Unemployment Insurance with Policy Differentiation

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Abstract

This paper studies policy differentiation in unemployment insurance (UI) theoretically and empirically. We provide a general sufficient statistics framework to assess the insurance-incentive trade-off from differentiating the duration of benefits. We show how differentiating UI redistributes welfare across heterogeneous unemployed workers. Our empirical implementation evaluates how workers' responses to and the welfare effects of UI vary with age and contribution time—two widely-used tags. We exploit numerous discontinuities in benefit duration in Germany to obtain a comprehensive set of elasticities. Duration responses to UI extensions decrease in short-term contribution time, while longer horizons and age are non-significant. The behavioral cost depends on duration and policy levels on top of responses. The social value of UI decreases in contribution time. The largest, negative welfare effects occur among workers who have contributed the longest, because they value UI the least. Our results support schedules where coverage increases in short-term contribution time, but flattens thereafter.

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1 Introduction

Asymmetric information about agents' risks and preferences presents a major challenge in regulating social insurance. A large literature has derived the properties of the optimal homogeneous policy that balances insurance value and incentive costs on average, following the tradition of Baily (1978) and Chetty (2006). Yet, when agents are heterogeneous, welfare gains might be achieved by tagging the generosity of coverage on observable characteristics that provide information about the insurance-incentive trade-off. While coverage differentiation is widespread in modern social insurance, supporting evidence is often lacking.[1] In many publicly-funded unemployment insurance (UI) systems, the potential benefit duration (PBD) increases in age and past contributions.

This paper examines the differentiation of UI in age and contribution time. We first study the general welfare implications of a differentiated policy theoretically. We show that differentiation can serve to redistribute welfare among heterogeneous beneficiary groups, complementing its core insurance function. In our empirical implementation, we estimate the welfare effects empirically using rich policy variation in the German UI system by age and contribution time. The estimates serve to locally evaluate the PBD schedules in Germany between 1994 and 2010 and to identify potential opportunities for enhancing welfare.

We begin by setting up a partial equilibrium job search model with a heterogeneous UI policy. We derive general sufficient statistics for the welfare derivative (social value minus behavioral cost) of extending the PBD for a specific population group defined by any pre-determined characteristics. These moments serve to evaluate the degree of differentiation of the existing policy by simply signing the difference in the welfare derivative of UI across groups. Importantly, this does not require establishing the local optimality within each group, which relies on assumptions on risk aversion.

When UI is financed by a uniform tax rate (as done in virtually all publicly-funded UI systems), the social value depends on the wedge between the consumption during unemployment of the group x benefiting from the extension, and the average consumption

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[1] Interestingly, in the case of income taxation, tagging on observable characteristics has gained much less traction in actual policy practice, although it has been more actively discussed in the literature. This idea goes back to Akerlof (1978), which argues for age-dependent taxation. See also, e.g., Fahri and Werning (2013); Stantcheva (2017) and Heathcote et al. (2020).

during employment across *all* groups $x' \in X$. Interestingly, the social value can become negative for groups which are able to consume more in unemployment than the average worker in employment, thanks to, e.g., assets. Negative social values are not possible by construction in the standard setup where the group (or the whole population in the case of a homogeneous policy) finances their own benefits. The behavioral cost measures the increase in income taxes on the employed needed to finance a PBD extension. It depends on the duration responses to UI, but also on their initial levels and the PBD. In other words, the heterogeneity in the fiscal externality of UI does not only stem from behavioral responses, but also from baseline risk and policy.

We focus on age and contribution time as tags due to their economic and practical importance. Over two thirds of OECD countries differentiate UI generosity in age or contribution time, or both.[2] The rationale is to discourage recurrent unemployment spells and to protect older workers against higher unemployment risk. Many other social insurance systems also vary coverage based on these tags,[3] which are observed at little cost and seen as feasible, in contrast to, e.g. gender or education.

Both age and contribution may shape the costs and value of UI directly and indirectly. They correlate—possibly differently—with key determinants of unobserved job search behavior (e.g., human capital, cost of search) and the ability to smooth consumption throughout unemployment (e.g., assets). A crucial advantage of the sufficient statistics approach is that it requires few structural assumptions on primitives and the heterogeneity underlying the tags.[4] We therefore do not have to explicitly model the many channels through which age and contribution shape welfare effects, which would be challenging.

Age measures the worker's position in their life cycle, which determines labor market experience and time until retirement. Younger workers face higher uncertainty and have an incentive to accumulate human capital and labor market experience to enhance their employment prospects (Fahri and Werning, 2013; Stantcheva, 2017). They may value UI more as they have lower means to smooth consumption. In contrast, older workers may find job search costlier due to lower expected returns and shorter remaining employment horizons (Hairault et al., 2010, 2012; Chéron et al., 2013). They may even use UI as a

[2]This includes Belgium, Czech Republic, Denmark, Estonia, Finland, Greece, France, Italy, Japan, Korea, Spain, Latvia, Lithuania, Luxembourg, Netherlands, Poland, Portugal, Slovenia, Spain, Sweden, Turkey, United Kingdom (source: OECD Benefits and wages, 2022 Policy tables, accessed 21.03.2024).

[3]For instance, retired workers receive more generous pensions if they have accumulated longer employment histories, and avoid penalties from early retirement if they retire at older ages. Disability insurance benefits are higher for workers with longer contributions. Health insurance covers additional checkups above certain age cutoffs.

[4]The behavioral cost depends on high-level elasticities and group-specific averages. The social value requires some structure on individual preferences, since the consumption smoothing benefits of UI depend on the marginal utility of consumption.

bridge into retirement.[5] Michelacci and Ruffo (2015) finds that workers in their forties exhibit less responsiveness to UI compared to younger workers. Contribution time measures actual employment and recurrent insurance use, *conditional on age*. A 50-year-old worker who has worked seven out of the last seven years likely has a different insurance-incentive trade-off than one that has only worked two out of the last seven years. Workers with stable employment may have higher human capital, returns to search, and assets, but also stronger preferences for work. Determining how to differentiate UI in age and contribution time is highly relevant due to an increasing share of workers with non-standard employment and gaps in contributions, the aging of the workforce, and increases in statutory retirement ages.

There is substantial cross-country and time variation in the degree of differentiation in both dimensions, as well as reference periods for contribution requirements.[6] This speaks to a lack of consensus and evidence on how to use these tags, despite close similarities in the building blocks of publicly-funded UI systems.[7] UI in Germany has a highly-differentiated PBD, which increases stepwise for every four months of contribution time within a reference period, and with the maximum jumping up at given age cutoffs. Meanwhile, in, e.g., the United States, Switzerland and Austria, PBD jumps only at contribution eligibility cutoffs, and at few age cutoffs, if any. The German schedule has been subject to several reforms in our study period spanning 1994 to 2016. Between 1987 and the mid 2000s, the PBD ranged from 6 to 32 months, i.e. a long-term employed 58-year-old worker could get 5.3 times longer coverage than one who just satisfied eligibility requirements. In 1997, the age cutoffs were shifted upwards by three years. In 2006, the differentiation was reduced to 6 to 18 months (threefold differentiation), with the removal of all but one age cutoff. In 2008, differentiation went back to ranging between 6 and 24 months (fourfold differentiation).

The first step of our empirical analysis is to estimate the duration elasticities for the behavioral cost by age and contribution time. We develop a multidimensional regression discontinuity (RD) design that leverages the rich social security data and policy variation in the PBD for workers aged 40 to 55 in the German UI system. Exploiting the many jumps in the schedule and their changes over time, we obtain elasticity estimates across over 400 cells defined by age and contribution time. We subject our estimates to extensive

[5]See, e.g., Sander and van Ours (2010); Baguelin and Remillon (2014); Inderbitzin et al. (2016); Gudgeon et al. (2023); Ye (2022) on early retirement via UI.

[6]Reference periods are, e.g., five quarters in the United States, two years in Switzerland, two to three years in France, and six years in Spain.

[7]In short, workers who satisfy eligibility criteria (minimum contribution to social security, and reason for job loss) receive constant benefit payments determined by an income replacement rate for a maximum PBD. The system is financed by social security contributions, which are a constant share of (potentially capped) labor income. See Schmieder and Von Wachter (2016) and Spinnewijn (2020) for overviews and comparisons of institutional settings.

validity checks to flag those that show evidence of sorting.

Both the elasticity of UI receipt duration (i.e. actual benefit receipt) and nonemployment duration (i.e. time from last to first job) are negative on average, consistent with existing evidence (Tatsiramos and van Ours, 2014; Schmieder and Von Wachter, 2016). We document substantial response heterogeneity in contribution time using meta regressions. Both elasticities are significantly negatively associated with contribution time in the last three years before job loss, holding constant age and the PBD level (i.e., the actual policy differentiation). Stable short-term employment is associated with smaller reductions in job search effort and smaller mechanical increases in transfers due to PBD extensions. The associations are barely affected by controlling for worker composition and the business cycle. Contribution time thus directly predicts job search behavior rather than simply capturing correlations with other observable factors. Meanwhile, age and longer contribution time horizons of five and seven years have little predictive power for responses to UI within our sample. These gradients are robust to a battery of methodological choices on cell construction and estimation.

The second step is a welfare analysis where we quantify the behavioral cost and social value of UI based on the sufficient statistics we derived. We use the duration elasticities to evaluate the behavioral cost in the age-by-contribution time space. The behavioral cost is positive across the board and ranges between 1 and 2.4 for the average worker in the policy regimes we analyze. That is, a EUR 1 increase in transfers per capita to workers in the average group requires that the planner raises EUR 1–2.4 in income taxes on the employed to break even (which corresponds to a negative fiscal externality). Importantly, the heterogeneity in duration and PBD levels typically dominates the duration elasticities in determining the behavioral cost. In the mid 1990s, the highest estimates are for workers over 50 who have contributed less than three out of the last seven years. In later periods, the highest estimates tend to be located among high contributors. The differences over time being driven by changes in the PBD levels themselves, as well as compositional changes in the unemployed population due to the German Reunification and the business cycle.

We estimate the social value of UI using a consumption-based approach (e.g., Gruber 1997; Kolsrud et al. 2018) and survey data from the German Socio-Economic Panel. The estimates decrease in contribution time from around 0.5 to nearly 0 for workers aged 40, with a steeper decrease at older ages. Under a uniform tax and an assumption of homogeneous preferences, the social value becomes negative at the censoring value of contribution, where workers have the most means to smooth consumption. PBD extensions in this group induce a welfare loss, as their marginal utility of consumption in unemployment is lower than the average marginal utility in employment. Old workers who have contributed up to one third of the reference period value UI the most, as they have few resources from a history of unstable employment.

Weighing the social value and behavioral cost against each other, we find negative welfare derivatives across the board for coefficients of relative of risk aversion below 4, i.e. in the upper range of conventional values. The most negative estimates are among full contributors. These groups have a large impact on welfare due their size; they are among the largest in the unemployed population due to bunching at the censoring value of contribution time. In sum, both age and contribution time are significant, albeit distinct drivers of heterogeneity in both the benefits and costs of UI. Both are relevant for policy differentiation, above and beyond other confounding factors, e.g. the business cycle. Furthermore, the mode of financing of PBD extensions matters for policy conclusions. The common uniform tax causes UI to redistribute welfare across groups under a differentiated policy. A group-specific tax eliminates this channel. This insight aligns with Ferey (2022), who shows that UI has redistributive properties when benefits depend on past earnings. Taken together, the heterogeneity in welfare effects we find speaks against UI systems where PBD increases systematically in contribution time and age. Instead, our results support PBD schedules that are flatter in age and that increase with contribution time for workers with unstable employment, but do not become more generous at higher contribution levels.

Related literature. Our paper makes both theoretical and empirical contributions. It adds to the broad literature on the reduced-form effect of UI. Of particular relevance are studies analyzing the intensive-margin effects of PBD extensions using RD designs.[8] A consistent finding is that PBD extensions induce positive duration responses, although estimates vary in magnitude. Our results help reconcile these discrepancies by showing that local effect estimates may mask substantial heterogeneity, and may not be extrapolated without accounting for age and contribution time.

Previous studies have analyzed the age-heterogeneity in responses to UI in Germany. Schmieder et al. (2012) exploit three age cutoffs (42, 44 and 49 years) to estimate heterogeneous responses over the business cycle. Gudgeon et al. (2023) expand on Schmieder et al. (2012) to include age cutoffs up to 55 (similarly to us), and study how older workers' responses to UI depend on retirement incentives. As most existing studies (see Appendix A), both papers focus on workers with uninterrupted long-term employment, i.e., at least

[8] See Appendix A for an overview of the key studies using RD designs, e.g., Card et al. (2007); Lalive (2008); Schmieder et al. (2012); Caliendo et al. (2013); Le Barbanchon (2016); Schmieder et al. (2016); Nekoei and Weber (2017) and Johnston and Mas (2018). Other recent studies using alternative identification strategies include, e.g., Lalive et al. (2006); van Ours and Vodopivec (2008); Card et al. (2015); Cottier et al. (2020) and Lichter and Schiprowski (2021). See Tatsiramos and van Ours (2014) and Schmieder and Von Wachter (2016) for reviews of the literature on UI effects.

five years over the last seven. Our results are consistent with these papers, as we find no significant pure age gradient in duration responses. Importantly, we identify contribution time as a welfare-relevant source of heterogeneity. While some studies have found bunching in job separations at the eligibility threshold (Brébion et al., 2023; Albanese et al., 2020), so far little is known on how the effects of UI vary among recurrent users of UI away from the eligibility threshold. An exception is Le Barbanchon (2016), who finds a large effect on nonemployment duration of a PBD extension for workers crossing 8 months of tenure in the last 12 months. Our results suggest that focusing on the long-term employed may lead to underestimating duration elasticities. They also highlight that PBD extensions have large welfare effects within this group.

