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When Institutions Interact: How the Effects of Unemployment Insurance are Shaped by Retirement Policies

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Abstract

This paper shows empirically that the non-employment effects of unemployment insurance (UI) for older workers depend in a first-order way on the structure of retirement policies. Using German data, we first present reduced-form evidence of these interactions, documenting large bunching in UI inflows at the age that allows workers to claim their pension following UI expiration. We then estimate a dynamic life-cycle model and use it to directly quantify how the effects of UI vary with retirement policies. Accounting for interactions across UI and retirement institutions also helps explain otherwise difficult-to-explain trends in the unemployment rate of older German workers.

JEL Codes: J26, J64, J65

Keywords: Unemployment insurance, moral hazard, retirement, older workers, interactions

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1 Introduction

Empirical studies in economics typically seek to estimate the effect of a policy change in isolation, i.e., holding other policies constant. For example, a large literature has estimated how unemployment insurance (UI) extensions or benefit changes affect non-employment durations. The elasticities identified in such reduced-form studies may not be applicable in different institutional contexts or after simultaneous reforms. While economists are certainly aware of the institutional dependence of estimated parameters, few empirical studies have attempted to directly estimate how much elasticities depend on other institutions.

In the context of unemployment insurance, the disincentive effects of the same UI extensions or benefit level change could differ under different non-UI institutions (for example, under varying levels of post-UI welfare generosity).¹ For older workers in particular, a population often at the forefront of UI policy discussions (e.g., [OECD, 2018a,b](#)), the effect of an otherwise identical UI change might differ under different retirement institutions. Knowing the extent to which this is the case is essential for helping policymakers understand whether and how to use prior reduced-form evidence to inform policy in new institutional environments.

This paper shows empirically and in the context of Germany that the non-employment effects of UI for older workers depend in a first-order way on retirement policies. Using social security data, we study older workers' employment patterns between 1975 and 2017, a period over which numerous reforms to both Germany's UI and retirement system altered the payoffs to entering UI and the search incentives of the unemployed. These reforms provide clean reduced-form variation – in the form of both bunching and regression discontinuity moments – which we leverage to estimate a dynamic labor supply model that endogenizes unemployment and retirement transitions. We use the model to directly show that the effect of the same UI extension has very different non-employment effects under different (historically observed) retirement regimes.

While interactions between UI and retirement institutions are likely relevant for many European countries ([Mirkin, 1987](#)), Germany provides a particularly interesting context for studying how the effects of UI extensions interact with retirement policies for two key reasons. First, estimating how the effects of UI vary under different institutional regimes requires extensive policy variation. There has been a tremendous amount of policy change in Germany over the past decades, with substantial reforms to both UI's maximum potential benefit duration (PBD) and to retirement rules.

¹For example, the effect of extending UI benefits by 1 month on non-employment durations appears to be about 2-3 times higher in U.S. studies (e.g., [Johnston and Mas, 2018](#); [Landais et al., 2015](#)) than in those conducted in Germany or Austria (e.g., [Lalive, 2008](#); [Schmieder et al., 2012](#)). Among other differences across these contexts, Germany has a more generous welfare system after UI benefits are exhausted than the U.S.

In the early 1980s, the maximum PBD was capped at 12 months regardless of age at UI entry and retirement was possible as early as age 60 following a UI spell.² Throughout the 1980s, maximum PBDs increased for older workers, reaching up to 32 months of UI benefits for the most senior group. After 1999, Germany reversed track. Maximum PBDs were reduced for older workers, and Germany began the process of eliminating early retirement and introducing penalties for retiring before the statutory retirement age. As a result, we observe individuals facing varying PBDs under different retirement policies.

Second, the unemployment rates among older workers in Germany over the past decades have exhibited a distinctive and challenging-to-explain pattern, diverging dramatically from those of younger workers in the 1990s. These trends are illustrated in Figure 1 (a), which shows that the unemployment rate for men aged 55 to 59 diverged from that of the other age groups in the early 90s, rising to more than 15 percent by 1997.³ In the mid 90s, over 50% of total West German UI benefits in any given month were paid to workers between age 55 and 64 (Figure 1 (b)). In stark contrast, in the U.S., for example, the different age groups largely move together. We will show that these unique trends in German old age unemployment are well explained by PBD extensions and retirement policy changes once interactions between UI and retirement are taken into account.⁴

We begin our empirical analysis by documenting reduced-form effects of UI. Conceptually, UI extensions can have quantitatively meaningful effects on the non-employment duration of individuals conditional on UI entry by affecting their search behavior⁵ — the intensive margin — as well as on the inflow rates into unemployment — the extensive margin.⁶ The latter may be particularly prominent in the context of older workers who might use UI as a bridge to retirement (e.g. [Inderbitzin et al., 2016](#)). Indeed, in our context, we see sharp and sizable bunching of UI inflows at precisely the age that allows workers to claim their pension right after UI expiration. Initially, when early retirement via UI was possible at age 60 with no penalty and maximum PBD was 12

²When referring to retirement ages we will always mean the age at which a person first claims their old-age pension.

³Note that much of this paper’s analysis focuses on men (though we also estimate and present all our key results for women), since retirement rules and bridge ages differ by gender due to the existence of a specific women’s pension (see Section 2). Over our sample period, at varying points in time, the always more generous terms of the women’s pension allowed women to enter retirement without a UI spell, enter retirement at earlier ages, or enter retirement with lower penalties for early retirement relative to men. As a result, the importance of the UI system as a vehicle for early effective retirement is lessened for women, but results are qualitatively similar for women as we discuss in Section 6.

⁴In our model, Germany’s PBD extensions will explain over half of the rise in old age unemployment between the early 80s and mid 90s. The effects we obtain are an order of magnitude larger than what we would have expected had we assumed away inflow responses and naively used pre-existing RD estimates to predict the effect of Germany’s PBD extensions on older workers.

⁵See [Katz and Meyer \(1990\)](#) as an early example and [Schmieder and von Wachter \(2016\)](#) for a review.

⁶See, for example, [Hartung et al. \(2022\)](#); [Jessen et al. \(2023\)](#); [Jäger et al. \(2023\)](#).

months, we see a spike in UI inflows at age 59. These inflow effects are very large: by age 60 over 10% — and sometimes up to 25% — of individuals in each, relevant, birth-year cohort receive UI benefits. Furthermore, UI inflows respond as expected to a series of UI extensions and pension rule changes. As maximum PBD was extended from 12 to 24 and then 32 months, this large UI inflow spike moves from age 59 to age 58, and then to 57 and 4 months. Later, as penalties for retiring early were enacted and as the earliest possible retirement age increased, UI inflow spikes diminished and moved rightward.⁷

Since workers' responses to UI extensions are not limited to UI inflow responses, we also present reduced-form evidence of the effect of UI extensions, conditional on UI entry. We do so by leveraging 8 different age cutoffs for workers in their 40s and 50s at which maximum PBD is discretely extended, estimating the intensive margin effect of UI extensions using regression discontinuity designs (RDs), thereby extending [Schmieder et al. \(2012\)](#) to older ages. For the cutoffs at which we can estimate plausibly valid RDs, our estimates suggest that the intensive margin effect is at least as large for workers in their early and mid-50s as it is for workers in their 40s. For example, men aged 52 spend an additional 0.128 months (4 days) non-employed for every additional month of PBD.

Without a model, there is no obvious way to combine the reduced-form evidence we obtain from RD estimates and UI inflow bunching moments to recover the total effect of PBD extensions on the non-employment duration of older workers. For this reason, we take a structural approach and specify a dynamic life-cycle model. Specifically, workers endogenously transition between employment, unemployment (with or without UI benefits depending on whether or not they have been exhausted), and being out of the labor force (an absorbing state). Employment relationships end efficiently due to a bad shock or a voluntary exit as a result of a worker's outside option (which depends on retirement and UI institutions) exceeding the value of continued employment. We model unemployment as a fully dynamic process with job search, allowing us to capture labor supply responses to changes in the structure of UI in a natural way.

We estimate our model by matching its simulated moments to actual employment-to-unemployment transitions, non-employment durations, and our RD estimates for select birth-year cohorts facing very different UI and retirement institutions. The extensive policy variation and clean reduced-form moments help identify the model's key parameters, disciplining our estimation. Our fairly standard model — built on clear economic incentives and interactions between incentives — is

⁷UI replacement rates are relatively generous in our context, with at most limited penalties for voluntarily quits, and no job search obligations for workers above age 58. Firms also contributed to generating worker inflow responses to UI extensions by negotiating collective labor agreements (CLAs) and 'social plans' during downturns with their workforce that often took UI and retirement-based incentives into account ([Trampusch, 2005](#)).

able to capture the trends in the empirical data well. We then simulate the model for all birth cohorts between 1924 and 1964 to assess model fit across a wide range of policy environments and in order to construct age-specific unemployment rates in calendar time. The simulated unemployment rates match both their empirical counterparts from the social security data and the OECD unemployment rates reported in Figure 1 relatively well.

We use several model simulations to better understand and quantify how the non-employment effect of UI extensions varies across institutional contexts. First, we show that extending maximum PBD by 1 year increases the simulated unemployment rates of slightly younger (aged 52-55) versus slightly older workers (aged 55-59) very differently. It increases the simulated unemployment rates of those aged 52-55 by 0.6pp in 1994. There is close to no effect on these workers' inflows into UI. In stark contrast, this same change increases the unemployment rate of those aged 55-59 by a comparatively huge 2.5pp in 1994, in large part due to UI inflow effects around bridge-to-retirement ages. Second, we assess the extent to which maximum PBD extensions explain the large 10pp increase in the unemployment rate of workers aged 55-59 from 1983 to 1994. When we simulate an environment in which maximum PBD had never been extended past 12 months, we find that the rise in unemployment rates of workers aged 56-59 would have been 57% lower. These PBD effects would not have been near as large under different retirement rules — when simulating an environment with less generous retirement policies, our model predicts significantly lower effects of the PBD extensions on the unemployment rates in the 90s.

These results speak to the importance of UI and retirement interactions. Our final exercise quantifies these directly by simulating how the effect of the same UI extension varies across different retirement regimes. We find that the non-employment effects of the same 1 year extension vary considerably between actual, current institutions and a setting that holds all else equal except for re-instituting Germany's historically more generous retirement rules. Specifically, a 12 month PBD extension increases the unemployment rate of older workers by 0.87pp under 2014 institutions and by 2.85pp when re-instituting more generous retirement rules.

Altogether, our paper makes several contributions to the literature. First and foremost, we emphasize the importance of considering potential UI and retirement interactions when designing UI policy. As concerns about aging populations and the sustainability of pension schemes grow and lead to retirement reform, policy interactions imply this will also alter the effects of UI and the impacts of future UI policy changes. Several papers have shown that generous UI benefit durations may be used as a bridge-to-retirement (Winter-Ebmer, 2003; Kyrrä and Wilke, 2007; Kyrrä and Ollikainen, 2008; Lalive, 2008; Tuit and van Ours, 2010; Baguelin and Remillon, 2014; Dlugosz et al., 2014; Inderbitzin et al., 2016; Kyrrä and Pesola, 2020; Riphahn and Schrader, 2022). Our

key innovation is that our model explicitly endogenizes this behavior as a function of the policy environment, allowing us to understand how *changes* to retirement rules alter the effect of UI for workers of different ages. One direct implication of our estimates is that extrapolating reduced-form evidence of UI extensions from younger workers (as reviewed in [Schmieder and von Wachter \(2016\)](#)) to older workers can be very misleading — in our case by an order of magnitude. The extent to which this is the case depends on retirement policies.⁸

The interaction effects for older workers are so large that they alter the welfare assessment of UI extensions for all workers. Consider an economist evaluating the PBD extension in Germany in the 1980s using the Baily-Chetty framework ([Chetty, 2008](#)). If this hypothetical economist based her estimate of the behavioral cost of the policy for all workers solely on intensive margin (RD) estimates of the policy ([Schmieder et al., 2012](#)), she would miss its extensive margin effects on older workers and, consequently, vastly underestimate the policy’s total moral hazard cost.

Our work also relates to a literature focused on Germany’s particular unemployment rate history. The drivers of Germany’s stark labor market improvements since the mid to late 90s have been the subject of many studies with authors highlighting factors ranging from the Hartz reforms to Germany’s governance structure (e.g. [Dustmann et al., 2014](#); [Hochmuth et al., 2021](#); [Hartung et al., 2022](#)). There is perhaps no more striking example of both Germany’s initial sluggishness and subsequent improvements than the massive rise and later decline in the unemployment rates among workers in their late 50s since the 1990s. We present novel evidence that changes in UI and retirement policies jointly played a substantial role in driving these unemployment rate trends.

While Germany’s frequent and sizable policy variation is instrumental in our analysis, we believe our findings about how retirement rules can alter the effects of UI for those close to retirement are relevant outside of the German context. [Mirkin \(1987\)](#) discusses UI-retirement pathways for Austria, Belgium, Denmark, Finland, France, Netherlands, Portugal, Sweden. More recent reduced-form evidence documents excess UI inflows among older workers in Austria ([Inderbitzin et al., 2016](#)), Finland ([Kyyrä and Ollikainen, 2008](#)), and Denmark ([Larsen and Pedersen, 2008](#)). Indeed, in 1995, these countries, like Germany, had an unemployment rate for older workers about twice as high as that of younger workers (see [Figure G.1](#)).⁹ Many European countries also provide more generous UI to older workers and are often interested in how unemployment reforms might differently affect older workers.¹⁰ Our work provides insight (and a potential modeling approach)

⁸UI inflow responses play an important role in our model. In highlighting the importance of UI inflow responses, we join a nascent literature emphasizing the potential importance of UI-induced inflows into non-employment ([Hartung et al., 2022](#); [Jäger et al., 2023](#); [Jessen et al., 2023](#)). Our focus is on how these effects are shaped by other institutions.

⁹Figures and tables starting with G and H are in the Online Appendix.

¹⁰[Michelacci and Ruffo \(2015\)](#) identify age-dependent UI benefits as a key parameter in optimal UI design.

to help better understand the potentially heterogeneous impacts of UI extensions for older workers.

Last, while our focus is on UI-retirement interactions, we think that interactions between UI and non-UI institutions more broadly (for e.g. welfare) are worthy of additional policy and research attention.¹¹ Indeed, our model suggests that the effect of the same UI extension differs, at all ages, under differentially generous post-UI welfare assistance.

2 Institutional Background and Data

2.1 Unemployment Insurance

The German unemployment insurance system provides income replacement to eligible workers who lose their job. Before 1985, eligible workers were entitled to at most 12 months of benefits. Net replacement rates (i.e. benefits divided by post-tax earnings) for UI are 67-68% for an individual with children and 60-63% for an individual without children and remained relatively stable over our study period (1980–present). Beginning in 1985, numerous reforms changed the maximum UI potential benefit duration (PBD) in a manner that tied the maximum PBD to recipients' exact age at the beginning of their UI spell.¹²

Reforms in 1985 and 1987 increased maximum PBDs for workers age 42 and older. The most generous PBD — up to 32 months — became available to workers aged 54 and up following the 1987 reform. Reforms in 1999 and 2006 gradually decreased the generosity of the system. In 1999, age thresholds were increased, and then, beginning in 2006, maximum PBD was reduced from 32 to 18 months for workers above age 55, while everyone else could only receive 12 months. There was a modest reversal of this trend in 2008 when PBD for workers above age 50 was extended again to between 15 and 24 months (depending on age).

Figure G.2 plots maximum PBD by age for older workers in each different institutional regime.¹³ Table H.1 provides details about each reform. These policy changes provide highly useful empirical variation, both at the age thresholds and by changing incentives on when to enter unemployment if using unemployment as a bridge-to-retirement.

Individuals who exhausted UI benefits before 2005 and whose net liquid wealth fell below a certain threshold were eligible for unemployment assistance (UA). In principle, UA replacement

¹¹A number of papers estimate program spillovers between UI and other transfer programs (e.g., Lindner, 2016; Mueller et al., 2016; Leung and O'leary, 2020). While we share their focus on the interplay between institutions, our paper is distinct in that we emphasize that the non-employment effects of UI depend on these other programs.

¹²See Hunt (1995); Fitzenberger and Wilke (2010) for an analysis and discussion of these reforms.

¹³We omit the short 1985 regime in the interest of brevity and because it appears that some individuals who entered UI in 1985 retroactively benefited from the UI extensions in later years. We only plot changes in maximum PBD from age 48 to 62 in Figure G.2 to focus on the changes in PBD at older ages.

rates were between 50% and 57% (in the presence of dependent children) but lower in practice due to deductions like spousal income (see [Schmieder et al. \(2012\)](#) for a discussion). From 2005 on, UA was replaced by unemployment insurance benefits 2 (UIB II), an entirely means-tested program. Both UA and UIB II are unlimited in duration but, especially due to the means-testing, a very imperfect substitute for UI for older workers.

2.2 Pension System and Early Retirement Via Unemployment

Germany has a pay-as-you-go public pension system with high effective replacement rates. Participation is mandatory, except for civil servants and the self-employed, who are not covered by our data. Pension benefits depend on workers' earnings, years of contributions, an adjustment factor, and the type of pension claimed. In 2017, pension benefits averaged approximately 50% of post-tax earnings in the year prior to retirement ([Deutsche Rentenversicherung \(2017\)](#)).

For most of our sample period, the statutory retirement age (SRA) for a regular old-age pension remained at 65, with the only prerequisite being 5 years of contributions. Beginning with the 1947 birth cohorts in 2012, the statutory retirement age was gradually raised, reaching age 67 for cohorts born after 1964. Early retirement was possible under several alternate pathways, each with its own eligibility conditions, a normal retirement age (NRA) — the age at which unpenalized pension payments can begin — and an early retirement age (ERA) — the earliest age at which pension payments can begin. For example, the long-term insured pathway, which required 35 years of contributions, had an ERA of 63 throughout our study period. Most relevantly, the pension due to the unemployment pathway (UI pathway) allowed for retirement after an unemployment spell.¹⁴

The UI pathway provided eligible workers with an option to retire early at the age of 60.¹⁵ The eligibility requirements for this pathway were: 1) at least 15 years of contributions, at least 8 of which must have occurred in the past 10 years, and 2) being unemployed for at least one year after the age of 58 and a half. The generosity of UI benefits, combined with lenient job search requirements for older workers, made old-age pensions due to unemployment attractive. After the late 1980s, unemployed individuals aged 58 and older were exempt from actively looking for

¹⁴The full list of alternative pathways to retirement can be found in [Table H.2](#) with associated discussion in [Appendix C.1](#). These pathways are old-age pensions for long-term insured, old-age pensions for women, old-age pensions due to unemployment (and, later, part-time work), and old-age pensions for severely disabled persons ([Boersch-Supan and Wilke, 2005](#)). We note that while early retirement due to disability is quantitatively important, [Riphahn \(1997\)](#) argues that in practice this is not a close substitute to retirement via unemployment and that retirement due to disability is usually associated with a health shock.

¹⁵For our first three focal cohorts (1924, 1929, and 1935), the unpenalized NRA and ERA via the UI pathway was age 60. Persons satisfying the requirements could retire at 60 with no penalty, missing out only on the marginal benefit gains from a few additional years of pension contributions. For later cohorts, the NRA and ERA increase.

a job or other obligations.¹⁶ Entering UI voluntarily is feasible in Germany and at most lightly penalized.¹⁷

This system incentivizes workers considering early retirement to time their entry into UI around the age that allows them to transition directly from UI to pensions, without any uncovered period. Put differently, the possibility of using UI as a bridge-to-retirement introduces a kink in a lifetime budget constraint relating lifetime income to the year of exit into UI.¹⁸ This kink occurs at the bridge-to-retirement age: $ERA - P$, with P being the maximum PBD. Individuals retiring before the bridge age are forced to spend time relying on other income sources, such as a spouse or unemployment assistance (UA/UIB II) before their pension, whereas individuals who leave at or after $ERA - P$ can transition directly into retirement from UI. This reduces the value of an extra year of work after the kink, decreasing the slope of the budget constraint. In general, the size of the kink is exacerbated by the generosity of the UI system, the replacement rate gap between UI and UA/UIB II, and how generously time on UI is counted towards pension contributions.¹⁹ We show that UI entries react to the location and size of the kink in Section 3.

The NRA and ERA via the UI pathway remained at 60 until a 1992 reform. Cohorts born between January 1937 and December 1941 saw their NRA increase in steps by birth month from 60 to 65. While they could continue to retire at the UI pathway ERA of 60, they now faced an actuarial adjustment in the form of a 0.3% permanent pension reduction per each month they retired in advance of the NRA. Cohorts born after January 1946 saw their ERA increase in steps by birth month from 60 to 63, ending with cohorts born in December 1948. This meant that these cohorts could no longer claim their pensions at age 60, even with a penalty. The ERA remained at age 63 for cohorts born between 1949 and 1951. The entire UI pathway was eliminated for cohorts born on or after January 1st, 1952.

2.3 Firms, Unions and Works Councils

Firms' incentives play an important role in workers' early exit from the labor force over our time period. After labor shortages in the 1960s and 1970s and extremely low unemployment rates ($\sim 1\%$), the German labor market worsened sharply after the 1973 oil crisis and even more so during

¹⁶This so-called "58er-Regelung" was formally introduced at the end of 1985 and in place until the end of 2007.

¹⁷A worker may be sanctioned if she quits a job voluntarily. These sanctions take the form of losing the first few weeks of benefits and vary from a 4-12 week penalty over the study period, but these sanctions do not always seem to be applied, could be offset by separations payments from firms, and are small relative to the length of maximum PBD. All told, they appear insufficient to offset the appeal of using UI as a pathway into retirement.

¹⁸Figure G.3 plots the evolution of stylized lifetime budget constraints for select cohorts experiencing different UI and pension regimes. Appendix C.2 describes how these budget sets are constructed.

¹⁹In practice, unemployment counts as an 80% contribution year calculated on pre-unemployment wages.

the 1982 recession. Shrinking labor demand led to fast-rising unemployment. Facing employment protection laws and powerful unions and work councils, firms and employer organizations sought to downsize employment through voluntary means by negotiating collective labor agreements (CLAs) and ‘social plans’ with their workforce. These agreements typically offered severance packages to older workers to voluntarily quit the firm and were often tied to a specific age threshold. These severance packages effectively constituted a way to buy workers out and represented a form of a mutually agreed-upon ending to the employment relationship. Appendix C.3 provides additional details.

Whether or not a worker would be willing to accept a severance package would depend on the worker’s outside option. In a labor market with high unemployment rates, like that in the 80s and 90s, exiting a job in one’s late 50s often meant accepting never to find work again, making the availability of unemployment benefits a crucial factor. Firms and labor unions who negotiated were aware of the institutional setting and would take the structure of UI benefits into account when negotiating workforce reductions and exit packages as part of CLAs. Indeed, [Trampusch \(2005\)](#) states that as early as the 1970s, “employees agreed to voluntary redundancy (that is they agreed to become unemployed at age 59) and began to draw unemployment pension after the lapse of unemployment benefits [...] Enterprises made this option attractive by topping up unemployment benefits with redundancy payments [...] Social plans providing for early exit spread quickly during the employment crisis of the 1970s and 1980s [...] work councils were more than happy to facilitate the exit of older workers under the generous terms offered by the social security system. In fact, they often found themselves under considerable pressure from older workers who wanted to retire under the existing provisions.”

These practices only gained steam in the 1980s and 90s as unemployment spiked, UI benefits were expanded to a maximum of 32 months, and CLAs with severance pay provisions proliferated. CLAs delineating retirement packages were often implemented at the sectoral level but could be specific to individual firms. The details of these CLAs, including the earliest exit age and the corresponding severance package, varied (see [Trampusch, 2005, 2009](#)), but tended to take age discontinuities induced by the UI and public pension system into account. [Trampusch \(2005\)](#) writes, “a side effect of the [law allowing older workers to draw unemployment benefits for a maximum of 32 months] was effectively to turn the previous ‘59 rule’ into a ‘57 rule’, as early retirement became even more attractive to firms. Now firms could retire employees at age 57. Workers could receive unemployment benefit [for] a period of thirty-two months, and then take advantage of the pension due to unemployment at age 60.” In cases where firms encourage workers to exit at those age thresholds with severance packages, one can view CLAs as a mechanism of

how age discontinuities lead to extensive margin responses. Of course, other factors could also influence the precise details of CLAs and associated age limits, potentially leading to bunching in UI inflows at age thresholds not directly related to retirement or UI institutions. CLAs using other forms of early retirement emerged as well and applied often to employees at age 55 (see Appendix C.3 for more detail).

2.4 Data

We use German Social Security data – the Integrated Employment Biographies (IEB) – from the Institute for Employment Research. This data provides detailed information about employment start and end dates, earnings, unemployment insurance spells, and various demographic characteristics for the years 1975 to 2017.

Sample Selection We study individuals’ labor market dynamics close to retirement age at the birth-year cohort level. While we ultimately use data from all birth cohorts from 1924–1964, for presentation purposes we initially focus on 6 cohorts that (a) represent periods of different UI generosity at older ages and (b) are not directly affected by a UI reform close to retirement: 1924, 1929, 1935, 1941, 1945, 1950, and 1952. Later, we will fit our model to three of these (1929, 1935, and 1950) and use the remaining three cohorts to visualize how our model performs out-of-sample in different regimes.²⁰ We primarily focus on West German men. We focus on men because for most of our sample men and women faced different retirement rules due to the presence of the women’s pension. This women’s pathway created different incentives to enter UI as compared to men (with women facing generally more muted incentives due to the ability to retire earlier, often with lower penalties, and without a preceding UI spell). Nevertheless, we discuss and report the full suite of reduced-form and structural results for women in Section 6 and Appendix F. We focus on West Germany as we do not observe employment histories for East Germany before reunification.

We select individuals with a stable employment history at age 50. Specifically, we select individuals who are employed on their 50th birthday and have worked continuously over the previous three years without any UI receipt. We only count periods of social security reliable employment, thereby excluding, for example, individuals who have only worked in marginal employment or other non-standard employment relationships. This employment history restriction increases the likelihood that these individuals are eligible for the maximum possible UI PBD, which can require

²⁰This helps keep exhibits focused and digestible, even though our eventual policy counterfactuals will be based off of model simulations for all cohorts between 1924 and 1964 (for transparency, we also show model fit for each of these cohorts in the Appendix). The specific institutional features affecting these cohorts are summarized in Table 1 and discussed further in the next section.

up to 6 years worked out of the previous seven years, but of course also means our focus is on older workers with high labor force attachment. In addition, we exclude some industries known for having special retirement policies or CLAs linked to age 55. Namely, we exclude mining and steel. For cohorts born in or after 1937, when CLAs expanded, we also exclude several additional industries, listed in Appendix A, with likely CLAs linked to early retirement at age 55.

Monthly Panel We generate a monthly balanced panel of each birth cohort that tracks an individual’s labor market status since age 50.²¹ We center the data around the cohort- and individual-specific bridge-to-retirement age, so that the first month after the bridge-to-retirement age starts with the exact date an individual faces a bridge to retirement. For all months, we assign individuals to one of five exclusive labor market states. Individuals can be employed (E), which includes all social security reliable employment, or in registered unemployment (UI), which consists of all periods of UI receipt. In addition, individuals can be outside of these observed employment and unemployment states.²² Here we distinguish between non-observed unemployment (Nu), which entails up to 3-month interruptions between E and UI, and temporary withdrawal from the labor force (Nt), which includes temporary employment interruption as well as interruptions between E and UI lasting longer than three months. Finally, individuals can withdraw permanently from the labor force (Np), denoted by an exit from E or UI that is not followed by any other E or UI spell. We construct all possible transitions between states where a transition is defined by comparing the current and previous state of an individual.

To plot UI inflows by age and to generate the moments used in structural estimation we condense these five states into three: Employment (E), Unemployment (UI or Nu), and Non-Employment (Nt or Np).²³ Appendix A contains additional details.

Regression Discontinuity Sample We construct a separate inflow sample into UI receipt to study the intensive margin responses to PBD extensions via a regression discontinuity design. Our sample construction largely follows Schmieder et al. (2012), with the main difference that we also include older ages and exclude mining and steel sectors for consistency. The sample is very similar to the cohort data except that we require individuals to have a work history such that they would qualify for the maximum PBD on the more generous side of the age discontinuity. Appendix B

²¹We also generate a complementary quarterly panel that we use in the structural estimation.

²²This includes individuals out of the labor force in genuinely unobserved states such as retirement, but also marginal employment or second-tier unemployment assistance that can sometimes be observed in the data but is not part of our E or UI definition.

²³If workers are sanctioned at the beginning of UI entry, they appear as Nu in the data and the relevant transition from work to unemployment occurs at the E to Nu transition.

has additional detail.

3 Reduced-Form Evidence

This section documents how older workers respond to UI PBD and retirement policy changes. Section 3.1 shows that UI inflows spike at the bridge-to-retirement age. Section 3.2 presents regression discontinuity (RD) estimates of the effects of PBD extensions for older workers. Together, these UI inflows and our RD estimates provide the moments that underlie the structural estimation described in Section 4.

3.1 Graphical Evidence of Extensive Margin (UI Entry) Responses

First, we document the behavior of older individuals entering UI over three decades. We present evidence of sizable extensive margin UI responses at the bridge-to-retirement kink and show that UI inflows react to UI and retirement policy changes.

Figure 2 shows the number of individuals entering UI by age for six select cohorts, each chosen to represent a different institutional regime (see Table 1). We opt to display these annual birth cohort-level graphs to keep retirement rules constant within-figure. When constructing cohort-by-cohort figures, the state of the economy is not fixed at one point in time, so we also plot the prevailing West German unemployment rate at the time for reference. Furthermore, since UI rules changed over time and were often tied to age at UI entry, UI entrants at different ages in the same cohort can have different maximum PBDs (see Table H.1). We convey this in the figure using the differently shaded gray boxes at the bottom.²⁴ Graphs of UI entrants by calendar year offer different trade-offs but ultimately yield a similar picture and are available upon request. Figure G.5 complements Figure 2 by plotting mean non-employment duration (until age 63) by age for each cohort. We now discuss each cohort in turn.

1924 Cohort Figure 2 (a) shows UI inflows for the 1924 cohort. Note that UI entries prior to age 59 rise with the unemployment rate (the dashed line). When this cohort was younger than age 61, their PBD was 12 months. Cohorts born before 1937, including this cohort, could retire without penalties as early as age 60 following a year of unemployment insurance. Since PBD was 12 months, individuals in this cohort could enter UI at age 59 and subsequently retire 12 months

²⁴From the perspective of a single cohort, UI can change for two reasons. It can change at age cutoffs (represented by the dashed red lines in Figure 2) which can be anticipated years in advance. Alternatively, UI can change above a certain age in a cohort due to a policy change that would not necessarily have been known before its implementation.

later without gaps. This ‘bridge-to-retirement’ pathway is indicated by the red and blue shaded areas under the figure.

We observe clear bunching in UI entries at age 59, precisely the age at which individuals can transition into retirement immediately following UI expiration. There is no comparable bunching elsewhere. Almost 4,000 individuals (more than 3% of a cohort of 128,000 workers), enter UI in the exact month they turn 59, with elevated inflows in the subsequent months as well. Figure G.4 (a) shows that these and past inflows imply that almost 10% of the entire birth-cohort is receiving UI between the ages of 59 and 60. Figure G.5 (a) plots the average non-employment duration (until age 63) for the individuals in Figure 2 (a). Non-employment durations at age 59 are very close to the maximum of 48 months (that is from age 59 to age 63, where we censor these durations), supporting the idea that the vast majority of entrants at this age are using UI as a bridge to retirement. Together, this is clear evidence of sizable, extensive margin responses to UI policy.²⁵ This view is reinforced below, where we examine UI entries for later cohorts facing longer PBDs and hence kinks at different, earlier ages.

1929 Cohort Figure 2 (b) shows UI entries for the 1929 cohort. This cohort faces the same retirement institutions as the 1924 cohort but has longer PBDs in their late 50s. Specifically, those who enter UI at age 58 have 24 months of PBD. This shifts the ‘bridge-to-retirement’ age to 58. Consistently, we now see clear bunching at age 58. Note that the UI retirement pathway also requires being unemployed for at least 12 months, implying there still is a small kink at age 59, and indeed, we note some excess mass at 59.

This figure also clearly shows bunching in UI entries at other non-kink points, particularly at ages 55 and 57. These likely represent collective bargaining agreements to release or buy out workers once they turn 55 or 57. This type of bunching is almost entirely absent in the years leading up to and including 1982, consistent with the timing of the first major CLAs specifying retirement ages (see [Trampusch et al., 2010](#)). Figure G.5 (b), which plots average non-employment duration, again suggests that almost all UI entrants at age 58 use UI as a bridge to retirement.

1935 Cohort The 1935 cohort continues to face the same retirement institutions as the prior cohorts but is entitled to even more generous UI. Workers entering UI at or after age 54 had a PBD of 32 months. Accordingly, Figure 2 (c) shows that UI entries exhibit substantial bunching at precisely age 57 and 4 months (32 months before the early retirement age of 60). We continue to see some excess bunching at age 59 (given the UI pathway’s eligibility requirement of 12 months

²⁵This bunching is reminiscent of bunching of retirement inflows at pension benefit thresholds in Austria ([Manoli and Weber, 2016](#)) and Germany ([Seibold, 2021](#)), except that in our setting labor force exits occur through the UI system.

of UI) as well as at some other non-kink points. Figure G.5 (c) confirms that people entering at the bridge-to-retirement age remain non-employed for close to the maximum duration.

1945 Cohort The 1945 cohort faces less generous retirement rules. This cohort could still retire at the ERA of 60 following a year of unemployment, but doing so meant accepting an 18% permanent pension reduction since the NRA was 65. PBD remained at 32 months for workers above age 54. In Figure 2 (d), we continue to see bunching at age 57 and 4 months, but the bunching mass is substantially smaller than it was for the 1935 cohort, consistent with the large penalty for retiring early. Moreover, in Figure G.5 (d) we now see that average non-employment durations drop substantially at age 57 and 4 months relative to what they were for the 1935 cohort at the same age. This suggests that some workers are returning to work instead of retiring at the penalized ERA.

1950 Cohort The 1950 cohort faced both reduced PBD at later ages and stricter retirement laws. Individuals born in 1950 could no longer retire early via unemployment at 60, but instead could draw pensions no earlier than age 63. They had to wait until age 65 to draw pensions without penalties (7.2% for retiring at 63). Figure 2 (e) shows some bunching at 61, consistent with an early retirement age of 63 and two years of PBD. Importantly, since the bridge-to-retirement age has moved to 61, the distribution of entries is now relatively smooth at ages 57-59.

1952 Cohort This cohort was no longer allowed to retire early via unemployment. However, individuals eligible for the old-age pension for the long-term insured could still retire at age 63. Since many in our sample were likely eligible for the long-term insured pathway, this cohort is not *effectively* that different from the 1950 cohort. Indeed, the distribution of UI entries continues to look relatively smooth before 61, tracking the official unemployment rate, and we continue to see some bunching at age 61.

We also note some bunching at age 58 (dashed red line), where PBDs are extended discontinuously. The 1952 cohort would have known that their PBD would increase from 18 months to 24 months at age 58 several years prior to turning 58. We discuss UI entry responses to these discontinuous increases in PBD as a result of the various PBD age cutoffs further in Section 3.2.

Overall, we observe clear bunching into UI at the bridge-to-retirement age. The bunching mass responds to UI extensions. There is also some bunching at other kink points in the distribution, at the age 59 kink due to the requirement that UI spells be at least one year long prior to claiming retirement-via-UI, and on occasion at age cutoffs where PBDs are extended discontinuously. Finally, we also see bunching at non-kink points related to CLAs, suggesting that the employer

side plays an important role. While we cannot easily identify the extent to which responses come from workers or firms, it is clear that a full accounting of the effects of UI extensions on non-employment needs to consider these extensive margin responses. Given that PBD extensions shift UI entries earlier (and many of these remain permanently non-employed), the non-employment effects of PBD extensions for older workers could be substantially larger than those for younger workers.

3.2 Regression Discontinuity Estimates of the Effects of PBD Extensions

In addition to changing UI inflows, PBD extensions also affect non-employment durations *conditional* on entering UI. These ‘intensive margin’ effects could vary with age and proximity to retirement. As in [Schmieder et al. \(2012\)](#), we exploit the numerous age cutoffs at which PBD increases discontinuously (see Figure G.2) in an RD design to estimate intensive-margin non-employment effects of UI extensions.²⁶ How these effects vary with age is interesting in its own right, but they also provide valuable reduced-form moments that discipline our structural estimation.

Starting in 1987, there are 12 age cutoffs across 4 distinct periods at which we can potentially estimate the non-employment effect of UI extensions using RDs (see Table H.1). These estimates require the standard RD assumptions, including no sorting into UI around age cutoffs. As we saw above, this is not always clearly satisfied at older ages. As a result, we only report estimates for the 8 cutoffs below age 55 for which density violations appear minimal. Appendix B discusses the sample and cutoff selection in more detail.

At each age cutoff, we estimate the following RD specification:

$$y_{ia} = \delta \mathbf{1}(a_i \geq A) \Delta PBD + f(a) + X_i \beta + \varepsilon_{ia} \quad (1)$$

y_{ia} is the non-employment duration (capped at 36) for individual i of age a , a_i is the age at the time of UI entry (measured on the daily level), and $\mathbf{1}(a_i \geq A)$ is a dummy variable indicating that an individual is above the age threshold A , where benefits are extended discontinuously by ΔPBD months. In this specification, δ measures the effect of a one-month increase in PBD. We specify $f(a)$ as a linear function, allowing different slopes on each side of the cutoff. X_i is a vector of additional controls. We use a rectangular kernel and cluster standard errors at the day level. We use a bandwidth of two years but restrict it to one year on the right side of the 49 and 54 age cutoffs during the 1987-1999 period due to the presence of other discontinuities at 50 and 55.

²⁶[Schmieder et al. \(2012\)](#) analyze age discontinuities up until age 49 and [Schmieder and Trenkle \(2015\)](#) at age 50. We extend this work to age discontinuities in the 50s.

Figure 3 (a) and Table H.4 show RD estimates of the jump in the density at the age threshold. Consistent with Schmieder et al. (2012), UI entries and other pre-determined outcomes are smooth around the younger age cutoffs. In contrast, sorting at the cutoff is a concern at the oldest age cutoffs. Consequently, we do not report RD estimates for the age 55 or higher cutoffs. Moreover, to minimize any potential bias due to sorting at the younger cutoffs, we exclude 2 months on each side of the cutoff – the donut hole – in all our regressions. Self-contained Appendix B includes additional details as well as validity and robustness checks.

