in inflows grew in an almost linear fashion while cohorts were aging through their work lives and stabilized at 35% in 2011, ten years after the reform became effective. We then validate this substantial reduction using representative household panel data from the German Socio-Economic Panel Study (SOEP). In particular, this first part illustrates that the reform had actual bite among the treated cohorts.

The second part of this paper studies interaction effects with the private individual DI market. The German private individual DI market is one of the biggest worldwide. It is almost exclusively an *individual long-term* market for ODI policies akin the German individual private long-term health insurance market (Atal et al., 2023). It is a long-term market as policies are not

<sup>&</sup>lt;sup>1</sup>In his (unpublished) job market paper, Seitz (2021) estimates a dynamic life-cycle model to conclude that, with a coexisting private market, the welfare-maximizing public DI program would be less generous than in a world without private markets. There exists also important research studying interdependencies of *coexisting social insurance systems* and spillover effects between those (cf. Lalive et al., 2015; Koch, 2015; Leung and O'Leary, 2020; Ahammer et al., 2023).

tied to the job. The median age of obtaining coverage is 32 after people have joined the labor market, and most policyholders keep their individually customized coverage until retirement. Further, the policies are experience-rated without guaranteed issue, resembling the private long-term care insurance market in the US (Brown and Finkelstein, 2008). We first characterize the individual private DI market and take-up pattern empirically along with discussing its regulation.

Next, using representative data and Regression Discontinuity (RD) approaches with birth year as running variable, we do not find much evidence that treated cohorts, whose public ODI was cut, purchased private ODI policies at significantly larger rates. The estimates let us exclude with 95% statistical certainty that take-up increased by more than 15ppt from a baseline of 32%, leaving the majority of affected households without ODI insurance. Then, we carve out three stylized empirical facts about this market: (1) Generally low take-up rates, in particular given the high lifecycle risk of work disability, and a low interaction elasticity with the public market. (2) Strong income and health gradients in take-up, and (3) an inversely related, much larger risk of work disability among low-income groups and those with high health risks.

Building on Braun et al. (2019), we then use a customized version of their general equilibrium model and inputs from various data sources to analyze the role of three key driving forces in producing these stylized market equilibrium outcomes. The three driving forces are: (i) the German means-tested basic income safety net program, (iii) private information, and (iii) administrative costs. The German safety net is known to be generous and provides a basic consumption floor like in most European countries. It plays a key role in explaining why low-income groups do not purchase private ODI policies at higher rates. Administrative costs are high and pervasive in this market increasing insurance premiums and thereby reducing demand. Fixed administrative costs such as broker fees account for several monthly premiums. Monthly premiums vary substantially by occupation, coverage and health and can amount to several hundred dollars. Variable administrative costs account for about 10% of annual premiums. Finally, we provide policy simulations. We are asking: "What factors could policymakers target to increase take-up rates, given the current regulation?" We find that targeting the high level of administrative costs appears to be an effective and feasible, bipartisan policy option.

# 2 The German Disability Insurance System

## 2.1 Social Insurance in Germany

In an international comparison, Germany has a generous social safety net consisting of public Unemployment Insurance (UI), Workers' Compensation (WC), Health Insurance (HI) and Long-Term Care (LTC) insurance (Schmieder et al., 2016; Bauernschuster et al., 2020; Fischer and Korfhage, 2023). Among employees, eligibility for sick and medical leave is universal (Ziebarth and Karlsson, 2010, 2014; Ziebarth, 2013).

Moreover, Germany has Statutory Pension Insurance (SPI) (Eibich, 2015; Geyer, 2021) which contains the public DI program (more details below), and also a universal means-tested basic income cash transfer program. This means-tested social safety net program provides a guaranteed minimum income floor of about \$950 per month (in 2022) for a single individual. <sup>2</sup> In the final part of the paper, we will analyze the role of this means-tested basic income program for the low private ODI take-up rate among low-income individuals.

These social insurance programs are funded through a mix of contribution rates for UI, WC, HI, LTC and SPI, employer mandates for paid sick leave, and general taxes for the means-tested basic income program. See Eichhorst et al. (2008); Ziebarth (2018); McVicar et al. (2022) for more detailed overviews.

#### 2.2 History of Public Disability Insurance in Germany: 1970 to 2001

Germany's public DI program is part of SPI. It provides benefits for both partially and fully disabled workers who have paid contributions during their work lives. Employers and employees are each subject to a payroll tax (since 2018: 9.3%) of their monthly gross wage up to the social insurance contribution ceiling ( $\in$  7,300 per month in 2023).<sup>3</sup>

Appendix Figure A1 shows the development of Germany's public DI caseload from 1970 to 2018 along with select reforms. Note that the figure shows the *stock* of all recipients. As such, even large declines in the inflow of new recipients only gradually translate into overall DI rate declines.

In the early 1970s, compared to other OECD countries, Germany had very high disability

<sup>&</sup>lt;sup>2</sup>For those who are able to work, it is called Unemployment Insurance II (*Arbeitslosengeld II*). For those who are unable to work, it is called Social Assistance Benefits (*Hilfe zum Lebensunterhalt*) and has no job search requirements; recipients are not part of the labor force (§§27-40 SGB XII). A structural reform in 2004 streamlined and re-redesigned those programs. It introduced the *Arbeitslosengeld II* program, decoupled means-tested benefits from previous income, and cut the maximal duration of standard UI benefits, see *Social Code Book II*. For more information about the reforms see, Eichhorst et al. (2008); Konle-Seidl (2012); Dustmann et al. (2014). The reforms did not differentially affect the treatment and control groups of the 2001 reform (see Section 2.3), but generally cut the generosity of these alternative social insurance strands.

<sup>&</sup>lt;sup>3</sup>The contribution ceiling is lower in East Germany at  $\in$  7,100.

recipiency rates (Burkhauser et al., 2016). In 1972, a major welfare expansion introduced new early retirement benefits without actuarial deductions. DI enrollment rates kept on rising, peaking at 5.8% of the workforce in 1984. In 1982, the newly elected center-right government restricted eligibility to employees who had paid pension contributions over the past three out of five years. As many housewives (and househusbands) did not meet these criteria, the strong decline in DI recipiency rates between 1984 and 1990 has been primarily linked to restricting access for women without much formal labor market attachment. (See Börsch-Supan and Jürges, 2012, for a more detailed discussion.)

In 1996, reforms introduced caps on the allowed labor market earnings of DI recipients. After the 2001 reform (see next subsection), a 2004 reform mandated employers to provide *Workplace Reintegration Management* ("Betriebliches Eingliederungsmanagement", §84 SGB IX). The idea is to overcome temporary disability and to prevent future deterioration in work capacity. However, this reform is beyond the focus of this paper and affected all birth cohorts equally. It likely had a gradual impact on the decreasing stock of DI recipients as seen in Figure A1.

## 2.3 The Fundamental Public Disability Insurance Reform of 2001

The German public DI system consists of two schemes: (a) work disability insurance (WDI), and (b) occupational disability insurance (ODI). The 2001 reform abolished public ODI for cohorts born after 1960 (our treatment group). Cohorts born before 1961 were grandfathered in (our control group) and were eligible for public ODI before *and* after the 2001 reform.<sup>4</sup> Figure 1 provides an illustration on the main principles after 2001.

The two-tiered system can also be thought of as a combination of a basic (WDI) and supplemental (ODI) scheme. It is important to note that the insurance value of ODI is higher for higher income groups. This higher value for better paying jobs is a function of the eligibility criteria. WDI provides insurance for *general work disability* when a poor health status prevents employees from working *in any job* in the labor market. ODI, by contrast, provides insurance for *occupational* work disability.<sup>5</sup> Importantly, "occupationally disabled" are those who (Deutsche Rentenversicherung, 2023a):

"[...] due to health reasons, are unable to work in either their trained or a comparable

<sup>&</sup>lt;sup>4</sup>In the course of the reform, an entirely new Social Code Book IX was passed. It regulates Rehabilitation and Participation in Social Life (*Rehabilitation und Teilhabe Behinderter Menschen*) for disabled and handicapped people in Germany. Before 2001, most of these regulations were included in the *Schwerbehindertengesetz*.

<sup>&</sup>lt;sup>5</sup>That is, occupational disability "to less than half of that of a physically, intellectually, and mentally healthy person with similar training, knowledge and abilities" (§43, §240 of Social Code Book VI; Viebrok (2018)).

occupation in terms of the education and skills required."

Note that German public ODI was never intended to provide the entire means for a living, but provide a benefit to compensate for a *partial* loss in work capacity due to which someone either has to switch to a lower paid occupation or from full to part-time work. Obviously, for the most basic and lowest paid jobs in the economy, WDI and ODI converge (Benen, 2023). In fact, the higher insurance value for higher social classes and its inequity implications was one reason for why ODI was eventually abolished. Note that individual private ODI is also available in other markets such as the U.S. where it is sold as "own-occupation DI" and marketed specifically to higher income professions such as physicians or lawyers (Brian SO Insurance, 2023).

#### [Insert Figure 1 about here]

**Work Eligibility Requirements.** The main work requirements to establish eligibility did not change in the course of the 2001 reform, see Table 1, column three. Applicants must have paid pension insurance contributions in the last three out of five years. There has also been a general waiting period of five years throughout the entire time period.

**Application & Health Assessment.** Details of the application procedure and health assessment are specified in German Social Law and Deutsche Rentenversicherung (2018). Applicants apply at an SPI field office by submitting all relevant documentation such as medical diagnoses and medical records. An independent third-party physician, certified to carry out medical assessments, then reviews the case.<sup>6</sup> Medical reviewers must not have any pre-existing relationship with the applicant. It is worthwhile to note that 44% of all applications are rejected; this share has remained stable since 2000 (Deutsche Rentenversicherung, 2023b).

Today, as all grandfathered cohorts have aged out of the possible age to apply, only public WDI exists. The main medical WDI criterion is whether applicants' health limitations prevent them from working three hours per day in *any* job (Table 1, column three). If applicants' work capacity is less than three hours per day, full WDI is granted (Deutsche Rentenversicherung, 2020). If applicants' work capacity lies between 3 and 6 hours per day, then partial WDI is granted (50% of full benefits). As with ODI, partial WDI intends to compensate for a partial work capacity loss.<sup>7</sup>

<sup>&</sup>lt;sup>6</sup>Sometimes these reviewers are state-employed physicians (*Amtsärzte*), and sometimes they are regular specialists practicing in the county of residence of the applicant.

<sup>&</sup>lt;sup>7</sup>However, if part-time jobs are unavailable, partial WDI can be converted to full WDI if the recipient cannot find part-time work within a year. The share of partial converted to full WDI has lied between 6 and 16% between 2001 and 2021 (Deutsche Rentenversicherung, 2022). Earlier data are not available. For grandfathered cohorts, the only criterion for ODI is whether applicants could work 6 hours per day in the previous occupation.

Benefits are granted for an initial period of three years and have to be re-certified. After nine years, the benefit becomes permanent. If the work capacity is not expected to improve, a permanent pension can be granted earlier, which applies to half of all new cases.

**Benefit Calculation.** As indicated in Table 1, benefits are calculated as an "early retirement pension" with actuarial reductions. Thus, they are a function of recipients' earnings histories and not adjusted for family composition, income or assets. They are calculated as old-age pensions, assuming that recipients' would have earned their pre-DI labor market income until age 60. Further, actuarial deductions of 3.6% per annum (0.3% per month) are applied for everyone receiving benefits before age 63 but are capped at 10.3%.<sup>8</sup> Before 2001, ODI benefits were two thirds of full WDI benefits. <sup>9</sup> After 2001, for the grandfathered cohorts, ODI benefits were 50% of full WDI benefits (Figure 1, column five).

Appendix B provides a detailed discussion and pre-post reform simulations of ODI benefits. Post-reform, the simulated replacement rate for a health shock at age 46 is 12% of average pre-DI gross earnings. In practice, in 2000, the average public ODI benefit was  $\in$  587 per month. The average public WDI benefits was  $\in$  731 per month (Deutsche Rentenversicherung, 2023b), see Figure 1.

**Changes of 2001 Reform.** The crucial and most relevant change in the course of the fundamental 2001 reform was the cut of public ODI for cohorts born after 1960. However, the entire reform package entailed various additional changes, some of which are listed above. Importantly, however, all these additional changes did not affect the birth cohorts differentially and, thus, should not be a threat to the main objective of the reduced-form part—namely, showing that the reform had actual bite.

For example, the reform also changed how work capacity was medically assessed: from an earnings capacity test<sup>10</sup> to the hour capacity test discussed above. Moreover, as discussed in Appendix B, WDI benefits were slightly reduced for all cohorts, and ODI benefits were reduced for the grandfathered cohorts. Obviously, this reduced benefit level decreased the relative attractiveness of applying for ODI for the grandfathered cohorts. Thus, the reduced-form

<sup>&</sup>lt;sup>8</sup> Several studies documented a high poverty risk among people on WDI (Krause et al., 2013; Märtin et al., 2012, 2014; Geyer, 2021; Becker et al., 2023). As a consequence, policymakers increased WDI benefits again by increasing the "reference age" to 62 in July 2014, and to 65 years and 8 months in 2019. Now it equals the statutory retirement age and will further increase to 67 years by 2031. Similarly, the age threshold for actuarial deductions has been raised.

<sup>&</sup>lt;sup>9</sup>However, if reasonable part-time work was unavailable due to the local labor market situation, full benefits could be granted (Viebrok, 2018). In other words, the local labor market situation mattered, especially when applicants could not be referred to another "reasonable" job, following a hierarchical scheme of four categories where workers could be referred to a job "one degree below" their actual category. In practice, case workers would ask the UI office if part-time jobs were available in the region.

<sup>&</sup>lt;sup>10</sup>Pre-reform, the applicant must not be able to earn more than 640 DM (about  $\in$  320 in 2001 or \$480 today).

estimates on how abolishing public ODI has affected overall DI inflows represent a lower bound estimate.

## 2.4 Private Disability Insurance in Germany

**Basic Principles.** The German private disability insurance market is overwhelmingly an individual market, not a group market like in the United States (Autor et al., 2014). Similar to the long-term health insurance market in Germany (Atal et al., 2019, 2023), the private individual ODI market is individually underwritten. Guaranteed issue does not exist. Private disability insurance follows private insurance law (*Versicherungsvertragsgesetz*). It is based on a private contract between the insurer and the insured which specifies conditions for the insured risk. Premiums depend on age, medical diagnoses, health behavior, income, and occupation. As a result, premiums can easily be several hundred dollars for high-risk occupations and, often, applicants are denied coverage.

**Coverage Denials.** Rating agency data from competing private insurers covering almost five million ODI policies show that, in 2019, 23% of new applications were either rejected (8%), included pre-existing condition clauses (11%), or included risk-premia (4%) due to pre-existing conditions (Morgen & Morgen, 2021). Note that these are *conditional* on applying for a policy. In reality, brokers and online calculators easily tell potential applicants in advance whether an application has some chance of success or not. In 2014, a highly respected consumer magazine reported that 235K applications per year would be rejected by the industry, and revealed that 81% of those who were offered a policy were offered a less generous coverage than desired (Ökotest, 2014).

**Age at Inception & Claiming.** The average age when signing a policy is 32, but the age distribution is left-skewed with 64% of new policyholders being below 31. The average age when becoming work disabled is 46, and the average contract runs until age 64. In 2019, the four main reasons that triggered an approved occupational disability in the private market were: mental diseases (32%), musculoskeletal diseases (20%), cancer (18%), and accidents (8%), see Morgen & Morgen (2021).

In our representative data, among those between the age of 20 and 59, about a third of all households with an employee or self-employed person as household head had private DI, which is almost always ODI coverage (Statista, 2014). In 2015, according to the German Association of Insurers (GDV), the average pension from a private ODI policy was  $\in$  629 per

month (Versicherungsbote, 2020). Our rating agency data yield an average insured annual ODI benefit of  $\in$  13,301 among all policies (Morgen & Morgen, 2021) and average premiums of  $\in$  923 per year. In 2014, a high-quality consumer rating report revealed monthly premiums between \$50 and \$200 for insured monthly benefits of between \$750 and \$2000 (Ökotest, 2014).

**Market Structure.** The ten biggest insurers hold more than 60% of the total market share and offer similar but not identical policies (Morgen & Morgen, 2021). The market is characterized by freedom of contract between insurers and applicants. Many online calculators yield advice on a wide range of policy elements that can be individually customized leading to hundreds of different actual policies. In an audit study, Ökotest (2014) found very large differences in premiums by occupation and health. Together with healthy profit margins, these facts suggest monopolistic market structures, which we assume later in the model.

In contrast to the U.S. market where private group DI usually includes "offset clauses" that may reduce public Social Security Disability Insurance benefits dollar for dollar (Burkhauser and Daly, 2012), in Germany, private and public DI benefits do not crowd each other out. In fact, they are independent and private ODI benefits top up public benefits. Further, the private insurance industry relies on their own medical examiners and there is no coordination between SPI and private insurers (BBP, 2020).

In the results section, we will further characterize the private German ODI market, carve out several stylized empirical facts, and then use a general equilibrium model to study the role of (i) the means-tested basic income program described above, (ii) private information as well as (iii) administrative costs for equilibrium market outcomes such as coverage denials and market selection.

## 3 Impact of the 2001 Reform on Public DI Inflows and Case Loads

In a first step, we provide evidence on the first-stage effects of the 2001 reform. That is, we show how it affected the inflow of new public DI recipients and the overall case load. note that both outcome measures represent *total public DI* cases, the sum of WDI and ODI as we do not observe the two DI schemes separately in the data. To do so, we use two types of datasets and two reduced-form identification approaches: (1) an administrative dataset on the inflow of cases by birth cohort and year in a difference-in-differences (DD) framework and (2) representative household panel data from the German Socio-Economic Panel Study (SOEP) in a regression-discontinuity (RD) design. We use (2) to validate the findings in (1) using the

universe of the underlying cohort populations, not just select inflows.

## 3.1 Impact on Public DI Inflows Using Administrative Data

First, we use administrative data from the SPI to estimate the impact of the 2001 reform on the total public DI inflow. The data are available by year, region, gender and birth year.