Our work adds to the literature on optimal UI that has assessed the welfare implications of response heterogeneity in various dimensions.[9] Our paper contributes by providing a framework for differentiating the PBD rather than benefit levels, as well as by filling the evidence gap on age and contribution time highlighted in Spinnewijn (2020). Closest to our paper is Michelacci and Ruffo (2015), which formulates a structural model of optimal UI over the life cycle. The authors find duration elasticities close to zero for workers younger than 40, but larger and significant ones for older workers (i.e., as in our sample) using state-level variation in benefit levels in the United States. Younger workers value UI more as they have fewer assets to smooth consumption throughout job loss. The authors conclude that welfare would increase if UI replacement rates decreased with age until age 40, and then stayed constant thereafter. In their economy, all periods of unemployment are covered by UI. Our paper complements this work by allowing for incomplete UI coverage with a maximum PBD, and showing that contribution time is a relevant tag for this key policy parameter. This result echoes Hopenhayn and Nicolini (2009), which shows that optimal UI contracts increase benefits in the length of past employment spells when unemployment is recurrent, and the planner cannot distinguish layoffs from job separations from firm-worker collusion.

The paper proceeds as follows. Section 2 introduces the theoretical framework for our analysis. Section 3 describes the German UI system and social security data. Section 4 presents the RD design used to obtain estimates of heterogeneous UI responses, and resulting estimates. Section 5 relates the estimates to age and contribution time in a meta regression. Section 6 implements the sufficient statistics for the welfare evaluation of existing PBD schedules in Germany. Section 7 draws broader insights for UI design, and

[9] E.g., Kolsrud et al. (2018) and Lindner and Reizer (2020) evaluate responses over the unemployment spell, and Schmieder et al. (2012), Kroft et al. (2016) and Landais et al. (2018) over the business cycle. See also Kroft and Notowidigdo (2016), Farber and Valletta (2015), Chodorow-Reich and Karabarbounis (2016) and Hagedorn et al. (2017) on UI generosity in the United States. Using a structural job search model, Birinci and See (2023) study how heterogeneity in wealth affects UI eligibility, take-up and replacement rates, as well as the resulting insurance-incentive trade-off.

Section 8 concludes.

2 Theoretical Model

2.1 Setup

In this section, we set up a partial-equilibrium model of job search with a differentiated UI policy. Specifically, PBD is allowed to vary across heterogeneous groups defined by a vector of any pre-determined worker characteristics $x \in X$.[10] Our empirical implementation will take $x = (a, c)$ to be specific combinations of age a and contribution time c. The model shows the redistributive welfare trade-offs induced by policy differentiation on top of the standard insurance-incentive trade-off of a homogeneous policy. We derive sufficient statistics that serve to locally evaluate the optimality of differentiated PBD schedules empirically using high-level moments. These moments make explicit the variables through which heterogeneity might occur, while limiting necessary structural assumptions, especially regarding deeper primitives shaping the environment and individual behavior. We describe the main components of our model below, and present further details and proofs in Appendix B.

Worker's problem. The model starts when workers enter unemployment at time $t = 0$. Workers in group x choose assets $A_{x,t} \geq A_{x,L}$, as well as their job search effort $s_{x,t}$, measured in terms of the job finding rate at every time t while being unemployed. Workers maximize their utility taking the UI policy as given. Until UI benefit exhaustion, the unemployed receive benefits $b_x = \rho(1-\tau)w_x < w_x$, where ρ is the UI replacement rate, w_x is the last wage, and $(1-\tau)w_x$ are net-of-tax past earnings. The benefit level is not explicitly differentiated in x, but varies with x via w_x.[11] Upon exhausting UI, the replacement rate falls and the worker draws unemployment assistance (UA) benefits $b_{0,x} < b_x$. Upon finding a job, workers pay a proportional income tax τ on their wage w_x, which is used to finance UI. In the baseline case, τ is uniform in x, as in virtually all publicly-funded UI systems, including Germany. In an extension, we allow for a group-specific tax rate τ_x. Such a tax is actuarially fair within group and there are no net transfers as each group x carries its own behavioral cost. Workers remain employed until the end of their working life in T_x. Wages are assumed to be constant, but we show in Section 2.4 that relaxing these assumptions does not affect our main conclusions. Workers' flow utility of consumption while unemployed is $u_x(c^u_{x,t})$ and while employed it is $v_x(c^e_{x,t})$.

[10] Our model extends the one in Schmieder et al. (2012), where policy is restricted to be homogeneous. It nests this case with either homogeneous or heterogeneous workers.

[11] Given our policy variation, we focus on the PBD and take the constant replacement rate as optimal across groups. Michelacci and Ruffo (2015) find that the optimal replacement rate is roughly constant above age 40, i.e. the lower age bound in our sample.

We assume that preferences are separable over consumption and leisure, and discuss this further in Section 6.

Planner's problem. We assume that the planner maximizes welfare for a cross-section of unemployed workers who enter unemployment within a given time frame, e.g. a calendar year, taking the composition of the cohort as given. For each cohort, the social planner chooses a PBD P_x for all $x \in X$ that maximizes welfare and may differ across groups x, while balancing the government budget for this cohort by adjusting the tax τ.[12] Social welfare at the beginning of the unemployment $t = 0$ aggregates welfare over all groups x accounting for their size:

$$W_0 = \sum_{x \in X} N_x [s_{x,0} V_{x,0}(P_x, \tau) + (1 - s_{x,0}) U_{x,0}(P_x, \tau) - \psi_x(s_{x,0})], \tag{1}$$

where N_x is the number of unemployed workers in group x in the cohort. $V_{x,0}(\cdot)$ is the life-time value of utility of a person who finds a job at time $t = 0$ and $U_{x,0}(\cdot)$ if they do not find a job. $\psi(s_{x,t})$ is the differentiable, increasing, and convex cost of job search. The planner's budget constraint is that the total tax revenue from all groups x equal total UI expenditures:

$$\tau \sum_{x \in X} N_x (T_x - D_x) w_x = \sum_{x \in X} N_x B_x b_x, \tag{2}$$

where $D_x = \sum_{t=0}^{T_x - 1} S_x(t)$ is expected nonemployment duration of group x with $S_x(t) = \prod_{i=0}^{T_x} (1 - s_{x,i})$ the survivor function at time t. $B_x = \sum_{t=0}^{P_x - 1} S_x(t)$ is expected UI benefit receipt duration, i.e. the part of nonemployment duration that is covered by UI. Dividing both sides of (2) by the total number N of workers in the cohort reveals that the planner needs to break even over a weighted average of group-specific tax revenue and UI expenditures, where the weights depend on group-specific (non-)employment and UI receipt durations. This dependency creates the possibility of redistribution. When only specific workers receive more generous UI, *all* workers share the tax burden. As we will show next, the behavioral responses in one group affect the welfare of others, who also bear the fiscal externality.

[12]Our model thus focuses on heterogeneity within a given cohort, and we suppress the dependence of all model parameters on the cohort to simplify notation. Unemployed workers can differ across cohorts due to, e.g. business cycle variation.

2.2 Fiscal Externality of Changing PBD

Consider now an extension of PBD P_x for group x.[13] To finance an increase in P_x, the planner needs to increase the tax τ for *all* employed workers. This policy change affects the government's budget constraint through labor supply responses, as workers do not internalize the fiscal externality that they create on the government's budget. Differentiating the budget constraint (2) with respect to P_x yields the following proposition.

PROPOSITION 1 (FISCAL EXTERNALITY). *Let $\bar{W} \equiv \sum_{x\in X} N_x(T_x - D_x)w_x$ denote total lifetime earnings that serve as the tax base for financing UI and $\bar{B} \equiv \sum_{x\in X} N_x B_x b_x$ total expenditures on UI such that $\tau = \bar{B}/\bar{W}$. The fiscal externality is given by:*

$$\frac{d\tau}{dP_x} = \frac{1}{\bar{W}} \sum_{x'\in X} \frac{dN_{x'}}{dP_x}\Big(B_{x'}b_{x'} - (T_{x'} - D_{x'})w_{x'}\frac{\bar{B}}{\bar{W}}\Big) + N_{x'}\Big(\frac{dD_{x'}}{dP_x}w_{x'}\frac{\bar{B}}{\bar{W}} + \frac{dB_{x'}}{dP_x}b_{x'}\Big). \tag{3}$$

See proof in Appendix B.

The fiscal externality has three components. First, changing P_x may affect group size $N_{x'}$ for some or all groups $x' \in X$, which can affect the size and the composition of the overall population of unemployed, as well as each group's. A larger share for a given group increases the weight this group has in tax revenue and UI expenditures even if its PBD is unchanged. In what follows, we assume that $\frac{dN_{x'}}{dP_x} = 0$ for all groups $x' \in X$. This rules out that workers in a given inflow cohort can manipulate the group x to which they belong when entering unemployment in response to the change in PBD. In the empirical implementation, we make a similar assumption when ruling out sorting around PBD cutoffs. Importantly, because the planner optimizes *within* cohort, this assumption does *not* rule out that a change in PBD in one cohort affects group-specific inflows into unemployment in later cohorts, e.g. by affecting future contribution time or the probability of becoming unemployed again.

The second component is the duration responses of group x that benefits from the increase in PBD. The derivative of nonemployment duration $\frac{dD_x}{dP_x}$ with respect to PBD captures the reduction in fiscal revenue from workers reducing job search efforts in response to longer coverage, which lengthens the time between the last and first job. The derivative of the duration of UI receipt $\frac{dB_x}{dP_x}$ captures the mechanical increase in transfers from longer coverage, as well as the behavioral cost from reduced job search effort by the unemployed over the period of coverage.

[13]To be able to work with derivatives with respect to P_x, we follow Schmieder et al. (2012) and assume that P_x can be increased by a fraction of 1, meaning that a fraction of the period $int(P_x)$ is covered by the higher benefit level b_x if P_x is not an integer number. Thus, benefits can change within a period and equals the fraction that is covered times b_x. In that case, a marginal change in P_x normalized by b_x is the same as a marginal change in b_x at time $t = P_x$.

Lastly, changes in job search effort of group x may have spillovers on the search outcomes $B_{x'}$ and $D_{x'}$ of other groups $x' \neq x$.[14] Our partial equilibrium approach rules out such spillovers and imposes $\frac{dD_{x'}}{dP_x} = \frac{dB_{x'}}{dP_x} = 0$ for all $x' \neq x$. It implies that firms do not adjust vacancy creation in response to changes in PBD and that workers' job-finding rates are unaffected by other workers' behavior.[15] Taken together, our assumptions yield a simplified formula for the fiscal externality which only stems from duration responses in group x itself:

$$\frac{d\tau}{dP_x} = \frac{N_x}{\bar{W}}\left(\frac{dD_x}{dP_x} w_x \frac{\bar{B}}{\bar{W}} + \frac{dB_x}{dP_x} b_x\right). \tag{4}$$

We discuss the general formula that does not rule out inflow and spillover effects in Section 2.4.

2.3 Welfare Effects of Policy Differentiation

Assuming no discounting and the absence of effects on group sizes, we show in Appendix B that the welfare effect of changing P_x can be written as:

$$\frac{dW_0}{dP_x} = N_x b_x \left[S_x(P_x) u_x'(c^u_{x,P_x}) - \left(\frac{dB_x}{dP_x} + \frac{dD_x}{dP_x}\frac{\bar{B}}{\bar{W}}\frac{w_x}{b_x}\right) \bar{v}'(c^e_{P_x}) \right], \tag{5}$$

where $S_x(P_x) = \prod_{i=0}^{P_x}(1 - s_{x,i})$ is the UI exhaustion rate of group x; $\bar{v}'(c^e_{P_x}) \equiv \sum_{x' \in X} \frac{\bar{W}_{x'}}{\bar{W}} v'_{x'}(c^e_{x',P_x})$ is the weighted average of the marginal utility of employed workers at time $t = P_x$;[16] and $\bar{W}_x \equiv N_x(T_x - D_x)w_x$ is expected lifetime earnings of group x.

The welfare derivative has three components. The first term $S_x(P_x)u_x'(c^u_{x,P_x})$ is the utility gain from longer UI coverage in group x that gets higher PBD, namely those who exhaust UI in group x. These workers value the additional transfers that smooth consumption between the employed and unemployed states. The second term in brackets is the unscaled fiscal externality in (4), i.e. the behavioral response to changing PBD. The last term $\bar{v}'(c^e_{P_x})$ measures the weighted average of the welfare losses of each group from reduced consumption while employed due to the higher tax paid by all workers in em-

[14]Reduced search effort of group x in response to the change in P_x may improve the job finding rate of the remaining groups if there is a fixed pool of vacancies at any t (Schmieder and Von Wachter, 2016).

[15]This is plausible for all groups x' that are sufficiently different from group x such that they do not compete in the same labor market. For the remaining groups, this will be more plausible the smaller group x is relative to all remaining groups that compete for the same vacancies.

