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

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Abstract

We show that the non-employment effects of unemployment insurance (UI) for older workers depend critically on retirement policy. Using German data, we document large bunching in UI inflows at the age that allows workers to claim their pension following UI expiration. Inflows respond strongly to several UI and pension reforms. We probe the implications of these behavioral responses using a dynamic model and find that Germany's UI and retirement policy changes had substantial effects on the unemployment rate of older workers. Furthermore, we calculate large fiscal externalities from extending UI for older workers, especially under generous retirement policies.

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Understanding how unemployment insurance (UI) generosity affects non-employment duration is central to UI design. Many studies, across varied contexts, have estimated the elasticity of non-employment with respect to benefit or duration changes for prime-age workers and probed their policy implications (Schmieder and von Wachter, 2016). However, it is difficult to know how well these estimates translate to older workers approaching retirement age. Even in the cases where we have relevant estimates of UI expansions for older ages, these effects may well differ if retirement policies change. Although it is well understood that reduced-form estimates are inherently context-specific, the extent to which UI and pension policy interactions actually shape estimates of the effects of UI for older workers and associated policy takeaways is less clear.

Germany offers an intriguing context to study how UI extensions interact with pension policies. The unemployment rate of German men aged 55–59 spiked dramatically during the 1990s, diverging significantly from those of slightly younger workers (Figure 1 (a)).[1] UI payments to this same age group ballooned (Figure 1 (b)). In later years, just as remarkably, the unemployment rate of older workers fell rapidly, converging with that of younger workers. Over a similar time horizon, Germany first substantially extended UI potential benefit durations (PBD), before later partially reversing these changes. Additionally, various pension reforms beginning in the late 1990s gradually reduced the attractiveness of early retirement. Did these changes in UI and later retirement policies significantly alter the aggregate unemployment trends of older workers? Would we reach similar policy conclusions based on pre-existing work focused on prime-age workers? This paper seeks to answer these questions using a combination of reduced-form evidence and a structural model estimated on German social security data between 1975 and 2017.

We begin our empirical analysis by documenting reduced-form bunching of UI inflows at precisely the age that allows workers to claim their pension right after UI expiration. For example, birth cohorts nearing retirement age in the early 1980s faced a maximum UI PBD of 12 months and could retire as early as age 60 with no penalty following a UI spell. [2] Accordingly, we see large and precise bunching of UI inflows for these birth cohorts at exactly age 59.[3] Most of these workers remain on UI until exhaustion.

Importantly, these UI inflows respond to a series of UI extensions and pension rule changes. Our study period encompasses numerous reforms to both Germany's UI and retirement system that altered the payoffs to entering UI and the search incentives of the unemployed, first through a series of PBD extensions and later

[1]This paper's analysis focuses on men (though we also estimate and present all our key results for women in a self-contained Online Companion Appendix), since retirement rules and bridge ages differ by gender due to the existence of a specific women's pension (Section I). Over our sample period, at varying points in time, the always more generous terms of the women's pension allowed women to enter early retirement without a UI spell, enter retirement at earlier ages, or enter early retirement with lower financial penalties relative to men. As a result, the importance of the UI system as a vehicle for early effective retirement is lessened for women. However, results are qualitatively similar when compared to men.

[2]Entering UI voluntarily in Germany is also feasible and at most lightly penalized. A worker may be sanctioned if they quit a job voluntarily. These sanctions take the form of losing the first few weeks of benefits, but these sanctions do not always seem to be applied, could be offset by severance payments from firms, and are small relative to the length of maximum PBD.

[3]UI replacement rates are relatively generous in our context, with at most limited penalties for voluntary 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).

through retirement rule changes such as implementing a financial penalty for retiring early. As maximum PBD was extended from 12 to 24 and then 32 months, the large UI inflow bunching mass moves from age 59 to age 58, and then to 57 and 4 months. For the 1935 birth cohort, which faced the most generous UI and retirement rules and worsening macroeconomic conditions, almost 12% of the sampled cohort bunched into UI at the bridge-to-retirement age and almost 25% of the cohort was receiving UI benefits at age 59. Later, as penalties for retiring early were gradually introduced but PBD remained fixed, UI inflow spikes diminished. And eventually, as the earliest possible retirement age also increased, the age at which bunching in UI inflows occurred increased as well. Thus, UI inflows at the bridge-to-retirement age respond to UI policy changes, but also to retirement policy changes when holding UI policy fixed.

These large, adaptable UI inflow responses strongly suggest that Germany's historical UI extensions — introduced during a period of relatively generous retirement rules — may have significantly affected the aggregate unemployment rates of older workers. It is also plausible that the impact of these extensions was substantially larger than what we would have expected based on preexisting estimates for prime-age workers, which tend to be relatively modest.[4] However, formally assessing how UI and retirement policy changes affected aggregate unemployment rates and comparing these conclusions to other approaches is a challenging problem that requires making additional modeling assumptions. We approach this problem by specifying and estimating a dynamic life-cycle model that uses our reduced-form estimates as target moments. While other, less structural approaches could potentially be used to obtain approximate answers to these questions, they have their limitations. One may not want to assume, for example, that the entire bunching mass at the bridge-to-retirement age would shift left or right as PBDs change (especially for non-marginal PBD changes). Indeed, the bunching mass at the bridge-to-retirement age takes substantially different shapes and sizes as the distance to retirement age changes, as macroeconomic conditions worsen, and as the penalty for early retirement increases.[5]

Instead, we specify a dynamic life-cycle model that allows workers to 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). Our model is able to generate UI inflow bunching at bridge-to-retirement ages while allowing for optimal search behavior. Specifically, employment relationships will end efficiently in the model and workers will enter UI when the value of non-employment exceeds the value of employment. This occurs 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 employ-

[4]For example, the regression-discontinuity evidence from Schmieder et al. (2012) suggests non-employment durations increase by around 3 days on average for each extra month of PBD. In this paper, we extend these RD estimates to workers in their early 50s and find that the intensive margin effect is at least as large for these workers as it is for workers in their 40s. For example, men aged 52 spend an additional 0.128 months (4 days) non-employed for each extra month of PBD.

[5]Potentially simpler bunching-based models could take some of these factors into account, but, among other drawbacks, these approaches do not allow for possible interactions between intensive (the non-employment duration of individuals conditional on UI entry) and extensive margin (inflows into UI) responses. Simple bunching models (Saez, 2010; Kleven, 2016), which have been used to estimate labor supply elasticities in similar contexts (e.g., Brown, 2013; Manoli and Weber, 2016), are also hard to reconcile with the fact that inflows into unemployment could be either voluntary or involuntary and can vary over time with the business cycle. Furthermore, bunching-based predictions can be sensitive to ad hoc restrictions about the counterfactual distribution (Blomquist et al., 2021).

ment. 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 productivity shocks, a given worker type would have a single optimal age to exit employment and go into UI/retirement. The distribution of worker types generates a smooth distribution of employment exit ages. The UI bridge age creates a kink in the value of non-employment, where many worker types locate (bunch) at the bridge age. Without productivity shocks, bunching would be sharp at the kink point. Productivity shocks generate random variation in the value of employment, which in turn somewhat spreads out the sharp bunching at the bridge age (with some people exiting slightly before or after) and produce employment exits at younger ages. Because our model includes a search component, workers can also return to work, allowing for intensive margin UI responses in addition to UI entry decisions, which together ultimately allow us to fit UI inflow and non-employment patterns.

We estimate our model by matching its simulated moments to actual employment-to-unemployment transitions, non-employment durations, and a regression discontinuity (RD) estimate of the intensive margin non-employment effect of extending PBDs across three birth-year cohorts facing distinct UI and retirement institutions. The sharp policy variation and clean reduced-form moments help identify the model's key parameters. We then simulate the model for all birth cohorts between 1924 and 1964 to assess the out-of-sample model fit across a wide range of policy environments. This also enables us to construct age-specific unemployment rates in calendar time.

Our fairly standard model — built on clear economic incentives and their interactions — is able to capture UI entries and non-employment duration trends in the empirical data relatively well. Our simulated unemployment rates mirror both their empirical counterparts from the social security data and the OECD unemployment rates. Furthermore, simple, model-based comparative statistics are consistent with what we would expect from the reduced-form data. For example, extending the maximum PBD by one year increases the simulated unemployment rates of slightly younger (aged 52-55) versus slightly older workers (aged 56-59) very differently. Under the generous retirement rules prevailing in the early 1990s, it increases the simulated unemployment rates of those aged 52-55 by 0.6pp. 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 56-59 by a comparatively high 2.5pp, in large part due to UI inflow effects around bridge-to-retirement ages.

With our model estimated, we return to the motivating questions surrounding Germany's older workers' unique unemployment trends. We ask to what extent Germany's PBD extensions explain the large 10pp increase in the unemployment rate of workers aged 56-59 between early 1980 and the mid 1990s. 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 58% lower. We also show that changes in UI and retirement policies played a key role in explaining the improved labor market performance of older workers in the late 1990s and 2000s.

These large effects of PBD extensions on older workers are partially a consequence of the relatively generous retirement institutions of the time. These PBD effects would not have been nearly 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 unemployment rates. We reinforce this point by showing how the effect of the *same UI extension* varies for same-aged workers across different (historically observed) retirement regimes (but with all else held constant). Model simulations show that the non-employment effects of an identical one-year extension vary considerably between actual, current institutions and a setting that re-institutes Germany's historically more generous retirement rules.

We conclude by showing that the behavioral costs of UI extensions for older workers can, under the right conditions, be sufficiently different from what has been previously estimated for younger workers to alter the welfare assessment of UI extensions. Specifically, building on Hendren and Sprung-Keyser (2020)'s marginal value of public funds (MVPF) framework, we calculate the fiscal externality of an extra dollar of spending on UI PBD extensions. Using intensive margin estimates for prime-age workers in Germany, Schmieder et al. (2016) show that the net cost of an extra dollar towards PBD extensions is around 1.41. Using a willingness to pay for an extra dollar of spending on PBD of 1.36 (Le Barbanchon et al., 2024), this yields an MVPF of 0.97.[6] Using our model, we calculate the fiscal externality associated with a PBD extension for older workers from each separate birth cohort. Using the 1935 cohort as an example, a cohort that faced generous retirement and PBD rules and a poor labor market, we find that the net cost of an extra dollar of spending on PBD extensions for workers aged 50 and up is \$5.62 (due to a large \$4.62 fiscal externality). If we use the same willingness to pay for a \$1 of PBD extensions for older workers as for younger workers (1.36), this implies an MVPF of 0.24 – considerably lower than 0.97. While one may still choose to nevertheless expand PBDs for older workers, it is clear that the inputs into the welfare assessment for such a policy can differ meaningfully from these better-established baselines.

Related Literature. Much of the empirical UI literature has focused on intensive margin (i.e., conditional on entry) effects of UI extensions for prime-age workers (Schmieder et al., 2016). This is most evident with numerous regression discontinuity papers that show no inflow bunching at policy thresholds as a standard RD check (e.g., Card et al., 2007; Lalive, 2007). More recently, however, there has been added emphasis on UI-induced inflows into non-employment with a growing number of papers documenting the importance of UI policies on job separation and UI inflow responses (Anderson and Meyer, 1997; Green and Riddell, 1997; Albanese et al., 2020; Leung and O'leary, 2020; Van Doornik et al., 2023; Khoury, 2023; Hartung et al., 2025; Jäger et al., 2023; Jessen et al., 2025).[7] Our work reinforces the importance of considering the UI inflow margin, which may be especially relevant for workers nearing retirement.

Several papers have also directly estimated UI effects for older workers across different countries (Winter-

[6] The willingness to pay for an extra dollar of spending on UI PBD, transferred to UI exhaustees with $t > P$, is the marginal rate of substitution between the unemployed and employed states: $WTP^{PBD} = \frac{u'(c_{u,t>P})}{v'(c_e)} = 1 + \frac{u'(c_{u,t>P}) - v'(c_e)}{v'(c_e)}$, where $u(\cdot)$ is the utility of consumption while unemployed and $v(\cdot)$ while employed. Following Le Barbanchon et al. (2024) and the limited available evidence, we use a 9.1% average drop in consumption for long term unemployed from Kolsrud et al. (2018) and a CRRA utility function with $\gamma = 4$ to obtain the 1.36 number.

[7] While Anderson and Meyer (1997); Green and Riddell (1997) show early empirical evidence of UI effects on separations linked to firms' experience requirement, Albanese et al. (2020); Leung and O'leary (2020); Van Doornik et al. (2023) use quasi-experimental evidence to estimate the impact of UI eligibility on separation. More recent literature, such as Khoury (2023); Hartung et al. (2025); Jäger et al. (2023); Jessen et al. (2025) show that among prime-age workers (up to 50 years old), UI policies (such as eligibility, replacement rate and PBD) affect UI inflows, formal employment probability and job separations.

Ebmer, 2003; Kyyrä and Wilke, 2007; Kyyrä and Ollikainen, 2008; Lalive, 2008; Tuit and van Ours, 2010; Baguelin and Remillon, 2014; Dlugosz et al., 2014; Inderbitzin et al., 2016; Kyyrä and Pesola, 2020).[8] Many of these papers either directly or indirectly emphasize the importance of early retirement incentives, and several have found relatively large UI effects for older workers. For example, Inderbitzin et al. (2016) who consider interactions between UI, retirement and disability insurance, apply the Baily-Chetty framework (Chetty, 2008) to Austria and find that UI for older workers was too generous. A handful of these papers also provide direct evidence of UI inflow bunching (Kyyrä and Wilke, 2007; Tuit and van Ours, 2010; Baguelin and Remillon, 2014; Kyyrä and Pesola, 2020). Our reduced-form evidence complements and expands on this prior work. Relative to these papers, which typically study a single PBD change in isolation, we document decades of inflow responses and show how UI inflow bunching changes following both multiple PBD reforms and, importantly, also pension reforms that made bridging into early retirement via UI less attractive by introducing a financial penalty for early pension claiming. The scope of our work illustrates how the effects of UI extensions can vary as pension rules change, even within the same broader context — at their most generous, UI inflow effects at the bridge-to-retirement ages were comparable in magnitude to direct bunching at the statutory retirement ages (Seibold, 2021), emphasizing how common a pathway retirement via UI was, but once retirement ages increase and penalties are introduced, this pathway, while still relevant, became less important.

Crucially, we also add to prior work by using our model to speak directly to how UI and retirement rules interact to impact market-level aggregates (e.g. old age unemployment) and alter policy takeaways.[9] By quantifying how UI and retirement policies affected Germany's unemployment trends, we relate to a literature focused on understanding the drivers of Germany's stark labor market improvements since the mid to late 90s. Germany's labor market 'miracle' has 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., 2025). While these studies focus on workers of all ages, 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. Our model simulations provide novel evidence that changes in UI and retirement policies jointly played a substantial role in driving the unemployment rate trends of workers in their late 50s. By using our model to explore the fiscal externalities of various UI policies, we join studies like Inderbitzin et al. (2016) in highlighting that the welfare implications of UI extensions for older workers can look less attractive than at younger ages. We further emphasize that when considering the welfare implications of UI policy for older workers it is critical to consider interactions between UI and retirement policies: the effects and policy implications of any UI extension can change within country over time as retirement policies adapt.

[8] There is also related work for Germany, including papers that study at least one of the reforms covered in our long time horizon (see, for example, among others, Fitzenberger and Wilke (2010); Dlugosz et al. (2014); Riphahn and Schrader (2023)).

[9] Our focus on the challenging question of how nation-wide policy changes affect market aggregates is shared with Autor and Duggan (2003), who are interested in how programmatic changes to disability insurance affected market-level labor force participation of low-skilled workers.

I Institutional Background and Data

I.A Unemployment Insurance

The German unemployment insurance system provides income replacement to eligible workers who lose their jobs. 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.[10]

Reforms in 1985 and 1987 increased maximum PBDs for workers aged 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 H.1 plots the maximum PBD by age for older workers in each different institutional regime.[11] Table I.1 provides details about each reform.

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 rates were between 50% and 58% of net wages (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.

I.B Pension System and Early Retirement Via Unemployment

Germany has a pay-as-you-go public pension system. Participation is mandatory, except for civil servants and the self-employed. 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

[10] See Hunt (1995); Lange (2003); Fitzenberger and Wilke (2010) for an analysis and discussion of these reforms.

[11] We 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 H.1 to focus on the changes in PBD at older ages.

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.[12]

The UI pathway provided eligible workers with an option to retire early at the age of 60.[13] 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 and the ability to retire earlier than other pathways, made the UI pathway attractive.[14]

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. This kink occurs at the bridge-to-retirement age: $ERA - P$, with P being the maximum PBD. We show that UI entries react to the location and size of the kink in Section II.

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 the ERA remained fixed at 60 meaning they could continue to retire at 60 via the UI pathway, they now faced an actuarial adjustment in the form of a 0.3% permanent pension reduction per month they retired in advance of their NRA. Furthermore, 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.

I.C Firms, Unions, and Works Councils

Firms' incentives play an important role in workers' early exit from the labor force during our time period. After labor shortages in the 1960s and 1970s and extremely low unemployment rates, the German labor market worsened sharply after the 1973 oil crisis and even more so during the 1982 recession. Shrinking labor demand led to rapidly rising unemployment. Facing employment protection laws and powerful unions and works councils, firms and employer organizations sought to downsize employment through voluntary

[12] The full list of alternative pathways to retirement can be found in Table I.2 with associated discussion in Appendix D.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, 2006). 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.

[13] For 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.

[14] After the late 1980s, unemployed individuals aged 58 and older were exempt from actively looking for a job or other obligations. This so-called "58er-Regelung" was formally introduced at the end of 1985 and remained in place until the end of 2007.

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. While severance payments are not observed in our data, Grund (2006) provides survey-level evidence consistent with this pattern.

Whether or not a worker would be willing to accept a severance package depends on the worker's outside option. In a labor market with high unemployment rates, like that in the 1980s 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 that 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 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. The details of these CLAs, including the earliest exit age and the corresponding severance package, varied across sectors and even individual firms (see Trampusch, 2005, 2009), but tended to take age discontinuities induced by the UI and public pension system into account.[15] 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 D.3 for more detail).

I.D 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 all jobs covered by the social security system for the years 1975 to 2017.[16]

[15] 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 benefits for a period of thirty-two months, and then take advantage of the pension due to unemployment at age 60."

[16] The main exceptions are civil servants and the self-employed, which are not covered by the data.

Sample Selection Because retirement rules vary by birth date, 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 often focus on six cohorts that (a) represent periods of different UI generosity at older ages and (b) for which workers close to the bridge-to-retirement age faced stable UI policies: 1924, 1929, 1935, 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.[17] The specific institutional features affecting these six cohorts are summarized in Table 1 and discussed further in the next section.

We restrict our focus to West German males with a stable employment history at age 50. 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.[18] Additionally, we study West Germany as we do not observe employment histories for East Germany before reunification. Because eligibility for the maximum PBD and for various retirement pathways depends on having made sufficient social security contributions in prior years, we select individuals who are employed on their 50th birthday and have worked continuously over the previous three years without any UI claims.[19] This employment history restriction increases the likelihood that these individuals are eligible for the maximum possible UI PBD, which can require up to six years worked out of the previous seven years. It also means our focus is on older workers with high labor force attachment. Lastly, we also exclude individuals who are employed (initially, at age 50) in 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 with likely CLAs linked to early retirement at age 55. Appendix A describes this sample selection process in more detail.

Primary Analysis Sample In order to study UI inflows and non-employment durations, we generate a monthly balanced panel of each birth cohort that tracks an individual's labor market status since age 50. We also generate an analogous quarterly panel that comprises the moments that are used in our structural estimation. To do so, 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.[20] 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

[17] This helps keep exhibits focused and digestible. Our eventual policy counterfactuals will be based on model simulations for all cohorts between 1924 and 1964 and we also show model fit for each of these cohorts in the Appendix.

[18] Women could retire earlier, often with lower penalties, and without a preceding UI spell (our Online Companion Appendix reports results for women).

[19] 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.

[20] This includes individuals out of the labor force in genuinely unobserved states such as retirement, but also in 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.

(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 the data. This allows us to follow individuals over time and construct all possible transitions between states.

For our reduced-form evidence and the structural model we focus in particular on two key moments for each birth cohort: i) inflows into unemployment insurance (UI inflows) at each monthly (or quarterly) age.[21] ii) non-employment durations conditional on entering UI at a given monthly (or quarterly) age, which we construct as the number of months out of work before the next employment spell up to age 63. We winsorize this variable at 36 months. Appendix A contains additional details.

Regression Discontinuity Sample We also construct a separate UI inflow sample that we use to obtain regression discontinuity estimates of intensive margin responses to PBD extensions. In our primary analysis sample our goal is to keep employment restrictions constant across cohorts while making it very likely that workers qualify for maximum PBD at each age. Hence, we restrict to workers with three years of continuous employment at age 50, as this restriction can be constantly observed and applied to all cohorts, even the earliest ones. Our RD sample differs slightly in that it imposes typically more restrictive work requirements to ensure the relevant discontinuity binds and, for power reasons, it pools all UI entries across calendar time under a stable PBD rule, so any given RD window spans multiple birth cohorts. Specifically, the RD sample imposes the following work history requirements (see also Schmieder et al. (2012)): we require that, at the time of separation, individuals worked in a social security reliable job for at least 12 months of the previous 3 years, worked for at least 52 months within the last 7 years, and had no intermittent UI spell in the previous 48 months. Appendix C contains additional details on the RD sample.

II Reduced-Form Evidence

This section documents how older workers respond to changes in UI PBD and retirement policy. In Section II.A, we show that UI inflows spike at the bridge-to-retirement age and that they respond to both UI and retirement rule changes. In Section II.B we present regression discontinuity (RD) estimates of the effects of PBD extensions for older workers.

II.A Evidence of Extensive Margin (UI Entry) Responses Under Different UI and Retirement Rules

Using over three decades of data, we document UI inflow responses at the bridge-to-retirement age (a kink in the lifetime budget constraint) across different birth cohorts facing different UI and retirement regimes.[22]

[21] In practice we will define UI inflows as inflows into UI or Nu because if 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.

[22] Intuitively, this kink at the bridge-to-retirement age occurs because 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

We focus on birth cohort-level data so as to keep retirement rules constant within samples. 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 I.1).

Excess UI Entries at the Bridge-to-Retirement Age We first present evidence of sizable extensive margin UI responses. Figure 2 shows the number of individuals entering UI by age for six selected cohorts, each chosen to represent a different institutional regime (see Table 1). We focus first on the 1924 cohort in panel (a). We see a large spike in UI inflows at the bridge-to-retirement age, the age at which individuals can transition into retirement immediately following UI expiration. Specifically, Figure 2 (a) shows a spike in UI inflows at age 59 when the ERA was 60 and maximum PBD was 12 months (1924 cohort). This 'bridge-to-retirement' pathway is indicated by the red and blue shaded areas under the figures, with red indicating the period over which someone exiting at the bridge-to-retirement age would be on UI and blue when they would be receiving a pension.

To quantify the extent of these extensive margin responses, we calculate and report measures of the excess bunching mass using standard bunching techniques (Kleven, 2016).[23] The estimated excess bunching mass is indicated by the shaded gray area in Figure 2. We also report the standard measure of excess mass (i.e. relative to the mean estimated counterfactual) as well as the excess mass relative to the entire sample size (i.e. the cohort share). The estimated excess mass of UI inflows for the 1924 cohort implies that 5.7% of the 1924 cohort sample entered UI at exactly age 59 as a response to the incentives created by the bridge-to-retirement kink.

Responses to PBD Changes, Holding Retirement Rules Fixed We next show that these UI inflows react to changes in maximum PBDs (and in turn a shift in the bridge-to-retirement age).

All cohorts born before 1937 faced the same pension rules. These cohorts could retire as early as age 60 with no actuarial penalties following a year of unemployment insurance. However, individuals in these cohorts experienced different maximum PBDs due to UI reforms. Panels (a), (b) and (c) show UI inflows for three such cohorts, facing different maximum PBDs when near bridge age: the 1924, 1929 and 1935 cohorts.

The UI inflow mass moves when PBD changes. Figure 2 shows how the spike in UI inflows at age 59 when the ERA was 60 and maximum PBD was 12 months (1924 cohort) moved to age 58 when maximum PBD was extended to 24 months (1929 cohort), and further to age 57 and 4 months when maximum PBD

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. In practice, unemployment counts as an 80% contribution year calculated on pre-unemployment wages. Figure H.3 plots the evolution of stylized lifetime budget constraints for select cohorts experiencing different UI and pension regimes. Appendix D.2 describes how these budget sets are constructed.

[23] We calculate the excess mass as the cumulative difference between the observed UI entries and the counterfactual UI entries from the bridge-to-retirement age to the earliest possible pension claiming age. The counterfactual is calculated by fitting a polynomial within a (usually) 5-year age window on each side of the cutoff, leaving out the bridge-to-retirement region. Normalized bunching is the excess mass divided by the number of individuals in the cohort. Standard errors are calculated using bootstrap with 1000 replications. See Appendix B for more details on the estimation.

was extended to 32 months (1935 cohort).[24] The excess UI inflows are 5.7%, 6.5% and 11.8% of the 1924, 1929, and 1935 cohort sizes, respectively. In other words, over 10% of the men meeting our sample criterion who were born in 1935 entered UI at the bridge age as a response to the kink in the lifetime budget set at this point. And, because UI durations tend to be long at these ages among all UI entrants, almost 25% of this cohort was receiving UI at around age 59 (see Figure H.5 (c)). As another point of comparison, Seibold (2021) estimates the excess mass of entering retirement (pension claiming) at the statutory retirement ages in Germany (relative to the counterfactual). He finds large normalized excess bunching mass ranging between 14 to 32 with a mean of 20. In other words, workers are on average 20 times more likely to enter pension receipt at the statutory retirement age then they would at the same age without a statutory retirement in place. Our normalized bunching masses for UI-inflows at bridge-to-retirement ages are similarly large, with workers entering UI at the bridge to retirement age 21 to 33 times more often than they would without the bridge to retirement in place. These large behavioral responses reflect how common a pathway retirement via UI was among these earlier cohorts.

A notable feature of the bunching mass is that it is visibly asymmetric around the bridge-to-retirement age, with a sharper drop-off on the left (younger) side and a more gradual tail on the right (older) side. To the left of the bridge age, entering UI as a bridge to retirement quickly becomes very unattractive, since it implies spending time without income (or at the much lower unemployment assistance rate) after UI is exhausted and before being eligible for early retirement; as a result, UI entry at these younger ages only occurs in response to very large productivity shocks. To the right of the bridge age, by contrast, the cost of shifting the timing of UI entry is low, so even relatively small changes in productivity shocks move workers to enter slightly earlier or later.

Figures H.7 (a), (b) and (c) show that average non-employment durations (until age 63) are very close to the maximum possible non-employment duration, indicating that almost all of these entrants end up using UI as a bridge to retirement. For example, in Figure H.7 (a) the average non-employment duration is very close to 48 months at age 59, the number you would obtain if everyone were non-employed between age 59 and the cap of 63. Altogether, there is clear evidence of quantitatively large, extensive margin responses to UI policy during this period when the ERA was 60.

Responses to Pension Rule Changes, Holding UI Rules Fixed Cohorts born after 1937 faced changing retirement rules. Cohorts born between 1937 and 1941 were still able to retire and claim pensions as early as age 60 (the ERA via UI was still 60), but faced increasing financial penalties from doing so due to a steadily rising NRA. Beginning in birth month January 1937, and increasing with each passing birth month until

[24]While there is no comparably large bunching elsewhere, it is worth noting a few other features of these UI entry distributions. First, note that the UI retirement pathway requires being unemployed for at least 12 months, implying that there is still a small kink at age 59 in the budget set. Indeed, we note some spikes at 59 in panels (b) and (c), which are counted as part of the excess mass. Second, this figure clearly shows bunching in UI entries at other non-kink points, particularly at ages 55 and 57 for cohorts 1929 and 1935. 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). Since these spikes occur at points in a lifetime budget set where there is no kink, our model will not be able to capture these spikes.

December 1941, the no-penalty retirement age via UI was gradually increased from 60 to 65. While one could still retire and claim pension at age 60, a permanent 3.6% reduction in pension payments was assessed for each year someone retired in advance of the no-penalty age. By the end of this phase-in period (i.e. for those born in December 1941), retiring at age 60 (instead of 65) would have meant accepting an 18% lower pension.[25] These rules remained stable for birth cohorts 1942-1945, after which the earliest possible retirement age for retiring via UI increased and this pathway eventually closed down entirely.