**DD Method.** We normalize the number of inflows by cohort for each year using population data from the Federal Statistical Office.<sup>11</sup> Further, we focus on cohorts born between 1954 and 1966 and the ages of 29 and 59 in a given calendar year. Then, using data from 1995 to 2019, we compare our treatment group—the affected cohorts who were ineligible for public ODI from January 2001, to our control group—the grandfathered cohorts who were born before 1961. We estimate the following Difference-in-Differences (DD) model:

$$y_{ct} = \alpha + \beta D_c \times T_t + \delta_t + \rho_c + \epsilon_{ct} \tag{1}$$

where  $y_{ct}$  denotes the share of new public DI recipients of cohort *c* in year *t*;  $D_c$  is a treatment dummy;  $T_t$  is a post-reform dummy that turns on after 2000;  $\delta_t$  are year fixed effects; and  $\rho_c$  are cohort fixed effects.  $\epsilon_c$  denotes the error term, which we cluster at the cohort level.

The main identification assumption implies that, absent the reform, the inflow of new public DI recipients of the treated cohorts would have developed in the same manner as those of the grandfathered control cohorts. Note that our setting is not prone to possible biases as in staggered DD settings (Goodman-Bacon, 2021).

**Results.** To illustrate the main findings, Figure 2 plots an event study using equation (1) but replaces  $T_t$  with a series of year dummies, where 2000 serves as the baseline year.

#### [Insert Figure 2 about here]

As seen, whereas the five pre-treatment years show no trending, and the relative inflow differences between treated and control cohorts are not significantly different from zero, we observe a sharp decline in inflows beginning in the first post-reform year 2001. This decline further accelerates in subsequent years, up to point estimates exceeding -0.2 percentage points, or about 35% relative to the pre-reform mean.

By 2011, one decade after the reform implementation, the inflow differential between the two groups had flattened out. From then on, it remained highly significant at -0.2 percentage points.

<sup>&</sup>lt;sup>11</sup>We use unconditional shares, i.e., we do not subtract the number of people currently receiving DI.

This represents the long-run effect of the reform.<sup>12</sup> Recall that ODI benefits also decreased for the grandfathered cohorts, see Appendix B for details. To the extend that these reduced benefits significantly affected the likelihood to apply for DI, our estimates here represent lower bound estimates.

Figure A2 (Appendix) shows the same event studies separately by gender. Again, we observe reassuringly stable pre-reform trends, followed by substantial inflow reductions among the notch cohorts. However, not surprisingly, the reform-induced decrease in inflows is substantially larger for males. The reason is that their eligibility rates are higher due to a stronger labor market attachment. Specifically, men are more likely to fulfill the eligibility requirement and have paid pension contributions during the last three out of five years. Moreover, men are more likely to work in physically demanding occupations and industry jobs that generally carry a higher work disability risk.

Table A1 (Appendix) shows the DD regression model equivalents. Panel A shows results for the full sample, Panel B shows results for men, and Panel C shows results for women. Each column in each panel stands for one separate DD model like in equation (1).

The findings in Table A1 are in line with the event study estimates. First, the estimates are robust to the inclusion of cohort and year fixed effects as well as controls for East Germany. The average decline in inflows for males translates into a 20% decrease, relative to the mean of the control group. The decline for women is only half as large at 10%. Note that the long-term effect from 2011 onwards is about twice as large (see Figure A2). However, when zooming-in and restricting the bandwidths of the cohorts considered, that is, cohorts born between 1959 and 1962, the effect sizes decrease to -12.5% for males and -7.9% for females—on average over *all* post-reform years 2001-2019. Reassuringly, these reform effects mirror the pre-2001 share of ODI pensions among all new recipients. Viebrok (2018) reports relatively stable shares of between 12 and 18% for men and about 8% for women in the 1980s and 1990s among new recipients.<sup>13</sup>

#### 3.2 Impact on Public DI Case Load Using SOEP Survey Data

**Data.** In a second step, we validate our first-stage findings above using representative household data from the German Socio-Economic Panel Study (SOEP) and an alternative identification approach. The SOEP allows us to observe *representative* samples of each cohort, not just inflows as with the administrative data, see Goebel et al. (2019) for more details on the SOEP.

 $<sup>^{12}</sup>$ For this number, we use as pre-reform mean the mean entry rate of untreated cohorts which was 0.58% for cohorts born between 1954 and 1960.

<sup>&</sup>lt;sup>13</sup>In addition, recall that many ODI pensions were converted to full WDI pensions if recipients could not be referred to a "reasonable" job, see Section 2.

We relegate most details to the appendix and now focus on the main approach and findings.

**Sample Selection.** We select years 1995 to 2016 and respondents between the age of 25 and 59 as we can then unambiguously identify whether they receive public DI. In addition, we focus on birth cohorts from 1950 to 1970. Table A2 shows the summary statistic, with our main outcome variables in the upper panel and the covariates in the lower panel.

**RD Method.** As we are now using a representative sample of the underlying population of interest, we are able to study the impact of the 2001 reform using a Regression Discontinuity (RD) design. The discontinuity is the birth year 1961. It determines whether respondents belong to the treated or the control cohorts. A standard linear parametric RD model is:

$$y_{it} = \alpha + \beta D_i + \psi (1 - D_i) f(z_i - c) + \gamma D_i f(z_i - c) T_t + X'_{it} \tau + \delta_t + \rho_s + \epsilon_{it}$$
<sup>(2)</sup>

where  $y_{it}$  indicates whether the respondent receives public DI benefits.  $D_i$  is one if the respondent belongs to the treated cohorts. The cohort measure  $z_i$  enters in difference to the reform cutoff c, 1961. Including linear trends and polynomials in the running variable  $f(z_i - c) = z_i - c$  allows for different slopes before and after the cutoff.

All regressions include year ( $\delta_t$ ) and state ( $\rho_s$ ) fixed effects.  $X'_{it}$  represents a rich set of sociodemographic, educational and job-related control variables as listed in Table A2. For example, 45 is the average age, 52% are women, and 71% are married. About 20% finished the highest educational track in Germany and 21% are part-time employed; 42% are white-collar employees.

We follow the recent literature on the topic and do not cluster standard errors  $\epsilon_{it}$  (Cunningham, 2021). Further, we follow the literature and estimate nonparametric local polynomial regressions with univariate weights and cubic terms as our baseline model (Calonico et al., 2014). In the main results, we present robust and bias-corrected estimates (Calonico et al., 2018). In the appendix, we vary the bandwidth, use data-driven bandwidth selection (Calonico et al., 2020), and covariates (Calonico et al., 2019) in the Appendix.<sup>14</sup> Moreover, our estimates are robust to implementing methods for discrete running variables following Kolesár and Rothe (2018).

Despite all econometric sensitivity checks, the main RD identification assumption implies that no other factor would have affected public DI caseload trends discontinuously at the birth year level. We are not aware of another reform or factor that could invalidate this assumption; the Appendix provides further evidence that other covariates trend smoothly at the cut-off *c*.

**Outcome.** The SOEP Group provides a time-consistent longitudinal binary variable that indicates whether individuals receive an old-age pension due to work disability. We call this

<sup>&</sup>lt;sup>14</sup>We also implement procedures for optimal local polynomial order selection following Pei et al. (2022).

variable *Public DI I*. Moreover, the SOEP Group provides a second generated variable indicating the annual income stream from old age, disability or civil servant pensions, which we use to create a second binary indicator, *Public DI II*.<sup>15</sup> According to Table A2 and *Public DI I*, 3.3% of the German working age population have been on DI between 1995 and 2016—this share matches the share from official data in Figure 1 very well.

**Results.** Figure 3 plots public DI recipiency rates by birth cohorts. It displays unconditional scatters by year of birth, overlaid with polynomial quadratic smoothing plots. The visual evidence from the representative SOEP corroborates the findings from the administrative data: we see a clear discontinuous decrease in the probability of receiving a public DI pension for the notch cohorts in post-reform years. Figure A3 shows no such discontinuity for the pre-reform years in the left column. Moreover, using either *Public DI I* (first row) or *Public DI II* (second row) yields robust findings.<sup>16</sup>

#### [Insert Figure 3 about here]

Table A3 shows the RD results using local polynomial RD methods for the post-reform period from 2001 to 2016. The column headers indicate the outcome measure; the lower panel adds socio-demographic and educational covariates as indicated. The models in columns (3) and (4) use *Public DI I* but restrict the sample to non-married respondents and single households, respectively. The table shows the results from 24 different models; for each column and panel, we present results from conventional, bias-corrected and robust RD models, see Calonico et al. (2014, 2017, 2019) for details.

As seen, we find statistically significant results for 22 out of 24 models; all 24 models produce consistently negative point estimates, in line with Figures 3 and A3. Our preferred bias-corrected and robust estimates of the first column are -1.6 percentage points (upper panel) and -1.5 percentage points (lower panel). Relative to the mean recipiency rate of the non-treated cohorts, 6.7%, the latter estimates translate into a decrease of 22%. The size of the decrease for households with one member is very similar, whereas the decrease for non-married people is even larger. Overall, the findings confirm and validate the results from administrative data that just focus on inflows.

The Appendix shows the results from various robustness checks. Figure A4 varies the bandwidth and also uses data-driven bandwidth selection methods (Calonico et al., 2020);

<sup>&</sup>lt;sup>15</sup>Here we use only respondents with a positive pension amount who do not receive a civil servant, a veteran's, a miners' or a farmers' pension.

<sup>&</sup>lt;sup>16</sup>Note that the DI level is higher for post-2001 years as our respondents are older compared to 1995 to 2000. The decreasing slopes imply decreasing DI rates by birth cohort.

Figure A5 shows that covariates such as age, children in the household, white collar, or Self Assessed Health (SAH) trend smoothly at the cutoff 1961. Figure A6 carries out a McCrary (2008) density plot of the running variable, and Figure A7 varies the polynomial (Pei et al., 2022), the weights, runs donut RD models, and adds a full set of covariates (Calonico et al., 2019).

**Pre- and Post-Reform Consequences of a Health Shock.** Next we ask the question: For the treated cohorts without access to public ODI, how does a health shock materialize, given other social insurance strands and intra-household risk sharing?

To investigate this question, Table A6 (Appendix) uses SOEP data from 2001 to 2016 and runs standard individual fixed effect OLS models. Each column is one model that includes as (lagged) regressors a binary indicator for severe health limitations, a dummy for whether respondents belong to the treatment group (born after 1960) as well as the interaction between the two. The dependent variables are whether, in the year after a severe health shock, (1) the respondent is on public DI, (2) the respondent is not employed, (3) the respondent's total (market and non-market) income as well as (4) her subjective well-being.

As seen in Table A6, the onset of a severe health limitation more than doubles the likelihood to be on public DI in the next year (column (1)) and, by the same share of 9ppt, increases non-employment. Further, total annual income decreases significantly by  $\in$  4.2K (-14%, cf. Table A2) as does subjective well-being (-0.18 points on a 0-10 Likert scale). Moreover, while the interaction term between the health shock and the treatment dummy yields a point estimate in line with the effects in Figure 3 and Table A3, it is imprecisely estimated. Similarly, the interaction effects suggest (imprecise) increases in non-employment by about 4ppt, and small and insignificant effects for changes in income and well-being. Overall, there is not much evidence that the treated cohorts did substantially and significantly worse in terms of income and well-being as a result of health shocks compared to the control cohorts.

## 4 The 2001 Public DI Reform and the Private DI Market

In this second part of the paper, we study interaction effects between the public and private DI market. Moreover, we provide general insights into the functioning of the German individual private DI market, one of the biggest in the world. Specifically, we carve out several empirical stylized facts in the context of its market regulation (see also Section 2). Then, building on Braun et al. (2019), we use a tailored version of their general equilibrium model (GEM) to explain these stylized empirical pattern. Specifically, the tailored GEM leverages three main

driving forces—the German means-tested basic income program, private information, and administrative costs—to explain various empirical stylized take-up pattern: (1) Given a high lifecycle risk of work disability, private ODI take-up rates are relatively low and unresponsive to losing public ODI. (2) Private ODI take-up rates increase strongly in good health and income, and (3) are inversely linked to the lifecycle work disability risk.

### 4.1 Impact of the 2001 Reform on the Private ODI Market

In a first step, we investigate whether the treated cohorts purchased private ODI policies at higher rates, relative to the control cohorts, to compensate for the loss of public ODI coverage. It is a straightforward hypothesis that the reform may have *crowded-in* demand for private ODI. A rich economics literature has studied the reverse effect, *crowd-out* of private health insurance through public health insurance expansions (Cutler and Gruber, 1996; Clemens, 2015).

This is one of the first studies to estimate the impact of *reductions* in public social insurance generosity on the market for private insurance. It is also one of the very first papers to study interaction effects between public and private DI markets, see Cabral and Cullen (2019) for a rare exception of published work.

**Data.** For this exercise, we rely on representative survey data from the SAVE survey (Saving for Old Age in Germany, *Sparen und AltersVorsorgE in Deutschland*). Coppola and Lamla (2013) provide a detailed overview of the dataset. The SAVE data include a very rich set of questions about preferences, savings, retirement, health as well as standard socio-demographics. Some of these measures are typically unobserved by researchers and insurers. This unique survey helps us to (a) mimic the risk classification of private ODI insurers and to (b) assess private information that drives insurance market selection in the spirit of Akerlof (1970) and Hendren (2017).

**Sample Selection.** We use all SAVE waves from 2001 to 2010, which were conducted annually (except for 2002 and 2004). We again focus on employees below the age of 60.<sup>17</sup> Table A4 shows the summary statistics of our main sample. 32% of all households are ODI policyholders, the average age is 41 and 41% hold the highest schooling degree in Germany after 13 school years. To identify the treated cohorts, we directly observe the birth year as a separate variable.

Figure 4 illustrates the main result for the full sample; Figure A8 (Appendix) shows robustness checks for alternative samples; clockwise, starting from the upper left: (1) the full sample

<sup>&</sup>lt;sup>17</sup>We ignore civil servants who were not affected by the DI reform.

as in Figure 4, (2) those eligible for public DI, (3) childless households, and (4) one-person households. In all graphs, the x-axis displays the birth year, and the y-axes display the outcome variable, *Private ODI*. We again plot unconditional scatters by birth year, overlaid with linear plots for each side of the cut-off.<sup>18</sup>

#### [Insert Figure 4 about here]

The figures show the following: First, the demand slope is clearly and strongly increasing in the birth cohorts. In other words, younger people are much more likely to be covered by a private ODI policy in Germany. This observation is not surprising. The reason is that, after a strong expansion of the welfare state in the decades after WWII (especially in the 1970s), German policymakers started to implement a series of structural reforms of the statutory pension and DI system in the 1980s and, to a great extent, the 1990s, see Figure 1. The structural reforms in the second half of the 1990s and early 2000s were accompanied with especially strong messaging, education (also in schools) by consumer advocates, and lobbying that private insurance policies for old age protection would be crucial for young people. In addition to shifts in the public perception of the importance of private insurance to cover future life shocks, younger cohorts are much less likely to be rejected by private ODI insurers and are offered lower premiums as they are healthier and have fewer pre-existing conditions, see Section 2.

Second, none of the figures shows an obvious discontinuous jump in the likelihood to have private ODI insurance for the notch cohorts. While single insurers may certainly have targeted subgroups that were affected by the 2001 reform (Seibold et al., 2022), representative data do not yield much evidence for a systematic and substantial crowding-in or substitution effect.

Table A5 shows the equivalent local polynomial RD results for Figure 4, following the same table setup as above. As seen, three of the four sample specifications with the associated 18 models show consistently non-significant point estimates. For example, for the full sample in column (1), we obtain bias-corrected and robust RD estimates of size -0.05 to -0.06. Overall, in Table A5, 19 out of the 24 estimates carry negative signs, not the hypothesized positive ones.

Robustness checks vary the bandwidth (Figure A9, Calonico et al. (2020), study discontinuities in covariates (Figure A10), plot the density of the running variable (Figure A11, McCrary (2008), and alter polynomials (Figure A12). These use our preferred model in column (1) with exogenous controls (age, gender, year and state fixed effects) and do not yield any evidence for positive and statistically significant effects. Further, correcting for the discrete running variable (Kolesár and Rothe, 2018) does not alter the findings (detailed results available upon request).

<sup>&</sup>lt;sup>18</sup>Linear slopes fit the data better than quadratic ones; however, we vary polynomials in robustness checks.

However, the robustness checks also illustrate that most point estimates carry relatively large standard errors. Nevertheless, in column (1) of Table A5, we can exclude with 95% statistical certainty that the treated cohorts took up private ODI insurance at a rate higher than 3 to 5 percentage points (ppt), relative to the baseline of 32% (Table A5) as a result of the reform.

## 4.2 Some Stylized Facts on the German Individual Private ODI Market

While there may be higher differential take-up of private ODI policies among subsamples or among single insurers, apparently, there is not much evidence for systematic, strong and significant increases in the general population. Even when considering the upper 95% bounds of the statistical confidence interval of our preferred specification in column (1) of Table A3, the increase in take-up was at most 5 percentage points off a baseline of 32%, leaving the majority of German employees uninsured. This begs the question "why is that?"

One possible interpretation could be a lack of demand, which may imply that people do not value ODI coverage highly. Under certain conditions, this could imply that the reform was welfare-improving. However, it should be kept in mind that the observed coverage outcomes are *equilibrium outcomes*. They are the result of an interplay between demand, supply and market regulation.

Thus, this section employs a general equilibrium framework based on Braun et al. (2019) to better understand and trace out underlying driving forces for the low post-reform take-up rates and interaction effects between the public and private DI system. We first present several stylized facts about employee health, the lifecycle risk of becoming work disabled, as well as take-up in the private German market for ODI policies. In this part, we will refer back to Section 2 and further elaborate on the market regulation. To reiterate: Unlike in the United States where the private market for disability policies is mostly a group market (Autor et al., 2014), the German market is almost exclusively an individual market without guaranteed issue, pre-existing condition clauses and risk rating. It resembles the U.S. private market for long-term care and life insurance. The regulation and features mirror the German private long-term health insurance market, see Atal et al. (2023) for further details. To produce these empirical stylized facts on the private DI market, we rely again on the representative SAVE and SOEP surveys.

**Health Risk Score.** Table A4 shows a detailed list of health measures contained in the representative SAVE survey. For example, SAVE does not just feature the standard self-assessed health (SAH) measure but also a 0-10 Likert scale health satisfaction measure along with questions on health concerns and whether respondents have serious health issues. Further, it includes a

list of the most common medical conditions such as heart disease, stroke, cancer, high blood pressure, high cholesterol, or chronic lung disease for each respondent. Smoking status is also sampled. Finally, SAVE elicits the number of doctor visits and hospital nights in the previous year. All these information reflect what private disability insurers ask in their health assessment questionnaires before making decisions about add-on premiums, pre-existing condition clauses or outright coverage denials.