[16]Here we follow Schmieder et al. (2012) and use the approximation that $E_{0,T_{x'}-1}[v'_{x'}(c^e_{x',t})] \approx v'_{x'}(c^e_{x',P_x})$. This approximates expected marginal utility while employed over the remaining working life in group x' with marginal utility at time $t = P_x$ in the unemployment spell where group x would exhaust UI. This is reasonable if nonemployment durations are short relative to lifetime employment, or if the people with shorter durations than P_x who have lower $v'_x(c^e_{x',t})$ are outweighed by individuals with longer durations.

ployment. The weights equal the share of expected lifetime earnings of group x' in total expected lifetime earnings, i.e. the share of group x' in the total tax base, $\bar{W}_{x'}/\bar{W}$.

To arrive at the final welfare formula and to allow better comparison with the previous literature, we start by normalizing the welfare derivative by group size N_x to resemble per capita quantities. Thereafter, we follow Schmieder and Von Wachter (2016). We divide by b_x to obtain marginal changes in transfers and by $S_x(P_x)$ as further normalizations. Next, we rescale the welfare derivative by $\bar{v}'(c^e_{P_x})$ such that the marginal welfare effect of a EUR 1 increase in the monetary value associated with an increase in P_x is measured in the units of marginal utility of a EUR 1 increase in consumption of the employed. Finally, we rewrite the duration derivatives in terms of the elasticities of UI duration and nonemployment duration to changing P_x. These elasticities are defined as $\varepsilon_{Y,x} = \frac{dY}{dP_x}\frac{P_x}{Y}$ for $Y \in \{B_x, D_x\}$ and correspond to what we estimate in reduced form in the empirical analysis.

PROPOSITION 2 (WELFARE FORMULA WITH UNIFORM TAX RATE). The welfare effect of changing P_x with a uniform tax rate can be written as:

$$\frac{d\tilde{W}_0}{dP_x} \equiv \frac{dW_0}{dP_x} \Big/ \Big(N_x b_x S_x(P_x) \bar{v}'(c^e_{P_x}) \Big) \tag{6}$$

$$= \underbrace{\frac{u'_x(c^u_{x,P_x}) - \bar{v}'(c^e_{P_x})}{\bar{v}'(c^e_{P_x})}}_{\substack{\text{Social value } SV_x \\ \text{of EUR 1 add. transfer}}} - \underbrace{\frac{1}{S_x(P_x)} \left(\varepsilon_{B,x} \frac{B_x}{P_x} + \varepsilon_{D,x} \frac{D_x}{P_x} \frac{\bar{B}}{\bar{W}} \frac{w_x}{b_x} \right)}_{\substack{\text{Behavioral cost } BC_x \\ \text{of EUR 1 add. transfer}}}. \tag{7}$$

See proof in Appendix B.

Interpretation. The first term on the right-hand side corresponds to the social value of increasing the per capita transfer to group x by EUR 1. It is equal to the relative gap between the marginal utility of benefit recipients in group x and the *average* marginal utility among *all* the employed. The second term is the behavioral cost generated by duration responses of group x to the PBD extension due to the taxes that the planner needs to raise to finance the EUR 1 increase in transfers.

The welfare formula aligns with the one in Schmieder and Von Wachter (2016), but adds key insights about policy differentiation. First, it illustrates how a uniform tax can create redistribution among the unemployed. The social value of a PBD extension for group x depends on the redistribution of welfare across unemployed and employed states not only within, but also across groups. This is because all the employed including all groups $x' \neq x$ pay a higher tax to finance the PBD extension for x. The social value decreases with increasing consumption of the unemployed in x. It increases with the expected consumption of the future employed within the current cohort of unemployed.[17] This makes the redistributive power of a differentiated policy salient, compared to the existing Bailey-Chetty frameworks with a homogenous UI policy. There, the social value equals the difference between the average marginal utilities in unemployment and employment, both averaged over all workers. Notice that $\bar{v}'(\cdot)$ gives more weight to groups that are larger, have a longer remaining working horizon, and earn higher wages. Since in practice these groups typically have higher consumption, they drive down the average marginal utility in employment with homogeneous preferences. This mechanism increases the social value of PBD extensions for groups with low consumption during unemployment. Raising the tax to finance P_x creates net transfers from employed high-consumers to unemployed low-consumers in group x.

Second, the social value can become zero or negative if the marginal utility of consumption during unemployment of group x is equal to or smaller than the average marginal utility of consumption during employment. That is, the utility gain from higher PBD in group x is smaller than the average utility loss from the higher tax among all of the employed. This case is excluded by the homogeneous policy case, under which the social value is always positive under imperfect insurance. In our case, negative gaps can occur, for example, if group x has higher-than-average wages or assets, which can happen for older workers or those with stable employment. When the social value is negative, the welfare derivative is negative even if the behavioral cost is zero. Then, extending PBD for group x does not increase welfare even without behavioral responses.

Sources of heterogeneity. Equation (7) reveals why the welfare derivative may differ across groups. The social value differs due to heterogeneous consumption levels during unemployment, which are driven by pre-unemployment earnings and savings. It can also differ in case of preference heterogeneity. The behavioral cost can vary across groups for two reasons. First, duration responses to a change in PBD in terms of B_x and D_x may be heterogeneous in x. Uncovering such heterogeneity in the duration elasticities is the key objective of our empirical analysis in Section 4. Second, the share of workers exhausting UI in group x as well as their average nonemployment and UI receipt durations relative to P_x determines the behavioral cost. Third, the behavioral cost varies with the PBD level at which the welfare derivative is locally evaluated. Thus, differences in duration and PBD levels under the actual policy matter on top of heterogeneity in duration elasticities. The term w_x/b_x in (7) is constant across groups in our setting because benefits are proportional to wages,[18] but the formula is more general.

Policy differentiation. The normalized welfare formula (7) lays out a framework to

[17]Since all individuals start unemployed in the model, this perspective ignores the possibility of redistribution across employed workers with different layoff risks (Ferey, 2022).

[18]Specifically, $b_x = \rho(1-\tau)w_x$ where $\tau = \bar{B}/\bar{W}$.

locally evaluate differentiated PBD schedules. Optimal UI policy maximizes social welfare, i.e., equalizes the social value and behavioral cost of UI evaluated at the actual PBD P_x for all groups x, such that $\frac{d\tilde{W}_0}{dP_x}\big|_{P_x} = 0$. If $\frac{d\tilde{W}_0}{dP_x}\big|_{P_x} > 0$, PBD for group x is too low, while it is too high if the welfare derivative is negative. In a homogeneous policy where $P_x = P$ for all $x \in X$, a necessary and sufficient condition for policy differentiation would be that $\frac{d\tilde{W}_0}{dP_x}\big|_{P_x} \neq 0$ for some $x \in X$.

Equation (7) further implies that comparing the welfare derivative across groups is sufficient to identify gains from marginally flattening or steepening the existing PBD schedule (Michelacci and Ruffo, 2015; Spinnewijn, 2020). If, for instance, $P_x \geq P_{x'}$ and $\frac{d\tilde{W}_0}{dP_x}\big|_{P_x} > \frac{d\tilde{W}_0}{dP_{x'}}\big|_{P_{x'}} > 0$, then the difference between P_x and $P_{x'}$ should increase (i.e. more differentiation), while the reverse inequality calls for less differentiation. If the welfare derivatives are the same for both groups, optimal PBD levels may be different than the existing ones but their optimal difference remains the same. It is a standard limitation of the sufficient statistics approach that it will not inform on the full optimal schedule, but in which direction to marginally alter PBD, in our case, for each group. In terms of differentiation, it will point towards a flatter or a more differentiated schedule.

Welfare-increasing, budget-neutral changes in PBD differentiation can exist if $\frac{d\tilde{W}_0}{dP_x}\big|_{P_x} > 0$ and $\frac{d\tilde{W}_0}{dP_{x'}}\big|_{P_{x'}} < 0$ for some $x \neq x'$. That is, the planner can increase welfare by making some groups better off during unemployment at the expense of others, without changing taxes. This is not possible when either workers or UI policies are restricted to be homogeneous. In Appendix B.5 we provide a more formal discussion of the conditions under which such changes in PBD schedules exist.

Total welfare derivative. Comparing the normalized welfare derivative in (7) across groups is informative about changes in PBD differentiation that increase welfare per capita. However, an important insight from our model is that the effect of an increase in transfers by EUR 1 on total welfare can differ across groups, even if the welfare gains per capita are the same. To see this, we can write the total welfare derivative rescaled by b_x and $\bar{v}'(c^e_{P_x})$ to resemble a marginal change in the transfer by EUR 1 measured in the units of marginal utility of a EUR 1 increase in consumption of the employed:

$$\frac{dW_0}{dP_x}\frac{1}{b_x\bar{v}'(c^e_{P_x})} = N_x S_x(P_x)\frac{d\tilde{W}_0}{dP_x} = N_x S_x(P_x)(SV_x - BC_x). \tag{8}$$

For the same per capita welfare derivative $\frac{d\tilde{W}_0}{dP_x}$, a EUR 1 change in the transfer will have a larger effect on total welfare for groups that are of larger size N_x, or have a higher benefit exhaustion rate $S_x(P_x)$. Moreover, even if the per capita welfare gains are larger for some groups than for others, changing their PBD may result in a total welfare gain that is smaller than for the other groups if any of the two parameters are sufficiently small compared to the other groups. Thus, comparing (8) across groups helps identify those groups for which changing PBD is most efficient.

2.4 Model Extensions

Group-specific tax rates. In the baseline case with a uniform tax rate *all* workers bear the fiscal externality of increasing PBD for group x, leading to redistribution of welfare across groups. As discussed above, this can lead to cases where the utility losses for tax payers exceed the utility gain of the group that receives higher PBD. An alternative tax policy that prevents redistribution across groups is to have group-specific tax rates τ_x that finance UI benefits for group x such that the government budget needs to be balanced within group. Imposing the same assumptions and following the same steps as before, the welfare formula with group-specific tax rates is given by:

PROPOSITION 3 (WELFARE FORMULA WITH GROUP-SPECIFIC TAX RATES). *If the planner obeys the budget constraints $(T_x - D_x)w_x\tau_x = B_x b_x$ for all $x \in X$, the welfare effect of changing P_x can be written as*

$$\frac{d\tilde{W}_0}{dP_x} = \underbrace{\frac{u_x'(c^u_{x,P_x}) - v_x'(c^e_{x,P_x})}{v_x'(c^e_{x,P_x})}}_{\substack{\text{Social value } SV_x \\ \text{of EUR 1 add. transfer}}} - \underbrace{\frac{1}{S_x(P_x)}\left(\varepsilon_{B,x}\frac{B_x}{P_x} + \varepsilon_{D,x}\frac{D_x}{P_x}\frac{B_x}{T_x - D_x}\right)}_{\substack{\text{Behavioral cost } BV_x \\ \text{of EUR 1 add. transfer}}}. \tag{9}$$

See proof in Appendix B.

Comparing (9) with (7) reveals that the social value of increasing P_x is higher with group-specific taxes if the marginal utility of employed workers in group x is smaller than average marginal utility, i.e. $v_x'(c^e_{x,P_x}) < \bar{v}'(c^e_{x,P_x})$, since group x suffers a smaller welfare loss from lower consumption when employed than the average worker in this case. This happens if group x consumes more when employed than the average worker. Moreover, within group the social value cannot become zero or negative under the assumptions of the model. As a result, the social value will always be higher with group-specific taxes for groups where $SV_x \leq 0$ under a uniform tax.

The behavioral cost is smaller if the group-specific tax is smaller than the uniform tax since $\frac{B_x}{T_x - D_x} < \frac{\bar{B}}{\bar{W}}\frac{w_x}{b_x} \Leftrightarrow \frac{B_x b_x}{(T_x - D_x)w_x} < \frac{\bar{B}}{\bar{W}} \Leftrightarrow \tau_x < \tau$. This is the case if the share of UI expenditures for group x in total expenditures is smaller than its share in the tax base, i.e. $\frac{\bar{B}_x}{\bar{B}} < \frac{\bar{W}_x}{\bar{W}}$, where $\bar{B}_x \equiv N_x B_x b_x$ denotes UI expenditures for group x and $\bar{W}_x \equiv N_x(T_x - D_x)w_x$ is its tax base. Ceteris paribus, this happens if the group's UI exhaustion rate $S_x(P_x)$ is below average, if it has above-average wages w_x, or if its post-UI employment duration $T_x - D_x$ is above average.

Whether UI benefits should be financed by uniform or group-specific taxes is a normative question that depends on the planner's preferences for redistribution. Group-specific taxes redistribute welfare across employment states within group. A uniform tax additionally redistributes welfare from other employed groups to certain unemployed groups. Moreover, both tax regimes will yield different optimal PBD schedules that result in different allocations of welfare across groups and employment states.

Inflow and spillover effects. In the baseline model, we focus on the case where group size is unaffected by changes in PBD and where there are no contemporaneous spillover effects across groups in the same inflow cohort. This is because this setting fits our empirical application well (see the discussion above and the evidence presented in the empirical part). For completeness, we derive the welfare formula that does not impose these assumptions in Appendix C.2. Note that allowing for manipulation of group size is equivalent to endogenizing the probability of becoming unemployed with characteristics x at a certain calendar time. An example for contemporaneous spillover effects across groups within inflow cohort is that other groups may find jobs easier if group s reduces search effort in response to higher PBD. These spillovers are different from effects of differentiated PBD schedules over the life cycle. In our application, workers who accumulate contribution time and become older move into different groups x over their working life. Accounting for this would require modeling endogenous (repeated) unemployment risk, such that workers can change group over time. More generous UI at older ages or with longer contribution time may then affect workers' current unemployment duration, and render both tags endogenous.