Figures 3 (c) and (d) provide two example RD figures, plotting mean non-employment duration (capped at 36 months) by age around the age 54 cutoff for the 1987 - 1994 period and around the 52 cutoff for the 1999-2006 period. Figure 3 (b) plots the 8 RD estimates for different age cutoffs with and without controls. These estimates are also reported in Table 2. Each dot in the figures corresponds to a marginal effect of one additional month of potential UI duration estimated at an age cutoff. The estimates average 0.09, suggesting that for each month of additional UI, affected workers spend around three more days in non-employment.²⁷ Estimates are relatively insensitive to controls. We do not have sufficient power to detect any clear variation by age, though we obtain the largest point estimates at the older ages. Importantly, we will target the 0.128 estimate at the age 52 cutoff between 1999 and 2006 in our structural estimation.

4 Dynamic Labor Supply Model

In this section we develop the life cycle model of labor supply, job search, and retirement decisions that we will fit to the preceding reduced-form moments using a method of moments estimator.

We believe our setting is an ideal one for a structural model, since we have clean reduced-form moments to target, but no natural way to generate meaningful counterfactuals without imposing additional structure. Prior work has focused on estimating RDs in the presence of manipulation of the forcing variable (see e.g.: Card and Giuliano (2014); Gerard et al. (2015); Barreca et al. (2016); Hoxby and Bulman (2016)), but this manipulation has typically been treated as a nuisance as opposed to an object of interest.²⁸ In our setting, whether and when to enter UI is a meaningful outcome. Bunching approaches (Saez, 2010; Kleven, 2016) can and have been used to estimate labor supply elasticities in similar contexts (e.g. Brown, 2013; Manoli and Weber, 2016), but have their limitations. They are typically based on a simple static life-cycle model that ignores the possible interactions of responding along the intensive and extensive margin. They are also hard to

²⁷Note that the point estimates are slightly smaller than in Schmieder et al. (2012), which is mostly due to our sample of only men. Table H.3 shows generally larger effects for women.

²⁸Citino et al. (2022) is an interesting exception.

reconcile with the fact that inflows into unemployment could be either voluntary or non-voluntary, can vary over time with the business cycle and changing labor-force attachment, and can be sensitive to ad hoc restrictions about the counterfactual distribution (Blomquist and Newey, 2017).

4.1 Model Set Up

The model is designed to capture work and retirement decisions over the lifecycle and includes unemployment and job search dynamics. In contrast to previous research with life cycle models that typically allow for a single or sometimes two unemployment states with no dynamics, we model unemployment as a fully dynamic process. This approach enables us to capture the duration of UI benefits and labor supply responses to changes in the structure of UI in a natural way.²⁹ This has the added benefit that our parameter estimates for the job search part can be compared with previous estimates of job search models (e.g., Paserman, 2008; DellaVigna et al., 2017, 2022).

States and Value Functions. Workers can be in one of three states: employed (E), unemployed (U), or out of the labor force (O). We assume that once a worker drops out of the labor force, she will not return; hence O is an absorbing state. We call a worker non-employed N if the worker is either unemployed or out of the labor force.

We assume that workers produce output p_t in each period, where p_t is i.i.d. according to some distribution $F(p)$. A critical state variable in our model is the total unemployment duration of a worker d^U . In practice, we will estimate our model starting at age 50, so that d^U will be the duration in unemployment since then. To keep the state space manageable, we also assume that workers initially are eligible for the maximum benefit duration but do not reaccumulate benefit eligibility if they are reemployed after losing a job. Under this assumption d^U is sufficient to both calculate remaining UI benefit durations for each individual as well as the pension of an individual if the person retires. We can therefore write the value functions as functions of p_t and d^U . Note that d^U is deterministic, while p_t is uncertain.³⁰

Workers have a utility function $u(\cdot)$, are paid $w_t(\cdot)$, and experience disutility from working (η).

²⁹Other structural life cycle papers (e.g. Haan and Prowse, 2010; García-Pérez and Sánchez-Martín, 2015; Michelacci and Ruffo, 2015) typically assume workers receive UI forever or model UI as a Markov process with a fixed transition probability to exhaustion.

³⁰A full accounting of the benefit eligibility in the presence of multiple unemployment spells would require to separately keep track of d^U as well as the remaining benefit duration in each unemployment spell and employment duration in each employment spell. This quickly becomes computationally very challenging due to the curse of dimensionality. As long as repeated unemployment spells with long in-between employment spells are rare, which they are in practice, our approach is only a very minor simplification that vastly reduces computational complexity.

The value of employment is:

$$V_t^E(p_t, d^U) = u(w_t(p_t)) - \eta + \beta E_{p_{t+1}} [\max \{V_{t+1}^E(p_{t+1}, d^U), V_{t+1}^N(d^U)\}] \quad (2)$$

For tractability, we will assume that workers have all the bargaining power and firms make zero profits so that $w_t = p_t$ in all periods.³¹ Workers will separate from their job whenever the expected value of future non-employment exceeds that of employment. This could occur for several reasons: workers could receive a low productivity draw (p_t) such that the employment relationship is no longer better than the worker's outside option. Alternatively, outside options could improve, such as an increase in UI or retirement benefits, which can push up $V_t^N(d^U)$ for workers close to the retirement age and increase the rate of job separations. We also allow for exogenous job destruction at the rate Λ_t . To operationalize this, we assume that workers face a (large) negative productivity shock ($-L$) with probability Λ_t . Otherwise, they draw a productivity level p_t from a lognormal distribution. These distributional assumptions enable us to derive closed-form solutions to all eventual transitions generated by the model.

When workers enter unemployment they engage in costly job search and receive payments $B(d^U)$. If the individual still has UI benefits remaining ($d^U < P$), she will receive UI benefits ($B(d^U) = b$). If not, the individual receives y^u ($B(d^U) = y^u$), which can be interpreted as unemployment assistance.³² An unemployed individual searches for a job and chooses an optimal level of search effort s which is normalized to the probability of finding a job. Generating search effort comes at a cost $\psi(s)$ which is increasing and convex. Finally, whether or not an individual receives a job offer, she can decide to retire at the end of the period. If she remains unemployed d^U increases by one period. The value of unemployment is thus:

$$V_t^U(d^U) = u(B(d^U)) + \max_s \{ \beta s E_{p_{t+1}} \max [V_{t+1}^E(p_{t+1}, d^U + 1), V_{t+1}^N(p_{t+1}, d^U + 1)] + \beta(1 - s) E_{p_{t+1}} V_{t+1}^N(d^U + 1) - \psi_t(s) \} \quad (3)$$

For increasing and convex $\psi(s)$ at an interior solution, optimal search effort will be given by

³¹Alternatively one could assume Nash bargaining over the surplus, but in that case, there is no closed form solution for the expected value of employment and solving the model becomes computationally challenging. Since we are not trying to match wages, this simplification strikes us as a worthwhile trade-off.

³²In practice, we set mean (net) wages to euro 1,950. This implies an approximate gross wage of 3000, which is in line with the average gross wage for those aged 50-60 with a UI spell across our 6 primary cohorts (euro 3,282). We set $b = 1,170$ for more recent cohorts (1,230 for earlier cohorts) which is a 0.39 replacement rate on gross wages as calculated directly from the data. We set $y^u = 500$, which is approximately half of what one would receive if on UA. We halve the amount as evidence in [Schmieder et al. \(2012\)](#) suggests that, due to deductions, the average UA benefit actually received falls substantially below the 53% nominal replacement rate on net wages and only 50% of UI exhaustees take-up UA.

$$s^* = \psi^{t-1} (\beta E \max [V_{t+1}^E(p_{t+1}, d^U + 1), V_{t+1}^N(d^U + 1)] - \beta V_{t+1}^N(d^U + 1)).$$

At any point, a worker can choose to transition to being out of the labor force O , which is an absorbing state. The value of O depends primarily on the value of one's pension y_t^p as determined by prevailing retirement institutions. y_t^p will depend on work history (d^U) and age at which the worker retires. Specifically, for a worker who lives until T^{Last} and is eligible to receive a pension at T^{ERA} , the value function for being out of the labor force is:

$$V_t^O(d^U) = \begin{cases} \sum_{k=t}^{T^{ERA}} \beta^{k-t} u(y^o) + \sum_{k=T^{ERA}}^{T^{Last}} \beta^{k-t} u(y_t^p) & \text{if } t \leq T^{ERA} \\ \sum_{k=t}^{T^{Last}} \beta^{k-t} u(y_t^p) & \text{if } t > T^{ERA} \end{cases} \quad (4)$$

The value of the pension depends on the relevant, cohort-specific retirement institutions in addition to the individual's work history (d^U). Individuals accrue pension benefits while they work or are on UI benefits (at 80%), but not otherwise. Starting with the 1937 cohort, people retiring at the ERA but before the NRA, receive a penalty. We assume all individuals in our sample are eligible for the long-term insured retirement pathway. Individuals are eligible for retirement via the UI pathway as long as they have one year of unemployment history (d^U). We allow individuals to choose the best retirement option available. In Appendix E.5, we outline in detail how we calculate V_t^O for each cohort.

Finally, the value of non-employment is defined as:

$$V_t^N(d^U) = \max (V_t^U(d^U), V_t^O(d^U)) \quad (5)$$

Heterogeneity in the disutility of work. Under our distributional and functional form assumptions, the preceding model generates closed-form solutions for all transitions between states (e.g. E to U) and can be used to calculate the expected non-employment duration for a given value of η . The closed form solutions, along with additional details, can be found in Appendix D.

We allow for heterogeneity (beyond randomness from the productivity distribution $F(p)$), by modeling different types of workers with varying levels of disutility of work η . We assume that individual workers draw their η from a cohort-specific distribution, integrating transitions and non-employment durations over the entire distribution. Specifically, we assume that η is normally distributed with mean $\bar{\eta}_{cohort}$ and a fixed standard deviation η_{sd} across cohorts. We implement this in practice by simulating the model for 25 different values of η and use Simpson's rule to approximate the full integral over the η distribution whenever we calculate cohort-level transitions and non-employment durations.

How does the model generate bunching? Individual workers in the model enter UI when the value of non-employment exceeds the value of employment: $V_t^N > V_t^E$ (see equation 2). As workers age, the value of employment falls and the value of non-employment rises as workers get closer to the point when they can retire. In the absence of a productivity shock (non-random p_t), a given worker type would have a single optimal age to exit employment and go into UI/retirement. The distribution of worker types η generates a smooth employment exit age distribution. The UI bridge age creates a kink in the value of non-employment, where V_t^N increases rapidly relative to V_t^E and thus many η types locate (bunch) at the bridge age. Without productivity shocks, bunching would be sharp at the kink point. The productivity shocks p_t generate random variation in V_t^E , which in turn somewhat spreads out the sharp bunching at the bridge age (some people exiting slightly before or after) and produces employment exits at younger ages.

4.2 Assumptions and Estimation

Here we lay out the functional forms and distributional assumptions underlying our baseline model and discuss estimation. Productivity p_t will be drawn from a mixture distribution in which workers have Λ_t probability of facing a (large) negative productivity shock ($-L$) that destroys the job with certainty. Meanwhile, with probability $1 - \Lambda_t$, workers draw a productivity level p_t from a lognormal distribution. This allows for exogenous job destruction at the rate Λ_t . Formally, p_t is drawn from a mixture distribution defined by $f(\ln(p_t)) = \Lambda_t f^L(\ln(p_t)) + (1 - \Lambda_t) f_{p,\sigma_p}^N(\ln(p_t))$ where $f^L(\ln(p_t)) = 1$ if $\ln(p_t) = -L$ and $f^L(\ln(p_t)) = 0$ otherwise and f_{p,σ_p}^N is a normal PDF with mean p and standard deviation σ_p . This allows for closed-form solutions to all eventual transitions generated by the model. For sufficiently large L the CDF of the mixture variable is effectively $F(\ln(p_t)) = \Lambda_t(1) + (1 - \Lambda_t)F_{p,\sigma_p}^N(\ln(p_t))$ where F_{p,σ_p}^N is the normal CDF with mean p and standard deviation σ_p .³³ In practice, we will allow the exogenous job destruction rate Λ_t to vary with the national male unemployment rate (UR). Specifically Λ_t will be a logistic function $\Lambda_t = \frac{1}{1+e^{-(\lambda_1+\lambda_2 UR_t+\lambda_3 \Delta UR_t)}}$ with parameters λ_2 and λ_3 allowing Λ_t to vary with the level and year-on-year change in the national male UR. We assume workers have log utility $u(\cdot) = \ln(\cdot)$. Firms pay the worker $w_t = p_t$ in all periods. Workers draw disutility η from a normal distribution ($\eta \sim N(\eta_{mean,cohort}, \eta_{sd})$). The search cost function is based on DellaVigna et al. (2022) with some

³³This definition applies for the relevant sample space of the lognormal part of the distribution (which is assumed positive), and it assumes that the CDF of the degenerated random variable is equal to 1 for (almost) every value of that sample space.

added flexibility. Specifically, we assume:

$$\psi_t = k_0 + k_1 \mathbf{1}(d^U = 0) + e^{k_2 \times d^U} \times k_3 \frac{s^{1+\gamma}}{1+\gamma} \quad (6)$$

Where k_0 is a fixed cost of being in unemployment, k_1 a fixed cost of entering unemployment for the first time, k_2 allows search to become more costly over the unemployment spell, and k_3 and γ govern the slope and curvature of the job search function.

We estimate the model using a minimum distance estimator to match our key empirical reduced-form moments. Denoting the parameters of the structural model as ξ , the vector of moments predicted by the model as $m(\xi)$, and the vector of observed moments as \hat{m} , the estimator chooses parameters $\hat{\xi}$ that minimize the distance $(m(\hat{\xi}) - \hat{m})' W (m(\hat{\xi}) - \hat{m})$ where W is a weighting matrix.

For moments, we focus on 3 cohorts: 1929, 1935, and 1950, where we match the quarterly E to U flows and average non-employment durations (until age 63). Furthermore, we use the RD estimate for $\frac{\partial Nonemp}{\partial P}$ for men at the age 52 cutoff of 0.128 (Table 2) to inform the intensive margin effect of UI for the 1950 cohort.

Our weighting matrix is block diagonal and uses a full covariance/variance matrix for all E to U transitions based on 200 simulations using the empirical data, and a diagonal variance matrix for both non-employment durations and $\frac{\partial Nonemp}{\partial P}$ based on the standard errors obtained when estimating these in the data. For the intensive margin RD moment, we use a larger weight (100x) since this is a causal estimate that we have significant confidence in given the research in this paper and many other well-identified estimates from the literature, and we want to make sure our fitted model generates realistic predictions for intensive margin responses.³⁴

We estimate the following parameters: The standard deviation of the productivity distribution (σ_p); three parameters that allow the exogenous job destruction rate Λ_t to vary with the level and year-on-year change in the national male unemployment rate ($\lambda_1 - \lambda_3$); five parameters in the search cost function ($k_0 - k_3$, and γ); and four parameters governing the η distribution: $\bar{\eta}_{1929}$, $\bar{\eta}_{1935}$, $\bar{\eta}_{1950}$, and η_{sd} (which does not vary by cohort). The institutional parameters used in the model are outlined in Table 1.

As a second step, we refit our model to all other cohorts. We estimate a single parameter per cohort, which is the mean of that cohort's η distribution ($\eta_{mean, cohort}$). In this estimation exercise, our target moments are transitions from E to U and non-employment durations. Refitting allows different cohorts to have different outside options or labor force attachment in a way that is not

³⁴This upweighting is in the same spirit as Armstrong and Kolesár (2021) and DellaVigna et al. (2022).

otherwise captured by retirement and UI institutions or other parameters.

The model is written in Python, using the package Numba to obtain fast numerical code via pre-compilation. We minimize the objective function using the optimization package **estimagic** (Gabler, 2022) to search for global minima using a multi-start algorithm paired with two local minimizers: Derivative-Free Optimizer for Least-Squares Minimization (DFO-LS) (Cartis et al., 2018) and POUNDERS (Wild, 2015). See Appendix E for more details.

5 Estimation Results and Model Fit

Figure 4 gauges our estimated model’s fit by comparing simulated E to U transitions and simulated non-employment durations to their empirical counterparts for the three cohorts matched in the estimation (1929, 1935, and 1950). Overall, our model captures the key empirical patterns of interest. It predicts UI inflow bunching at the bridge-to-retirement age and generally gets the size of the bunching mass right. It captures overall E to U transition trends and it matches older workers’ actual mean non-employment duration.³⁵ The model also matches other relevant data features, such as the dip in non-employment duration for the 1950 cohort between ages 56 and 58 when maximum PBD decreased. However, while the model fits the key patterns of interest well, it does not perfectly fit all the empirical moments’ features. For instance, the model systematically under-fits UI inflow spikes at ages prior to the bridge-to-retirement age (e.g. 55 and 57 for the 1929 cohort). As discussed in Section 3 in reference to Figure 2, these spikes are most likely due to collective labor agreements linked to specific ages but not to any corresponding kink in these individual’s budget sets. Consequently, nothing in our model can (nor should) generate bunching at these points. While the model does well at predicting non-employment duration for workers close to the bridge-to-retirement, it has some difficulty matching non-employment duration at younger ages: over-predicting non-employment duration for the 1935 cohort and under-predicting them for the 1950 cohort.

In addition to matching E to U transition and non-employment duration moments, our model also targets our RD estimate of $\frac{\partial N_{onemp}}{\partial P}$ at age 52 for the 1952 cohort (0.128). This is calculated as the simulated change in the non-employment duration among new UI entrants from an extra month of maximum potential benefit duration, holding the worker type distribution (of disutility of work η) among new entrants constant so as to mimic a pure intensive-margin effect. The model fits this RD moment very well (0.124) indicating that younger workers’ non-employment responses to UI extensions in our model will be close to what we would predict using reduced-form RD evidence.

³⁵Non-employment durations at each age are calculated as the expected non-employment until age 63 among first-time UI entrants.

Table H.12 column (1) shows our model’s estimated parameters and corresponding standard errors. Standard errors tend to be small, suggesting that parameters are locally identified. While our parameters are generally not directly comparable to estimates in other settings, our search cost function shares some features with those in DellaVigna et al. (2017, 2022). We estimate the curvature of the search cost function γ (i.e. the inverse of the elasticity of search effort with respect to the net value of employment) to be 0.80, which is comparable to the single type δ -discounting reference-dependent model estimate in DellaVigna et al. (2017) (0.81) as well as to the composite curvature in DellaVigna et al. (2022) estimated on German data. The slope of the search cost function (53) is comparable to that of the medium-cost searcher in the standard 3-type model in DellaVigna et al. (2017). The estimated duration dependence is larger in our setting, implying higher search costs later on in an unemployment spell, perhaps in part because we focus on older workers closer to retirement.

To simulate our model for out-of-sample cohorts we require estimates of $\bar{\eta}_{cohort}$, i.e. the cohort-specific average disutility of work. As discussed in Section 4, for all out-of-sample cohorts between 1924 and 1963, we estimate a cohort-specific $\bar{\eta}$ by refitting the model to match that cohort’s non-employment duration and transitions, holding all other parameters constant. Figure G.11 plots estimated $\bar{\eta}$ across all cohorts, revealing a relatively continuous pattern, with cohorts born prior to 1935 having lower disutility of work. The trends in $\bar{\eta}$ roughly mirror the changes in national unemployment rate between the mid-80s and early 2000s (approximately when these workers turned 60). This is consistent with $\bar{\eta}$ helping our model capture changes in the outside options of workers that are not otherwise well captured by the model’s productivity distribution or job destruction rate.

Figure 5 shows how well the model performs out of sample for the remaining three focal cohorts in Figure 2: the 1924, 1945, and 1952 cohorts, which faced different UI and retirement institutions.³⁶ Despite using parameters estimated from other cohorts (aside from $\bar{\eta}_{cohort}$), our model performs well, broadly matching overall UI inflows, the spike in UI inflows at the bridge-to-retirement age, and non-employment durations. The model still struggles to capture spikes in inflows prior to the bridge to retirement and under-predicts non-employment duration at younger ages for more recent cohorts. Overall, model fit is similar both in- and out-of sample.

Figure 5 also performs a first counterfactual exercise to illustrate how the model works. We simulate a counterfactual in which the PBD is one year longer for all individuals. Using the 1945 cohort as an example (panels c and d), we can see how this extension affects UI entries and non-employment duration at different ages. For those whose inflows are mostly unaffected by this extension, for example, younger workers who experience an exogenous job loss, responses are

³⁶Figures G.12–G.13 shows model fit for all cohorts between 1924 to 1963.

primarily governed by the standard intensive margin, $\frac{\partial Nonemp}{\partial P}$ effect estimated in the RDs.³⁷ For those closer to retirement age, the PBD extension moves the bridge-to-retirement left by one year, causing some (but not necessarily all) to enter UI up to one year earlier as can be seen in panel (c). Since these exiting individuals typically remain non-employed until retirement, this also generates a large increase in non-employment durations at the new bridge age (which, in panel (d), is at age 56 and 4 months as compared to 57 and 4 months initially) relative to the lower PBD counterfactual. At older ages, the vast majority of UI entries stay non-employed until retirement anyway, so the intensive margin effect of PBD extensions matters little.

Table H.11 shows simulated $\frac{\partial Nonemp}{\partial P}$ at different ages holding disutility of work constant, and reveals similar lessons. Notice that $\frac{\partial Nonemp}{\partial P}$ is close to 0.128 initially, and initially increasing with age (a pattern also seen in Table 2, albeit noisily). At the oldest ages $\frac{\partial Nonemp}{\partial P}$ declines, even reaching 0 for the pre-1950 cohorts, since everyone who enters UI at these ages stays non-employed until age 63, regardless of PBD. Overall, this counterfactual illustrates the mechanics of our model and how it allows for a range of responses to policy changes across the age distribution.

In order to provide a single figure that captures the key information from our model across all cohorts, we use the model to construct an analogue to Figure 1. Specifically, we simulate our model for all birth cohorts from 1924 to 1963 and obtain the resulting E to U transitions and non-employment durations. We then use these transitions and non-employment durations to predict the share of workers who are unemployed – or more precisely, non-employed following first UI entry – for each cohort \times year cell.³⁸ Consequently, at any given point in calendar time (e.g. calendar year) we can aggregate predicted unemployment shares for any given age range. We focus on ages 52-55 and 56-59, but also present some results for those 60-62.³⁹ We perform this exercise both using our model’s simulated E to U transitions and non-employment durations, as well as separately using the empirical transitions and non-employment durations.

Figure 6 (a) shows the empirical and simulated unemployment rates (as defined above) separately for each age group. The empirical unemployment rates we construct roughly follow the OECD unemployment rates reported in Figure 1. Our model fits the empirical pattern remarkably well. Notice that this exercise also serves as a joint test of fit across all cohorts’ non-employment

³⁷In practice, $\frac{\partial Nonemp}{\partial P}$ is estimated both in the model and in the data on non-employment durations that are capped at 36 months while this figure plots uncapped non-employment durations until age 63. The effect of changing PBD on these uncapped durations is larger.

³⁸To simplify this procedure and to make it directly comparable with what we can easily export from the admin data, we do this calculation assuming a constant hazard of exiting unemployment, rather than allowing for the full duration dependence. By applying this approach uniformly to both the model simulations and empirical moments, we ensure that the two unemployment rates are directly comparable.

³⁹Since everyone in the empirical data is employed at age 50, we prefer starting at age 52 to allow some time for unemployment spells to begin.

duration and transitions. At younger ages, we fit the empirical pattern closely. At older ages, we also generally do well but occasionally under-fit the empirical unemployment rate. In the early years, this is a result of under-predicting the bunching mass at the bridge to retirement; in later years it is predominantly a consequence of under-predicting non-employment durations. Nevertheless, given that we fit a relatively parsimonious model to 40 cohorts of data, holding all but one parameter constant across cohorts, the model captures the key patterns in both the empirical and OECD data very well. The model clearly captures the striking 10pp rise in the unemployment rate of workers aged 56-59 between 1983 and 1994 and its contrast with the much smaller rise in the unemployment rate of younger workers over the same period. It also captures the equally striking decline in the unemployment rate of older workers between 1994 and the mid-2000s, over a time period when the unemployment rate of younger workers barely changed.

We can now explore how counterfactual scenarios affect not just the cohort-specific moments, but how they change overall unemployment rates. Figure 6 (b) revisits the exercise from Figure 5 of increasing PBD by one year for everyone. Consistent with the changes we saw for the select cohorts in Figure 5, we find that extending PBD by one year for everyone has a limited effect on the unemployment rate of those aged 52-55. The PBD extension has close to no effect on these workers' inflows into UI but has the standard effect of lengthening non-employment durations conditional on entry. As a result, simulated unemployment rates increase, but only by a modest 0.6pp in 1994 (see Table 3). In contrast, this same PBD extension increases the unemployment rate of older workers by a comparatively large 2.5pp in 1994. This is a consequence of many older workers now entering UI a full year earlier (at the new bridge-to-retirement age) and provides a first glimpse of how the effect of the same UI extension can have substantially different impacts under differing circumstances.

6 Policy Simulations

We now use our model to perform a series of counterfactual simulations that exemplify how the non-employment effects of UI extensions depend on and interact with retirement institutions. First, we revisit the rapid rise and later fall of old age unemployment in Germany over the 1990s and 2000s and show that, because of workers using UI as a bridge to retirement, PBD extensions can account for much of the observed unemployment rate changes. Second, we show directly that the same UI extension can have different effects under different retirement policies. We conclude this section with model estimates for women and an assessment of model robustness.

6.1 Counterfactual Policies

First, we ask whether UI and retirement policy changes can explain the massive rise and subsequent decline in the unemployment rates of workers 55 and older in the mid-1990s shown in Figure 1. Figures 7 and 8 conduct a variety of counterfactual policy simulations to answer this question.

We begin by investigating what the rise in unemployment among older workers would have been had maximum PBD remained at the 1984 level of 12 months, rather than increasing to 32 months. Figure 7 (a) and (b) show, in the red dash-dotted line, what the 1935 cohort's UI inflows and non-employment duration would have looked like under this counterfactual scenario. We find that keeping PBD fixed at 12 would have massively reduced non-employment durations for workers in their late 50s, as the bridge-to-retirement age would have remained at age 59. Figure 8 (a) shows how keeping PBD fixed at 12 months affects the overall unemployment rate of younger and older workers from all cohorts. We find, at the peak in 1994, unemployment rates of workers aged 56-59 would have been 5.7pp lower (see Table 3 for a precise decomposition). In other words, PBD extensions explain 5.7pp of the 10.0pp increase (or 57%) in the unemployment rate from 1983 to 1994.

This point would have been almost entirely missed had we simply extrapolated how the PBD extensions might affect older workers using prior intensive-margin, RD estimates from workers in their late 40s. To make this point explicit, we take our baseline model simulation and fix inflows, but replace non-employment durations with what we would naively predict them to be for lower PBD (= 12 months), using an elasticity of uncapped non-employment duration with respect to PBD of 0.13 from Schmieder et al. (2012). In 1994, this 'naive' approach yields that the unemployment rate of older workers would have been 0.4pp lower ($16.1-15.7=0.4$; see Table 3) had PBD remained fixed at 12 months. Instead, when inflows also adjust, we see a 5.7pp lower unemployment rate. In other words, the naive prediction is off by an order of magnitude.

In a similar vein and in contrast to what we find for workers aged 56-59, the effects of Germany's PBD extensions on both relatively younger and older workers are much more muted, though for different reasons. Table 3 shows that, had PBD remained at 12 months, the unemployment rate of workers aged 52-55 would have been 0.4pp lower in 1994. The unemployment rate of workers aged 60-62 would have been 0.7pp lower. For younger ages the PBD change did not affect inflows, so the change in the unemployment rate is close to what we would have expected from RD estimates of $\frac{\partial Nonemp}{\partial P}$. For older workers entering UI in their 60s the primary margin of adjustment was instead through a change in inflows, since most remain non-employed until retirement once non-employed. Inflows increase somewhat at these later ages under the counterfactual (as in Figure 7 (a)), but these changes are modest since entering UI so close to retirement

is relatively unappealing.

Altogether, Table 3 column (4) shows that PBD extensions explain 50% of the overall unemployment rate of those aged 52-62 (2.4/4.8), in large part due to the massive effects these extensions had on workers aged 56-59. While other factors clearly mattered, Germany's PBD extensions played a large role in increasing the unemployment rate of workers in their late 50s in the early 1990s by shifting the bridge-to-retirement leftwards.

In Figure 8 (b), we consider a second policy simulation that leaves PBD as it was but instead imagines that the UI retirement pathway never existed, making age 63 the earliest possible retirement age available. It is of course still possible to bridge into retirement at age 63 minus maximum PBD, for example at 60 and 4 months for the 1935 cohort when maximum PBD was 32 months, but this would primarily affect UI inflows of workers aged 60 and up. The green dashed line in Figure 7 (a) shows how the 1935 cohort would have behaved had the UI pathway been closed. While there is still a lot of bunching at 60 and 4 months, this change would have greatly reduced UI inflows and non-employment durations of workers aged 60 and below. Accordingly, Figure 8 (b), which combines model simulations from all birth cohorts, shows that closing the UI pathway would have had a dramatic impact on the unemployment rates of workers aged 56-59 prior to 2006.⁴⁰ Had the UI pathway not been available to workers in pre-1946 birth cohorts, older workers' unemployment rates would have been far more comparable to those of younger workers, despite Germany's large UI reforms. Older workers' unemployment rates would still have increased faster than those of younger workers during the PBD extension years (consistent with higher $\frac{\partial Nonemp}{\partial P}$ and potentially still larger inflow responses), but these differences would have been much less dramatic. As such, retirement institutions clearly shape the effects of UI extensions on workers at various ages.

If changes in maximum PBD (together with the existence of the UI pathway) help explain much of the increase in the unemployment rate of older workers, what explains its more recent decline? We consider a range of potential policy explanations. In 1994 institutions were near their most generous. Workers aged 58 in 1994 (1936 cohort) had a maximum PBD of 32 months and could retire via-UI at age 60 without penalty. Thereafter, PBDs eventually decreased, pension penalties for retiring at age 60 started to kick in, and the earliest possible age for retirement via UI increased. In order to understand how these changes affect unemployment rates, Figure 8 (c) first simulates a world in which none of these changes occurred, with all institutions remaining at their generous 1994 levels, and then simulates how each separate component of these reforms would have affected unemployment rates. For intuition, Figures 7 (c) and (d) show how each of

⁴⁰The convergence in the unemployment rate after 2006 stems from the fact that the ERA via the UI pathway increased from age 60 to 63 between the 1946 (aged 60 in 2006) and 1948 birth cohorts, and was formally closed starting with the 1952 cohort.

these simulations affects the 1952 cohort. The dashed blue line in Figure 8 (c) shows that had all institutions remained fixed at their (generous) 1994 levels, the unemployment rate of workers aged 56-59 would have only declined by 3.1pp between 1994 and 2014 (due to non-policy or economic reasons) instead of declining by 12.1pp (the solid, dark blue line). Thus, the retirement and UI policy changes can explain 8.9pp (or 74%) of the observed decline between 1994 and 2014 (see also Table 3).

To see which of these policy changes mattered most, we simulate the model changing one policy at a time. The dotted yellow line in Figure 8 (c) shows what would have happened had only PBD changed relative to 1994, but not retirement institutions. Relative to holding all institutions fixed at their 1994 levels (dashed blue line), this line shows that the 2006 reform that reduced PBD would have reduced the unemployment of older workers by 3.0pp. The dashed green line shows what would have happened had only the penalty for retiring via UI at 60 been implemented, but PBD and early retirement ages remained fixed in 1994. The penalty alone accounts for a 5.4pp decline in the unemployment rate. Finally, the purple line shows that simply increasing the earliest possible age for retirement via UI (which affected birth cohorts after 1945) would have had a large 7.8pp effect on unemployment rates. As can also be seen in Figure 7, increasing the ERA UI age basically eliminates bunching in inflows at ages below 60.

Altogether, these policy counterfactuals leave us with several takeaways. First, we note that the total non-employment effects of UI extensions for older workers are historically much larger than what we might have naively predicted by applying RD estimates from younger workers, due in large part to inflow responses. Second, our model provides new insight into what drove the striking historical trends in Germany's older workers' unemployment rates (Figure 1). It suggests that the PBD extensions in the late 80s explain over half of the rise in the unemployment rate of older workers between 1983 and 1994, while retirement reforms and PBD cuts explained most of the subsequent decline. Third, our model and simulations also indirectly suggest that the non-employment effects of UI extensions (and how much inflow vs. intensive margin responses matter) depend on non-UI institutional features such as retirement rules or the state of the economy. We reinforce this point next using a more direct approach.

6.2 UI Extensions Interacting with Other Institutions

The previous results show implicitly that how reforms to the UI system affect labor market outcomes depends on interactions between the UI system and other institutions in addition to the state of the labor market. To make this comparison explicit, we show in Table 4 how extending UI benefits by 12 months would affect the unemployment rate given the actual institutions in 2014, as

well as under various hypothetical scenarios.

Table 4 column (1) shows that for the actual institutions extending PBD by 12 months would increase the unemployment rate for workers in their early 50s by 0.34pp. In contrast, it would increase the unemployment rate of workers in their late 50s by more than double that (0.87pp). The intensive margin effect of UI extensions $\frac{\partial Nonemp}{\partial P}$ is 0.13 at age 52 and 0.17 at age 57. The elasticity of the unemployment rate with respect to PBD is 0.30 for workers in their early 50s and 0.43 for older workers. Column (2) considers how the effects of the same 12 month PBD extension would have looked under a different pension regime. Specifically, we re-introduce the UI retirement pathway allowing for retirement at age 60 with the early retirement penalty. In this case, the effect of the UI extension on the unemployment rate of older workers almost doubles (from 0.87 to 1.50pp) and the elasticity of the unemployment rate with respect to PBD increases from 0.43 to 0.56. Column (3) shows that these patterns are even more pronounced if we re-introduce the UI pathway *and* repeal the penalty for retiring early (thus returning to the pre-2000s institution), with the same UI extension now increasing the unemployment rate by a full 2.85pp (off of a higher base). Interestingly $\frac{\partial Nonemp}{\partial P}$, which captures an intensive-margin effect, actually declines for older workers relative to column (1), since even without the extensions many of the workers displaced in their late 50s now would not have returned to the labor market. With the extensions, they are even less likely to ever return, limiting the scope for any positive intensive-margin effect. Despite this, the elasticity increases relative to column (1) due to the importance of extensive margin, inflow effects.

In the remaining columns we show that the role of retirement institutions in shaping the non-employment effects of UI is comparable in importance to the role of changing UI benefits or changing the gap between UI and UA. In columns (4) and (5) we consider a world in which UI benefits (b) are 20% higher and lower respectively than column (1) and otherwise all else is as in column (1). Both the change in the unemployment rate resulting from the PBD extension and the associated elasticity are substantially larger under high b than low b , especially for older workers. Columns (6) and (7) show that elasticities are also larger under low UA benefits relative to high UA benefits (i.e. under a larger gap between b and UA benefits), just as they might be in the U.S. relative to Germany.

While it is generally well-known that causal policy estimates (e.g. RD estimates) are not structural parameters and may have limited external validity, this analysis highlights how even in the same broader context the magnitude of such estimates may fluctuate substantially depending on the exact environment. Moreover, it shows that the non-employment effects of the same UI extension differ substantially under more generous retirement rules; the change in the unemployment rate of

those aged 56-59 resulting from the same PBD extension is more than three times as large under historical retirement rules than current retirement rules. These differences are on par with those that arise from changing other important institutional parameters, like UI or UA replacement rates.

6.3 Model Estimation and Policy Simulations for Women

Our discussion so far has focused on men. Women faced somewhat different incentives since, for most of our study period, women with sufficient contribution years were entitled to claim a pension for women. For qualifying women, the UI pathway is generally irrelevant as the women's pension always allowed women to retire as early or earlier than men, often under more generous terms, and without going through unemployment. In Appendix F, we replicate and discuss all of our main analyses (both reduced-form and structural) for women. Due to space constraints, we engage in a limited discussion here. Overall, patterns for women are qualitatively similar to those of men (with a few differences, such as virtually no UI inflows after the ERA for women), despite women not needing to use the UI pathway. Model fit is good and our takeaways regarding the importance of interactions between UI and retirement institutions and their implications are similar. Table 5 column (1) shows that older women started out from a higher unemployment rate in 1983 (10.3%) which rose to 16.0% in 1994 and then fell to 8.0% in 2014. As with men, the same PBD extension has a substantially larger effect on women aged 56-59 than 52-55 (see Figure G.16). Moreover, Germany's PBD increases in the late 80s played a similarly important role in explaining the rise in the unemployment rate of older women in the 80s and 90s, accounting for 4.9 of the observed 5.7pp increase (Table 5). The model also attributes a meaningful portion of the subsequent fall in the unemployment rate of older women from 1994 to 2014 to institutional factors (2.8 of 8.0pp).

6.4 Robustness

We probe the robustness of our conclusions regarding the various policy counterfactuals in columns (2)-(7) of Table 5. We re-estimate our model under five alternative modeling choices and repeat our policy simulations for each of these alternate models. Columns (3)-(5) consider alternate search cost functions. Column (3) uses a linear instead of exponential specification for duration dependence (k_2), column (4) shuts down duration dependence entirely, column (5) shuts down the fixed cost of UI entry ($k_1 = 0$), column (6) imposes a higher UA replacement rate (increasing UA benefits from 500 to 750). SSEs and policy takeaways (e.g. share of the 1983-1994 change explained by PBD) are broadly stable under the different duration dependence models. SSEs are substantially worse without a fixed cost of entering UI, but policy takeaways remain qualitatively similar.

Column (7) re-estimates the entire model with a single, as opposed to cohort-specific, mean for the disutility of work ($\bar{\eta}$). This means that the entire model is only ever fit to our three main cohorts and there is no refitting across all the other cohorts. While overall SSE unsurprisingly rises, our key policy takeaways remain broadly stable, with PBD changes continuing to explain a large portion of the rise in the unemployment of older workers from 1983-1994.