## [Insert Figure 5 about here]

We use these information in conjunction with a principal component analysis to summarize and aggregate all available objective and subjective health measures into a continuous health risk score (Jolliffe, 2002)). The distribution of this normalized health risk score ranges between 0 and 1 and is in Figure 5. It is reassuring to see a typical left-skewed health risk distribution with a long right rail (Karlsson et al., 2016, cf.).

Next, we circle back to the representative household panel SOEP. The SOEP has existed since 1984 and allows us to leverage and trace out variation in the *lifecycle risk to become work disabled*. As mentioned, we obtained market-level data form a rating agency on the universe of contracts from 64 competing private insurers covering almost five million ODI policies Morgen & Morgen (2021). The average age when people purchase policies is 32, but the age distribution is left-skewed with 64% of new policyholders being below 31. The average age when becoming work disabled is 46, and the average contract runs until age 64.

Consequently, we use the SOEP to mimic these lifecilye pattern. We focus on a sample of respondents whom we observe at least once working full-time between the ages of 25 and 35, when Germans typically enter the labor market and decide on signing ODI policies. We cut the SOEP lifecycle sample such that we also observe *the same individuals* at least once between the age of 55 and 60. By doing so and following Burkhauser and Schroeder (2007) in generating work disability measures using the SOEP, we elicit a broad and representative measure of the lifecycle risk of work disability among German employees.

### [Insert Figure 6 about here]

**Lifecycle Risk for Severe Health Limitations.** Figure 6a plots the lifecycle risk of having a severe health limitation (at least once) against the quintiles of self-reported health satisfaction between 25 and 35. We use this measure of health satisfaction as a proxy for health when entering the labor market. <sup>19</sup> It also stratifies the risk by the quintiles of household net income.

<sup>&</sup>lt;sup>19</sup>Unfortunately, the SOEP only includes health satisfaction (and the standard SAH measure) over the whole 33 years that we use. The quintiles are not exact quintiles as they are derived from the 0-10 Likert scale.

We summarize Figure 6a as follows: first, the lifecycle risk of a severe health limiting shock is large. Second, it remains significant even for the healthiest employees. On average (not shown in Figure 6a), it is 49% for those 20% with the lowest health satisfaction, then drops to 26% for the next quintile and further drops to 8% for those who are most satisfied with their health. Third, it entails a clear income gradient. It is 31% for the lowest income quintile, 20% for the second lowest, and then drops to 10% for the richest quintile.

Figure 6b shows the same graph but first traces out socio-demographics, job and educational characteristics (but not income and health). As seen, the curves flatten substantially over the baseline health status but maintain a clear income gradient. Further, the lifecycle risk remains high, above 20% for most health and income groups. For example, averaged over all health quintiles, the lowest income quintile carries a work life risk of 37%, the second lowest of 24%, and the highest of 16%. All these pattern are very consistent with Meyer and Mok (2019) who report similar statistics for the United States using the PSID.

**Stylized Facts on ODI Take-Up.** Figure 7 summarizes some key stylized facts of private ODI take-up in a compact manner. The figure shows take-up on the y-axis and the population quintiles of the health risk score in Figure 5 on the x-axis. The downward sloping lines are again stratified by quintiles of net household income.

### [Insert Figure 7 about here]

We can summarize: First, we see that take-up strongly decreases from the second lowest to the highest health risk quintile where a higher quintile indicates *worse* health. This pattern is not surprising, given that insurers can deny coverage and premiums are risk-rated. As discussed in Section 2, even conditional on applying for coverage, 24% of all policies are either rejected, contain a pre-existing condition clause or have health risk add-ons.

Second, Figure 7 shows that, across the entire health risk distribution, the lowest income quintile has take-up rates that are substantially lower than all other income quintiles, between 25% for the healthiest and below 10% for the sickest health risk quintile. In other words: The poorest 20% of the population have take-up rates of only 10 to 25%. The second lowest income quintile has also substantially lower take-up rates than quintiles three to five (but higher rates than the lowest quintile). For all income groups, we observe clear health gradients in take-up, meaning that take-up always drops significantly with worse health status.

In conclusion: (i) the lifecycle risk for severe health limitations is high—even corrected for socio-demographics and job characteristics—and between 15% and 40% for different levels of

the health risk and income distribution. Further, (ii) this lifecycle risk increases with worse health and lower income. Nevertheless, (iii) private ODI take-up rates remain low, even after substantial reductions in public DI generosity, and are between 10% and 50% for different parts of the health and income distribution. However, importantly and paradoxically, (iv) take-up is *inversely related* to the lifecycle work disability risk as the sickest and poorest have the lowest take-up rates despite having the highest work disability risk.

Finally, as before, Figure 8 plots private ODI take-up rates on the y-axis and the five risk score quintiles on the x-axis. However, the two lines differentiate by whether SAVE respondents expect to stop working before age 60 which proxies for expected work disability. As seen, over the entire declining health distribution, those who expect work disability have substantially higher take-up rates. While this empirical pattern is no definite proof of an adversely selected market, we interpret it as suggestive evidence for it.

## 5 General Equilibrium Model to Explain Stylized Facts

This section employs a variant of the general equilibrium model (GEM) by Braun et al. (2019), which is based on Rothschild and Stiglitz (1976), Stiglitz (1977) as well as Chade and Schlee (2020). While the seminal Rothschild and Stiglitz (1976) model focuses on the role of private information to study adverse selection, every individual is insurable in this model. In addition to private information, Braun et al. (2019) enrich a monopolistic market model by adding administrative costs following Stiglitz (1977) as well as Chade and Schlee (2020). Chade and Schlee (2020) show that the existence of administrative costs can explain the empirically observed and economically relevant coverage denials to bad risks in insurance markets. In the standard adverse selection models, only good risks can go uninsured—voluntarily. Braun et al. (2019) develop a variant of Rothschild and Stiglitz (1976), as in Stiglitz (1977), to study the role of three key factors in insurance take-up: Medicaid (public insurance for low-income individuals in the United States), administrative costs as well as private information.

We build on Braun et al. (2019) and the literature above, but customize the GEM to capture the institutional details of the German private ODI market. The model by Braun et al. (2019) explains features and empirical puzzles of the U.S. private long-term care insurance market. However, it is flexible enough for us to tailor it to explain empirical equilibrium outcomes in the German private ODI market.

Specifically, our model leverages three main driving forces to explain low ODI insurance take-up after the fundamental public DI reform of 2001: (i) The German means-tested basic

income program, (ii) private information, and (iii) administrative costs. Despite its simplicity, the model is powerful enough to capture the main regulatory framework of the private ODI market in Germany that leads to high denial rates for certain health risks, income and occupational groups. Appendix C discusses optimal contracts and market equilibria, given (i) to (iii). Note that the model is a standard GEM; it is not a behavioral model that explains low take-up rates by, for example, biased perceptions of work disability risk.

### 5.1 Quantitative Model

#### 5.1.1 Individuals

From the empirical facts, see Section 2, we know that individuals purchase private ODI insurance at an average age of 32. The average age when health shocks lead to occupational work disability is 46, and the average contract runs until age 64, shortly before individuals hit the statutory retirement age of 65. Accordingly, an individual's decision-making problem entails three time periods as illustrated in Figure 9.

#### [Insert Figure 9 about here]

**Period 1: Labor Market Entry and Endowments.** In the first period, individuals enter the labor market between age 25 and 30. At the time, they draw a health endowment *h*, an economic endowment—consisting of wage  $w_1$ —and an occupation *o*. Individuals decide on how much to consume ( $c_1$ ) and how much to save (s):<sup>20</sup>  $c_1 = w_1 - s$ . Health, wages and occupation are jointly distributed with density  $f(h, w_1, o)$ .

**Period 2: ODI Offers and Purchase Decisions.** While insurers observe health, wages and occupation, those are solely noisy indicators of the true work disability risk,  $\theta_{h,w,o'}^i$  with i = b, t. This true risk is an individual's private information. With probability  $\rho = b$ , individual *i* is at the bottom, and with probability  $1 - \rho = t$  she is at the top of this probability distribution. Thus, the population share of those who incur a health shock which leads to occupational disability is  $\eta \equiv \rho \theta^b + (1 - \rho)\theta^t$ .

The insurer operates in a monopolistic market, following Stiglitz (1977) and Braun et al. (2019), and maximizes profits, subject to participation and incentive constraints, see below. The insurer observes policyholders' h, w, o and either denies coverage or offers a menu of ODI

<sup>&</sup>lt;sup>20</sup>At this time, educational decisions—a major driver of occupation and lifecycle income is completed for the great majority of the population (Carneiro et al., 2011; Atal et al., 2023). When using SOEP and SAVE data, we condition the empirical moments for Period 1 on individuals who we observe working full-time between age 25 and 35.

contracts ( $\Pi(h, w, o)$ , b), where  $\Pi(.)$  is the insurance premium and b are contracted insurance benefits in case of occupational work disability. As discussed in detail in Braun et al. (2019) and Chade and Schlee (2020), under the existence of fixed and variable administrative costs, insurers may deny entire risk groups coverage as they become unprofitable.

Individuals may or may not purchase ODI coverage that tops-up the basic public insurance due to several reasons.<sup>21</sup> First, in contrast to the insurer, they know whether their true disability risk is high or low, but they do not know their actual risk with certainty. They weigh the risk of occupational disability against paying a monthly premium  $\Pi$  to insure this risk.

Second, the *participation constraint* (see below) ensures that each type *i* prefers, if offered, the specifically customized ODI policy over no insurance.<sup>22</sup> And the *incentive compatibility constraint* ensures that each type *i* prefers the specifically customized policy over the policy customized for the other type.

Finally, individuals also consider uncertainty about their future income,  $\tau$ , that is unrelated to work disability, but may reduce or increase household income. The German social safety net provides a consumption floor that is means-tested at the household level to all residents. Thus, absent uncertainty toward the future rank in the income distribution, agents at the lower end of the income distribution have little incentive to buy private ODI insurance. Individuals in the upper end of the income distribution, on the other hand, may also become eligible for means-tested basic income program in case of a negative shock to their household income (which is unrelated to work disability).

**Period 3: Income and Health Shocks.** Period 3 represents the main work life of individuals and stretches from age 35 to retirement. In Germany, the earliest possible age to receive a statutory early retirement pension is 62.

As mentioned, individuals are aware that future labor market incomes  $w_2$  are uncertain with density  $q(\tau)$ , where  $\tau \in [\underline{\tau}; \overline{\tau}]$ . A potential income shock may lead to eligibility for means-tested basic income that provides a consumption floor *C*.

**Modeling of Occupational Disability.** Moreover, individuals may experience a health shock that leads to occupational disability. As discussed in Section 2, occupational disability implies that individuals cannot work in the previous occupation anymore, or only part-time. It

<sup>&</sup>lt;sup>21</sup> The "means-tested basic income program" and "public (W)DI" set very similar consumption floors and the former tops-up the latter if the WDP falls below the basic income level of roughly  $\in$  1,000 per month (Bundesagentur für Arbeit, 2019). The average monthly WDP pension for fully work disabled new recipients was  $\in$  730 in 2005, see Figure 1. In 2022, after various benefit increases over time, see Section 2, it was basically identical to the basic income level and  $\in$  1,007 (Deutsche Rentenversicherung, 2023b).

<sup>&</sup>lt;sup>22</sup>In the model, insurers would deny coverage if policies become unprofitable at reasonable premiums; hence, "only reasonable" policies are offered in this environment without guaranteed issue.

is important to reiterate that the insurance value of private ODI is higher, the better paid the previous job and the higher the social status; for the most basic and highest risk manual work, general work disability and occupational disability converge. Hence, individuals' income losses due occupational disability may vary substantially, depending on their former occupation.

Consequently, we model the costs of occupational disability through an occupation-riskspecific cost gradient. Specifically, we assume—following the institutional framework—that the lowest risk occupations in quintile 1 occur wage losses of half of their wage  $w_2$ . An example of this case is when individuals have to downgrade from full- to part-time work due to occupational disability. For the second-lowest risk group, the costs would be 60% of the previous wage, then 70%, next 80%, up to a full loss of the entire previous income for the highest risk occupations which are typically also the lowest paid jobs in an economy with little formal education. On average, the costs of occupational DI are thus  $l(h_i)$ , where  $h_i$  stands for the health risk score quintile.

$$l(h_i) = \begin{cases} 0.5 * w_2, & \text{if } h_i == 1\\ 0.6 * w_2, & \text{if } h_i == 2\\ 0.7 * w_2, & \text{if } h_i == 3\\ 0.8 * w_2, & \text{if } h_i == 1\\ w_2, & \text{if } h == 5 \end{cases}$$
(3)

However, after an occupational disability and its resulting wage losses, following reality, the model checks whether the remaining work capacity produces enough market income to earn above or below the means-tested basic income threshold of about  $\in$  1000. For example, let us assume that a highly qualified white collar worker with a monthly income of  $\in$  10,000 would incur a health shock that forces her to switch from full to part-time work, hence making  $\in$  5,000. If that person holds a private ODI that pays a monthly ODI benefit of  $\in$  2,000, her income after a health shock would be  $\in$  7,000 and the occupational disability costs would be  $0.5 * w_2 - b = \in$  3,000. However, a low-income laborer in the second highest risk quintile with a monthly income of  $\in$  2,000 would lose 80% of her income by (3), and thus fall below the basic income threshold. She would receive *C* and her occupational disability costs would be  $w_2 - C = \in$  1000.<sup>23</sup> Thus, in case of occupational work disability, those without private ODI incur

<sup>&</sup>lt;sup>23</sup>The average German gross wage was  $\in$  47,928 or about \$50K in 2019 (Statistisches Bundesamt, 2022). Average private ODI premia are currently  $\in$  923 or \$1000 per year according to our data from a big rating agency (Morgen & Morgen, 2021). Hence, individuals spend on average \$14K in premiums between ages 32 to 46 when the average health shock occurs. The average insured benefit for occupational disability was  $\in$  13,301 p.a in 2019 (Morgen & Morgen, 2021). Given these numbers, an average occupational disability shock that would lead to a loss in work

average costs of min[ $w_2 - C$ ;  $l(h_i) * w_2$ ], and those with a policy incur costs min[ $w_2 - C + b - \Pi$ ;  $l(h_i) * w_2 + b - \Pi$ ] resulting in consumption  $c_{ODI}$ .

$$c_{ODI} = (1 - \tau)w_2 - l(h_i) * w_2 + (1 + r)s - \Pi + b + \Psi$$
(4)

where *r* is the real interest rate on savings, *s*, and  $\Psi$  is a social insurance transfer, for example, the German means-tested basic income or reduced income whichever is higher, where  $\Psi = max[0, C - ((1 - \tau)w_2 + (1 + r)s - \Pi + b)]$ . Individuals who buy a private ODI policy but do not occur occupational disability, pay premia  $\Pi$  but incur no wage losses:

$$c_0 = (1 - \tau)w_2 + (1 + r)s - \Pi \tag{5}$$

In reality, the private ODI market provides hundreds (if not thousands) of different plans. Experts suggest to insure an income level of 70% of the gross wage, whereas various online calculators provide information on the trade-offs between premium and coverage levels as a function of h, o and  $w_2$  (Allianz, 2022). Consequently, individuals solve the following maximization problem, where we omit subscripts for readability:

$$U(h, w, o) = \max_{c,s,C} u_1(c_1) + \beta[\rho u_2(h, w_2, o, \theta^b, \Pi, b) + (1 - \rho)u_2(h, w_2, o, \theta^t, \Pi, b)]$$
(6)

where

$$u_{2}(h, w_{2}, o, \theta^{i}, \Pi, b) = \int_{\underline{\tau}}^{\overline{\tau}} u(\tau w_{2}) + \alpha [\theta^{i} u(c_{ODI}) + (1 - \theta^{i}) u(c_{0})] q(\tau) d\tau$$

where  $\alpha$  and  $\beta$  are discount factors.

#### 5.1.2 Insurers

Applicants for private ODI indicate h, w, and o on their application, whereas the true work disability risk  $\theta^i_{h,w,o}$  remains private information. The insurer either denies coverage or offers a menu of contracts { $\Pi(h, w, o), b$ } to profitable applicants. The insurer maximizes profits  $\Xi$  as follows:

$$\Xi(h, w, o) = \max_{\Pi, b} \rho[\Pi^b - \theta^b[\lambda b^b + \gamma I(b^b > 0))] + (1 - \rho)[\Pi^t - \theta^t(\lambda b^t + \gamma I(b^t > 0))]$$
(7)

capacity of 74% of the previous wage, the simple average in equation (3), would result in low- or part-time market income of  $\in$  12,461, just above the basic income floor. Those who hold private ODI would earn a total income of  $\in$  25,762.

where variable insurer costs are  $\lambda$  and fixed insurer costs are  $\gamma$ . An example of the former are costs to process claims, whereas broker commissions are an example for the latter. The incentive compatibility constraint is

$$u_2(s,\theta^i,\Pi^i,b^i) \ge u_2(s,\theta^i,\Pi^j,b^j) \ \forall i,j \in \{t,b\}, i \neq j$$
(8)

and the participation constraint is

$$u_2(s,\theta^i,\Pi^i,b^i) \ge u_2(s,\theta^i,0,0) \; \forall i \in \{t,b\}$$
(9)

#### 5.1.3 Parameters and Parameterization of Model

We follow Braun et al. (2019) in their parameterization strategy; for example, we set the real interest rate r to zero. Further, we employ a standard utility function with constant-relative risk aversion

$$u(c) = \frac{c^{1-\sigma}}{1-\sigma}$$

and set the risk aversion parameter  $\sigma$  to 2. There are a series of additional model parameters that we calibrate in a first step. The objective of the calibration is always to match actual data moments. To do so, we rely on various data sources and the stylized facts as presented in Section 4.2. Table 2 lists the main model parameters.

#### [Insert Table 2 about here]

**First step: Calibration of Model Parameters.** A first important step is to model the representative health risk score distribution in Figure 5. A beta distribution with  $\beta$ (1.2269; 6.9219) approximates this skewed distribution reasonably well. As illustrated in Figures 6 to 8, to keep the data and modeling process tractable, we categorize the continuous health risk score as well as household income and focus on population quintiles. The mean risk scores by the five income quintiles are in Table A7. We assume that their joint distribution follows a Gaussian copula with parameter  $\varphi$ , chosen to match the data points in Table A7.

We use the representative SOEP to extract the wage distribution of those who enter the labor market at the beginning of their work lives between age 25 and 35. We model it as a log normal distribution and normalize Period 1 (Figure 9) to 1. Again, following Braun et al. (2019), we express the consumption floor as a share of *permanent* lifecycle income, which is 0.1258

for Germany.<sup>24</sup> Similarly calculated are the cost of work disability  $w_2 - C$  which uninsured individuals incur for 16 years, on average between age 46 and early retirement at age 62, see Figure 9.<sup>25</sup> For the fixed ( $\gamma$ ) and variable ( $\lambda$ ) administrative costs, we take industry averages of 3% of lifetime and 10% of annual premiums, respectively (Finanzberatung Bierl, 2023).