Heterogeneous welfare weights. In Appendix C.3 we allow for heterogeneous welfare weights in the spirit of Saez and Stantcheva (2016) where the planner can give a weight to each group x that may differ from its size N_x. We show that such weights do not affect the per-capita welfare formula (7) but the total welfare derivative (8) that aggregates over groups. Thus, increasing PBD for certain groups may be beneficial despite small per-capita gains and group size if their welfare weight is sufficiently large.

Wage effects of changing PBD. Appendix C.4 derives the welfare formula for the case where changing PBD may affect reemployment wages, which extends Nekoei and Weber (2017) to the case with heterogeneous workers and UI policy. Allowing for wage effects only changes the behavioural cost, which now includes the elasticity of reemployment wages to changes in PBD. Wage effects affect the government budget via the taxes collected from employed workers. In our empirical application, we estimate wage responses that are very small and not statistically significant at conventional levels, which supports our more parsimonious model.

3 Institutional Setting and Data

3.1 Unemployment Insurance in Germany

Eligibility and PBD determination. In Germany, laid off workers are eligible for unemployment benefits, provided they have contributed to social security for at least 12 months over a given eligibility time horizon before job loss.[19] Unemployment benefits are determined by a constant income replacement rate of 60% for workers without and 67% with dependent children, respectively, and exhaust at the PBD.[20] Our study period starts in January 1994 because the replacement rate has been unchanged since then, such that we can focus on variation in the PBD.

The PBD for new claims is a stepwise function of the worker's age and their contribution time at entry into UI. Contribution time is the number of months contributed to social security within a given time horizon before job separation. PBD typically increases by 2 months for every additional 4 months of contribution between the minimum requirement for UI eligibility and the age-specific maximum. Crossing age thresholds allowed workers to climb the ladder further, or jump to the age-maximum directly. Any unexpired leftover PBD from past unemployment spells is added up to the age-specific maximum. Appendix D.1 provides further institutional details on eligibility and PBD determination.

PBD regimes. Figure 1 shows the four different PBD schedules applied during our study period. The UI regimes were otherwise broadly comparable. In regime 1 (Panel a), the PBD ranged from 6 to 32 months. In 1997 (regime 2, Panel b), the age cutoffs were increased by three years. In February 2006 (regime 3, Panel c), the differentiation between age groups was sharply reduced. The maximum PBD decreased to 18 months for workers who worked the full 3 years before job loss, with only one age cutoff at 55. The reform also reduced the time horizon to determine eligibility from 36 to 24 months, and the PBD-determinant horizon from 84 to 36 months. Finally, in January 2008 (regime 4, Panel d), the schedule changed back to a middle ground, setting the maximum PBD at 24 months, and a PBD-determinant horizon of 60 months. The PBD was prolonged retroactively for ongoing claims.

Until 2005, individuals could go into means-tested unemployment assistance at benefit exhaustion. Unemployment assistance benefits were determined by a lower income replacement rate of 57% with and 53% without dependent children, respectively, and

[19]Few exceptions apply to, e.g., seasonal workers. Voluntary quits are penalised with a waiting time of up to 3 months. Non-compliance with job search requirements or refusal to accept suitable jobs can result in PBD sanctions.

[20]Insured earnings are capped, such that effective replacement rates are lower for older individuals with longer contribution times since a higher share reach the cap. However, the cap concerns about 1% of our sample, and does not affect our results.

depended on household wealth. In January 2005, the Hartz IV reform introduced means-tested, flat-rate benefits independent of previous earnings (Wunsch, 2005).

3.2 Social Security Data

We use social security records from the Integrated Employment Biographies (IEB) provided by the Institute of Employment Research (IAB). The data contain full records for a random sample of 10% of individuals who were ever in UI between January 1, 1994 and December 31, 2016. For each UI spell, the unemployment records contain the exact beginning and end dates of benefit payments, the PBD left at the end of the spell, and the amount of daily benefits. We observe a rich set of individual characteristics (age, gender, marital status, nationality, education, and region of residence).

Unemployment spells are matched to the full day-to-day social security records dating back to 1985. This includes employment subject to social security contributions, i.e. about 84% of all employment, with the main exceptions being students, self-employed workers, and civil servants (Price, 2019). We can hence impute the workers' contribution time, and match job characteristics before and after unemployment (daily wage, part-time job, industry, occupation, firm identifier).

Analysis sample. We select unemployment spells that start in the years 1994 to 2010 to avoid censoring outcomes (see the discussion below). After correcting for overlap and regrouping of consecutive spells, we obtain approximately 1.4 million spells of workers aged 40 to 55 at entry into UI.[21] As presented in Section 4, we estimate the effect of PBD extensions using an RD design at treatment boundaries in age and contribution time. The lower age bound thus ensures common support, since the lowest age cutoff in our study period is at 42 years of age. Furthermore, workers in their forties have typically participated long enough in the labor market to be able to reach any contribution cutoff. The upper bound serves to avoid confounding incentives for early retirement via UI.

For the sample at the age cutoffs (*age sample*), we take workers aged at most 2 years from the closest age cutoff, who satisfy the minimum contribution requirement to be eligible for the age-specific maximum above that cutoff. As for sample at the contribution cutoffs (*contribution sample*), we select spells with a new PBD equal to given steps of the schedule (e.g., 8, 10, 12 months). This automatically restricts the sample to workers eligible for a new UI claim under regular eligibility rules (i.e. excludes seasonal workers). We use the leftover PBD to recover the *new PBD* for spells below the age-specific maximum (see Appendix D.1). Leftover PBD is reported reliably as it is determined by the accounting system to define the duration of payments. This approach ensures that we correctly classify workers into PBD levels. That is, there is no misclassification of treat-

[21] Appendix D contains further details on data preparation and sample selection.

ment status, and we only consider spells with a *true* contribution time within a narrow window of 4 months on both sides of each cutoff. Contribution time as a running variable has to be recovered based on past social security records. We describe our procedure in detail in Appendix D.3. Despite having day-level social security records, there might be measurement error in our imputed measure.[22] In Section 4, we further discuss the advantages of our step-based approach in tackling the challenges to RD-based identification and estimation posed by measurement error in contribution time.

3.3 Descriptive Statistics

Observable characteristics. Panel (a) of Appendix Table D.3 presents summary statistics for observable characteristics in the analysis sample. The age and the contribution samples are both 48 years old on average. The age sample is more likely to be male, German, and to reside in West Germany. It also displays higher rates of UI use in the last 7 years, and shorter leftover and beginning PBDs on average.[23] By construction, the age sample has longer employment histories, as well as tenure in the last job.

Labor market outcomes. The key components needed to compute the fiscal externality are the elasticity of UI receipt duration (registered unemployment), and nonemployment duration (the time between the start of benefit payments and the first observed employment spell with a positive wage). Following Schmieder et al. (2012), we cap nonemployment duration at 36 months for longer or censored spells. Our main results are robust to alternative choices of this cap, which is higher than the highest possible PBD of 32 months. Panel (b) of Appendix Table D.3 shows that the age sample displays a slightly lower average nonemployment duration than the contribution sample at around 17 and 18 months, respectively. These lengths are close to Schmieder et al. (2012) and Schmieder et al. (2016) that use the same data in Germany, but a more restrictive sample of workers with stable contribution histories. They are however longer than averages reported in settings with similar UI institutions and data (e.g., Card et al. 2007 for Austria), and shorter than those reported in the United States (e.g., Card et al. 2015; Johnston and Mas 2018). The share of spells with censored duration is around 31%.

Figure 2 illustrates strong raw correlations between labor market outcomes and age, as well as contribution time in the analysis sample. Nonemployment and UI receipt

[22] This may be due to unobservable worker characteristics subject to special PBD determination rules (e.g. penalties for not accepting a suitable job, seasonal workers), or imprecisions in the social security records (e.g., overlapping spells, gaps in the labor market history, waiting times, misreporting of employment durations by firms for short-term contracts). Our sample restrictions aim to eliminate cases with more complex employment histories and non-standard UI incentives.

[23] Appendix Table D.5 presents further descriptive statistics, and compares our analysis sample to the initial sample of inflows. Our sample is representative of inflows eligible for more than the minimum new PBD and to which standard UI incentives apply.

durations are both positively associated with age. Older workers have on average higher survival rates at any given time in the unemployment spell, as well as benefit exhaustion rates. This influences both the value and cost of PBD extensions at the point of benefit exhaustion. In contrast, the durations decrease in contribution time, *despite longer PBDs*.

3.4 Implicit Tagging on Other Observables

Tagging on age and contribution time may lead to implicitly tagging on other correlated, mutable or immutable characteristics. We describe how age and contribution relate to other observables in Table 1.[24] Workers who are female, living in East Germany, with a low education tend to be more represented among older unemployed workers. The relationships are of the opposite sign and larger magnitude for a one-year difference in contribution time. In terms of labor market history, older workers tend to have higher earnings and are more likely to have held part-time jobs. Again, the correlations with contribution time are much stronger. Workers with stable employment have higher last-job and 10-year earnings.

These correlations imply that the policy implicitly tags on other immutable characteristics that are associated with higher vulnerability on the labor market (e.g. gender), but are typically not usable tags in practice. Second, it mechanically tags on other variables correlated with employment stability. This has implications for how tagging shapes the welfare effects of UI across population groups, in particular over the income distribution. In our analysis of response heterogeneity, we will explore whether pre-determined characteristics are sources of confounding in how age and contribution determine responses to UI.

4 Reduced-Form Analysis of Response Heterogeneity

Our characterization of the heterogeneous responses to PBD extensions proceeds in two steps. First, we exploit the many discontinuities in the German PBD schedule in an RD design to estimate duration elasticities across many cells of workers defined by age and contribution time. Second, we regress the cell-level estimates on age and contribution to uncover any systematic relationship.

4.1 Multidimensional RD Design

The PBD schedule in Germany allows for a sharp RD design augmented in two key dimensions compared to standard single-cutoff, single-score designs. Unemployed workers

[24]The cell-level sample shows virtually identical results (not shown).

have two running variables measured at entry into UI: their age in years a_i, and their contribution time in months c_i.[25] Additionally, workers face multiple cumulative cutoffs in both running variables. This translates into a set of treatment boundaries in age and contribution time at which PBD changes discontinuously. Panel (a) of Figure 3 illustrates these boundaries in the age-contribution treatment plane for the first regime in our observation period. Take an individual who is 48 years old and has 53 months of contribution. Being one year older would increase their PBD from 22 to 26 months as they would cross the 49-years age boundary. However, increasing their contribution time only would not lead them to increase their PBD, since they are already at the age-specific maximum.

The design relies on a local continuity assumption to identify treatment effects at the boundaries: The expected potential outcomes and density of the running variables are continuous around the boundaries, and provide valid counterfactuals in both treatment states. In other words, the labor market outcomes would not change sharply at the boundaries in their absence as no other changes than the PBD occur there. This also implies that workers or employers cannot precisely manipulating the timing of job separations around the boundaries. In particular, workers cannot delay their entry into UI in order to select into higher PBD steps. We systematically test the plausibility of these assumptions across all cells in Appendix E.[26]

4.2 Cell-Level Estimation

Pooling all cutoffs identifies a weighted average of local elasticities at each cutoff value, weighted by the probability of facing a particular cutoff (Cattaneo et al., 2016). While this parameter is certainly relevant, it may hide substantial heterogeneity in age and contribution that is informative for policy differentiation. Our goal is therefore to produce additional moments to identify any systematic response heterogeneity. To this end, we estimate the effects within disjoint cells as illustrated in Panel (b) of Figure 3. Splitting the sample along all regime-specific age and contribution boundaries, as well as by year yields 434 cells. Appendix E.1 provides further details on cell construction. Figure E.3 shows the actual position of these cells, which provide good coverage of the treatment plane. A cell includes about 1,200 spells on average (Appendix Table E.2). The largest cells are located at prime-age and low contribution cutoffs, as well as higher age and contribution cutoffs. Intermediate contribution cutoffs that only apply to older workers have the least observations. Splitting the plane involves a trade-off between the precision

[25] The time horizon for contribution time differs across regimes. We refrain from regime-specific notation for ease of exposure, but take these differences into account in our implementation.

[26] We assume throughout the analysis that our sample is drawn from a well-defined, representative population of unemployment spells, and that the stable unit treatment value assumption holds, in that there are no spillovers between the unemployed with different PBD levels, in line with our theoretical model.

of single RD point estimates, and the amount of point estimates to feed into the elasticity regression. In robustness checks, we show that the precision of our RD estimates increases when cells are aggregated.