7 Conclusion

We specify a life-cycle labor supply model that explicitly accounts for transitions between employment, unemployment, and retirement and how they are affected by the structure of UI benefits and parameters of the old age pension system. We estimate this model using empirical moments of the German labor market for forty birth cohorts under widely varied policy regimes. The model shows that the same UI extension can have substantially different effects on the unemployment rates of older workers under different retirement institutions. Taking this into account is consequential: our model suggests that unemployment insurance extensions played a large role in explaining Germany's remarkable historical rise in the unemployment rate of older workers — a much larger role than what the use of standard (primarily intensive margin) estimates of the non-employment effects of UI from younger workers would have predicted. The model also suggests, that changes to both the UI and retirement system played an important and underappreciated role in the German “labor market miracle” after 2005, when Germany's UR fell from around 12 to 5 percent.

These latter results also clearly show that the bridge-to-retirement effect on UI inflows is by no means a necessary effect of the UI system. The changes to the German pension system (retirement ages and penalties) essentially eliminated this effect. It also seems likely that other policies, such as the experience rating in the US UI system, may similarly avoid the bridge-to-retirement effect of UI.

While we quantify how retirement policies shape UI effects for older workers, something we expect to be relevant for many countries, other institutional changes can also materially influence the effects of UI. For example, changing UI benefit levels or post-UI welfare benefits could alter the effects of UI extensions for all ages. Future work, complementing existing reduced-form estimates with credible models that capture how much these other institutional changes matter could help policy makers better predict the effects of UI policy changes in new institutional environments.

We conclude with several important, open questions. First, our work is conducted in a country with relatively generous UI and where firm and sectoral-level labor agreements play important roles. The extent to which other institutions affect UI responses likely depends not only on retire-

ment rules and PBDs, but on the incentives of firms and other such contextual factors. Second, separations in our model are efficient in the sense that joint surplus would turn negative if the employment relationship were to continue. [Jäger et al. \(2023\)](#) raise the possibility that this need not be the case. Future work exploring the nature of separations and the role that layoff protections, CLAs and works councils play would help to make progress on the normative implications of our findings. Last, we study only one of many inputs into optimal UI design and our partial equilibrium approach leaves open several questions about possible general equilibrium effects. As but one example, it is possible that even though they increased the non-employment duration of older workers, Germany's maximum PBD extensions in the 80s and related policies paved the way for younger workers to retain or get jobs while smoothing the transitions out of employment for older workers.

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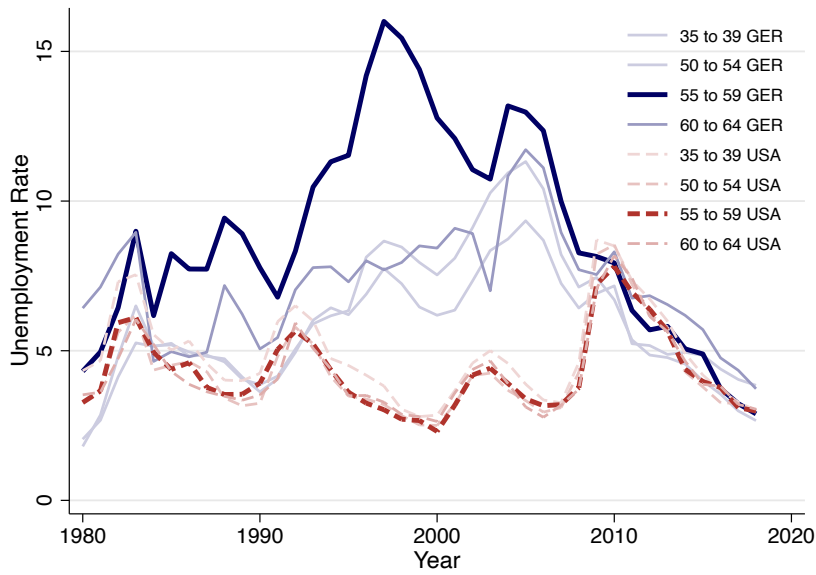
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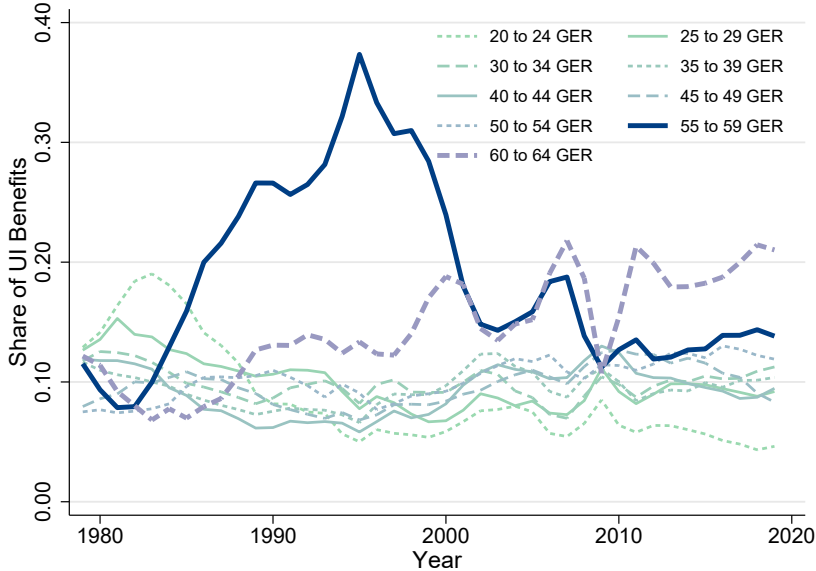
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Figures

Figure 1: Unemployment Rates and Share of Total UI Benefits by Age Group



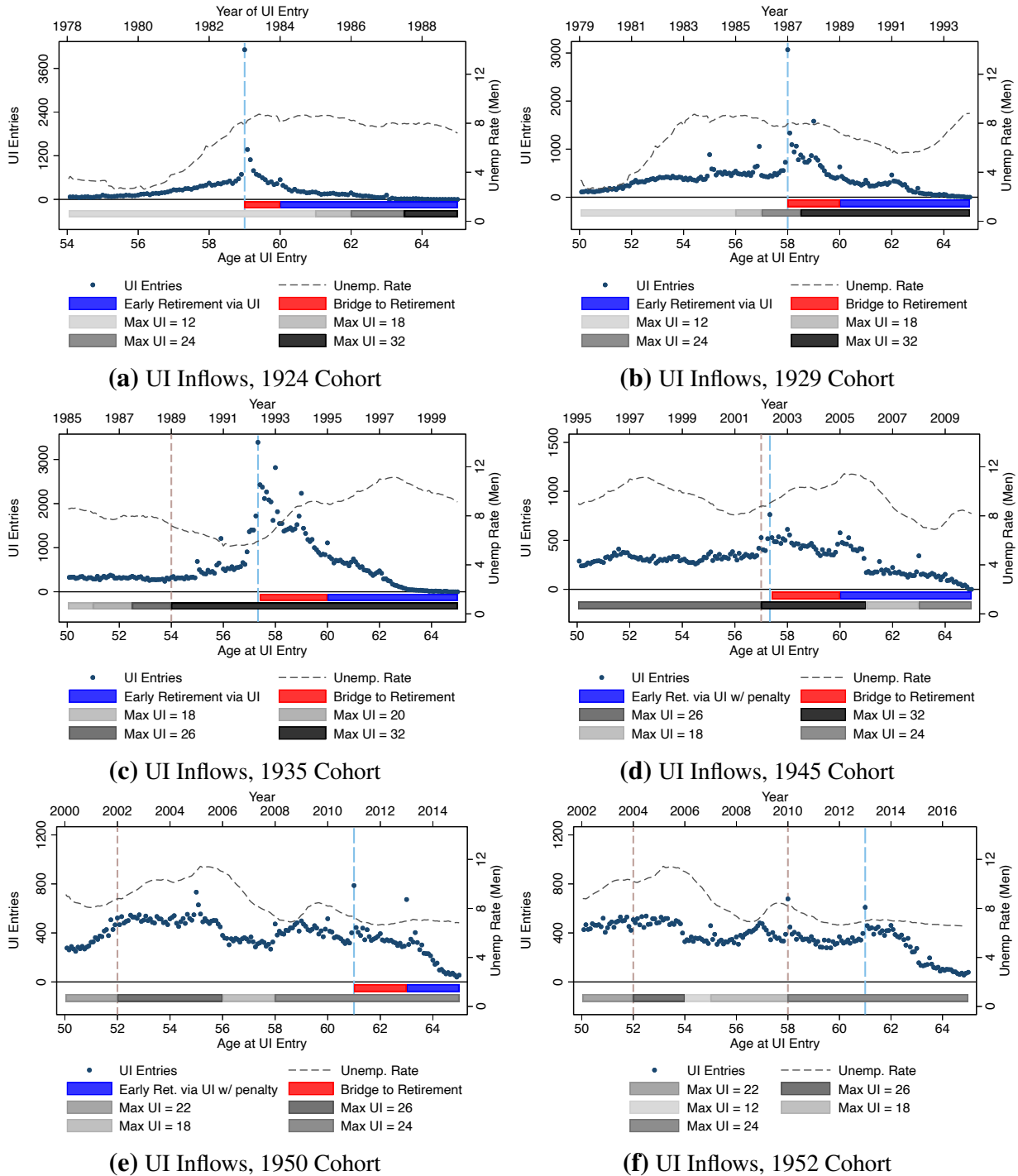
(a) Male Unemployment Rates by Age Group: West Germany and U.S.A



(b) Share of Total Benefits by Age Group in West Germany

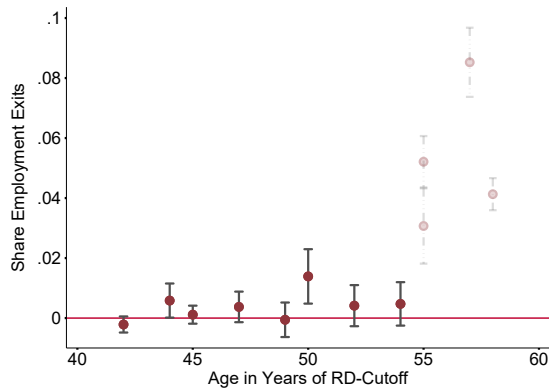
Notes: Panel (a) shows the male unemployment rate for select age groups in West Germany and the USA from 1980 until 2018, using data from the OECD. Panel (b) shows how UI payments are distributed across age and over time among West German men. Each line plots the share of UI payments in a given year that are paid out to UI recipients in the stated age group. In each year, the shares across all age groups add up to one. Results are based on own calculations using a 2 percent random sample of the Integrated Employment Biographies (IEB).

Figure 2: UI Inflows by Age for Different Cohorts in Germany, Men

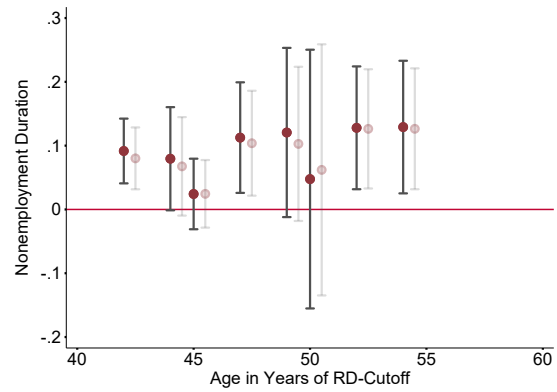


Notes: This figure plots the number of UI inflows per month (transitions from employment (E) to unemployment (UI or Nu)) by age at entry for different cohorts of West German men in our sample (left axis). It also plots the male, seasonally adjusted unemployment rate as a dashed gray line (right axis). The red bar under the figure indicates the period over which an individual would receive UI before drawing pension if he entered UI at the bridge-to-retirement age, indicated by the vertical dashed blue line. The blue bar indicates the period over which such an individual would receive their pension. The different shades of grey represent different maximum PBD eligibility for UI, which can change because of an existing age-cutoff (the red dashed line) or because of an overall UI policy change enacted in that year.

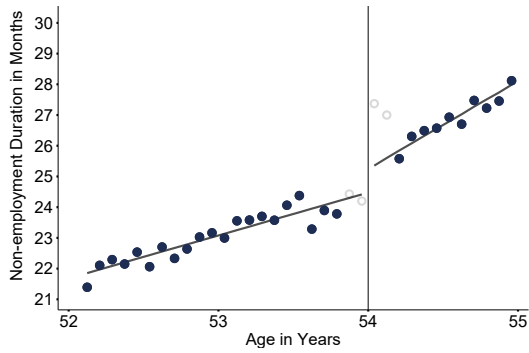
Figure 3: RD Estimates of the Effect of PBD Extensions on Non-Emp. Duration, Men



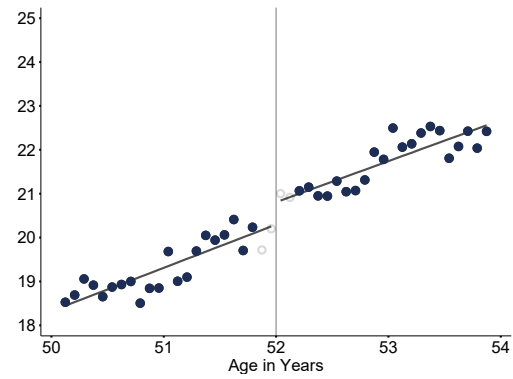
(a) Density Estimates



(b) RD Estimates for Non-Emp. Duration



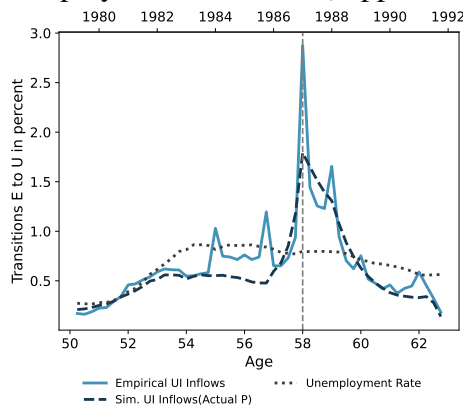
(c) Mean Non-Emp. Duration, Jul 1987 - Feb 1994, cut-off: age 54, Δ PBD = 6



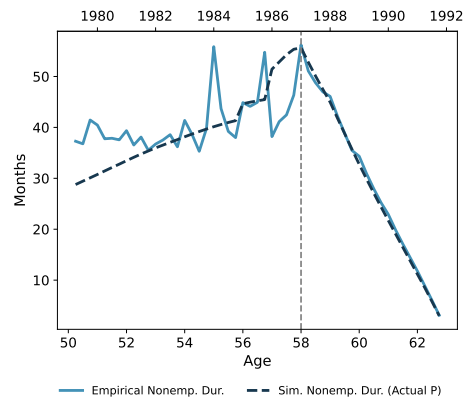
(d) Mean Non-Emp. Duration, Mar 1999- Jan 2005, cut-off: age 52, Δ PBD = 4

Notes: This figure plots RD estimates and corresponding density tests of the effect of a one-month PBD extension at each age possible age cut-off. Panel (a) shows estimates of density discontinuities at each cutoff. The grayed out cutoffs at age 55 and above are cutoffs we exclude from our analysis due to the observed density discontinuities. Panel (b) plots RD estimates of an extra month of PBD on months spent non-employed (capped at 36 months), with grayed out coefficients corresponding to estimates with controls. Both panels show 95% CIs. Panel (c) shows how mean non-employment duration varies around the age 54 cutoff, between Jul 1987- Feb 1994, at which PBD is discontinuously extended by 6 months (from 26 to 32 months). Panel (d) shows how mean non-employment duration (capped at 36 months) varies around the age 52 cutoff, between Mar 1999-Jan 2005, at which PBD is discontinuously extended by 4 months (from 22 to 26). The solid line shows the best linear fit on each side of the cutoff, omitting the closest 2 months on each side. The jump at the cutoff corresponds to our RD estimate. See Table 2 for more details.

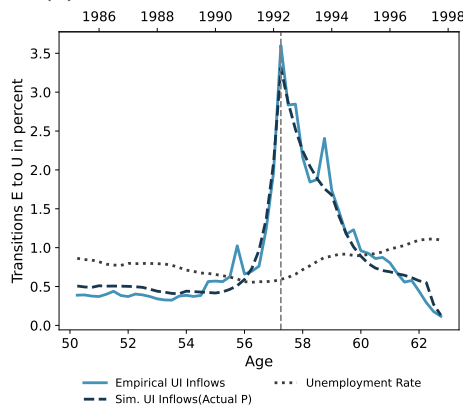
Figure 4: In-Sample Fit of Life-Cycle Model for Transitions from Employment to UI and Non-Employment Durations (capped at age 63)



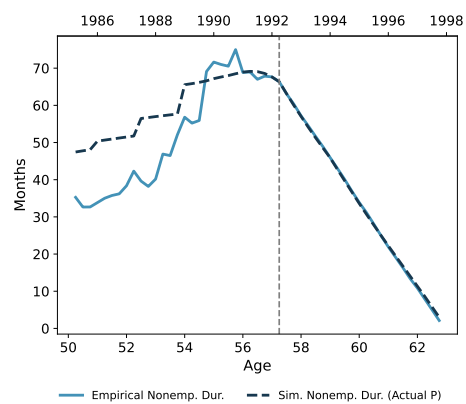
(a) Transitions from E to U, 1929



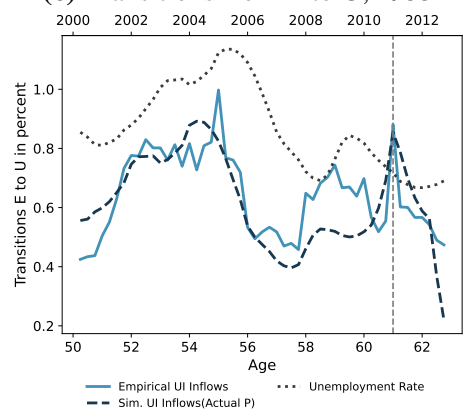
(b) Non Employment Duration, 1929



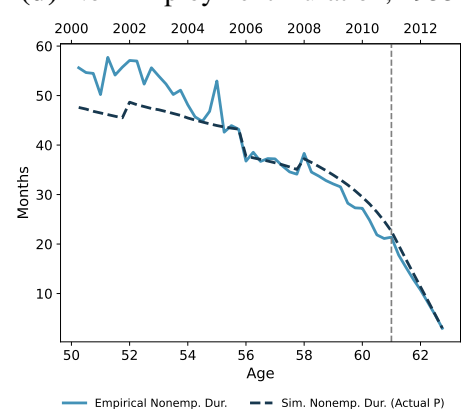
(c) Transitions from E to U, 1935



(d) Non Employment Duration, 1935



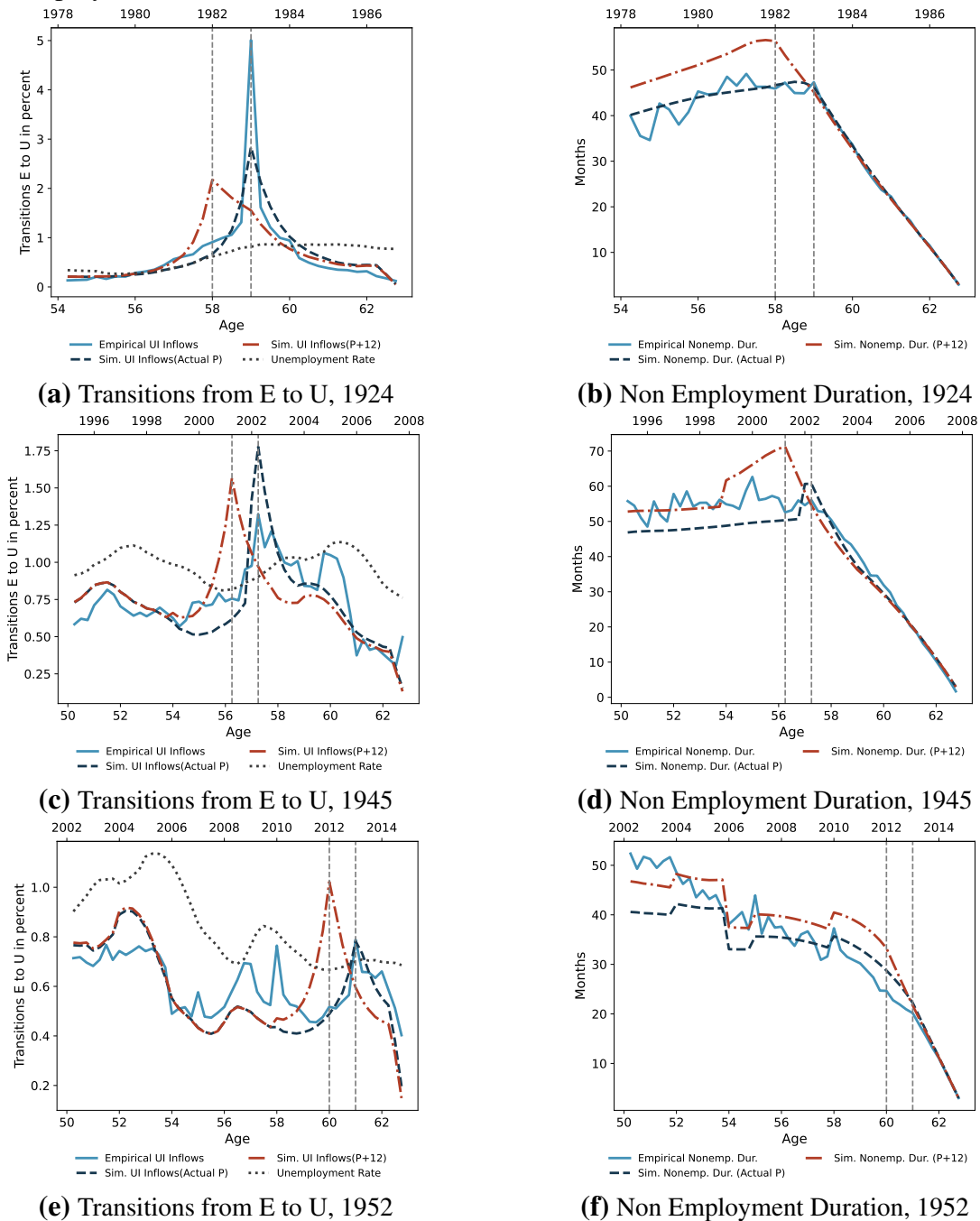
(e) Transitions from E to U, 1950



(f) Non Employment Duration, 1950

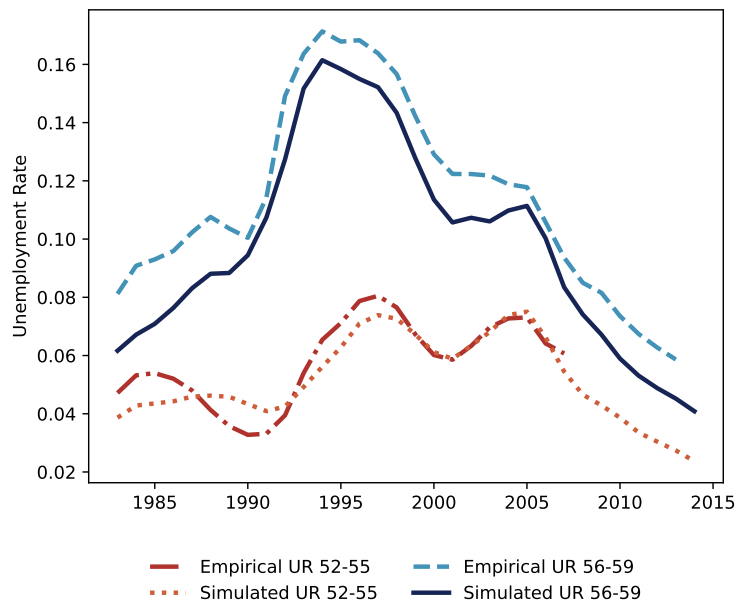
Notes: This figure compares our model-generated moments to their corresponding empirical moments for in-sample cohorts (1929, 1935, 1950), aggregated to the quarterly level. Panel (a) compares the transitions from employment to unemployment for the 1929 cohort whereas panel (b) compares non-employment durations for the 1929 cohort. Panels (c) and (d) show the same comparisons for the 1935 cohort, and panels (e) and (f) for the 1950 cohort. Non-employment duration is measured as time non-employed until age 63.

Figure 5: Out-of-Sample Fit of Life-Cycle Model for Transitions from Employment to UI and Non-Employment Durations, Baseline Model and Counterfactual 1: $P + 12$

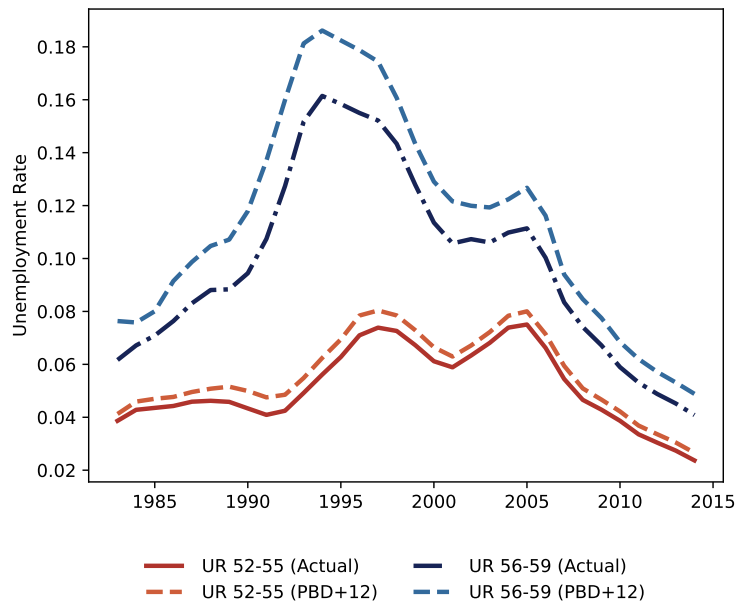


Notes: This figure compares our model-generated moments to their corresponding empirical moments for select out-of-sample cohorts (1924, 1945, 1952), aggregated to the quarterly level. Model-generated moments include the baseline specification (dashed blue line) and a counterfactual model where we increase potential benefit duration of UI by 12 months at all ages (dash-dotted red line). Panel (a) shows transitions from employment to unemployment for the 1924 cohort whereas panel (b) shows non-employment durations (until age 63) for the 1924 cohort. Panels (c) and (d) show the same comparisons for the 1945 cohort, and panels (e) and (f) for the 1952 cohort.

Figure 6: Empirical and Simulated Unemployment Rate by Age Group



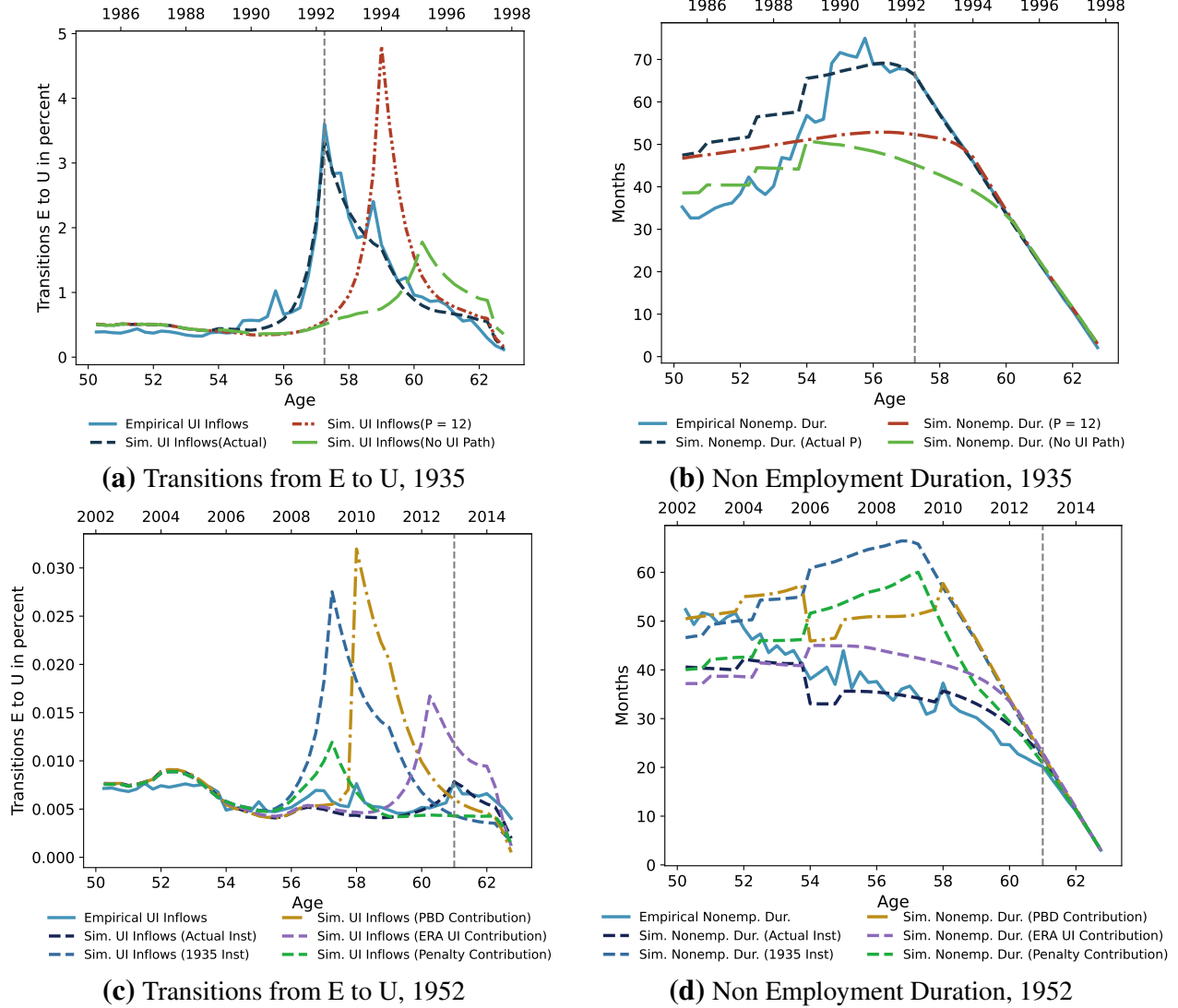
(a) Empirical and Simulated Unemployment Rate



(b) Extending UI PBD by 12 months

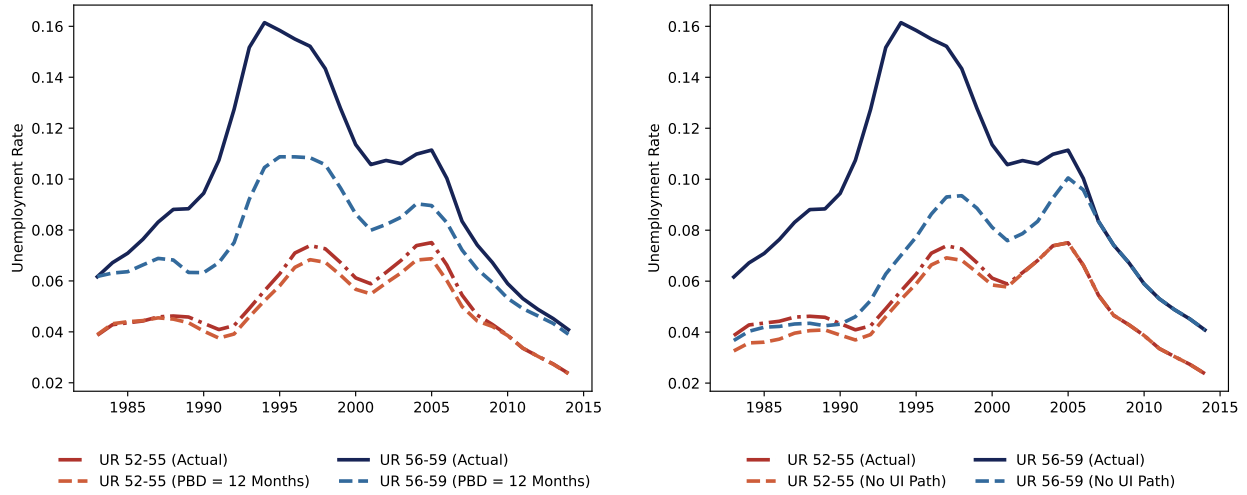
Notes: Panel (a) shows the empirical and simulated unemployment rate from the model for two age groups: 52-55 years old and 56-59 years old. Panel (b) shows the simulated unemployment rate under the actual institutions and the simulated unemployment rate when maximum potential benefit durations are increased by 12 months at all ages.

Figure 7: Model Simulations for Counterfactual Policies



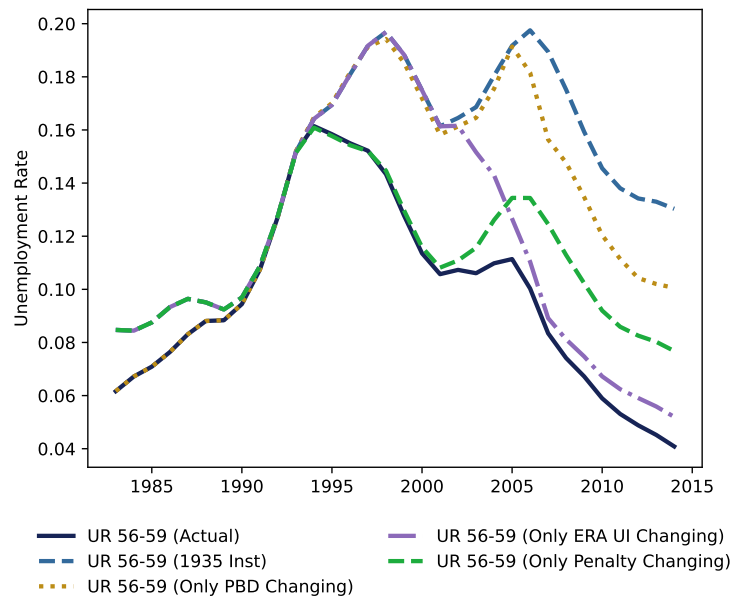
Notes: To show how the policy counterfactuals we consider are working in our model, this figure compares our baseline model-generated moments to simulated moments under various counterfactuals for two illustrative cohorts (1935, 1952). In panels (a) and (b), for the 1935 cohort, model-generated moments include the baseline specification (dashed blue line), a counterfactual model where we keep PBD fixed at 12 at all ages (dash-dotted red line), and a counterfactual model where we leave PBD to evolve as it did in actuality but instead imagine that the UI pathway into retirement never existed (long-dashed green line). Actual empirical inflows from the data are depicted in solid light blue. In panels (c) and (d), for the 1952 cohort, model-generated moments include the baseline specification (dashed dark blue line), a counterfactual model where we keep retirement rules (penalty, ERA, and NRA) and PBD fixed at 1994 levels (dashed lighter blue line), and three other counterfactual models that hold institutional rules fixed in 1994 but allow one institutional component to evolve as it did in actuality at a time: i) in dashed-dotted yellow, we allow PBD to evolve but keep retirement institutions at their 1994 levels, ii) in dashed green, we allow penalties for pensions to kick in but keep the ERA and PBD fixed at their 1994 levels, and iii) in dashed purple, we allow the ERA to increase but not penalties or PBD.

Figure 8: Simulated Unemployment Rates under Alternative Policy Regimes



(a) PBD fixed at 12 months

(b) No UI Pathway



(c) The Influence of Policy Changes after 1994

Notes: Panel (a) shows the model-simulated unemployment rate at baseline and for a counterfactual model that sets PBD=12 at all ages. This is presented for two age groups: age 52-55 and age 56-59. Panel (b) shows the model-simulated unemployment rate at baseline and for a counterfactual model that imagines the UI pathway never existed and earliest possible retirement was at 63. It considers the same age ranges as panel (a). Panel (c) plots simulated UR rates for the baseline specification (solid dark blue line), a counterfactual model where we keep retirement rules (penalty, ERA, and NRA) and PBD fixed at 1994 levels (dashed lighter blue line), and three other counterfactual models that hold institutional rules fixed in 1994 but allow one institutional component to evolve as it did in actuality at a time: i) in dashed-dotted yellow, we allow PBD to evolve but keep retirement institutions at their 1994 levels, ii) in dashed green, we allow penalties for pensions to kick in but keep the ERA and PBD fixed at their 1994 levels, and iii) in dashed purple, we allow the ERA to increase but not penalties or PBD.

Tables

Table 1: Institutional Parameters for focal Cohorts (Men)

	1924	1929	1935	1945	1950	1952
Statutory retirement age	65	65	65	65	65+4/12	65+6/12
ERA (earliest possible) for long-term insured*	63	63	63	63	63	63
NRA (no penalty) for long-term insured	63	63	63	65	65+4/12	65+6/12
Penalty for retire at ERA for long-term insured	0	0	0	0.072	0.084	0.09
ERA (earliest possible) via UI	60	60	60	60	63	-
NRA (no penalty) via UI	60	60	60	65	65	-
UI Bridge Age	59	58	57+1/3	57+1/3	61	61**
PBD at ERA via UI bridge age	12m	24m	32m	32m	24m	24m**
UI replacement rates on net wages at UI bridge age	0.63	0.63	0.63	0.60	0.60	0.60
Conversion rate to UI replacement rate on gross wages	0.65	0.65	0.65	0.65	0.65	0.65
Pension replacement rates per year of contribution on gross wages	0.0104	0.0104	0.0100	0.0099	0.0095	0.0094
Pension contribution years at age 54 cond. on being emp. at 50	32.5	32.5	32.8	31.8	31.6	31.1
N	65,172	94,790	111,730	73,113	99,260	100,635
Penalty for retiring at the ERA via UI	0	0	0	0.18	0.072	-

Source: Sozialgesetzbuch (SGB) Sechstes Buch (VI) and see Appendix C and Appendix E for more details.

Notes: This table outlines key institutional parameters used in our structural model for our 6 focal birth-year cohorts. *Individuals were eligible for the long-term insured pathway after 35 years of retirement contributions. **The old-age pension for unemployment pathway is abolished for cohorts born in 1952 and after. Therefore, the bridge age via UI here refers to the age at which individuals can take the full UI and then transition directly into receiving their old-age pension for the long-term insured.