**Second step: Matching Simulated Moments.** In a second step, we calculate model equilibria and set key parameters to minimize the distance between the actual data moments and the model equivalents. Note that the model has a very high computational intensity and, thus, is not formally estimated, see Braun et al. (2019). One reason for this computational intensity is that the menus of optimal insurance policies that insurers offer must be calculated for each of the 750 different risk groups. The risk groups consist of combinations of health risk (*h*), income (*w*), and occupational groups (*o*).

We simultaneously set parameters to minimize the distances between the actual data moments and equilibrium model outcomes: the distribution of income uncertainty  $\tau$ , the work disability risk  $\theta$  by health and income, a fraction of good types  $\psi$  and the preference parameter  $\beta$ . For example, one target is the 25 work disability probability moments by income and health risk quintiles as in Figure 6.<sup>26</sup> Table A7 shows the actual data moments and model counterparts for health risk by the five income quintiles. As seen, the model produces a very close match between the two.

**Intuition of Mechanism of General Equilibrium Model.** The model features an optimal contracting framework that includes a means-tested basic income program, private information, and administrative costs. These ingredients are powerful enough to replicate the stylized empirical facts of ODI take-up that we observe in representative data. In particular, they reproduce rising take-up rates in better health and income, although the work disability risk *decreases* in better health and income. Appendix C provides a discussion of possible equilibria and optimal insurance policies for the two risk groups by the insurer.

One main underlying mechanism for low take-up rates is coverage denial, as frequently observed in reality. Insurers decide whether to offer coverage to a risk group after having observed h, w, o. If contracts with reasonable premiums for applicants are unprofitable for the

<sup>&</sup>lt;sup>24</sup>Permanent income is simply the average gross wage (2019:  $\in$  47,928, Statistisches Bundesamt (2022)) multiplied by the average contract duration (31.5 years), which is roughly the number of years between signing a contract and retirement. The consumption floor equals the value of the means-tested basic income (2019:  $\in$  11,868, Bundesagentur für Arbeit (2019)).

 $<sup>^{25} (\</sup>in 47,928 \in 11,868) \times 16/(\in 47,928 \times 31.5)$ 

<sup>&</sup>lt;sup>26</sup>Following Braun et al. (2019) we assume that the work disability risk is invariant within each of the 25 cells and that applicants know their true risk ( $\theta^t$ ,  $\theta^b$ ).

insurer, they deny coverage to some of the 750 risk groups in Period 2. The technical reason for unprofitable contracts are administrative costs, see Chade and Schlee (2020), but also the social safety net, see Braun et al. (2019).

Further, insurers are aware of individuals' optimization problem and that low-income individuals may be better off not paying premiums  $\Pi$  for ODI insurance that provides little insurance value and thus utility, given that they likely qualify for the means-tested basic income program after an income or health shock. Insurers do not know whether applicants' true work disability risk is high or low, given their observables *h*, *w*, *o*. This is private information to the individual.

#### 5.1.4 Baseline Economy

Panel A of Table 3 shows the 25 ODI take-up moments by income and health quintiles as shown in Figure 7. The columns indicate the five health risk quintiles. The first five rows indicate the income quintiles. The cell in the upper left corner indicates a take-up rate of 25.9% for the bottom income and upper health quintile. Take-up rates increase with higher income quintiles to 45.2% for the richest and healthiest quintile. They fall in bad health to 9.6% for the poorest and sickest quintile, and to 29.1% for the richest and sickest quintile (see also Figure 7).

#### [Insert Table 3 about here]

Panel B of Table 3 shows the 25 ODI take-up moments by income and health quintiles as produced by the model. As seen, the fit between the empirical and model moments is very close but naturally not perfect. For example, the model produces a private ODI take-up rate of 25.7% instead of 25.9% for the poorest but healthiest quintile; for the healthiest and richest quintile it is 47.9% instead of 45.2%, and for the poorest and sickest quintile it is 11.4% instead of 9.6%.

## 5.1.5 Reform Validation

Next, we simulate the reform of the public ODI system and validate it with our empirically elicited reform effects by health risk quintiles. Figure 10 shows the reform effects by quintiles of the health risk score. It is estimated using our standard bias-correct local polynomial RD regressions (Calonico et al., 2014, 2017, 2018), see equation (2) and Section 4.1,

#### [Insert Figure 10 about here]

While the average effect in Figure 4 is statistically insignificant, Figure 10 shows a positive and significant reform effect for the healthiest quintile by more than 20 percentage points.

However, for the other three health risk quintiles, the point estimates are close to zero but imprecisely estimated. Nevertheless, we can exclude with 95% statistical certainty that the reform increased take-up in quintile 2 by more than 12 percentage points, and in quintile 5 by more than 23 percentage points.

Unfortunately, no pre-reform SAVE data exist. Consequently, we use the model to simulate the *reverse* reform effect in order to validate it. To do so, we simulate the pre-reform replacement rate for public ODI to assess the costs of an occupational disability in percent of former income. Appendix B illustrates the details of our stylized benefit simulation. Importantly, we assume that the individual starts working at age 25 and earns 60% of the average German wage when entering the labor market. We assume that the wage position would increase linearly to 140% if the individual worked until age 65. Figure B2 (Appendix) plots the gross replacement rate as a function of the occupational disability age on the x-axis. As seen, it is decreasing from age 25 to 60 because of the linearly increasing wage over the same time period and actuarial deductions. After age 60, when people are closer to the actual retirement age, it sharply increases again. Over the lifecycle, the average gross replacement rate is 18% of the previous gross wage.

We apply this 18% pre-reform replacement rate to the lowest risk quintile implying that their costs of an occupational disability increased from 32% to 50% of the previous wage due to the reform. In addition to the wage loss due to an occupational disability,  $l(h_i)$ , we assume decreasing public ODI replacement rates simulating the fact that the insurance value of ODI is much larger for lower risk groups, e.g. white collar as compared to blue collar workers.<sup>27</sup> As Figure 10 shows, the simulation yields a reform effect that is very close to the empirically elicited reform effect for the top health risk quintile, namely 18 percentage points (vs. 23ppt). Further, the reform effects for the other quintiles lie within the confidence intervals of the true reform effects and show the same general pattern.

## 5.1.6 Policy Simulation

Finally, we use the model to simulate policy counterfactuals. Specifically, we leverage the three main elements of the model which are capable of producing the empirically observed income and health gradients in take-up: the social safety net, private information, and administrative costs.

<sup>&</sup>lt;sup>27</sup>Specifically, we assume that, due to the reform,  $l(h_i)$  increased from 50 to 60% of the previous wage for the second lowest risk group, from 60 to 70% for the third, and remained constant for quintiles four and five at 80% and 100%. Further, we take into account that through several reforms of the German social insurance system, the consumption floor in the pre-reform era was more generous. For simplicity, we assume a flat 10% higher consumption floor pre-reform.

### [Insert Figure 11 about here]

Figure 11 simulates and illustrates the changes in private ODI take-up rates for the three scenarios. Here, we solely show the results by health risk quintiles, defined as before. In the baseline scenario and for the healthiest three quintiles of the population, average take-up rates are relatively stable—just below 40%—but decrease to 30% and below 20% for quintiles four and five, respectively, see black solid line in Figure 11.

The full information scenario—where insurers would perfectly observe not just  $\theta_{h,w,o}^{i}$  but could also differentiate between the bottom and top tails of the distribution  $\theta^{t}$ ,  $\theta^{b}$ —would shift take-up rates up, almost in a parallel fashion, by around 20 percentage points for most quintiles. The reason is the elimination of frictions and uncertainty, resulting in more targeted offers and policies. Figure 12 shows that denial rates, however, remain relatively stable across the health distribution, reinforcing that take-up increases thanks to more targeted offers and a reduction in uncertainty. However, besides the question of how a realistic policy option to achieve "full information" could look like, we note that we would still observe a clear health gradient in take-up, see Figure 11.

#### [Insert Figure 12 about here]

By contrast, imagine the German welfare state would not exist and would not provide a hard—and in an international comparison generous—consumption floor. Note that, in this simulation, for reasons of internal consistency, we also assume the abolishment of the public WDI system, see Figure 1.<sup>28</sup> The dashed line in Figure 11 illustrates that the social safety net matters substantially across the entire health risk distribution, and even more so for the higher risk groups who see increases in take-up by 70 to 80ppt to basically 100%. The reason is intuitively plausible because we model the costs of occupational disability,  $l(h_i)$  see equation 3, as decreasing in the occupational health risk. Hence, without the consumption floor and public WDI, being aware that they are at a very high risk of becoming work disabled and losing their entire income without any safety net, they would demand substantially more private insurance, and their utility from private ODI would also be much higher.<sup>29</sup> This would significantly affect the amount of offered contracts and thus take-up—denial rates would plummet to zero, see Figure 12. It is worthwhile to note that the scenario without a public safety net produces private

<sup>&</sup>lt;sup>28</sup>Keeping WDI would lower take-up across the entire health distribution but more so for the high risk occupational groups. The results are available upon request.

<sup>&</sup>lt;sup>29</sup>As discussed, in the model framework, insurers are aware of individuals' optimization procedure—only the unobserved health type is private information; thus, they are much more likely to offer them (still profitable) coverage absent the safety net, knowing that they are more likely to accept these offers, given the participation and incentive compatibility constraints.

ODI coverage gradients that align with the underlying work disability risk (Figure 6), producing a gradient that slopes *upward* instead of downward in bad health.

Finally, a world without administrative costs would substantially increase take-up rates by between 20 to 30ppt for all health risk quintiles. Take-up lies now between 60 and 70% for all quintiles and the gradient is essentially eliminated. Recall that administrative costs are substantial in this individual market—fixed costs like broker commissions amount to an estimated 3% of lifetime premium payments over 31.5 years, in addition to 10% reoccurring annual administrative costs. All these costs drive up the price for insurance coverage. They lead to high denial rates and applicants who are unwilling to pay these high premiums—given the consumption floor provided by the welfare state, their expected lifetime income (including income shocks) as well as expected health shocks during their main working age. Consequently, eliminating administrative costs would strongly reduce denial rates across the health risk distribution (Figure 12).

Next, we differentiate the policy scenario concerning administrative costs and simulate to either abolish the fixed or the variable administrative costs. Figure A13 graphically shows take-up rates and A14 denial rates for these cases. As seen, the increase in take-up for the healthiest 40% is largely due to the elimination of initial administrative costs such as broker fees. The increase is relatively and absolutely smaller for the sickest 40%. Equivalently, the decrease in denial rates is steeper for the healthier quintiles. By contrast, reducing annual administrative costs would increase take-up rates and reduce denial rates more for sicker individuals and less for the healthier quintiles and would entirely eliminate the health gradient in take-up. Appendix Table A8 shows the full simulated take-up rates by the different policy scenarios, not only by health, but also by income.

Table 4 shows overall take-up rates, the share of insured costs, loading factors and profits for the baseline economy and various policy scenarios.

Here, we differentiate between good and bad risk types, that is,  $\theta^b$  and  $\theta^t$ . As shown in Table 2, 73% fall into the bottom of the disability risk distribution. If insurers could identify the true types with certainty absent information asymmetries, optimal policies would entail a smaller share of insured risk for the good types, but a substantially higher share of insured risk for the bad types.<sup>30</sup> Moreover, the share of insured risk would be relatively even across health risks, without much of a gradient, see Appendix Figure A15. The reason is that insurers would offer lower and higher coverage contracts that are better tailored for the lifecycle optimization problem of the good and bad risks, respectively, given their expected income and health shocks and the

<sup>&</sup>lt;sup>30</sup>The share of insured risk equals the ODI replacement rate.

guaranteed consumption floor by the government. Interestingly, the absence of information frictions would benefit the bad risks, as their take-up rates would almost double and their contracts insure a much greater share of the work disability risk.

As final outcomes, the model produces predictions for the loading factor, which is defined as one minus the ratio of the expected value of benefits to premia; thus a load of zero would indicate an actuarially fair contract. In the baseline scenario, insurers load contracts for good risks substantially, whereas the loads for bad risks are negative, that is, we observe cross-subsidization. The loads become even more negative in the three scenarios without administrative costs (relatively evenly) but remain relatively constant above 0.6 for the good types. In other words, insurers would pass through cost savings to further lower the premia for the bad risks; however, as also seen, profits increase under all five scenarios.

Summary. When holistically assessing the counterfactual simulations in conjunction with their implied policy alternatives, a relatively clear picture emerges. First, as Germany has just increased the means-tested safety net benefits by 12%, its asset eligibility thresholds by 50% (Deutscher Bundestag, 2022), WDI benefits in 2014 and 2019 (see footnote 8), and also reduced possibilities to sanction those who receive cash benefits but are unwilling to cooperate with caseworkers, political reforms to lower the consumption floor are very likely politically infeasible. In a 2018 representative poll, 53% of Germans found the basic income benefit levels inappropriately low (YouGov, 2018). Second, while eliminating frictions and asymmetric information would be desirable, given the relatively unregulated market and wide possibilities to risk-rate policies, there is no obvious policy to address this issue. Policymakers could allow genetic sampling which, however, would not eliminate private information and would be highly controversial, especially in Germany with its history. Moreover, this policy option would not eliminate the strong health and income gradients in coverage. The final option, reducing administrative costs, clearly emerges as the most desirable and feasible of all policy alternatives. Our findings show: the potential to increase take-up is substantial and the health gradient in coverage would be substantially reduced. Most importantly, there exist clear regulatory tools with bipartisan support to implement such a policy, for example, a cap on commission fees or minimum benefit ratios. Benefit loss ratios would cap the ratio of benefit payouts to administrative costs, e.g. spending on marketing by insurers.

# 6 Discussion and Conclusion

This paper studies a structural reform of the disability insurance market in Germany, both empirically and theoretically using reduced-form approaches and a general equilibrium model. The reform cut access to public occupational disability insurance (ODI) for cohorts born after 1960 starting 2001.

Unlike older cohorts and during the generous post-WWII German welfare state, these cohorts could no longer apply for public benefits when a health shock prevented them from working in their previous *occupation*. This paper first studies the first-stage effects on public DI inflows to demonstrate that the reform had "bite." Then it studies interaction effects with the biggest private individual ODI market in the world. However, this private individual market is relatively unregulated. Guaranteed issue does not exist, premiums are risk rated and coverage denials common. Applicants purchase policies at an average age of 32, after having entered the labor market and when settling down and starting a family. They keep their policies for an average of 31 years, covering the crucial time period of their work lives until early statutory retirement is possible.

While we find that the reform reduced public DI inflows by more than 30% in the long-run, we do not find much evidence that the treated cohorts purchased private ODI policies at much higher rates than the control cohorts. We can exclude increases of 5 percentage points with 95% probability at the population level. Standard welfare models that infer insurance values from demand elasticities and take-up may imply that people do not value this type of supplemental insurance sufficiently. And that the reform increased welfare.

However, the small interaction effects are just an equilibrium outcome. Hence, we employ a general equilibrium model and tailor it to the German case, modeling the regulatory framework. The model features three main driving forces: (i) the German means-tested basic income program which provides a guaranteed consumption floor to all residents of about 100% FPL; (ii) private information, and (iii) administrative costs. We show that the model and these three driving forces are powerful enough to explain stylized empirical take-up pattern in the private ODI market: (1) despite a high disability risk over the work life, take-up rates are below 50% across all health and income groups. We find at best modest interaction effects with public DI. (2) strong positive take-up gradients in good health and higher income, (3) inversely related negative gradients in work disability risk.

Our simulations suggest that policymakers could increase take-up rates substantially by either (A) streamlining the means-tested basic income program (which would be politically difficult and may have unintended consequences), or (B) allowing insurers to collect even more data to further reduce private information, e.g. via genetic samples (politically even more difficult and with potentially more severe unintended consequences), or (C) implementing market-based reforms that would lower the high administrative costs in this market. For example, it is very common that broker commissions amount to several monthly ODI premiums, where a monthly premium can be as high as several hundred dollars for high risk groups. Concrete policy proposals could cap or even ban such high commission fees. Alternative policy proposals could limit "benefit loss ratios" akin to the regulation of U.S. health insurers through the Affordable Care Act that imposed medical loss ratios. Targeting administrative costs could not just substantially increase take-up rates across the entire risk distribution but also substantially reduce the health gradient in take-up, even under risk rating. Our simulations predict denial rates to fall for all, and even more so for bad risks; simultaneously, the disability risk covered by the private ODI policies would increase, and loads decrease, for both high and low risk types.

Finally, note that this paper deliberately abstains from drawing overall welfare conclusions. Assuming an average ODI benefit as in Figure 1 and a decrease in inflows by a third per cohort and year, the reform reduced expenditures of the German Statutory Pension Insurance by 789 million in the first year, or about  $\leq 12$  billion after 15 years, when the first affected cohorts aged through their work lives. Assuming that the reduced spending would be passed entirely through to SPI contribution rates, it would equal a reduction of one percentage point. However, to assess the overall welfare effects of the reform, researchers would need to estimate increased revenues in taxes and other social insurances as well as increased expenditures in social assistance. Moreover, it would be necessary to specify welfare functions with additional assumptions. For example, future work could estimate the causal reductions in household consumption as a result of the reform and then assess welfare effects in a Baily-Chetty welfare framework.