Estimation in age cells. We estimate nonparametric local polynomial regressions at age cutoffs:

$$Y_{i,s} = \alpha^a_{s,+} + \beta^a_{s,+} f^p(\tilde{a}_{i,s}) + \nu^a_{i,s} \tag{10}$$

where $Y_{i,s}$ is the outcome of interest (nonemployment duration, UI receipt duration, or wages at reemployment) of unemployment spell i in cell $s = 1, \ldots, S^a$. $f^p(\cdot)$ is a polynomial of order p in age centered at the cell-specific cutoff, $\tilde{a}_{i,s} \equiv a_{i,s} - \bar{a}_s$. Age is measured precisely in our data. Within each sample, we conduct the estimation separately to the right (+) and to the left (–) of the cutoff, using weighted least squares with a kernel function in centered age (Cattaneo et al., 2020). The nonparametric RD effect estimate in cell s is the difference in intercepts above and below the cutoff, $\hat{\delta}^a_s = \hat{\alpha}^a_{s,+} - \hat{\alpha}^a_{s,-}$. Standard errors are obtained using a block-bootstrap with replacement and clusters at the individual level. Our preferred estimator uses a linear polynomial, a triangular kernel, and a bandwidth equal to the minimum between 2 years and the midpoint to the adjacent cutoff on each side. We exclude spells in a window of two weeks around the cutoff to avoid manipulation issues (Schmieder et al., 2012) and since age is rounded to three days in our data. Our results are robust to these choices, as well as the inclusion of covariates (Appendix Table G.3).

Estimation in contribution cells. We assign observations to cells based on new PBD. This approach identifies which 4-month window true contribution time lies in, and ensures correct classification into treatment within cell, although the exact position relative to the cutoff remains uncertain. To estimate the treatment effects, we impose a parametric assumption on the potential outcome function and use the following specification:

$$Y_{i,s} = \alpha^c_s + \delta^c_s D_{i,s} + \beta^c_s f^p(\tilde{c}^*_{i,s}) + \nu_{i,s} \tag{11}$$

in all contribution cells $s = 1, \ldots, S^c$, where $D_{i,s}$ denotes the true treatment status. The specification allows for a linear ($p = 1$) effect of centered, imputed contribution time $\tilde{c}^*_{i,s} \equiv c^*_{i,s} - \bar{c}_s$, separately for treated and control observations. The treatment effect estimate is given by $\hat{\delta}^c_s$. The smaller size of contribution cells compared to age cells requires restricting the estimator's flexibility. The closeness of the contribution cutoffs limits our ability to increase the bandwidth for power. Local linear regressions are imprecise in cells with few observations at the cutoffs.

Knowing the true treatment and the narrow contribution window it corresponds to has two key advantages. First, it allows verifying whether a discontinuity in treatment assignment exists as a function of imputed contribution time, and to learn about the distribution of measurement error. If measurement error affects a large share of observations, the first-stage discontinuity in treatment assignment may fade out, causing strong attenuation bias in the RD estimation (Battistin et al., 2009; Davezies and Le Barbanchon, 2017; Pei and Shen, 2017). Appendix Figure D.1 shows a sharp jump in the true treatment status as a function of imputed contribution time centered at the closest cutoff. The share of observations correctly classified based on imputed contribution equals 85% within a 4-month bandwidth. These findings indicate that imputed contribution time is a mix of correct and mismeasured observations, with a low share of the latter. RD-based identification is possible, but estimates may be attenuated (Battistin et al., 2009; Le Barbanchon, 2016; Davezies and Le Barbanchon, 2017; Bartalotti et al., 2021).[27]

Second, the narrow window makes the functional form assumption less restrictive. To illustrate this, we run difference-in-means RD estimates that simply compare the average outcomes below and above the cutoff, without using imputed contribution time.[28] This produces very similar results in terms of the moments of the elasticity distribution, as well as the meta regression results, compared to RD estimates as in (11). This check supports that biases from measurement error or functional form misspecification are likely to be small.

Validity of the RD design. PBD determines the value of unemployment relative to working and other transfer programs. Jumps in PBD may incentivize the delay of job separations such that workers become eligible for (more generous) coverage. Selection can locally invalidate the RD design. In line with previous studies, our data show a spike in inflows into UI at 12 months of contribution, as well as among workers eligible for early retirement via UI.[29] Therefore, we focus on the interior of the treatment plane and exclude the two lowest contribution cutoffs, which use just-eligible workers as either treated or control observations. We also exclude age cutoffs larger than 55.[30] In a second

[27] An option to correct for the attenuation bias is to use a fuzzy RD estimator. Le Barbanchon (2016) estimates the effect of UI eligibility using a cutoff in contribution time. The author uses a sharp RD in his main analysis, with the treatment imputed based on past employment records. Additionally, he implements a fuzzy RD where the imputed treatment is used as an instrument for the eligibility entered manually by caseworkers in the unemployment records, in the spirit of Battistin et al. (2009). We are underpowered to implement this approach, which yields noisy results, available upon request.

[28] This estimation can be interpreted as based on an identifying assumption of local randomization rather than local continuity (Cattaneo et al., 2020).

[29] While beyond the scope of our intensive-margin analysis, this pattern suggests that shifting the cutoffs at the extremes of the schedule is likely to have substantial welfare implications. For evidence on early retirement via UI, see, e.g. Sander and van Ours (2010); Baguelin and Remillon (2014); Inderbitzin et al. (2016); Ye (2022). For evidence on inflow effects at eligibility thresholds, e.g. Winter-Ebmer (2003); Khoury (2023); Citino et al. (2022); Albanese et al. (2020); Brébion et al. (2023).

[30] Gudgeon et al. (2023) impose the same age restriction in the German UI setting when estimating RD-based intensive-margin responses to UI among older workers.

step, we flag cells that display evidence of selection by running RD validity checks (e.g. no sorting in covariates, smooth density of the running variable), described in detail in Appendix E.2.

Figure E.3 shows the position of the cells failing any of the validity checks in the treatment plane—a first interesting result of our cell-based approach. There is no systematic pattern of selection in the interior of the plane, which supports the validity of our local estimates. The lack of local manipulation at the boundaries also limits concerns about workers selecting into PBD levels over longer time horizons. Precisely selecting into specific PBD steps would require a thorough knowledge of the complex PBD determination rules in Germany, one's exact contribution time, and very precise control over the timing of job separations.[31] Moving forward, we use the 314 valid cells (72 percent) that pass all criteria in the interior of the treatment plane. Excluding invalid cells from the interior does not affect our main conclusions.

4.3 Regression of Elasticity Estimates

Our cell-based RD estimation produces a large set of effect estimates that are allowed to vary flexibly along the age and contribution boundaries. Together with regime changes, this variation helps uncover any systematic relationship between tags and responses by estimating a function $\varepsilon_Y(a,c,Z)$.

Estimation. We pool the effects and bring onto a comparable metric by rescaling them into elasticities $\hat{\varepsilon}_{Y,s} = \frac{\hat{\delta}_s/\bar{Y}_s}{\Delta P_s/P_s}$, as the baseline duration, $\bar{Y}_s$, PBD levels, P_s, and PBD changes, ΔP_s, vary across cells. We then regress the elasticity estimates at the cell level with the following specification:

$$\hat{\varepsilon}_{Y,s} = \theta \bar{a}_s + \zeta \bar{c}_s + \sum_{j=1}^{J} \eta_j \bar{Z}_{j,s} + \mu_t + \upsilon_s, \tag{12}$$

where $\hat{\varepsilon}_{Y,s}$ is the estimated elasticity of Y (nonemployment and UI receipt duration) w.r.t. PBD in cell s; $\bar{a}_s$ measures age; and $\bar{c}_s$ contribution in years. For estimates based on age cutoffs, age is equal to the value of the cutoff and contribution to the sample average, and vice versa for estimates based on contribution cutoffs. We use contribution measured over three, five and seven years (as implemented in actual regimes) to assess which horizon is most predictive of responses. $\bar{Z}_s$ is a vector of covariates; μ_t are regime fixed effects; and υ_s is the error term. The estimation uses least-squares and inverse-variance weights to account for the precision of the underlying estimates.

[31] In Denmark, where unemployed job seekers can extend their PBD by taking up temporary or part-time jobs, Altmann et al. (2022) find that job seekers have limited knowledge regarding the entitlement rules and personal entitlements.

Interpretation and confounders of response heterogeneity. The coefficient on age θ can be interpreted as the change in the elasticity for a one-year increase in age at job loss, holding everything else constant. Similarly, ζ measures the change for a one-year increase in contribution time over the specified horizon.

We control for cell-level differences to assess whether age and contribution carry unconditional information about job search behavior, or also about other correlated determinants of responses. First, we include the PBD level to estimate policy-invariant response heterogeneity. Older workers with longer contribution reach a higher PBD level by design, and these extensions occur at different points in the unemployment spell.[32] By holding constant the PBD, we check whether the coefficients measure response heterogeneity driven by the tags used for policy differentiation, or by the policy differentiation itself. Second, we control for observable compositional differences across cells. This allows checking whether the coefficients on age and contribution absorb any underlying heterogeneity in correlated characteristics which are not used as tags, e.g. gender or education. Third, the share of spells by quarter and regime fixed effects account for economic conditions and regime-specific incentives, which have been shown to matter for responses to UI in our setting (Schmieder et al., 2012).

Extrapolation. The two-step estimation handles response identification separately from extrapolation with tractable and transparent assumptions. In the RD step, we can conduct validity checks along the boundaries to identify those parts affected by selection around the cutoff, and focus on credibly-identified estimates. A single, global estimation would require the identifying assumptions to hold across the board. In the regression step, the comprehensive coverage of the treatment plane and regime changes provide independent variation that allows teasing out response heterogeneity in age and contribution, conditional on other sources of cell-level heterogeneity. Although the coefficients cannot be interpreted causally, the regression uses causal estimates based on exogenous variation in the two dimensions of interest. The estimated linear function $\varepsilon_Y(a,c,Z)$ can be used to predict the structural elasticity over the treatment plane (e.g. for a representative unemployed worker or for given groups $x=(a,c)$). To this end, the estimated elasticity should not systematically differ from the structural one in ways that are correlated with age and contribution, e.g. due to measurement error or violations of the local continuity assumption. While we cannot test the former, we present evidence supporting that the probability

[32] Behavioral responses may vary with time in unemployment depending on the strength of anticipation and dynamic selection effects. On the one hand, increasing generosity later in the spell might be costlier as it discourages both short- and long-term unemployed to decrease their job search efforts in anticipation of longer coverage. On the other hand, workers may respond less as the PBD extension comes later in the spell and concerns only a selected group of long-term unemployed. There is however little empirical evidence for a tilt in this profile. Kolsrud et al. (2018) show that the average duration response is the relevant quantity in case of a flat benefit profile. In their implementation, the authors find that the moral hazard cost of UI is larger early in the spell, if anything.

that a cell is valid is not significantly associated with age and contribution time (Table E.2). An example of a similar two-step regression is Seibold (2021), who uses multiple kinks in the German retirement schedule to evaluate how retirement behavior depends on financial incentives and retirement norms.

5 Response Heterogeneity in Age and Contribution Time

5.1 Descriptive Statistics for Elasticity Estimates

Elasticity of nonemployment duration. Our results show that PBD extensions reduce job search effort. The upper-left panel of Figure 4 presents binned raw averages of the nonemployment duration elasticity, which is positive across the board.

We find average elasticities of 0.38 in valid age cells, 0.16 in contribution cells, and 0.26 when pooling both types of valid cells. This is in line with the 0.2–0.4 benchmark range in the review in Tatsiramos and van Ours (2014). As seen in panel A of Table 3, the moments are very close when taking only valid, and all cells (columns 1 and 2). 16 percent of estimates are positive and significant at the 5 percent level splitting the RD cells by year (column 1). This is similar to Nekoei and Weber (2017), who report 21 percent of duration effects as significant at the 5 percent level in a subsample analysis with a virtually-identical average sample size of 1130 spells. The lower share we estimate is likely due to the sample spanning a broader range of cutoffs, some of which are less salient. The share of positive significant estimates increases to 38 percent when cells are split by regime and gain power (column 3). The share of statistically significant negative estimates is below 5 percent across all versions, and is likely due to noise.[33] We return to the issue of statistical power at our two estimation steps below.

Elasticity of UI receipt duration. The average elasticity equals 0.73 for age cells, 0.59 in contribution cells, and 0.65 when pooling both (panel B of Table 3). Consistent with previous studies, and as seen in Figure 4, the estimates are larger than for nonemployment duration as they reflect a mechanical cost of PBD extensions. They are more precise as they rely directly on UI spell dates. The share of statistically significant positive estimates is of 44 percent. This share increases to 74 percent when splitting cells by regime instead of year. Very few estimates are negative and significant.

5.2 Regression Results

We now test for heterogeneity in responses to UI using meta regressions of the elasticity estimates. Table 2 shows coefficient estimates on age and contribution time from (12).

[33] Appendix Figure F.1 shows the distribution of estimates by statistical significance.

Our findings highlight heterogeneity in short-term contribution time, revealing that elasticities are approximately half as large for individuals who have worked continuously over the last three years compared to those who worked for half of this period.

Elasticity of nonemployment duration. The coefficient on age is statistically insignificant, even when controlling for compositional differences, time effects, and PBD levels. This indicates that older workers do not exhibit systematic differences in their behavioral response to PBD extensions, consistent with findings in Schmieder et al. (2012).

Workers with longer recent contribution periods (last 3 years) show significantly smaller elasticities in nonemployment duration, after adjusting for PBD levels. Specifically, individuals with stable short-term employment reduce their job search efforts less in response to PBD extensions, all else being equal. This gradient, initially nonsignificant without controlling for the PBD level (column 1), becomes significant and equals a decrease of 31 percentage points for every additional year contributed in column (2), when controlling for PBD. This highlights that the existing policy differentiation is an important confounder due to its mechanical correlation with age and contribution time.

In contrast, we find that adjusting for sample composition and time effects has minimal impact on the estimates. This indicates that short-term contribution time drives behavior beyond other correlated determinants of labor market outcomes. Individual characteristics show limited predictive power for elasticities.[34] Our design offers little power to assess the heterogeneity driven by non-tag characteristics due to less variation across cells.