Table 2: Intensive Margin Effects of UI Extension on Nonemployment Duration

		No Controls	Controls
Period Jul 1987 - Feb 1999			
Age 42, P: (12-18), Δ P: 6	$\frac{dy}{dP}$	0.092 [0.026]**	0.080 [0.025]**
N		173,313	173,313
Mean Dep. Var		16.049	16.049
Age 44, P: (18-22), Δ P: 4	$\frac{dy}{dP}$	0.079 [0.041]+	0.068 [0.039]+
N		170,270	170,270
Mean Dep. Var		17.046	17.046
Age 49, P: (22-26), Δ P: 4	$\frac{dy}{dP}$	0.121 [0.068]+	0.103 [0.062]
N		107,255	107,255
Mean Dep. Var		18.568	18.568
Age 54, P: (26-32), Δ P: 6	$\frac{dy}{dP}$	0.129 [0.053]*	0.126 [0.048]**
N		66,720	66,720
Mean Dep. Var		24.331	24.331
Period Mar 1999 - Jan 2006			
Age 45, P: (12-18), Δ P: 6	$\frac{dy}{dP}$	0.024 [0.028]	0.024 [0.027]
N		156,927	156,927
Mean Dep. Var		15.637	15.637
Age 47, P: (18-22), Δ P: 4	$\frac{dy}{dP}$	0.113 [0.044]*	0.104 [0.042]*
N		148,285	148,285
Mean Dep. Var		16.794	16.794
Age 52, P: (22-26), Δ P: 4	$\frac{dy}{dP}$	0.128 [0.049]**	0.126 [0.048]**
N		113,128	113,128
Mean Dep. Var		20.546	20.546
Period Jan 2008 - Dec 2010			
Age 50, P: (12-15), Δ P: 3	$\frac{dy}{dP}$	0.048 [0.103]	0.062 [0.100]
N		57,116	57,116
Mean Dep. Var		18.539	18.539

Notes: This table shows RD estimates of the effect of a 1 month UI PBD extension at various age cutoffs on non-employment duration in months (capped at 36 months). Estimates are obtained using local polynomial regressions controlling linearly for age (allowing for different slopes on each side of cutoff), using a rectangular kernel and a bandwidth of 2 years on each side of the cutoff, except for the 49 and 54 age cutoffs where we use a bandwidth of one year on the right due to other discontinuities. We exclude the 2 closest months on each side of the cutoff. Standard errors (in brackets) clustered on day level (+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$).

Table 3: Policy Simulations - Key Predictions of Model

	(1)	(2)	(3)	(4)
	Age 52-55	Age 56-59	Age 60-62	Age 52-62
Unemployment Rate				
1983, Actual Inst.	3.9%	6.2%	10.6%	6.7%
1994, Actual Inst.	5.6%	16.1%	13.0%	11.5%
1994, PBD=PBD+12	6.2%	18.6%	13.2%	12.6%
1994, PBD=12	5.2%	10.5%	12.3%	9.0%
1994, PBD=12, naive	5.5%	15.7%	12.2%	11.0%
1994, No UI Path	5.3%	7.0%	7.2%	6.4%
2014, Actual Inst.	2.4%	4.1%	5.5%	3.8%
Change in UR from 1983 to 1994				
Overall change	1.7 pp	10.0 pp	2.4 pp	4.8 pp
Change due to PBD change	0.4 pp	5.7 pp	0.7 pp	2.4 pp
Change due to other reasons	1.4 pp	4.3 pp	1.7 pp	2.4 pp
Change in UR from 1994 to 2014				
Overall change	-3.2 pp	-12.1 pp	-7.5 pp	-7.6 pp
Change due to PBD and Retirement Policies	-0.8 pp	-8.9 pp	-9.4 pp	-6.1 pp
Change due to other reasons	-2.5 pp	-3.1 pp	1.9 pp	-1.5 pp
Change due to PBD change	-0.2 pp	-3.0 pp	-0.2 pp	-1.2 pp
Change due to UI ERA change	-0.5 pp	-7.8 pp	-5.4 pp	-4.5 pp
Change due to penalty	-0.2 pp	-5.4 pp	-7.3 pp	-4.0 pp

Notes: The table shows model-generated output (levels and changes in unemployment rates) for the different counterfactual policy simulations discussed in Section 6. Results are presented for four age groups: age 52-55, age 56-59, age 60-62, and age 52-62 in columns (1)-(4), respectively. pp stands for percentage point changes.

Table 4: Illustrating Interactions between UI and Retirement Policies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Baseline Institutions in 2014	UI Pathway ERA at age 60 w/ Penalty	UI Pathway ERA at age 60 No Penalty	High UI	Low UI	High UA	Low UA
Age 52-55							
UR, Actual PBD.	2.70%	2.90%	3.20%	2.81%	2.56%	3.43%	2.15%
UR, PBD + 12	3.04%	3.33%	3.62%	3.20%	2.84%	3.76%	2.44%
Change in UR	0.34 pp	0.43 pp	0.42 pp	0.40 pp	0.28 pp	0.33 pp	0.29 pp
dD/dP at age 52	0.13	0.15	0.16	0.15	0.10	0.11	0.14
Elasticity of UR w.r.t PBD	0.30	0.35	0.31	0.33	0.25	0.23	0.32
Age 56-59							
UR, Actual PBD.	4.57%	5.93%	11.07%	4.77%	4.31%	5.49%	3.73%
UR, PBD + 12	5.44%	7.44%	13.92%	5.89%	4.93%	6.39%	4.52%
Change in UR	0.87 pp	1.50 pp	2.85 pp	1.11 pp	0.61 pp	0.90 pp	0.79 pp
dD/dP at age 57	0.17	0.18	0.14	0.20	0.14	0.14	0.21
Elasticity of UR w.r.t PBD	0.43	0.56	0.57	0.52	0.33	0.38	0.48

Notes: The table shows model simulations for different counterfactual policies for the year 2014. Column (1) shows simulation results (UR under regular PBD and under PBD+12 months, dD/dP , and the elasticity of UR with respect to PBD) from our model for the actual institutional and other parameters in 1994. To simplify matters and for comparability purposes, we set $P=24$ for all ages considered at baseline, so that $P + 12$ corresponds to 36 months PBD for all ages. Column (2) shows the same results but alters institutions to allow for retirement via UI at age 60 with penalty (relative to the actual NRA). Column (3) is like (2) but also eliminates the penalty for retiring at 60. Columns (4) and (5) are like (1) but set UI benefits to be 20% higher and 20% lower respectively. Columns (6) and (7) are like (1) but set UA benefits to be 20% higher and 20% lower respectively.

Table 5: Results for Women and Robustness to Alternative Model Specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Women	Baseline Men	Linear Time Trend in Cost	No Trend in Cost	No Fixed Cost of UI Entry	Higher UA	Constant Eta
Model Fit							
SSE	5,547	18,017	18,310	21,391	43,182	17,940	26,620
dD/dP age 52	0.065	0.124	0.117	0.114	0.101	0.126	0.132
Unemployment Rate (Age 56-59)							
1983, Actual Inst.	10.3%	6.2%	6.0%	5.8%	6.4%	6.2%	5.3%
1994, Actual Inst.	16.0%	16.1%	16.3%	16.0%	13.4%	16.4%	13.1%
1994, PBD=PBD+12	21.6%	18.6%	19.0%	18.8%	14.5%	19.2%	19.8%
1994, PBD=12	11.0%	10.5%	10.1%	10.0%	9.8%	10.3%	6.8%
1994, No UI and no Women's Path	11.8%	7.0%	6.9%	6.8%	7.3%	6.9%	6.5%
2014, Actual Inst.	8.0%	4.1%	4.1%	4.1%	3.4%	4.3%	4.6%
Change in UR (Age 56-59) from 1983 to 1994							
Overall change	5.7pp	10.0pp	10.2pp	10.2pp	7.0pp	10.3pp	7.8pp
Change due to PBD change	4.9pp	5.7pp	6.2pp	6.1pp	3.5pp	6.1pp	6.2pp
Change due to other reasons	0.8pp	4.3pp	4.0pp	4.2pp	3.4pp	4.2pp	1.5pp
Change in UR (Age 56-59) from 1994 to 2014							
Overall change	-8.0pp	-12.1pp	-12.1pp	-11.9pp	-10.0pp	-12.1pp	-8.5pp
Change due to PBD and Retirement Policies	-2.7pp	-8.9pp	-8.7pp	-7.8pp	-3.1pp	-10.7pp	-3.8pp
Change due to other reasons	-5.2pp	-3.1pp	-3.4pp	-4.1pp	-6.9pp	-1.5pp	-4.6pp
Change due to PBD change	-1.8pp	-3.0pp	-3.2pp	-2.9pp	-0.8pp	-3.8pp	-2.5pp
Change due to UI ERA change	-2.2pp	-7.8pp	-7.7pp	-6.8pp	-2.5pp	-9.2pp	-3.2pp
Change due to penalty	-2.2pp	-5.4pp	-5.5pp	-4.6pp	-1.7pp	-8.7pp	-3.3pp

Notes: The table shows key simulation results for alternative samples and models. Column (1) shows the results from estimating the model on women (using both empirical moments and the relevant institutional parameters for women). Column (2) replicates the baseline model for men for ease of comparison with successive columns. Column (3) estimates the model using a linear as opposed to exponential time trend in the cost of job search. Column (4) estimates the model assuming no time trend in the cost of job search. Column (5) estimates the model assuming that there is no fixed cost of entering UI. Column (6) estimates the model after increasing UA from 500 to 750. Column (7) estimates the model imposing a constant mean of the disutility of work $\bar{\eta}$ across all cohorts (in-sample and out-of-sample).

Appendix For Online Publication

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A Data Appendix for Cohort Data

Data We use German Social Security data – the Integrated Employment Biographies (IEB) – from the Institute for Employment Research. This data provides detailed information about employment start and end dates, earnings, unemployment insurance spells, and various demographic characteristics for the years 1975 to 2017. We use IEB-Versions v14.00 and (especially for the later cohorts) v16.00.

Sample Selection We use the labor market history of selected birth-years to track individual labor market dynamics when approaching retirement age. Each birth year is called a cohort which we construct separately for men and women. We study all birth-year cohorts between 1924 and 1963. For illustration purposes, we highlight cohorts that i) represent periods of different UI generosity at older ages and ii) are not directly affected by a UI reform close to retirement. These focal cohorts are 1924, 1929, 1935, 1945, 1950, and 1952. The relevant institutional features faced by each cohort are summarized in Tables 1 and H.10 with full details on UI and retirement policies and reforms shown in Tables H.1 and H.2. For each of these cohorts we select all individuals with a stable employment history on their 50th birthday. Specifically, we select individuals that are in social security reliable employment on their 50th birthday and have at this point worked in social security reliable employment continuously over the previous three years without any UI receipt during this period.⁴¹ In addition, we exclude some industries that are known for having special early retirement practices. Namely we exclude mining and steel construction. For cohorts 1937 and later we exclude additional industries that have excess exits from employment at age 55 in the 1941 cohort based on visual inspection. This approach should partially screen for industries with CLAs that specified an early retirement agreement at age 55. In particular we exclude the following three digit industry codes based on the 2008 industry classification: 291 (manufacturing of cars), 201 (production of base chemicals), 351 (electricity supply), 701 (business administration), 234 (production of other porcelain and ceramics), 642 (holdings), 212 (production of other pharmaceuticals), 204 (production of cleaning and toilet products), 192 (petroleum refinement) and 262 (production of data processing devices).

States and Transitions for a Monthly Balanced Panel We generate a monthly balanced sample of each birth cohort that tracks an individual’s labor market status since age 50.⁴² We center the data

⁴¹For the 1924-1927 cohorts we start later, at their 54th-51st birthdays, respectively, due to not having data prior to 1975 and requiring 3 years to establish stable employment.

⁴²We also generate a complementary quarterly panel that we use in the structural estimation.

around the cohort- and individual-specific bridge to retirement age, so that the the first month after the bridge to retirement age starts with the exact date an individual faces a bridge to retirement.

For all months, we assign individuals to one of five exclusive labor market states. Individuals can be employed (E), which includes all social security reliable employment, or in registered unemployment (UI), which consists of all periods of UI receipt. In addition, individuals can be outside of the observed E and UI states.⁴³ We distinguish between non-observed unemployment (Nu), which entails up to 3-month interruptions between E and U , and temporary withdrawal from the labor force (Nt), which includes temporary employment interruption as well as interruptions between E and UI lasting longer than three months. Finally, individuals can withdraw permanently from the labor force (Np), denoted by an exit from E or UI that is not followed by any other E or UI spell in our data. If individuals are in multiple states in a given months – due to the transition date being in the middle of the month – we select one state with the rule that UI is preferred over Nu which is preferred over E , which is preferred over Nt and Np . If an individual has, for example, an employment spell (E) in the first half of a month and an Nu spell in the second half of the month, the individual is assigned Nu for the month. We construct all possible transitions between states where a transition is defined by comparing the current and previous state of an individual.

For simplicity, we later condense these five states into three: Employment (E), Unemployment (UI or Nu), and Non-Employment (Nt or Np). The main reason for combining Nu and UI , is that if workers are sanctioned at the beginning of an UI entry, they would appear as Nu in the data and the relevant transition from work to unemployment occurs at the E to Nu transition.

B Additional Details and Results for the RD Specification

This section describes the sample used for the RD analysis, validity tests, the main findings, and associated robustness checks.

B.1 Data and Sample Construction

We construct an inflow sample into UI receipt based on the IEB, largely following [Schmieder et al. \(2012\)](#), with two main differences: First, we also include older individuals. Second, to be consistent with our cohort data we also exclude individuals that were employed in mining or steel construction prior to job loss.

⁴³This includes other states such as marginal employment or second-tier unemployment assistance that could sometimes be observed in the data as well as states that are genuinely never observed in the data, such as retirement.

We select West German individuals that, based on their pre-UI history, are eligible for the maximum (age and cohort-specific) potential benefit duration (PBD), as summarized in Table H.1. In particular, we restrict to individuals who worked at least 12 months in a social security reliable job for the previous 3 years and also worked 52 months within the last 7 years with no intermittent UI spell in the previous 48 months. We further restrict to cases of UI take-up within 28 days after job separation. Our main sample restricts to male individuals, but we provide complementary evidence for females and for the pooled sample of men and women.

As Table H.1 illustrates, the German UI system has had several historical periods with different age-specific PBDs. We select all age cutoffs below age 55 from the 1987 period onwards.⁴⁴ This leaves us with 8 age cutoffs from 3 periods. For the remaining cutoffs that seem to exhibit density violations — namely the age cutoffs 54 and 52 — we further exclude years from the end of the period where the violation is most severe. For the 54 age cutoff we exclude the last 5 years (07/1995 - 03/1999) of the period 07/1987-03/1999, for the 52 age cutoff, we exclude the last year (04/2005-01/2006) in period 03/1999-01/2006.

Outcomes Our main outcome is an individual’s non-employment duration, measured as the duration in months between the start of UI receipt and the start of the next job. We topcode values above 36 to reduce the influence of outliers and to be consistent with prior work. In addition, we use several predetermined variables for balance checks and/or as control variables. In particular, we use the daily pre-UI wage, a dummy for foreign nationality, the years of education, years of firm-, industry- and occupation- specific tenure as well as the time in months between job loss and UI claim.

Main Specifications For each cutoff, we estimate a separate RD specification. The main specification employs a two-year bandwidth on each side of the cutoff with the exception of the 49 and 54 age cutoff where it is only one year on the right due to other policy discontinuities above one year. Because of sorting, especially at some of the older cutoffs, we use a donut-hole approach and exclude 2 months just to the left and right of each cutoff. We control for a linear trend in the running variable which is allowed to differ on each side of the cutoff. We estimate the model via OLS, clustering standard errors at the age (in days) level. We also provide a range of robustness checks and alternative specifications discussed in the next section.

⁴⁴We discard some earlier periods because of their short duration and some open questions regarding the implementation, especially unclear evidence for a first stage.

B.2 Description of Findings

Validity Checks Before turning to the main findings, we conduct balance and density checks. Figure G.9 explores the smoothness of the density around the cutoffs for men, plotting the number of UI entries by age separately around each cutoff. There is some evidence of sorting directly around the cutoffs, i.e. a missing mass directly left to the cutoff and an excess mass right to the cutoff. This sorting appears somewhat stronger for older workers and females.⁴⁵ Importantly, though, sorting is mostly restricted to the plus or minus 2 months on each side of the cutoff that are excluded in the main specification. There appears to be no or at most small evidence of a density shift for men.

To further quantify the presence (or absence) of a shift in a density, Column (1) of Tables H.4 (males), H.5 (females) and H.6 (both), report estimates of the marginal increase in the number of UI entries which is rescaled around the sample mean for each of the cutoff to make the estimates more comparable between periods and cutoffs. For males, most estimates are precisely estimated and very close to zero. The strongest exception is the 50 cutoff in the most recent period, where the estimated increase in the density is about 1.5% relative to the mean. For females, the shift in density is somewhat larger, and in several cases statistically significant. For example, at age 50 the estimated increase is 2.1% relative to the mean. As such, it is possible that the RD estimates for women at some of the older cutoffs suffer from some degree of bias despite the donut hole, though the actual RD estimates at these cutoffs appear robust to the inclusion of detailed controls. We also examine whether pre-determined variables are balanced across the cutoffs in columns (2) - (7) of Tables H.4, H.5 and H.6. In particular we check for balance in the daily pre-UI wage, a dummy for foreign nationality, years of education, years of firm-, industry- and occupation- specific tenure as well as the time in months between job-loss and UI claim. Most estimates are insignificant and close to zero, with most estimates precise enough to rule out economically meaningful sorting along the dimensions considered. The one notable exception is a positive effect on pre-UI wages at the age 54 cutoff for both males and females and at the age 52 cutoff for females.

Main Findings Figure G.10 (males) plots mean non-employment duration as a function of age so that our RD estimates can be inspected visually.⁴⁶ The linear specification used on each side of the cutoff appears to be a reasonable approximation of the underlying conditional expectation.

Estimates of the effect of a one month increase in PBD on non-employment duration are re-

⁴⁵Figures exploring the smoothness of the density for the women's sample and the pooled (men and women) sample are available upon request.

⁴⁶Figures plotting mean non-employment duration for the women's sample and the pooled (men and women) sample are available upon request.

ported in Table H.3. Column (1) shows the main results for males without controls and column (2) shows it with controls. Most estimates are in a similar ballpark as those in Schmieder et al. (2012), with estimated effect sizes for older workers tending to be slightly (though not statistically significantly) larger. For example, the baseline estimate at the age 42 cutoff in Period 07/1987-02/1999 implies an increase in non-employment duration of 0.092 months for an additional month of PBD (s.e.=0.026), whereas the estimated effect at age 54 is 0.129 months (s.e.=0.053). Adding controls barely moves the coefficients. If anything, the effect sizes tend to get a little smaller, though the differences are not statistically significant. Columns (3) and (4) report the corresponding estimates for females. Females tend to be somewhat more responsive to UI extensions (as documented in Schmieder et al. (2012)) and the age gradient also appears slightly larger. To take the same cutoffs as before, the baseline estimate for the age cutoff 42 in Period 07/1987-02/1999 implies an increase in non-employment duration by 0.124 months for an additional month of PBD (s.e.=0.025), whereas the estimated effect at age 54 is 0.203 (s.e.=0.040). These results are robust to the inclusion of the additional controls. Finally, Columns (5) and (6) show results for the pooled (men and women) sample. As expected, these lie between the estimates for males and those for females and are more precisely estimated.

Additional Robustness We complement our findings with a number of robustness checks, reported in Tables H.7 (males), H.8 (females) and H.9 (both). In particular, we examine the robustness to the inclusion of more granular controls including detailed industry and regional controls (Column (2)), extending the excluded area around the cutoff to 3 months (Column (3)), reducing the bandwidth to one year (Column (4)), and using a triangular kernel instead of a uniform one (Column (5)). Overall, our findings are relatively robust: most estimates are similar, or at least in the same ballpark, as the baseline estimates, though sometimes less precisely estimated.

C Additional Institutional Details

C.1 Pension Institutions and Pension Reforms in Germany

Over our sample period, several pension reforms altered the incentives to claim pension early and the various pathways into retirement. Table H.2 summarizes the reforms for all of the different pathways over our study period (elaborated upon below). There are six main pathways: Standard old-age pension, old-age pensions for the long-term insured, old-age pensions due to unemployment (and part-time work), old-age pensions for women, old-age pensions for disabled workers, old-age pension for especially long-term insured. The 5 non-standard pathways allow for early re-

tirement under specific conditions. Each pathway has its own eligibility conditions, normal retirement age (NRA), or the age at which pension can be drawn without penalties, and early retirement age (ERA), the earliest possible age pension can be drawn.

Standard old-age pension: Workers can claim the standard old-age pension (SGB VI §235) at age 65 throughout our sample period. The eligibility condition is at least 5 years of contributions. For cohorts 1947 to 1964, this age will gradually increase by one month for each birth-year from age 65 to 67. These changes began in 2012 and will be complete in 2030 (See SGB VI §235(2)).

Old-age pension for long-term insured: The long-term insured pathway allows workers with at least 35 years of contributions to claim pension as early as age 63 (SGB VI §236). The NRA without penalty for early claims was 63 until the 1936 cohort. It was increased gradually, in monthly steps, from age 63 to 65 for cohorts 1937 to 1938 and remained at 65 until the 1948 cohort. The NRA was again increased to 65 and 3 months for the 1949 cohort and will increase at the same pace as the SRA for cohorts 1950 to 1964, reaching age 67 in 2030. The ERA, meanwhile, remained stable at age 63. Hence, workers eligible for this pathway could always claim as early as age 63, however they faced an actuarial adjustment in the form of a 0.3% permanent pension reduction per each month they retired in advance of the NRA.

Old-age pension due to unemployment or part-time work: Cohorts born before 1952 could claim pensions early via this pathway (SGB VI §237). The eligibility requirements for the UI pathway were: 1) at least 15 years of contributions, at least 8 of which must have occurred in the past 10 years, and 2) being unemployed for at least 1 year after the age of 58 and a half, or in old-age part-time work.⁴⁷ The ERA was 60 for cohorts younger than 1946 and then started to gradually increase, in monthly intervals, from 60 to 63 for cohorts 1946 to 1948. It then remained at age 63 until it was abolished for cohorts born in or after 1952 (SGB VI appendix 19). The NRA for claiming a pension without penalty was 60 until the 1936 cohort. It increased gradually from 60 to 65 between the 1937 and 1941 cohorts, and then remained at age 65 until this pathway was abolished.

Old-age pension for women: Women with at least 15 years of contributions, of which at least 10 must have occurred after age 40, were eligible for the women's pathway. The ERA remained at 60 throughout the sample period until this pathway was abolished for cohorts born in or after 1952. The NRA was 60 until the 1939 cohort, when it began to gradually increase, reaching 65 for the 1944 cohort (SGB VI appendix 20). The NRA then remained at age 65 until the pathway was abolished. Notice that these changes occurred later than those for the UI pathway, so that the

⁴⁷The part-time work component is granted by the partial retirement law (Altersteilzeitgesetz), which provided a maximum public subsidy for up to five years if older workers switch from full-time to part-time work. This program was enacted in the mid-1990s and was suspended in 2009.

women's pathway always offered early retirement on more generous terms.

Old-age pension for disabled workers: Workers who have lost their earnings capacity can claim the old-age pension for disabled workers. This pathway is also referred to as invalidity pathway. The eligibility condition is having lost of at least 50% of one's earnings capacity and at least 35 years of waiting period, which include, for example, periods of raising a child who is less than 10 years old. It allows eligible, severely disabled persons to claim pension before the statutory retirement age. The ERA for this pathway was 60 throughout the sample period and is scheduled to gradually increase to age 62 between the 1952 and 1963 cohorts. The NRA was 60 for workers born between 1920 and 1940. It was raised gradually by 1 month for each month of birth from 60 to 63 for cohorts 1941 to 1943, and remained at 63 until the 1951 cohort (SGB VI appendix 22). It is scheduled to gradually increase from age 63 to 65 for the 1952 to 1963 cohorts.

Old-age pension for especially long-term insured: The 2014 pension reform introduced the old-age pension for the especially long-term insured. Since July 2014, this pathway allowed workers with at least 45 contributory years to draw a pension without deductions as early as age 63. The first cohort that could use this pathway is the 1951 cohort. From birth cohort 1953 onwards, the NRA increases by two months for each birth cohort reaching 65 for persons born in 1964.

The last way for workers to leave the labor force and receive regular payments is via disability insurance. Disability insurance is available for workers with at least 5 years of contributions of which at least 3 need to be in the 5 years prior to claiming. Disability insurance can be claimed at any age. Workers who are officially recognized as having low earnings capacity, which entails permanently not being able to work more than 3 hours per day in any job, can claim disability insurance. For active DI recipients, benefits are converted into an old-age pension when they reach statutory retirement age. In Germany, the health assessment for disability insurance is relatively strict. About half of applications are rejected. Therefore, using disability pensions as a pathway to retire is difficult and typically not an attractive option.

C.2 Budget Set Calculations for Figure G.3

Here we detail how we calculate the lifetime budget constraints depicted in Figure G.3. Note that these are primarily used for illustrative purposes, though the structural model uses related components. We assume individuals earn a constant (after tax) wage w and at retirement receive total pension payments $y^R(E)$ and UI payments $y^{UI}(E)$, where E is age at exiting employment. Thus, the total years worked is $S = E - s$, where s indicate years of schooling.

This yields a budget constraint of the form

$$C = w(E - s) + y^{UI}(E) + y^R(E)$$

Let ρ be the replacement rate per year of pension contribution on net wage. In other words, each year of work with wage of w will increase pension benefits $y^R(E)$ by ρw . Each year spent on UI increases pension benefits $y^R(E)$ by $0.8 \times \rho w$. We assume individuals take their full UI duration upon exit and then rely on UA until they retire at age T^R . For illustration purposes, we assume UA provides zero income. In the model, we will assume UA yields 500 per month (y^u) and workers spend $T^R - E - P$ on UA if there is a period without other income support before they can claim pensions.

The budget constraint is thus given by:

$$C = w(E - s) + \underbrace{bD + 0.8 \times \rho w D \times [T - \max\{T^R, E - s + T^u\}]}_{y^{UI}(E)} + \underbrace{\rho w(E - s) \times [T - \max\{T^R, E - s + T^u\}]}_{y^R(E)}$$

where D is UI duration, T^u is unemployment duration, and P is maximum potential UI duration, b is UI benefit level. By definition, $T^u = D \geq P$. The stylized budget sets in Figure G.3 assume that a worker always retire at the earliest possible retirement age ($T^R = ERA$).

Therefore,

$$C = Y = \begin{cases} w(E - s) + bP + \rho w \times (E - s + 0.8P) \times [T - T^R] & \text{if } E < T^R - P \\ w(E - s) + b(T^R - E) + \rho w \times (E - s + 0.8(T^R - E)) \times [T - T^R] & \text{if } E \geq T^R - P \end{cases}$$

$$\frac{dY}{dE} = \begin{cases} w + \rho w \times [T - T^R] & \text{if } E < T^R - P \\ w - b + \rho w(1 - 0.8) \times [T - T^R] & \text{if } E \geq T^R - P \end{cases}$$

In the case of a change in the maximum potential UI duration P over the life cycle (e.g., changes from P_1 to P_2 at age T^{RD}). The P just before ERA defines the bridge age ($ERA - P_2$). Then the budget sets is the following:

$$Y = \begin{cases} w(E - s) + bP_1 + \rho w \times (E - s + 0.8P_1) \times [T - ERA] & \text{if } E < T^{RD} \\ w(E - s) + bP_2 + \rho w \times (E - s + 0.8P_2) \times [T - ERA] & \text{if } T^{RD} \leq E < ERA - P_2 \\ w(E - s) + b(ERA - E) + \rho w \times (E - s + 0.8(ERA - E)) \times [T - ERA] & \text{if } E \geq ERA - P_2 \end{cases}$$

When there exists a financial penalty to claim pension at ERA , we adjust the $y^R(E)$ by multiplying $(1 - (NRA - ERA) * 3.6\%)$.

Let's take the 1924 cohort as an example (where $P = 1$ and $T^R = 60$). Therefore, the budget set is

$$C = Y = \begin{cases} w(E - s) + bP + \rho w \times (E - s + 0.8P) \times [T - 60] & \text{if } E < 60 - P \\ w(E - s) + b(60 - E) + \rho w \times (E - s + 0.8 * (60 - E)) \times [T - 60] & \text{if } E \geq 60 - P \end{cases}$$

The baseline budget sets by cohort are constructed for the sample of married couples without dependent children. Given that in our sample, around 80% are married and around 15% have dependent children, the life time budget constraint for married couples without children is likely a reasonable approximation of reality. We use the following parameters: $s = 20$, $T = T_{last} = 78$ and $a = 0.8$. For the other parameters, we use the same institutional parameters as described in Appendix section E.4.

In Figure G.3 (a)-(c), representing the 1924, 1929, and 1935 cohorts respectively, the NRA and ERA for retirement via unemployment were age 60, but maximum PBD varied. In panel (d), representing the 1945 cohort, the ERA remained at 60 but the un-penalized NRA was increased to around 64, with slight variation by month of birth. This amounted to a financial penalty for retiring at age 60 of approximately 18% of gross lifetime pension benefits. In panel (e), representing the 1950 cohort, the ERA was increased to 63 and the NRA was 65.18. The penalty for retiring at age 63 via unemployment was thus 7.2%. In panel (f), representing the 1952 cohort, the pathway into retirement via unemployment was abolished, leaving the earliest possible retirement age as 63 for long-term insured workers with over 35 years of qualified contributions. The penalty for retiring at age 63 via the long-term insured pathway was 9%.

C.3 UI as a Bridge to Retirement and Other Ways to Retire Early

Evolution of the UI bridge over time The use of UI as a bridge to retirement dates back to the Weimar Republic. The “59 rule” originated in the economic crisis of 1929-1930, allowing white-collar workers to retire at age 60 after receiving UI for one year. After WWII, the rule was extended to blue-collar workers in 1957 (Trampusch, 2005; Trampusch et al., 2010). The popularity of UI as a bridge to retirement increased in the early 1980s. After the 1982 recession, using UI as a bridge to retirement became a popular way to manage layoffs (Trampusch et al., 2010). The increase of PBD in several steps from 12 to 32 months in 1987 for workers above 54 (see Table H.1) increased the attractiveness of this pathway and shifted the earliest age where one could use the UI pathway from 59 down to 57 and 4 months. In addition, the so-called “58-rule” came into effect at the end of 1985, which allowed workers to stay on UI without any job search

obligations ([Bundesgesetzblatt, 1985](#)). It provides additional incentives to use UI as a bridge to retirement ([Schneider and Stuhler, 2007](#)). Starting in 1997, the reduction in the generosity and phase-out of the early retirement system after UI made the UI pathway less attractive (see section [C.1](#)). In addition, the 2006 UI reform cut back PBD for workers 55 and older from (up to) 32 months to a maximum of 18 months. PBDs were increased back to 24 months in 2010 (see Table [H.1](#)). The “58-rule” was abolished for new UI entries from 2007 onwards ([Schneider and Stuhler, 2007](#)), further decreasing the attractiveness of UI as a bridge to retirement. In the environment since 2010, UI can still be used as a bridge to retirement, though at later ages and to less generous terms.

Public perceptions The norm of using UI as a bridge to retirement changed over time. Describing the situation before the oil crisis of 1973, ([Trampusch, 2005](#), p. 206) writes “*The operation of early retirement (...) made it popular with a wide and diverse constituency. (...) The policy was widely seen as a particularly humane solution to structural adjustment...*”. With the increased usage of the bridge, this changed over time. The news magazine “Der Spiegel” described the situation in 1995 ([Der Spiegel, 1995](#)), when UI receipt for the affected age group (55-59) was at its historical high: the article — titled “*Sliding into retirement*” (German: Gleitend in die Rente, own translation) — emphasizes that using the bridge to retirement puts high pressure on the social security system making the current practice unsustainable, while also displaying some sympathy for retiring early. The labor minister is cited as warning representatives of the Employer Organizations and Unions of “*misusing the retirement system*” who were at that time still making heavy use of the early retirement options via UI. The leader of the metal union (IG-Metal) at that time is quoted in defense of the UI pathway.

The tone of a news article from 2017 again by the Spiegel — now titled “*double dipping*” (German: Doppelt Kassieren, own translation) — has considerably shifted against the usage of the bridge ([Fröhlingsdorf, 2017](#)). The article describes and denounces the practice of using UI as a bridge to retirement at a large private bank and a leader of the service union (Verdi) is calling out this practice.

Usage in practice and the role of different stakeholders In Germany, older workers with long tenure benefit from strong layoff protections in Germany (see [EPL Database \(2015\)](#) for more details). Consequently, laying off older workers prior to retirement age often occurs with the workers’ explicit consent to the terms and conditions of the separation (see [Fröhlingsdorf \(2017\)](#) for a concrete example). This can occur in individual cases, but commonly involves different pillars of

Germany's industrial relations system, including Works Councils and managers on the establishment level as well as Unions and Employer Organizations on the sectoral level (see Jäger et al. (2022) for a review of these institutions and Trampusch (2005); Trampusch et al. (2010) for their role in using the UI bridge as a separation policy). In the post-1982 period, when usage of the UI bridge picked up, sector-level collective bargaining agreements (CBAs) that defined the conditions of early-retirement practices became prevalent (Trampusch et al., 2010). Social plans often accompanied these agreements — agreements between works councils and the establishment management on how to manage separations— further cementing the usage of these rules (Trampusch, 2005). Fröhlich et al. (2013) describes the practice of different pathways into early retirement in the early 2010s in six different industries, including a detailed portrait of one firm in each sector. In two out of the six sectors (the chemical industry and private banking), the portrayed firm used UI as a bridge to retirement in the recent past (Fröhlich et al., 2013, p. 339-340, p. 475-476). In both cases, the bridge to retirement models involved an explicit or implicit agreement between management and the works council and generous severance payments to top up UI benefits. These policies guaranteed a fixed replacement rate of the previous net wage (between 70% and 90%) and the coverage of all social security and tax contributions for the period between layoff and earliest possible retirement, under the assumption that workers took-up and exhausted completely the UI benefits. In the case of the portrayed bank, the policy explicitly offered workers to assist in claiming UI benefits. For the same sector, (Fröhlingsdorf, 2017) reports high demand of the UI bridge among workers at a large firm, and a take-up rate of 96% among those workers the policy has been offered to. In this firm, the management decides whom to offer the policy on a case by case basis.

Knuth and Kalina (2002) document high usage of the bridge in the manufacturing sector, among high income workers, and in large (≥ 500 employees) establishments.

Alternative Pathways The government also supported CLAs on early retirement in other forms, such as subsidizing employers' costs of buying-out older workers through the so-called partial retirement law (Altersteilzeitgesetz). This partial retirement law (Altersteilzeitgesetz) was enacted in mid-1990s and was suspended in 2009. Most CLAs on early retirement based on this law were not renewed. It was realized by halving older workers' working time (either via part-time work or early retirement). The employer paid 50% of the previous full-time income and the state government provided the remaining 50% to the employers, but only under the condition that the vacancy was replaced by an unemployed person or a freshly trained apprentice. In addition, the government supported this early retirement option by topping up the pension contribution of the workers who entered early retirement. This partial retirement law provided a maximum public

subsidy for up to five years. Combined with the ERA being at age 60, this requirement meant that the CLA early retirement option applied most directly to employees age 55 and older (Trampusch, 2005). Age 55, and to a lesser extent, age 56, became a common cutoff used in CLAs (in addition, of course, to CLAs based around the bridge-to-retirement age).

D Model Details

This appendix sets up and solves our labor supply model.

D.1 Model Set Up

States Workers can be in one of three states: Employed (E), Unemployed (U), or out of the labor force (O). We assume that once a worker drops out of the labor force he or she will not return, hence O is an absorbing state. We call a worker Non-Employed N if the worker is either unemployed or out of the labor force.

We assume that workers produce output p_t in each period, where p_t is i.i.d. according to some distribution $F(p)$. Another important state variable in our model is the total unemployment duration of a worker d^U . In practice we will estimate our model starting at age 50, so that d^U will be the duration in unemployment since then. To keep the state space manageable, we also assume that workers initially are eligible to the maximum benefit duration but do not reaccumulate benefit eligibility if they are reemployed after losing a job. Under this assumption d^U is sufficient to both calculate remaining UI benefit durations for each individual as well as the pension of an individual if the person retires. A full accounting of the benefit eligibility in the presence of multiple unemployment spells would require to separately keep track of d^U as well as the remaining benefit duration in each unemployment spell and employment duration in each employment spell. This quickly becomes computationally very challenging due to the curse of dimensionality. As long as repeated unemployment spells with long in-between employment spells are rare, which they are in practice, our approach is only a very minor simplification that vastly reduces the computational complexity. We can therefore write the value functions for the firm and worker as functions of p_t and d^U , where d^U is deterministic, while p_t is uncertain.

Value Function For Employment Workers have a utility function $u(\cdot)$, are paid $w_t(\cdot)$, and experience disutility from working (η), which will be drawn from a cohort specific distribution. The

Value Function for Employment is:

$$V_t^E(p_t, d^U) = u(w_t(p_t)) - \eta + \beta E_{p_{t+1}} [\max \{V_{t+1}^E(p_{t+1}, d^U), V_{t+1}^N(d^U)\}] \quad (\text{C.1})$$

Workers will separate from their job whenever the expected value of future non-employment exceeds that of employment. This could occur for several reasons: workers could receive a low productivity draw (p_t) such that the employment relationship is no longer better than the worker's outside option. Alternatively, outside options could improve. For example, an increase in retirement benefits will push up $V_t^N(d^U)$ for workers close to the retirement age and can increase the rate of jobs ending.