Figure 3 plots excess UI inflows relative to cohort size for birth cohorts before, during, and after this penalty phase-in period. Specifically, in panel (a), we plot bunching masses *for each* birth cohort between 1933 and 1945 – i.e. for four years before the penalty phase-in, during the penalty phase-in, and four years after the penalty phase-in. Maximum PBD remained stable at 32 months for those close to the bridge age across all these cohorts. UI inflows were stable and large prior to penalty phase-in, then dropped gradually as the penalty was phased in, until they finally reached a new, lower, and relatively stable level between 1940 and 1945. Figure 2 (d) plots UI entries for the 1945 cohort, which exemplifies the new, lower rate of inflows (3% of the cohort or an excess mass of 13 times the counterfactual). In Figure 3 panel (b), we also report findings from a simpler approach that does not require fitting a bunching model and follows in the spirit of a difference-in-differences design.[26] Specifically, we simply add up the UI inflows between ages 57.33 and 60 for each cohort and plot these relative to cohort size in the blue series. Then, we add up the UI inflows between ages 52.33 and 55 for the cohort born five years later (keeping actual calendar time fixed), which serves as a possible control group for macroeconomic conditions (in the green series). The gap between the two series thus reflects differential changes in UI inflows between older and younger ages in the same calendar years.[27] Panel (b) reinforces the findings from panel (a): UI inflows of older workers initially differed massively from those of younger workers under the high maximum PBD and relatively generous retirement regime, but this gap narrowed considerably following the introduction of the retirement penalty.

Finally, Figures 2 (e) and (f) show UI inflows for the 1950 and 1952 cohorts. Both cohorts were eligible for 2 years of maximum PBD over the relevant ages, but faced very different pension rules from earlier cohorts. The 1950 cohort was still eligible to retire at age 63 via the UI pathway (or the long-term insured pathway, which requires at least 35 years of pension contributions), but with a two-year penalty applied. And there is indeed evidence of bunching at age 61. We also see some bunching (not shaded) at age 63, two years before the no-penalty retirement age of 65. However, bunching masses are now much lower (on the order of 1% of the cohort size) than in earlier years. The 1952 cohort saw the retirement via UI pathway abolished entirely, meaning retiring at 63 via the long-term insured pathway (if qualified) was the earliest available option. Here, too, we see a spike and some excess mass on the order of 1% at age 61. For both cohorts,

[25]Individuals who qualified for retirement via the long-term insured pathway could continue to retire at age 63, but also faced a 7.2% penalty for doing so if born in 1939 or later.

[26]We do this because the underlying UI inflow graphs in each year can be somewhat noisy, likely due to the fact that policy changes occurring at the birth-month level rather than birth-year level, and to potential adjustment frictions. Furthermore, fitting these bunching masses requires making some subjective choices. See Appendix B and Figure H.9 for details on the cohort-specific inflow graphs and construction of the counterfactual.

[27]The standard errors in this panel are minuscule, because these are simply scaled, raw counts of UI inflows in large data.

the combination of the early retirement penalty, not actually being able to retire much earlier than the likely alternative for our sample despite bridging via UI, and the declining macroeconomic unemployment rates, has led to still-present but far fewer excess UI entries among older workers than in earlier decades.

Overall, we observe clear and sizable bunching into UI at the bridge-to-retirement age. The bunching mass responds to both UI PBD changes and to changes in retirement rules. Under the relatively generous PBD and retirement policies of the 90s, excess UI inflows of older workers were particularly large, and they only declined substantially following many years of penalty and eventually retirement age increases, as well as declining maximum PBD, among other changes.

II.B Evidence of Intensive Margin Responses from Regression Discontinuity Estimates

The preceding cohort-by-cohort UI inflow and non-employment duration moments are used to identify our structural model. However, in addition to changing UI inflows, PBD extensions also affect non-employment durations *conditional* on entering UI and these 'intensive margin' effects could vary with age and proximity to retirement. Before turning to the model, we briefly discuss and, to the extent that we have valid RD-induced variation, estimate these effects for older workers.

Prior work on UI extensions has predominantly estimated these intensive margin effects for prime-age workers.[28] While whether or not these effects vary with age is interesting in its own right, it is also crucial for our model estimation. Since our model starts with workers aged 50 and above and has a search component, it is helpful to be able to target well-identified moments for how the non-employment rate among older workers, conditional on claiming UI, differs when PBD is extended. Hence, we extend Schmieder et al. (2012) RD approach and estimate intensive-margin non-employment effects of UI at older age discontinuities for workers in their 50s, which will ultimately result in an age 52 RD moment that we have confidence in and use (in addition to the UI inflow and non-employment duration moments) to discipline search behavior in our model.[29]

Beginning in 1987, there are 12 age cutoffs across four distinct periods at which we can potentially estimate the non-employment effects of UI extensions using RDs (see Table I.1), seven of which are for workers aged 50 and above. These estimates require the standard RD assumptions, including no sorting into UI around the cutoffs. Unfortunately, and consistent with the UI inflow responses seen above, this assumption is not always satisfied at older ages. Figure 4 (a) shows RD estimates of the jump in the density at the age threshold, revealing strong sorting at the 55+ cutoffs. Since the model and data condition on being employed at age 50, we would like to be able to target estimates at ages above 50. Fortunately, there are two candidate RD estimates past age 50, at ages 52 and 54, that are plausibly identified, with the age 52 RD in 1999-2006 ultimately being the one we have the most confidence in and decide to target.[30]

[28]In our context, Schmieder et al. (2012) analyze age discontinuities up until age 49 and Schmieder and Trenkle (2020) at age 50.

[29]Note that our need to restrict to non-violated cutoffs also raises econometric challenges. If, for example, the degree of density violation is correlated with the intensive margin response, extrapolating estimates to close-but-violated cutoffs might be misleading. We abstain from such comparisons. In the model section, we target the estimate of age-cutoff 52 to match behavior at that age, and let the model simulate both intensive-margin and extensive margin responses at other ages.

[30]This exhibits a somewhat smoother density close to the cutoff than the 54 cutoff (Figure H.11). In addition, unlike at the age

For completeness and to see if we can detect any hints of patterns across ages, at each age cutoff below age 55, we estimate the following RD specification:

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

Where 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 ages 50 and 55. We also exclude two months on each side of the cutoff – the donut hole – in all our regressions to minimize any potential bias due to sorting around the cutoffs. Self-contained Appendix C includes additional details as well as validity and robustness checks.

Figure 4 (b) plots the eight RD estimates for different age cutoffs with and without controls. These estimates are also reported in Table I.3. 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.[31] 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.

We target the RD moment at age 52 (the larger dot in Figure 4 (a) and (b)) in our structural model, for which balance and density checks all pass and standard errors are relatively precise. Figure 4 (c) shows the RD figure for this target estimate, plotting mean non-employment duration (capped at 36 months) by age around the age 52 cutoff for the 1999-2006 period. The point estimate at this cutoff, and hence our target parameter, is 0.128.[32]

III Dynamic Labor Supply Model

We have documented large bunchings of UI inflows at the ages that allow workers to claim their pension following UI expiration and shown that these inflows respond to various pension and UI reforms. In addition, extending UI affects non-employment durations conditional on entry into UI. These overall large behavioral responses suggest that Germany's historical UI extensions and retirement changes might have had a substantial impact on older workers' aggregate trends and perhaps larger fiscal externalities than one

54 cutoff where we see hints of imbalance on pre-unemployment wages, all predetermined variables are balanced at the age 52 cutoff and the standard errors of the estimates are slightly lower.

[31] Note that the point estimates are slightly smaller than in Schmieder et al. (2012), which is mostly due to our sample of men only.

[32] The age-54 moment has a fair amount of bunching inside the donut hole. While excluding the donut hole likely yields plausible results and almost the same point estimate as the age 52 moment, the age 52 moment is arguably identified more cleanly.

might have anticipated based on prior work for prime-age workers. Formalizing and quantifying these conjectures requires a model that is capable of capturing the key margins of adjustment to UI and pension policies. As such, in this section, we develop a dynamic life-cycle model of labor supply, job search, and retirement decisions that we will fit to the preceding reduced-form UI inflow, non-employment duration, and RD moments.

III.A Model Set Up

The model captures work and retirement decisions over the life cycle and includes unemployment and job search dynamics.

States and Value Functions Workers can be in one of three states: employed (E), unemployed (U), or out of the labor force (O). Once a worker drops out of the labor force, he 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.

Workers produce output p_t in each period, which is subject to shocks over time. 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. 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 calculate the remaining UI benefit duration 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.[33]

Workers have a utility function $u(\cdot)$, are paid $w_t(\cdot)$, and experience disutility from working (η). The value of employment is:

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

For tractability, we assume workers have all the bargaining power and firms make zero profits so that $w_t = p_t$ in all periods.[34] We also assume that workers have correct beliefs about future UI and retirement policies, which seems plausible given the slow, cohort-based phase-in of retirement reforms and that for our key cohorts the bridge age does not occur close to UI reforms. Workers will separate from their jobs whenever the expected value of future non-employment exceeds that of employment. This could occur for several reasons:

[33] A full accounting of the benefit eligibility in the presence of multiple unemployment spells would require separately keeping 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.

[34] Alternatively 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.

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, e.g., due to 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, workers face a (large) negative productivity shock ($-L$) with probability Λ_t.[35] Otherwise, they draw a productivity level p_t from a lognormal distribution.

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.[36] When workers enter unemployment they engage in costly job search and receive payments $B(d^U)$. Prior to UI benefits exhaustion ($d^U < P$), a worker receives benefits ($B(d^U) = b$). Afterwards, the individual receives y^u ($B(d^U) = y^u$), 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, he can decide to retire at the end of the period. If he remains unemployed d^U increases by one period. The value of unemployment is thus:

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

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

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

At any point, a worker can choose to transition 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. This value depends on the work history (d^U) and the 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 of being out of the labor force is:

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

The value of the pension depends on the relevant, cohort-specific retirement institutions in addition to

[35] We also assume that workers have foresight with respect to the future exogenous job destruction probability Λ_t. This seems like a reasonable trade-off for tractability since it mostly determines UI inflows for younger workers. As a robustness check, we will also show results where Λ_t is constant over time.

[36] Other 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. Our approach 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).

the individual's work history (d^U). Appendix F.5 details how V_t^O is calculated for each cohort.

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

$$V_t^N(d^U) = \max\left(V_t^U(d^U), V_t^O(d^U)\right) \tag{5}$$

Heterogeneity in the disutility of work Under our distributional and functional form assumptions described below, the preceding model generates 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 disutility of work, η.

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. 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). The value of employment falls as workers age and the value of non-employment rises as workers approach the age at which they can draw their pensions. In the absence of a productivity shock (non-random p_t), a given worker type has a single optimal age to exit employment and go into UI/retirement. The distribution of worker types η (disutility of work) 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 the value of employment, 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 and produces employment exits at younger ages.

III.B Assumptions and Parameters

We now briefly discuss the key functional forms and distributional assumptions used in our baseline model and lay out the parameters we estimate and those we fix based on institutional features. Self-contained Appendices E-F provide additional details.

Productivity p_t is 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 distribution with density $f(ln(p_t)) = \Lambda_t f^L(ln(p_t)) + (1 - \Lambda_t) f^N_{p,\sigma_p}(ln(p_t))$, where $f^L(ln(p_t)) = 1$ if $ln(p_t) = -L$ and $f^L(ln(p_t)) = 0$ otherwise. f^N_{p,σ_p} 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 $F(ln(p_t)) = \Lambda_t(1) + (1 - \Lambda_t)F^N_{p,\sigma}(ln(p_t))$, where F^N_{p,σ_p} is the normal CDF with mean p and standard deviation σ_p.[37] In practice, we 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 added flexibility. Specifically, we assume:

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

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. With our functional form assumptions, the model leads to closed-form solutions (which can be found in Appendix E) for all transition probabilities and can be solved via backwards induction from the last period.

We fix a number of parameters based on institutional details or data-derived values. We set mean (net) monthly wages to EUR 1,950, the natural logarithm of which equals p, the mean of the normal PDF in the mixture distribution for productivity shocks (p_t). This corresponds to an approximate gross wage of EUR 3000, which is in line with the average gross wage for those aged 50-60 with a UI spell across our six primary cohorts (EUR 3,282). Based on the 0.39 UI replacement rate on gross wages calculated in the data, we set unemployment benefits b = 1,170 for more recent cohorts (1,230 for earlier cohorts given their higher replacement rates). We set unemployment assistance $y^u = 500$.[38] The key institutional parameters necessary for calculating pension values are outlined in Table 1. Individuals start out in our model with contribution years as shown in Table 1 and receive the stated pension replacement rate; these values are calculated using administrative dataset from the German Pension Register. Starting with the 1937 cohort, people retiring at the ERA but before the NRA, receive a 3.6% reduction for each year they retired in advance of the NRA. Individuals accrue pension benefits while they work or are on UI benefits (at 80%), but not otherwise. Individuals are eligible for retirement via the UI pathway as long as they have one year of unemployment history (d^U). Since we cannot observe long enough work histories to ascertain long-term insured statuses, we assume all individuals in our sample are eligible for the long-term insured retirement pathway. If multiple pathways are available at a point in time, we allow individuals to choose the best

[37] This definition applies to 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.

[38] This 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. We set income while out of the labor force but not receiving pension (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.

retirement option available.

We estimate the following 13 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).

III.C Estimation

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 $(m(\xi) - \hat{m})' W (m(\xi) - \hat{m})$ where W is a weighting matrix.

For moments, we focus on three cohorts: 1929, 1935, and 1950, for whom we match the quarterly E to U flows and expected non-employment durations (until age 63) of workers entering unemployment in each quarter. Furthermore, we use the RD estimate for $\frac{\partial Nonemp}{\partial P}$ for men at the age 52 cutoff of 0.128 (Table I.3) to inform the intensive margin effect of UI for the 1950 cohort.[39]

Our weighting matrix is based on the empirical variances/covariances of our target moments. We obtain a covariance/variance matrix for each cohort and all E to U transitions based on 200 simulations using the empirical data. We obtain a diagonal variance matrix for each cohort for the non-employment durations at all ages (based on the standard errors of the mean duration), as well as the variance of $\frac{\partial Nonemp}{\partial P}$ based on the standard errors obtained when estimating these in the data. We stack all these variances into a single block-diagonal covariance matrix. For our purposes, we are particularly interested in matching the intensive margin RD moment. This is a causal estimate that we have significant confidence in, based on the analysis in this paper as well as many other well-identified estimates from the literature. We want to make sure our fitted model generates realistic predictions for intensive margin responses and is thus comparable to other approaches. To assure that our model matches this moment closely, we upweight the RD moment by 35.[40] Our results are quantitatively very similar if we use the diagonal weighting matrix or if we re-estimate the model without upweighting in the robustness section.

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 otherwise captured by retirement and UI institutions or other parameters. See Appendix F for details about the estimation.

[39] The moments and the parameters they primarily identify are summarized in Table I.6. We discuss identification in the next subsection.

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

III.D Discussion of Modeling Choices and Identification

Modeling Choices Our model focuses on two primary choice variables of workers: labor market state transitions and job search effort. This allows for rich economic responses to retirement rules and UI institutions both along the intensive and extensive margin, covering the wide range of institutional configurations that we observe over our long time horizon. To keep things tractable, we also abstract from several other dimensions that the prior UI and retirement literature has investigated.

First, we assume that workers are hand-to-mouth consumers and do not allow for savings in our model. Recent papers that investigated consumption and savings among UI recipients (Ganong and Noel, 2019; Gerard and Naritomi, 2021) found that consumption smoothing is quite limited and observed sharp drops in consumption at UI entry and exhaustion. These papers further show that the observed patterns can be rationalized if workers exhibit plausible degrees of present bias (in the form of $\beta\delta$-discounting). In the same spirit, DellaVigna et al. (2017) showed that present bias is key in their estimation of a UI search model with endogenous savings and leads to almost the same model fit as assuming hand-to-mouth consumers. Similarly, several recent papers have investigated how retirement institutions affect individual savings behavior. These papers generally found only muted savings responses.[41] Overall, we believe assuming hand-to-mouth consumers is a reasonable simplification. As a simple robustness check, we also provide estimates below with a higher level of consumption when being out of the labor force.

We also take the simplifying approach to only focus on transitions and unemployment durations as target moments, rather than wages. On the one hand, this decision is motivated by the growing body of literature that has found that UI policy changes affect search effort while showing little impact on reservation wages (see Le Barbanchon et al. (2024) for a comprehensive discussion of the recent evidence). On the other hand, we believe that transitions and unemployment durations respond in a direct and transparent way to policy changes. Pre- and post-unemployment wages are in principle also informative about selection into UI and in returning to work, but the selection also makes the observed moments more complex to interpret. As a robustness check, we develop an alternative model variant with heterogeneous severance pay that targets pre-UI wage moments in addition to transition moments and find very similar policy takeaways (column (9) of Table 4; see also Appendix Figure H.22). We view richer modeling of wages and firm behavior as a natural direction for future work.

Another simplification is that we focus purely on financial incentives for the individual worker, ignoring both household considerations as well as other factors such as retirement norms. The large inflow responses to the UI system indicate that individual incentives are first-order drivers for the retirement decisions of individual workers. While household and joint retirement considerations may play a role, we are clearly capturing an important margin. It is also plausible that since we are focusing on men, who for our birth co-

[41] For example, Lachowska and Myck (2018) shows that less than a third of a pension benefit cut in Poland was offset by higher personal savings. Similarly, Etgeton et al. (2023) found that an increase in retirement age in Germany led to a small decrease in savings rates, while García-Miralles and Leganza (2024) found that an increase in retirement age in Denmark only affected total savings due workers staying employed longer rather than a change in savings rates. Haan and Prowse (2014) estimate a structural life-cycle model with savings in the German retirement context and find that savings are almost unaffected by policy changes.

horts are still typically older and higher earning than their spouses, the incentives for the men will dominate. We also do not model retirement norms. Seibold (2021) showed that German workers often retire at the statutory retirement ages (SRA), even if the budget set at those ages actually exhibits a convex, rather than the standard concave kink. Seibold (2021) attributes this to norms around retirement and active promotion by the German pension fund. Our focus is on workers retiring at the ERA and via the UI path (and thus at younger ages than the SRA), which, while common, was arguably not a norm and was not actively promoted by policymakers.

Identification Our model has 13 parameters that are pinned down by a total of 307 empirical moments. Each parameter captures a slightly different channel for how the mechanisms determine inflows and unemployment durations over the life cycle and affects the predicted moments in unique ways. Identification comes from the joint fit of age-by-cohort inflow profiles, age-specific non-employment durations, and the response of durations to policy-induced changes in potential benefit durations. In the appendix, we show how the different model parameters influence the predicted moments (Figure H.25 and Table I.10). We also present the sensitivity of model parameters to empirical moments (Figure H.27 and Table I.11), following Andrews et al. (2017).

We provide a detailed discussion of these patterns in Appendix G, but present a few takeaways here. Cross-age variation and bunching around the bridge age discipline the dispersion of exits and the level of inflows, which pin down the volatility of productivity shocks (σ) and the fixed costs of search and UI entry (k_0, k_1). The patterns of unemployment durations for younger workers identify the marginal cost parameters of search (k_2, k_3) and the elasticity of the cost with respect to effort (γ). Exogenous separation parameters ($\lambda_1, \lambda_2, \lambda_3$) are identified by the level and cyclical co-movement of inflows with the unemployment rate and its changes, while the distribution of preferences for non-employment (η_{mean} by cohort and η_{SD}) is pinned down by cross-cohort shifts in inflow levels and the substitution of entries across ages. Policy variation provides an additional, sharp source of identification. The sensitivity of durations to changes in potential benefit duration, the $\frac{\partial D}{\partial P}$ moment, relates to the returns-to-search margin and thus primarily disciplines γ.[42]

IV Estimation Results and Model Validation

In this section, we summarize the estimation results and gauge the ability of the model to fit the in-sample target moments as well as the out-of-sample moments of non-targeted cohorts. We also show how the model can be used to construct unemployment rates for counterfactual policy scenarios.

IV.A Estimation Results and In-Sample Fit

Table 2 reports the estimated parameters with bootstrapped standard errors. Standard errors are generally small, suggesting local identification of the main parameters. We estimate a substantial standard deviation

[42]Identification is also supported by the fact that a large number of different starting points for the estimation and algorithms yield similar fits, parameter values, standard errors, and qualitative and quantitative patterns regarding the effects of different policies.

of the productivity shock σ, which is necessary to generate the observed diffuse bunching around the UI bridge age. We also find a sizable fixed cost of UI entry k_1, consistent with norms or stigma around UI take-up or the bureaucratic cost of applying; without this cost, the model predicts a large inflow just before retirement.[43] Search costs display meaningful duration dependence: the k_2 term raises marginal costs later in the unemployment spell. The slope of the cost schedule k_3 and the curvature parameter $\gamma = 0.82$, imply relatively elastic search effort with respect to the returns to search and are in line with the prior literature.[44] The λ parameters capture baseline variation in job destruction that tracks the business cycle, allowing the model to fit changes in unemployment inflows over time without overstating search responses. Finally, we estimate substantial heterogeneity in worker types. The η parameters show the expected cross-cohort pattern: higher η_{1935} and η_{1950} coincide with weaker labor markets and generally higher inflows, consistent with greater average disutility of work (or lower job values) in those cohorts.[45] The fact that η_{1935} is similar to η_{1950} also suggest that the main way the model explains lower bunching in the later cohorts is via the institutions rather than simply fitting this cohort-specific parameter.

Figure 5 gauges our estimated model's in-sample 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). The figure also shows gray 95% confidence intervals for the simulated moments, which are quite narrow.[46] 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 matches older workers' actual mean non-employment duration.[47] 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. While the model fits the key patterns of interest well, it does not perfectly fit all the empirical moments' features. The model systematically underfits UI inflow spikes at ages prior to the bridge-to-retirement age (e.g., 55 and 57 for the 1929 cohort). These spikes are likely due to collective labor agreements linked to specific ages rather than budget set kinks that our model would capture. The model predicts non-employment duration for workers close to the bridge-to-retirement age well, but has some difficulty at younger ages, where it overpredicts non-employment duration for the 1935 cohort and under-predicts 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 $\frac{\partial Nonemp}{\partial P}$ at age 52 for the 1952 cohort (0.128). This is calculated as the simulated change

[43]Evaluated at the marginal utility of consumption for the average worker ($1/w$), $k_1 = 5.66$ corresponds to approximately EUR 11,000, consistent with UI entry being unattractive for short spells but worthwhile for longer bridge-to-retirement spells.

[44]Our $\gamma = 0.82$ closely matches the single-type δ-discounting reference-dependent estimate in DellaVigna et al. (2017) (0.81) and is comparable to the composite curvature reported in DellaVigna et al. (2022) using German data. The estimated slope of the search cost function ($k_3 = 51$) is also similar in magnitude to the medium-cost searcher in the standard three-type model of DellaVigna et al. (2017).

[45]The flow utility of employment can be written as $\ln(w \cdot e^{-\eta})$, so η is equivalent to an effective wage reduction: workers behave as if they earned $w \cdot e^{-\eta}$ with no disutility. At average net wages of EUR 1,950, the 1929 cohort's $\bar{\eta} = 0.42$ implies an effective wage of EUR 1,281/month.

[46]The confidence intervals are bootstrapped, by randomly drawing target moments from a multivariate normal distribution with a mean equal to the empirical moments and using the estimated covariance matrix.

[47]Non-employment durations at each age are calculated as the expected non-employment until age 63 among UI entrants.

in the non-employment duration among new UI entrants from an extra month of maximum PBD, holding the worker type distribution (of disutility of work η) constant among new entrants, so as to mimic a pure intensive-margin effect. The model fits this RD moment very well (0.127).

Table I.7 shows simulated $\frac{\partial Nonemp}{\partial P}$ at different ages. Note that for a given cohort $\frac{\partial Nonemp}{\partial P}$ at age 50 starts between 0.11 and 0.14 and then increases with age (a pattern also seen in Table I.3, 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, leaving no room for durations conditional on UI entry to change with PBD. Conditional on age, cohorts facing worse macroeconomic conditions also have higher $\frac{\partial Nonemp}{\partial P}$.

IV.B Out-of-Sample Performance

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, which we estimate by refitting the model to match the cohort's non-employment duration and transitions, holding all other parameters constant. Figure H.15 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 the 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 6 shows how 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.[48] 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. Overall, the model fit is similar both in- and out-of-sample.

To provide an initial sense of how the model works, Figure 6 shows (in red) what happens when we extend PBD by one year for all individuals. Consider the 1945 cohort (panels (c) and (d)). For younger workers, who mostly enter UI as a consequence of exogenous job loss, UI inflows do not change, but non-employment durations shift upwards. Their non-employment responses thus primarily reflect the standard intensive margin, $\frac{\partial Nonemp}{\partial P}$ effect estimated in the RDs.[49] For workers close to retirement, the PBD extension moves the bridge-to-retirement age left by one year, causing some (but not necessarily all) to enter UI up to one year earlier (panel (c)). Since these 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

[48] Figures H.16–H.19 shows model fit for all cohorts between 1924 to 1963.

[49] In 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.

margin effect of PBD extensions matters less.

IV.C Constructing Model-Based Unemployment Rates

We now use model simulations for all birth cohorts between 1924 and 1963 to construct model-based, age-specific unemployment rates in calendar time (e.g., unemployment rates for ages 56-59 in 1994). These act as an additional out-of-sample validation exercise in that they can be compared directly to analogously constructed unemployment rates from the social security data and, visually, to the OECD data in Figure 1. Most importantly, they will allow us to directly explore how different counterfactual scenarios affect older workers' unemployment trends.

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.[50] Consequently, at any given point in calendar time (e.g., calendar year) we can aggregate predicted unemployment shares for any given age range (e.g., age 52-62).[51] We perform this exercise both using our model's simulated E to U transitions and non-employment durations, as well as, separately, using their empirical counterparts.

We plot these empirical and simulated unemployment rates separately for those aged 52-55 and 56-59 in Figure 7 (a). The empirical unemployment rates we construct roughly follow the OECD unemployment rates reported in Figure 1. Our model fits these empirical rates remarkably well, which also indicates that we jointly fit non-employment duration and transitions well across all cohorts. At younger ages, we fit the empirical pattern almost perfectly. At older ages, we also generally do well but occasionally underfit the empirical unemployment rate. In the earlier 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 effectively. 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 cohort-specific moments and overall unemployment rates. Figure 7 (b) revisits the exercise from Figure 6 of increasing PBD by one year for everyone. Consistent with the changes we saw for the selected cohorts in Figure 6, we find that extending PBD by

[50] To 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.

[51] Since 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.

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 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.

V Effects of UI and Retirement Policies on Aggregate Unemployment Rates

We now use our model to quantify how Germany's historical UI and retirement policies affected the aggregate unemployment rate. We will show that PBD extensions and later retirement rule changes account for a large share of the rapid rise and subsequent fall in Germany's old-age unemployment rate. We conclude this section with a discussion of the policy costs, specifically the fiscal externalities, of UI extensions for older workers.

V.A The Effects of Germany's UI and Retirement Policy Changes on Aggregate Older Workers' Unemployment

Rise between 1983 and 1994 We begin by asking 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. First, Figure 8 (a) and (b) illustrates what this change does for a single cohort. The red dash-dotted line shows what the 1935 cohort's UI inflows and non-employment duration would have looked like under this counterfactual scenario. The spike in UI inflows would have remained at age 59 instead of at 57 and 4 months, and the non-employment durations of workers in their late 50s would have been substantially lower. Figure 7 (c) shows how keeping PBD fixed at 12 months affects the overall unemployment rate of younger and older workers across all cohorts. We find that, at the peak in 1994, unemployment rates of workers aged 56-59 would have been 5.7pp lower (see Table 3). In other words, PBD extensions explain 5.7pp of the 9.9pp increase (or 58%) in the unemployment rate from 1983 to 1994.

In contrast to the large 5.7pp decline that we see for workers aged 56-59 under this 12-month PBD counterfactual, the effects on both relatively younger and older workers are more muted. 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 and the unemployment rate of workers aged 60-62 would have been 0.9pp lower. At younger ages, the PBD change does not meaningfully 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 on UI, meaning their non-employment durations can only increase by entering earlier. Inflows do increase a little at these later ages under the counterfactual (as can be seen for the 1935 cohort in

Figure 8 (a)), but these changes are relatively modest since entering UI very close to retirement is relatively unappealing.

Altogether, Germany's PBD increases account for a large share of the *overall* unemployment rate change for those aged 52-62. Table 3 column (4) shows that PBD extensions explain half of the *overall* unemployment rate increase for those aged 52-62 (2.4%/4.6%), due in large part to the large effects these extensions had on workers aged 56-59. While other factors clearly mattered, Germany's PBD extensions played a primary role in increasing the unemployment rate of workers in their late 50s in the early 1990s by shifting the bridge-to-retirement age earlier.

Decline between 1994 and 2014 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 both UI and retirement 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 7 (d) simulates a world in which none of these changes occurred, with pension and UI policies remaining stable at their generous 1994 levels. The dashed blue line in Figure 7 (d) 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 3.0pp between 1994 and 2014 (due to factors like changing economic conditions or other policy/systemic changes not considered), instead of declining by 11.8pp (the solid, dark blue line).[52] Thus, the retirement and UI policy changes can explain 8.8pp (or 75%) of the observed decline between 1994 and 2014 (see also Table 3).