Meanwhile, longer horizons of five and seven years are not significantly associated with duration elasticities, even after controlling for PBD. This may be due to attenuation bias or potential nonlinearities in the relationship, although we do not have sufficient power and variation to identify those, and as the potential for measurement error increases with the horizon over which we impute contribution time. Table 5 presents alternative specifications with includes a dummy for cells where contribution in the last 84 months exceeds 80 months. Although this dummy also captures the maximum PBD level, the significant negative point estimate suggests that the long-term contributors differ in their behavior and drive part of the linear gradient. At around –25 percentage points, the coefficient on contribution time in the last three years remains close to our main estimate.

The right-hand panel in Figure 4 presents adjusted (based on column 2) estimates by age and contribution time in the last three years, which is the most relevant horizon for differentiation. Adjusted elasticities are close to zero for older workers with stable contribution and reach up to 0.56 for prime-age workers with unstable employment in the

[34] Detailed results for the adjusted specification in column (2) are provided in Appendix Table G.1.

last three years.

Elasticity of UI receipt duration. The portion of nonemployment duration covered by UI mechanically increases with PBD, even in the absence of behavioral responses. Initially, we observe a positive and significant coefficient on age at 2.1 percentage points without adjusting for PBD. However, this coefficient diminishes to approximately 0.8 percentage points and loses significance in PBD-adjusted specifications. If anything, there appears to be a slightly higher transfer cost due to increased benefit exhaustion rates among older workers, resulting in a larger proportion benefiting from PBD extensions.

The elasticity of UI receipt duration significantly decreases by 26 percentage points for each additional year contributed in the last three years, after adjusting for sample composition and PBD level. This point estimate is slightly smaller than the one for nonemployment duration, suggesting that the gradient primarily stems from behavioral responses. We find no discernible heterogeneity across longer contribution horizons. Figure 4 illustrates that the adjusted elasticity of UI receipt duration ranges from 0.39 for prime-age workers with stable employment to 0.85 for the oldest age group with unstable employment histories.

Discussion. These results offer several key insights. First, contribution in the last three years carries the most information regarding unobservable factors that influence the mechanical and moral hazard responses to UI. This horizon aligns with the one that determines eligibility for unemployment benefits. Another explanation is that short-term contribution time serves as a stronger proxy for recent unemployment and current human capital. In contrast, longer contribution horizons seem to be a noisier signal. Given this, our robustness checks focus on the three-year contribution horizon. Second, controlling for PBD level is crucial for revealing gradients in contribution time but not in age. Third, in our sample aged 40-55 not yet eligible for early retirement, age alone does not predict heterogeneous responses, when conditioned on contribution time. This finding highlights that the two tags capture distinct determinants of job search behavior.

The magnitude of our elasticity estimates for the long-term contributors and lack of an age gradient are in line with Schmieder et al. (2012). The authors do not find age heterogeneity even when lifting the restriction of maximum eligibility, although they do not account for differences in PBD levels. Our analysis adds to their results by showing that contribution time is an important determinant of job search behavior, and that accounting for the underlying policy differentiation matters for eliciting response heterogeneity.

5.3 Robustness Checks

We assess the robustness of our reduced-form results by varying several methodological choices and sample restrictions.

RD validity criteria. So far, we have used valid cells and discarded those displaying selection effects. We present results using all cells in column (2) of Table 3. The means of the elasticities are somewhat larger, which suggests that our validity criteria do exclude estimates with negative selection. However, the key associations in terms of sign and magnitude are robust, with slightly smaller standard errors. This comparison reassures that our validity criteria—and the underlying methodological choices and compositional changes—do not drive the results. Age and contribution are not predictive of cell validity in the interior of the treatment plane (Table E.2).

Aggregation level. As discussed earlier, there is trade-off in statistical power between the two stages of estimation. More disaggregation in the RD estimation may lead to noisier estimates but provides more degrees of freedom in the meta regression. To test for this, we increase the level of aggregation of cells. We maintain the age-by-contribution split as in Figure 3, but pool years within regimes (Table 3 columns 3 and 4), and biannually (column 5). Our findings confirm this trade-off. The average elasticity varies little across versions, for both nonemployment (0.24–0.28) and UI receipt duration (0.61–0.66). Compared to the main version by year (column 1), estimates are more precise when splitting by regime or biannually. The mean standard error decreases substantially, and the share of statistically significant positive estimates increases from 0.16 to 0.38 for nonemployment duration, and from 0.44 to 0.74 for UI receipt duration. This supports that the significant estimates in column (1) are not a result of sampling error.

While, as expected, the meta regression standard errors increase, our qualitative conclusions remain robust. For nonemployment duration, the point estimates stay within a close range for both tags. The coefficient on contribution time increases with aggregation. It grows and becomes nonsignificant for the valid cells by regime, though that regression uses only 47 cells. From the perspective of statistical power, this pattern suggests that our main, most disaggregated version provides a conservative estimate of how the moral hazard cost of UI varies with contribution time.

As for UI receipt, the point estimates on contribution time remain negative but display more sensitivity to the validity and aggregation of cells. They remain smaller in absolute value than for nonemployment duration, supporting our conclusion that behavior drives duration responses. An explanation for the higher sensitivity to aggregation of the UI receipt duration compared to nonemployment duration is that the former is more strongly correlated with the business cycle (Schmieder et al., 2012). Aggregating years within regimes pools together different points of the business cycle, and restricts the ability to control for time effects.

Measurement error and RD estimator. We now provide suggestive evidence on how measurement error in contribution time influences results. In column (6) of Table 3, we use a subsample of spells where contribution time is more precisely measured. The so-called *consistent sample* contains spells where the new PBD equals the imputed PBD based on age and contribution time (i.e. imputed contribution lies in the corresponding 4-month window). This sample is similar to the main analysis sample in terms of demographic characteristics, but has more stable employment histories, i.e. fewer gaps in social security records that we cannot characterize (Table D.5). This suggests that the consistent sample is positively selected on employment stability, which may correlate with measurement error. Le Barbanchon (2016) also finds this type of selection. The average UI receipt and nonemployment duration elasticity are higher at 0.74 and 0.37, respectively. The meta regression point estimate on contribution time is larger in absolute magnitude for nonemployment duration. These results suggest that measurement error may introduce attenuation bias at both the RD and the meta regression stages of our estimation. Again, this suggests that our estimates of the elasticity gradient in contribution time are conservative.

As discussed in Section 4, we assess whether our results are sensitive to our choice of RD estimator. In particular, we vary the flexibility of the functional form on both sides of the cutoff, and control for covariates. Appendix Figure F.2 shows the distribution of elasticity estimates across alternative estimators. We then run the meta regression using the elasticities from alternative combinations of estimators (Table G.3). The point estimates stay within the same range across all versions, except when using a quadratic polynomial for age cells. Importantly, using a difference-in-means estimation for the contribution cutoffs (i.e. not making use of imputed contribution time, column 1) yields very similar estimates to the main version (column 2).

Finally, we check whether our findings are driven by specific labor market pathways. In column (1) of Table 4, we exclude spells with contribution times equal to a round year, e.g. due to selection at the boundary, or fixed-term contracts which are likely over-represented just above contribution time cutoffs, as in Le Barbanchon (2016). The conclusions remain unchanged, with a larger point estimate for contribution, which indicates that our findings are unlikely to be driven by selected individuals with fixed-term contracts.

5.4 Additional Labor Market Outcomes and Subsample Analyses

Job quality and further outcomes. In Table G.2, we present results from meta regressions of the elasticities of other labor market outcomes, to inform on mechanisms. Our results are robust to capping nonemployment duration at 48 and 60 instead of 36 months.

We find little evidence for heterogeneity in the wage elasticity, besides a small negative coefficient on age. If anything, wage responses represent a small part of the gradient in the fiscal externality of UI, as elasticities are small relative to the duration-related components. This finding is expected given that the estimates are small and imprecise. They fall into the range of mixed estimates in the literature (Nekoei and Weber, 2017; Schmieder et al., 2016; Le Barbanchon, 2016). Our cell-based approach has limited power to detect wage effects.

The probability of being unemployed again within 36 months (after finding a job) is not significantly associated with age nor contribution time. This suggests that PBD increases do not necessarily affect the future recurrence of unemployment. We find no significant age nor contribution gradient in the probability of earning over 80% of the last wage one year after job loss, the tenure in the first job, the probability of the first job being part-time, and the cumulative earnings within 60 months after job loss as alternative proxies for job quality. Very few of the underlying elasticity estimates are statistically significant.

Time effects. In columns (3) and (4) of Table 4, we test the stability of our findings over time, in particular before and after the UA reform in 2005 which altered benefits after UI exhaustion. The estimates do not display significant differences before and after the reform, although the post-2005 contribution point estimate is less precise due to the smaller number of cells entering the meta regression. This reassures that the change in the time profile of post-unemployment benefits does not alter our main conclusions.

Macroeconomic conditions in Germany varied over our study period, with two recessions in 2001–2003 and 2008–2009. The business cycle has shown to matter for the fiscal externality of UI (Schmieder et al., 2012). In our preferred specification, we account for time effects by including regime fixed effects and the national unemployment rate. Our results are robust to alternatively including year fixed effects to control more flexibly for fluctuations in economic conditions (column 5).

6 Welfare Analysis

This section estimates the welfare effects of a PBD extension for a *specific age-by-contribution group x* using our sufficient statistics. The estimates shed light on heterogeneity, underlying mechanisms, and the local optimality of each of the four UI regimes in our observation period.

6.1 Empirical Implementation

We compute the welfare derivative in (7) for each group x, which corresponds to a bin defined by 1-year age in the range 40-55 and 4-month contribution time over the reference period used in the regime.[35] We evaluate $\frac{d\tilde{W}_0}{dP_x} = SV_x(P_x) - BC_x(P_x)$ at the *actual* P_x, which varies across regimes. We do not restrict heterogeneity across bins, even those that have the same PBD level. In other words, we take the PBD schedule as given, but our evaluation may reveal finer heterogeneity for differentiation within PBD steps. We use the full, representative sample of inflows into UI within our age range in each regime.

Behavioral cost. We take bin-level averages for $S(P_x), P_x, B_x, D_x, w_x, b_x$, as well as to compute the constant $\bar{B}/\bar{W}$. To extrapolate the duration elasticities $\varepsilon_{Y,(a,c)}$ over the entire treatment plane, we use our estimates of the fully-adjusted functions $\varepsilon_Y(a,c,Z)$ (see Table 2), which account for P_x. The elasticities are the only parametrically-estimated components of the behavioral cost.

Social value. To estimate the social value of UI across groups x, we rely on a consumption-based approach (Gruber, 1997; Chetty, 2006), which requires several assumptions on the utility function. First, we assume that preferences are separable over consumption and leisure, and are employment-state independent, such that $\partial u_x(c,s)/\partial c = \partial u_x(c)/\partial c = \partial v_x(c)/\partial c$.[36] Second, we assume that preferences are homogeneous $u_x(c) = u(c)$. We discuss the implications of heterogeneous preferences in Section 6.3. Third, we use a first-order Taylor approximation[37] of the marginal utilities $u'(c_x^u)$ around c_x^u, and $v'(c_x^e)$ around the average consumption just before job loss, $\bar{c}^e \equiv E_x[c_x^e]$, where E_x takes the weighted average with weights $\frac{\bar{W}_{x'}}{\bar{W}}$. Fourth, using state independence and the approxima-

[35] The bin size ensures that bins have a sufficient number of observations, and that bins do not cross existing PBD cutoffs. We drop any bins with fewer than 30 observations.

[36] This rules out complementarities between consumption and leisure. Although standard in consumption-based valuations of UI, this assumption is not trivial when analyzing heterogeneity. For instance, individuals may substitute food expenditures for home production during unemployment. Recurrent users of UI may be more experienced in smoothing consumption with home production, and generally in adapting their use of financial and time resources to job loss. As discussed in Hen (2199) and Kolsrud et al. (2018), the implications of the state-independence assumption for inferring the social value of UI are ambiguous. On the one hand, home production reduces the drop in actual consumption, and thus the marginal benefit of UI extensions. On the other hand, complementarity between expenditures and home production mays decrease the marginal benefit. See also Aguiar and Hurst (2005) for a discussion in the context of retirement. Ultimately, our analysis relies on consumption expenditures and simulated values of risk aversion to yield accurate measures of the marginal utility of actual consumption.

[37] Assuming that higher-order terms are negligible means ignoring the term which contains the coefficient of relative prudence, and captures precautionary saving motives (Chetty, 2006).

tion $E_x[v'(c_x^e)] \approx v'(\bar{c}^e) = u'(\bar{c}^e)$,[38] the social value in (7) becomes:

$$\frac{u'(c_x^u) - v'(\bar{c}^e)}{v'(\bar{c}^e)} = \gamma \frac{\bar{c}^e - c_x^u}{\bar{c}^e},$$

where $\gamma \equiv -\bar{c}^e \frac{u_x''(\bar{c}^e)}{u_x'(\bar{c}^e)}$ is the coefficient of relative risk aversion. We can recover the social value as the wedge in consumption levels between employed and unemployed states, scaled by the coefficient of relative risk aversion.