Value Function For Unemployment When workers leave to unemployment they engage in costly job search and receive payments $B(d^U)$. If the individual still has Unemployment Insurance benefits remaining ($d^U < P$), he or she will receive UI benefits ($B(d^U) = b$). If not, the individual receives y^u , which can be interpreted as unemployment assistance. An unemployed individual searches for a job and chooses an optimal level of search effort s which is normalized to the probability of finding a job. Generating search effort comes at a cost $\psi(s)$ which is increasing and convex. Finally, whether or not an individual receives a job offer she can decide to retire at the end of the period. If she remains unemployed d^U increases by one period. The Value Function for Unemployment is thus:

$$\begin{aligned} V_t^U(d^U) = & u(B(d^U)) + \max_s \{ \beta s E_{p_{t+1}} \max [V_{t+1}^E(p_{t+1}, d^U + 1), V_{t+1}^N(p_{t+1}, d^U + 1)] \\ & + \beta(1-s) E_{p_{t+1}} V_{t+1}^N(d^U + 1) - \psi_t(s) \} \end{aligned} \quad (\text{C.2})$$

Individuals choose search effort so that the marginal return to search equals the marginal cost up to the constraint that $s \leq 1$. For an interior solution, the first order condition for the optimal level of search effort s^* is:

$$\psi'(s^*) = \beta E \max [V_{t+1}^E(p_{t+1}, d^U + 1), V_{t+1}^N(d^U + 1)] - \beta V_{t+1}^N(d^U + 1)$$

Since we assume that $\psi(\cdot)$ is increasing and convex, optimal search effort at an interior solution is:

$$s^* = \psi'^{-1} (\beta E \max [V_{t+1}^E(p_{t+1}, d^U + 1), V_{t+1}^N(d^U + 1)] - \beta V_{t+1}^N(d^U + 1)) \quad (\text{C.3})$$

Value Function For Out of the Labor Force At any point, a worker can choose to transition to being out of the labor force O , which is an absorbing state. The value of O depends primarily on the value of one's pension y_t^p as determined by prevailing retirement institutions. y_t^p will depend on work history (d^U) and age at which the worker retires. Specifically, for a worker who lives until T^{Last} and is eligible to receive pension at T^{ERA} , the value function for being out of the labor force is:

$$V_t^O(d^U) = \begin{cases} \sum_{k=t}^{T^{ERA}} \beta^{k-t} u(y^o) + \sum_{k=T^{ERA}}^{T^{Last}} \beta^{k-t} u(y_t^p) & t \leq T^{ERA} \\ \sum_{k=t}^{T^{Last}} \beta^{k-t} u(y_t^p) & t > T^{ERA} \end{cases} \quad (\text{C.4})$$

The value of the pension depends on the relevant, cohort-specific retirement institutions in addition to the individuals work history (d^U). Individuals accrue pension benefits while working and while on UI benefits (at 80%), but not otherwise. Persons retiring at the earliest allowable retirement age (ERA) but before the normal retirement age (NRA) begin receiving a penalty starting with the 1937 cohort. We assume all individuals in our sample are eligible for the long-term insured retirement pathway and eligible for the retirement via UI pathway as long as they have 1 year of unemployment history (d^U). We allow individuals to choose the best retirement option available. In Section E.5 below, we outline in detail how we calculate V_t^O for each cohort.

Value Function For Non-Employment Finally the value of non-employment is defined as $V_t^N(d^U) = \max(V_t^U(d^U), V_t^O(d^U))$.

D.2 Heterogeneity in the Disutility of Work

We introduce an additional layer of heterogeneity (beyond the productivity distribution $F(p)$), by integrating the preceding model over a distribution of disutility of work types (η -types).

Under our distributional and functional form assumptions (laid out in detail next), the preceding model generates closed form solutions for all transitions between states (e.g. E to U) and can be used to calculate expected non-employment durations for a given value of η . We will assume individual workers draw their η from a cohort-specific, distribution and integrate transitions and non-employment durations over the entire distribution. Specifically, we will assume that η is normally distributed with mean $\eta_{mean,cohort}$ and standard deviation η_{sd} (which is fixed across cohorts). We implement this in practice by simulating the model for 25 different values of η and

use Simpson’s rule to approximate the full integral over the η distribution whenever we calculate cohort-level transitions and non-employment durations.

D.3 Distributional and Functional Form Assumptions

Here we lay out the functional forms and distributional assumptions underlying our baseline model.

Productivity p_t will be drawn from a mixture distribution in which workers have Λ_t probability of facing a (large) negative productivity shock ($-L$) that destroys the job with certainty. Meanwhile, with probability $1 - \Lambda_t$, workers draw a productivity level p_t from a lognormal distribution. This allows for exogenous job destruction at the rate Λ_t . Formally, p_t is drawn from a mixture distribution defined by $f(\ln(p_t)) = \Lambda_t f^L(\ln(p_t)) + (1 - \Lambda_t) f_{p,\sigma_p}^N(\ln(p_t))$ where f_{p,σ_p}^N is the normal PDF and $f^L(\ln(p_t)) = 1$ if $\ln(p_t) = -L$ and $f^L(\ln(p_t)) = 0$ otherwise. This allows for closed form solutions to all eventual transitions generated by the model. For sufficiently large L the functional form for the CDF of the mixture variable is $F(\ln(p_t)) = \Lambda_t(1) + (1 - \Lambda_t) F_{p,\sigma_p}^N(\ln(p_t))$ where F_{p,σ_p}^N is the normal CDF. Additionally, we will allow the exogenous job destruction rate Λ_t to vary with the national male unemployment rate (u.r.). Specifically Λ_t will be a logistic function $\Lambda_t = \frac{1}{1 + e^{-(\lambda_1 + \lambda_2 u.r._t + \lambda_3 \Delta u.r._t)}}$ with parameters λ_1 to λ_3 allowing Λ_t to vary with the level and year-on-year change in the national male unemployment rate.

We assume workers have log utility $u(\cdot) = \ln(\cdot)$. Firms make zero profits and hence pay the worker $w_t = p_t$ in all periods. Workers draw disutility η from a normal distribution ($\eta \sim N(\eta_{mean,cohort}, \eta_{sd})$).

The search cost function is based on [DellaVigna et al. \(2022\)](#) with some added flexibility. Specifically we assume:

$$\psi_t = k_0 + k_1 \mathbf{1}(dU = 0) + e^{k_2 \times dU} \times k_3 \frac{s^{1+\gamma}}{1 + \gamma} \quad (C.5)$$

Where k_0 is a fixed cost of being in unemployment, k_1 a fixed cost of entering unemployment the first time, k_2 allows search to become more costly later on in unemployment spells, while k_3 and γ govern the slope and curvature of the job search function.

D.4 Closed Form Solutions For Each Value Function

Value Function For Employment Let ω_{t,d^U} be the ‘reservation productivity’ such that $V_t^E(\omega_{t,d^U}, d^U) = V_t^N(d^U)$. Further, let $\bar{\omega}_{t,d^U} \equiv \frac{\ln(\omega_{t,d^U}) - p}{\sigma_p}$.

Since $V_t^E(p_t, d^U) = \ln(p_t) - \eta + \beta E_{p_{t+1}} [\max \{V_{t+1}^E(p_{t+1}, d^U), V_{t+1}^N(d^U)\}]$, plugging in ω_{t,d^U}

for p_t and rearranging $V_t^E(\omega_{t,d^U}, d^U) - V_t^N(d^U) = 0$ gives:

$$\ln(\omega_{t,d^U}) = \eta - \beta E_{p_{t+1}} [\max \{V_{t+1}^E(p_{t+1}, d^U), V_{t+1}^N(d^U)\}] + V_t^N(d^U) \quad (\text{C.6})$$

Given the distribution of p_t :

$$\begin{aligned} E_{p_{t+1}} [\max \{V_{t+1}^E(p_{t+1}, d^U), V_{t+1}^N(d^U)\}] &= [\Lambda_{t+1} + (1 - \Lambda_{t+1})\Phi(\bar{\omega}_{t+1,d^U})] V_{t+1}^N(d^U) \\ &+ [1 - \Lambda_{t+1} - (1 - \Lambda_{t+1})\Phi(\bar{\omega}_{t+1,d^U})] E \left[V_{t+1}^E(p_{t+1}, d^U) \mid \frac{\ln(p_{t+1}) - p}{\sigma_p} \geq \omega_{t+1,d^U} \right] \end{aligned}$$

Note that the conditional expectation at the end of this equation is ‘‘as if’’ is normally distributed, for the relevant sample space of productivity values. Using the fact that $E(X|Z < \bar{\omega}_{t+1}) = p - \sigma_p \frac{\phi(\bar{\omega}_{t+1})}{\Phi(\bar{\omega}_{t+1})}$ and $E(X|Z \geq \bar{\omega}_{t+1}) = p + \sigma_p \frac{\phi(\bar{\omega}_{t+1})}{1 - \Phi(\bar{\omega}_{t+1})}$ for a random variable $Z \sim N(0, 1)$ and for $X = \sigma Z + \mu \sim N(\mu, \sigma)$, we obtain:

$$\begin{aligned} E \left[V_{t+1}^E(p_{t+1}, d^U) \mid \frac{\ln(p_{t+1}) - p}{\sigma_p} \geq \omega_{t+1,d^U} \right] &= p - \eta \\ &+ \beta E_{p_{t+2}} [\max \{V_{t+2}^E(p_{t+2}, d^U), V_{t+2}^N(d^U)\}] + \sigma_p \frac{\phi(\bar{\omega}_{t+1}(d^U))}{1 - \Phi(\bar{\omega}_{t+1}(d^U))} \end{aligned}$$

And hence

$$\begin{aligned} E_{p_{t+1}} [\max \{V_{t+1}^E(p_{t+1}, d^U), V_{t+1}^N(d^U)\}] &= [\Lambda_{t+1} + (1 - \Lambda_{t+1})\Phi(\bar{\omega}_{t+1,d^U})] V_{t+1}^N(d^U) \\ &+ [1 - \Lambda_{t+1} - (1 - \Lambda_{t+1})\Phi(\bar{\omega}_{t+1,d^U})] \\ &\times \left\{ p - \eta + \beta E_{p_{t+2}} [\max \{V_{t+2}^E(p_{t+2}, d^U), V_{t+2}^N(d^U)\}] \right. \\ &\left. + \sigma_p \frac{\phi(\bar{\omega}_{t+1}(d^U))}{1 - \Phi(\bar{\omega}_{t+1}(d^U))} \right\} \end{aligned}$$

Similarly,

$$\begin{aligned} E_{p_{t+2}} [\max \{V_{t+2}^E(p_{t+2}, d^U), V_{t+2}^N(d^U)\}] &= [\Lambda_{t+2} + (1 - \Lambda_{t+2})\Phi(\bar{\omega}_{t+2,d^U})] V_{t+2}^N(d^U) \\ &+ [1 - \Lambda_{t+2} - (1 - \Lambda_{t+2})\Phi(\bar{\omega}_{t+2,d^U})] \\ &\times \left\{ p - \eta + \beta E_{p_{t+3}} [\max \{V_{t+3}^E(p_{t+3}, d^U), V_{t+3}^N(d^U)\}] \right. \\ &\left. + \sigma_p \frac{\phi(\bar{\omega}_{t+2}(d^U))}{1 - \Phi(\bar{\omega}_{t+2}(d^U))} \right\} \end{aligned}$$

And so forth, until the final period T^{Last}

$$E_{p_{T^{Last}}} [\max \{V_{T^{Last}}^E(p_{T^{Last}}, d^U), V_{T^{Last}}^N(d^U)\}] = V_{T^{Last}}^N(d^U) = V_{T^{Last}}^O(d^U)$$

Hence, the value of employment in any given period can be determined using backward induction. For convenience, we define $\Omega_{t,d^U} \equiv E \max [V_t^E(p_t, d^U), V_t^N(d^U)]$. This allows us to express $V_t^E(p_t, d^U) = u(w_t(p_t, d^U)) - \eta + \beta \Omega_{t+1,d^U}$.

Altogether, these results and Equation C.6 imply: $\bar{\omega}_{t,d^U} \equiv \frac{\ln(\omega_{t,d^U}) - p}{\sigma_p} = \frac{\eta - \beta \Omega_{t+1,d^U} + V_t^N(d^U) - p}{\sigma_p}$.

Value Function For Unemployment Given the above, we can rewrite the value of unemployment as a function of

$$V_t^U(d^U) = u(B(d^U)) + \max_s \{ \beta V_{t+1}^N(d^U + 1) + \beta s (\Omega_{t+1,d^U+1} - V_{t+1}^N(d^U + 1)) - \psi_t(s) \}$$

and

$$s^* = \psi'^{-1} (\beta \Omega_{t+1,d^U+1} - \beta V_{t+1}^N(d^U + 1))$$

Transitions Individuals can be in any of the following N_s states: employed with $d^U = 0$ to $d^U = T$, unemployed with $d^U = 0$ to $d^U = T$, or out of the labor force. Let $\mathbf{h}_t \equiv (h_{t,E,d^U=0}, \dots, h_{t,E,d^U=T}, h_{t,U,d^U=0}, \dots, h_{t,U,d^U=T}, h_{t,O})$ be the vector describing the number of individuals across states at each time period. Let the $m_{t,i,j}$ be the probability of an individual transitioning from state i at time t to state j at time $t + 1$. Let \mathbf{M}_t be the transition matrix across states where $m_{t,i,j}$ is the element of the i^{th} row and j^{th} column.

The transition matrix describes the evolution of the number of individuals across states:

$$\mathbf{h}_{t+1} = \mathbf{h}_t \mathbf{M}_t$$

Define $\zeta_{d^U} \equiv \Lambda_{t+1} + (1 - \Lambda_{t+1})\Phi(\bar{\omega}_{t+1,d^U})$ and $\zeta_{d^U+1} \equiv \Lambda_{t+1} + (1 - \Lambda_{t+1})\Phi(\bar{\omega}_{t+1,d^U+1})$

The transition matrix \mathbf{M}_t is given by:

	Employed d^U	Employed $d^U + 1$	Unemployed d^U	Unemployed $d^U + 1$	OLF
...					
Employed d^U	$1 - \zeta_{d^U}$	0	$\zeta_{d^U} \mathbf{1} \left(\begin{array}{l} V_{t+1}^U(d^U) \\ \geq \\ V_{t+1}^O(d^U) \end{array} \right)$	0	$\zeta_{d^U} \mathbf{1} \left(\begin{array}{l} V_{t+1}^O(d^U) \\ > \\ V_{t+1}^U(d^U) \end{array} \right)$
...					
Unemployed d^U	0	$s[1 - \zeta_{d^U + 1}]$	0	$\left\{ (1 - s) + s(\zeta_{d^U + 1}) \right\} \times \mathbf{1} \left(\begin{array}{l} V_{t+1}^U(d^U + 1) \\ \geq \\ V_{t+1}^O(d^U + 1) \end{array} \right)$	$\left\{ s\zeta_{d^U + 1} + (1 - s) \right\} \times \mathbf{1} \left(\begin{array}{l} V_{t+1}^O(d^U + 1) \\ > \\ V_{t+1}^U(d^U + 1) \end{array} \right)$
...					
OLF	0	0	0	0	1

As an example, a transition from employed with $d^U \rightarrow$ unemployed with d^U occurs with $prob[V_{t+1}^E(p_{t+1}, d^U) < V_{t+1}^N(d^U)] \mathbf{1}(V_{t+1}^U(d^U) \geq V_{t+1}^O(d^U))$.

This can be simplified to:

$$\begin{aligned}
&= prob[\ln(p_{t+1}) < V_{t+1}^N(d^U) + \eta - \beta \Omega_{t+2, d^U}] \mathbf{1}(V_{t+1}^U(d^U) \geq V_{t+1}^O(d^U)) \\
&= F(V_{t+1}^N(d^U) + \eta - \beta \Omega_{t+2, d^U}) \mathbf{1}(V_{t+1}^U(d^U) \geq V_{t+1}^O(d^U)) \\
&\text{Recall } \bar{\omega}_{t+1, d^U} = \frac{V_{t+1}^N(d^U) + \eta - \beta \Omega_{t+2, d^U} - p}{\sigma_p}, \text{ hence:} \\
&= [\lambda_{t+1} + (1 - \lambda_{t+1}) \Phi(\bar{\omega}_{t+1, d^U})] \mathbf{1}(V_{t+1}^U(d^U) \geq V_{t+1}^O(d^U)) \\
&= \zeta_{d^U} \mathbf{1}(V_{t+1}^U(d^U) \geq V_{t+1}^O(d^U))
\end{aligned}$$

Model Output: Aggregate Transition Probabilities and Non-Employment Durations We first simulate the model for 25 different realizations of the distribution of disutility of work. For each of them, we calculate simulated moments such as transitions between employment statuses and non-employment durations. For transitions, we sum across the elements of the transition matrix that correspond to each moment. For non-employment durations, we employ a backwards induction procedure that assumes that all workers are not employed by the last period, and then it considers the probability of entering non-employment recursively. This approach allows us to generate the expected value for non-employment duration for new entrants into UI ($d^U = 0$) for every period. After calculating these moments, we aggregate all realizations by integrating over the distribution of η using Simpson's rule.

E Estimation Details

E.1 Estimation Procedure

In-Sample Cohorts We estimate the model structurally, using a minimum distance estimator to match the empirical reduced form moments from Section 3. Denote as ξ the parameters of the structural model. Furthermore, let $m(\xi)$ be the vector of moments predicted by the model as a function of the parameters ξ , and by \hat{m} the vector of observed moments. We estimate the model using 3 cohorts: 1929, 1935, and 1950 on quarterly data. The moments $m(\xi)$ we use for matching are i) the monthly transition probabilities of workers from E to U (i.e. UI or Nu in the data) between age 50 and 63, ii) the non-employment durations (calculated from job exit until age 63), and iii) $\frac{\partial Nonemp}{\partial P}$ at age 52 = 0.128 for the 1950 cohort (from Table 2).⁴⁸

⁴⁸While we observe UI receipt, we cannot distinguish unemployment from OLF after UI benefits are exhausted. For this reason we simply distinguish between non-employment and employment, which we can easily generate from

The estimator chooses the parameters $\hat{\xi}$ that minimize the distance:

$$(m(\xi) - \hat{m})' W (m(\xi) - \hat{m}) \quad (\text{C.1})$$

Where W is a weighting matrix. We simulate all transitions using the empirical data to construct the full covariance matrix for the transitions. We use diagonal covariance matrices based on the estimated standard errors for the non-employment durations and for $\frac{\partial N_{onemp}}{\partial P}$.

For the intensive margin RD moments, we use a larger weight ($\times 100$) since this is a causal estimate that we have significant confidence in given the research in this paper and many other well identified estimates from the literature and we want to make sure our fitted model generates realistic predictions for intensive margin responses. We omit the first and last quarter from the estimation.

Out-of-Sample Cohorts In the second step of the model we refit our model to all other cohorts by estimating a single parameter per cohort - the mean of that cohort's η distribution ($\eta_{\{mean, cohort\}}$). For this estimation exercise, our target moments are transitions from E to U and non-employment durations. Since this parameter was already estimated within our in-sample cohorts, refitting does not change the model parameters for our in-sample cohorts, but allows different cohorts to have different outside options / workforce attachment that are not otherwise captured by other features of the model and institutional parameters. We also employ a minimum distance estimator using the same specifications previously described.

E.2 Estimated Parameters

We estimate the following parameters: standard deviation of the distribution of productivity σ_p ; parameters of exogenous job loss shock $\lambda_1 - \lambda_3$; search cost function parameters $k_0 - k_3$ and γ ; and parameters for the cohort-specific distribution of disutility of work $\eta_{mean,1929}$, $\eta_{mean,1935}$, $\eta_{mean,1950}$, and η_{sd} .

E.3 Numerical Optimization

The model is simulated in Python. We carefully optimized our code using the Python package Numba to pre-compile the code which greatly speeds up computation times. We then estimate the model by numerically minimizing the objective function (Equation C.1). For this we rely on the optimization package **estimagic** (see [Gabler \(2022\)](#)), which provides an elegant way to search for

the model predictions by pooling the unemployed and OLF states.

global minima using a multi-start algorithm, that can be distributed over many computing cores and nodes and allows for easily switching between alternative local optimizers. For our problem, we found that two derivative free least squares optimizers work well: Derivative-Free Optimizer for Least-Squares Minimization (DFO-LS) (Cartis et al., 2018) and POUNDERS (Wild, 2015). A noteworthy practical point is that these least-squares optimizers perform vastly better than a wide range of black box optimizers that we tried (such as newtonian, quasi-newtonian, trust-region, and genetic algorithms).

Our algorithm is the following: We use 18 compute nodes with 28 cores each. We then draw 280 random starting values on each node using latin hypercube sampling (to guarantee good coverage of the parameter space). On each node we then pick the 28 best starting values (lowest SSE) and run a local minimizer (in half the cases DFO-LS in the other half POUNDERS) on them with a walltime of 10 hours. The total compute time is thus $18 \cdot 28 \cdot 10 = 5040$ hours. We can assess convergence by comparing the best solutions from each of the 18 nodes. They are fairly close to each other, both in terms of SSE and the parameter estimates, suggesting that we reliably find a global minimum or at least a point very close to the global minimum.

E.4 Institutional and Other Non-Estimated Parameters Used in the Model

We set $T^{Last} = 78$ and $\beta = 0.95$.

Average Wages/Productivity: Mean (net) wages are set at euro 1,950, so the mean of the p_t distribution is the logarithm of 1950. This implies an approximate gross wage of 3000, which is in line with average gross wages for men aged 50-60 with a UI spell (3,282 across all 6 select cohorts). We use a constant conversion rate between gross and net wages of 0.65.⁴⁹

UI and UA replacement rates: UI reforms in the past decades also changed the UI replacement rates. The replacement rates on net wages stay at 63% for an individual without children and 67% for an individual with children till end of 1993. Starting January 1994, the replacement rates reduced to 60% and 67%, respectively. Since most of our sample will no longer have eligible children, we use the 63% and 60% rates. We apply the UI replacement rates on net wages for each cohort based on when they reach the UI bridge age. In practice, this means we set $b = 1230$ for 1936 and earlier cohorts and $b = 1170$ for 1937 and later cohorts. We set $y^u = 500$, which is approximately half of what one would receive if on UA with no deductions. We halve the amount as evidence in Schmieder et al. (2012) suggests that due to deductions average UA benefits actually

⁴⁹This conversion rate comes from the data. Specifically, for cohorts 1935 and later, we take all individuals in the cohort with a UI spell in the IEB-data aged 50-60 and compare their actual UI benefits to their gross income. For each cohort, we obtain an average gross replacement rate of 0.39, implying a constant conversion rate from net UI replacement rates to gross UI replacement rates of 0.65. We assume this conversion rate also applied to prior cohorts.

received are substantially below the 53% nominal replacement rate on net wages and only 50% of UI exhaustees take-up UA.

Pension replacement rate: ρ represents the pension replacement rate on gross wages per one additional year of employment. We calculate the values for an average earner born in the cohort based on the pension benefit formula in Germany. For each cohort, we take the value of ρ in the years when they are between 60 and 63 years old, which we calculate on cohort-by-cohort basis as described below. Several pension reforms in the past decades have changed the pension benefit formula.

Before 1992, the pension benefit size was determined by four factors: the relative earnings of the insured, the aggregate annual pension value, the number of insurance years, and an adjustment factor, which was set at 1.5 for old-age pensions. For an average earner with 45 years of contribution, the gross annual pension benefit was the annual pension value $\times 45 \times 1.5$. Therefore, the pension replacement rate on gross wage is $(\text{annual pension value} \times 45 \times 1.5) / \text{average annual income}$. The pension replacement rate on gross wages per one additional year of employment is calculated from the monthly pension benefits net of health care and long-term care contribution (ssc) : $(\text{annual pension value} \times 1.5)(1 - \text{ssc}) / \text{average annual income}$.

After 1992, the monthly pension benefit amount is obtained by multiplying the personal pension base by the monthly pension value (PV). The personal pension base is the sum of the earnings points (EPs) accumulated over the entire working history. For example, an average wage earner with 45 contribution years will accumulate 45 EPs. At the time of retirement, this personal pension base is scaled up by the pension value at the time of retirement, which is determined aggregately by factors such as the average wage of all insured, the contribution rate, and demographic changes. For example, one EP was equivalent to 29.21 euro per month in 2015. Therefore, the pension replacement rate on gross wage earnings was $(45 \times PV \times 12) / \text{average annual income}$. The pension replacement rate on gross wages of an additional year of contribution net of ssc is $(PV \times 12)(1 - \text{ssc}) / \text{average annual income}$.

We obtain the pension values, the average annual income of all insured, and health care and long-term care contribution rates for the years 1980 to 2016 from the German pension statistics office and social code book VI. The pension values are from [Zahlen und Tabellen vom 1.1. bis 30.6.2020](#). The average annual income of all insured is from Appendices 1 and 2 of the social code book VI. The average social security contribution rates are from the [German pension insurance annual report 2019](#).

We set the income tax rate on pension benefit to zero for two reasons. First, for individuals

who retire before 2005, pension income is tax-free.⁵⁰ Second, for individuals who retire after 2005, only 50 percent of their gross pension benefit is recognized as taxable income. However, there is an annual income threshold that is exempt from income tax, regardless of income sources. This threshold was 9000 euro per single individuals in 2018 and 7356 euro in 2005. For an average earner with 40 years of contributions who retires in 2005, the annual pension benefits are around EUR 12,500. Much of this amount is below the taxable income threshold, which is why it is reasonable to set the income tax for pension benefits to zero.

Using these data and assumptions we calculate a ρ for each cohort and we use these values in our model. The value of ρ is shown for select cohorts in Table 1.

Years of contribution made before age 54. We obtain the average years of contribution at age 54 by using the scientific use file of the Insurance Account Sample (Versicherungskontenstichprobe, SUFVSKT) of the German Federal Pension Register. Each wave of SUFVSKT contains 5% random sample of individuals with an active public pension insurance account in Germany, who were between the ages of 30 and 67 at the time of data collection. Each wave also contains the earnings biographies from age 14 onwards, at a monthly frequency. For cohorts from 1935 to 1946, we calculate the average years of employment at age 54 for West Germans employed at age 50 using the wave SUFVSKT2002. We obtain the values for cohorts from 1947 to 1952 by using the waves SUFVSKT2010 and SUFVSKT2018. However, we cannot observe cohorts older than 1935 because the earliest publicly available SUFVSKT wave is 2002. Cohorts born before 1935 are older than 67 in 2002. To obtain reasonable values of employment years before age 54 for these older cohorts, we use the average values for cohorts from 1935 to 1940 as a proxy for the older cohorts' years of contribution made before age 55.

Discounted pension accrual rates while on UI and UA The time spent on unemployment insurance also increase pension benefits, because the UI agency contributes to the pension scheme on behalf of the unemployed. During the periods of claiming UI, contributions are paid on the basis of 80% of previous gross earnings (SGBVI §166 Paragraph 1 No. 2)). Therefore, one additional year of time spent on UI increases the future pension benefits by $\rho \times 80\%$. During the periods of claiming unemployment insurance benefits 2 (UIB II), which is means-tested and paid at a lower rate, and unemployment assistance (UA), no financial contributions are counted towards

⁵⁰The proportion of the income subject to tax varies with the year of retirement at which the individual first started drawing the pension. Pensions starting before 2005 are tax-free. For pensions beginning in 2005, 50 percent of the gross pension benefit is recognized as taxable income. This portion remains fixed for the pensioners who retire in 2005 and subsequent years. Until 2020, the taxable part of the pension increases by 2 percentage points per year and from 2020 until 2040, it will increase by one percentage point per year. In 2015, 70% of the pension income is taxable. The statutory health and long-term care insurance contributions are exempt from the taxable income. For more details about the schedule, see [German statutory pension insurance website](#).

the pension (OECD: pension at a glance 2019).

The model also takes as inputs the relevant earliest available retirement age (ERA), the age at which you can collect pension without penalties (NRA), and the accrual adjustment penalty for retiring at the ERA (simply a function of the difference between the NRA and ERA) for both the UI and long-term insured pathways.

E.5 Retirement Details: How We Calculate the Value of Out Of the Labor Force

To calculate the value of being out of the labor force (OLF), we first calculate the income from pension at any given point in time. This depends on the worker's contribution years (from employment, unemployment and welfare), working years, duration of unemployment d^U , reference income, pension replacement rates, potential UI duration, and the pension contribution discount while on UI. In the model, we take average contribution years from the data as described above at the starting age of the model and then allow individuals' contribution years to evolve based on individuals' simulated employment in subsequent years. Gross reference income is euro 3000 per month and pension replacement rates on gross income are listed in Table 1. Contribution years on UI count for 0.8 and contribution years from UA count for 0. Pensions taken at the ERA but before the NRA are further penalized by 3.6% per year retiring in advance of the NRA. Once we know the value of the pension at each point in time, we generate an age-specific OLF income path, which comprises home production before retirement (y^o) and pension income (after early retirement penalties) after retirement.⁵¹ This income stream will depend on cohort-specific institutional values such as early and normal retirement ages.

This whole procedure is done for each relevant pathway, namely, the UI pathway and the long-term insured pathway. That is, we calculate the present discounted value of OLF at each point in time for both pathways following Equation C.4. The worker then endogenously assigns the value of OLF to the pathway that provides higher value (if both are available and feasible, otherwise, as for later cohorts when the UI pathway was closed, this choice is determined for them).

For women, all is as above except we also allow women to take the women's pathway into retirement, which in practice will be as or more attractive than the UI pathway. Average contribution years prior to starting age in the model also differ for women.

⁵¹We set home production (y^o) to a low value, 50, so individuals in our model will typically remain employed or on UI/UA prior to the earliest age at which they could claim their pension, but model fit is relatively insensitive to the exact choice of y^o .

F Reduced-Form and Structural Results for Women

Women faced somewhat different incentives due to having the option of the woman's pension. This pathway gave qualifying women the option to retire at an ERA of 60, without needing a UI spell, all the way until the pathway was abolished for cohorts born in or after 1952. The NRA for the women's pathway was 60 until the 1939 cohort and gradually increased to 65 for cohorts 1940 to 1944, remaining at 65 until its abolition. As a result, the woman's pathway was also more generous in terms of both ERA and penalties than the UI pathway (since the ERA never increased and the NRA only increased for later cohorts). To be eligible for this pathway, women must have had at least 15 years of contributions, with 10 of these years occurring after age 40.

Due to the women's pathway always being equally or more generous than the UI pathway for qualifying women, the UI pathway itself is largely irrelevant. Of course, women could still use UI as a bridge to retirement even though they are not required to be unemployed at least one year past the age of 58 and a half to claim pensions.

In this section, we present a full suite of reduced-form and structural results for women. Figure G.6 shows the number of women entering UI by age for the six focal cohorts. We observe bunching in UI entries at age 60-PBD in all pre-1952 cohorts. For cohorts 1924, 1929 and 1935, the ERA and NRA for women's pathway are both 60, while the maximum PBD was 12 months, 24 months, and 32 months, respectively. Similar to men, we observe bunching in UI inflows at ages 59, 58 and 57 and 4 months. However, the amount of bunching is not as large as that of men. For example, for cohort 1924, around 1100 women enter UI and the share of women on UI between 59 and 60 is around 5% (see Figure G.7) in contrast to 10% for men. Figure G.8 complements Figure G.6 by plotting mean non-employment duration by age for each cohort until age 63. It confirms that women entering at the bridge-to retirement age remain non-employed for close to the maximum duration, similar to men. The 1945 cohort of women faced less generous retirement rules; they could retire at age 60, but the NRA was 65, meaning they faced an 18% permanent pension reduction for retiring at 60. As a result, we see substantially less bunching. Unlike men, women born in 1950 could still draw pensions at age 60 (albeit with penalty), resulting in some bunching at age 58. Beginning with the 1952 cohort, the woman's pathway was closed (as was the UI pathway) and women were no longer allowed to retire early at 60. Like men, women eligible for the old-age pension for the long-term insured, could still retire at age 63, and indeed we see some bunching at age 61. Overall, women behave similarly to men, but their inflow responses are slightly more muted, consistent with not requiring a UI spell to draw pensions and generally more generous early retirement options.

Next we turn to the RD estimates of the intensive margin effect of UI extensions for women.

Table H.5 presents RD estimates of the jump in the density at the age threshold for women, using the same specification as for the male sample. We exclude 2 months on each side of the cutoff – the donut hole – in all our regressions. Relative to men, the density appears less continuous at several cutoffs potentially introducing bias, though the magnitude of these density jumps is modest and results are relatively robust to the inclusion of additional controls. The 8 RD estimates for the different age cutoffs, with and without controls, are reported in Table H.3. The estimates average 0.10, suggesting that for each month of additional UI, female workers spend around three more days in non-employment. These estimates are quite similar to our baseline estimates for men. For women, we use the 0.064 estimate at the age 52 cutoff between 1999 and 2006 as a target moment in our structural estimation. Table H.8 assesses the robustness of the RD estimates for women by varying controls, sample restrictions (excluding 3 months around the cutoffs), bandwidth choice (12 months), and using triangular kernel. Results are reassuringly stable. For a more detailed discussion of these RD results, please refer to Appendix B.

Turning to the structural model estimation and results, we note that the model setup for women is almost identical to that for men. However, due to the women’s pension and differences in real world average contribution years of women, we have to make some adjustments. Because we allow individuals to choose the best retirement option available, women will always choose the women’s pathway over the UI pathway. The value of OLF for women depends on the two potential retirement pathways (women’s pension and the long-term-insured pathway). If the women’s pension is not available (for cohorts born since 1952), then the value of OLF is that of the long-term-insurance pathway. If both are available, then the maximum value between the two options will be the value of OLF. Table H.10 lists the institutional parameters that differ for women relative to men, namely the ERA and NRA (due to the women’s pension) and average contribution years at age 54.

Figure G.14 assesses our estimated model’s in sample fit for women by comparing simulated E to U transitions and simulated non-employment durations to their empirical counterparts for the three cohorts matched in the estimation (1929, 1935 and 1950). Overall, our model captures the key empirical patterns of interest. The fit is even slightly better than that of the male sample. In particular, we better fit UI inflow spikes and non-employment durations at ages prior to the bridge retirement age. This could be due to the fact women are less likely to be protected by collective labor agreements, which are linked to specific ages that are not featured in our model.

Figure G.15 shows how well the model performs out-of-sample for the 1924, 1945, and 1952 cohorts for the women sample. Despite primarily using parameters estimated from other cohorts (we only re-estimate one parameter out of sample – the cohort specific disutility of work), our model clearly fits the broad empirical patterns of interest, matching overall UI inflows, the spike in

UI inflows at the bridge-to-retirement age, and non-employment durations relatively well. Figure G.15 also conducts the same counterfactual exercise as in Figure 5, in which we simulate what happens when PBD is one year longer for all individuals. Using the 1945 cohort as an example (panels (c) and (d)), we can see workers shift their bridge-to-retirement age from 57 and 4 months to 56 and 4 months. For younger workers, whose inflows are largely unaffected by this extension, the increase in non-employment durations largely matches what would be expected due to intensive margin responses.

Figure G.16 (a) shows the empirical and simulated unemployment rates for women, separately for each age group. Compared to men, women aged 56 to 59 experience a slightly smaller, but still quite pronounced, increase in their unemployment rates in the 90s. The unemployment rate rose sharply in the 80s, increasing from near 10% in 1983 to 15% in the late 1980s, eventually peaking at nearly 18% in 1994. Subsequently, the rate declined to 7% by 2014. Our model fits the empirical pattern well. At younger ages we fit the empirical pattern closely, under-fitting by at most 1 percentage point between 1990 and 2005. At the older ages the model fits the pattern very closely in the 80s but tends to under-predict the empirical unemployment rate in the 90s and 00s, and over-predicts in the last years. The overall fit, though, is similar to that of the men.

Figure G.16 (b) shows the impact of extending PBD by one year. As in Figure 6 (b), the extension has a modest effect on individuals aged 52-55 driven by intensive margin responses. In contrast, this same PBD extension raises the unemployment rate of older workers substantially.

Figures G.17 and G.18 conduct our other counterfactual policy simulations for women. Figure G.17 illustrates that keeping PBD fixed at 12 months would have massively reduced non-employment duration for 1935 cohort women in their late 50s, as the bridge-to-retirement age would have remained at age 59 instead of moving to earlier ages. Figure G.18 (a) shows how keeping PBD fixed at 12 would have affected the overall unemployment rate of both younger and older workers. Our analysis indicates that in 1994, unemployment rates for workers aged 56-59 would have been 4.9pp lower (see column (1) of Table 5).

Figure G.18 (b) considers an alternative policy simulation that assumes PBD evolves as it did in real life but imagines that both the women's pathway and UI pathway into retirement never existed, making age 63 the earliest possible retirement age for all birth cohorts. As for men, closing these pathways would have made a substantial difference for the unemployment rates of older workers (but not so for those of slightly younger workers).

Like Figure 8 (c), Figure G.18 (c) examines what would have happened in later years if institutions had remained at their 1994 levels (or changed one by one instead of all together).⁵² The

⁵²To build intuition, Figures G.17 (c) and (d) show how these same changes look for a single cohort – the 1952 cohort.

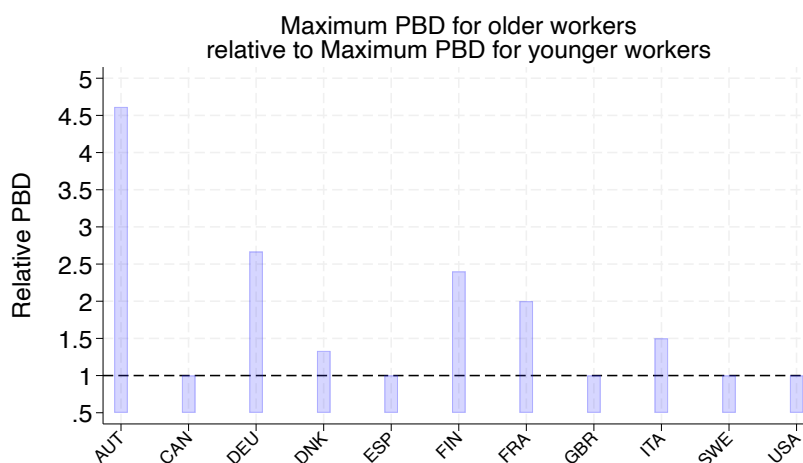
dashed blue line shows that, had all institutions remained fixed at their (generous) 1994 levels, the unemployment rate would have only declined by 5.2pp between 1994 and 2014 (due to non-policy or economic reasons) instead of declining by 8.0pp (the solid, dark blue line). Thus, the retirement and UI policy changes account for 2.8pp (or 35%) of the observed decline between 1994 and 2014. Altogether, the main takeaways from these simulated results for women are similar to those for men.