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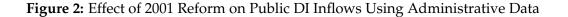
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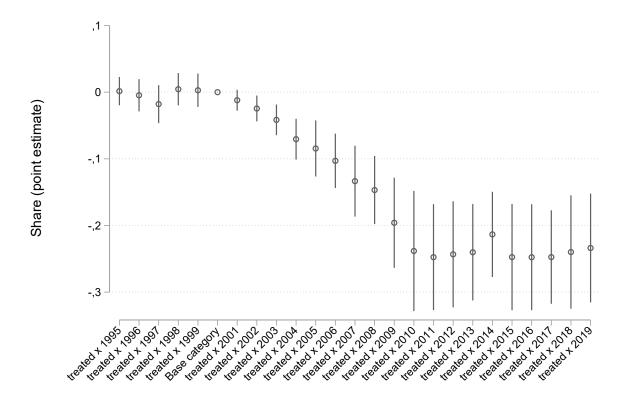
### Figure 1: Illustration of WDI and ODI Schemes

Scheme	Main criterion	Work eligibility	Health Assessment	Benefits	Calculation (Appendix B)	Notes
Work DI	Work disability in	Social contributions	Does health status	100%	Similar to early retirement	Available
(WDI)	any job	paid in last 3/5 years.	allow 3 hours of		pension. Assuming applicant	throughout entire
			work per day in any	2000: €731	would have earned last wage	time period for all
		5 years waiting	job?	2005: €730	until 60. Actuarial deduction	cohorts.
		period.			of 3.6% for each life year of	
					receipt before 63 up to 10.3%	
Occupational DI	Work disability in	Social contributions	Does health status	50%	Same as WDI but is supposed	Cut for cohorts born
(ODI)	last or trained	paid in last 3/5 years.	allow 6 hours of	(same as partial	to solely compensate for	after 1960.
	occupation		work per day in	WDI post-20001)	partial work capacity loss.	
		5 years waiting	previous/trained			
		period.	occupation?	2000: €587	About 12% of gross wage	Effective insurance
				2005: €515	with average age at first	value higher, the
					receipt of 47, see Appendix B	higher wage in last
					for details.	occupation. WDI
						and ODI converge
						for low-income jobs

<sup>1</sup> Work capacity between 3 and 6 hours per day results in partial WDI at 50% of the benefits. Pre-2001, ODI benefit was 2/3 of WDI.

*Source:* own illustration. See main text for details. ODI was abolished for cohorts born after 1960 effective 2001. Appendix B provides details on the benefit calculation; changes in benefits affected all birth cohorts equally. Further, pre-2001, the health assessment applied an earnings threshold. The change to an "hours capacity assessment" also affected all cohorts equally.





*Source:* Administrative SPI data on new public DI recipients by cohort and year. Treated cohorts are those born after 1960 and the treatment group; grandfathered cohorts are those born before 1961 and the control group. Figure plots  $\beta D_c \times T_t$  estimates from equation 1 but with the post-reform indicator  $T_t$  replaced by a series of year dummies where 2000 is the base year.

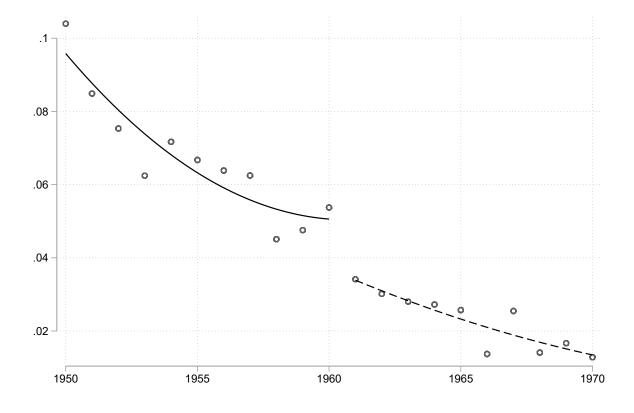


Figure 3: Effect of 2001 Reform on Public DI Case Loads Using Representative SOEP Data

*Source:* SOEP v.33 – 95% sample. Sample is restricted to post-reform years. The figure is from one RD model similar to equation 2, estimated using quadratic trends in the running variable  $f(z_i - c) = z_i - c$  to allow for different slopes before and after the cutoff. Robustness checks show results for an alternative *PublicDI II* measure and the pre-reform period (Figure A5), vary the bandwidth (Figure A6), study the smoothness of covariates (Figure A7), carry out density plots of running variables (Figure A8), and vary polynomials as well as carry out donut RDs (Figure A8).

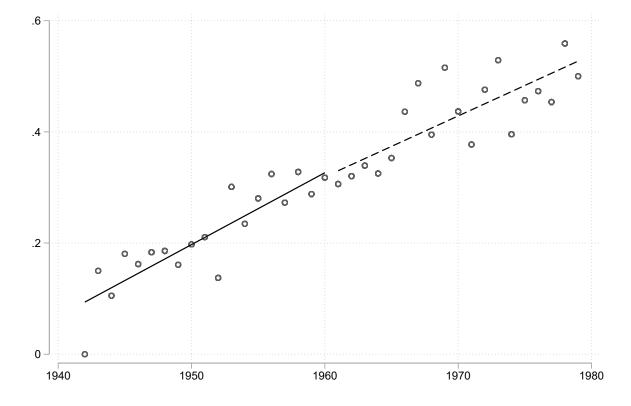
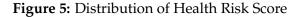
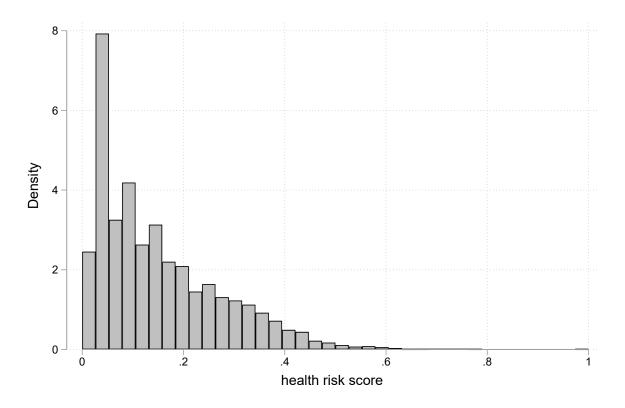


Figure 4: Effect of 2001 Reform on Private ODI Policies Using Representative SAVE Data

*Source:* SAVE data 2001-2010. The figure shows the raw nonparametric means of private ODI coverage by birth year, overlaid with separate linear trends before and after the cutoff. Other robustness checks vary the sample (Figure A8), vary the bandwidth (Figure A10, Calonico et al. 2020), study the smoothness of covariates (Figure A11), carry out density plots of the running variable (Figure A12, McCrary 2008), and vary polynomials as well as run donut RDs (Figure A8).





*Source:* SAVE data 2001-2010. Health risk score is produced using principal component analysis and subjective as well as objective health measures from SAVE.

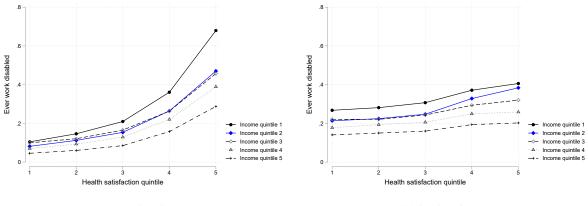


Figure 6: Lifecycle Risk of Work Disability by Income and Health Risk Score

(a) good risk type

(b) bad risk type

*Source:* SOEP v.33 – 95% sample. Figure 6a plots the unconditional risk of a severe health limitation over the working ages by the health satisfaction quintiles and the five net household income quintiles. Figure 6b first regresses the lifecycle risk of severe health limitations on socio-demographics, job and educational characteristics, predicts the risk at the individual level and then plots this conditional risk by the health satisfaction quintiles and the five net household income quintiles.

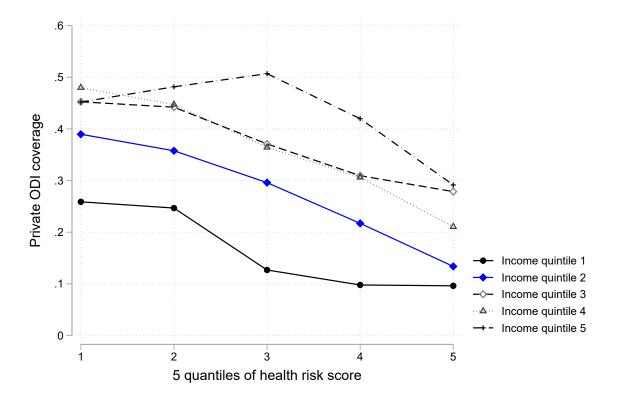
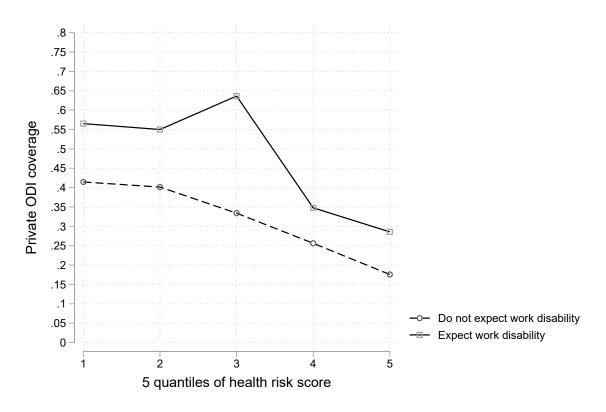


Figure 7: Take-Up of Private ODI Policies by Health Risk and Income

*Source:* SAVE data 2001-2010. Figure plots take-up rates of private ODI policies against the quintiles of the health risk score in Figure 5 and stratifies these curves by the five net household income quintiles.



### Figure 8: Take-Up by Health Risk and Private Information

*Source:* SAVE data 2001-2010. Figure plots take-up rates of private ODI policies against the quintiles of the health risk score in Figure 5 and stratifies these curves by expected retirement before age 60. The latter information is directly elicited in the SAVE survey and proxies expected work disability.

Period 1: 25-30	Period 2: 30-35	Period 3: 45-60	
<ul> <li>Endowments</li> <li>Health h</li> <li>Occupation o</li> <li>Wage w</li> <li>Saving s</li> </ul>	<b>Disability risk</b> $\theta_{h,w,o}^i$ • $\rho=t$ (prob top) • $1-\rho=b$ (bottom)	Draw income shock $ au$ , creates uncertainty about eligibility for means-tested basic income program Draw disability risk $ heta^i_{h,w,o}$ :	
f(h, w, o) observed	$ heta^i_{h,w,o}$ private Information	<ul> <li>If occupational work disability, receive: min[w–C; l(h*w)]</li> </ul>	
	-	If work disabled with ODI:	
	Insurer offers pair of contracts ( $\pi^i, b^i$ )	min[w–C+b–π ; l(h)*w+b–π]	
→ save s,	$\rightarrow$ purchase ODI	$\rightarrow$ Occupational disability or not	
consume w-s	(average age 32)	(average age 46)	-> Age

### Figure 9: Illustration of Lifecycle Time Periods in Baseline Model

*Source:* The figure illustrates the lifecycle decision-making process of a customized version of the GEM model by Braun et al. (2019). For more details, please see main text.

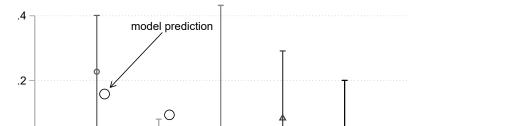


Figure 10: Effect of 2001 Reform on Private ODI Policies by Health Risk Quintile

*Source:* SAVE data 2001-2010. The figure shows the 2001 reform effect by health risk score quintiles using our standard RD models similar to equation (2), estimated using local polynomial regressions with linear polynomials and univariate weights (Calonico et al. 2014, 2017, 2018). See main text for more details.

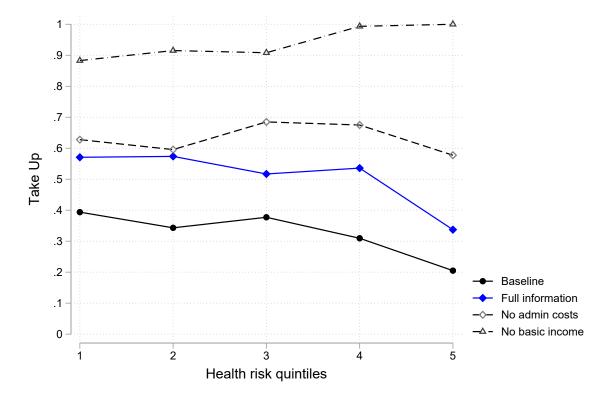


Figure 11: Take-Up Rates by Health Risk Score: Baseline vs. Policy Simulations

*Source:* The solid black line represents the baseline private ODI take-up rates by the quintiles of the health risk score in Figure 5. The other lines show take-up rates for alternative policy simulations by health risk quintiles using the general equilibrium model (see Section 5).

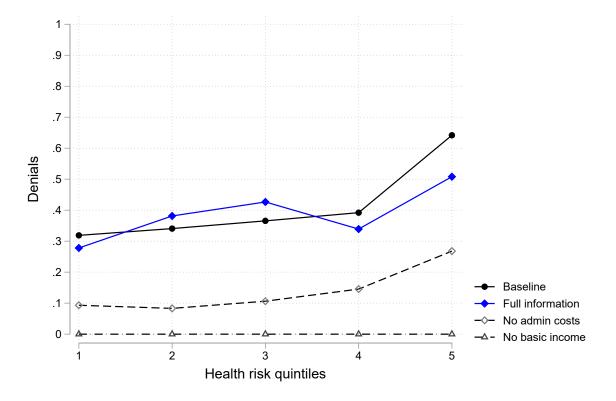


Figure 12: Denial Rates by Health Risk Score: Baseline vs. Policy Simulations

*Source:* The solid black line represents the baseline denial rates by the quintiles of the health risk score in Figure 5. The other lines show take-up rates for alternative policy simulations by health risk quintiles using the general equilibrium model (see Section 5).

		-		
	(1)	(2)	(3)	(4)
	Full sample	SPI insured	No kids	One-person HH
Conventional	-0.045	-0.053	-0.017	0.021
conventional	(0.0348)	(0.0443)	(0.0494)	(0.0691)
Bias-corrected	-0.048	-0.051	0.041	0.029
	(0.0348)	(0.0443)	(0.0494)	(0.0691)
Robust	-0.048	-0.051	0.041	0.029
11000000	(0.0417)	(0.0509)	(0.0572)	(0.0794)
	(010117)	(0.000)	(0.007 _)	
Year FE	yes	yes	yes	yes
State FE	yes	yes	yes	yes
Age + gender	yes	yes	yes	yes
Work + education	no	no	no	no
Socio-dems	no	no	no	no
Conventional	-0.057	-0.075**	-0.060	-0.034
	(0.0464)	(0.0351)	(0.0506)	(0.0671)
Bias-corrected	-0.059	-0.100***	-0.052	-0.010
	(0.0464)	(0.0351)	(0.0506)	(0.0671)
Robust	-0.059	-0.100**	-0.052	-0.010
	(0.0536)	(0.0421)	(0.0596)	(0.0760)
Year FE	yes	yes	yes	yes
State FE	yes	yes	yes	yes
Age + gender	yes	yes	yes	yes
Work + education	yes	yes	yes	yes
Socio-dems	yes	yes	yes	yes
Observations	12822	9,580	6,236	2,281

*Source:* SOEP v.33 – 95% sample. Table reports estimates for RD models similar to equation (2), estimated using local polynomial regressions with linear polynomials and univariate weights (Calonico et al. 2014, 2017, 2018). Other robustness checks vary the bandwidth (Figure A9, Calonico et al. 2020), study discontinuities in covariates (Figure A10), carry out density plots of the running variable (Figure A11, McCrary 2008), and vary polynomials as well as run donut RDs (Figure A12)

Interest rate	r	0
Risk aversion	$\sigma$	2
Health risk distribution	f	$\beta(1.2269; 6.9219)$
Copula parameter	φ	-0.29
Period 1 wage distribution	w	$\ln(w) \sim N(-0.32, 0.64)$
Basic cash income consumption floor	С	0.1258
Work disability costs $(w - C)$	т	0.3822
Insurer's variable costs	λ	1.1
Insurer's fixed costs	$\gamma$	1.03
Preference discount factor	β	0.94
Income shock distribution	$\tau$	1- $\tau$ truncated log normal
au bounds	$\mu_{\tau}$	[-2;0.5]
Fraction good types	ψ	0.73

#### Table 2: Model Parameters

*Source:* SAVE for frailty distribution, SOEP for young endowment distribution, demand shock distribution,  $\tau$ , own calculations and various sources for insurer administrative costs and the welfare consumption floor (Bundesagentur für Arbeit, 2019).

	Health Risk Quintile					
Income	Q1	Q2	Q3	Q4	Q5	
Quintile						
Panel A: Data						
Q1	0.2588	0.2468	0.1268	0.0978	0.0962	
	0.3896	0.3577	0.2959	0.2171	0.1337	
	0.4525	0.4420	0.3709	0.3094	0.2786	
	0.4799	0.4474	0.3643	0.3064	0.2105	
Q5	0.4521	0.4815	0.5069	0.4198	0.2914	
Panel B: Mode	el					
Q1	0.2567	0.2834	0.1468	0.0971	0.1135	
	0.4027	0.3673	0.3078	0.2188	0.1531	
	0.4447	0.4445	0.3988	0.3166	0.2782	
	0.5100	0.5010	0.3661	0.2526	0.1842	
Q5	0.4786	0.4666	0.4948	0.4442	0.3009	

Table 3: Private ODI Take-Up Rates by Income and Health Quintiles: Data and Model Fit

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Table shows private ODI take-up rates by Health Risk (columns) and Income Quintiles (Rows). Q1 is the healthiest and poorest quintile, whereas Q5 is the sickest and richest quintile. Panel A shows the raw data from SAVE and Panel B show the private ODI take-up rates as produced by the general equilibrium model.