Consumption data. We use survey data on consumption from the German Socio-Economic Panel (GSOEP). The GSOEP is a representative longitudinal survey of households in Germany. Consumption was surveyed in 2010 only, i.e. the last year in our IEB analysis sample. The household head is asked to report household consumption in terms of the average monthly or yearly expense, retrospectively for 2009. The GSOEP is the only dataset in Germany which contains information on both consumption and employment, as well as a rich set of individual characteristics also available in the IEB data. This allows imputing consumption in the IEB data based on these characteristics. A caveat of having only one wave of consumption data is that we have to rely on cross-sectional comparisons, and cannot track within-individual consumption dynamics. This implementation also takes consumption to be constant throughout the unemployment spell.

The time at which the survey is administered may differ from the time of job loss. We draw two samples which maximize the alignment between the timing of employment status and of consumption. To approximate consumption during unemployment, we select individuals between the ages of 40 and 55 who were unemployed in 2009, and employed at any point in 2008, with information on total household consumption.[39] Since respondents are asked to report consumption expenditures retrospectively for the previous year, the average for the unemployed at the time of survey may be contaminated by periods of employment. Together with the exclusion of the long-term unemployed, the average in this sample likely overstates the consumption during unemployment. We account for this by adjusting consumption by the number of months in unemployment reported for 2009. To obtain consumption before job loss for a comparable group of workers at risk of unemployment, we consider individuals in the same age bracket who were employed in 2009 and at the time of the survey in 2010, but became unemployed within the next two years.[40]

[38] Ignoring Jensen's gap in averaging $u'(c_x^u)$ within group x and $v'(\bar{c}^e)$ across groups $x' \in X$ leads to understating the value of UI by concavity of the utility function.

[39] Consumption is in prices from 2010 and excludes rent and housing expenditures. To account for any differences in household size, we use individual-level measures obtained by dividing household consumption by the number of adults plus half of the number of children. We exclude the ten observations which belong to the same household.

[40] These sample selection criteria follow previous studies using consumption-based approaches to esti-

To impute consumption in the IEB sample, we regress consumption in the GSOEP on characteristics present in both databases. These variables are age, gender, nationality, education, job tenure, quintile of monthly wage, and any unemployment observed in the past five years. We focus on employment variables which are based on retrospective questions, rather than relying on the longitudinal nature of the data to minimize attrition bias, and which can be constructed in the IEB data. These variables are also strongly correlated with contribution time, which we cannot recover in the GSOEP. Finally, we use the estimated coefficients to predict consumption in the IEB data, and average by bins. This approach assumes that the relationship between observable characteristics and consumption has remained stable over time.

Table D.5 presents the summary statistics for these variables for the unemployed and employed GSOEP samples, and compares them to the IEB-based samples. The GSOEP samples are similar to each other in terms of demographic and socioeconomic characteristics. The employed sample contains more women, white collar workers, and individuals earning above EUR 1800 (roughly the IEB median in prices from 2010), and workers with previous UI use. The GSOEP samples are on average about 3 years younger than the IEB sample. Individual characteristics are similar across datasets, except for a higher share of workers living in East Germany, which also contributes to a lower share earning below EUR 1800.

6.2 Results

Figure 5 presents heat plots of our estimates of the social value, behavioral cost and welfare effects of UI by age-by-contribution bins for each regime. These estimates are based on a uniform tax rate as used in Germany and most UI systems. They reflect the per-capita effects of a marginal change in P_x for group x. The black lines represent the regime-specific PBD schedule to visualize the existing policy differentiation.

Due to their local nature, the estimates cannot be directly compared across regimes without keeping in mind differences in worker composition, policy and time effects. In particular, PBD levels vary considerably and endogenously determine benefit exhaustion rates and unemployment durations, which directly enter in the behavioral cost of UI. There are bins with the same PBD in all regimes (e.g. age below 45 or less than 28 months of contribution time). Still, the composition of all bins varies across regimes due business cycle effects and differences in the reference periods for contribution time. We discuss this point further below.

The findings we document below reveal substantial heterogeneity in the insurance-incentive trade-off of UI, both within and between PBD steps, which has important im-

mating the social value of UI, e.g. Kolsrud et al. (2018); Hen (2199).

plications for policy differentiation. We first present all results, and discuss policy implications thereafter in Section 7.

Social value. The social value decreases with contribution time (left panel of Figure 5), as the worker's ability to smooth consumption increases. Workers with unstable employment have lower past earnings, unemployment benefits, and assets. As a result, they benefit more from increased coverage at the margin. In regimes 2 to 4, the contribution gradient steepens at older ages. Old low contributors value insurance the most, because they have experienced unstable employment even longer throughout the life cycle. Their marginal utility of consumption in unemployment is much higher than the average in employment. Although these bins contain fewer observations and are estimated less precisely, the differences to the average worker are statistically significant. Table 6 provides point estimates and standard errors for differences between the average worker and workers at the corners of the plane. Differences are statistically significant across all comparisons.

The social value drops for the full contributors at the highest contribution bin, reaching negative values between -0.01 and -0.27 across regimes, especially among older groups in regimes 1 and 2. These workers, who have high pre-unemployment wages and assets, tend to consume more during unemployment compared to the average worker during employment. As a result, the marginal benefit of increasing their consumption during unemployment is outweighed by the marginal cost of raising taxes on all employed workers. Consequently, the welfare derivative remains negative, regardless of the behavioral cost.

The drop at the highest contribution bin is sharper in regimes 3 and 4 than in the first two regimes, but the negative estimates are closer to zero. This can be explained by the different reference periods for contribution requirements. The reference period censors contribution time, and generates bunching in the number of workers at the maximum. The shorter the reference period, the more heterogeneous the group within the highest bin becomes. For instance, full contributors in regime 3, with a three-year reference period, may have contributed between three and seven years over the past seven years relevant to the first two regimes, where full contributors all have seven years. For the same reason, the share of workers with above-average consumption during unemployment is smaller in groups with shorter reference periods, explaining the less negative social values.

The patterns we document are in line with studies which have found lower consumption drops among workers with a greater ability to smooth consumption with assets and liquidity (Michelacci and Ruffo, 2015; Kolsrud et al., 2018). In particular, Michelacci and Ruffo (2015) find that the optimal replacement rate decreases up to age 40 due to asset accumulation. In our data, the estimated consumption drop is cross-sectionally correlated with assets. To show this, we impute assets before job loss for each bin using

GSOEP data from 2007 with the same procedure as for consumption (Section 6.1). We find a positive gradient in age, but also in contribution time, which is steeper in older age groups (Figure H.2). Workers with unstable employment are more likely to have lower assets and live hand-to-mouth. In fact, the variance is lower among low contributors, but increases with contribution time. Assets jump for the full contributors. This gradient reflects the one in the consumption drop.

In sum, we find that heterogeneity in age and contribution time is statistically and economically significant. The heterogeneity we find is similar across regimes but the levels differ somewhat due to compositional differences. Importantly, unemployed workers with the longest contribution times and the highest PBD value UI the least. Together with the duration elasticities decreasing in contribution time, this speaks against workers adversely selecting into more generous parts of the PBD schedule, which supports our empirical approach.

Behavioral cost. The behavioral cost is positive (i.e. the fiscal externality is negative) across the board (middle panel of Figure 5), but varies considerably across groups and regimes. For the average worker, it ranges from 1.21 (SE 0.48) to 2.34 (SE 0.72) across regimes. That is, for each additional EUR of transfer to a worker with average values for age and contribution time, the planner incurs a behavioral cost of EUR 1.21–2.34. As seen in equation (7), the duration elasticities are not sufficient to characterize the behavioral cost with a differentiated policy, since duration levels and benefit exhaustion rates matter as well. In our results, these variables often dominate duration responses in driving heterogeneity in the behavioral cost.

In regime 1, the largest behavioral cost occurs among workers older than 50 who have short PBDs because they contributed less than three out of the last seven years. At a value of 2.5, their behavioral cost is over two times larger than for the average worker in that regime. This is largely driven by higher elasticities of UI benefit receipt, and longer unemployment durations that are not covered by UI in this group. The smallest estimates are located among workers younger than 45, who also display little heterogeneity in the contribution dimension. Young low contributors generate a cost of about 1, similar to the average worker and the old high contributors, despite PBD increasing from 8 to 32 months on that diagonal.

In regime 2, workers with the most stable employment, and the highest PBD generate the highest costs, valued at 2.46. In contrast, old low contributors incur only half the behavioral cost of the same group in regime 1, with a value of 1.28. These differences are primarily driven by variations in benefit exhaustion rates, which scale the fiscal externality in the welfare formula (7). Benefit exhaustion rates are significantly lower for old high contributors in regime 2 compared to regime 1, and higher for old low contributors. This reflects compositional and institutional difference due to German Reunification. In the mid-1990s under regime 1, many high contributors from East Germany were encouraged to leave the labor market through UI, benefiting from generous transitional unemployment benefits that could be drawn for up to three years from age 57 without a job search requirement. Such benefits were eliminated in regime 2. Additionally, in the late 1990s and beyond, there was an increase in East German unemployed with high benefit exhaustion rates and unstable employment histories due to disruptions following reunification.

In regimes 3 and 4, the behavioral cost is higher across nearly all bins compared to the previous regimes. There are two main reasons for this. First, PBD is significantly shorter for most workers, resulting in longer periods of uncovered unemployment, which increase the behavioral cost. Second, the composition of workers within each bin changes because contribution time is measured over a shorter reference period. The highest estimates are concentrated among older workers just below the highest contributors, while the latter have below-average estimates. As previously discussed, due to the lower censoring of contribution time, the highest contribution bin in regimes 3 and 4 includes more diverse groups of workers than in regimes 1 and 2 who may respond differently as observed in the earlier regimes.

Welfare derivative. The right panel of Figure 5 displays the difference between the social value and the behavioral cost (i.e. the per capita welfare derivative). The behavioral cost dominates the social value in terms of magnitude, while heterogeneity is driven by both. The welfare derivatives are negative across the board, meaning that PBD was too high for all groups in all regimes. However, the level of the social value is scaled by the relative risk aversion parameter. It takes a $\gamma > 4$, i.e. on the high end of the range of conventional values and in many bins much higher numbers, for the social value to balance the behavioral cost, and so across all regimes.

To evaluate the degree of policy differentiation under homogeneous preferences, only the comparison of welfare derivatives across groups matters. We start by locally evaluating the existing PBD steps by comparing the welfare derivatives in the bins just below and above given age or contribution cutoffs where PBD jumps. If the welfare derivative becomes more negative when PBD increases, then flattening the schedule by reducing PBD more above than below the boundary brings the policy closer to the optimum. Steepening the schedule is optimal when the welfare derivative becomes less negative above the boundary. Our results show no consistent patterns at any of the cutoffs, as there are both more and less negative welfare derivatives observed when crossing a PBD boundary.

The reason is that the welfare derivatives differ quite strongly across groups with the same PBD both close to and further away from the boundaries. Our results reveal significant heterogeneity within PBD steps, indicating that more differentiated schedules could enhance welfare. Specifically, we find a more negative welfare derivative for longer contributors within a given PBD step, suggesting that PBD should be reduced more based on contribution time, holding age constant. Similarly, the welfare derivative often decreases with age within the same PBD step, meaning that PBD should be lowered with age, holding contribution time constant. The negative gradient in contribution time is primarily driven by a decline in social value, while the negative gradient in age is mainly due to increasing behavioral costs. These findings speak against substantially increasing PBD for high contributors at older ages, as done in the first two regimes in Germany.

6.3 Extensions

Heterogeneous welfare weights. So far, we have considered welfare effects per capita, which are informative for understanding heterogeneity in individual behavior. The total effect of dP_x depends on the weight group x gets in the social welfare function, which can be specified by the planner (Saez and Stantcheva, 2016). Even when the per capita effect is small, the total effect may be large with a large weight. Weights that naturally arise from the model are the size of the population in group x that exhausts UI and benefits from the extension.

To illustrate the role of heterogeneous weights for policy conclusions, we compute size-weighted welfare derivatives. Specifically, we compare $N_x S_x(P_x)(SV_x - BC_x)$ across groups, rescaled by the same quantity evaluated for the average worker in a given regime for easier interpretation.[41] The results are displayed in Figure H.5. A value above one means that changing the transfer in this group has a stronger effect on total welfare than changing it in the same direction for the average worker, while a value below one implies the opposite.[42]

We find that the groups with the largest impact on welfare are those with maximum contributions, particularly at the oldest ages, as these groups are significantly larger due to bunching at the maximum values of age and contribution. Consequently, reducing PBD for full contributors, especially older ones, yields the greatest welfare gains. For other groups in the first two regimes, small welfare gains could potentially be achieved by steepening the PBD schedule in contribution time among old short contributors, and by flattening it for longer contributors. In contrast, in the much less differentiated regimes 3 and 4, there is significantly less heterogeneity in relative welfare derivatives beyond the group of full contributors, supporting the optimality of less differentiation in these

[41] If welfare weights differ from group size, the relevant quantitity would be $\omega_x N_x S_x(P_x)(SV_x - BC_x)$ (see Appendix C.3).

[42] Negative values would imply that PBD should change in the opposite direction than for the average worker. In our case, however, PBD reductions are optimal for all groups, such that the ratios displayed in Figure H.5 are always positive.

regimes.