G Appendix Figures

Figure G.1: Unemployment rates and UI policies for older and younger people in OECD countries



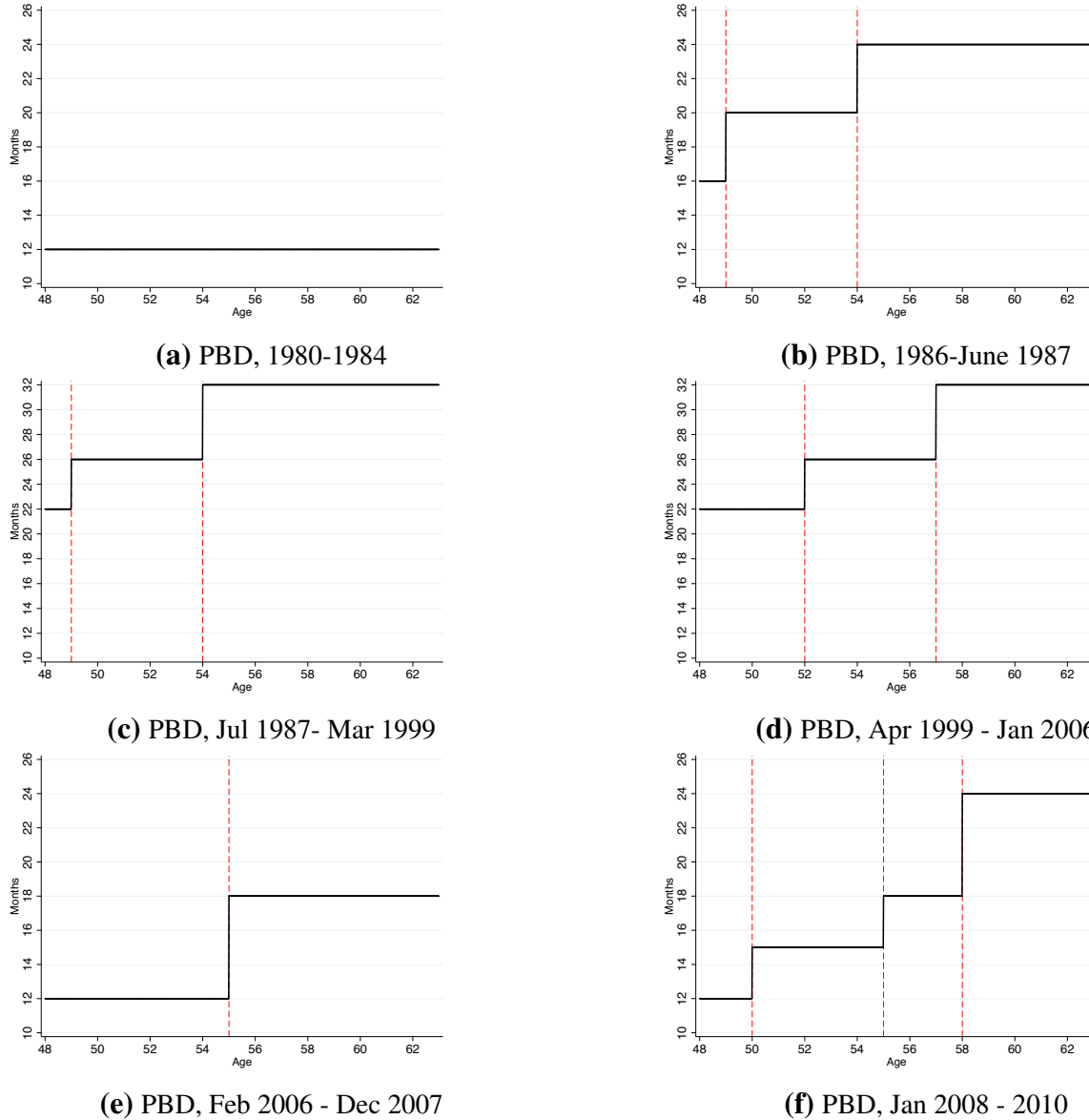
(a) Relative unemployment rate (old v.s. young)



(b) Relative maximum PBD (old v.s. young)

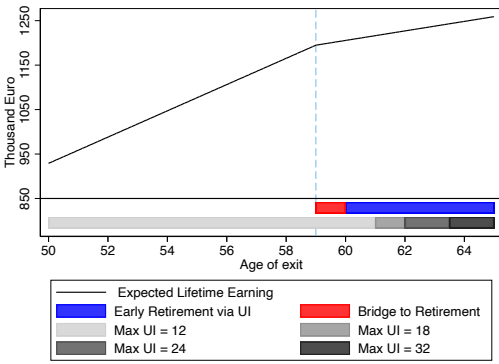
Notes: Panel (a) shows the unemployment rate for people aged 55 to 59 relative to those aged 35 to 44 in 1995. The unemployment rate statistics are obtained from [OECD.Stat](#). Panel (b) shows the maximum UI potential benefit duration for older workers (older than 50 or 55, depending on the specific policy design of the country) relative to younger workers in 2001, the earliest available year provided by [OECD Benefits and wages](#).

Figure G.2: Maximum Potential UI Benefit Durations (PBDs) by Age for Different Time Periods in Germany

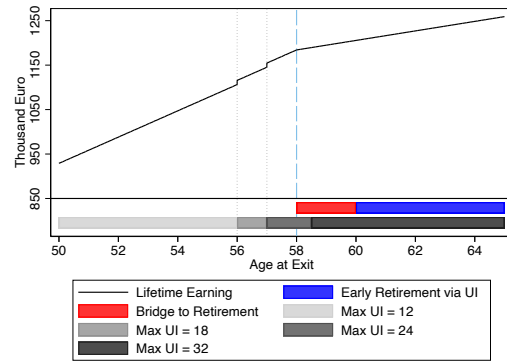


Notes: The figure shows how maximum potential unemployment insurance (UI) benefit durations vary with age and over time in Germany from 1980 to 2010. We drop the brief 1985 regime for presentation purposes. Each figure corresponds to a different UI regime. Appendix Table H.1 contains more detailed information on each institutional regime, including eligibility requirements and benefit levels. The vertical red dash-dotted lines mark the age cutoffs for increases in potential UI durations at different ages.

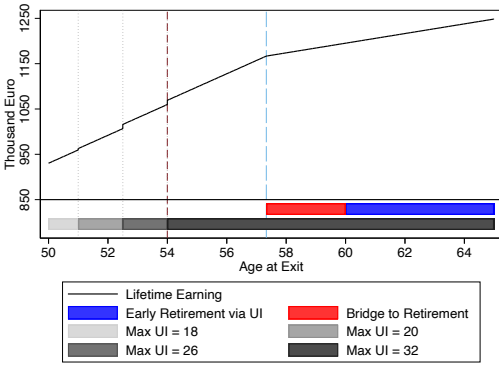
Figure G.3: Stylized Budget Sets for Different Cohorts in Germany, Men



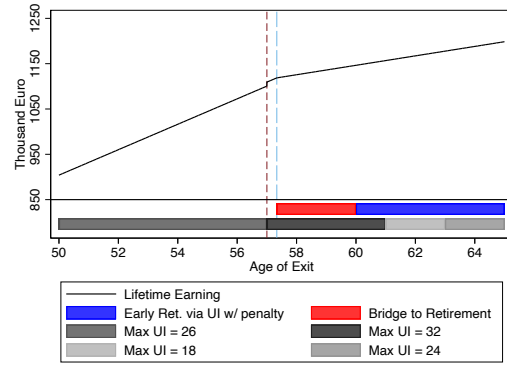
(a) Lifetime Income, 1924 Cohort



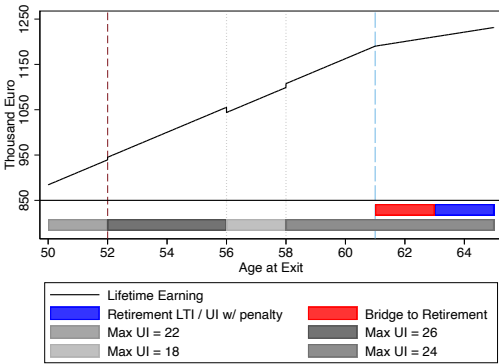
(b) Lifetime Income, 1929 Cohort



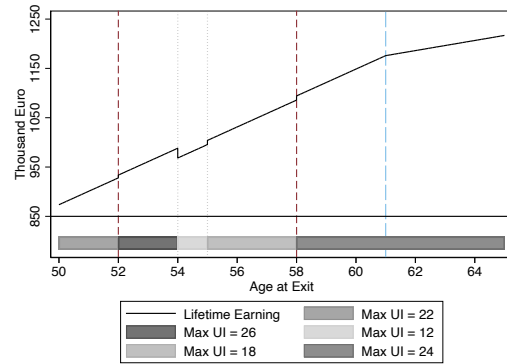
(c) Lifetime Income, 1935 Cohort



(d) Lifetime Income, 1945 Cohort



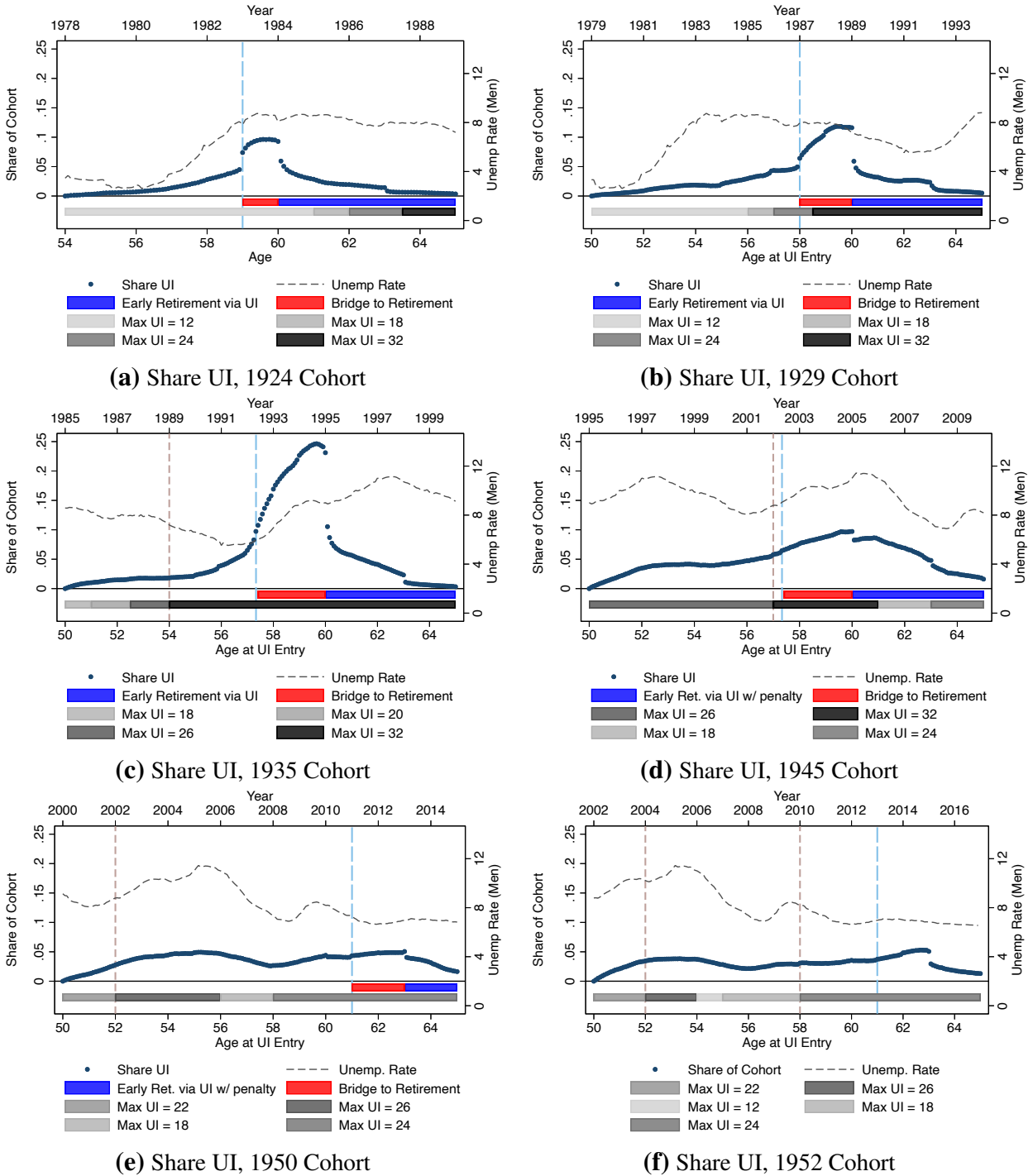
(e) Lifetime Income, 1950 Cohort



(f) Lifetime Income, 1952 Cohort

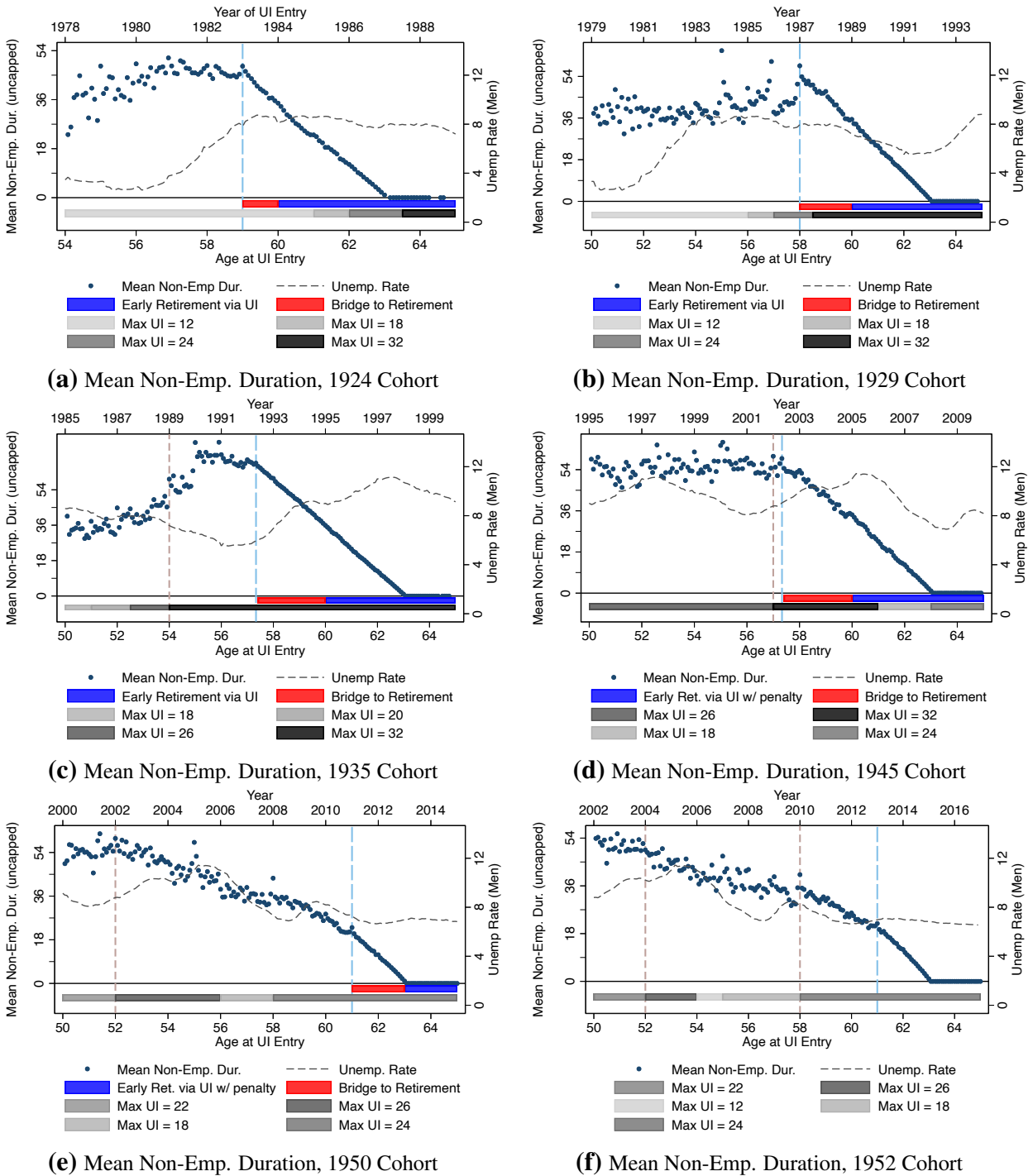
Notes: This figure plots stylized lifetime budget sets by age for different cohorts of West German men in our sample. The red bar under the figure indicates the period over which an individual could receive UI before drawing pension if he entered UI at the bridge-to-retirement age (the blue dashed line). The blue bar indicates the period over which such an individual would receive their pension. The different shades of gray represent different maximum PBD eligibility for UI, which can change because of an existing age-cutoff (the red dashed line) or because of an overall UI policy change enacted in that year (the gray dotted line).

Figure G.4: Share UI by Age for Different Cohorts in Germany, Men



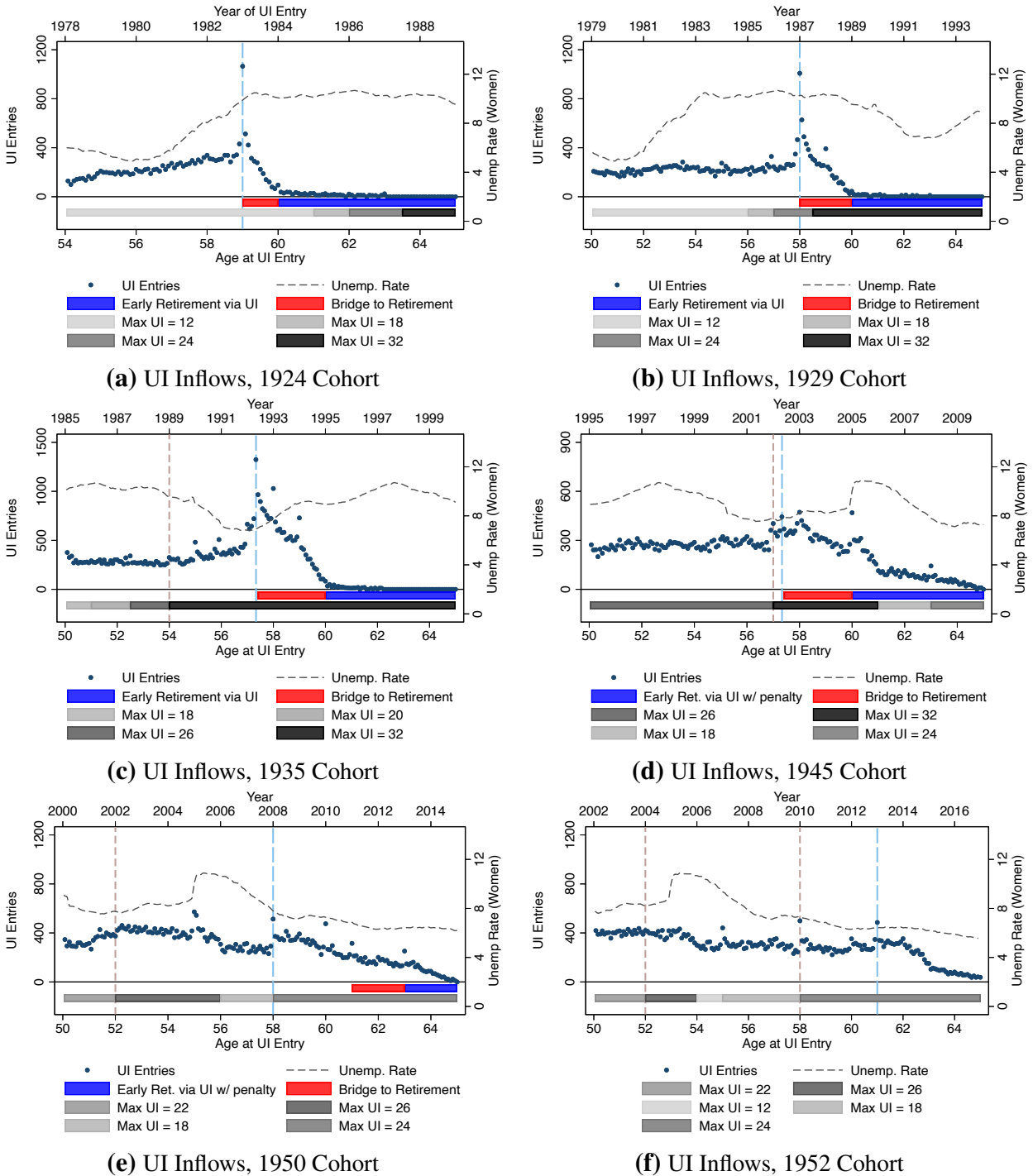
Notes: This figure plots the share of the cohort in UI by age for different cohorts of West German men in our sample (left axis). It also plots the male, seasonally adjusted unemployment rate as a dashed gray line (right axis). The red bar under the figure indicates the period over which an individual could receive UI before drawing pension if he entered UI at the bridge-to-retirement age (blue dashed line). The blue bar indicates the period over which such an individual would receive their pension. Different shades of gray represent different maximum PBD eligibility for UI, which can change because of an age-cutoff (red dashed line) or because of an overall UI policy change enacted in that year (gray dotted line).

Figure G.5: Mean Non-Emp. Duration by Age for Different Cohorts in Germany, Men



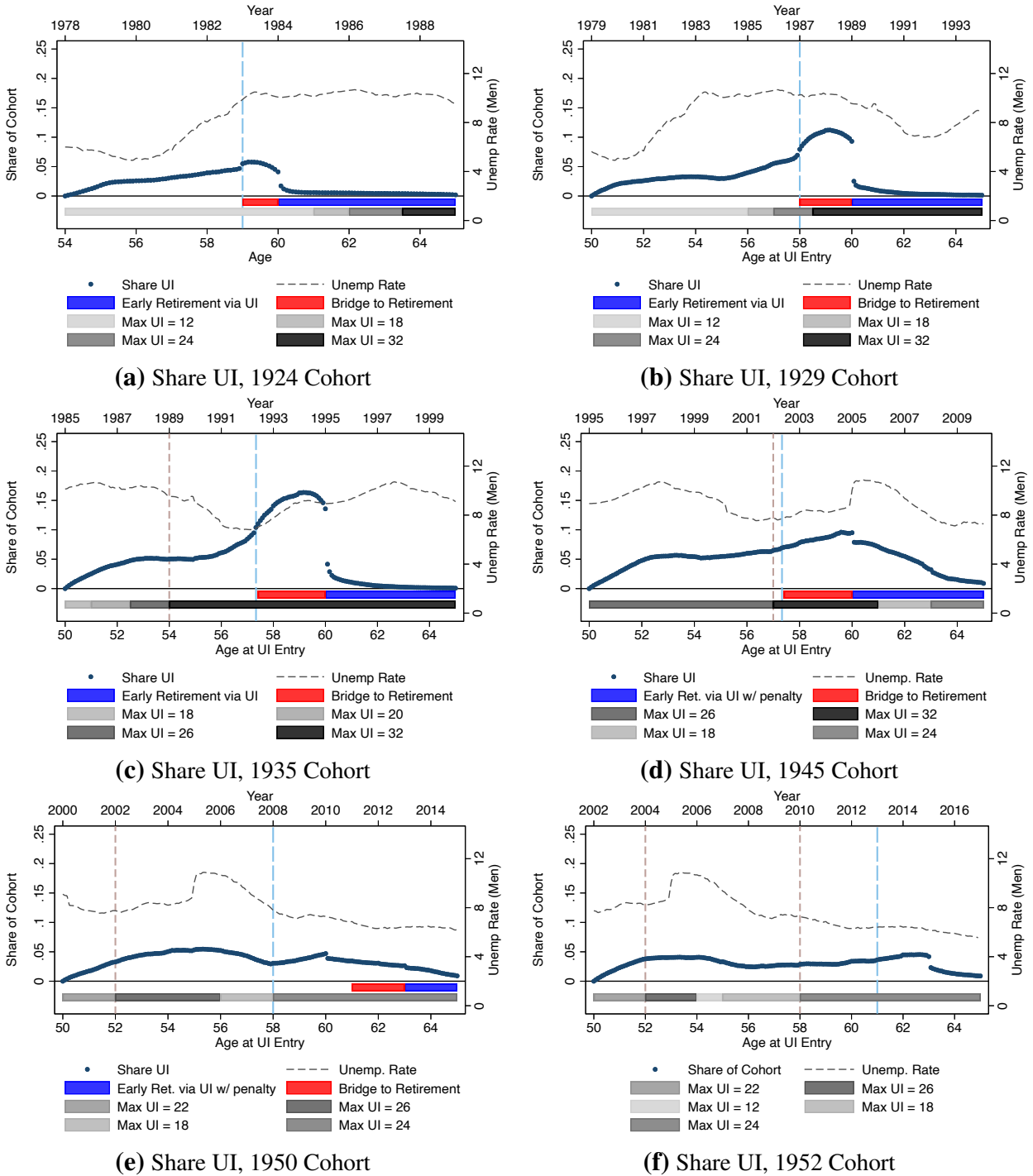
Notes: This figure plots mean non-employment duration (up to age 63) for different cohorts of West German men in our sample (left axis). It also plots the male, seasonally adjusted unemployment rate as a dashed gray line (right axis). The red bar under the figure indicates the period over which an individual could receive UI before drawing pension if he entered UI at the bridge-to-retirement age (blue dashed line). The blue bar indicates the period over which such an individual would receive their pension. Different shades of gray represent different maximum PBD eligibility for UI, which can change because of an age-cutoff (red dashed line) or because of an UI policy change enacted in that year (gray dotted line).

Figure G.6: UI Inflows by Age for Different Cohorts in Germany, Women



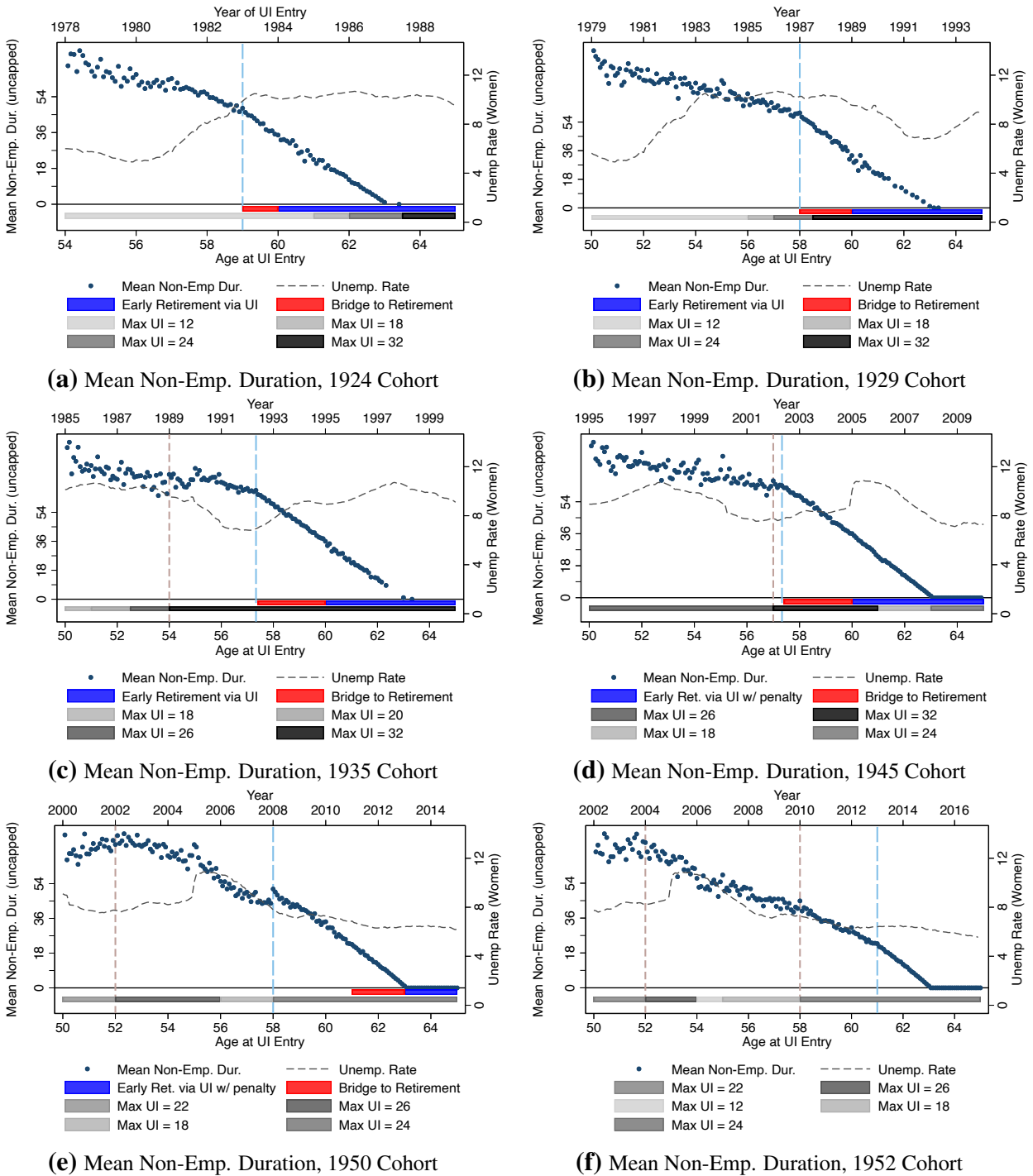
Notes: This figure plots UI inflows (transitions from employment to unemployment) by age for different cohorts of West German women in our sample (left axis). It also plots the female, seasonally adjusted unemployment rate as a dashed gray line (right axis). The red bar under the figure indicates the period over which an individual could receive UI before drawing pension if he entered UI at the bridge-to-retirement age (the blue dashed line). The blue bar indicates the period over which such an individual would receive their pension. Different shades of gray represent different maximum PBD eligibility for UI, which can change because of an age-cutoff (red dashed line) or because of an UI policy change enacted in that year (gray dotted line).

Figure G.7: Share UI by Age for Different Cohorts in Germany, Women



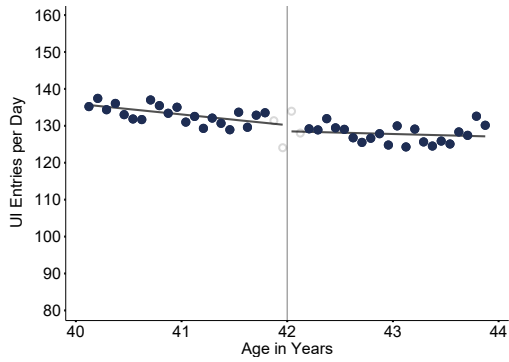
Notes: This figure plots the share of the cohort in UI by age for different cohorts of West German women in our sample (left axis). It also plots the female, seasonally adjusted unemployment rate as a dashed gray line (right axis). The red bar under the figure indicates the period over which an individual could receive UI before drawing pension if he entered UI at the bridge-to-retirement age (blue dashed line). The blue bar indicates the period over which such an individual would receive their pension. The different shades of gray represent different maximum PBD eligibility for UI, which can change because of an age-cutoff (red dashed line) or because of an UI policy change enacted in that year (gray dotted line).

Figure G.8: Mean Non-Emp. Duration by Age for Different Cohorts in Germany, Women

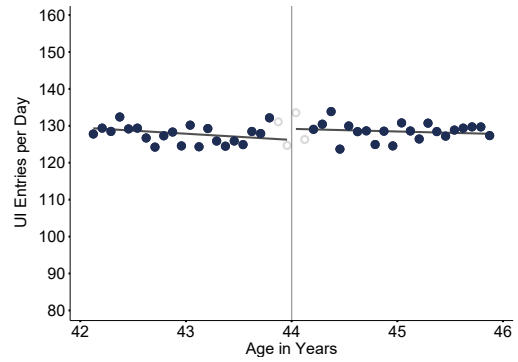


Notes: This figure plots mean non-employment duration (up to age 63) for different cohorts of West German women in our sample entering unemployment at the given age (left axis). It also plots the female, seasonally adjusted unemployment rate as a dashed gray line (right axis). The red bar under the figure indicates the period over which an individual could receive UI before drawing pension if he entered UI at the bridge-to-retirement age (the blue dashed line). The blue bar indicates the period over which such an individual would receive their pension. Different shades of gray represent different maximum PBD eligibility for UI, which can change because of an age-cutoff (the red dashed line) or because of an UI policy change enacted in that year (gray dotted line).

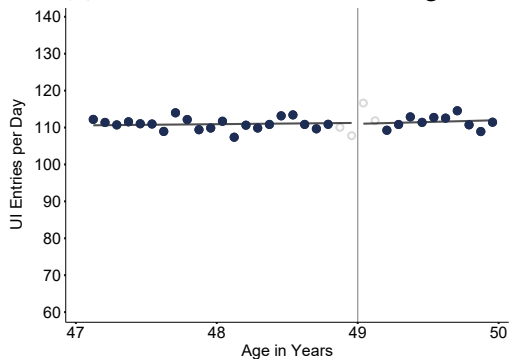
Figure G.9: RD Density Plots, Men



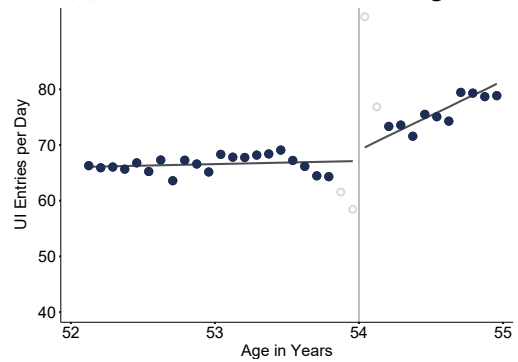
(a) Period 07/1987-03/1999, Age 42



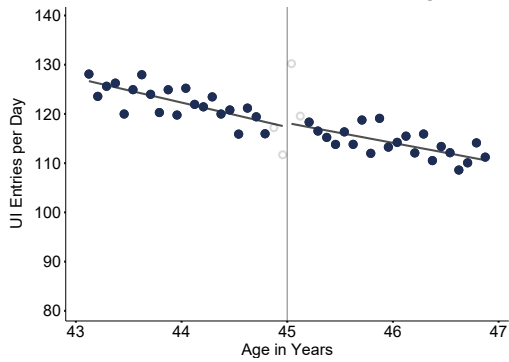
(b) Period 07/1987-03/1999, Age 44



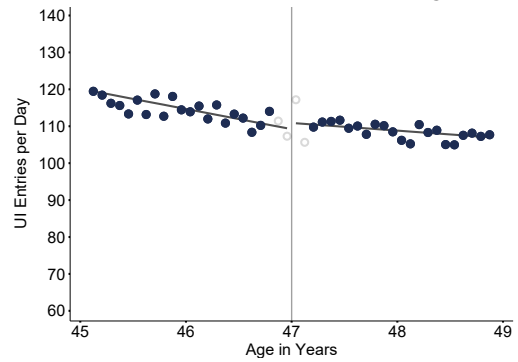
(c) Period 07/1987-03/1999, Age 49



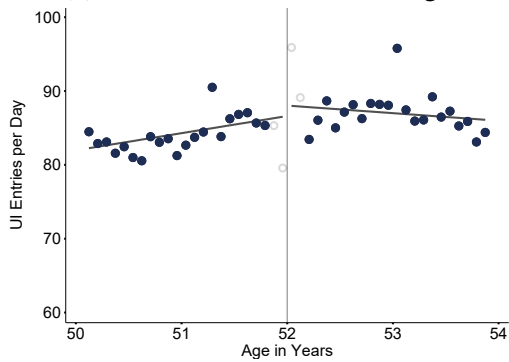
(d) Period 07/1987-03/1999, Age 54



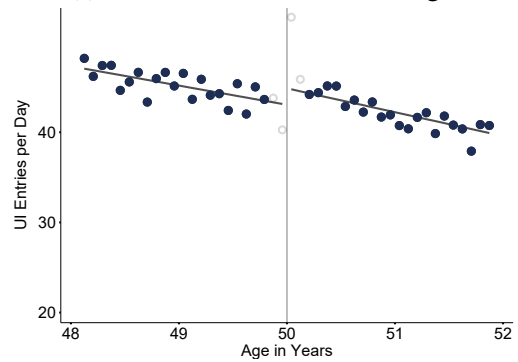
(e) Period 04/1999-01/2006, Age 45



(f) Period 04/1999-01/2006, Age 47



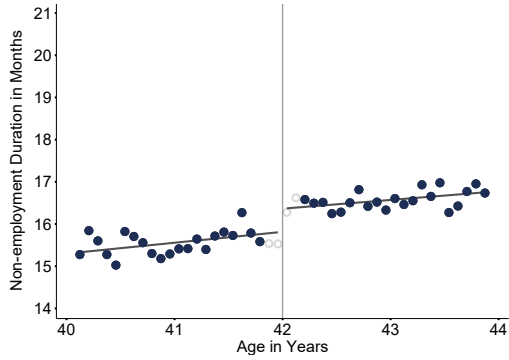
(g) Period 04/1999-01/2006, Age 52



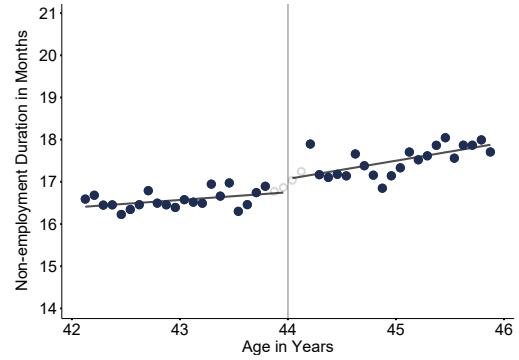
(h) Period 01/2008-12/2010, Age 50

Notes: This figure shows the average number of UI entries by age. Each dot shows this mean over a one-month window. Transparent dots close to the cutoff mark the leave-out region and solid lines show the line of best fit in the running variable.