We can also probe which of these specific policy changes (PBD decreases, retirement penalty introduction for retiring at the ERA, and the ERA itself) mattered the most. To do so, we simulate the model by changing one policy at a time. Table 3 shows what would have happened had only PBD changed relative to 1994, while retirement institutions has not. Relative to holding all institutions fixed at their 1994 levels, the reductions in PBD until 2014 would have reduced the unemployment of older workers by 2.9pp. Instead, if PBD and early retirement ages remained fixed in 1994, but the penalty for retiring via UI at 60 (due to increasing NRA) had been implemented, the unemployment of older workers would have declined by 5.4pp. Finally, simply increasing the earliest possible age for retirement via UI (which affected birth cohorts after 1945) would have eventually had a large 7.8pp effect on unemployment rates of workers aged 56-59. As the ERA increases gradually, eventually reaching 63 for those born in December of 1951, UI inflow bunching moves towards age (63-PBD), and as a result there are now far fewer UI inflows between ages 56-59 and among those who do enter between 56 and 58, several now return to work. As such, while PBD changes

[52]For intuition, Figures 8 (c) and (d) show how keeping UI and retirement institutions fixed at their 1994 levels affects the 1952 cohort. The dashed green lines here show that had PBD remained at 32, and the ERA and NRA for retiring via UI at 60, the spike in UI inflows would have remained at age 57 and 4 months and non-employment durations would have been substantially higher.

alone would have mattered, the retirement institution changes appear particularly relevant when it comes to explaining the decline of older workers' unemployment rates since the mid-1990s.

Altogether, these policy counterfactuals provide new insight into what drove the striking historical trends in Germany's older workers' unemployment rates (Figure 1). Our model suggests that 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 can account for much of the subsequent decline.

Robustness In Table 4, we probe the robustness of these policy takeaways to various modeling choices. We re-estimate our model under seven alternative modeling choices and repeat our policy simulations for each of these alternative models. Column (1) reproduces the baseline results for comparison. Columns (2) and (3) consider alternative weighting schemes. Using a diagonal weighting matrix (2) mechanically reduces the SSE, but otherwise the results are very similar. The main difference is that the model attributes more of the decline in the unemployment rate from 1994 to 2014 to changes in the institutional environment. Not upweighting the $\frac{\partial D}{\partial P}$ moment leads to a similar model fit. The SSE is slightly lower (somewhat mechanical due to the lower weight on $\frac{\partial D}{\partial P}$) and the predicted $\frac{\partial D}{\partial P}$ is 0.111, lower than our RD estimate. The policy predictions from this model are quantitatively very similar to the baseline. For consistency with related literature and our reduced-form analysis, we prefer the model with upweighting, but the takeaway is very similar.

In column (4), we investigate the importance of the cyclical productivity shocks in our model by shutting off the dependence of the exogenous shock on the unemployment rate (setting $\lambda_2, \lambda_3 = 0$). The model fit becomes significantly worse (SSE increases from 18 to 27 thousand), which is entirely driven by the fact that the model now cannot fit the cyclical variation in UI entries for younger workers (before the bridge age). However, the fit around the bridge-to-retirement ages (spike in inflows and pattern of non-employment duration) is very similar, and the model predictions for counterfactual policies are again almost identical to the baseline model. Likewise, we eliminate the cohort-specific disutility levels η_{cohort} in column (5), instead allowing only for a single constant term across cohorts. This means that the entire model is only ever fit to our three focal cohorts, and there is no refitting across all the other cohorts. Unsurprisingly, the overall SSE rises. However, PBD changes continue to explain a large portion of the rise in the unemployment of older workers from 1983-1994 and the later retirement and PBD changes still explain 45% of the subsequent unemployment decline.

Column (6) assumes a higher UA replacement rate (increasing UA benefits from 500 to 750). This improves the model fit slightly, and the model now attributes more of the variations in the unemployment rate to policy changes, since this makes the UI pathway even more attractive. Since we do not incorporate endogenous savings in our model, column (7) examines the impact of higher consumption after retirement by setting a much higher value for home production when out of the labor force (500 instead of 50). This generally reduces the impact of retirement policies somewhat and makes the model fit slightly worse; however, the main message remains: policy changes still account for about two-thirds of the increase until 1994 and more than half of the decrease in the UR until 2014. Finally, we verify the importance of retirement norms (as proposed by Seibold, 2021) in our context in column (8). We do so by adding an additional parameter that provides a utility boost to the value function for exiting the labor force, if the exit occurs at an exact retirement age (any of the ERA or NRA listed in I.2). Given that we are estimating an additional parameter and that this model fully nests our baseline model, the SSE is now smaller than before. However, the difference in SSE is negligible and the policy predictions are essentially identical to our baseline model. The estimated utility 'boost' is actually slightly negative and not statistically significant. It seems plausible that the ERA via UI pathway was not a "Norm" in the same way as retirement ages studies in Seibold (2021) and were not, for example, promoted by the pension system. We also do not have a great setting to identify norms at the NRA since we do not target retirements directly from employment (without UI).

Finally, column (9) addresses the concern that our baseline model does not incorporate wage heterogeneity. Our baseline specification fixes wages at their mean and captures worker heterogeneity solely through the disutility of work (η_i). While this is a limitation, we note that in our model η_i plays a role analogous to any unobserved factor that raises a worker's outside option and makes separation more likely. To probe this, we develop an alternative model variant that replaces the heterogeneous disutility of work with heterogeneous per-period severance pay (δ_i) received while on UI. This is motivated by institutional evidence that firms, particularly larger ones, frequently offered severance packages to older workers exiting via the UI bridge, with substantial variation across workers and firms (Grund, 2006). In this variant, higher-δ_i workers have a higher outside option and are more likely to separate, playing a similar role to η_i in the baseline. Since we do not observe severance pay directly, we link the implied severance among exiters to observable pre-UI wages and firm size (measured at age 50, before any separation decision) via auxiliary log-linear regressions, and then target the resulting empirical wage-at-age-50 moments in addition to our baseline transition moments. This link is reasonable if severance pay tends to be larger for higher-wage workers, for example because buy-outs are more common for workers whose pay has begun to exceed their productivity. Appendix Figure H.22 shows that both empirical and model-predicted wages and firm size increase as the entry age approaches the bridge-to-retirement age, suggesting that the heterogeneity we estimate corresponds to real differences across workers and firms. Reassuringly, this alternative model, where unobserved heterogeneity is now disciplined by both transition patterns and wage selection patterns, yields similar policy takeaways to our baseline.

V.B The Effects of UI Extensions Depend on Retirement Institutions

Across different model specifications, we consistently find that Germany's PBD extensions played an important role in driving older workers' unemployment trends in the 1990s. As PBDs increase, we see larger UI inflows at earlier ages and, since many of these stay on UI until retirement, also larger average non-employment durations. These large non-employment responses to PBD extensions thus appear intrinsically linked to the prevailing retirement policies. To reinforce this point, we conduct two additional exercises.

First, in Figure H.24, we consider a policy simulation that leaves Germany's PBD extensions in place, but instead imagines that the UI retirement pathway never existed, making age 63 the earliest possible retirement age available. Under this counterfactual, it is 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 primarily affects UI inflows of workers aged 60 and up. The green dashed line in Figure 8 (a) shows how the 1935 cohort would have behaved had the UI pathway been closed. While there is now bunching at 60 and 4 months, this change greatly reduces UI inflows and non-employment durations of workers aged 60 and below. Accordingly, Figure H.24, 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. 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 (6.9% instead of 16% in 1994), *despite Germany's large PBD extensions*.[53] As such, retirement institutions clearly shape the effects of UI extensions on workers at various ages.

As a final way to reinforce the dependence of UI effects on retirement policy, in Table 5, we consider how the effect of the same UI extension in 2014, holding all else equal, would differ under different retirement policies. Column (1) shows the effect of extending PBD by 12 months on the unemployment rate, given the actual 2014 institutions. Extending PBD by 12 months increases the unemployment rate for workers in their early 50s by 0.34pp while the same PBD extension increases the unemployment rate for workers in their late 50s by 0.90pp. 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 0.28 for workers in their early 50s and 0.45 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 reintroduce 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 0.90 to 1.62pp) and the elasticity of the unemployment rate with respect to PBD increases from 0.45 to 0.61. Column (3) shows that these patterns are even more pronounced if we reintroduce the UI pathway *and* repeal the penalty for retiring early (thus returning to the pre-2000s retirement institutions), with the same UI extension now increasing the unemployment rate by a full 3.01pp.[54]

V.C Fiscal Externalities and the Marginal Value of Public Funds for UI Extensions

The preceding findings suggest that a welfare evaluation of the UI extensions for older workers might look substantially different from one for younger workers, at least under certain retirement regimes. To formalize this, we turn to the Marginal Value of Public Funds (MVPF) framework proposed by Hendren and Sprung-Keyser (2020) and calculate the fiscal externality (FE) and the MVPF associated with a UI extension for

[53] The 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.

[54] Interestingly, $\frac{\partial Nonemp}{\partial P}$ at age 57, which captures an intensive-margin effect, actually declines relative to column (1), since in this policy environment many of the workers displaced at age 57 would not have returned to the labor market even prior to the PBD extension. Despite this, the overall elasticity of the unemployment rate with respect to PBD increases relative to column (1) due to the importance of extensive margin, inflow effects.

workers aged 50 and above.

The marginal value of public funds of a policy that spends an extra dollar on UI by extending PBDs is defined as the willingness to pay of the recipients divided by the net costs: $MVPF_{PBD} = \frac{\sum_i WTP^{PBD}}{NetCost}$ (Hendren and Sprung-Keyser, 2020). Using the framework in Le Barbanchon et al. (2024), the willingness to pay for an extra dollar of spending on UI PBD, transferred to UI exhaustees (such that $t > P$), is the marginal rate of substitution between the relevant unemployed and employed states: $WTP^{PBD} = \frac{u'(c_{u,t>P})}{v'(c_e)} = 1 + \frac{u'(c_{u,t>P}) - v'(c_e)}{v'(c_e)}$, where $u(\cdot)$ is the utility of consumption while unemployed and $v(\cdot)$ while employed. Since behavioral responses generate a negative fiscal externality, the denominator of the MVPF formula is $NetCost = 1 + FE$, where FE is the fiscal externality per dollar of transfer. Prior work by Schmieder and von Wachter (2016) (also reported in Le Barbanchon et al. (2024)) calculates the fiscal externality across many different papers with estimates of PBD extensions from Europe, including Germany, using a Bailey-Chetty (Chetty, 2008) style expression for the fiscal externality under only intensive-margin effects. This work places the fiscal externalities for German prime-age workers between 0.38-0.42, implying a net cost of around 1.41 per dollar of UI PBD spending. The mean net cost across all the different papers in a European setting is 2.31. Le Barbanchon et al. (2024) then use a constant 1.36 for the WTP for PBD extensions (the numerator in the MVPF) for all the European papers under consideration. This comes from using the 9.1% average drop in consumption for the long term unemployed in Sweden estimated in Kolsrud et al. (2018) and a CRRA utility function with $\gamma = 4$. We will also use this as our numerator in our calculations below. Taking this WTP for UI PBD and dividing it by the net cost yields an MVPF for each study which we then average to obtain an average MVPF of 0.967 for Germany and 0.691 across all European studies (Table I.8).

How does this picture change when we instead calculate fiscal externalities for the older workers in our setting taking into account inflow responses? In order to calculate the fiscal externalities of PBD extensions using our model, we note that the fiscal externality of a policy change is the ratio of the behavioral cost (BC) to the mechanical cost (MC). For any policy change, the mechanical cost is the change in total spending on the policy, holding behavior constant. For a UI extension, this is the increase in benefit payments due to the increased PBD coverage holding unemployment durations and UI inflows constant: $MC = dB|_{mechanical}$. This mechanical cost will be proportional to the UI exhaustion rate, since only exhaustees benefit from the policy if behavior is unchanged. The behavioral cost, by contrast, is the change in tax revenue (dR) due to increased time in non-employment as well as the increase in total benefit payments (dB) minus the mechanical increase ($dB|_{mechanical}$). dR and dB capture both intensive-margin responses as well as the inflow response. Thus the full fiscal externality in the presence of inflow responses is given as $FE = \frac{BC}{MC} = \frac{dB + dR - dB|_{mechanical}}{dB|_{mechanical}}$.[55] We calculate these components using our model, by simulating the model with the actual PBD policies as well as for the counterfactual where PBDs are increased by one period (3 months). The FE components are then simply the change in total benefit payments and revenue for the two

[55] An important input into the fiscal externality calculation is the effective tax rate on the employed, which determines the revenue loss from non-employment. As Lawson (2017) pointed out, using UI taxes alone severely understates this revenue loss. We therefore follow Schmieder et al. (2016) and Hendren and Sprung-Keyser (2020) and use the average tax wedge on labor as the tax rate in the FE calculations.

simulations.

We focus first on the 1935 cohort, since this cohort faced the most generous retirement and UI schemes we studied, as well as relatively high and rising unemployment rates. When we do so, we obtain a fiscal externality of 4.62, for a total net cost of 5.62. This is almost 4 times as large as the net cost for prime-age workers in the same context. Using the same WTP for an extra dollar of UI PBD of 1.36 as above (Le Barbanchon et al., 2024), this would translate into an MVPF for older workers of 0.242, compared to the 0.967 MVPF in the same context for younger workers. We note that while it is possible that the willingness to pay for older workers might differ from that of younger workers, evidence from the U.S. suggests that the consumption losses at unemployment are smaller for older workers than younger ones with fewer means to smooth consumption (Michelacci and Ruffo, 2015), implying, if anything, a lower WTP and hence an even lower MVPF than we find. In our setting, older workers entering UI at the bridge age also tend to have slightly higher pre-UI wages (Appendix Figure H.22) and may receive severance pay, factors that would further support a lower WTP. Thus, extending PBD for older workers involves substantially different welfare tradeoffs than what we would have anticipated based on prior work for younger workers in the same context.

Another way to illustrate this point, while highlighting the importance of inflow responses for older workers, is to calculate the fiscal externality of UI extensions based only on expected intensive margin adjustments and shutting down inflow responses. Specifically, we take the 1935 cohort under actual PBD policies and hold UI inflows at each age fixed at their baseline levels. We then increase non-employment durations at each entry age by the amount implied by our preferred RD estimate of $\frac{\partial D}{\partial P} = 0.128$ at age 52, applied to the change in PBD at each age. This isolates the intensive-margin duration response and shuts down the extensive-margin inflow response, yielding FE components that are comparable to the Bailey-Chetty style calculations in prior work for prime-age workers (Schmieder and von Wachter, 2016). Under this exercise, the behavioral cost is driven entirely by longer non-employment spells among *existing* UI entrants (through lost tax revenue and extended benefit receipt), while the mechanical cost reflects the additional benefit payments to those who would have exhausted their benefits even without behavioral changes. Table I.9 reports the full decomposition into revenue losses (dR), benefit increases (dB), behavioral costs, and mechanical costs for both the naive and full model calculations across cohorts. When we do so, we obtain a net cost to the government of 1.90, which is much closer to the 1.41 for younger ages.[56] Hence, a lot of the fiscal externality arises as a consequence of changing UI inflows in response to PBD. This also means that counterfactuals that only alter survival functions (and thus focus on the intensive-margin response), like Johnston and Mas (2018), would not be very accurate when considering older workers in this context.

Figure 9 plots the net cost to the government and the MVPF that we obtain using our model, and compares them to those for other social programs from Hendren and Sprung-Keyser (2020), as well as to US and EU averages for UI programs (the numbers and sources for which are documented in Table I.8).

[56] The slightly higher number is driven by the fact that older workers have much larger baseline PBDs in this cohort, compared to younger workers, with similar non-employment durations. This in turn means that the UI exhaustion rate and, therefore the mechanical cost of a policy change is lower for older workers.

UI extensions for older workers in our context stand out in terms of their particularly high net cost and relatively low MVPF. While one may well still choose to spend a dollar on policies with low MVPFs, it is nevertheless clear that the welfare assessment of PBD extensions for older workers differs substantively from these prior benchmarks.

Given that the behavioral costs of UI extensions vary with retirement institutions, among other contextual factors like the macroeconomic unemployment rate, it is also the case that these fiscal externalities differ across cohorts. In Figure H.29, we calculate FE and the associated net costs for all cohorts for which we have data for ages 50 and up. While net costs are always substantially above those of younger workers in the same context and those obtained when shutting down inflow effects, they do differ by cohort. Net costs started out lower for the 1929 cohort, when PBD was still relatively short at most ages and thus exhaustion rates were high. Then net costs rose sharply and were largest for birth cohorts in the mid 1930s, who faced large PBD, generous retirement, and high unemployment rates. They fall from a peak above 5 to around 3 as retirement rules made UI entry in one's 50s less attractive and as unemployment rates fell. Altogether, our evidence suggests that the non-employment effects of UI extensions can be large and fiscally expensive for older workers, especially under the right institutional and macroeconomic conditions.

VI Conclusion

We specify a dynamic 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 unemployment insurance extensions played a large role in explaining Germany's remarkable historical rise in the unemployment rate of older workers. The model also suggests that changes to both the UI and retirement systems played an important and underappreciated role in the German "labor market miracle" after 2005 by reducing older workers' unemployment rates. These large policy effects arise because retirement and UI institutions interact — the retirement policies that prevailed for older workers in the 1990s encouraged UI inflows among older workers and heightened the behavioral impact of additional UI extensions. In contrast, later retirement rules made retirement via UI less attractive. Altogether, our work suggests that changes in retirement institutions can meaningfully alter the effects of UI extensions and that the fiscal externalities associated with UI extensions can, under the right conditions, be substantially larger than typically understood.

An advantage of our setting is that we can study how changes in UI and retirement rules alter the effects of UI within the same broader context, but this also raises questions about what to expect in other contexts. We study a case with relatively generous UI rules and where firm and sectoral-level labor agreements play important roles. The extent to which retirement institutions affect UI responses likely depends on the incentives of firms and other such contextual factors. For example, in a setting like the United States UI system which uses experience rating and generally does not allow for UI following quits, we might expect dampened bridge-to-retirement effects. Nevertheless, we suspect our general message that the design of retirement institutions can meaningfully alter the effects of UI to be relevant in other countries. Evidence consistent with UI inflow bunching into retirement (our key behavioral mechanism) has been documented in other European settings (e.g. Kyyrä and Wilke, 2007; Tuit and van Ours, 2010; Baguelin and Remillon, 2014; Kyyrä and Pesola, 2020). While the fiscal externalities we estimate for older workers are substantially larger than what prior work has found for prime-age workers, they are comparable in size to those estimated by Inderbitzin et al. (2016), who study a PBD extension for those aged 50-57 in Austria. These findings, which reflect similar underlying economic behavior, strengthen our confidence that our broader conclusions are not confined to the German setting.

We conclude with several avenues for future work. We model separations as being efficient in that the 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. 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. Further, 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 one example, it is possible that, even though Germany's maximum PBD extensions in the 80s increased the non-employment duration of older workers, they might also have paved the way for younger workers to retain or get jobs while smoothing older workers' transitions out of employment. Last, other institutional changes besides retirement policies, such as changing UI benefit levels or post-UI welfare benefits, could also significantly alter the effects of UI extensions for all ages. Quantifying and modeling how much these other institutional changes matter could help policymakers better predict the effects of UI policy changes in new institutional environments.

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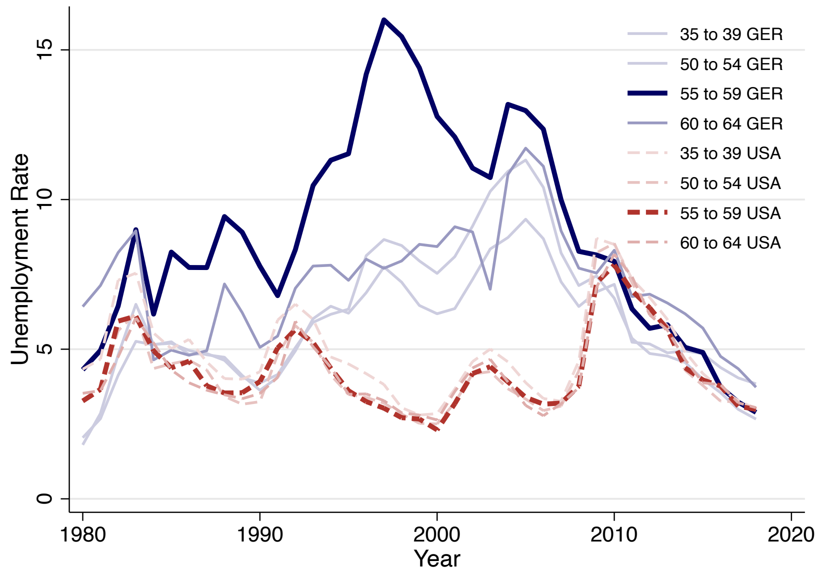
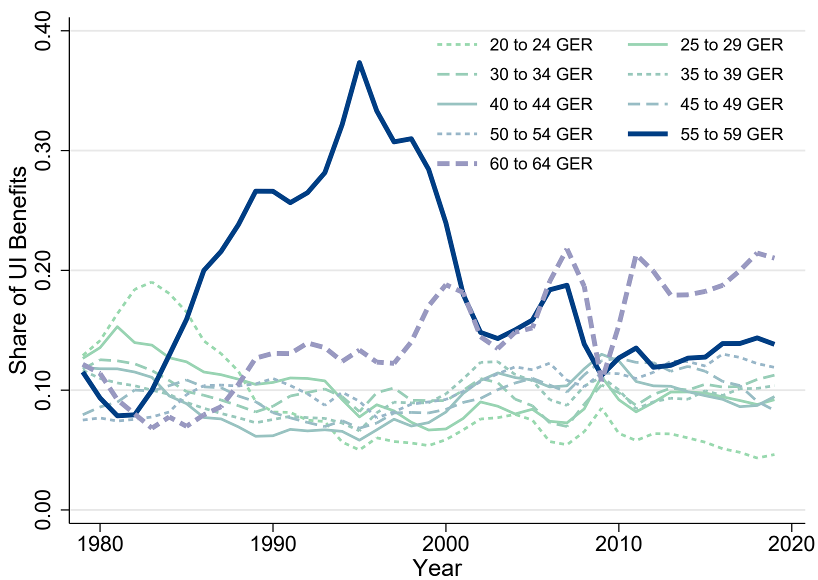
Figures

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



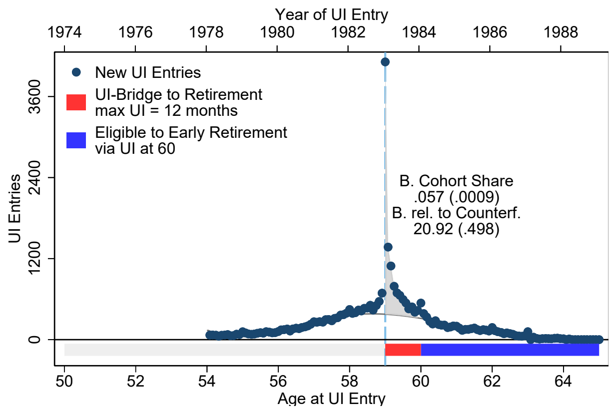
(a) Male Unemployment Rates by Age Group: West Germany and U.S.A



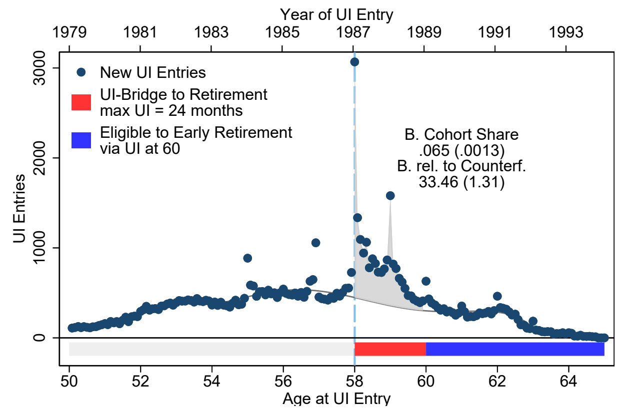
(b) Share of Total Benefits by Age Group in West Germany

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).

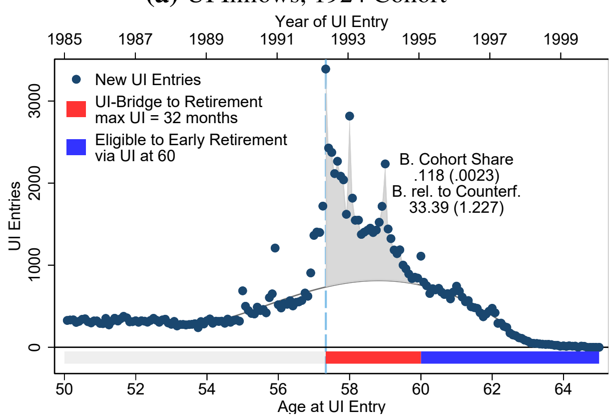
Figure 2: UI Inflows by Age for Different Cohorts in Germany, Men



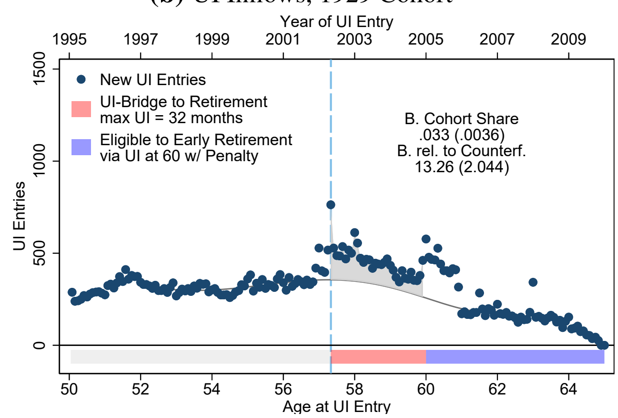
(a) UI Inflows, 1924 Cohort



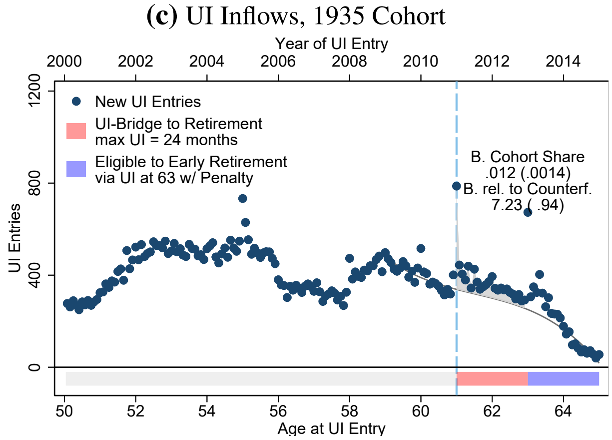
(b) UI Inflows, 1929 Cohort



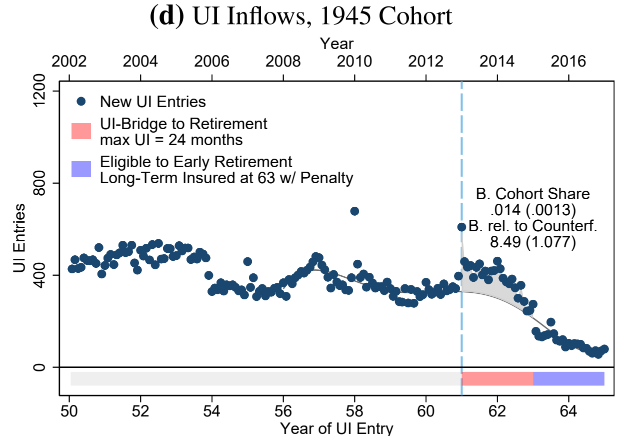
(c) UI Inflows, 1935 Cohort



(d) UI Inflows, 1945 Cohort



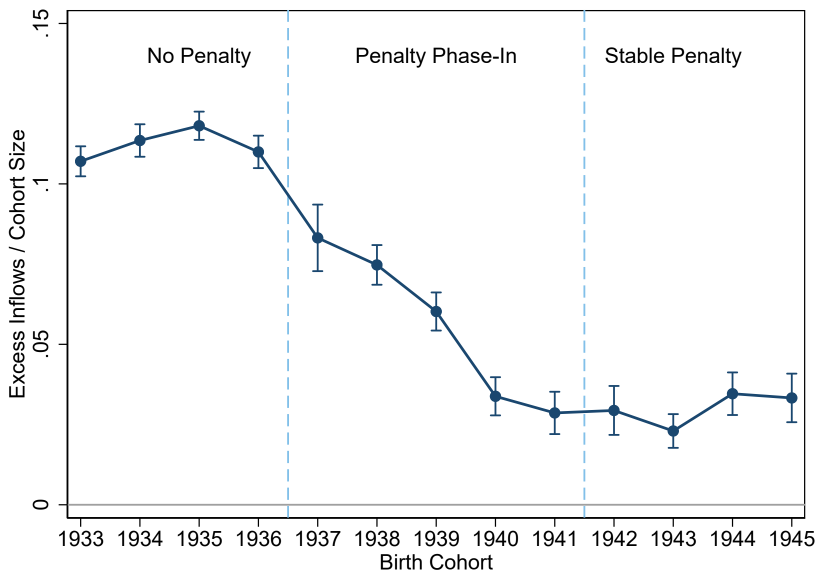
(e) UI Inflows, 1950 Cohort



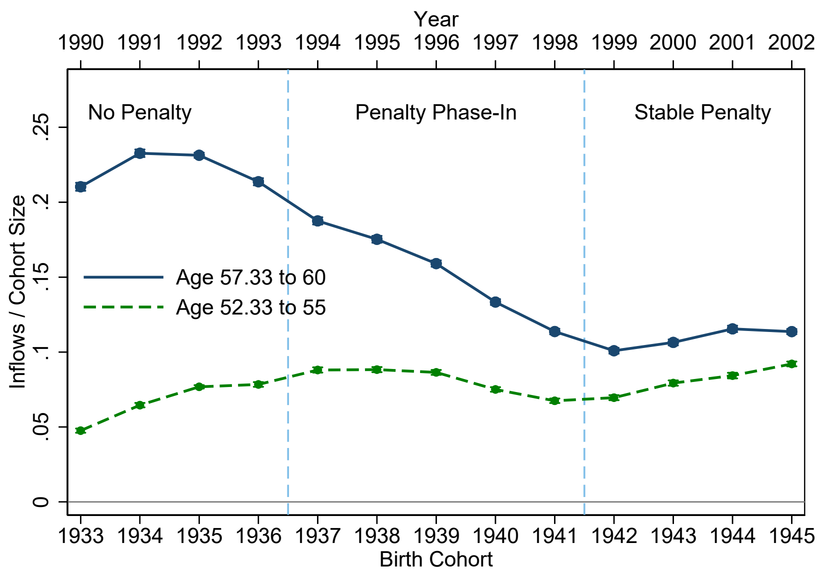
(f) UI Inflows, 1952 Cohort

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. The red shaded bar under each subfigure denotes time spent on UI if one starts receiving UI at the bridge-to-retirement age, indicated by the vertical dashed blue line. The blue bar denotes time spent receiving a pension if one starts receiving their pension as early as possible (via the UI pathway in panels (a)-(e), and via the long-term insured pathway in panel (f). Lighter colors in panels (d)-(f) indicate periods where early pension receipt is penalized. The excess bunching mass (shaded in gray) is calculated as cumulative difference of the observed UI entries minus the counterfactual UI entries between the bridge-to-retirement age and the earliest possible pension age. For further details on the estimation of the counterfactual, see Appendix B. We report two different normalizations for this excess mass, the first relative to the number of individuals in the cohort-sample, and the second relative to the mean counterfactual. Standard errors (in parenthesis) are obtained via bootstrap, by resampling from the actual distribution with replacement 1000 times.