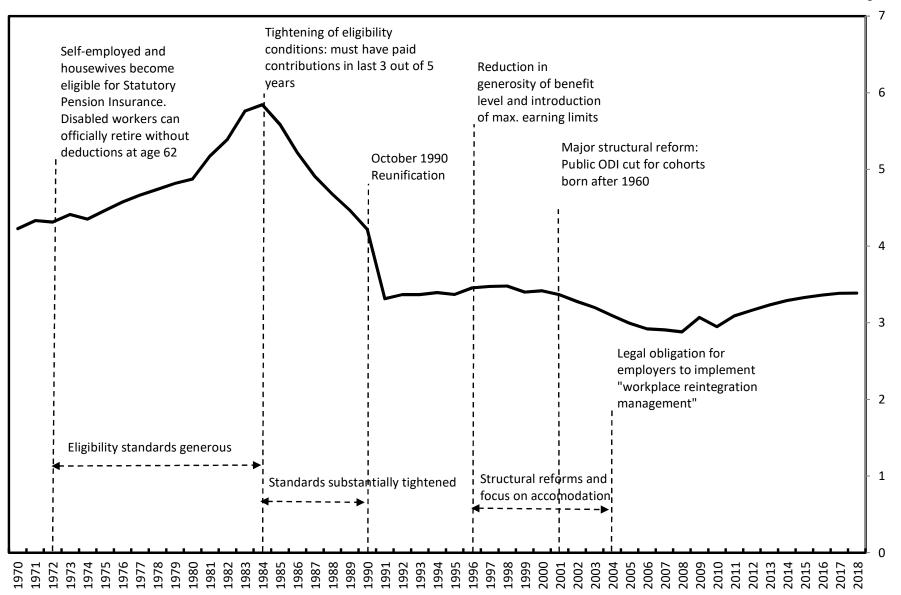
	Baseline	No Admin	No fixed ad-	No vari-	No Basic	Full Info
		Costs	min	able admin	Income	
Panel A: Total						
Take-up rate	0.3258	0.6321	0.4480	0.5475	0.9399	0.5069
Share of costs insured	0.6111	0.6674	0.6062	0.6776	0.7011	0.8345
Loading	0.2745	0.2942	0.2715	0.3051	0.6726	0.4844
Total profits	0.0167	0.0341	0.0200	0.0288	0.3210	0.0456
Panel B: Bad risks						
Take-up rate	0.1965	0.5195	0.3138	0.4324	0.9103	0.4894
Share of costs insured	0.4498	0.5230	0.4733	0.5256	0.6360	0.9297
Loading	-0.0021	-0.1540	-0.0916	-0.1135	0.2909	0.2700
Panel B: Good risks						
Take-up rate	0.5881	0.8607	0.7204	0.7814	1	0.5424
Share of costs insured	0.7281	0.8443	0.7239	0.8485	0.8215	0.6603
Loading	0.6906	0.6600	0.6822	0.6778	0.8791	0.6009

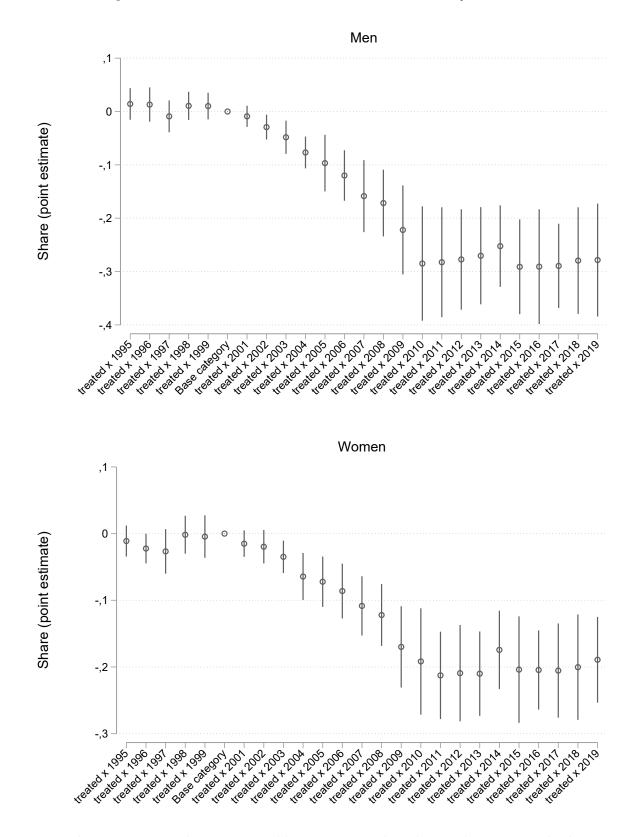
Table 4: Take-Up, Loading, and Risk Insured: Baseline vs. Policy Simulations

Table shows private ODI take-up rates, share of costs insured and loading factors by scenarios and types.

# For Online Publication Appendix A

Percentage





*Source:* Administrative SPI data on new public DI recipients by cohort and year. Treated cohorts are those born after 1960 and the treatment group; grandfathered cohorts are those born before 1961 and the control group. Figure plots  $\beta D_c \times T_t$  estimates from equation 1 but with the post-reform indicator  $T_t$  replaced by a series of year dummies where 2000 is the base year.

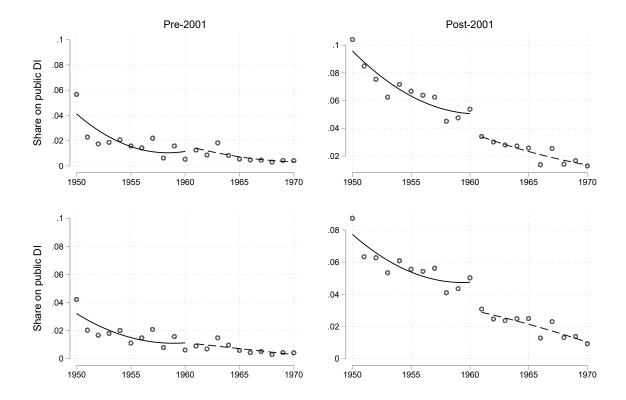


Figure A3: Effect of 2001 Reform on Public DI Using Representative SOEP Data (II)

*Source:* SOEP v.33 – 95% sample. Left column shows pre-reform and right column shows post-reform years. The first row shows *Public DI I* and the second row shows *Public DI II*. All figures show the raw nonparametric means of public disability receipt by birth year, overlaid with separate quadratic trends before and after the cutoff. Other robustness checks vary the bandwidth (Figure A4, Calonico et al. (2020), study the smoothness of covariates (Figure A5), carry out density plots of the running variable (Figure A6, McCrary (2008), and vary polynomials as well as run donut RDs (Figure A7).

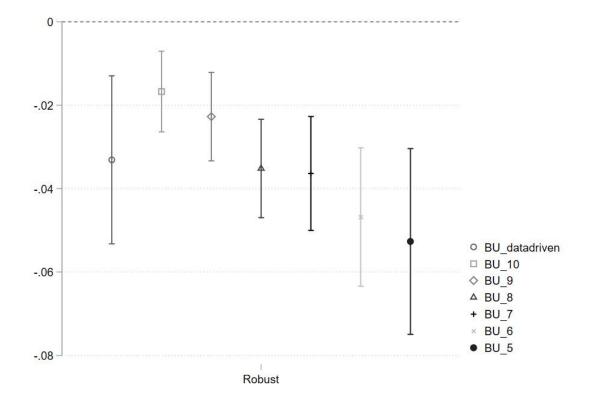
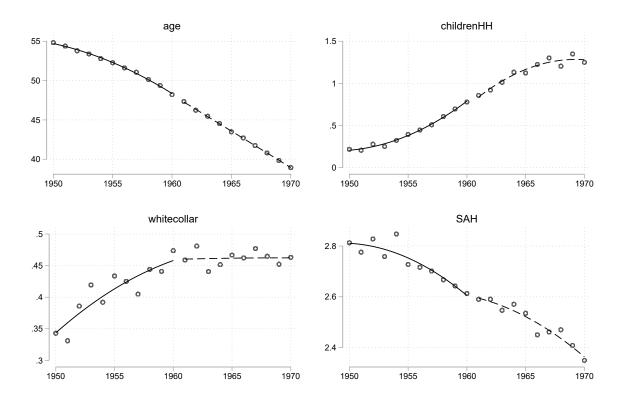


Figure A4: Effect of 2001 Reform—Local Polynominal RD Regressions Varying Bandwidth

*Source:* SOEP v.33 – 95% sample. The figures show point estimates of robustness checks varying the bandwidths of RD models similar to equation (2), estimated using local polynomial regressions with quadratic polynomials and univariate weights (Calonico et al. 2014, 2017, 2018). Other robustness checks vary the sample and indicator (Figure A3), vary the bandwidth (Figure A4, Calonico et al. 2020), study the smoothness of covariates (Figure A5), carry out density plots of running variables (Figure A6, McCrary 2008) and vary polynomials as well as run donut RDs (Figure A7).



*Source:* SOEP v.33 – 95% sample. The figures show the raw nonparametric means of covariates as indicated, by birth year, overlaid with separate quadratic trends before and after the cutoff. Other robustness checks vary the sample and indicator (Figure A3), vary the bandwidth (Figure A4, Calonico et al. 2020), carry out density plots of running variables (Figure A6, McCrary 2008), and vary polynomials as well as carry out donut RDs (Figure A7).

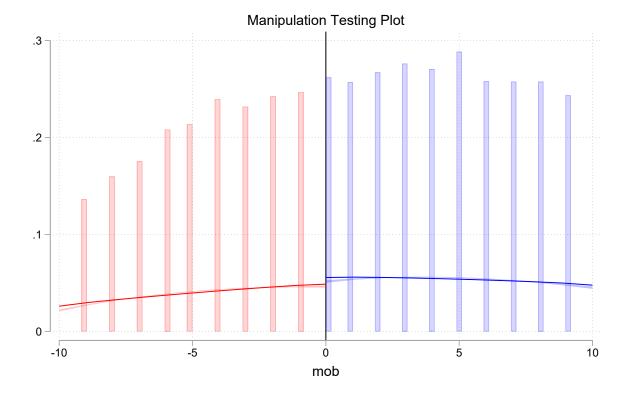


Figure A6: Effect of 2001 Reform—Density Plot

*Source:* SOEP v.33 – 95% sample. The figures shows a density plot of the running variable for RD models similar to equation (2), estimated using local polynomial regressions with quadratic polynomials and univariate weights (Calonico et al. 2014, 2017, 2018). Other robustness checks vary the sample and indicator (Figure A3), vary the bandwidth (Figure A4, Calonico et al. 2020), study the smoothness of covariates (Figure A5), carry out density plots of running variables (Figure A6, McCrary 2008) and vary polynomials as well as run donut RDs (Figure A7).

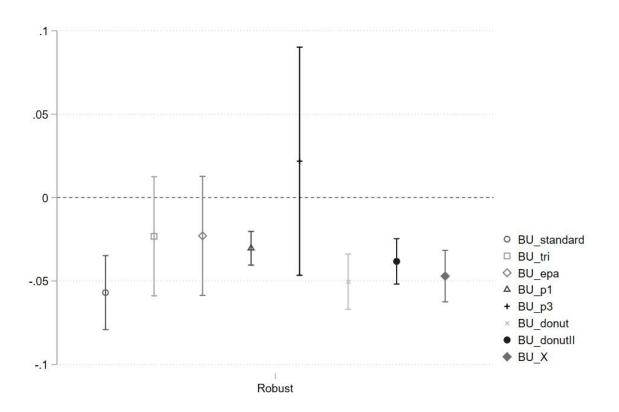
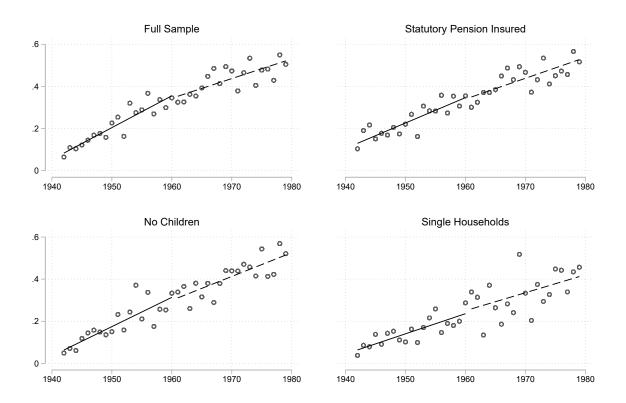


Figure A7: Effect of 2001 Reform—Local Polynominal RD—-Further Robustness

*Source:* SOEP v.33 – 95% sample. The figure shows the point estimates of a robustness check varying the order of the polynomials, varying weights, adding covariates, m and running donut RD models similar to equation (2), estimated using local polynomial regressions (Calonico et al. 2014, 2017, 2018, 2019). Other robustness checks vary the sample and indicator (Figure A3), vary the bandwidth (Figure A4, Calonico et al. 2020), study the smoothness of covariates (Figure A5), carry out density plots of running variables (Figure A6, McCrary 2008) as carry out donut RDs (Figure A7).



*Source:* SAVE data 2001-2010. The figures show the raw nonparametric means of private ODI coverage by birth year, overlaid with separate linear trends before and after the cutoff. The upper left graph is the default Figure (4), the upper right figure focuses on those eligible for Public DI, the bottom left focuses on the childless, and the bottom right on one-person households. Other robustness checks vary the bandwidth (Figure A9, Calonico et al. 2020), study discontinuities in covariates (Figure A10), carry out density plots of the running variable (Figure A11, McCrary 2008), and vary polynomials as well as run donut RDs (Figure A12).

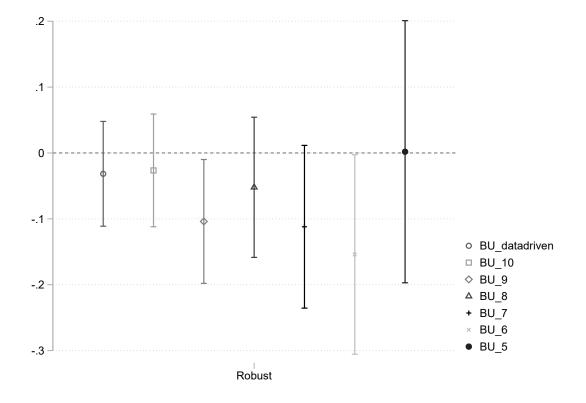
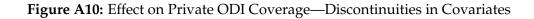
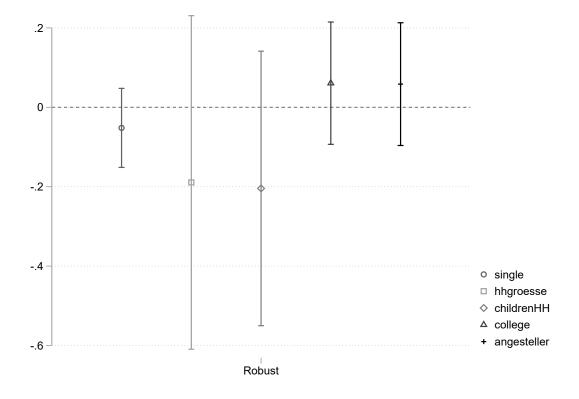


Figure A9: Effect on Private ODI Coverage—Local Polynominal RD Varying Bandwidth

*Source:* SAVE data 2001-2010. The figures show point estimates of robustness checks varying the bandwidths of RD models similar to equation (2), estimated using local polynomial regressions with quadratic polynomials and univariate weights (Calonico et al. 2014, 2017, 2018). Other robustness checks vary the sample (Figure A8), study discontinuities in covariates (Figure A10), carry out density plots of running variables (Figure A11, McCrary 2008) and vary polynomials as well as run donut RDs (Figure A12).





*Source:* SAVE data 2001-2010. The figures show point estimates of robustness checks testing for discontinuities in covariates using RD models similar to equation (2), estimated using local polynomial regressions with quadratic polynomials and univariate weights (Calonico et al. 2014, 2017, 2018). Other robustness checks vary the sample (Figure A8), vary the bandwidth (Figure A9, Calonico et al. 2020), carry out density plots of running variables (Figure A11, McCrary 2008), and vary polynomials as well as carry out donut RDs (Figure A12).

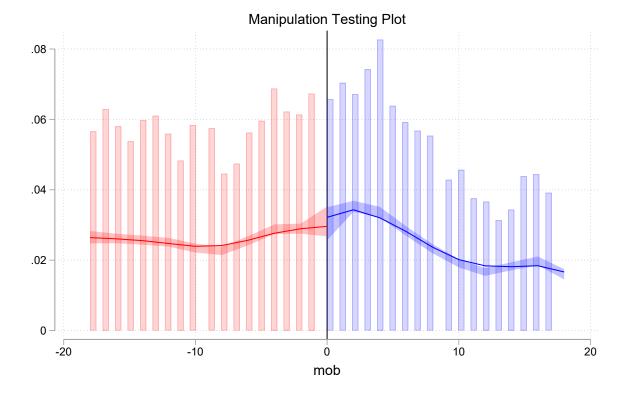


Figure A11: Effect on Private ODI Coverage—Density Plot

*Source:* : SAVE data 2001-2010. The figures shows a density plot of the running variable for RD models similar to equation (2), estimated using local polynomial regressions with quadratic polynomials and univariate weights (Calonico et al. 2014, 2017, 2018). Other robustness checks vary the sample (Figure A8), vary the bandwidth (Figure A9, Calonico et al. 2020), study discontinuities in covariates (Figure A10), carry out density plots of running variables (Figure A11, McCrary 2008) and vary polynomials as well as run donut RDs (Figure A12).

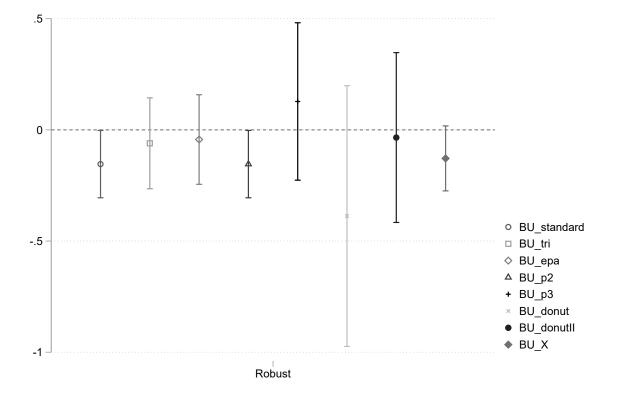


Figure A12: Effect of 2001 Reform: Local Polynominal RD---Further Robustness

*Source:* SAVE data 2001-2010. The figure shows the point estimates of a robustness check varying the order of the polynomials, varying weights, adding covariates, and running donut RD models similar to equation (2), estimated using local polynomial regressions (Calonico et al. 2014, 2017, 2018, 2019). Other robustness checks vary the sample (Figure A8), vary the bandwidth (Figure A9, Calonico et al. 2020), study discontinuities in covariates (Figure A10), and carry out density plots of running variables (Figure A11, McCrary 2008).

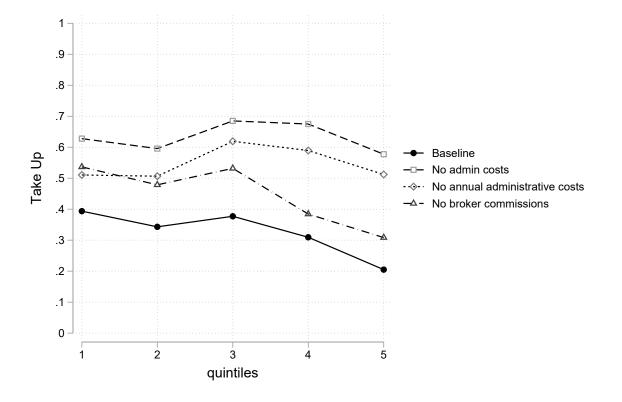


Figure A13: Take-Up Rates by Health Risk Score: Baseline vs. no admin costs variants

*Source:* The solid black line represents the baseline private ODI take-up rates by the quintiles of the health risk score in Figure 5. The other lines show take-up rates for alternative policy simulations by health risk quintiles using the general equilibrium model (see Section 5).