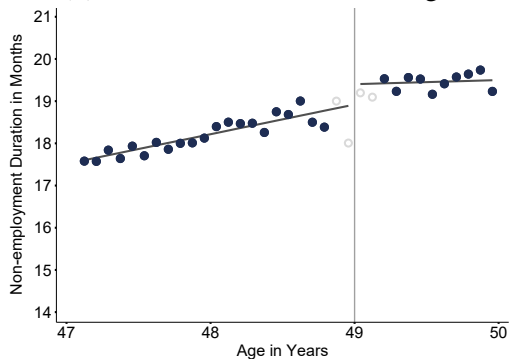
Figure G.10: RD Figures: Non-employment Duration, Men



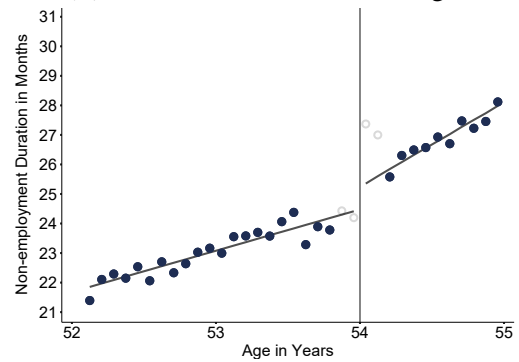
(a) Period 07/1987-03/1999, Age 42



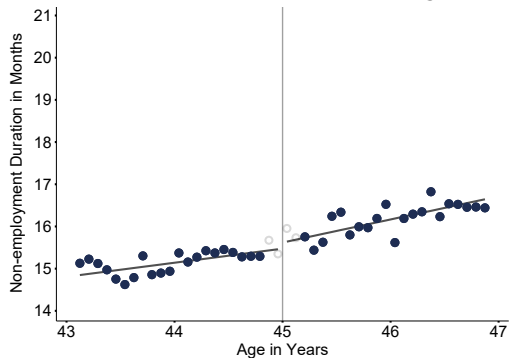
(b) Period 07/1987-03/1999, Age 44



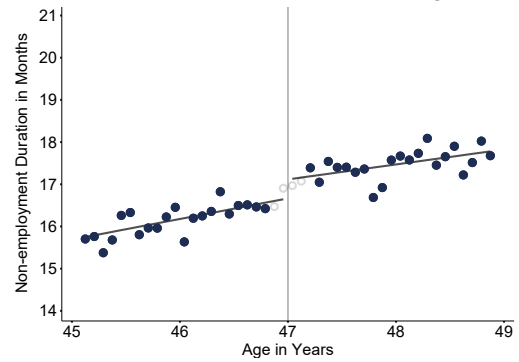
(c) Period 07/1987-03/1999, Age 49



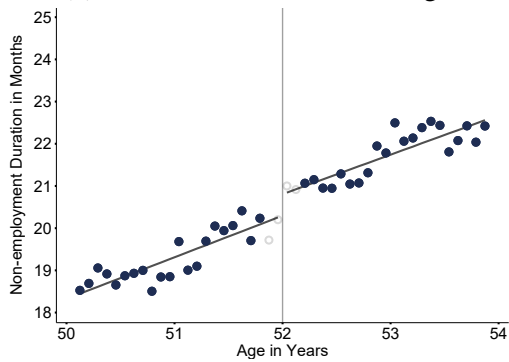
(d) Period 07/1987-03/1999, Age 54



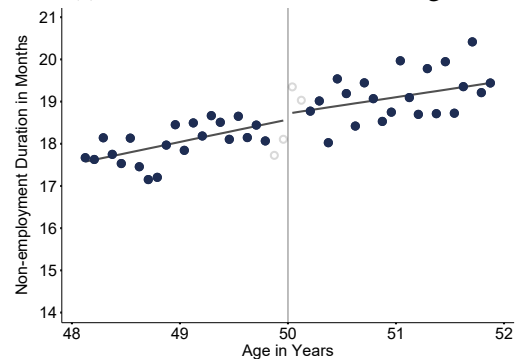
(e) Period 04/1999-01/2006, Age 45



(f) Period 04/1999-01/2006, Age 47



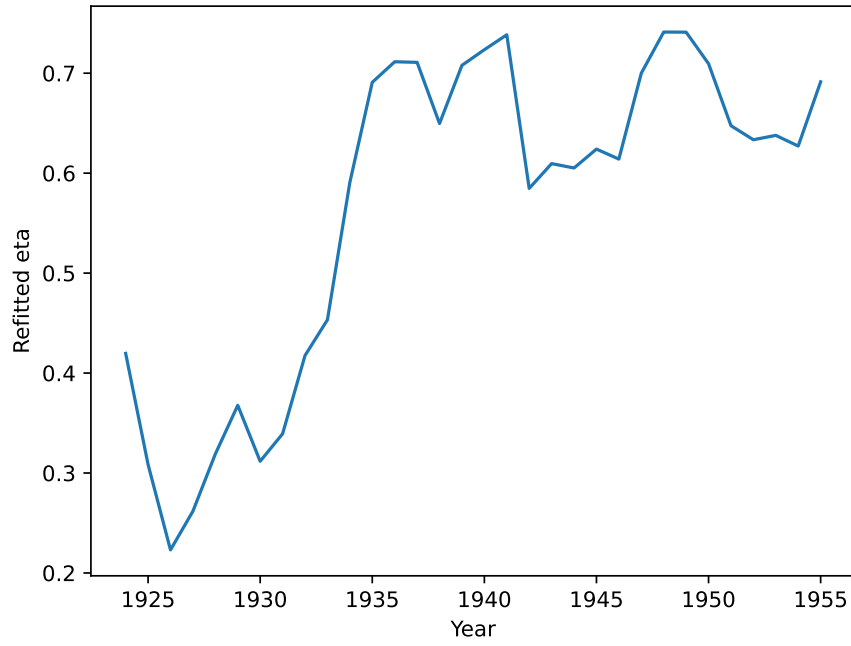
(g) Period 04/1999-01/2006, Age 52



(h) Period 01/2008-12/2010, Age 50

Notes: This figure shows the average non-employment duration (capped at 36 months) around the different age cutoffs. Each dot shows this mean over a one-month window. Translucent dots close to the cutoff mark the leave-out region and solid lines show the line of best fit in the running variable.

Figure G.11: Cohort-specific estimates of mean disutility of work ($\bar{\eta}$)



Notes: This figure plots our model's cohort-specific estimates of the mean disutility of work ($\bar{\eta}$). For the three in-sample cohorts, this is estimated directly along with all other parameters. For the out-of-sample cohorts this single parameter is estimated (taking all other parameters as given) to fit E to U transitions and nonemployment durations.

Figure G.12: Empirical and Simulated UI Inflows for all Cohorts (Baseline Model)

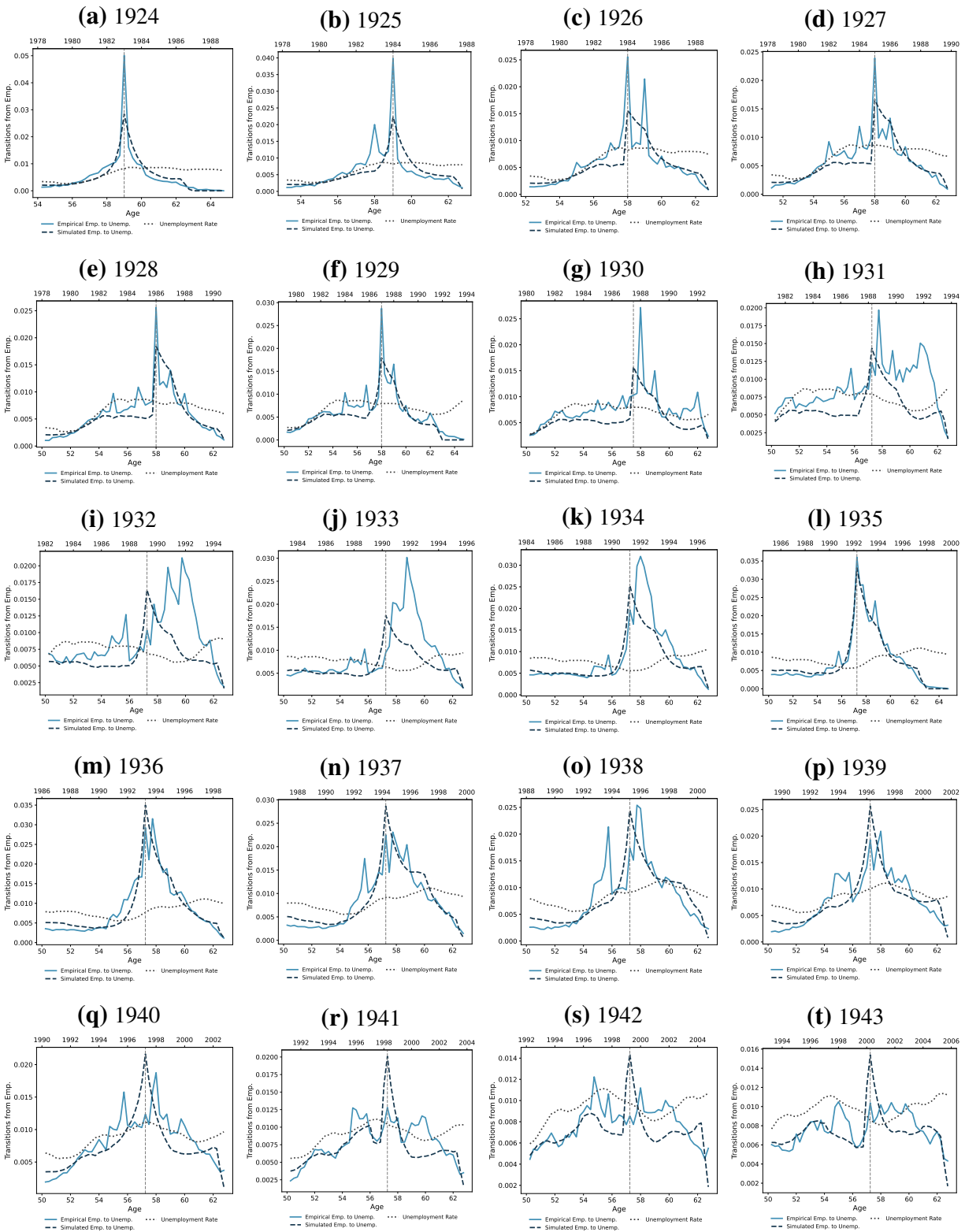
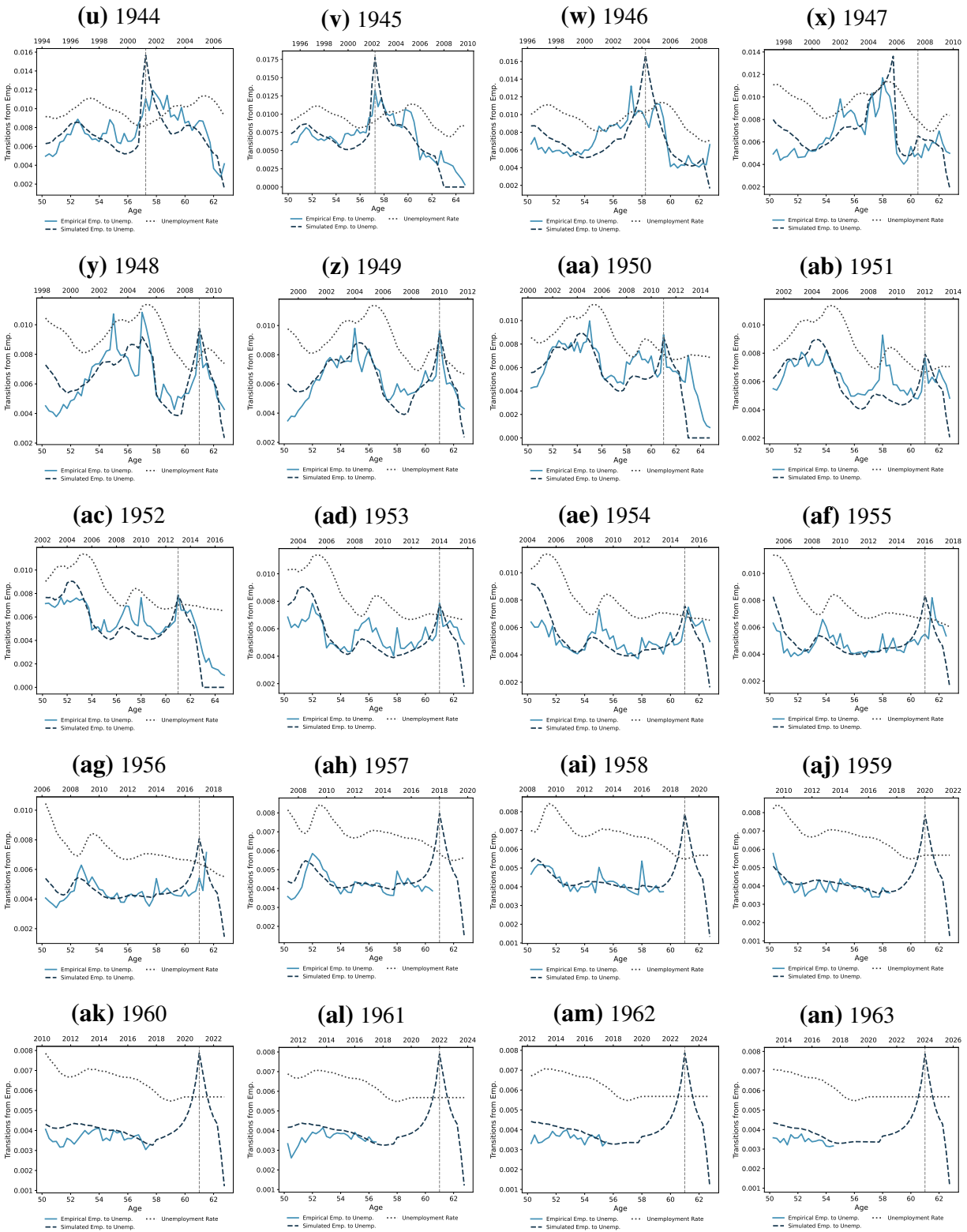


Figure G.12: Empirical and Simulated UI Inflows for all Cohorts (Baseline Model), continued



Notes: These figures compare the model-based transitions from employment to unemployment to their corresponding empirical moments for all cohorts, aggregated to the quarterly level.

Figure G.13: Empirical and Simulated Nonemployment Durations for all Cohorts (Baseline Model)

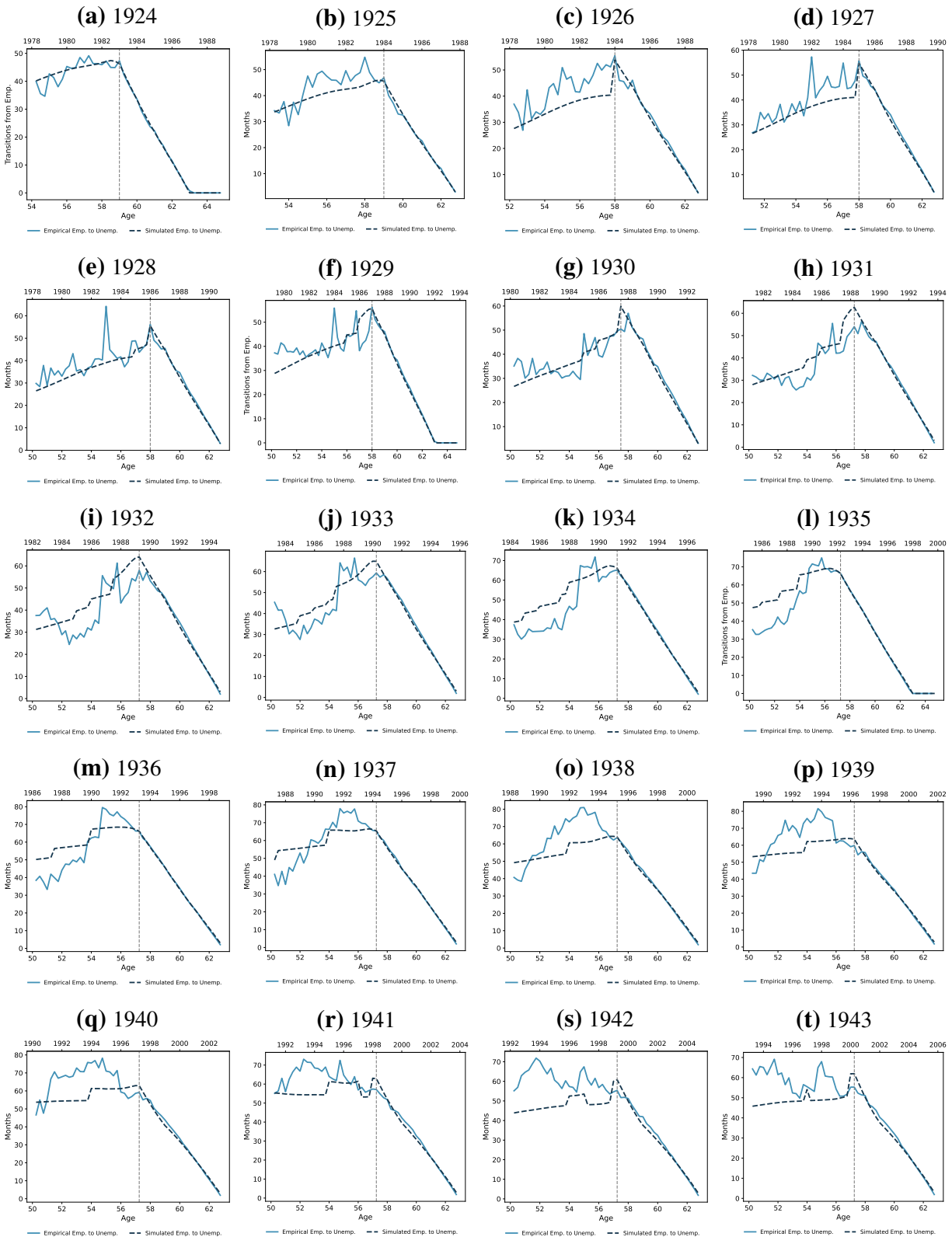
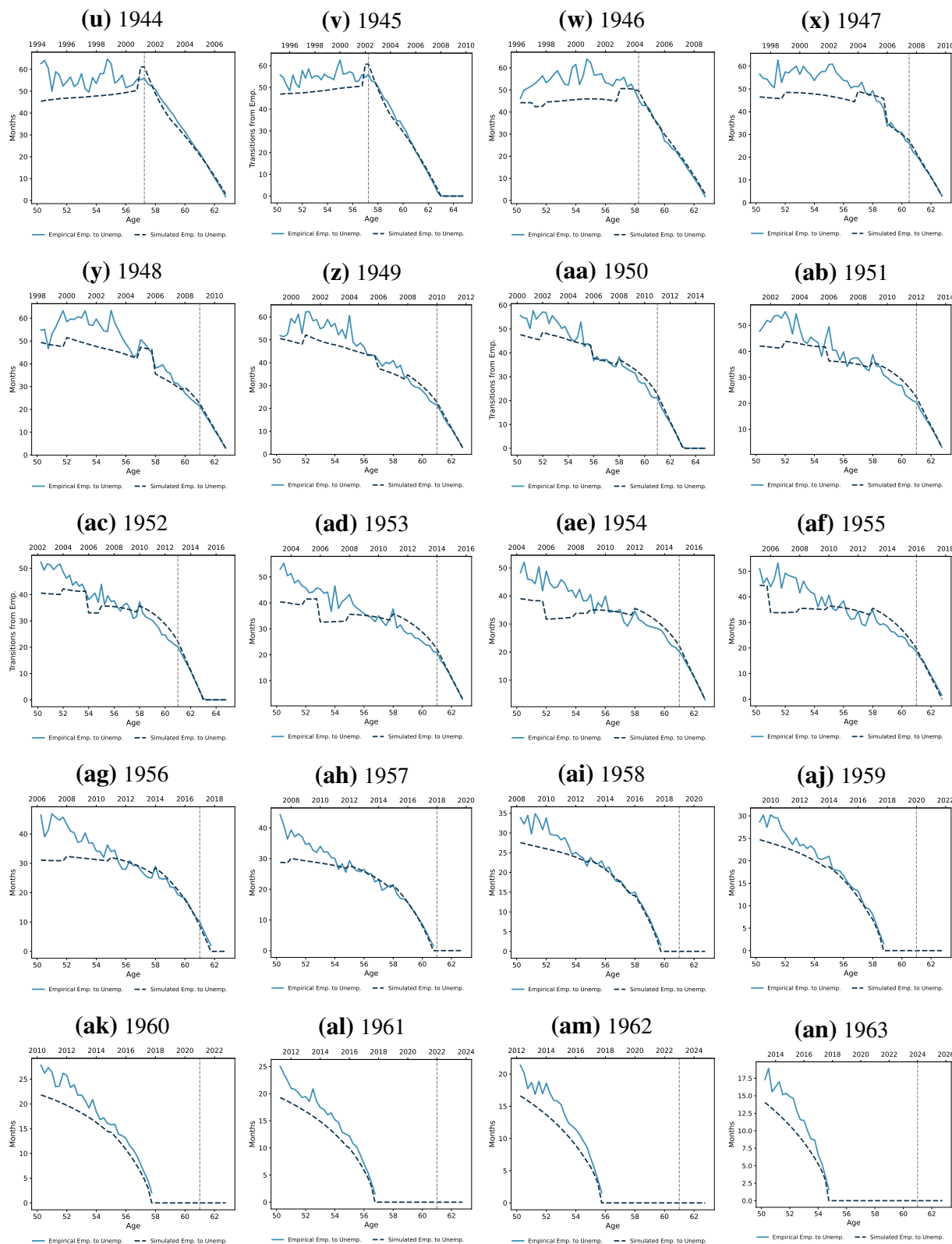
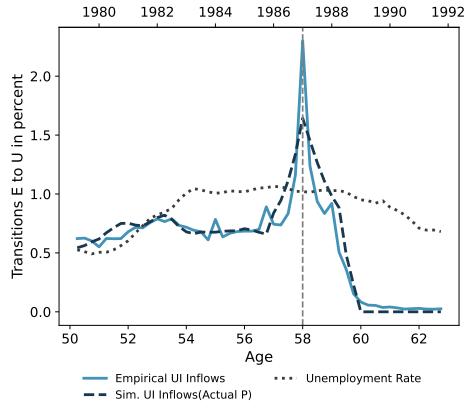


Figure G.13: Empirical and Simulated Nonemployment Durations for all Cohorts (Baseline Model), continued

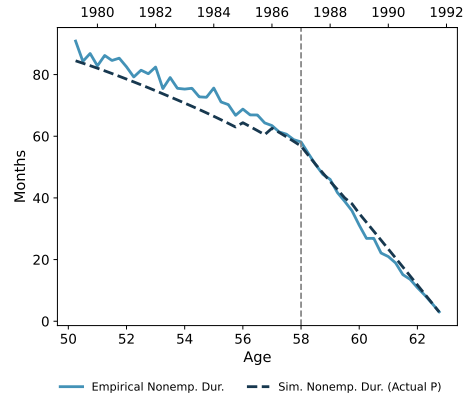


Notes: These figures compare model-based non-employment durations to their corresponding empirical moments for all cohorts, aggregated to the quarterly level.

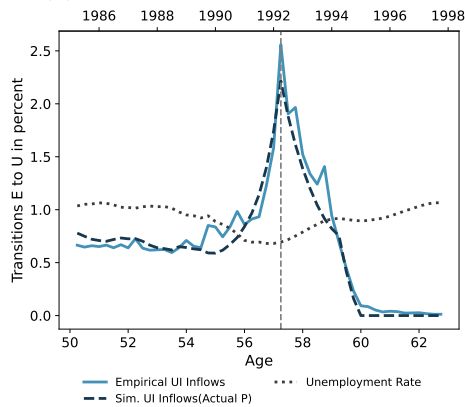
Figure G.14: In-Sample Fit of Life-Cycle Model - Women



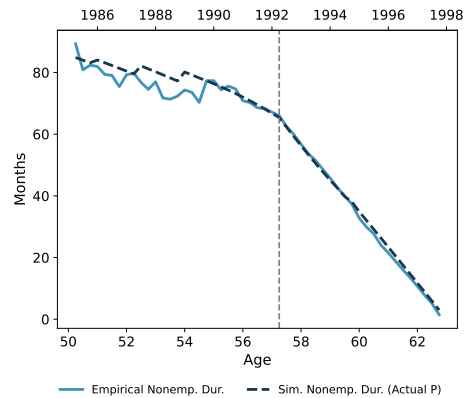
(a) Transitions from E to U, 1929



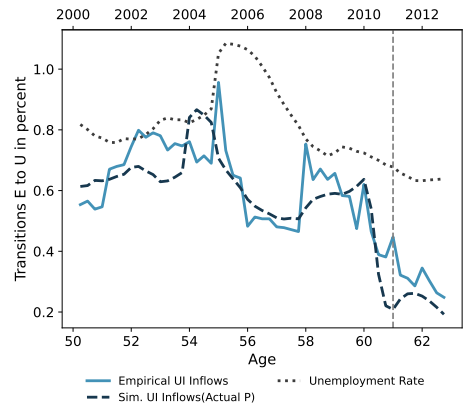
(b) Non Employment Duration, 1929



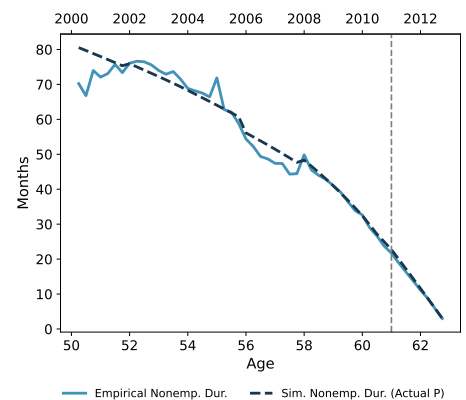
(c) Transitions from E to U, 1935



(d) Non Employment Duration, 1935



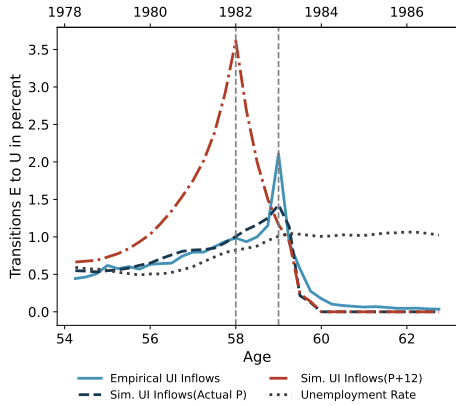
(e) Transitions from E to U, 1950



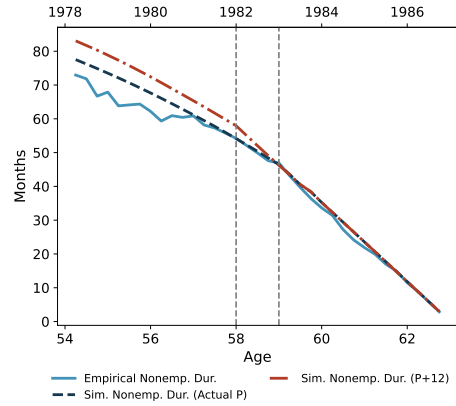
(f) Non Employment Duration, 1950

Notes: This figure is the analogue of Figure 4 in the main paper for the women sample.

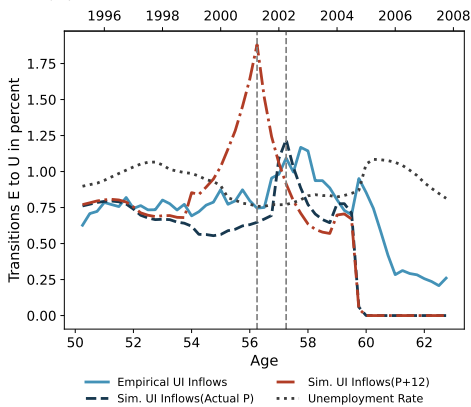
Figure G.15: Out-of-Sample Fit of Life-Cycle Model - Women



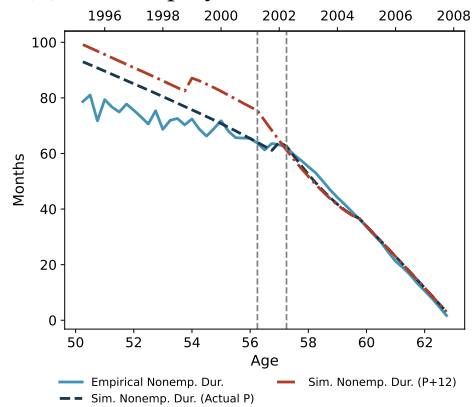
(a) Transitions from E to U, 1924



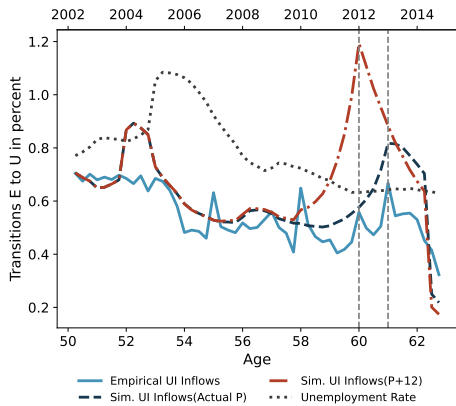
(b) Non Employment Duration, 1924



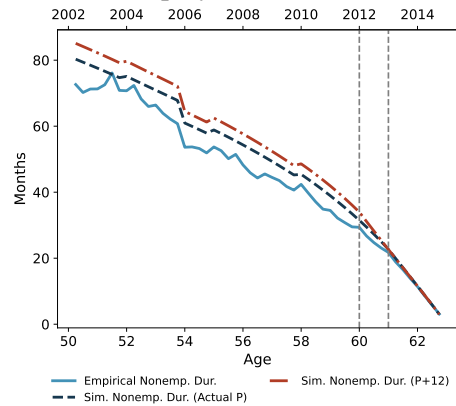
(c) Transitions from E to U, 1945



(d) Non Employment Duration, 1945



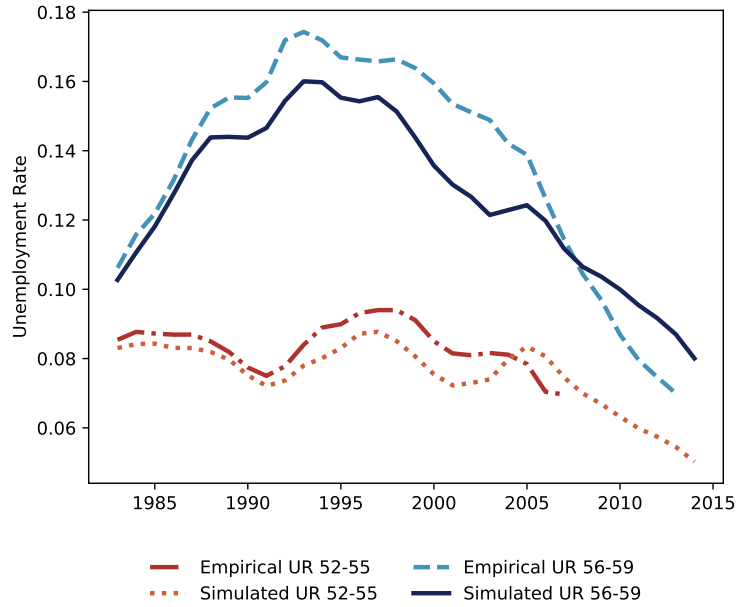
(e) Transitions from E to U, 1952



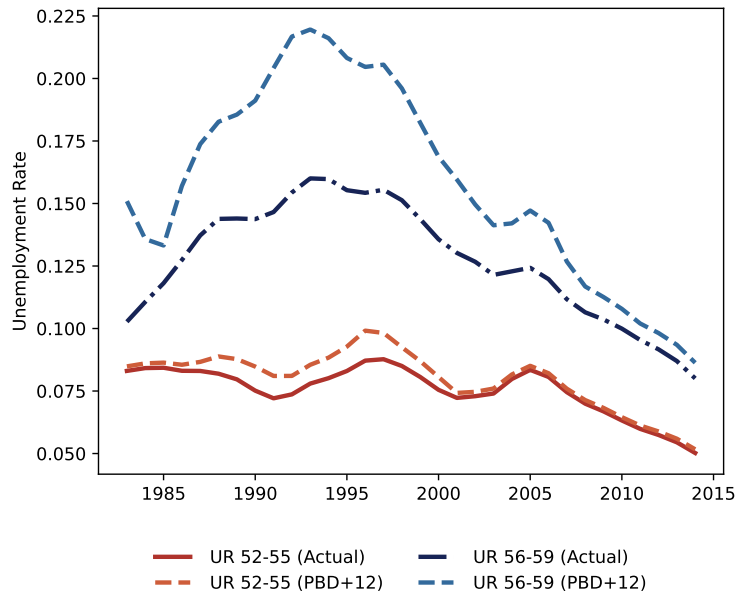
(f) Non Employment Duration, 1952

Notes: This figure corresponds to Figure 5 in the main paper, but is for the women sample.

Figure G.16: Empirical and Simulated Unemployment Rate - Women



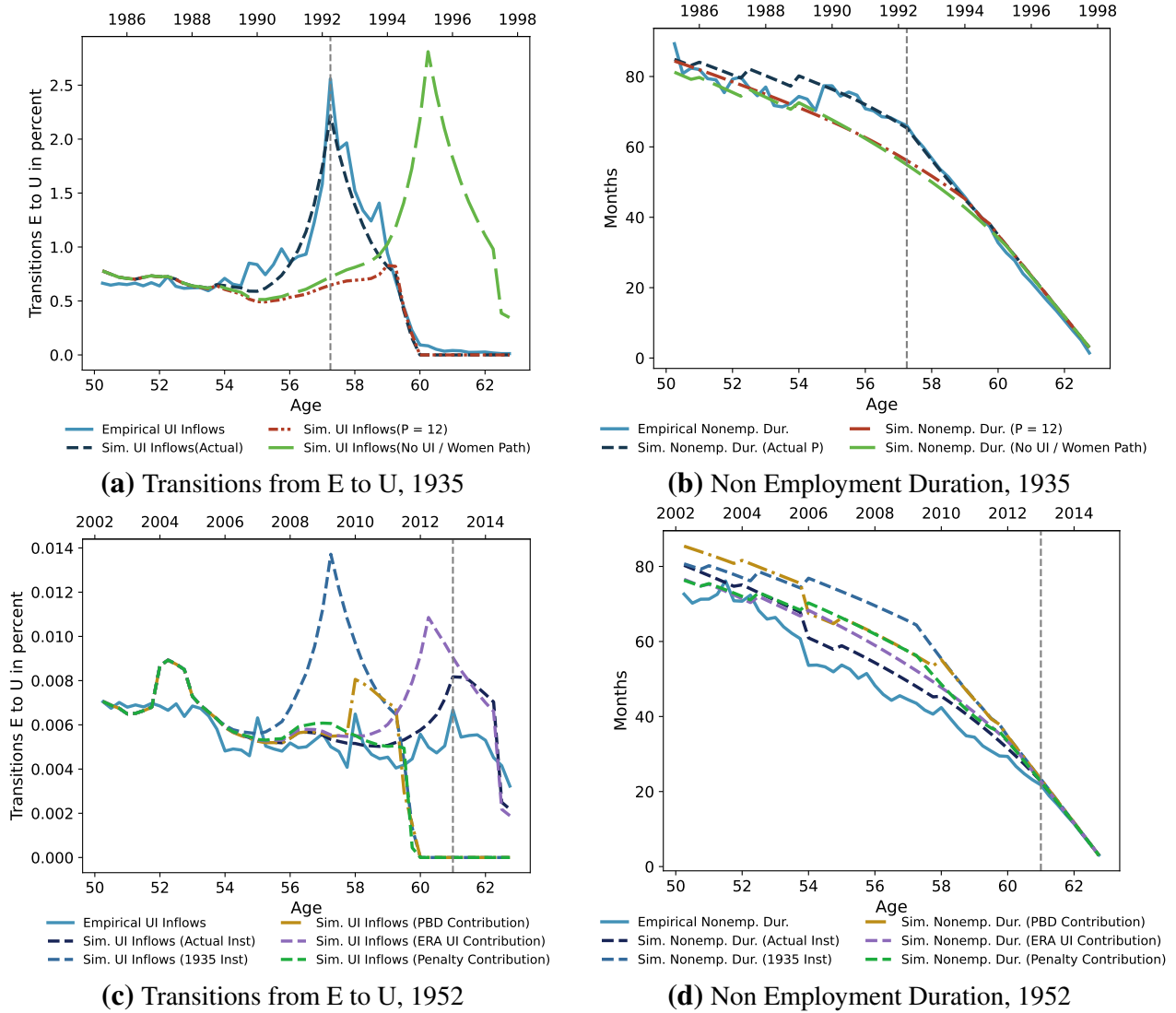
(a) Empirical and Simulated Unemployment Rate



(b) Extending UI PBD by 12 months

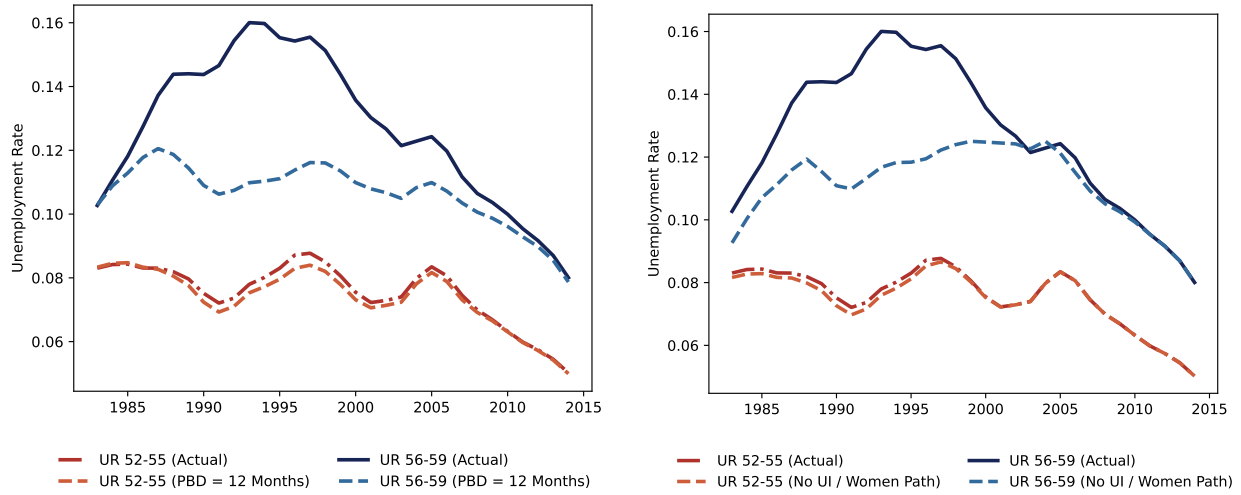
Notes: This figure corresponds to Figure 6 in the main paper but is for the women sample.