Figure 3: Evolution of UI Entries Around Phase-In of Retirement Penalty



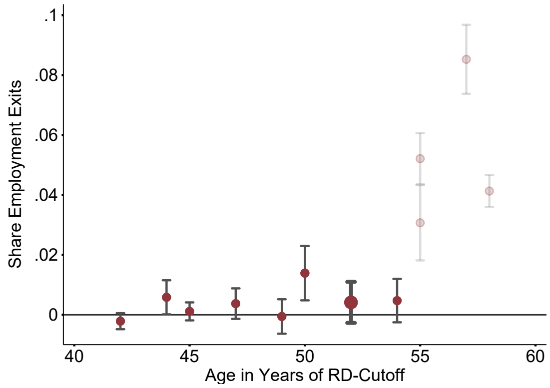
(a) Excess Bunching Mass Relative to Cohort Size



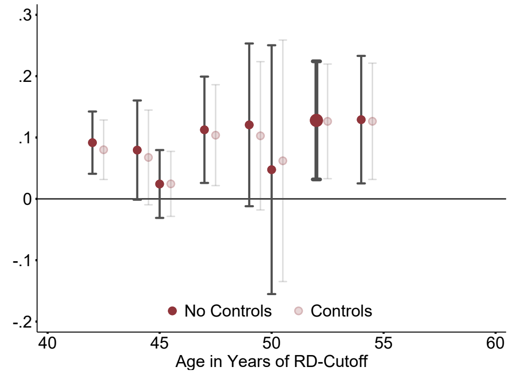
(b) UI Inflows Relative to Cohort Size

Notes: This figure shows the evolution of UI entries before, during and after the introduction of the penalty for early retirement via unemployment insurance. Panel (a) shows bunching estimates of the period-specific excess number of UI inflows relative to the number of individuals in the respective cohort. The excess mass is estimated using standard bunching techniques, with details laid out in Appendix B. 95% confidence intervals constructed via bootstrap with 500 replications are depicted. As an alternative to relying on bunching estimates, Panel (b) directly plots UI inflow shares (UI inflows divided by cohort size). The blue series plots the share of UI entries between age 57.33 and 60 for the stated birth cohort. The green series shows the share of UI entries between age 52.33 and age 55 for a 5-year younger cohort, so as to keep calendar time fixed. As such the birth cohort axis applies only to the blue series. 95% confidence intervals are depicted for each series in panel b), but are extremely small given these are based on raw counts in large data.

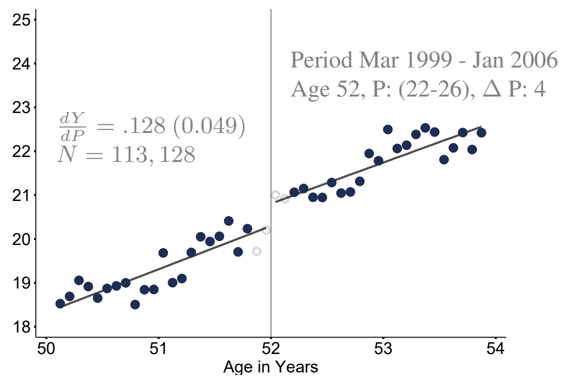
Figure 4: RD Estimates of the Effect of PBD Extensions on Non-Emp. Duration, Men



(a) Density Estimates



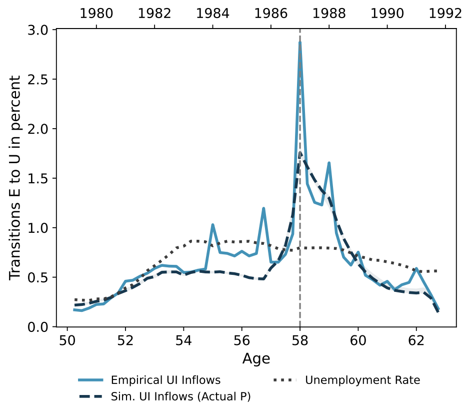
(b) RD Estimates for Non-Emp. Duration



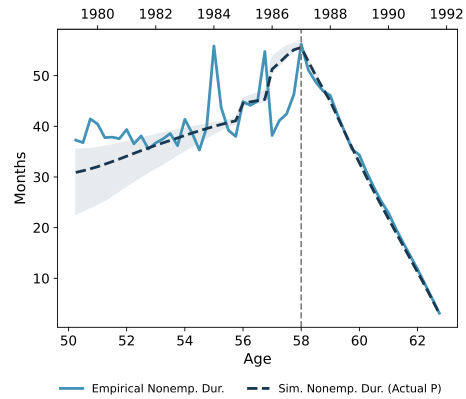
(c) Visualization of Target RD Estimate

Notes: This figure plots RD estimates and corresponding density tests of the effect of a one-month PBD extension at each possible age cutoff. 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. The age 52 cutoff is highlighted in bold. 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 (capped at 36 months) varies around the age 52 cutoff, between Mar 1999-Jan 2006, 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. The RD estimate (scaled ΔPBD) is .128 with a standard error (clustered on the age-day level) of 0.049 based on a sample size of 113,128 observations. This RD estimate constitutes our target parameter in the structural estimation. See Table I.3 for RD-estimates at all cutoffs.

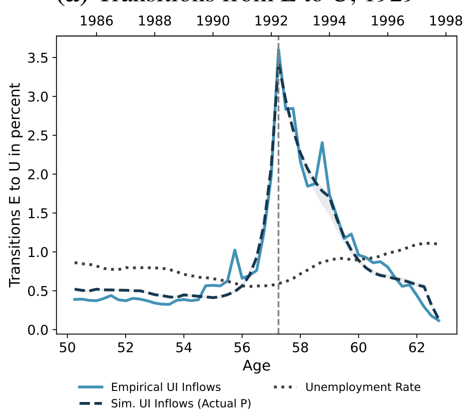
Figure 5: In-Sample Fit of Life-Cycle Model for Transitions from Employment to UI and Non-Employment Durations (capped at age 63)



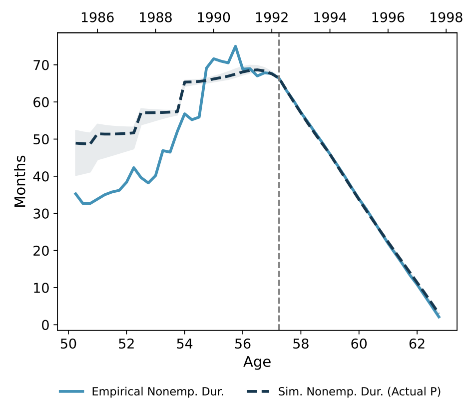
(a) Transitions from E to U, 1929



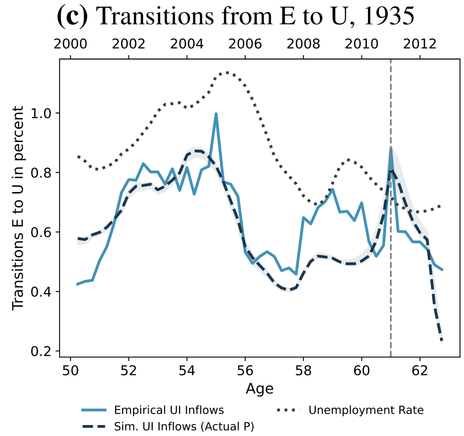
(b) Non Employment Duration, 1929



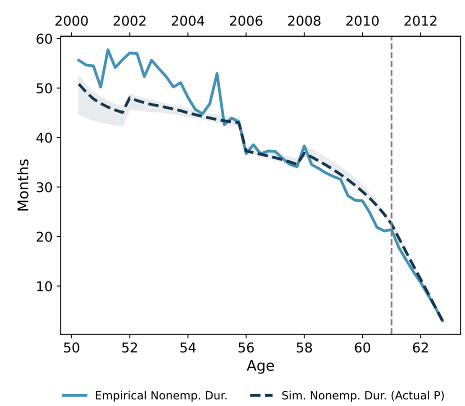
(c) Transitions from E to U, 1935



(d) Non Employment Duration, 1935



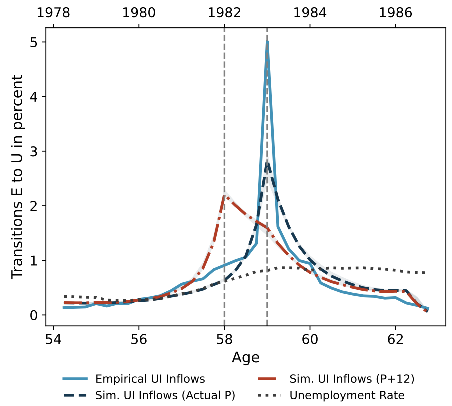
(e) Transitions from E to U, 1950



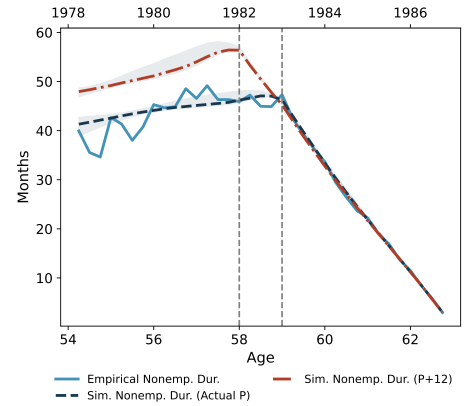
(f) Non Employment Duration, 1950

Notes: This figure compares our quarterly model-generated moments to their corresponding empirical moments for in-sample cohorts (1929, 1935, 1950). 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. Gray bands around simulated moments are 95% bootstrap confidence intervals.

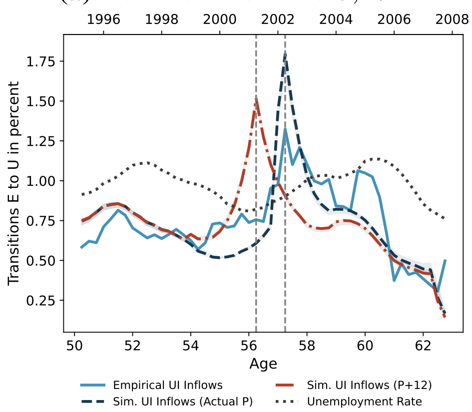
Figure 6: Out-of-Sample Fit of Life-Cycle Model for Transitions from Employment to UI and Non-Employment Durations, Baseline Model and Counterfactual 1: $P + 12$



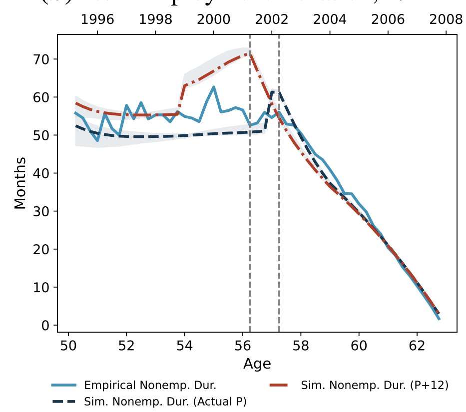
(a) Transitions from E to U, 1924



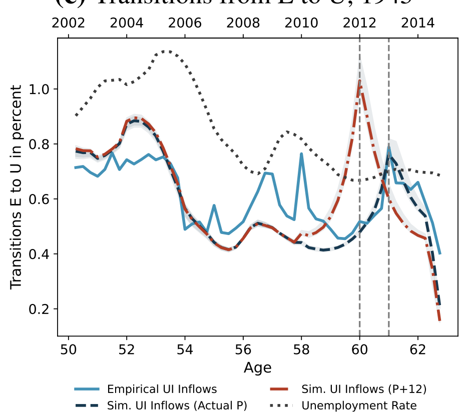
(b) Non Employment Duration, 1924



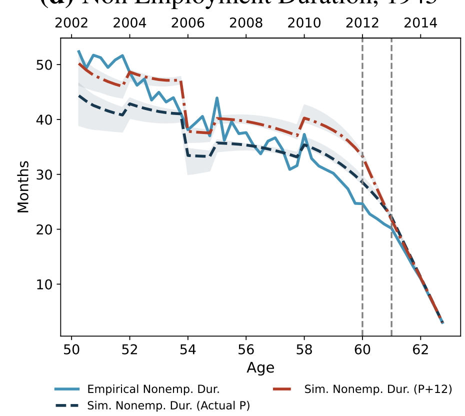
(c) Transitions from E to U, 1945



(d) Non Employment Duration, 1945



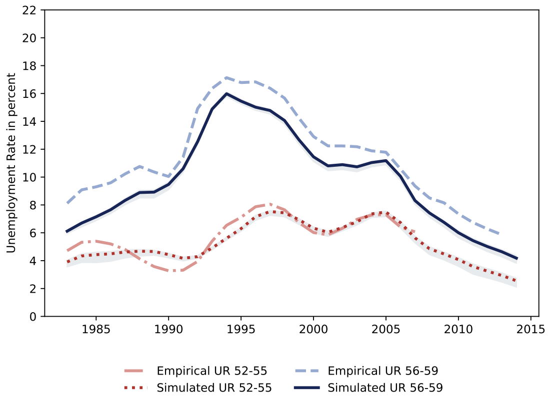
(e) Transitions from E to U, 1952



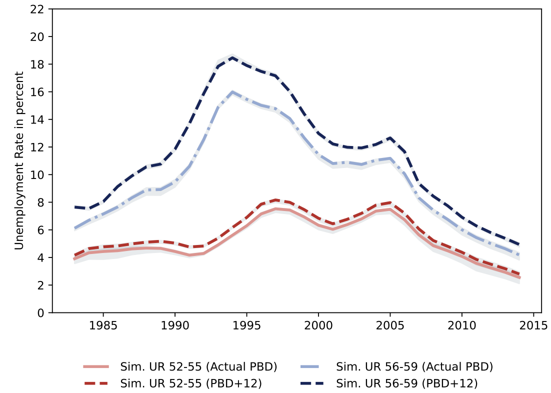
(f) Non Employment Duration, 1952

Notes: This figure compares our quarterly model-generated moments to their corresponding empirical moments for select out-of-sample cohorts (1924, 1945, 1952). 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. Gray bands around simulated moments are 95% bootstrap confidence intervals.

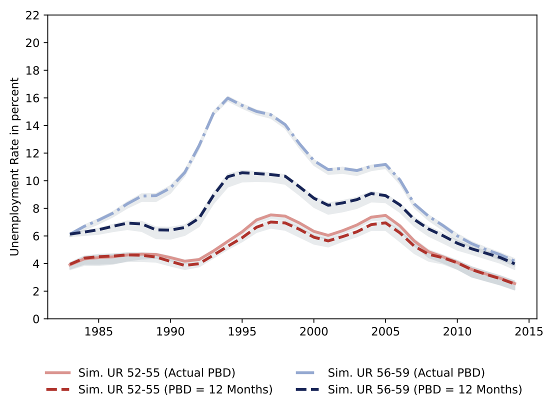
Figure 7: Empirical and Simulated Unemployment Rates by Age Group



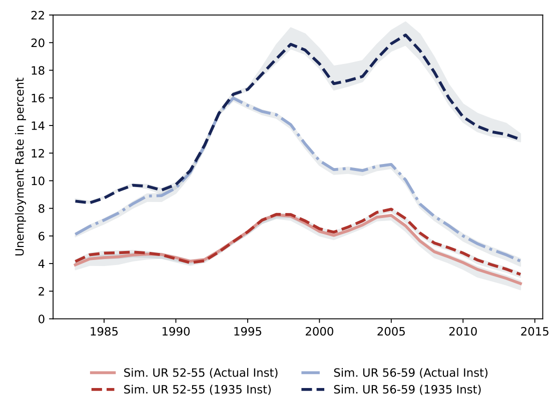
(a) Empirical and Model-Based Unemployment Rates



(b) Simulating a constant UI PBD increase of 12 months



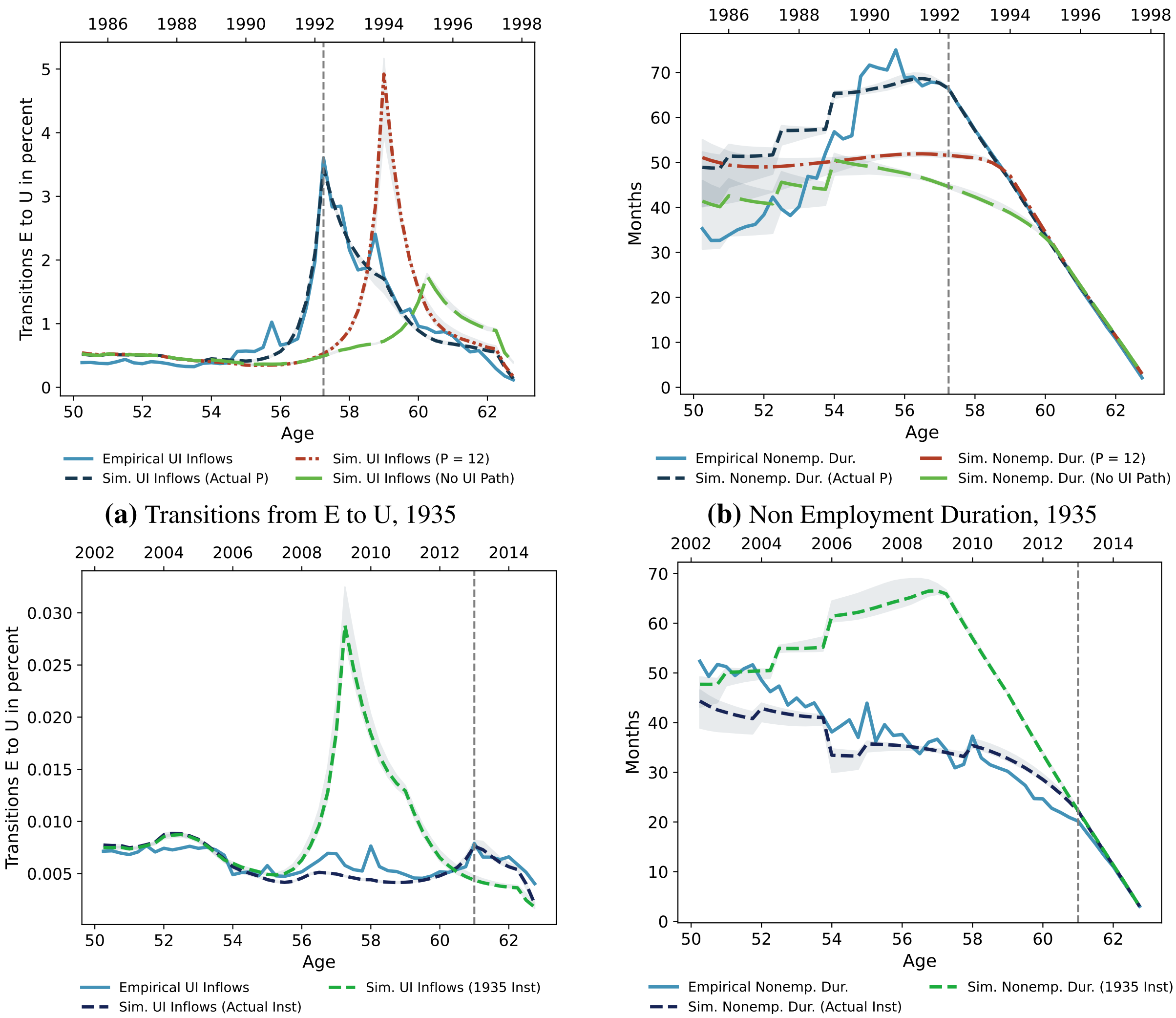
(c) The Influence of Germany's PBD extensions:
Had PBD remained fixed at 12 months



(d) The Influence of Policy Changes after 1994:
Had UI and retirement policies remained fixed in 1994

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. Panel (c) shows the model-simulated unemployment rate at baseline (solid lines) and for a counterfactual in which PBD's never increased and instead remained fixed at 12 months (dashed lines). Panel (d) plots simulated unemployment rates for the baseline specification (solid lines) and a counterfactual model where we keep retirement rules (penalty, ERA, and NRA) and PBD fixed at 1994 levels (dashed lines). Gray bands around simulated moments are 95% bootstrap confidence intervals.

Figure 8: Model Simulations for Counterfactual Policies



(a) Transitions from E to U, 1935

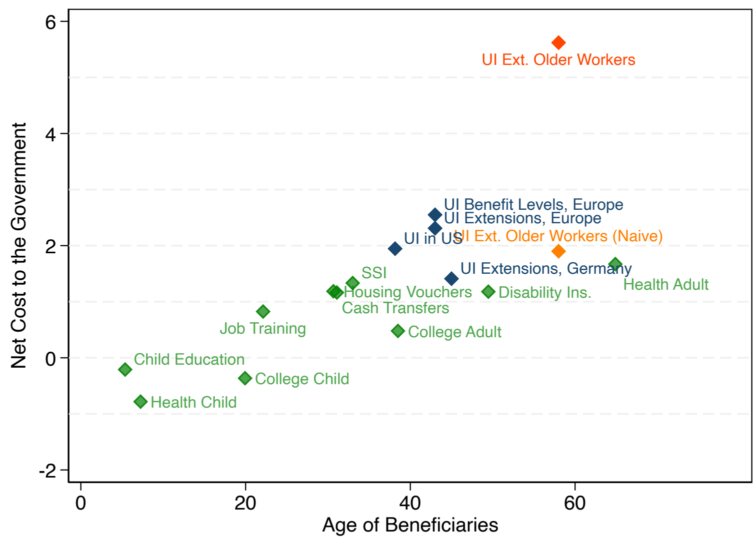
(b) Non Employment Duration, 1935

(c) Transitions from E to U, 1952

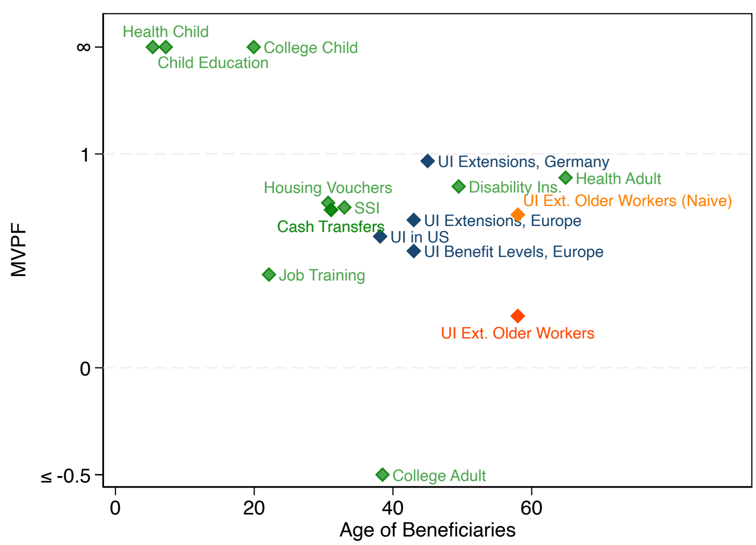
(d) Non Employment Duration, 1952

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 moments from the data are depicted in solid light blue. In panels (c) and (d), for the 1952 cohort, we compare the baseline model output (dashed dark blue line) to a counterfactual model (dashed green line) where we keep retirement rules (penalty, ERA, and NRA) and PBD fixed at their 1994 levels. Actual empirical moments from the data are depicted in solid light blue. Gray bands around simulated moments are 95% bootstrap confidence intervals.

Figure 9: MVPF and Net Cost to the Government of Different UI and Other Expenditures



(a) Net Cost



(b) MVPF

Notes: This figure plots the net cost to the government (= 1+Fiscal Externality) and the associated marginal value of public funds (MVPF) for various policies. The green diamonds are program groups taken directly from Hendren and Sprung-Keyser (2020). The four blue diamonds are UI policies; UI in U.S. is the group-level average of U.S. UI policies as reported in Hendren and Sprung-Keyser (2020). The points for "UI extensions, Europe", and "UI benefit levels, Europe", are averages across all PBD and all Benefit policies, respectively, taken from Le Barbanchon et al. (2024). We omit two papers (Lalive, 2007, 2008) from these averages, where the constant hazard approximation used to calculate the values performs poorly. "The UI Extensions, Germany" point reports the fiscal externality and MVPF associated with Germany's 3 prime age PBD extensions studied in Schmieder et al. (2012) for workers ages 42, 44, and 49. Finally, in orange and red we report the results from this paper for the effects of extending PBD among older workers (specifically for the 1935 birth cohort), based on our model. The dark red "UI Ext. Older Workers" contains the full model results. The lighter orange "UI Ext. Older Workers (Naive)" shows what we obtain from our model when we allow PBD to only affect UI durations and not inflows.

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 D and Appendix F 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 a pension for the long-term insured.

Table 2: Parameter Estimates

	(1) Baseline
Std. dev. of productivity shock σ	2.18
	(0.10)
Fixed cost of job search k_0	0.61
	(0.06)
Cost of UI entry k_1	5.66
	(0.12)
Exp. time trend in search cost k_2	1.12
	(0.26)
Slope parameter of search cost k_3	51.27
	(5.65)
Elasticity of search cost γ	0.82
	(0.02)
Parameters of job destruction rate	
λ_1	-6.61
	(0.02)
λ_2	0.17
	(0.00)
λ_3	0.15
	(0.01)
Disutility of work distribution (mean: $\bar{\eta}$ and SD η_{SD})	
$\bar{\eta}_{1929}$	0.42
	(0.04)
$\bar{\eta}_{1935}$	0.73
	(0.01)
$\bar{\eta}_{1950}$	0.75
	(0.04)
η_{SD}	0.51
	(0.05)
SSE	18,302

Notes: The table shows the parameter estimates for the baseline model. Standard errors are reported in parentheses and are calculated by bootstrapping by drawing sample moments from a multivariate normal distribution with a mean equal to the sample moments and a covariance matrix equal to the sample covariance matrix.