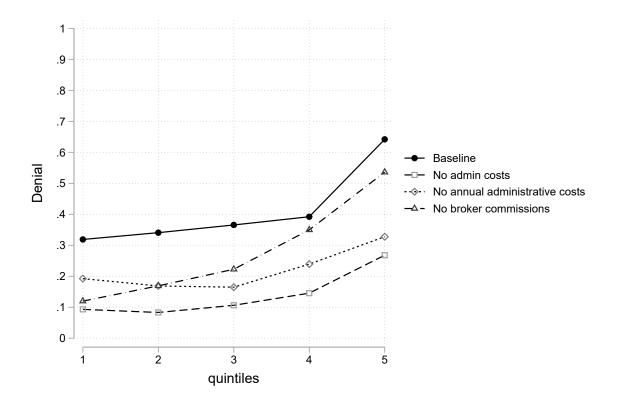


Figure A14: Denial Rates by Health Risk Score: Baseline vs. no admin costs variants

*Source:* The solid black line represents the baseline denial rates by the quintiles of the health risk score in Figure 5. The other lines show take-up rates for alternative policy simulations by health risk quintiles using the general equilibrium model (see Section 5).

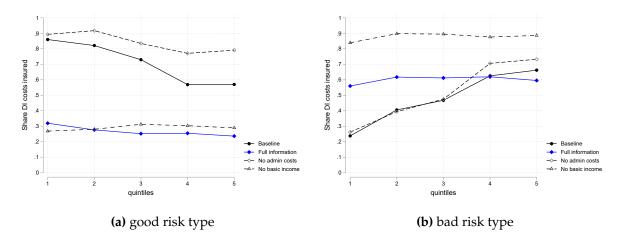


Figure A15: Share of Insured Risk by Good and Bad Risk Type: Baseline vs. Policy Simulations

*Source:* The solid black line represents the share of insured work disability risk by the quintiles of the health risk index in Figure 5. The other lines show take-up rates for alternative policy simulations by health risk quintiles using the general equilibrium model (see Section 5). Subfigure (a) shows the results for the good risk types and subfigure (b) for the bad risk types.

Panel A. All	(1)	(2)	(3)	(4)	(5)
$D_c \times T_t$	-0.0907***	-0.0907***	-0.0907***	-0.144***	-0.0514***
	(0.0293)	(0.0219)	(0.0184)	(0.00992)	(0.0105)
$D_c$	0.364***	0.485***	0.485***	0.762***	0.774***
	(0.0199)	(0.0344)	(0.0289)	(0.0192)	(0.0204)
$T_t$	-0.159***	-0.266***	-0.266***	-0.397***	-0.0782***
	(0.0255)	(0.0290)	(0.0243)	(0.0137)	(0.0101)
Ν	1,300	1,300	1,300	1,164	388
Control group mean	0.61	0.61	0.61	0.58	0.50
Panel B. Men					
$D_c \times T_t$	-0.127***	-0.127***	-0.127***	-0.174***	-0.0649**
	(0.0224)	(0.0230)	(0.0231)	(0.0275)	(0.0170)
Ν	650	650	650	582	194
Control group mean	0.65	0.65	0.65	0.61	0.52
Panel C. Women					
$D_c \times T_t$	-0.0548**	-0.0548**	-0.0548**	-0.115***	-0.0378**
	(0.0221)	(0.0227)	(0.0227)	(0.0177)	(0.0100)
Ν	650	650	650	582	194
Control group mean	0.56	0.56	0.56	0.54	0.48
Year FE	no	yes	yes	yes	yes
Cohort FE	no	yes	yes	yes	yes
East German + gender	no	no	no	yes	yes
Age groups	29-59	29-59	29-59	32-58	32-58
Cohorts	1954-1966	1954-1966	1954-1966	1954-1966	1959-1962

Table A1: Impact on Public DI Inflows Using Administrative SPI Data

*Source:* German Pension Insurance, administrative data on public DI inflows, 1995-2019. Each column in each panel is from one DD model as in equation 1. Panel A also control for East Germany and gender, and Panels B and C control for  $D_c$ ,  $T_t$  but all those coefficients are omitted for readability. See main text for more details.

	Mean	SD	Min	Max	Ν
Panel A. Outcomes					
Public DI I	0.0331	0.1790	0	1	163574
Public DI II	0.0289	0.1676	0	1	163574
Severe health limitations	0.01842	0.134464	0	1	163574
Non employed	0.1865	0.3895	0	1	163574
Full-time employed	0.5951	0.4909	0	1	163574
Individual total income (equivalized)	28,574	30,981	0	2,580,000	163574
Subjective well-being	6.9350	1.7781	0	10	163574
Panel B. Socio-demographics					
Age	44.5985	7.7230	25	59	163574
Female	0.5223	0.4995	0	1	163574
Married	0.7098	0.4539	0	1	163574
Single	0.1289	0.3351	0	1	163574
Children in household	0.9130	1.0672	0	10	163574
Adults in household	0.3596	0.6707	0	7	163574
Household size	1.2726	1.1667	0	12	163574
Dropout	0.0229	0.1496	0	1	163574
Schooling 9 yrs	0.2556	0.4362	0	1	163574
Schooling 10 yrs	0.3595	0.4798	0	1	163574
Schooling 13 yrs	0.2045	0.4033	0	1	163574
Civil servant	0.0594	0.2363	0	1	163574
Self-employed	0.0965	0.2952	0	1	163574
White collar	0.4230	0.4940	0	1	163574
Public Sector	0.2085	0.4063	0	1	163574
Part-time employed	0.2148	0.4107	0	1	163574
In job training	0.0024	0.0491	0	1	163574

Table A2: Descriptive Statistic, SOEP Data, 1995-2016

*Source:* SOEP v.33 – 95% sample. Years 1995 to 2016. Only respondents below the age of 60 and birth cohorts 1950 to 1970 are included. See Goebel et al. (2019) for more details about the SOEP.

Panel A	Public DI I (1)	Public DI II (2)	Non-Married (3)	Single Households (4)
Conventional	-0.012***	-0.014***	-0.005	-0.016**
	(0.0038)	(0.0037)	(0.0086)	(0.0077)
Bias-corrected	-0.016***	-0.022***	-0.035***	-0.022***
	(0.0038)	(0.0037)	(0.0086)	(0.0077)
Robust	-0.016***	-0.022***	-0.035***	-0.022*
	(0.0061)	(0.0058)	(0.0134)	(0.0121)
Year FE	yes	yes	yes	yes
State FE	yes	yes	yes	yes
Age & Gender	yes	yes	yes	yes
Panel B.				
Conventional	-0.012***	-0.014***	-0.006	-0.014*
	(0.0038)	(0.0036)	(0.0085)	(0.0077)
Bias-corrected	-0.015***	-0.021***	-0.037***	-0.018**
	(0.0038)	(0.0036)	(0.0085)	(0.0077)
Robust	-0.015**	-0.021***	-0.037***	-0.018
	(0.0060)	(0.0058)	(0.0133)	(0.0120)
Year FE	yes	yes	yes	yes
State FE	yes	yes	yes	yes
Age & Gender	yes	yes	yes	yes
Socio-demographics	yes	yes	yes	yes
Education & labor controls	yes	yes	yes	yes
Ν	120,211	120,211	34,958	41,434

### Table A3: Effect of 2001 Reform on Public DI Using Representative SOEP Data

*Source:* SOEP v.33 – 95% sample. Years 2001 to 2016. Only respondents below the age of 60 and birth cohorts 1950 to 1970 are included. See Goebel et al. (2019) for more details about the SOEP. The tables shows the point estimates using local polynomial regressions similar to equation (2) (Calonico et al. 2014, 2017, 2018, 2019) using a bandwidth of ten, a univariate kernel, and a quadratic polynomial. Column (2) shows results for an alternative *PublicDI II* measure. Column (3) selects on non-married respondents and column (4) selects on single households. Other robustness checks show results for the pre-reform period (Figure A3), vary the bandwidth (Figure A4), study the smoothness of covariates (Figure A5), carry out density plots of running variables (Figure A6), and vary polynomials as well as carry out donut RDs (Figure A7).

	Mean	SD	Min	Max	Ν
Panel A. Key variables					
Private ODI	0.3239	0.4680	0	1	12822
Expects Retirement Pre-60	0.02597	0.1591	0	1	12822
Panel B. Socio-demographics					
Age	41.01	10.62	20	59	12822
Female	0.4981	0.5000	0	1	12822
Married	0.6490	0.4773	0	1	12822
Single	0.1926	0.3943	0	1	12822
Children in household	0.8262	1.0383	0	8	12822
Household size	2.5944	1.2643	1	13	12822
Schooling degree 13 yrs	0.4122	0.4922	0	1	12822
Master degree	0.2738	0.4459	0	1	12822
College degree	0.6076	0.4883	0	1	12822
Full-time	0.4786	0.4996	0	1	12822
Part-time	0.1267	0.3326	0	1	12822
Blue collar	0.1756	0.3805	0	1	12822
White collar	0.3343	0.4718	0	1	12822
Self employed	0.0790	0.2698	0	1	12822
Household net income (in 000s)	2.4875	2.4465	0	120	12822
Panel C. Subjective and Objective Health					
Health satisfaction 0-4/10	6.6458	2.4761	0	10	12822
Concerns about own health	0.2011	0.4008	0	1	12822
Smoker	0.3436	0.4749	0	1	12822
SAH	2.4166	0.8377	1	5	9580
Serious Health Issues	0.4564	0.4981	0	1	9580
Heart disease diagnosed	0.0707	0.2563	0	1	9580
Stroke	0.01831	0.1341	0	1	9580
Chronic Lung Disease	0.05481	0.2276	0	1	9580
Cancer	0.0409	0.1982	0	1	9580
High Blood Pressure	0.2292	0.4203	0	1	9580
High Cholesterol	0.13921	0.34618	0	1	9580
# doctor visits	0.6018	0.8131	0	9	8029
# days hospital	0.1926	0.8813	0	27	8029
Normalized health risk score	0.1515	0.1212	0	1	8029
Panel D. Expectations and attitudes					
Subj. life expectancy low	0.2033	0.4025	0	1	8029
Subj. life expectancy high	0.1208	0.3259	0	1	8029
Savings 4 Unexpected	0.7139	0.4520	0	1	8029
Savings 4 OldAge Important	0.7426	0.4373	0	1	8029
No savings possible	0.2034	0.4025	0	1	8029
No savings, enjoy life	0.0242	0.1536	0	1	8029
Higher income expected	2.1876	3.0344	0	10	12822
Inheritance expected	0.8179	2.0289	0	10	12822

## Table A4: Descriptive Statistic, SAVE Data, 2001-2010

*Source:* SAVE data 2001-2010. Only respondents below the age of 60 and birth cohorts 1950 to 1970 are included. See Coppola and Lamla (2013) for more details about SAVE.

	Full Sample	Public Pension	No Children	Single Households
Panel A	(1)	(2)	(3)	(4)
Conventional	-0.045	-0.053	-0.017	0.021
	(0.0348)	(0.0443)	(0.0494)	(0.0691)
Bias-corrected	-0.048	-0.051	0.041	0.029
	(0.0348)	(0.0443)	(0.0494)	(0.0691)
Robust	-0.048	-0.051	0.041	0.029
	(0.0417)	(0.0509)	(0.0572)	(0.0794)
Year FE	yes	yes	yes	yes
State FE	yes	yes	yes	yes
Age & Gender	yes	yes	yes	yes
Panel B.				
Conventional	-0.057	-0.075**	-0.060	-0.034
	(0.0464)	(0.0351)	(0.0506)	(0.0671)
Bias-corrected	-0.059	-0.100***	-0.052	-0.010
	(0.0464)	(0.0351)	(0.0506)	(0.0671)
Robust	-0.059	-0.100**	-0.052	-0.010
	(0.0536)	(0.0421)	(0.0596)	(0.0760)
Year FE	yes	yes	yes	yes
State FE	yes	yes	yes	yes
Age & Gender	yes	yes	yes	yes
Socio-demographics	yes	yes	yes	yes
Education & labor controls	yes	yes	yes	yes
Ν	11,973	9,526	6,236	2,281

### Table A5: Effect on Private ODI Coverage Using Representative SAVE Data

*Source:* SAVE data 2001-2010. Only respondents below the age of 60 and birth cohorts 1950 to 1970 are included. See Coppola and Lamla (2013) for more details about SAVE. The tables shows the point estimates using local polynomial regressions similar to equation (2) (Calonico et al. 2014, 2017, 2018, 2019) using a bandwidth of ten, a univariate kernel, and a linear polynomial. Column (1) is the default sample, column (2) focuses on those eligible for Public DI, column (3) focuses on the childless, and column (4) on one-person households. Other robustness checks vary the bandwidth (Figure A9, Calonico et al. 2020), study discontinuities in covariates (Figure A10), carry out density plots of the running variable (Figure A11, McCrary 2008), and vary polynomials as well as run donut RDs (Figure A12)

	Public DI (1)	Not Employed (2)	Total Income (3)	SWB (4)
Severe Health Limitation (t-1)	0.0907***	0.0929***	-4,117***	-0.1765**
	(0.0162)	(0.0183)	(623)	(0.0847)
Treated×	-0.0115	0.0397	125	-0.1463
Severe Health Limitation (t-1)	(0.0203)	(0.0252)	(828)	(0.1112)
Treated (t-1)	-0.0056	-0.2161	-17,365	-1.6655**
	(0.0274)	(0.3367)	(14,193)	(0.6866)
Ν	45,571	45,571	45,571	45,446
$R^2$	0.0593	0.0314	0.0469	0.0094
Control group mean	0.56	0.56	0.56	0.54
Year + State FE	yes	yes	yes	yes
Socio-demgraphics	yes	yes	yes	yes
Education	yes	yes	yes	yes

Table A6: Health Shocks as Predictors of Labor Market Outcomes: Treated vs. Nontreated

*Source:* SOEP v.33 – 95% sample. Years 2001 to 2016. Only respondents below the age of 60 and birth cohorts 1950 to 1970 are included. See Goebel et al. (2019) for more details about the SOEP. See Burkhauser and Schroeder (2007) for more details about the creation of the *Severe Health Limitations* variable. The indicator is lagged by one period along with the treated dummy that takes one the value one for respondents born after 1960. The dependent variables are indicated in the column headers; column (3) measures total individual income, including various streams of social insurance benefits such as unemployment benefits, sick and maternity leave benefits and all types of pension benefits. SWB stands for subjective well-being.

Table A7: Mean Health Risk Score b	y Income Quintiles (SAVE)
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	Income Q1	Income Q2	Income Q3	Income Q4	Income Q5
Health Risk SAVE	0.1882	0.1648	0.1436	0.1338	0.1196
Health Risk Model	0.1848	0.1583	0.1428	0.1292	0.1056

*Source:* Tables shows the average health risk score as in Figure 5 by income quintiles. The first row shows the empirical moments form SAVE and the second row those produced by the model.

Health Risk Quintile           Income         Q1         Q2         Q3         Q4         Q5           Quintile         Panel A: Baseline         Q1         0.2567         0.2834         0.1468         0.0971         0.1135           Q1         0.2567         0.2834         0.1468         0.0971         0.1135            0.4027         0.3673         0.3078         0.2188         0.1531            0.4447         0.4445         0.3988         0.3166         0.2782            0.5100         0.5010         0.3661         0.2526         0.1842           Q5         0.4786         0.4666         0.4948         0.4442         0.3009           Panel B: No Admin Costs         Q1         0.4457         0.7196         0.7134         0.6950         0.2323            0.6110         0.4383         1         0.7371         0.6622         0.6523            0.6110         0.4383         1         0.7371         0.6254            0.4314         0.4521         0.9773         0.2867         0.7387           Q5         0.6375         0.6599         0.7747         0.5300
Panel A: BaselineQ1 $0.2567$ $0.2834$ $0.1468$ $0.0971$ $0.1135$ $0.4027$ $0.3673$ $0.3078$ $0.2188$ $0.1531$ $0.4447$ $0.4445$ $0.3988$ $0.3166$ $0.2782$ $0.5100$ $0.5010$ $0.3661$ $0.2526$ $0.1842$ Q5 $0.4786$ $0.4666$ $0.4948$ $0.4442$ $0.3009$ Panel B: No Admin CostsQ1 $0.4457$ $0.7196$ $0.7134$ $0.6950$ $0.2323$ $0.5274$ $0.6879$ $0.8541$ $0.6622$ $0.6523$ $0.6110$ $0.4383$ $1$ $0.7371$ $0.6254$ $0.4314$ $0.4521$ $0.9773$ $0.2867$ $0.7387$ Q5 $0.6375$ $0.6599$ $0.7747$ $0.5307$ $0.6353$ Panel B: No Admin Costs (k0)Q1 $0.2843$ $0.4549$ $0.3015$ $0.2190$ $0.1854$ $0.4437$ $0.4183$ $0.4370$ $0.3300$ $0.1562$ $0.4437$ $0.4183$ $0.4370$ $0.3300$ $0.1562$ $0.4437$ $0.4183$ $0.4370$ $0.3300$ $0.1562$ $0.4437$ $0.4183$ $0.4546$ $0.4442$ $0.6334$ Panel B: No Admin Costs (lambda1)Q1 $0.40767$ $0.6930$ $0.6830$ $0.4478$ $0.1943$ $0.4762$ $0.6539$ $0.7354$ $0.5889$ $0.4546$ <
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Q5         0.4786         0.4666         0.4948         0.4442         0.3009           Panel B: No Admin Costs         Q1         0.4457         0.7196         0.7134         0.6950         0.2323            0.5274         0.6879         0.8541         0.6622         0.6523            0.6110         0.4383         1         0.7371         0.6254            0.4314         0.4521         0.9773         0.2867         0.7387           Q5         0.6375         0.6599         0.7747         0.5307         0.6353           Panel B: No Admin Costs (k0)         Q1         0.2843         0.4549         0.3015         0.2190         0.1854            0.4437         0.4183         0.4370         0.3300         0.1562            0.4437         0.4183         0.4370         0.3300         0.1562            0.4426         0.5123         0.5042         0.7018         0.4480            0.41437         0.4874         0.2526         0.4653           Q5         0.8158         0.4666         0.4948         0.4442         0.6334           Panel B: No Admin Costs (lambda1) <t< td=""></t<>
Panel B: No Admin Costs           Q1         0.4457         0.7196         0.7134         0.6950         0.2323            0.5274         0.6879         0.8541         0.6622         0.6523            0.6110         0.4383         1         0.7371         0.6254            0.4314         0.4521         0.9773         0.2867         0.7387           Q5         0.6375         0.6599         0.7747         0.5307         0.6353           Panel B: No Admin Costs (k0)         Q1         0.2843         0.4549         0.3015         0.2190         0.1854            0.4437         0.4183         0.4370         0.3300         0.1562            0.4437         0.4183         0.4370         0.3300         0.1562            0.4826         0.5123         0.5042         0.7018         0.4480            0.5100         0.7214         0.4874         0.2526         0.4653           Q5         0.8158         0.4666         0.4948         0.4442         0.6334           Panel B: No Admin Costs (lambda1)         Q1         0.407467         0.6930         0.6830         0.4478         <
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0.5274       0.6879       0.8541       0.6622       0.6523          0.6110       0.4383       1       0.7371       0.6254          0.4314       0.4521       0.9773       0.2867       0.7387         Q5       0.6375       0.6599       0.7747       0.5307       0.6353         Panel B: No Admin Costs (k0)         Q1       0.2843       0.4549       0.3015       0.2190       0.1854          0.4437       0.4183       0.4370       0.3300       0.1562          0.4826       0.5123       0.5042       0.7018       0.4480          0.5100       0.7214       0.4874       0.2526       0.4653         Q5       0.8158       0.4666       0.4948       0.4442       0.6334         Panel B: No Admin Costs (lambda1)       Q1       0.407467       0.6930       0.6830       0.4478       0.1943          0.4762       0.6539       0.7354       0.5889       0.4546          0.4762       0.6539       0.7354       0.5889       0.4546          0.4314       0.4521       0.8370       0.2867       0.4869
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Q1         0.407467         0.6930         0.6830         0.4478         0.1943            0.4762         0.6539         0.7354         0.5889         0.4546            0.5412         0.3159         1         0.7770         0.4387            0.4314         0.4521         0.8370         0.2867         0.4869           Q5         0.6375         0.6599         0.5408         0.4795         0.4306           Panel C: No Private Information           Q1         0.1826         0.2678         0.8177         0.1583         0.3477
0.4762       0.6539       0.7354       0.5889       0.4546          0.5412       0.3159       1       0.7770       0.4387          0.4314       0.4521       0.8370       0.2867       0.4869         Q5       0.6375       0.6599       0.5408       0.4795       0.4306         Panel C: No Private Information         Q1       0.1826       0.2678       0.8177       0.1583       0.3477
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Q5         0.6375         0.6599         0.5408         0.4795         0.4306           Panel C: No Private Information         0.1826         0.2678         0.8177         0.1583         0.3477
Panel C: No Private Information           Q1         0.1826         0.2678         0.8177         0.1583         0.3477
Q1 0.1826 0.2678 0.8177 0.1583 0.3477
0 732642 0 3827 0 1717 0 8222 0 6128
0.752072 0.5627 0.1717 0.6222 0.0126
0.307529 0.0060 1 0.7466 0.5043
0.481908 0.2899 0.7491 0.9100 0.3995
<b>Q5</b> 0.522401 0.3079 0.4774 0.6570 0.6758
Panel D: No Basic Income
<b>Q1</b> 1 1 1 1 1
1 1 1 1 1
0.5550 0.9612 1 1 1
0.4505 0.9637 1 1 1
<b>Q5</b> 0.3313 0.5335 1 1 1