Figure G.17: Model Simulations for Counterfactual Policies - Women



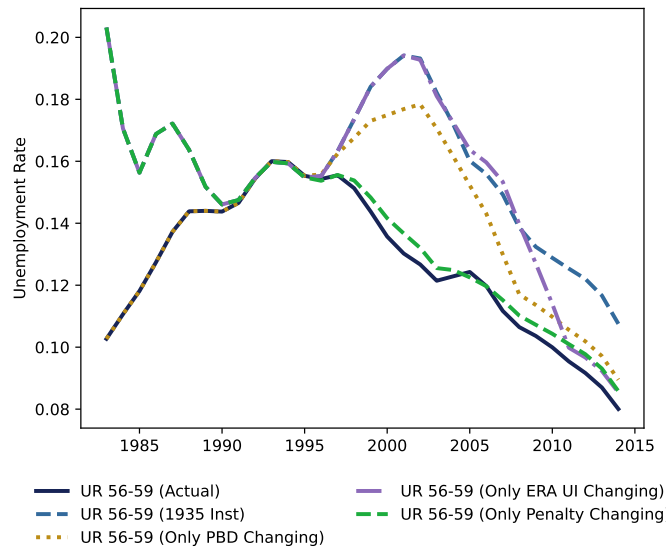
Notes: This figure corresponds to Figure 7 in the main paper but is for the women sample.

Figure G.18: Simulated Unemployment Rates under Alternative Policy Regime - Women



(a) PBD fixed at 12 months

(b) No UI Pathway



(c) The Influence of Policy Changes after 1994

Notes: This figure corresponds to Figure 8 in the main paper but is for the women sample.

H Appendix Tables

Table H.1: Potential Unemployment Insurance Benefit (UIB) Durations as a Function of Age and Months Worked in Previous 7 Years.

Months Worked in prev. X years	January 1983- December 1984	January 1985- December 1985	January 1986- June 1987	July 1987- March 1997	April 1997* - January 2006	February 2006 - December 2007	January 2008 - Present
12	4	4	4	6	6	6	6
16	4	4	4	8	8	8	8
18	6	6	6	8	8	8	8
20	6	6	6	10	10	10	10
24	8	8	8	12	12	12	12
28	8	8	8	14 (>42)	14 (>45)	12	12
30	10	10	10	14 (>42)	14 (>45)	15 (>55)	15 (>50)
32	10	10	10	16 (>42)	16 (>45)	15 (>55)	15 (>50)
36	12	12	12	18 (>42)	18 (>45)	18 (>55)	18 (>55)
40	12	12	12	20 (>44)	20 (>47)	18 (>55)	18 (>55)
42	12	14 (>49)	14 (>44)	20 (>44)	20 (>47)	18 (>55)	18 (>55)
44	12	14 (>49)	14 (>44)	22 (>44)	22 (>47)	18 (>55)	18 (>55)
48	12	16 (>49)	16 (>44)	24 (>49)	24 (>52)	18 (>55)	24 (>58)
52	12	16 (>49)	16 (>44)	26 (>49)	26 (>52)	18 (>55)	24 (>58)
54	12	18 (>49)	18 (>49)	26 (>49)	26 (>52)	18 (>55)	24 (>58)
56	12	18 (>49)	18 (>49)	28 (>54)	28 (>57)	18 (>55)	24 (>58)
60	12	18 (>49)	20 (>49)	30 (>54)	30 (>57)	18 (>55)	24 (>58)
64	12	18 (>49)	20 (>49)	32 (>54)	32 (>57)	18 (>55)	24 (>58)
66	12	18 (>49)	22 (>54)	32 (>54)	32 (>57)	18 (>55)	24 (>58)
72	12	18 (>49)	24 (>54)	32 (>54)	32 (>57)	18 (>55)	24 (>58)
Rahmenfrist - Min emp dur. for new UI eligibility	12	12	12	12	12	12	12
X - Base Period for P>12	7	7	7	7	7	5	5
X - Base Period for P<12	4	4	4	3	3	2	2
Replacement Rates on Net Wages in Percent:							
UI (children)	68	68	68	67 [‡]	67	67	67
UI (no children)	63 [†]	63	63	60 [‡]	60	60	60
UA (children)	58	58	58	57 [‡]	57	UIB II	UIB II
UA (no children)	53 [†]	53	53	50 [‡]	50	UIB II	UIB II

Source: Hunt (1995), Bundesgesetzblatt (1983-2015) and Dlugosz et al (2013).

Notes:*The reform in 1997 was phased in gradually: For workers who had worked for more than one year during the three years before April 1997, the old rules applied until March 1999 (See Arntz, Simon Lo, and Wilke 2007).

[†] UI and UA replacement rates were lowered starting in January 1984. Until December 1983, ALG was 68 percent and ALH 58 percent of the previous net wage, irrespective of whether the recipient had children.

[‡] UI and UA were lowered starting in January of 1994.

Table H.2: Retirement age by retirement pathways from 1957 till now

Pathways	Time of implementation	Affected cohorts	SRA		Reform
Standard old-age pension (Years of contribution: 5 ⁵³)	1957 - 2011	<1947 Jan	65	-	
	2012 - 2030	1947 Jan- 1964 Jan	65 to 67	-	2007 Reform
	> 2031	≥1964 Jan	67	-	
			NRA (no penalty)	ERA (earliest possible)	
Old-age pension for long-term insured (Years of contribution :35)	1972 - 1999	1909 Jan - 1936 Dec	63	-	1972 Reform †
	2000 - 2003	1937 Jan - 1938 Dec	63 to 65	63	1992 Reform §
	2004 - 2010	1939 Jan - 1947 Dec	65	63	
	2011 - 2030	1949 Jan - 1964 Jan	65 to 67	63	2007 Reform *
Old-age pension due to unemployment or part-time work (at least 52 weeks unemployed after 58½, or 2 years part-time) (Years of contribution: 15(8 in last 10 yrs))	1972 - 1996	< 1937 Jan	60	-	1972 Reform
	1997 - 2006	1937 Jan - 1941 Dec	60 to 65	60	1992/99 Reform
		1942 Jan - 1945 Dec	65	60	
	2006 - 2011	1946 Jan - 1948 Dec	65	60 to 63	1992 Reform
	2012 - 2016	1949 Jan - 1951 Dec	65	63	
> 2017.1	> 1952 Jan	Phased out	-	2007 Reform	
Old-age pension for women (Years of contribution: 15 (10 after age 40))	1957 - 2000	<1940 Jan	60	-	
	2000 - 2009	1940 Jan - 1944 Dec	60 to 65	60	1992 Reform
	2010 - 2016	1945 Jan - 1951 Dec	65	60	
	> 2017.1	> 1952 Jan	Phased out	-	2007 Reform
Old-age pension for disabled workers (Years of contribution: 35) (Loss of at least 50 percent of earnings capability)	1972 - 1977	1911 - 1917	62	-	1972 Reform
	1978 - 1980	1918 Jan - 1919 Dec	62 to 60	-	1978 Reform
	1981 - 2000	1920 Jan - 1940 Dec	60	-	
	2001 - 2006	1941 Jan - 1943 Dec	60 to 63	60	1992 Reform
	2007 - 2011	1944 Jan - 1951 Dec	63	60	
	2012 - 2025	1952 Jan - 1963 Dec	63 to 65	60 to 62	2007 Reform
	> 2026	> 1964 Jan	65	62	
Old-age pension for especially long-term insured (qualifying period of 45 years)	2014-2016	1951- 1953	63	-	
	2016 - 2028	1953 Jan - 1963 Dec	63 to 65	-	2014 Reform
	> 2029.1	> 1964.1.1	65	-	
Disability pension : independent of age	<1985	5 years of contribution			
	> 1985	5 yrs with minimum 3 in last 5 yrs			1984 Reform

Source: Sozialgesetzbuch (SGB) Sechstes Buch (VI), Börsch-Supan and Jürges (2012), Börsch-Supan and Wilke (2006), Giesecke and Kind (2013).

Notes: † The German public pension system distinguishes "old-age pensions" from "disability pensions": old-age pensions for workers aged 60 and older; and disability benefits for workers below age 60, which at the statutory retirement age are converted to old-age pensions at age 65.

‡ The 1972 reform made "flexible retirement" after age 63 with full benefits possible for the long-term insured; Moreover, retirement at age 60 with full benefits became possible for women, the unemployed, and older disabled workers.

§ The 1992 reform introduced actuarial adjustment. Since then, we distinguish ERA and NRA. It also increased NRA to 65 for all pathways except for disabled workers. It increased ERA for the unemployed to 63 (See SGB VI Appendix 19).

* The 2007 reform announced the stepwise increase of SRA between 2012 and 2029 from 65 to 67 for both men and women (see SGB VI 235). For cohorts older born in 1952 and after, old-age pension for women and old-age pension due to unemployment are abolished.

Table H.3: RD Estimations of the Effects of UI PBD Extensions on Nonemployment Duration for Men and Women

		Male		Female		Male and Female	
		Base	Controls	Base	Controls	Base	Controls
Period Jul 1987 - Feb 1999							
Age 42, P: (12-18), Δ P: 6	$\frac{dy}{dP}$	0.092	0.080	0.124	0.124	0.107	0.100
		[0.026]**	[0.025]**	[0.027]**	[0.026]**	[0.019]**	[0.018]**
N		173,313	173,313	148,220	148,220	321,533	321,533
Mean Dep. Var		16.049	16.049	17.736	17.736	16.827	16.827
Age 44, P: (18-22), Δ P: 4	$\frac{dy}{dP}$	0.079	0.068	0.056	0.049	0.066	0.060
		[0.041]+	[0.039]+	[0.038]	[0.037]	[0.028]*	[0.026]*
N		170,270	170,270	152,092	152,092	322,362	322,362
Mean Dep. Var		17.046	17.046	18.777	18.777	17.863	17.863
Age 49, P: (22-26), Δ P: 4	$\frac{dy}{dP}$	0.121	0.103	0.105	0.107	0.119	0.107
		[0.068]+	[0.062]	[0.065]	[0.063]+	[0.049]*	[0.046]*
N		107,255	107,255	91,736	91,736	198,991	198,991
Mean Dep. Var		18.568	18.568	20.920	20.920	19.652	19.652
Age 54, P: (26-32), Δ P: 6	$\frac{dy}{dP}$	0.129	0.126	0.203	0.222	0.173	0.181
		[0.053]*	[0.048]**	[0.040]**	[0.039]**	[0.034]**	[0.032]**
N		66,720	66,720	66,823	66,823	133,543	133,543
Mean Dep. Var		24.331	24.331	28.639	28.639	26.486	26.486
Period Mar 1999 - Jan 2006							
Age 45, P: (12-18), Δ P: 6	$\frac{dy}{dP}$	0.024	0.024	0.118	0.115	0.067	0.067
		[0.028]	[0.027]	[0.029]**	[0.028]**	[0.020]**	[0.020]**
N		156,927	156,927	132,763	132,763	289,690	289,690
Mean Dep. Var		15.637	15.637	15.605	15.605	15.622	15.622
Age 47, P: (18-22), Δ P: 4	$\frac{dy}{dP}$	0.113	0.104	0.128	0.124	0.120	0.112
		[0.044]*	[0.042]*	[0.044]**	[0.043]**	[0.031]**	[0.029]**
N		148,285	148,285	132,154	132,154	280,439	280,439
Mean Dep. Var		16.794	16.794	17.214	17.214	16.992	16.992
Age 52, P: (22-26), Δ P: 4	$\frac{dy}{dP}$	0.128	0.126	0.064	0.066	0.101	0.097
		[0.049]**	[0.048]**	[0.048]	[0.046]	[0.034]**	[0.033]**
N		113,128	113,128	106,936	106,936	220,064	220,064
Mean Dep. Var		20.546	20.546	22.619	22.619	21.553	21.553
Period Feb 2006 - Dec 2007							
Age 50, P: (12-15), Δ P: 3	$\frac{dy}{dP}$	0.048	0.062	0.151	0.142	0.096	0.103
		[0.103]	[0.100]	[0.097]	[0.096]	[0.073]	[0.072]
N		57,116	57,116	52,647	52,647	109,763	109,763
Mean Dep. Var		18.539	18.539	18.077	18.077	18.317	18.317

Notes: This table shows RD estimates of UI extensions at various cutoffs on nonemployment duration in months (capped at 36 months). Estimates are obtained using local polynomial regressions controlling linearly for age (allowing for different slopes on each side of cutoff), using a rectangular kernel and a bandwidth of 2 years on each side of the cutoff, except for age cutoff 49 and 54 who have only a bandwidth of one year on the right due to other discontinuities. Standard errors (in brackets) clustered on day level (+ p<0.1, * p<0.05, ** p<0.01).

Table H.4: Placebo Outcomes, Men

		Fraction of UI entries per day	Pre UI Wage	Foreign Citizen	Years of Education	Occ. Tenure Last Job	Ind. Tenure Last Job	Times until UI Claim
Period Jul 1987 - Feb 1999								
Age 42, P: (12-18), Δ P: 6	$\frac{dy}{dP}$	-0.002	0.083	0.001	0.007	-0.000	0.011	0.000
		[0.001]	[0.069]	[0.001]*	[0.006]	[0.011]	[0.011]	[0.006]
N		173,313	173,313	173,313	173,313	173,313	173,313	173,313
Mean Dep. Var		1.000	80.712	0.134	12.911	9.955	8.921	1.517
Age 44, P: (18-22), Δ P: 4	$\frac{dy}{dP}$	0.006	0.027	0.000	0.012	-0.008	0.000	0.013
		[0.003]*	[0.107]	[0.001]	[0.010]	[0.018]	[0.019]	[0.009]
N		170,270	170,270	170,270	170,270	170,270	170,270	170,270
Mean Dep. Var		1.000	80.460	0.147	12.851	10.626	9.578	1.526
Age 49, P: (22-26), Δ P: 4	$\frac{dy}{dP}$	-0.001	-0.255	-0.000	-0.001	0.017	0.047	-0.008
		[0.003]	[0.165]	[0.002]	[0.016]	[0.027]	[0.028]	[0.009]
N		107,255	107,255	107,255	107,255	107,255	107,255	107,255
Mean Dep. Var		1.000	81.666	0.175	12.755	12.342	11.258	1.036
Age 54, P: (26-32), Δ P: 6	$\frac{dy}{dP}$	0.005	0.496	-0.002	-0.008	0.023	0.025	0.007
		[0.004]	[0.151]**	[0.001]	[0.010]	[0.018]	[0.020]	[0.006]
N		66,720	66,720	66,720	66,720	66,720	66,720	66,720
Mean Dep. Var		1.000	75.899	0.143	11.566	12.178	11.842	0.906
Period Mar 1999 - Jan 2006								
Age 45, P: (12-18), Δ P: 6	$\frac{dy}{dP}$	0.001	-0.036	0.000	-0.003	0.016	0.019	-0.007
		[0.002]	[0.079]	[0.001]	[0.007]	[0.014]	[0.014]	[0.006]
N		156,927	156,927	156,927	156,927	156,927	156,927	156,927
Mean Dep. Var		1.000	78.133	0.083	13.467	11.736	5.542	1.271
Age 47, P: (18-22), Δ P: 4	$\frac{dy}{dP}$	0.004	-0.129	0.001	0.019	-0.007	-0.010	-0.011
		[0.003]	[0.131]	[0.001]	[0.011]	[0.024]	[0.022]	[0.009]
N		148,285	148,285	148,285	148,285	148,285	148,285	148,285
Mean Dep. Var		1.000	77.292	0.082	13.424	12.750	5.957	1.287
Age 52, P: (22-26), Δ P: 4	$\frac{dy}{dP}$	0.004	-0.088	0.000	-0.012	0.055	0.045	-0.004
		[0.003]	[0.162]	[0.001]	[0.011]	[0.029]+	[0.031]	[0.010]
N		113,128	113,128	113,128	113,128	113,128	113,128	113,128
Mean Dep. Var		1.000	76.409	0.089	13.139	15.562	8.502	1.413
Period Jan 2008 - Dec 2008								
Age 50, P: (12-15), Δ P: 3	$\frac{dy}{dP}$	0.014	0.462	-0.000	0.013	0.029	0.007	-0.007
		[0.005]**	[0.286]	[0.002]	[0.020]	[0.059]	[0.009]	[0.010]
N		57,116	57,116	57,116	57,116	57,116	57,116	57,116
Mean Dep. Var		1.000	75.830	0.089	12.548	13.415	6.020	0.453

Notes: This table shows RD estimates of UI extensions at various cutoffs on different placebo outcomes. For details on the specification see the notes to Table H.3. Standard errors (in brackets) clustered on day level (+ p<0.1, * p<0.05, ** p<0.01).

Table H.5: Placebo Outcomes, Females

		Fraction of UI entries per day	Pre UI Wage	Foreign Citizen	Years of Education	Occ. Tenure Last Job	Ind. Tenure Last Job	Times until UI Claim
Period Jul 1987 - Feb 1999								
Age 42, P: (12-18), Δ P: 6	$\frac{dy}{dP}$	0.001	0.120	0.000	0.002	0.019	0.013	0.003
		[0.001]	[0.061]*	[0.001]	[0.008]	[0.012]	[0.012]	[0.007]
N		148,220	148,220	148,220	148,220	148,220	148,220	148,220
Mean Dep. Var		1.000	52.560	0.122	12.756	7.801	6.850	1.371
Age 44, P: (18-22), Δ P: 4	$\frac{dy}{dP}$	-0.001	0.045	-0.001	0.002	0.001	0.013	-0.013
		[0.003]	[0.095]	[0.001]	[0.011]	[0.019]	[0.018]	[0.010]
N		152,092	152,092	152,092	152,092	152,092	152,092	152,092
Mean Dep. Var		1.000	52.242	0.123	12.817	7.798	6.921	1.358
Age 49, P: (22-26), Δ P: 4	$\frac{dy}{dP}$	0.008	-0.076	0.000	0.005	0.021	0.026	-0.004
		[0.003]*	[0.134]	[0.001]	[0.016]	[0.030]	[0.029]	[0.009]
N		91,736	91,736	91,736	91,736	91,736	91,736	91,736
Mean Dep. Var		1.000	53.000	0.104	12.821	8.617	7.865	0.866
Age 54, P: (26-32), Δ P: 6	$\frac{dy}{dP}$	0.016	0.452	-0.002	-0.009	0.015	-0.010	-0.007
		[0.003]**	[0.107]**	[0.001]**	[0.010]	[0.022]	[0.023]	[0.006]
N		66,823	66,823	66,823	66,823	66,823	66,823	66,823
Mean Dep. Var		1.000	50.236	0.059	11.662	8.369	8.157	0.770
Period Mar 1999 - Jan 2006								
Age 45, P: (12-18), Δ P: 6	$\frac{dy}{dP}$	0.005	0.003	0.000	-0.000	-0.002	0.009	-0.007
		[0.002]**	[0.070]	[0.001]	[0.007]	[0.015]	[0.012]	[0.007]
N		132,763	132,763	132,763	132,763	132,763	132,763	132,763
Mean Dep. Var		1.000	49.867	0.065	13.574	8.275	3.821	1.134
Age 47, P: (18-22), Δ P: 4	$\frac{dy}{dP}$	0.007	0.083	-0.000	0.023	0.010	-0.003	-0.004
		[0.003]**	[0.108]	[0.001]	[0.012]*	[0.026]	[0.019]	[0.010]
N		132,154	132,154	132,154	132,154	132,154	132,154	132,154
Mean Dep. Var		1.000	49.352	0.072	13.596	8.715	4.047	1.145
Age 52, P: (22-26), Δ P: 4	$\frac{dy}{dP}$	0.012	0.326	0.001	-0.007	0.066	0.048	0.013
		[0.003]**	[0.126]*	[0.001]	[0.013]	[0.029]*	[0.026]+	[0.010]
N		106,936	106,936	106,936	106,936	106,936	106,936	106,936
Mean Dep. Var		1.000	48.233	0.082	13.569	10.014	5.545	1.202
Period Jan 2008 - Dec 2010								
Age 50, P: (12-15), Δ P: 3	$\frac{dy}{dP}$	0.021	-0.187	-0.000	-0.020	-0.047	-0.041	0.008
		[0.005]**	[0.241]	[0.002]	[0.021]	[0.057]	[0.020]*	[0.011]
N		52,647	52,647	52,647	52,647	52,647	52,647	52,647
Mean Dep. Var		1.000	47.291	0.070	12.328	9.267	3.631	0.469

Notes: This table shows estimates of UI extensions at various cutoffs on different placebo outcomes. For details on the specification see the notes to Table H.3. Standard errors (in brackets) clustered on day level (+ p<0.1, * p<0.05, ** p<0.01).

Table H.6: Placebo Outcomes, Women + Men

		Fraction of UI entries per day	Pre UI Wage	Foreign Citizen	Years of Education	Occ. Tenure Last Job	Ind. Tenure Last Job	Times until UI Claim
Period Jul 1987 - Feb 1999								
Age 42, P: (12-18), Δ P: 6	$\frac{dy}{dP}$	-0.001	0.079	0.001	0.004	0.007	0.010	0.001
		[0.001]	[0.051]	[0.001]+	[0.005]	[0.008]	[0.008]	[0.005]
N		321,533	321,533	321,533	321,533	321,533	321,533	321,533
Mean Dep. Var		1.000	67.735	0.128	12.839	8.962	7.966	1.450
Age 44, P: (18-22), Δ P: 4	$\frac{dy}{dP}$	0.003	0.077	-0.000	0.008	-0.000	0.010	0.001
		[0.002]	[0.079]	[0.001]	[0.008]	[0.013]	[0.013]	[0.007]
N		322,362	322,362	322,362	322,362	322,362	322,362	322,362
Mean Dep. Var		1.000	67.146	0.136	12.835	9.292	8.324	1.447
Age 49, P: (22-26), Δ P: 4	$\frac{dy}{dP}$	0.004	-0.233	-0.000	0.002	0.010	0.029	-0.006
		[0.002]+	[0.120]+	[0.001]	[0.012]	[0.020]	[0.020]	[0.007]
N		198,991	198,991	198,991	198,991	198,991	198,991	198,991
Mean Dep. Var		1.000	68.451	0.142	12.786	10.625	9.694	0.957
Age 54, P: (26-32), Δ P: 6	$\frac{dy}{dP}$	0.011	0.409	-0.002	-0.008	0.010	-0.002	-0.000
		[0.002]**	[0.101]**	[0.001]*	[0.008]	[0.016]	[0.017]	[0.004]
N		133,543	133,543	133,543	133,543	133,543	133,543	133,543
Mean Dep. Var		1.000	63.058	0.101	11.614	10.272	9.998	0.838
Period Mar 1999 - Jan 2006								
Age 45, P: (12-18), Δ P: 6	$\frac{dy}{dP}$	0.003	-0.049	0.000	-0.002	0.004	0.013	-0.007
		[0.001]*	[0.055]	[0.000]	[0.005]	[0.010]	[0.009]	[0.004]
N		289,690	289,690	289,690	289,690	289,690	289,690	289,690
Mean Dep. Var		1.000	65.179	0.075	13.516	10.150	4.753	1.208
Age 47, P: (18-22), Δ P: 4	$\frac{dy}{dP}$	0.005	-0.050	0.000	0.021	-0.002	-0.008	-0.008
		[0.002]**	[0.090]	[0.001]	[0.008]*	[0.018]	[0.015]	[0.007]
N		280,439	280,439	280,439	280,439	280,439	280,439	280,439
Mean Dep. Var		1.000	64.125	0.077	13.505	10.848	5.057	1.220
Age 52, P: (22-26), Δ P: 4	$\frac{dy}{dP}$	0.008	0.059	0.000	-0.009	0.049	0.040	0.004
		[0.002]**	[0.112]	[0.001]	[0.009]	[0.022]*	[0.021]+	[0.007]
N		220,064	220,064	220,064	220,064	220,064	220,064	220,064
Mean Dep. Var		1.000	62.717	0.086	13.348	12.866	7.065	1.310
Period Jan 2008 - Dec 2010								
Age 50, P: (12-15), Δ P: 3	$\frac{dy}{dP}$	0.017	0.119	-0.000	-0.003	-0.012	-0.019	0.000
		[0.003]**	[0.199]	[0.001]	[0.014]	[0.041]	[0.011]	[0.007]
N		109,763	109,763	109,763	109,763	109,763	109,763	109,763
Mean Dep. Var		1.000	62.142	0.080	12.443	11.426	4.874	0.461

Notes: This table shows RD estimates of UI extensions at various cutoffs on different placebo outcomes. For details on the specification see the notes to Table H.3. Standard errors (in brackets) clustered on day level (+ p<0.1, * p<0.05, ** p<0.01).

Table H.7: Robustness for RD-Estimates, Men

	(1) baseline estimate	(2) more controls	(3) exclude 3 months	(4) bw 12 months	(5) kernel triangular
Period Jul 1987 - Feb 1999, Age 42					
$\frac{dy}{dP}$	0.0916**	0.0679**	0.0741*	0.0734	0.0854**
	[0.0259]	[0.0249]	[0.0289]	[0.0448]	[0.0294]
N	173313	173313	165203	78519	173313
Period Jul 1987 - Feb 1999, Age 44					
$\frac{dy}{dP}$	0.0795+	0.0522	0.0507	0.189**	0.0991*
	[0.0412]	[0.0378]	[0.0444]	[0.0685]	[0.0451]
N	170270	170270	162222	77334	170270
Period Jul 1987 - Feb 1999, Age 49					
$\frac{dy}{dP}$	0.137*	0.0650	0.0854	0.180**	0.139*
	[0.0589]	[0.0518]	[0.0681]	[0.0692]	[0.0589]
N	128050	128050	119883	80498	128050
Period Jul 1987 - Feb 1999, Age 54					
$\frac{dy}{dP}$	0.129*	0.0813+	0.150*	0.180**	0.147**
	[0.0530]	[0.0451]	[0.0584]	[0.0624]	[0.0518]
N	66720	66720	62507	43057	66720
Period Mar 1999 - Jan 2006, Age 45					
$\frac{dy}{dP}$	0.0242	0.0225	0.0201	0.0116	0.0153
	[0.0282]	[0.0261]	[0.0300]	[0.0465]	[0.0305]
N	156927	156927	149712	71417	156927
Period Mar 1999 - Jan 2006, Age 47					
$\frac{dy}{dP}$	0.113*	0.0920*	0.0908+	0.139+	0.120*
	[0.0442]	[0.0407]	[0.0469]	[0.0729]	[0.0479]
N	148285	148285	141405	67315	148285
Period Mar 1999 - Jan 2006, Age 52					
$\frac{dy}{dP}$	0.128**	0.108*	0.128*	0.0547	0.0637
	[0.0491]	[0.0468]	[0.0550]	[0.0855]	[0.0561]
N	113128	113128	107910	51966	113128
Period Jan 2008 - Dec 2010, Age 50					
$\frac{dy}{dP}$	0.0476	0.0895	0.0289	0.117	0.0150
	[0.103]	[0.0931]	[0.108]	[0.166]	[0.109]
N	57116	57116	54455	26172	57116

Notes: This table explores robustness of the RD estimates in Table 2. Column (1) copies the baseline results. Column (2) adds to the baseline controls in addition one-digit industry controls, state fixed effects as well as calendar month and year FE. Column (3) excludes three instead of two months on each side of the cutoff, column (4) uses a bandwidth of 24 months and column (5) uses a triangular kernel. Standard errors (in brackets) clustered on day level (+ p<0.1, * p<0.05, ** p<0.01).

Table H.8: Robustness for RD-Estimates, Women

	(1) baseline estimate	(2) more controls	(3) exclude 3 months	(4) bw 12 months	(5) kernel triangular
Period Jul 1987 - Feb 1999, Age 42					
$\frac{dy}{dP}$	0.124**	0.120**	0.112**	0.137**	0.123**
	[0.0266]	[0.0264]	[0.0306]	[0.0477]	[0.0312]
N	148220	148220	141468	67098	148220
Period Jul 1987 - Feb 1999, Age 44					
$\frac{dy}{dP}$	0.0558	0.0445	0.0539	0.131+	0.0766+
	[0.0384]	[0.0390]	[0.0454]	[0.0702]	[0.0462]
N	152092	152092	144991	69463	152092
Period Jul 1987 - Feb 1999, Age 49					
$\frac{dy}{dP}$	0.0649	0.0697	0.0646	0.0367	0.0576
	[0.0589]	[0.0540]	[0.0685]	[0.0694]	[0.0591]
N	115576	115576	108182	72433	115576
Period Jul 1987 - Feb 1999, Age 54					
$\frac{dy}{dP}$	0.203**	0.197**	0.168**	0.221**	0.209**
	[0.0403]	[0.0394]	[0.0489]	[0.0515]	[0.0425]
N	66823	66823	62537	42085	66823
Period Mar 1999 - Jan 2006, Age 45					
$\frac{dy}{dP}$	0.118**	0.115**	0.109**	0.131**	0.118**
	[0.0289]	[0.0273]	[0.0312]	[0.0485]	[0.0319]
N	132763	132763	126625	60612	132763
Period Mar 1999 - Jan 2006, Age 47					
$\frac{dy}{dP}$	0.128**	0.124**	0.0746	0.282**	0.167**
	[0.0443]	[0.0418]	[0.0482]	[0.0747]	[0.0490]
N	132154	132154	126025	59650	132154
Period Mar 1999 - Jan 2006, Age 52					
$\frac{dy}{dP}$	0.0638	0.0633	0.0626	0.149+	0.0729
	[0.0484]	[0.0471]	[0.0544]	[0.0845]	[0.0555]
N	106936	106936	101891	49396	106936
Period Jan 2008 - Dec 2010, Age 50					
$\frac{dy}{dP}$	0.151	0.157	0.166	0.232	0.194+
	[0.0971]	[0.0975]	[0.111]	[0.174]	[0.114]
N	52647	52647	50282	24037	52647

Notes: This table explores robustness of the RD estimates in Table H.3 for women. Column (1) copies the baseline results. Column (2) adds to the baseline controls in addition one-digit industry controls, state fixed effects as well as calendar month and year FE. Column (3) excludes three instead of two months on each side of the cutoff, column (4) uses a bandwidth of 24 months and column (5) uses a triangular kernel. Standard errors (in brackets) clustered on day level (+ p<0.1, * p<0.05, ** p<0.01).

Table H.9: Robustness for RD-Estimates, Women+Men

	(1) baseline estimate	(2) more controls	(3) exclude 3 months	(4) bw 12 months	(5) kernel triangular
Period Jul 1987 - Feb 1999, Age 42					
$\frac{dy}{dP}$	0.107**	0.0922**	0.0918**	0.107**	0.104**
	[0.0191]	[0.0182]	[0.0211]	[0.0327]	[0.0214]
N	321533	321533	306671	145617	321533
Period Jul 1987 - Feb 1999, Age 44					
$\frac{dy}{dP}$	0.0657*	0.0514+	0.0489	0.157**	0.0860**
	[0.0283]	[0.0273]	[0.0318]	[0.0491]	[0.0323]
N	322362	322362	307213	146797	322362
Period Jul 1987 - Feb 1999, Age 49					
$\frac{dy}{dP}$	0.105*	0.0758*	0.0762	0.115*	0.102*
	[0.0421]	[0.0375]	[0.0484]	[0.0492]	[0.0418]
N	243626	243626	228065	152931	243626
Period Jul 1987 - Feb 1999, Age 54					
$\frac{dy}{dP}$	0.173**	0.151**	0.164**	0.205**	0.185**
	[0.0340]	[0.0302]	[0.0386]	[0.0410]	[0.0340]
N	133543	133543	125044	85142	133543
Period Mar 1999 - Jan 2006, Age 45					
$\frac{dy}{dP}$	0.0673**	0.0657**	0.0611**	0.0670*	0.0625**
	[0.0201]	[0.0189]	[0.0217]	[0.0336]	[0.0220]
N	289690	289690	276337	132029	289690
Period Mar 1999 - Jan 2006, Age 47					
$\frac{dy}{dP}$	0.120**	0.108**	0.0827*	0.206**	0.142**
	[0.0312]	[0.0293]	[0.0337]	[0.0522]	[0.0343]
N	280439	280439	267430	126965	280439
Period Mar 1999 - Jan 2006, Age 52					
$\frac{dy}{dP}$	0.101**	0.0883**	0.0995*	0.110+	0.0755+
	[0.0341]	[0.0333]	[0.0388]	[0.0603]	[0.0396]
N	220064	220064	209801	101362	220064
Period Jan 2008 - Dec 2010, Age 50					
$\frac{dy}{dP}$	0.0955	0.125+	0.0931	0.168	0.0982
	[0.0732]	[0.0675]	[0.0775]	[0.120]	[0.0787]
N	109763	109763	104737	50209	109763

Notes: This table explores robustness of the RD estimates in Table H.3 for women and men. Column (1) copies the baseline results. Column (2) adds to the baseline controls in addition one-digit industry controls, state fixed effects as well as calendar month and year FE. Column (3) excludes three instead of two months on each side of the cutoff, column (4) uses a bandwidth of 24 months and column (5) uses a triangular kernel. Standard errors (in brackets) clustered on day level (+ p<0.1, * p<0.05, ** p<0.01).

Table H.10: Institutional Parameters for the Key Cohorts, Women

Women	1924	1929	1935	1945	1950	1952
ERA (earliest possible) via women's pension	60	60	60	60	60	-
NRA (no penalty) via women's pension	60	60	60	65	65	-
UI Bridge Age	59	58	57+1/3	57+1/3	58	61*
PBD at bridge age	12m	24m	32m	32m	24m	24m*
Pension contribution years at age 54 cond. on being emp. at 50	23.9	23.9	24.8	22.9	27.0	25.9
Penalty for retiring at ERA via women's path	0	0	0	0.18	0.18	-

Source: Sozialgesetzbuch (SGB) Sechstes Buch (VI) and see Appendix C and Appendix E for more details. **Notes:** * The old-age pension for women pathway is abolished for cohorts born in 1952 and after. Therefore, the bridge age via UI here refers to the age at which individual take the full UI and transition into the old-age pension for long-term insured if they are eligible for this pathway.

Table H.11: Model-estimated dD/dP

	In-Sample Cohorts			Out-of-Sample Cohorts		
	1929	1935	1950	1924	1945	1952
dD/dP (target=0.128; age 52 in 1950)						
dD/dP at age 50	0.117	0.142	0.112		0.128	0.107
dD/dP at age 52	0.145	0.164	0.124		0.147	0.123
dD/dP at age 55	0.193	0.167	0.148	0.189	0.175	0.153
dD/dP at age 57	0.174	0.093	0.172	0.198	0.150	0.172
dD/dP at age 59	0.000	0.000	0.164	0.000	0.000	0.170

Notes: This table shows the model's estimated dD/dP at different ages. The targeted empirical moment is 0.128 at age 52 in 1950 and the corresponding estimate, shown in bold, is 0.124.

Table H.12: Parameter Estimates of Baseline Model and Alternative Models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Baseline	Linear Time Trend in Cost k_2	No Trend in Cost	No Fixed Cost of UI Entry ($k_1 = 0$)	Constant $\bar{\eta}$	Higher Welfare	Women
Std. dev. of productivity shock σ	2.336 (0.022)	2.355 (0.021)	2.494 (0.025)	0.687 (0.006)	1.928 (0.019)	1.711 (0.016)	3.246 (0.071)
Fixed cost of job search k_0	0.632 (0.006)	0.568 (0.007)	0.613 (0.008)	0.520 (0.004)	0.041 (0.004)	0.552 (0.006)	0.228 (0.003)
Cost of UI entry k_1	5.604 (0.067)	5.698 (0.064)	5.578 (0.079)		6.710 (0.007)	5.710 (0.084)	6.675 (0.014)
Time trend in search cost (exp. or linear) k_2	1.322 (0.089)	61.400 (1.774)		2.861 (0.377)	0.090 (0.002)	1.009 (0.040)	0.264 (0.008)
Slope parameter of search cost k_3	52.700 (0.429)	0.487 (0.035)	112.514 (1.647)	74.333 (0.585)	111.308 (1.870)	29.967 (0.191)	145.684 (3.156)
Elasticity of search cost γ	0.801 (0.008)	0.747 (0.006)	0.703 (0.005)	0.606 (0.009)	0.999 (0.009)	0.794 (0.006)	0.939 (0.014)
Parameters of job destruction rate							
λ_1	-6.646 (0.014)	-6.643 (0.014)	-6.711 (0.015)	-6.286 (0.012)	-6.673 (0.013)	-6.648 (0.014)	-5.488 (0.018)
λ_2	0.173 (0.002)	0.174 (0.002)	0.180 (0.002)	0.129 (0.001)	0.183 (0.002)	0.172 (0.002)	0.059 (0.002)
λ_3	0.166 (0.003)	0.151 (0.003)	0.158 (0.003)	0.192 (0.003)	0.122 (0.003)	0.161 (0.003)	0.133 (0.004)
Disutility of work distribution (mean: $\bar{\eta}$ and SD η_{SD})							
$\bar{\eta}_{1929}$	0.368 (0.007)	0.393 (0.007)	0.332 (0.009)	-0.440 (0.009)	0.793	0.652 (0.006)	0.973 (0.007)
$\bar{\eta}_{1935}$	0.691 (0.005)	0.704 (0.005)	0.680 (0.006)	-0.025 (0.006)		0.851 (0.006)	0.947 (0.006)
$\bar{\eta}_{1950}$	0.710 (0.009)	0.725 (0.009)	0.718 (0.012)	-0.295 (0.010)	(0.002)	0.912 (0.007)	0.854 (0.009)
η_{SD}	0.560 (0.005)	0.527 (0.005)	0.597 (0.006)	0.833 (0.006)	0.100 (0.002)	0.327 (0.003)	0.221 (0.005)
SSE	18,017	18,310	21,391	43,182	26,620	17,940	5,547

Notes: The table shows the parameter estimates for the baseline model (column 1) and the alternative specifications in the robustness table (columns 2 to 6) as well as the estimates for women (column 7). Column (2) estimates the model using a linear time trend in the cost of job search. Column (3) estimates the model assuming no time trend in the cost of job search. Column (4) estimates the model assuming that there is no fixed cost of entering UI. Column (5) imposes a constant mean of the disutility of work $\bar{\eta}$ across all cohorts (in-sample and out-of-sample). Column (6) estimates the model assuming welfare benefits (y^u) of 750. Column (7) shows the estimates for women.

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