Table 3: Quantifying the Effects of Germany's UI and Retirement Policy Changes on Unemployment Rates

	(1)	(2)	(3)	(4)
	Age 52-55	Age 56-59	Age 60-62	Age 52-62
Unemployment Rate				
1983, Actual Inst.	3.9%	6.1%	10.3%	6.7%
1994, Actual Inst.	5.6%	16.0%	12.7%	11.3%
1994, PBD=PBD+12	6.2%	18.5%	12.9%	12.5%
1994, PBD=12	5.3%	10.3%	11.8%	8.9%
1994, No UI Path	5.3%	6.9%	6.9%	6.3%
2014, Actual Inst.	2.6%	4.2%	5.5%	4.0%
Change in UR from 1983 to 1994				
Overall change	1.7 pp	9.9 pp	2.4 pp	4.6 pp
Change due to PBD change	0.4 pp	5.7 pp	0.9 pp	2.4 pp
Change due to other reasons	1.3 pp	4.2 pp	1.5 pp	2.2 pp
Change in UR from 1994 to 2014				
Overall change	-3.1 pp	-11.8 pp	-7.2 pp	-7.4 pp
Change due to PBD and Retirement Policies	-0.7 pp	-8.8 pp	-9.3 pp	-6.0 pp
Change due to other reasons	-2.4 pp	-3.0 pp	2.1 pp	-1.4 pp
Change due to PBD change	-0.2 pp	-2.9 pp	0.0 pp	-1.1 pp
Change due to UI ERA change	-0.4 pp	-7.8 pp	-5.1 pp	-4.4 pp
Change due to penalty	-0.2 pp	-5.4 pp	-7.1 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 V. 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: Robustness to Alternative Model Specifications

	(1) Baseline Men	(2) Diagonal Weighting	(3) No Upweighting	(4) No Cyclical Shocks $\lambda_2, \lambda_3 = 0$	(5) Constant Disutility η	(6) Higher UA	(7) Higher Home Production	(8) Retirement Norms	(9) Severance Pay
Model Fit									
SSE	18,302	15,195	18,240	32,263	27,122	17,954	20,930	18,279	43,084
dD/dP age 52	0.127	0.129	0.111	0.127	0.128	0.127	0.125	0.125	0.180
Number of Parameters	13	13	13	11	11	13	13	14	14
Unemployment Rate (Age 56-59)									
1983, Actual Inst.	6.1%	6.2%	6.2%	6.4%	5.5%	6.2%	5.5%	6.1%	5.1%
1994, Actual Inst.	16.0%	16.2%	16.2%	15.8%	13.1%	16.3 %	14.8%	16.0%	12.9%
1994, PBD=PBD+12	18.5%	19.0%	18.7%	18.2%	20.1%	19.0%	17.2%	18.4%	18.3%
1994, PBD=12	10.3%	10.2%	10.3%	10.1%	6.8%	10.3%	8.8%	10.3%	6.2%
1994, No UI Path	6.9%	6.7%	7.0%	6.4%	6.5%	7.0%	5.3%	6.8%	7.6%
2014, Actual Inst.	4.2%	4.3%	4.2%	4.3%	4.4%	4.4%	3.2%	4.2%	3.7%
Change in UR (Age 56-59) from 1983 to 1994									
Overall change	9.9pp	10.0pp	10.0pp	9.3pp	7.6pp	10.1pp	9.3pp	9.9pp	7.8pp
Change due to PBD change	5.7pp	6.0pp	5.9pp	5.7pp	6.3pp	6.0pp	6.1pp	5.7pp	6.7pp
Change due to other reasons	4.2pp	4.0pp	4.2pp	3.6pp	1.3pp	4.1pp	3.2pp	4.2pp	1.1pp
Change in UR (Age 56-59) from 1994 to 2014									
Overall change	-11.8pp	-11.9pp	-11.9pp	-11.4pp	-8.7pp	-11.9pp	-11.7pp	-11.8pp	-9.2pp
Change due to PBD and Ret. Policies	-8.8pp	-11.1pp	-8.2pp	-8.8pp	-3.9pp	-10.5pp	-6.4pp	-8.6pp	-3.6pp
Change due to other reasons	-3.0pp	-0.8pp	-3.7pp	-2.6pp	-4.9pp	-1.5pp	-5.3pp	-3.1pp	-5.7pp
Change due to PBD change	-2.9pp	-3.9pp	-2.8pp	-2.8pp	-2.6pp	-3.6pp	-2.1pp	-2.9pp	-2.2pp
Change due to UI ERA change	-7.8pp	-9.9pp	-7.3pp	-7.8pp	-3.2pp	-9.0pp	-5.8pp	-7.7pp	-2.5pp
Change due to penalty	-5.4pp	-7.2pp	-5.0pp	-5.2pp	-3.3pp	-8.4pp	-5.0pp	-5.3pp	-2.6pp

Notes: The table shows key simulation results for alternative samples and models. Column (1) shows the results for the baseline specification for men for ease of comparison. Column (2) estimates the model using a diagonal weighting matrix. Column (3) presents results for a specification that does not up-weight the intensive-margin RD-moments at age 52 compared to other moments. Column (4) sets the parameters λ_2 and λ_3 that are meant to capture cyclical shocks to zero. Column (5) provides results where the disutility of work parameter is set constant across all cohorts. Column (6) increases the value of second-tier unemployment benefits (UA) to a higher value from 500 to 750 Euro per month. Column (7) increases the value of home production from 50 to 500 per month. Column (8) includes a retirement norm parameter that adds additional utility for exiting the labor force at an exact retirement age (ERA or NRA). Column (9) shows results from a model where workers are offered a severance pay at the time of leaving a job in the form of an annuity that pays while either being unemployed or OLF. This model replaces heterogeneity in the disutility η with heterogeneity in severance pay and estimates a standard deviation of severance pay across individuals and cohort specific mean severance pay. This model also targets wage heterogeneity in the form of wage-at-age-50 moments.

Table 5: Illustrating Interactions between UI and Retirement Policies

	(1) Baseline Institutions in 2014	(2) UI Pathway ERA at age 60 w/ Penalty	(3) UI Pathway ERA at age 60 No Penalty
Age 52-55			
UR, Actual PBD.	2.79%	3.01%	3.30%
UR, PBD + 12	3.13%	3.42%	3.70%
Change in UR	0.34 pp	0.41 pp	0.40 pp
	[0.29, 0.38]	[0.36, 0.46]	[0.35, 0.45]
dD/dP at age 52	0.130	0.150	0.162
	[0.127, 0.133]	[0.148, 0.152]	[0.160, 0.163]
Elasticity of UR w.r.t PBD	0.28	0.32	0.29
Age 56-59			
UR, Actual PBD.	4.61%	5.82%	11.04%
UR, PBD + 12	5.51%	7.44%	14.06%
Change in UR	0.90 pp	1.62 pp	3.01 pp
	[0.80, 1.01]	[1.45, 1.79]	[2.74, 3.28]
dD/dP at age 57	0.177	0.180	0.147
	[0.174, 0.179]	[0.177, 0.183]	[0.138, 0.153]
Elasticity of UR w.r.t PBD	0.45	0.61	0.60

Notes: The table reports model-simulated effects of PBD extensions in the year 2014, first leaving institutions as they were in 2014 and then for counterfactual scenarios in which retirement rules are more generous (but all else is held constant). Numbers in parentheses are 95% confidence intervals. 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 2014. 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.

Appendix For Online Publication

Contents

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 (who make up about 60% of individuals meeting all other sample restrictions) and women (who make up around 40%). 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 Table 1 with full details on UI and retirement policies and reforms shown in Tables I.1 and I.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 regular social security reliable employment continuously over the previous three years without any UI receipt during this period which amounts to 60% of all individuals observed in any type of employment. [57] In addition, we exclude some industries that are known for having special early retirement practices. Namely we exclude mining and steel construction (about 5% of workers after applying the stable employment restriction). 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 (about 15% of workers). 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.[58] We center the data 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),

[57] For 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.

[58] We also generate a complementary quarterly panel that we use in the structural estimation.

which consists of all periods of UI receipt. In addition, individuals can be outside of the observed E and UI states.[59] 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 Bunching Estimation Details

We estimate the excess bunching mass using standard bunching techniques (Kleven, 2016). We fit a polynomial to estimate a counterfactual distribution of monthly UI entries around each cohort's UI-bridge age, leaving out the bridge period—the interval between the UI-bridge age (early retirement age minus potential benefit duration) and the earliest possible retirement age. When estimating the polynomial, we extend the leave-out region beyond the bridge period, i.e. below the UI-bridge age or above the earliest retirement age, using cohort-specific parameters. These extensions account for example for non-sharp bunching patterns in specific cohorts. We also exclude round ages with visible sharp bunching outside the regular bridge period. Table B.1 summarizes the period-specific parameters.

We calculate the excess mass as the cumulative difference between actual and counterfactual UI entries over the bridge period (shaded region in figures 2 and H.9). We report two normalized excess mass measures: First, the cohort-size adjusted excess bunching mass (CBM), calculated as excess mass divided by cohort size, estimates the share of each cohort entering UI in response to the UI-bridge. Second, the normalized bunching mass (NBM) divides the excess mass by the counterfactual distribution's UI entries at the UI-bridge age. Standard errors are calculated via bootstrap resampling with replacement (number of draws are indicated in figure notes).

Our setting differs conceptually from other bunching applications because bunching may arise from two sources: individuals relocating their exit timing to the bunching region (creating missing mass elsewhere) or additional exits by individuals who would not have entered UI absent the UI-bridge but transition di-

[59] This 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.

rectly from employment to retirement. Given this possibility of additional UI-exits, we do not impose the restriction that the excess bunching mass equals a missing mass outside of the bunching region.

Table B.1: Bunching Parameters

Institutional Parameters																	
Cohort	'24	'29	'33	'34	'35	'36	'37	'38	'39	'40	'41	'42	'43	'44	'45	'50	'52
Ret. Age (yrs)	60	60	60	60	60	60	60	60	60	60	60	60	60	60	60	63	63
PBD (mo.)	12	24	32	32	32	32	32	32	32	32	32	32	32	32	32	24	24
UI-Br. Age (yrs)	59	58	$57\frac{1}{3}$	$57\frac{1}{3}$	$57\frac{1}{3}$	$57\frac{1}{3}$	$57\frac{1}{3}$	$57\frac{1}{3}$	$57\frac{1}{3}$	$57\frac{1}{3}$	$57\frac{1}{3}$	$57\frac{1}{3}$	$57\frac{1}{3}$	$57\frac{1}{3}$	$57\frac{1}{3}$	61	61
Cohort-Specific Bunching Parameters																	
Poly. deg. (p)	5	5	5	5	5	3	5	5	5	3	5	5	5	5	5	3	5
BW below (mo.)	60	60	60	60	60	60	60	60	60	36	60	60	60	60	60	24	60
BW above (mo.)	60	60	60	60	60	36	60	60	60	60	60	60	60	60	60	48	48
L-O below (mo.)	3	3	0	0	3	18	30	0	3	30	3	3	3	3	3	0	3
L-O above (mo.)	3	3	0	3	3	9	3	3	3	12	3	12	3	3	12	9	3
Ages excl.	55,56,57	55,56,57	55,56,57	55,56,57	55,56,57	55,56	55,56	55,56	54,55,60	54,55,60	54,55,60	54,55,60	54,55,60	55	57	60,63	58,60

Notes: Cohort-specific bunching parameters for estimating counterfactual UI-entries and excess mass. Abbreviations: Ret.=Retirement, PBD=potential benefit durations, UI-Br.=UI-Bridge, Poly. deg.=degree of polynomial, BW=bandwidth, L-O=leave-out, Bunch.=bunching, Ages excl.=round ages that are excluded due to bunching outside of UI-bridge period.

C 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.

C.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 who were employed in mining or steel construction prior to job loss.

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 I.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 I.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.[60] This leaves us with 8 age cutoffs from 3 periods. For the remaining cutoffs that seem to exhibit density violations — namely

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

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.

Difference to the Prime Analysis Sample The main differences between the RD sample and the prime analysis sample are two-fold: First, in the RD-sample we pool all cohorts that belong to one constant PBD regime in order to increase power instead of showing results for each cohort separately. Second, we apply somewhat different employment restrictions. In the RD-sample we set employment restrictions *at the time of separation* such that individuals would be eligible to full PBD at all of the age cutoffs.

Restricting to 12 months of social security contributions in the previous three years allows for more gaps in the recent history than the prime analysis sample, that restricts to three years of continuous working history. At the same time, the RD-sample has a larger requirement for total employment duration by requiring more than 4 years of working history in the previous seven years. An additional difference regarding the employment restriction is *when* it applies. In the RD-sample, the restriction applies at the time of job-separation, the time for determining UI eligibility. In the primary analysis sample in contrast the restriction applies at age 50 without reinforcing the restrictions later, which allows for a constant sample within cohort.

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 cutoffs, 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.

C.2 Description of Findings

Validity Checks Before turning to the main findings, we conduct balance and density checks. Figure H.11 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.[61] 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 Table I.4 reports 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. We also examine whether pre-determined variables are balanced across the cutoffs in columns (2) - (7) of Table I.4. 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 H.13 plots mean non-employment duration as a function of age so that our RD estimates can be inspected visually.[62] 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 reported in Table I.3. Column (1) shows the main results 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.

Additional Robustness We complement our findings with a number of robustness checks, reported in Table I.5. 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.

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

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

D Additional Institutional Details

D.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 I.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 retirement 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 one year after the age of 58 and a half, or in old-age part-time work.[63] 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 abolihed for cohorts born in or after 1952. The NRA was 60 until

[63]The 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.

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 abolihed. Notice that these changes occurred later than those for the UI pathway, so that the 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.

D.2 Budget Set Calculations for Figure H.3

Here we detail how we calculate the lifetime budget constraints depicted in Figure H.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 H.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 lifetime 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 F.4.

In Figure H.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%.

D.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 I.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 D.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 I.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 ($\geq$ 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).

E Model Details

This appendix sets up and solves our labor supply model.

E.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 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 ofp_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:

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

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 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, he can decide to retire at the end of the period. If he remains unemployed d^U increases by one period. The Value Function for Unemployment is thus:

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

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:

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

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

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

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 the 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:

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

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 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 one year of unemployment history (d^U). We allow individuals to choose the best retirement option available. In Section F.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 $V_t^N(d^U) = \max\left(V_t^U(d^U), V_t^O(d^U)\right)$.

E.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 a 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 Gaussian integration to approximate the full integral over the η distribution whenever we calculate cohort-level transitions and non-employment durations.

E.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 $f(ln(p_t)) = \Lambda_t f^L(ln(p_t)) + (1 - \Lambda_t) f^N_{p,\sigma_p}(ln(p_t))$ where f^N_{p,σ_p} 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 $F(ln(p_t)) = \Lambda_t(1) + (1-\Lambda_t)F^N_{p,\sigma}(ln(p_t))$ where F^N_{p,σ_p} 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 $u(.) = \ln(.)$. 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:

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

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.

E.4 Closed Form Solutions For Each Value Function

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

Since $V^E_t(p_t, d^U) = ln(p_t) - \eta + \beta\, E_{p_{t+1}}\left[\max\left\{V^E_{t+1}(p_{t+1}, d^U), V^N_{t+1}(d^U)\right\}\right]$, plugging in ω_{t,d^U} for p_t and rearranging $V^E_t(\omega_{t,d^U}, d^U) - V^N_t(d^U) = 0$ gives:

$$ln(\omega_{t,d^U}) = \eta - \beta\, E_{p_{t+1}}\left[\max\left\{V^E_{t+1}(p_{t+1}, d^U), V^N_{t+1}(d^U)\right\}\right] + V^N_t(d^U) \tag{C.6}$$

Given the distribution of p_t:

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

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:

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

And hence

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

Similarly,

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

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

$$
E_{p_{T^{Last}}}\left[\max\left\{V^E_{T^{Last}}(p_{T^{Last}}, d^U), V^N_{T^{Last}}(d^U)\right\}\right] \quad = \quad V^N_{T^{Last}}(d^U) = V^O_{T^{Last}}(d^U)
$$

Hence, the value of employment in any given period can be determined using backward induction. For convenience, we define $\Omega_{t,d^U} \equiv E\max\left[V^E_t(p_t, d^U), V^N_t(d^U)\right]$. This allows us to express $V^E_t(p_t, d^U) = u(w_t(p_t, d^U)) - \eta + \beta\,\Omega_{t+1,d^U}$.
Altogether, these results and Equation C.6 imply: $\bar{\omega}_{t,d^U} \equiv \frac{ln(\omega_{t,d^U})-p}{\sigma_p} = \frac{\eta - \beta\,\Omega_{t+1,d^U} + V^N_t(d^U) - p}{\sigma_p}$.

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

$$
V^U_t(d^U) = u(B(d^U)) + \max_s \left\{\beta V^N_{t+1}(d^U+1) + \beta s\left(\Omega_{t+1,d^U+1} - V^N_{t+1}(d^U+1)\right) - \psi_t(s)\right\}
$$

and

$$
s^* = \psi'^{-1}\left(\beta\Omega_{t+1,d^U+1} - \beta V^N_{t+1}(d^U+1)\right)
$$

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 $\mathbf{h}_t \equiv (h_{t,E,d^U=0}, ...h_{t,E,d^U=T}, h_{t,U,d^U=0}\cdots, h_{t,U,d^U=T}, h_{t,O})$ 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 andj^{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 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	$\zeta_{d^U} \mathbf{1}\left(V^U_{t+1}(d^U) \geq V^O_{t+1}(d^U)\right)$	0	$\zeta_{d^U} \mathbf{1}\left(V^O_{t+1}(d^U) > V^U_{t+1}(d^U)\right)$
...					
Unemployed d^U	0	$s[1-\zeta_{d^U+1}]$	0	$\left\{(1-s)+s(\zeta_{d^U+1})\right\} \times \mathbf{1}\left(V^U_{t+1}(d^U+1) \geq V^O_{t+1}(d^U+1)\right)$	$\left\{s\zeta_{d^U+1}+(1-s)\right\} \times \mathbf{1}\left(V^O_{t+1}(d^U+1) > V^U_{t+1}(d^U+1)\right)$
...					
OLF	0	0	0	0	1

As an example, a transition from employed with $d^U \rightarrow$ unemployed with d^U occurs with $prob[V^E_{t+1}(p_{t+1}, d^U) < V^N_{t+1}(d^U)]\mathbf{1}\left(V^U_{t+1}(d^U) \geq V^O_{t+1}(d^U)\right)$.
This can be simplified to:

=$prob[ln(p_{t+1}) < V^N_{t+1}(d^U) + \eta - \beta\,\Omega_{t+2,d^U}]\mathbf{1}\left(V^U_{t+1}(d^U) \geq V^O_{t+1}(d^U)\right)$

=$F(V^N_{t+1}(d^U) + \eta - \beta\,\Omega_{t+2,d^U})\mathbf{1}\left(V^U_{t+1}(d^U) \geq V^O_{t+1}(d^U)\right)$

Recall $\bar{\omega}_{t+1,d^U} = \frac{V^N_{t+1}(d^U)+\eta-\beta\,\Omega_{t+2,d^U}-p}{\sigma_p}$, hence:

=$[\lambda_{t+1} + (1-\lambda_{t+1})\Phi(\bar{\omega}_{t+1,d^U})]\mathbf{1}\left(V^U_{t+1}(d^U) \geq V^O_{t+1}(d^U)\right)$

=$\zeta_{d^U}\mathbf{1}\left(V^U_{t+1}(d^U) \geq V^O_{t+1}(d^U)\right)$

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 Gaussian integration.

F Estimation Details

F.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 II. 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 quarterly 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 I.3).[64]

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

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

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 $\frac{\partial Nonemp}{\partial P}$.

For the intensive margin RD moments, we use a larger weight ($\times 35$) 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.

F.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}.

[64]While 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 model predictions by pooling the unemployed and OLF states.

F.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 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*28*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.

F.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.[65]

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 68 % for an individual with children until the end of 1993. Starting January 1994, the replacement rates were 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

[65] This 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 applies to prior cohorts.

deductions. We halve the amount as evidence in Schmieder et al. (2012) suggests that, due to deductions, average UA benefits actually 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 a 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 (annual pension value$\times 45 \times 1.5$)/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) : (annual pension value$\times 1.5$)(1-ssc)/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$\times 12$)/average annual income. The pension replacement rate on gross wages of an additional year of contribution net of ssc is (PV$\times 12$)(1-ssc)/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.[66] 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

[66]The 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.

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 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.

F.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.[67] 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.

G The Relationship between Moments and Model Parameters

This section documents the relationship between the 13 model parameters and the empirical moments used for their estimation. We proceed in two parts. First, we analyze the influence of marginal changes in model parameters on the moments (i.e., the partial derivatives $\frac{\partial m_i}{\partial \xi_j}$). Second, we conduct a sensitivity analysis, following Andrews et al. (2017), to quantify how the parameter estimates respond to changes in the empirical moments (i.e., $\frac{\partial \xi_j}{\partial \hat{m}_i}$).

Influence of Model Parameters on Moments

We begin by examining how model parameters influence the simulated moments, a relationship captured by the Jacobian of the model function that generates simulated moments from the vector of model parameters $m(\xi)$. Each element of this Jacobian, $\frac{\partial m_i}{\partial \xi_j}$, represents the marginal effect of a parameter ξ_j on a simulated moment m_i. To facilitate comparison across parameters and moments of different magnitudes, our analysis focuses on the elasticities, defined as $\frac{\partial m_i}{\partial \xi_j} \times \frac{|\xi_j|}{m_i}$. For a tractable exposition, we focus on the 1935 cohort, as the insights are broadly applicable to other cohorts. The influence of the parameters on the 1935 inflow and duration moments are presented in Figure H.25 and Table I.10 for all cohorts and the dD/dP moment.

σ (Standard Deviation of Productivity Shocks) A larger σ increases job destruction for younger workers, as they are more likely to experience large negative shocks that result in job loss (Figure H.25(a)). As

[67] We 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.

workers near retirement, the effect of σ on inflows to non-employment becomes more complex. Initially, a higher σ increases inflows before the bridge age, as some workers who would have otherwise waited until the bridge age leave their jobs earlier due to shocks. At the bridge age itself, however, the influence of σ becomes negative. The productivity shocks spread out exits around the bridge age: negative shocks precipitate earlier exits, while positive shocks delay them. This dilutes the sharp bunching pattern. At older ages, the influence of σ on inflows becomes positive again.

As shown in Figure H.25(b), σ has a relatively small effect on non-employment durations. For younger workers, higher σ slightly increases durations as they wait for more favorable productivity shocks before accepting a job. For older workers approaching retirement, higher σ alters the composition of the unemployed, leading to a higher share of workers who are effectively retiring, which in turn increases average durations.

k_0 **(Fixed Cost of Job Search)** A higher k_0 increases the cost of job search, making unemployment less attractive. Consequently, it reduces inflows to non-employment, particularly for younger workers and those approaching the bridge age. For workers just past the bridge age, a higher k_0 can lead to a small increase in inflows due to a substitution effect, as some workers delay their entry into unemployment.

k_1 **(Fixed Cost of Entering UI)** k_1 represents a one-time cost of entering UI. A higher k_1 discourages entry into non-employment, an effect that is most pronounced for workers near the bridge age who are on the margin between working and not working. As shown in Figure H.25(c), this parameter is crucial for preventing a large, counterfactual spike in UI entries just before retirement, when the returns to continuing work diminish. Since k_1 is a one-time cost at the beginning of a non-employment spell, it has a negligible effect on subsequent job search effort and thus on non-employment durations.

k_2**,** k_3 **and** γ **Parameters (Marginal Cost of Job Search)** k_2, k_3 and γ are the parameters governing the marginal cost of job search, since $\psi_t'(s) = e^{k_2 * d^U} \times k_3 s^{\gamma}$. k_2 is the duration dependence of the cost of job search, where positive values of k_2 imply that the cost of job search increases the longer the job search lasts. k_3 is a scalar multiplying the marginal cost of job search. For younger workers, increases in k_2 and k_3 increase the marginal cost of job search, and therefore increase unemployment durations. γ is the elasticity of the cost of job search. Since larger values of γ yield smaller marginal costs of job search (recall s is between 0 and 1), increasing γ reduces unemployment durations. Workers past the bridge age are mostly not searching anyways and thus there is not much of an effect on durations of any of the three parameters. The first order conditions of the model imply that $\frac{1}{\gamma}$ is the elasticity of search effort with respect to the returns to search. For this reason, γ is the key parameter determining the effect of UI extensions on unemployment durations, which can be clearly seen in Table I.10, where gamma has the largest impact on the dD/dP moment. Inflows are not much affected by any of the three parameters.

λ **Parameters (Exogenous Job Destruction)** The λ parameters govern the exogenous job destruction rate. λ_1 acts as a level shifter, increasing job destruction across all ages. In elasticity terms, its impact is largest for younger workers who have a lower baseline separation rate. λ_2 links job destruction to the unemployment rate, with a higher unemployment rate leading to more separations, an effect also concentrated among younger workers. Both λ_1 and λ_2 have a positive influence on non-employment inflows at all ages. The effect of λ_3, which captures the role of the change in the unemployment rate, can be positive or negative depending on the direction of the change. The λ parameters primarily affect inflows and have only small, indirect effects on non-employment durations through compositional changes.

η Parameters (Preferences for Non-employment) The η parameters characterize the distribution of worker preferences for non-employment. A higher mean of this distribution, η_{mean}, implies that more workers are close to the margin of indifference between working and not working. Consequently, an increase in η_{mean} raises non-employment inflows at most ages. For the oldest workers (ages 61 and above), this effect is reversed due to a substitution effect: higher inflows at younger ages mean fewer workers are left to enter non-employment later. The standard deviation of the η distribution, η_{SD}, has a similar effect, as a wider distribution also increases the mass of workers near the indifference point. As the influence plots are shown for the 1935 cohort, only $\eta_{\text{mean},1935}$ and η_{SD} are influential, whereas the mean parameters for other cohorts have no effect. Regarding durations, a higher η_{mean} makes work less attractive, reducing search effort and thus leading to longer non-employment spells, particularly for younger workers.

Sensitivity of Model Parameters to Moments

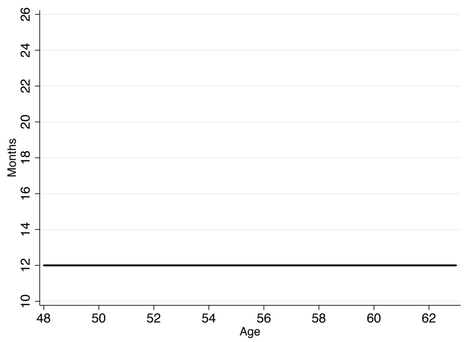
We now turn to the sensitivity of parameter estimates to changes in the empirical moments. Following Andrews et al. (2017), sensitivity is calculated as $\Lambda = -(S'WS)^{-1}S'W$, where S is the Jacobian matrix of $m(\xi)$ and W the weighting matrix. We refer to individual elements of this sensitivity matrix as: $\frac{\partial \xi_j}{\partial \hat{m}_i}$. To facilitate comparisons of magnitudes, we follow Andrews et al. (2017)'s suggestion and scale each element by multiplying with the standard error of the respective moment and dividing by the parameter value: $\frac{\partial \xi_j}{\partial \hat{m}_i} \times SD(\hat{m_i}) \times \frac{1}{|\xi_j|}$, where $\hat{m_i}$ is an empirical moment. The interpretation of this scaled sensitivity is that it is the percentage change in the parameter estimate for a 1 standard error change in the moment. The results are presented in Table I.11 and Figure H.27.

The interpretation of these sensitivity measures is complicated by the inter-dependencies among the parameters. Consider, for instance, the η parameters. Within the 1935 cohort, only $\eta_{\text{mean},1935}$ and η_{SD} directly affect inflows. However, a change in an inflow moment for this cohort will affect the estimated values of all η parameters. For example, if we were to increase the inflow moment at the bridge age for the 1935 cohort, the model could match this by increasing either $\eta_{\text{mean},1935}$ or η_{SD}. The positive sensitivity of $\eta_{\text{mean},1935}$ to the inflow moment at the bridge age (as shown by the positive sensitivity in Table I.11) suggests that an increase in inflows at the bridge age will lead to an increase in $\eta_{\text{mean},1935}$. However, increasing this parameter alone would also raise inflows at other ages in 1935. To counteract this, the model reduces η_{SD}. This reduction, in turn, lowers inflows in the other cohorts, which is then compensated by increases in $\eta_{\text{mean},1929}$ and $\eta_{\text{mean},1950}$.

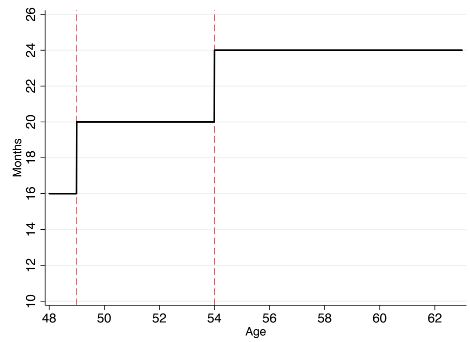
Since these interactions are complex and we have many moments and parameters, we will refrain from going over all parameters in detail. However, overall, the sensitivity analysis broadly confirms the intuition from the influence analysis. For example, σ is identified primarily by inflow moments around the bridge age. Similarly, the search-related cost parameters k_0 and k_1 are more sensitive to inflow moments than to duration moments, while the parameters governing the marginal cost of search (k_2, k_3, γ) are sensitive to both. Finally, the η and λ parameters are, as expected, more sensitive to inflow moments than to duration moments.