Table A8: Private ODI Take-Up Rates by Income and Health Quintiles: Policy Simulations

Table shows private ODI take-up rates for several policy simulations by Health Risk (columns) and Income Quintiles (Rows). Q1 is the healthiest and poorest quintile, whereas Q5 is the sickest and richest quintile. Panel A shows the baseline scenario and replicates Panel B of Table 3. Panel B shows the scenario without administrative costs, Panel C the scenario with full information and Panel D the scenario without a means-tested basic income cash transfer program.

### **Appendix B: Benefit Calculation**

We illustrate the effects of the 2001 pension reform on benefits by running a simple simulation assuming a stylized employment history. As explained in Section 2, public DI is a part of SPI. Therefore, we first explain the main method of calculating statutory retirement benefits. Then we explain how disability benefits are calculated.

The German SPI is based on a point system. The gainfully employed earn pension points  $(pp_{it})$  during their work lives. A pension point equals the ratio of *individual* labor income  $(I_{it})$  to *average* labor income  $(\bar{I}_t)$  in a given year *t*:

$$pp_{it} = \frac{I_{it}}{\bar{I}_t} \tag{10}$$

At retirement, the sum of pension points is multiplied by the current "point value" (*CPV*<sub>t</sub>, in  $\in$ ). The value is indexed annually to gross wages and a few other variables. Further, pensions are multiplied by a "pension type factor" (*PT*<sub>i</sub>) which equals one for regular old-age pensions and full WDI pensions. Since 2001, it is 0.5 for partial WDI and ODI benefits. Moreover, there is a fourth factor accounting for actuarial deductions (*AD*<sub>i</sub>) if people retire before the statutory retirement age. Deductions amount to 0.3% per month before reaching the statutory retirement age. The pension, *P*<sub>it</sub>, is then calculated as:

$$P_{it} = \sum p p_{it} \times CPV_t \times AD_i \times PT_i \tag{11}$$

**DI Benefits.** They are calculated like regular old-age pensions. However, as work disability implies leaving the labor market prior to the statutory retirement age, pensions based on prior contributions would be relatively low. Hence disability benefits assume a "reference age." For the period between entry of work disability and this reference age, individuals' *average* pension points are applied. Before 2001, the reference age was 55 and the years until age 60 were valued with  $1/3 \times$  average pension points. That is, a person who entered DI at age 40 would get an additional 15 + 5/3 years of her average pension points. Before 2001, there were no actuarial deductions for WDI or ODI ( $AD_i = 1$ ). The factor  $PT_i$  was 0.66 for ODI, and 1 for full WDI benefits. Starting 2001,  $PT_i$  has been 0.5 for partial WDI and grandfathered ODI, and remained 1 for full WDI benefits.

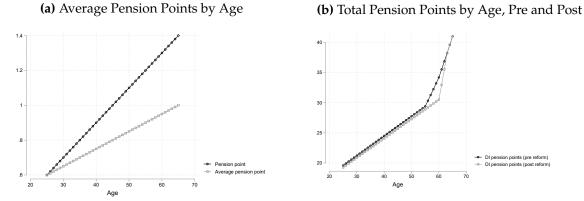
The reform in 2001 also increased the reference age to 60, but introduced actuarial deductions for retirement before age  $60.^{31}$  These deductions are capped at 36 months or 10.8% ( $AD_i = 0.892$ ).

<sup>&</sup>lt;sup>31</sup>In the meantime, the reference age has further increased to 63.

As the large majority of disability inflows occur before age 60, the share of DI recipients with maximum deductions of 10.8% exceeds 90%.

**Simulation.** Next, we simulate the effects of the 2001 reform on benefits for a stylized individual. We assume an increasing relative wage position that approximately equals 1 over the lifecycle. The individual starts working at age 25 and earns 60% of the average wage ( $pp_{it} = 0.6$ ). The wage position then increases linearly to 1.4 until age 65. Figure B1a shows average pension points by age.

Figure B1: Pension Points by Age and Pre-vs. Post-Reform

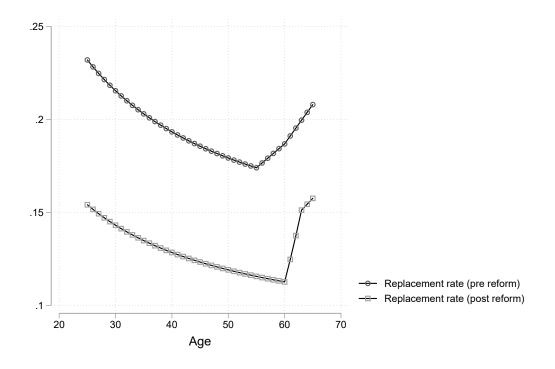


*Source:* own illustration. Note that the post-reform benefits apply either to the grandfathered cohorts who can still claim ODI benefits or the newly introduced partial DI benefits for people who are able to work more than 3 but less than 6 hours a day in any job.

The introduction of actuarial deductions and the increase of the reference age to 60, approximately cancel each other out for most ages. Figure B1b shows that the sum of pension points is slightly lower in the post-reform period. The largest difference applies between ages 56 to 61.<sup>32</sup>

In a next step, we calculate replacement rates by age assuming a single individual without other income. To calculate the replacement rate, we divide disability benefits by labor income. Figure B2 shows ODI replacement rates in the pre and post-reform periods. Before 2001, the replacement rate was highest at 0.23 at age 25 and then decreased linearly to 0.17 up to the reference age of 55, after which it sharply increased again. After 2001, the general pattern did not change but we observe a downward level shift with a lower replacement rate of between 0.11 and 0.16. Note that these benefit reductions solely applied *for the grandfathered cohorts*. (And for partial WDI, that is, people who are able to work more than 3 but less than 6 hours a day in any job.) At age 46, the mean age of DI entries, the stylized replacement rate is at 0.18 (pre-reform) and 0.12 (post-reform).

 $<sup>^{32}</sup>$ As mentioned, *PT<sub>i</sub>* decreased from 0.66 to 0.5. As a result, benefits—for partial WDI and for the grandfathered cohorts who are still eligible for ODI—are lower as well. The treated cohorts are ineligible for ODI post-reform.



### Figure B2: Replacement rate (pre and post-reform)

*Source:* own illustration. Note that the post-reform benefits apply either to the grandfathered cohorts who can still claim ODI benefits or the newly introduced partial DI benefits for people who are able to work more than 3 but less than 6 hours a day in any job.

# **Appendix C: Optimal ODI Contracts**

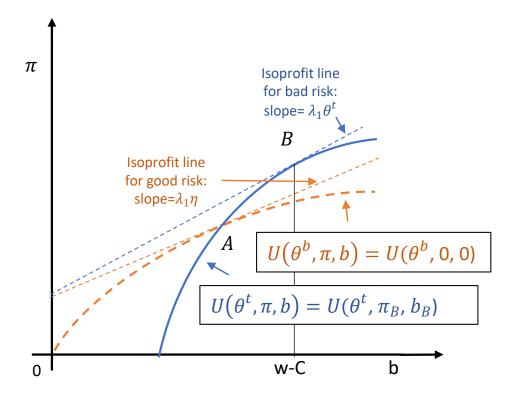
This section summarizes optimal insurance contracts in the standard model with private information, when adding administrative costs, and when allowing for a (means-tested) consumption floor. We rely heavily on and refer the interested reader to Braun et al. (2019), especially the proofs therein. For reasons of tractability, we assume a single monopolistic insurer and a single risk group that includes a continuum of risk-averse individuals who know that they are either good risk and at the bottom of the disability risk distribution,  $\theta^b$ , or bad risk and at the top,  $\theta^t$ .

#### C1 Standard Case: Just Private Information

The core of the standard case goes back to Rothschild and Stiglitz (1976) and Stiglitz (1977). The insurer maximizes profits (see equation (7)), given the participation and incentive compatibility constraints. Figure C1 illustrates optimal contracts under the standard case. The x-axis shows the insured benefit *b* and the costs of an occupational disability, w - C, where *w* represents the wage in the trained occupation and *C* is the consumption floor. The y-axis shows the premium  $\Pi$  which increases in coverage levels *b*.

The flatter indifference curve represents the good risks and the steeper indifference curve represents the bad risks. The slopes indicate the willingness to pay for a marginal increase in benefits. As seen, the bad risks have a higher marginal willingness to pay. The dashed curve that intersects with (0,0) represents the participation constraint when it binds. The participation constraint—indicating that good and bad risks prefer the contracts designed for them over no insurance—binds in the standard case for the good risks. The incentive compatibility constraint—indicating that good and bad risks prefer the contracts designed for them over the other contract—binds in the standard case for the bad risks; the bad risks' indifference curve intersects with the good risks indifference curve. Along the indifference curves, we observe combinations of possible insurance contracts ( $\Pi$ , b) that produce the same utility for individuals, given the participation and incentive compatibility constraints (which are both binding in the standard case).

Consequently, we obtain the optimal contract for the good types where the flatter isoprofit curve of the insurer touches the indifference curve of the good risks at point A. Compared to the optimal contract for the bad risks at B, both the benefits and premium are lower; the contract solely provides partial insurance, whereas the optimal contract for the bad risks in B provides full insurance with  $w_o - w_l = b$ . We obtain a separating equilibrium.



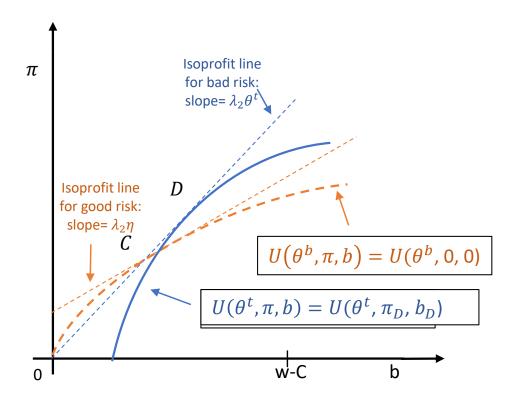
*Source:* The dashed indifference curve shows optimal contracts for good risks at the bottom of the work disability distribution  $\theta^b$  trading off premia ( $\Pi$ ) on the y-axis and coverage levels (b) on the x-axis. The solid indifference curve shows optimal contracts for bad risks at the top of the work disability distribution  $\theta^t$ . The flatter dotted linear line is the insurer's isoprofit curve for the good risks, and the steeper dotted line is the isoprofit curve for the bad risks.

As discussed, the standard case cannot produce coverage denials by insurers. Only the good risks can be voluntarily uninsured with (0,0) and produce an ODI take-up that is not 100%. In other words, insurers always offer policies. Such as scenario can happen when the share of the population with low occupational disability risk,  $\rho$ , is small, but the dispersion of the true disability risk  $\theta^i$ —that is unobserved by the insurer—large. In this case, the good types are offered a profitable contract by the insurer, but they prefer to remain uninsured.

#### C2 Extended Case I: Private Information and Administrative Costs

Chade and Schlee (2020) show theoretically that including administrative costs can produce coverage denials by insurers, as observed in reality. Braun et al. (2019) build on this insight and integrate administrative costs into their model. They show that coverage denials can produce four different scenarios: (i) separating equilibria, (ii) pooling equilibria, (iii) no insurance for anyone, and (iv) and, in practice, a rather unlikely case where only the bad risks are insured.

Once variable administrative costs are introduced, optimal contracts for both good and bad risks never provide full insurance. Further, it could be that all members of a risk group are denied coverage. These are the two relevant cases in practice. As seen in Figure C2, administrative costs



*Source:*: The dashed indifference curve shows optimal contracts for good risks at the bottom of the work disability distribution  $\theta^b$  trading off premia (II) on the y-axis and coverage levels (*b*) on the x-axis. The solid indifference curve shows optimal contracts for bad risks at the top of the work disability distribution  $\theta^t$ . The flatter dotted linear line is the insurer's isoprofit curve for the good risks, and the steeper dotted line is the isoprofit curve for the bad risks.

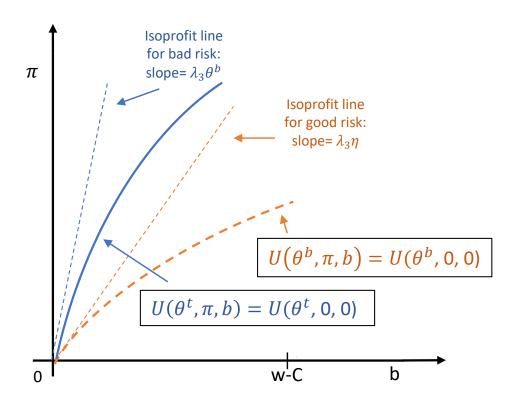
lead to steeper isoprofit curves for insurers. This implies that, in a separating equilibrium, the insurer offers policies with lower benefits and premiums. Hence, in Figure C2, optimal contracts for both groups provide less coverage, but also lower premiums (points C and D).

An alternative case would be a pooling equilibrium (not shown), when administrative costs are even higher and where both types are offered the same contract—under the assumption that marginal variable administrative costs are higher for the bad risks. This pooling contract offers even lower coverage, premiums and profits ('skinny plans').

Under certain conditions, when administrative costs are very high, Figure C3 shows a scenario where the entire risk group gets denied coverage. This is because there exists no profitable contract with positive coverage that the insurer can offer. The result is a pooling contract with (0,0) and nobody has insurance. Please see Chade and Schlee (2020) and Braun et al. (2019) for more details and a formal proof.

#### C3 Extended Case II: Private Information and Social Insurance

Braun et al. (2019) introduce an extension where they include a means-tested public insurer for long-term care costs ('Medicaid') that crowds-out private insurance benefits dollar-by-dollar.



*Source:*: The dashed indifference curve shows optimal contracts for good risks at the bottom of the work disability distribution  $\theta^b$  trading off premia ( $\Pi$ ) on the y-axis and coverage levels (b) on the x-axis. The solid indifference curve shows optimal contracts for bad risks at the top of the work disability distribution  $\theta^t$ . The flatter dotted linear line is the insurer's isoprofit curve for the good risks, and the steeper dotted line is the isoprofit curve for the bad risks.

This is not the case in Germany where private ODI benefits top-up either the means-tested basic income cash transfer or the basic WDI benefits. This implies that the German private ODI also provides utility with public benefits, unlike in the US case. Nevertheless, the main underlying mechanisms are the same in the German ODI case: the presence of a public social insurance can lead to optimal contracts with partial coverage. Further, they can lead to the denial of coverage.

Social insurance as a safety net generally increases individuals' utility in the case of no private insurance and thus reduces demand for private insurance; and also profits of private insurers. It increases the individual's outside option and thus the insurer lowers the premium (to satisfy the participation constraint). However, if the consumption floor is large enough, the insurer is unable to offer contracts that are still profitable (and provide a sufficiently high utility for individuals). As a result, the insurer denies coverage, see Braun et al. (2019) for details. This case becomes relevant in Germany where the consumption floor is relatively high, especially compared to the initial endowment and occupational disability costs. In this context, uncertainty about future income shocks that may (or may not) result in eligibility for the means-tested basic income affects demand for private ODI insurance. As explained, we use the representative SOEP to model the income shock distribution over the lifecycle and set the bounds for  $\tau$  empirically

(see Figure 9 and Table 2). As with administrative costs, whether an insurer denies coverage to entire risk groups also depends on the dispersion of private information and the population share of the good risks  $\rho$ .

In conclusion, the cutomized general equilibrium model includes multiple risk groups that carry observable h, w, o whereas  $\theta^i$  is private information. An ODI take-up rate of less than 100% is produced via two different channels. First, insurers deny coverage to entire groups. Second, some individuals are offered a profitable optimal policy but those individuals prefer to self-insure.