H Appendix Figures

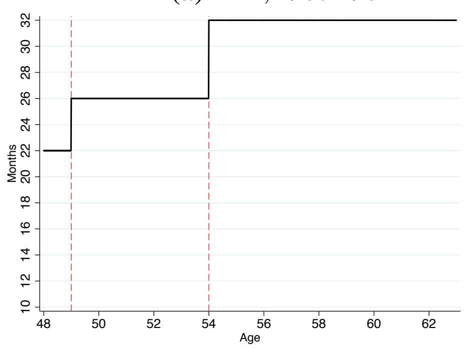
Figure H.1: Maximum Potential UI Benefit Durations (PBDs) by Age for Different Time Periods in Germany



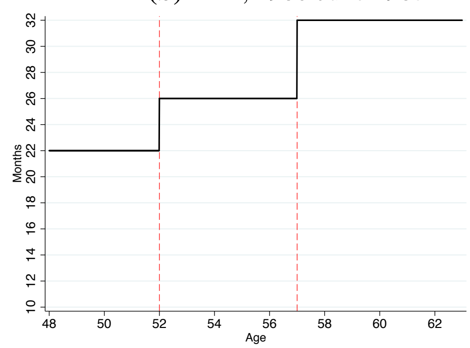
(a) PBD, 1980-1984



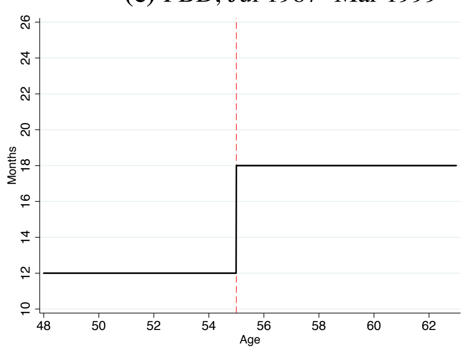
(b) PBD, 1986-June 1987



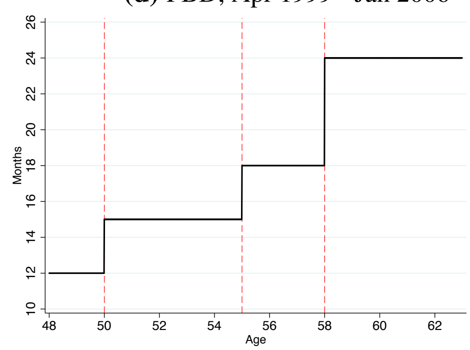
(c) PBD, Jul 1987- Mar 1999



(d) PBD, Apr 1999 - Jan 2006



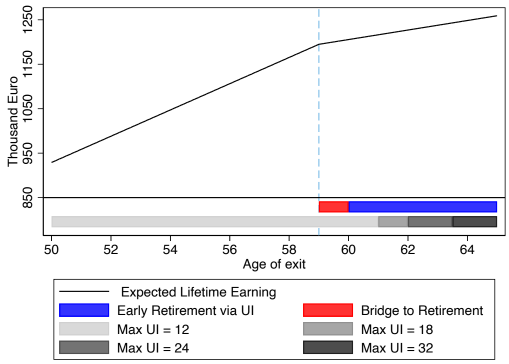
(e) PBD, Feb 2006 - Dec 2007



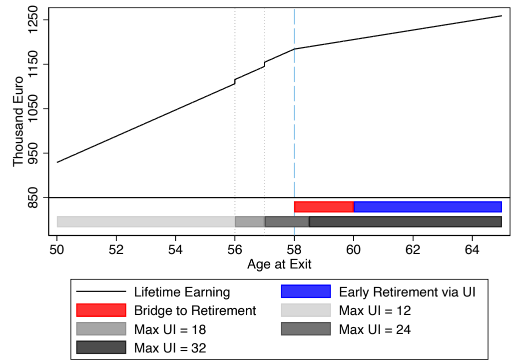
(f) PBD, Jan 2008 - 2010

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 I.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.

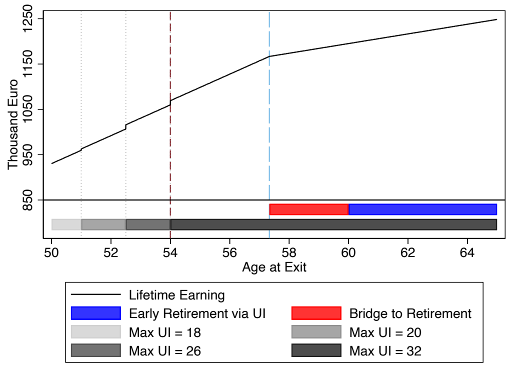
Figure H.3: Stylized Budget Sets for Different Cohorts in Germany, Men



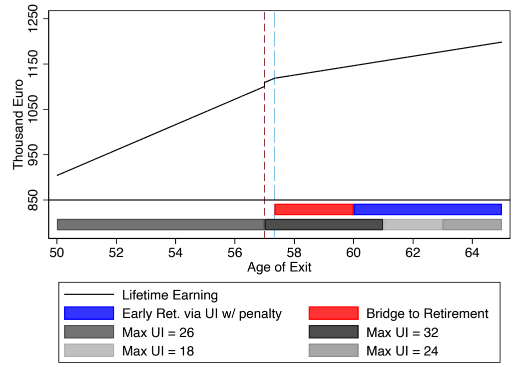
(a) Lifetime Income, 1924 Cohort



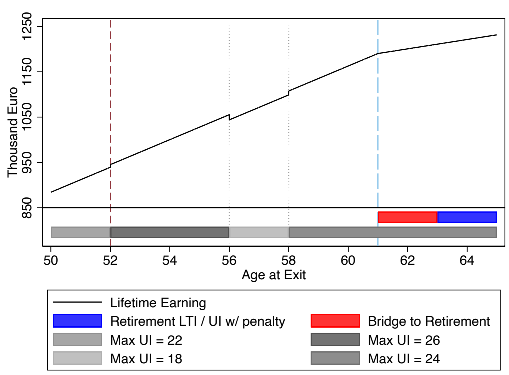
(b) Lifetime Income, 1929 Cohort



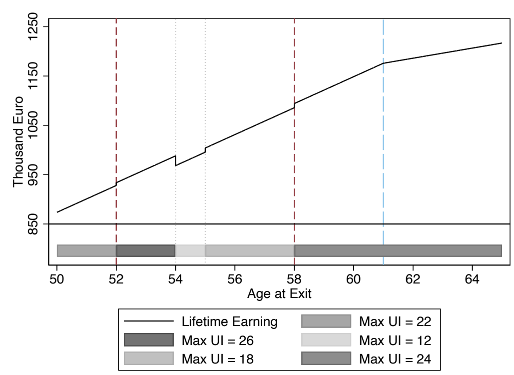
(c) Lifetime Income, 1935 Cohort



(d) Lifetime Income, 1945 Cohort



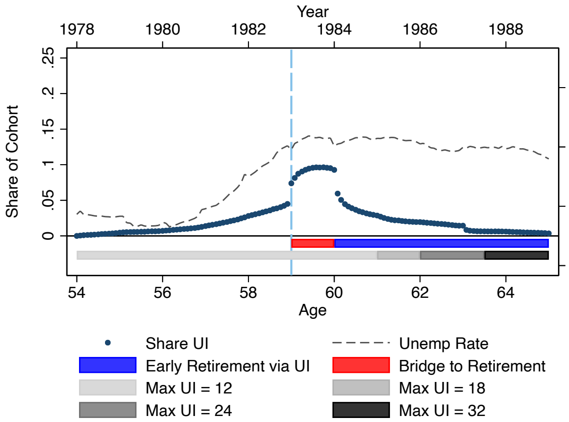
(e) Lifetime Income, 1950 Cohort



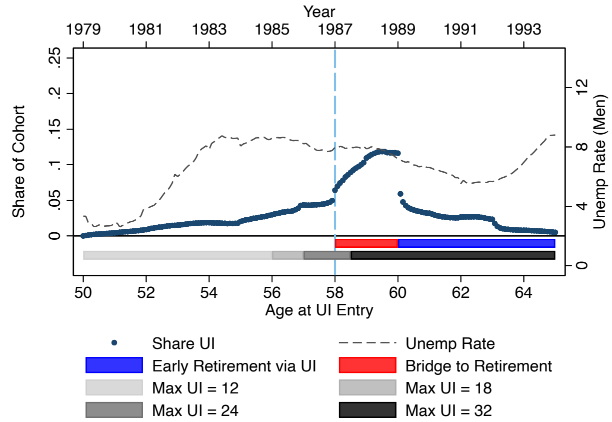
(f) Lifetime Income, 1952 Cohort

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 a 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).

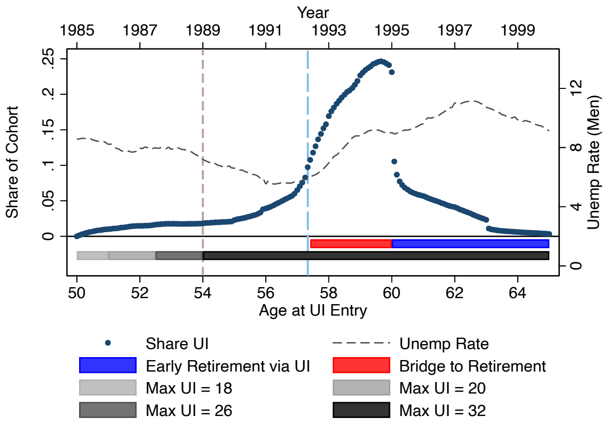
Figure H.5: Share UI by Age for Different Cohorts in Germany, Men



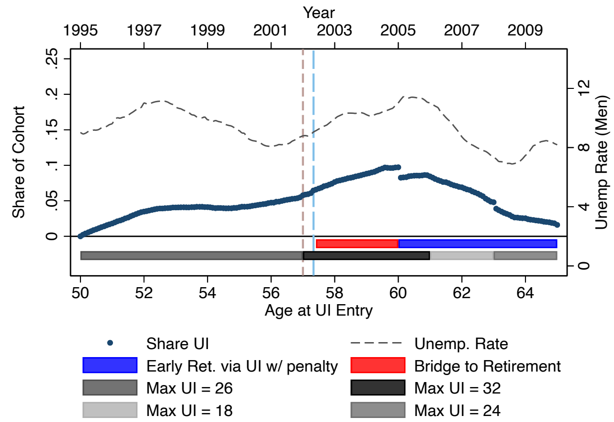
(a) Share UI, 1924 Cohort



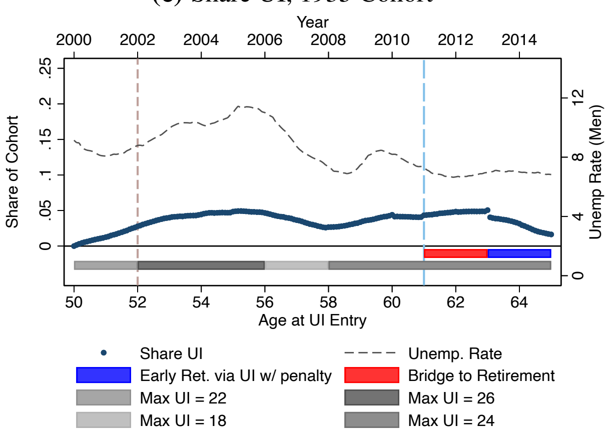
(b) Share UI, 1929 Cohort



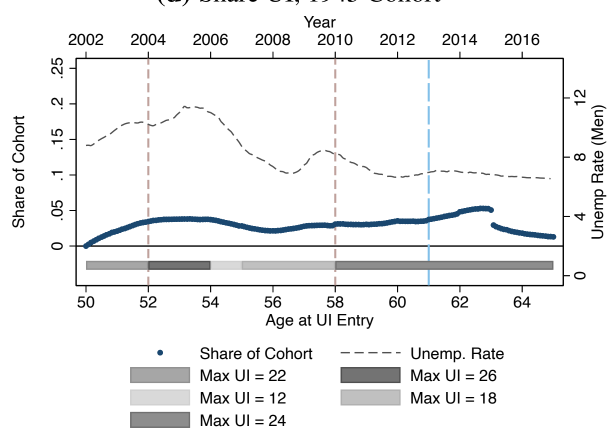
(c) Share UI, 1935 Cohort



(d) Share UI, 1945 Cohort



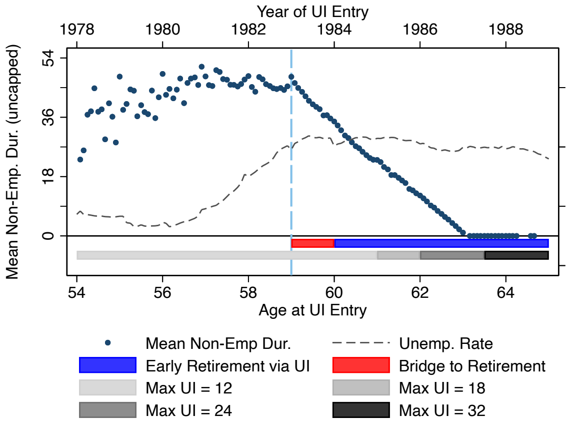
(e) Share UI, 1950 Cohort



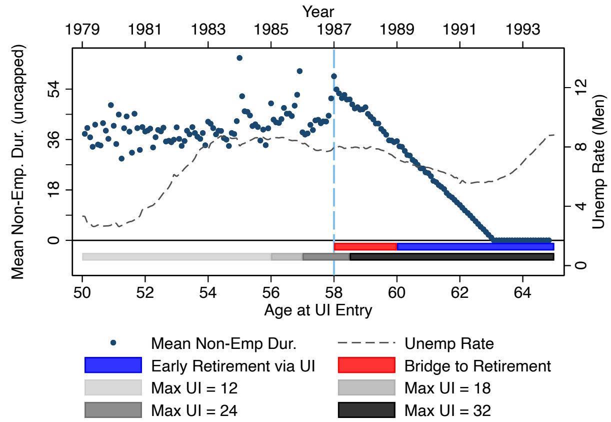
(f) Share UI, 1952 Cohort

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).

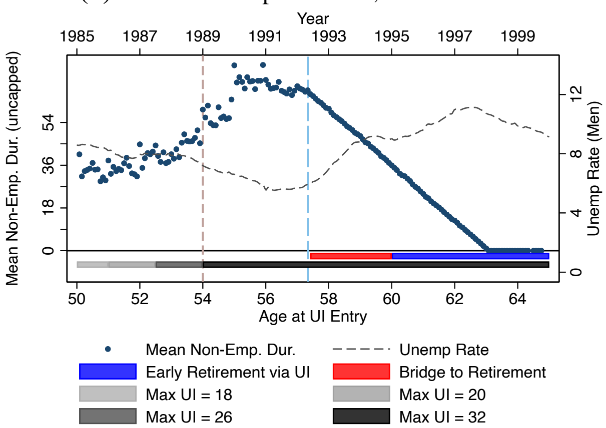
Figure H.7: Mean Non-Emp. Duration by Age for Different Cohorts in Germany, Men



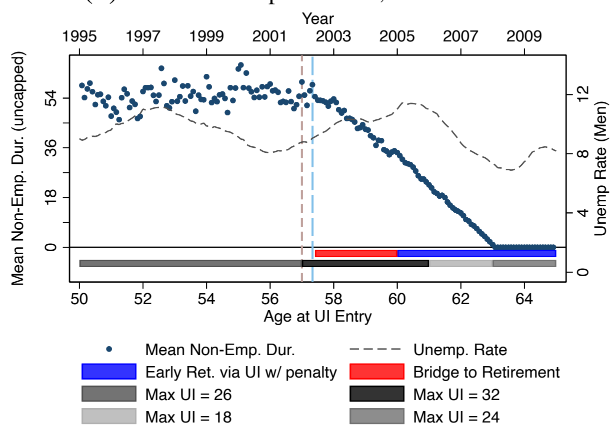
(a) Mean Non-Emp. Duration, 1924 Cohort



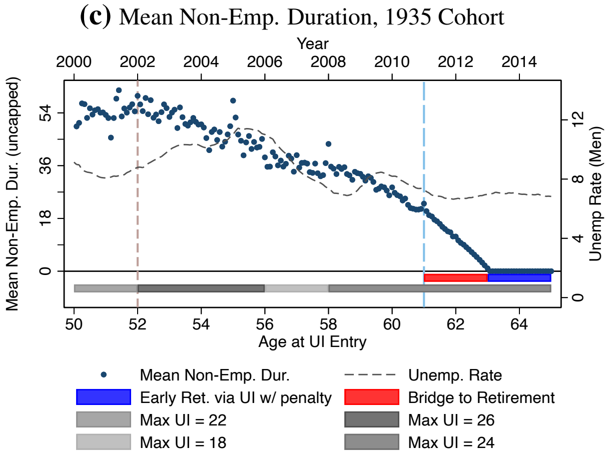
(b) Mean Non-Emp. Duration, 1929 Cohort



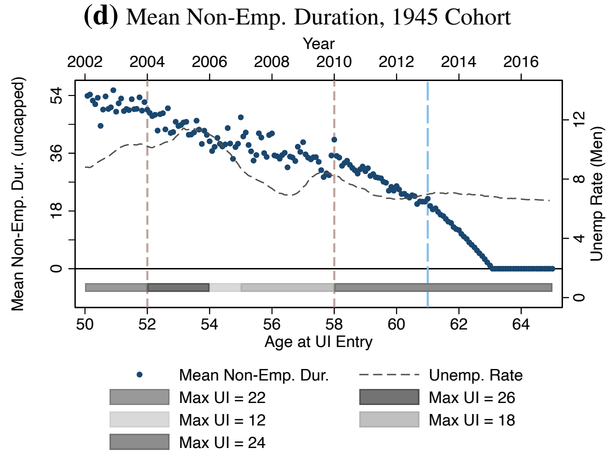
(c) Mean Non-Emp. Duration, 1935 Cohort



(d) Mean Non-Emp. Duration, 1945 Cohort



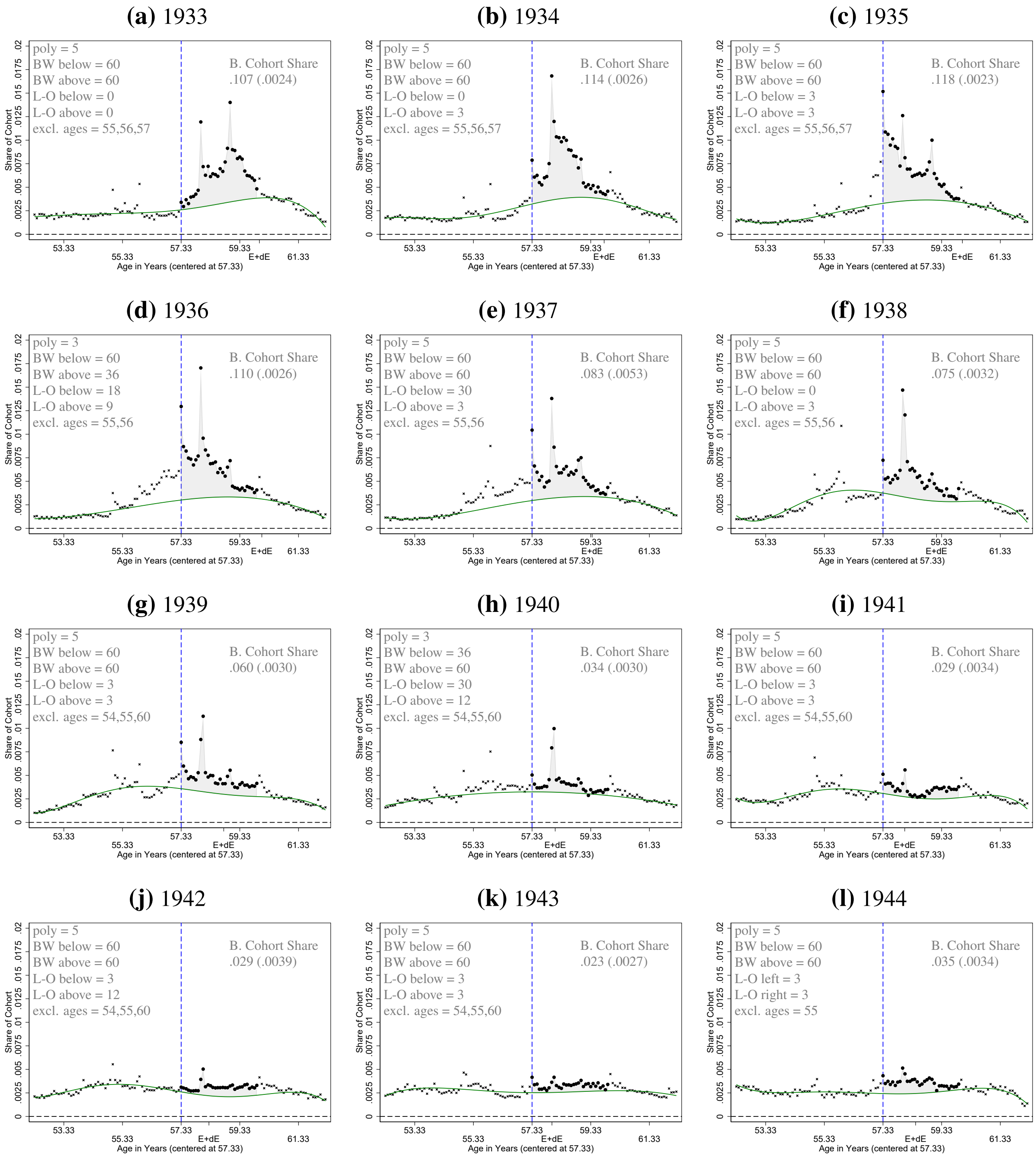
(e) Mean Non-Emp. Duration, 1950 Cohort



(f) Mean Non-Emp. Duration, 1952 Cohort

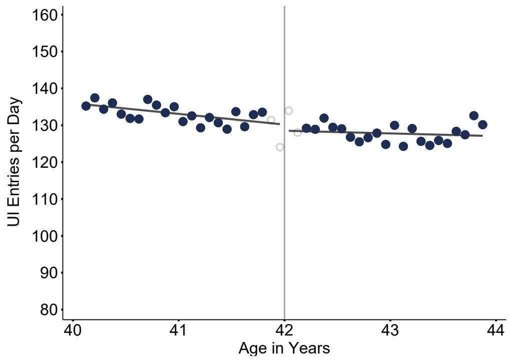
Notes: This figure plots mean non-employment duration (up to age 63) for different cohorts of West German men in our sample (left axis). It also plots the male, seasonally adjusted unemployment rate as a dashed gray line (right axis). The red bar under the figure indicates the period over which an individual could receive UI before drawing a 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 H.9: Bunching Figures for Cohorts Around the Retirement Penalty Phase-In

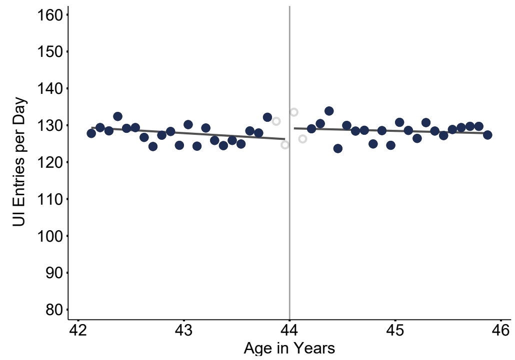


Notes: These figures shows cohort specific number of UI entries relative to the overall number of individuals in the cohort sample (black dots) the estimated counterfactual distribution (green solid line) and the resulting estimated excess bunching (shaded gray area) for cohorts displayed in figure 3 (cohort 1945 excluded due to redundancy to figure 2). The estimates of the excess bunching mass as a share of the cohort are depicted on the upper right of each sub-figure (standard errors are in parentheses). Cohort-specific parameters when estimating the counterfactual are depicted on the upper left. "Poly" refers to the degree of polynomial, "BW" the bandwidth, "L-O" to the leave-out region above and below the UI-bridge period. "excl. ages" refers to round ages outside the bunching region that are excluded due to the excess mass. For further details on the bunching estimation, see also Appendix B.

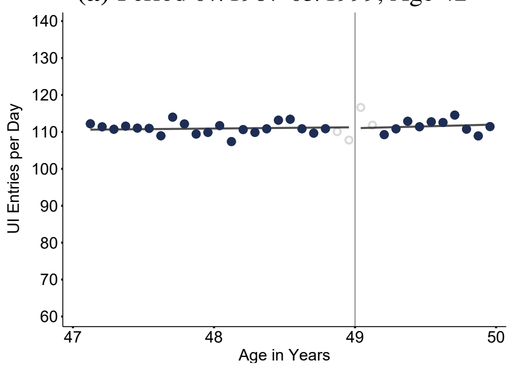
Figure H.11: RD Density Plots, Men



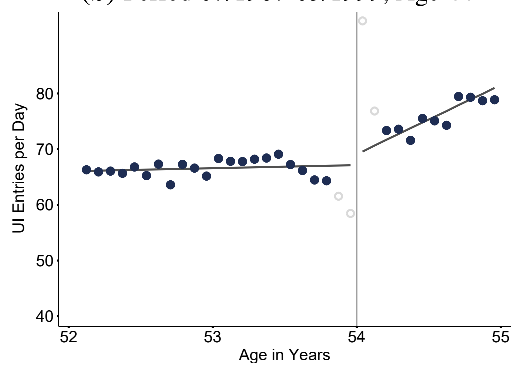
(a) Period 07/1987-03/1999, Age 42



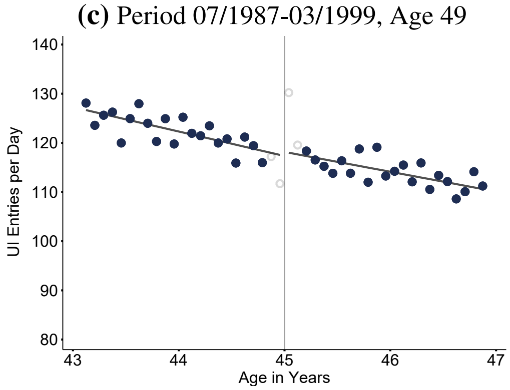
(b) Period 07/1987-03/1999, Age 44



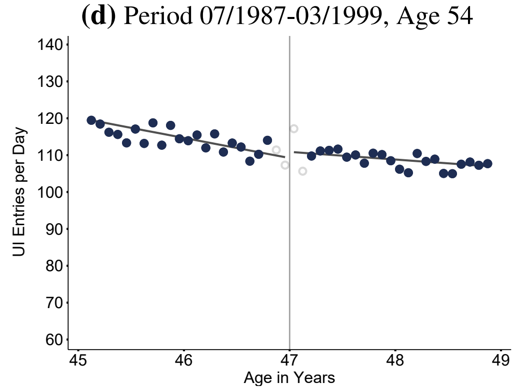
(c) Period 07/1987-03/1999, Age 49



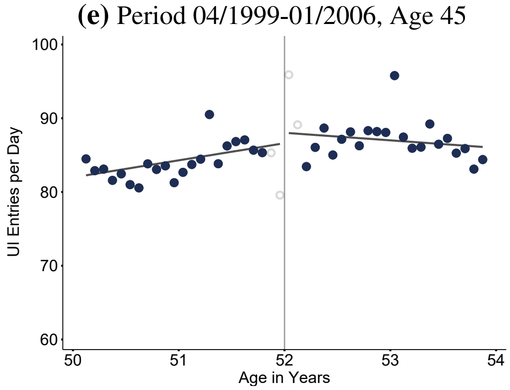
(d) Period 07/1987-03/1999, Age 54



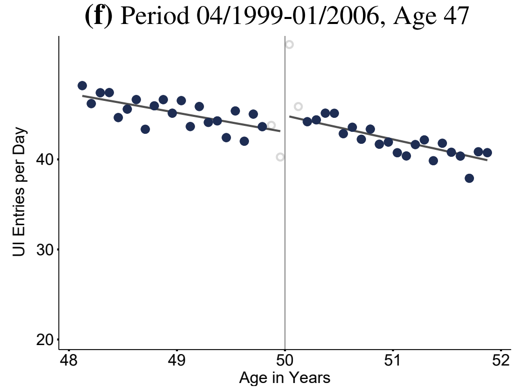
(e) Period 04/1999-01/2006, Age 45



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



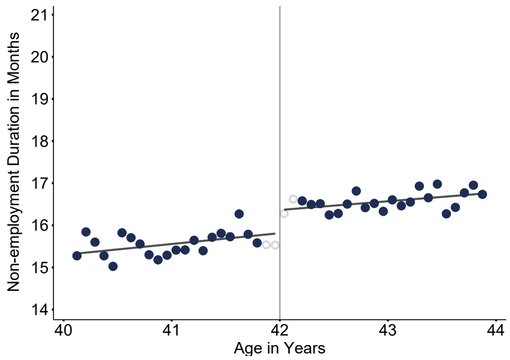
(g) Period 04/1999-01/2006, Age 52



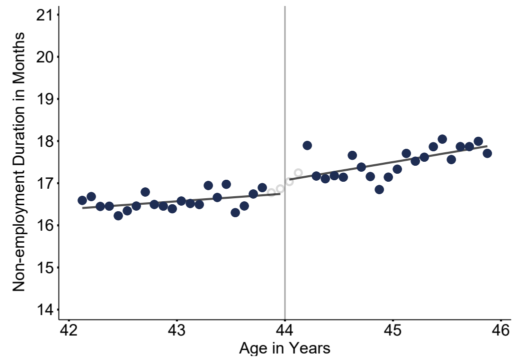
(h) Period 01/2008-12/2010, Age 50

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.

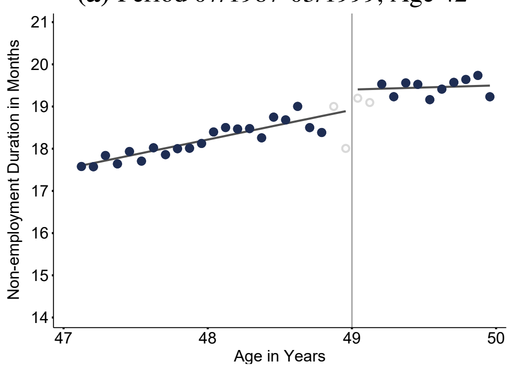
Figure H.13: RD Figures: Non-employment Duration, Men



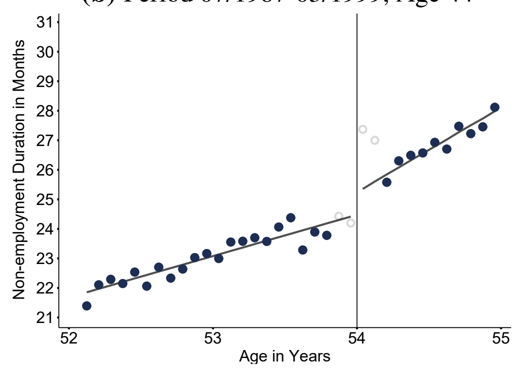
(a) Period 07/1987-03/1999, Age 42



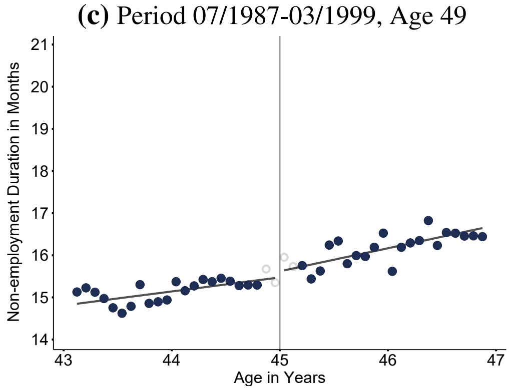
(b) Period 07/1987-03/1999, Age 44



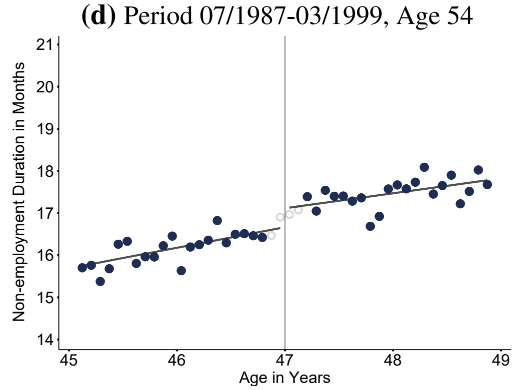
(c) Period 07/1987-03/1999, Age 49



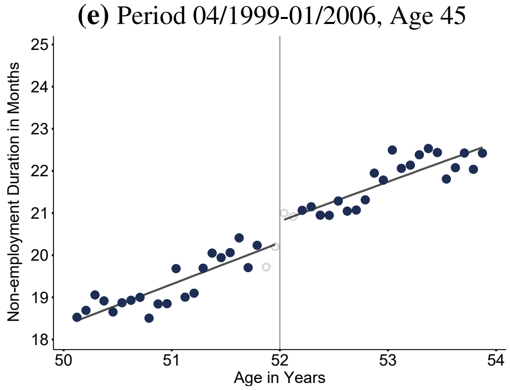
(d) Period 07/1987-03/1999, Age 54



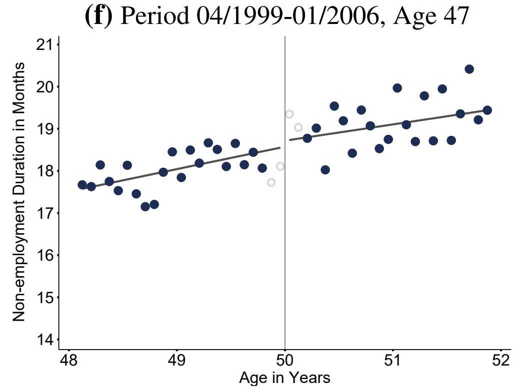
(e) Period 04/1999-01/2006, Age 45



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



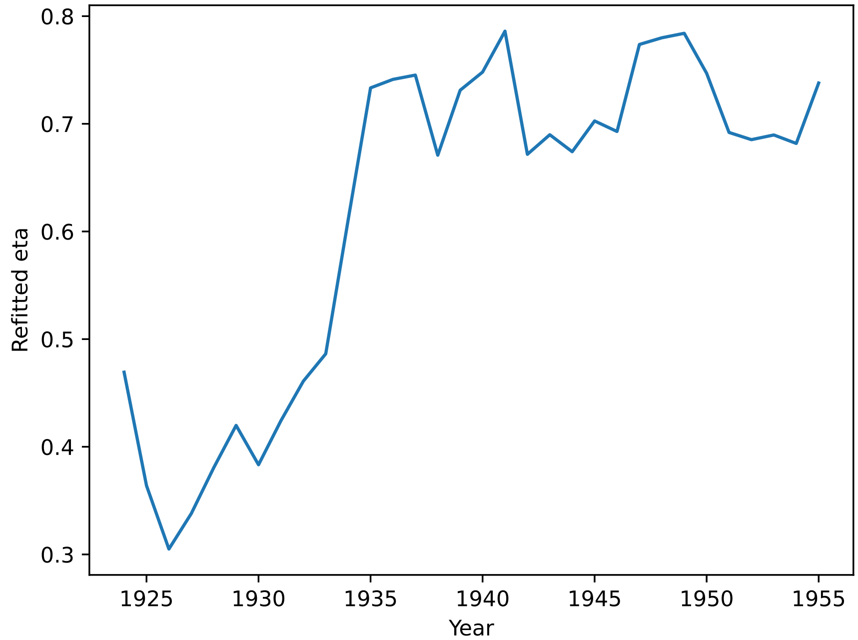
(g) Period 04/1999-01/2006, Age 52



(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. 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 H.15: 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 H.16: Empirical and Simulated UI Inflows for all Cohorts (Baseline Model)

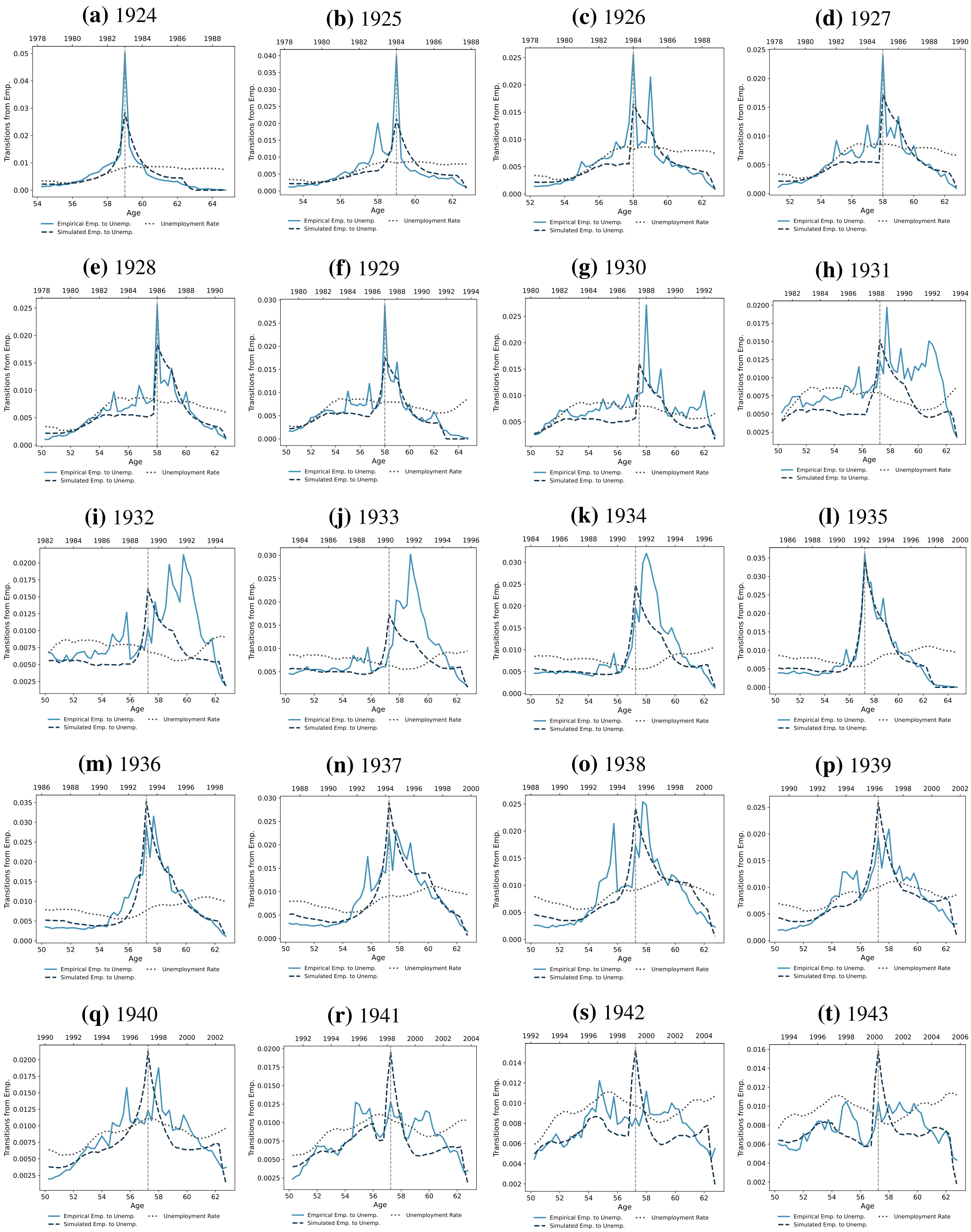
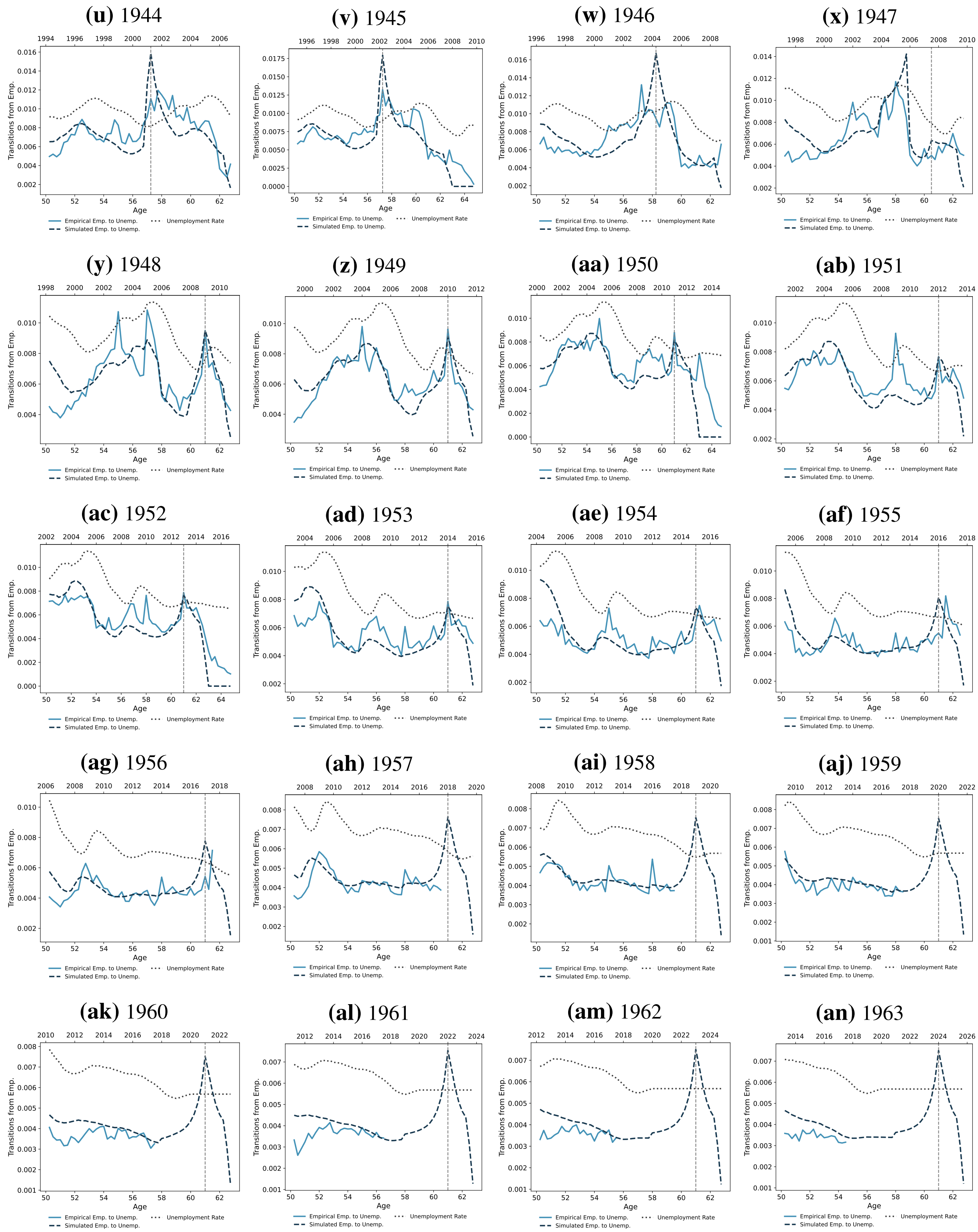
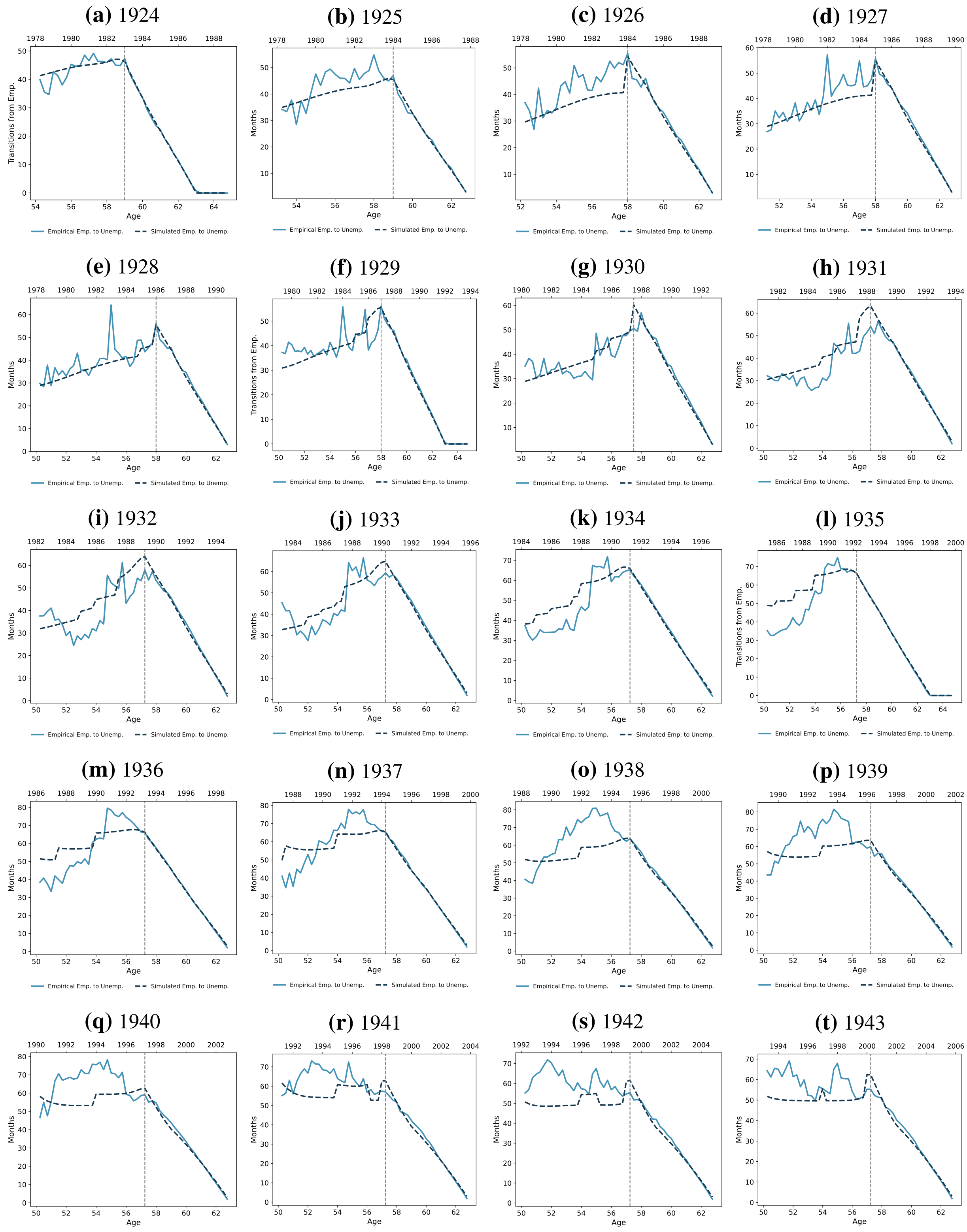


Figure H.17: Empirical and Simulated UI Inflows for all Cohorts (Baseline Model), continued



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 H.19: Empirical and Simulated Nonemployment Durations for all Cohorts (Baseline Model)



(a) 1924 **(b)** 1925 **(c)** 1926 **(d)** 1927

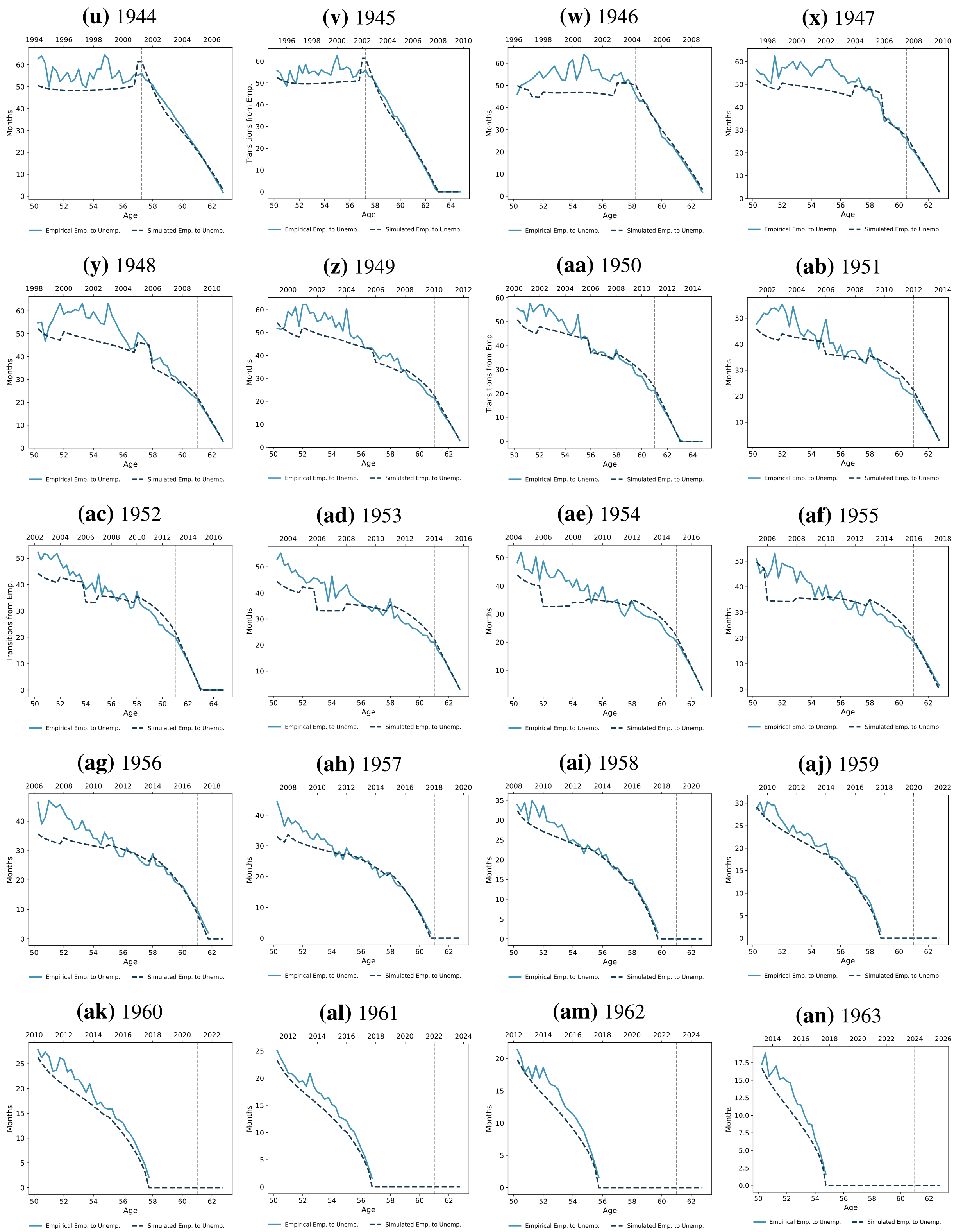
(e) 1928 **(f)** 1929 **(g)** 1930 **(h)** 1931

(i) 1932 **(j)** 1933 **(k)** 1934 **(l)** 1935

(m) 1936 **(n)** 1937 **(o)** 1938 **(p)** 1939

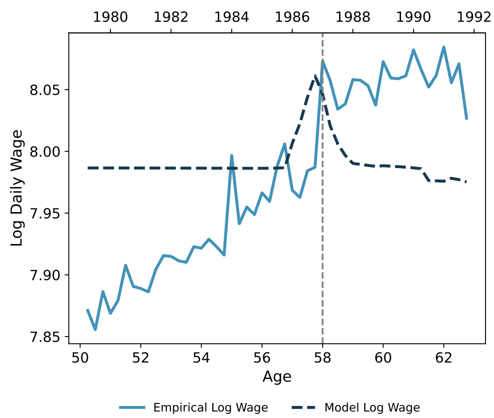
(q) 1940 **(r)** 1941 **(s)** 1942 **(t)** 1943

Figure H.20: Empirical and Simulated Nonemployment Durations for all Cohorts (Baseline Model), continued

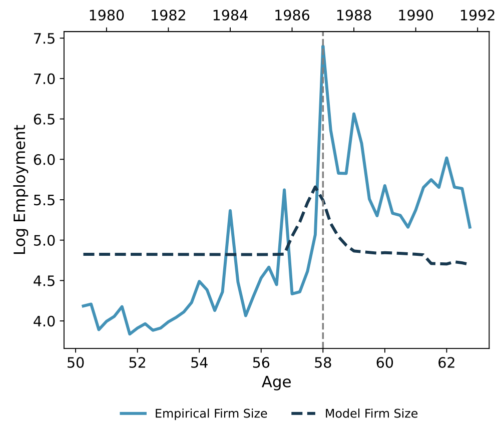


Notes: These figures compare model-based non-employment durations to their corresponding empirical moments for all cohorts, aggregated to the quarterly level.

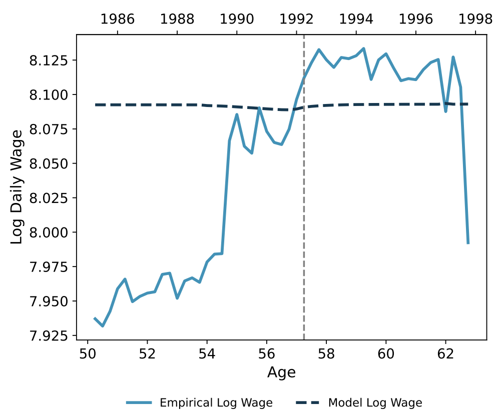
Figure H.22: Pre-Unemployment Log Wage and Firm Size of UI Entrants by Age



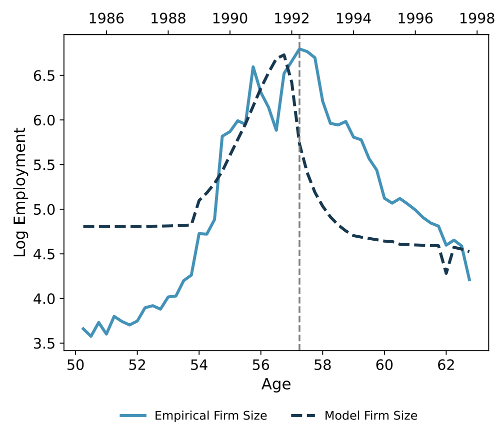
(a) Log Wage - Cohort: 1929



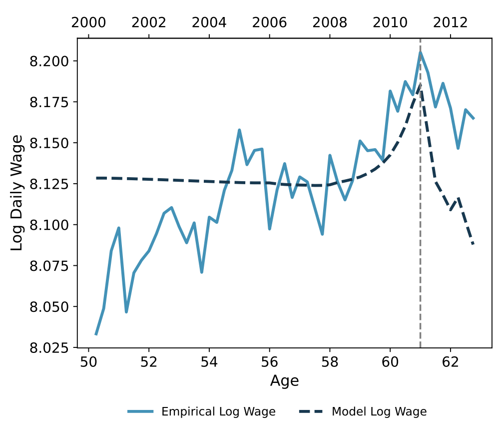
(b) Firm Size - Cohort: 1929



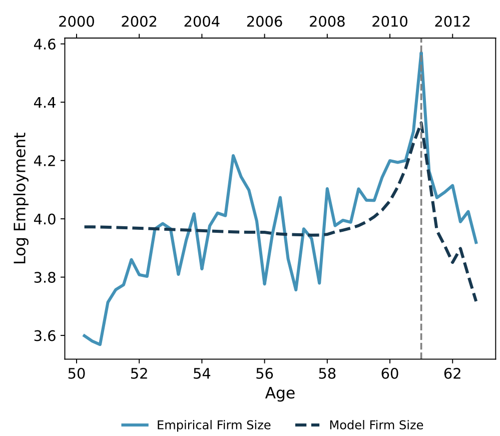
(c) Log Wage - Cohort: 1935



(d) Firm Size - Cohort: 1935



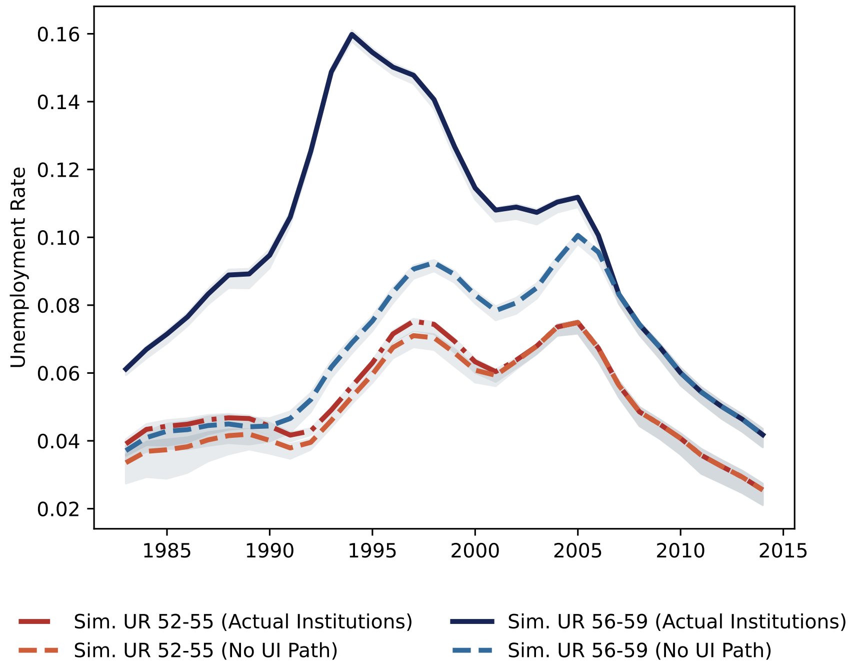
(e) Log Wage - Cohort: 1950



(f) Firm Size - Cohort: 1950

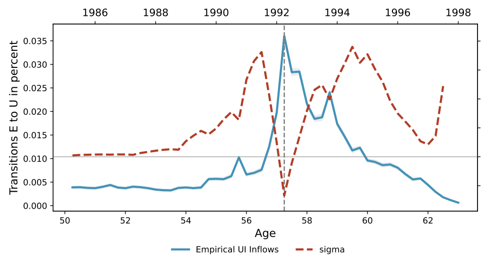
Notes: This figure shows the pre-unemployment log wage and firm size (log of the number of employees) of UI entrants by age of entering UI. The log wage and firm size is the measured at age 50 (the beginning of our sample period). The model log wages and firm sizes are computed from the severance pay model (see section V.A Robustness) and show the predicted values of a (cohort specific) regression of log wage and log firm size on the log of severance pay.

Figure H.24: Simulated Unemployment Rate by Age Group: Actual vs. No UI Pathway

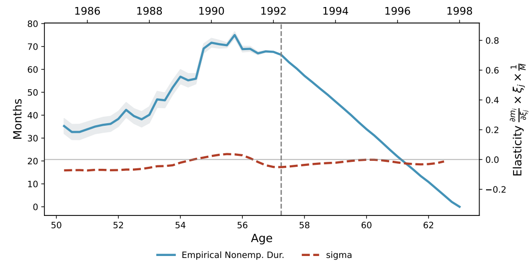


Notes: This figure shows the simulated unemployment rate from the model for two age groups: 52-55 years old and 56-59 years old under two scenarios. The solid lines show the model simulation under the actual institutions, the dashed lines show model simulations for a counterfactual in which the UI pathway does not exist, and hence the earliest possible retirement age was at 63.

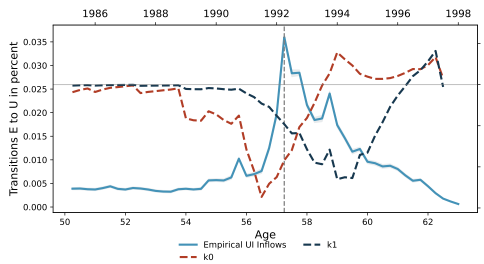
Figure H.25: Influence of Model Parameters on Simulated Moments – 1935 Cohort



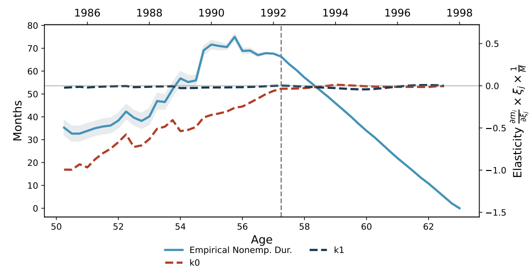
(a) Std. dev. of productivity shock (sigma) (Transitions)



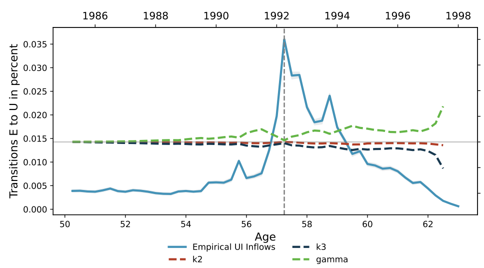
(b) Std. dev. of productivity shock (sigma) (Durations)



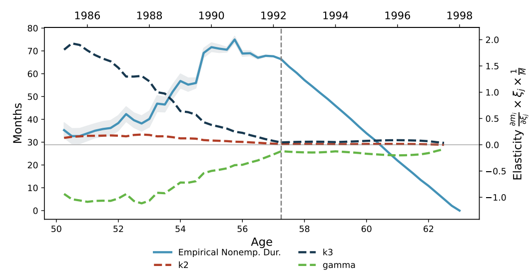
(c) Fixed costs of Job Search (k0) and Entering UI (k1) (Transitions)



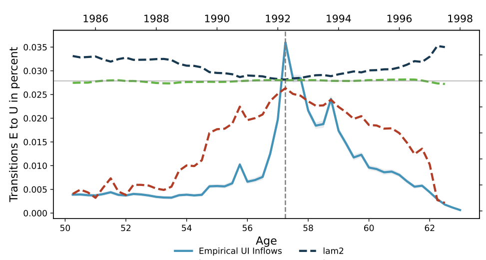
(d) Fixed costs of Job Search (k0) and Entering UI (k1) (Durations)



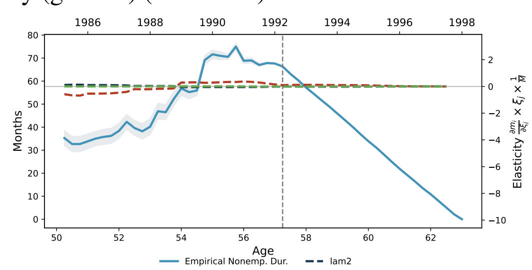
(e) Search cost trend (k2), slope (k3), and elasticity (gamma) (Transitions)



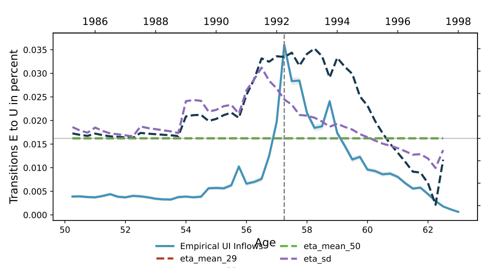
(f) Search cost trend (k2), slope (k3), and elasticity (gamma) (Durations)



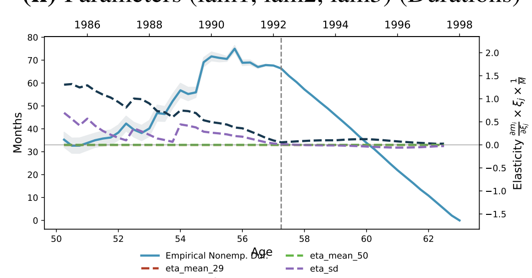
(g) Parameters (lam1, lam2, lam3) (Transitions)



(h) Parameters (lam1, lam2, lam3) (Durations)



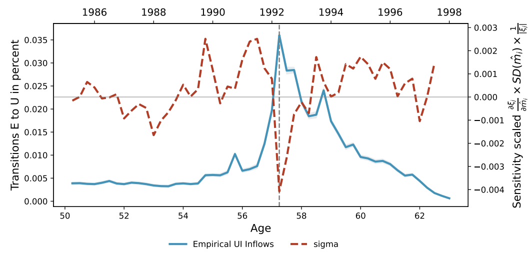
(i) Eta means and standard deviation (Transitions)



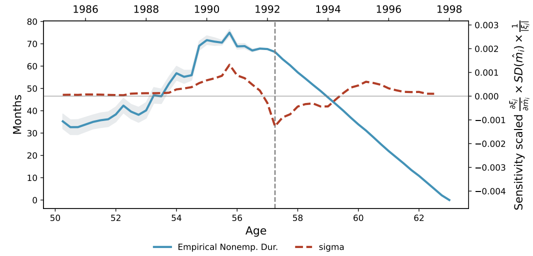
(j) Eta means and standard deviation (Durations)

Notes: These figures show the influence of the model parameters on the simulated moments for the 1935 cohort. The influence is calculated as $\frac{\partial m_i}{\partial \xi_j} \times \frac{|\xi_j|}{m_i}$.

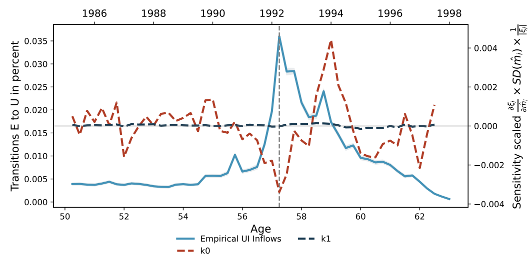
Figure H.27: Sensitivity of Model Parameters to Empirical Moments – 1935 Cohort



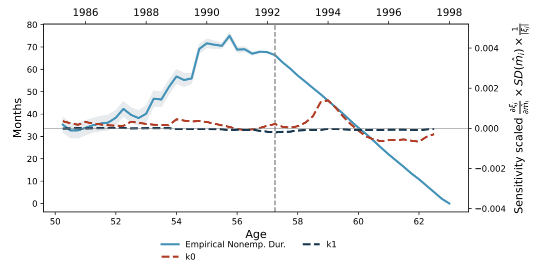
(a) Std. dev. of productivity shock (sigma) (Transitions)



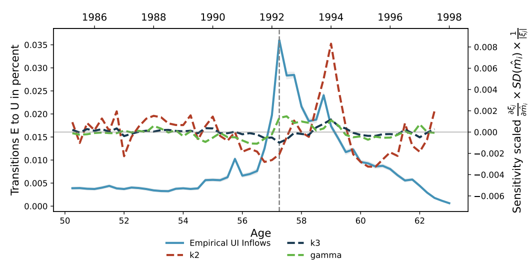
(b) Std. dev. of productivity shock (sigma) (Durations)



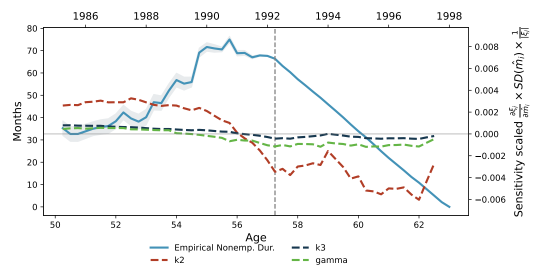
(c) Fixed costs of Job Search (k0) and Entering UI (k1) (Transitions)



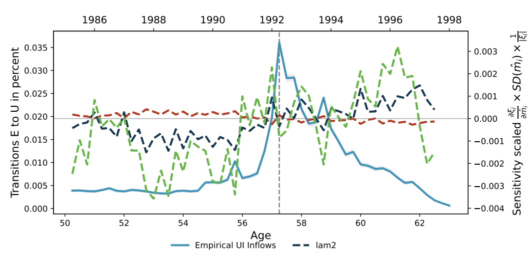
(d) Fixed costs of Job Search (k0) and Entering UI (k1) (Durations)



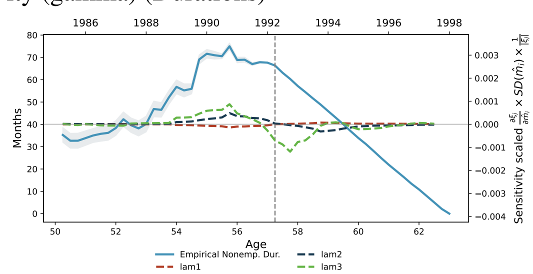
(e) Search cost trend (k2), slope (k3), and elasticity (gamma) (Transitions)



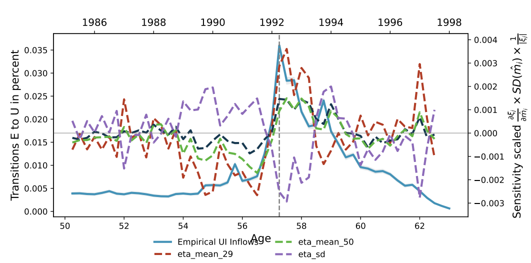
(f) Search cost trend (k2), slope (k3), and elasticity (gamma) (Durations)



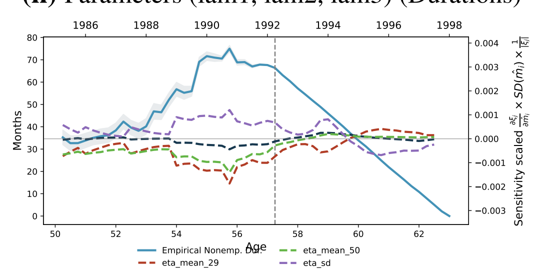
(g) Parameters (lam1, lam2, lam3) (Transitions)



(h) Parameters (lam1, lam2, lam3) (Durations)



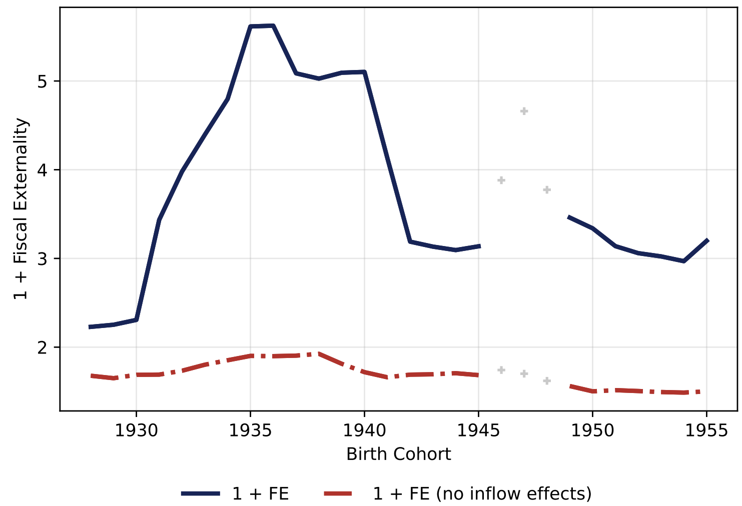
(i) Eta means and standard deviation (Transitions)



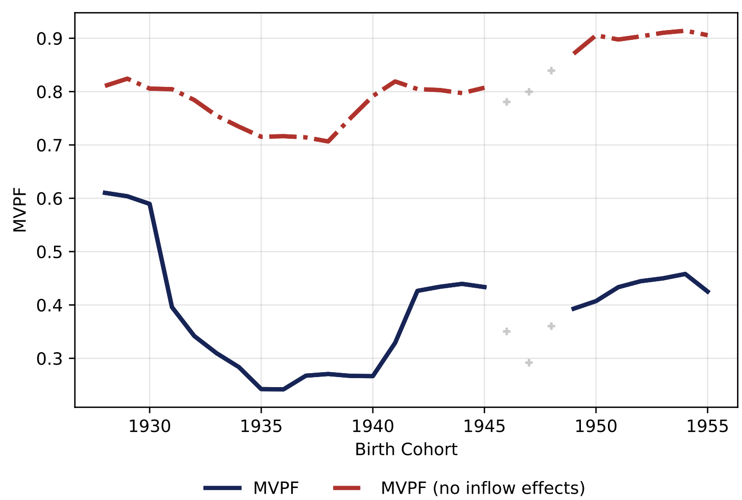
(j) Eta means and standard deviation (Durations)

Notes: These figures show the sensitivity of the model to the parameters to empirical moments for the 1935 cohort (Andrews et al., 2017). The sensitivity is calculated as $\frac{\partial \xi_j}{\partial \hat{m}_i} \times \frac{SD(\hat{m}_i)}{|\xi_j|}$.

Figure H.29: The Marginal Value of Public Funds and the Net Cost to Government (1+FE) by Birth Cohort



(a) Net Cost to Government (1 + FE)



(b) MVPF

Notes: Panel (a) shows the net cost to government, i.e., one plus the fiscal externality, of spending an additional Euro to extend the UI benefit duration for each cohort. Panel (b) shows the MVPF, i.e., the ratio of the net cost to the government to the WTP. The birth cohorts 1946, 1947, and 1948 are grayed out since they are unusual in that they were affected by two reforms: the increase in the early retirement age via UI as well as a sharp reduction in the maximum potential benefit duration in 2006 (see Dlugosz et al. (2014)), which led to a sharp increase in UI inflows in 2006 which leads to a larger fiscal externality in these cohorts.

I Appendix Tables

Table I.1: Potential Unemployment Insurance Benefit (UIB) Durations as a Function of Age and Months Worked in the 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 etal (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 I.2: Retirement age by retirement pathways from 1957 till now

Pathways	Time of implementation	Affected cohorts	SRA		Reform
Standard old-age pension	1957 - 2011	<1947 Jan	65	-	
(Years of contribution: 5[68])	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	1972 - 1999	1909 Jan - 1936 Dec	63	-	1972 Reform ‡
(Years of contribution:35)	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	1972 - 1996	< 1937 Jan	60	-	1972 Reform
	1997 - 2006	1937 Jan - 1941 Dec	60 to 65	60	1992/99 Reform
(at least 52 weeks unemployed after $58\frac{1}{2}$, or		1942 Jan - 1945 Dec	65	60	
2 years part-time)	2006 - 2011	1946 Jan - 1948 Dec	65	60 to 63	1992 Reform
(Years of contribution: 15(8 in last 10 yrs))	2012 - 2016	1949 Jan - 1951 Dec	65	63	
	> 2017 Jan	> 1952 Jan	Phased out	-	2007 Reform
Old-age pension for women	1957 - 2000	<1940 Jan	60	-	
(Years of contribution: 15 (10 after age 40))	2000 - 2009	1940 Jan - 1944 Dec	60 to 65	60	1992 Reform
	2010 - 2016	1945 Jan - 1951 Dec	65	60	
	> 2017 Jan	> 1952 Jan	Phased out	-	2007 Reform
Old-age pension for disabled workers	1972 - 1977	1911 - 1917	62	-	1972 Reform
(Years of contribution: 35)	1978 - 1980	1918 Jan - 1919 Dec	62 to 60	-	1978 Reform
(Loss of at least 50 percent of earnings	1981- 2000	1920 Jan - 1940 Dec	60	-	
capability)	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	2014-2016	1951- 1953	63	-	
(qualifying period of 45 years)	2016 - 2028	1953 Jan - 1963 Dec	63 to 65	-	2014 Reform
	> 2029 Jan	> 1964 Jan	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 born in 1952 and after, the old-age pension for women and the old-age pension due to unemployment are abolished.

Table I.3: 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	0.080
		[0.026]**	[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	0.068
		[0.041]+	[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	0.103
		[0.068]+	[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	0.126
		[0.053]*	[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	0.024
		[0.028]	[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	0.104
		[0.044]*	[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	0.126
		[0.049]**	[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	0.062
		[0.103]	[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 I.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 untill 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 I.3. Standard errors (in brackets) clustered on day level (+ $p<0.1$, * $p<0.05$, ** $p<0.01$).

Table I.5: 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 I.3. Column (1) copies the baseline results. Column (2) adds to the baseline controls, in addition to 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 I.6: Description of Moments

Moments	**Description**	**Primarily Identifying**
E to U inflows by age 50-63 (Quarterly), 1929 cohort E to U inflows by age 50-63 (Quarterly), 1935 cohort E to U inflows by age 50-63 (Quarterly), 1950 cohort	Following everyone in the birth cohort sample who is employed at age 50, we track their labor market state in each quarter since age 50. Quarterly UI inflows are the share of the sample with a transition from E to UI or Nu in the given quarter.	*UI inflows around the bridge age:* $\sigma, k_0, k_1, \bar{\eta}_{1929}, \bar{\eta}_{1935}, \bar{\eta}_{1950}, \eta_{sd}$ *UI inflows at younger ages:* $\lambda_1, \lambda_2, \lambda_3$
Average Non-Employment Duration by age 50-63 (Quarterly), 1929 cohort Average Non-Employment Duration by age 50-63 (Quarterly), 1935 cohort Average Non-Employment Duration by age 50-63 (Quarterly), 1952 cohort	For the same sample, we construct non-employment durations conditional on entering UI or Nu at the given quarterly age as the number of months out of work before the next employment spell until age 63, winsorized at 36 months	*Nonemp. Dur. at younger ages:* k_2,k_3,γ
$\frac{dNonEmp}{dP}$ at age 52, 1950 cohort	RD estimate of the non-employment duration effects (capped at 36 months) of a 1 month PBD extension, based on the age 52 cutoff for the 1999-2006 period	k_0, k_2, k_3, γ

Notes: This table describes the moments used to estimate our model. The final column describes which parameters the moments primarily identify. This is based on the absolute values of the influence elasticities in Table I.10.

Table I.7: Model-estimated dD/dP

	In-Sample Cohorts			Out-of-Sample Cohorts		
dD/dP (target=0.128; age 52 in 1950)	1929	1935	1950	1924	1945	1952
dD/dP at age 50	0.120	0.144	0.114		0.130	0.110
dD/dP at age 52	0.148	0.168	**0.127**		0.152	0.123
dD/dP at age 55	0.196	0.182	0.152	0.194	0.183	0.155
dD/dP at age 57	0.183	0.089	0.176	0.205	0.157	0.178
dD/dP at age 59	0.000	0.000	0.179	0.000	0.000	0.182

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 0.127.

Table I.8: MVPF when UI and Retirement Interact

Program	**Source**	**WTP**	**Net Cost to Gvt 1+FE**	**MVPF**
UI in US - Summary	Hendren & Sprung-Keyser (2019)	1.2	1.95	0.61
UI Extensions, Europe, Prime Age	Schmieder and von Wachter (2016) Le Barbanchon, Schmieder, Weber (2025)	1.36	2.31	0.691
UI Extensions, Germany, Prime Age	Schmieder, von Wachter, Bender (2012)	1.36	1.41	0.967
UI Benefit Levels, Europe	Schmieder and von Wachter (2016) Le Barbanchon, Schmieder, Weber (2025)	1.18	2.55	0.546
UI Extensions - Older Workers Naïve - 1935 Cohort	**This Paper**	**1.36**	**1.9**	**0.716**
UI Extensions - Older Workers Full Model - 1935 Cohort	**This Paper**	**1.36**	**5.62**	**0.242**

The first row is taken from Hendren and Sprung-Keyser (2019).
The second and fourth row is based on averaging the values across all the relevant studies covered in Le Barbanchon, Schmieder, and Weber (2025), which in turn uses values from Schmieder and von Wachter (2016). We omit the values corresponding to Lalive (2007) and Lalive (2008), which had very large UI extensions and where the constant hazard approximation used by Schmieder and von Wachter (2016) appears to be problematic.
The third row is taken from Schmieder, von Wachter, Bender (2012).
The last two rows are based on the model simulations in this paper.

Table I.9: The Marginal Value of Public Funds of UI Extension across Cohorts

Variable	**1929**	**1935**	**1945**	**1950**	**1952**
Full Model (intensive and extensive margin responses)					
Revenue Loss dR	321.00	1121.43	612.70	779.72	644.13
Benefit Increase dB	293.39	582.04	409.38	537.84	488.93
Benefit Increase (Mechanical) dB	272.77	303.37	325.84	394.53	370.35
Behavioral Cost BC	341.63	1400.09	696.25	923.03	762.71
Mechanical Cost MC	272.77	303.37	325.84	394.53	370.35
Fiscal Externality FE	1.25	4.62	2.14	2.34	2.06
Net Cost to Government $1 + FE$	2.25	5.62	3.14	3.34	3.06
WTP	1.36	1.36	1.36	1.36	1.36
MVPF	0.60	0.24	0.43	0.41	0.44
Naive Calculation (only intensive margin response)					
Revenue Loss dR	172.61	263.92	212.49	179.59	169.38
Benefit Increase dB	277.46	312.92	336.44	412.98	388.10
Benefit Increase (Mechanical) dB	277.46	312.92	336.44	412.98	388.10
Behavioral Cost BC	177.30	273.46	223.10	198.04	187.13
Mechanical Cost MC	277.46	312.92	336.44	412.98	388.10
Fiscal Externality FE	0.65	0.90	0.68	0.50	0.51
Net Cost to Government $1 + FE$	1.65	1.90	1.68	1.50	1.51
WTP	1.36	1.36	1.36	1.36	1.36
MVPF	0.82	0.72	0.81	0.91	0.90

WTP taken from Le Barbanchon et al. (2024).

Naive response uses RD estimate to predict intensive margin response and assumes no inflow changes.

Table I.10: The Influence of Model Parameters on Simulated Moments, $\frac{\partial m_i}{\partial \xi_j} \times \frac{|\xi_j|}{m_i}$

	Transitions						**Durations**						dD/dP
	Workers Age 52			Workers at Bridge Age			Workers Age 52			Workers at Bridge Age			
Age				58	57.4	61				58	57.4	61	52
Cohort	1929	1935	1950	1929	1935	1950	1929	1935	1950	1929	1935	1950	1950
Productivity Shocks													
Std. dev. of productivity shock σ	0.0016	0.0154	0.0471	-0.0600	-0.4898	0.3968	-0.0565	-0.0752	0.0221	-0.0564	-0.0501	-0.0229	-0.0435
Job Search Parameters													
Fixed cost of job search k_0	-0.0024	-0.0187	-0.2358	-1.7297	-1.6817	-1.1423	-0.5323	-0.7080	-0.8421	-0.0937	-0.0344	-0.0779	-0.2435
Cost of UI entry k_1	-0.0006	-0.0033	-0.0329	-1.4315	-0.8778	-2.0045	-0.0014	-0.0048	-0.0446	-0.0394	0.0019	-0.0769	-0.0000
Exp. time trend in search cost k_2	0.0010	-0.0001	0.0000	-0.0064	-0.0015	-0.0250	0.0369	0.1827	0.0834	0.0241	0.0122	0.0157	0.2883
Slope parameter of search cost k_3	-0.0071	-0.0190	-0.0169	-0.0818	-0.0435	-0.2573	1.4746	1.5534	0.9660	0.1023	0.0439	0.0768	-0.1645
Elasticity of search cost γ	0.0007	0.0115	0.0117	0.1131	0.0576	0.3355	-0.5252	-1.0836	-0.5526	-0.2091	-0.1206	-0.1643	-1.0160
Exog. job destruction rate													
λ_1	-6.9744	-8.4665	-6.2265	-2.6752	-1.0302	-3.5463	-0.6453	-0.4968	-0.4635	0.3112	0.0955	0.1877	0.2370
λ_2	0.6975	1.7235	1.4000	0.5511	0.1861	0.5911	0.1226	0.0945	0.1236	-0.0636	-0.0138	-0.0356	-0.0503
λ_3	0.3603	-0.0077	0.1808	-0.0218	0.0748	-0.0402	0.0098	-0.0020	-0.0103	-0.0004	-0.0037	0.0026	0.0014
Disutility of work													
$\bar{\eta}_{1929}$	0.0013	-0.0000	-0.0000	2.4937	-0.0000	-0.0000	0.4517	-0.0000	-0.0000	0.1349	-0.0000	-0.0000	-0.0000
$\bar{\eta}_{1935}$	-0.0000	0.0212	-0.0000	-0.0000	3.3159	-0.0000	-0.0000	0.9855	-0.0000	-0.0000	0.0546	-0.0000	-0.0000
$\bar{\eta}_{1950}$	-0.0000	-0.0000	0.2887	-0.0000	-0.0000	1.9106	-0.0000	-0.0000	1.0674	-0.0000	-0.0000	0.1423	0.3136
η_{SD}	0.0146	0.0659	0.4950	4.0442	1.5855	1.5563	0.1791	0.1616	0.8126	0.1341	0.0130	0.0461	-0.1876

Notes: The table shows elements of the Jacobian matrix of $m(\xi)$, where $m(\xi)$ is the mapping from model parameters ξ to simulated moments m. The table scales these elements $m_i(\xi_j)$ as elasticities (preserving the sign): $\frac{\partial m_i}{\partial \xi_j} \times \frac{|\xi_j|}{m_i}$. Cells are shaded as darker blue for larger absolute values of the elasticity.

Table I.11: The Sensitivity of Model Parameters to Empirical Moments, $\frac{\partial \xi_j}{\partial \hat{m}_i} \times \frac{SD(\hat{m}_i)}{|\xi_j|}$

	Transitions						**Durations**						dD/dP
	Workers Age 52			Workers at Bridge Age			Workers Age 52			Workers at Bridge Age			
Age				58	57.4	61				58	57.4	61	52
Cohort	1929	1935	1950	1929	1935	1950	1929	1935	1950	1929	1935	1950	1950
Productivity Shocks													
Std. dev. of productivity shock σ	-0.0073	-0.0926	-0.0061	-0.1568	-0.4077	-0.0043	-0.0039	0.0045	-0.0041	-0.0565	-0.1268	-0.0035	0.0250
Job Search Parameters													
Fixed cost of job search k_0	0.0401	-0.1582	0.0287	-0.0312	-0.3393	0.0178	-0.0609	0.0131	0.0314	-0.0356	0.0211	-0.0212	-0.0348
Cost of UI entry k_1	-0.0058	-0.0029	0.0028	-0.0117	-0.0023	-0.0387	0.0033	0.0007	0.0034	-0.0057	-0.0213	-0.0102	0.0220
Exp. time trend in search cost k_2	0.0344	-0.2270	-0.0733	0.0276	-0.2089	-0.3481	-0.0279	0.2905	-0.0327	-0.2108	-0.3470	-0.3083	2.2754
Slope parameter of search cost k_3	0.0127	-0.0379	-0.0153	-0.0319	-0.0995	-0.0548	0.0486	0.0656	0.0293	-0.0302	-0.0434	-0.0344	-0.1926
Elasticity of search cost γ	-0.0158	0.0128	-0.0372	0.0158	0.1331	-0.0853	0.0421	0.0541	0.0045	-0.0566	-0.1146	-0.0600	0.1570
Exog. job destruction rate													
λ_1	0.0036	0.0012	-0.0206	-0.0065	0.0153	-0.0154	-0.0002	0.0009	-0.0000	-0.0054	0.0003	-0.0007	0.0039
λ_2	-0.0258	0.0281	0.1300	0.0295	-0.0345	0.0526	0.0087	-0.0002	-0.0078	0.0222	0.0029	-0.0012	-0.0132
λ_3	0.3208	0.0032	0.3581	0.0980	-0.0841	0.1839	0.0002	-0.0058	-0.0216	0.0218	-0.0706	0.0066	-0.0068
Disutility of work													
$\bar{\eta}_{1929}$	-0.0777	0.1448	-0.0635	0.1138	0.2863	-0.1254	0.0892	-0.0213	-0.0437	0.0678	-0.0738	0.0042	0.1234
$\bar{\eta}_{1935}$	-0.0196	0.0081	-0.0208	-0.0185	0.1464	-0.0428	0.0101	0.0052	-0.0057	-0.0105	-0.0109	-0.0062	0.0280
$\bar{\eta}_{1950}$	-0.0282	0.0261	0.0092	-0.0179	0.0948	0.0908	-0.0049	-0.0460	0.0749	-0.0105	-0.0280	0.0512	0.0767
η_{SD}	0.0606	-0.1519	0.0596	0.0527	-0.2520	0.0961	-0.0763	0.0120	0.0466	-0.0082	0.0681	-0.0123	-0.0906

Notes: The table shows the sensitivity of model parameters ξ_j with respect to empirical moments $\hat{m}_i$. The table scales these elements by multipliying them with the standard error of the moment $SE(\hat{m}_i)$ and dividing by the absolute value of the parameter (to preserve the sign): $\frac{\partial \xi_j}{\partial \hat{m}_i} \times \frac{SE(\hat{m}_i)}{|\xi_j|}$. Cells are shaded in darker green for larger absolute values of the sensitivity.

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