Group-specific tax. We now turn to the welfare effects of a group-specific tax, where each group finances its own benefits, in Figure H.3. With group-specific taxes, PBD extensions in one group do not lead to redistribution of welfare away from employed workers in other groups. As a result, the within-group social value is weakly positive for *all* groups and its heterogeneity decreases. Most importantly, full contributors no longer negatively affect others because they fully finance their own long PBD. The social value for low contributors becomes much smaller because they bear their future tax burden at low consumption levels. The behavioral cost is very similar with and without a uniform tax despite the differences in the formula.

Despite the differences in social value, the heterogeneity patterns in welfare effects per capita remain consistent with those observed under a uniform tax. The same applies to the group size-adjusted welfare effects, as shown in Figure H.5. However, the shift in social values leads to less negative welfare derivative for high contributors and more negative ones for low contributors under group-specific taxes compared to a uniform tax. This suggests that group-specific taxes would require smaller PBD reductions for high contributors and larger reductions for low contributors compared to a uniform tax system. As a result, groups-specific taxes call for UI policies that are closer to existing schemes with PBD schedules that increase in contribution time than the common uniform tax systems. This finding underscores the importance of the financing mode for policy conclusions, which has received little attention in the literature so far.

Preference heterogeneity. Our welfare analysis so far uses an assumption of homogeneous risk preferences.[43] In practice, individuals are likely to differ in their risk preferences. There is little consensus on the value of the coefficient of relative risk aversion in the literature, let alone heterogeneity therein.

Preference heterogeneity complicates the aggregation of individual utilities into a welfare function (Chetty, 2006). They can also alter the conclusions of the welfare analysis when the behavioral cost is correlated with risk aversion. To shed some light on this issue, we use Taylor expansions around $\bar{c}^e$ for each group, together with the state-independence and separability assumptions to approximate the social value:

$$\frac{u_x'(c_x^u) - v'(\bar{c}^e)}{v'(\bar{c}^e)} \approx \frac{u_x'(\bar{c}^e)\left(1+\gamma_x \frac{\bar{c}^e - c_x^u}{\bar{c}^e}\right) - E_x\left[u_x'(\bar{c}^e)\left(1+\gamma_x \frac{\bar{c}^e - c_x^e}{\bar{c}^e}\right)\right]}{E_x\left[u_x'(\bar{c}^e)\left(1+\gamma_x \frac{\bar{c}^e - c_x^e}{\bar{c}^e}\right)\right]}. \tag{13}$$

This expression highlights that the social value is larger, if individuals in x have a higher

[43] The well-known result that the sufficient statistics formulas are robust to individual-level heterogeneity in behavioral responses also applies to within-group heterogeneity in our case.

marginal utility of consumption, risk aversion, and consumption drop relative to average consumption during employment. Conversely, the social value decreases in the average (taken across all groups) marginal utility, risk aversion, and difference in consumption during employment relative to the average. Similar to the homogeneous preferences case, the social value can be negative if the marginal benefit of an increase in resources during unemployment is lower for group x than the average cost of decreasing consumption in employment. With a group-specific tax, knowledge about relative preferences across groups $\gamma_x/\gamma_{x'}$ is sufficient to draw policy conclusions about differentiation. Equation (13) reveals that this is not the case with a uniform tax. The second term also hints at a role for the covariance between risk aversion and the consumption gap in employment.[44]

In our setting, bins differ by construction in age, which has been found to be associated with risk aversion. Cohen and Einav (2007) find a U-shaped relationship with a sample mean at 40, i.e. the lower bound in ours. Our results suggest that for the social value to become positive, risk aversion would need to increase steeply with age and contribution time to offset the lower marginal utility of consumption. As seen in Table 1, age and contribution are also associated with other correlates of risk preferences. Further knowledge on the empirical distribution of risk preferences is an important input in the evaluation of differentiated policies.

7 Summary and Discussion

Our findings yield several insights for UI policy, and for tagging it on age and contribution time. First, short-term contribution time is a strong predictor of duration responses to UI generosity, holding constant the existing policy, worker composition, and time effects. Short-term contribution carries information on individual responses to PBD extensions. Age, or contribution time over longer reference periods is not strongly predictive of response heterogeneity.[45] A key implication of this finding is that local estimates for responses at specific cutoffs cannot be extrapolated without accounting for differences in short-term contribution time.

Second, characterizing the heterogeneity in duration responses in the reduced-form analysis is not sufficient to explain the heterogeneity in the fiscal externality of UI under a differentiated policy. We document that the behavioral cost varies considerably with both age and contribution time. While duration responses explain some of this variation,

[44]The sign of this correlation is empirically ambiguous. For instance, workers with higher consumption may be more risk averse and prefer reducing their unemployment risk. However, they may also be locally less risk averse, e.g. if risk aversion declines in wealth. This intution mirrors the result in Andrews and Miller (2013) for a homogeneous insurance and tax policy with heterogeneous agents.

[45]Notice that other systems, e.g., in the United States, determine coverage based on the monetary value of past contributions rather than time. This would be another dimension to explore.

duration levels and benefit exhaustion rates, which directly depend on actual UI policies, often dominate.

Third, policy-relevant heterogeneity also exists in the social value, even under homogeneous preferences. Consistent with their higher assets and better consumption-smoothing ability, we find that unemployed workers with longer contribution time value UI less, especially as they age. Yet, these workers often have the highest PBDs, suggesting that UI has been overly generous for them. In fact, our results suggest that PBD levels were too high across the board since 1994 in Germany, despite reductions in the differentiation of the PBD schedule over time. The heterogeneity in welfare effects we find speaks against UI systems where PBD increases systematically in contribution time and age. Instead, our results support PBD schedules that are flatter with respect to age and that increase with contribution time for workers with unstable employment, but do not become more generous at higher contribution levels. Conclusions about optimal policy are however sensitive to modelling assumptions, especially with respect to risk preferences.

Fourth, we find that the groups with the largest impact on welfare are located at the censoring value of contribution time, i.e. the time horizon over which contribution time is measured (3 to 7 years in Germany). This is because these groups are large as many workers contribute the full reference period, which is short relative to their entire employment history in our sample aged 40 and above. Additionally, the welfare effects for these groups differ significantly from those with shorter contribution histories. Our findings suggest that PBD for workers with full contribution histories should be reduced compared to those who have contributed about two-thirds of the required period at the same PBD level. While most previous studies have evaluated the German UI system based on full contributors, our results underscore contribution time as a key dimension for policy evaluation. Furthermore, group size is important for evaluating the welfare effects of differentiated UI policies.

Fifth, policy conclusions are sensitive to the mode of financing of PBD extensions. We show that a differentiated UI policy with a uniform tax, as implemented in many countries, creates redistribution across groups. Increasing PBD in one group of unemployed generates utility gains only in this group while employed workers in all groups suffer from utility losses due the increase in the tax burden. If the utility gain is larger than average utility losses, the welfare derivative becomes negative, even before subtracting the behavioral cost. Empirically, this consistently occurs among full contributors. In contrast, group-specific taxes, where each group finances its own benefits, ensure non-negative social values. Consequently, the actual PBD schedule is closer to the optimum if changes are financed by group-specific taxes (starting from the existing uniform tax system) rather than a uniform tax. Additionally, group-specific taxes offer the advantage of more easily accommodating preference heterogeneity into the model and welfare analysis.

8 Conclusion

This paper studies how the welfare effects of UI vary in two key dimensions—age and contribution time at unemployment. It thereby bridges evidence, theory and practice, as both are widely-used tags for the generosity of UI. Understanding heterogeneity in age and contribution time is also important in light of the rising shares of workers with non-standard employment and gaps in social security contributions, as well as policies increasing the statutory retirement age.

We set up a job search model with heterogeneous workers and differentiated UI policy that characterizes the moments needed to evaluate the trade-off between the fiscal externality and the insurance value of UI across heterogeneous groups of workers. Focusing on workers aged 40 to 55, we estimate these moments for all groups in the age-by-contributions space. To obtain our estimates, we exploit the rich policy variation in the German UI system, where PBD is highly differentiated and increases with age and contribution time.

We find substantial heterogeneity in duration elasticities of UI in short-term contribution time, as workers with stable employment exhibit smaller behavioral duration responses to UI. The duration responses are, however, not significantly associated with age nor with longer contribution time horizons in our sample of workers aged 40 to 55. Our results support the use of past employment history for the modeling and assessment of government transfer programs. This insight complements previous studies highlighting the welfare gains from age-dependent taxation and UI systems (Akerlof, 1978; Fahri and Werning, 2013; Stantcheva, 2017). For a broader age range in the United States, Michelacci and Ruffo (2015) find that the optimal policy combining an age-dependent replacement rate with age-dependent taxes yields 90 percent of the welfare gains from a first-best where search effort is observable. However, our theoretical and empirical results show that behavioral duration responses are not sufficient to describe heterogeneity in the fiscal externality. Duration levels and benefit exhaustion rates, which directly depend on the PBD level, matter as well and are often the dominant driver of heterogeneity in the behavioral cost of UI. We find that the behavioral cost of UI varies considerably with both age and contribution time over different horizons. Thus, these observable characteristics carry relevant information for differentiating UI generosity.

In our local welfare evaluation, the insurance value decreases with increasing contribution time and age. This finding is in line with older workers and workers with more stable employment having higher assets and better consumption-smoothing ability. The welfare derivative estimates for existing regimes in Germany suggest that the optimal policy should not increase systematically in contribution time and age. Our results support PBD schedules that are flatter in age and steeper in contribution time for workers with relative unstable employment. But PBD should remain flat for long-term contributors. We further show that the mode of financing of PBD extensions matters. With group-specific taxes, where each group finances its own benefits instead of a uniform tax levied on all workers as in the vast majority of existing UI systems, the optimal policy is closer to existing PBD schedules.

Our analysis has some limitations which leave open questions for future research. First, our analysis excludes the boundaries of the PBD schedule, especially eligibility cutoffs (e.g. for UI or for alternative social programs such as early retirement), where previous studies have found selection effects that may have implications for welfare (e.g. Gudgeon et al. 2023). We focus on the interior of existing PBD schedules to ensure credible identification of duration elasticities in reduced form and abstract from selection into specific parts of the UI policy. Adding extensive-margin estimates to our intensive-margin perspective would be valuable for evaluating the differentiated schedule, especially at the boundaries. Moreover, exploring general-equilibrium effects induced by the policy differentiation itself would be an interesting avenue for future research.

Second and related, bunching at the eligibility cutoff (which we leave out due to selection) and at the maximum values of the running variables suggests that their range and censoring are important policy parameters, especially for the reference period for contribution time. While we find that contribution time in the last three years predicts duration responses to UI, our welfare analysis shows that short-term horizons mask significant heterogeneity in the social value and behavioral cost of UI due to bunching at the censoring value. Specifically, the group of full contributors over the last three years before unemployment includes workers with widely varying wages, assets, and liquidity.

Finally, our welfare analysis does not allow for conclusions about optimal policy over the business cycle. Our reduced-form estimates of duration elasticities net out any time effects. However, the behavioral cost of UI additionally depends on duration levels and benefit exhaustion rates which fluctuate over the business cycle, but also across regimes due to the differences in PBD. More broadly, welfare effects vary with worker composition, PBD and time effects. Given the magnitude of the heterogeneity we find in age and contribution despite differences in these dimensions, our results confirm, however, that both tags are relevant for policy differentiation above and beyond business cycle effects.

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Tables and Figures

Table 1: Observable Predictors of Age and Contribution Time at Job Loss

	(1) Age	(2) Contribution in last 3 years	(3) Contribution in last 5 years	(4) Contribution in last 7 years
Age		-0.058***	-0.019***	0.001*
		(0.001)	(0.001)	(0.001)
Contribution in last 36 mths	-0.063***			
	(0.001)			
Female	0.049***	0.105***	0.151***	0.162***
	(0.001)	(0.001)	(0.001)	(0.001)
Non-German	-0.002	-0.044***	-0.019***	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
Residence in East Germany	0.021***	0.002	0.056***	0.111***
	(0.001)	(0.001)	(0.001)	(0.001)
No secondary schooling	-0.057***	-0.002	-0.051***	-0.071***
	(0.002)	(0.002)	(0.002)	(0.002)
Without vocational training	0.013***	-0.043***	-0.005***	0.022***
	(0.001)	(0.001)	(0.001)	(0.001)
Academic degree	0.014***	-0.006***	-0.031***	-0.045***
	(0.002)	(0.002)	(0.002)	(0.002)
Last job part-time	0.023***	-0.001	0.050***	0.076***
	(0.001)	(0.001)	(0.001)	(0.001)
Log earnings past 10 yrs	0.102***	0.309***	0.645***	0.793***
	(0.001)	(0.001)	(0.001)	(0.001)
Spells	1120861	1120861	1120861	1120861
Mean outcome	47.112	29.917	47.913	64.015

Notes: The table displays the point estimates from regressions of age (in years) and contribution time (in months) on observable characteristics at the unemployment spell level. Standard errors are clustered at the individual level. $* \ p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$.

Table 2: Meta Regression of Duration Elasticities W.r.t. Potential Benefit Duration

	(1)	(2)	(3)	(4)	(5)	(6)
Panel (a) Elasticity of nonemployment duration						
Age	0.001	-0.016	-0.001	-0.015	-0.002	-0.012
	(0.0100)	(0.0121)	(0.0095)	(0.0116)	(0.0092)	(0.0118)
Years contributed in last 3	-0.065	-0.306*				
	(0.1204)	(0.1625)				
Years contributed in last 5			0.018	-0.086		
			(0.0564)	(0.0679)		
Years contributed in last 7					0.041	0.006
					(0.0295)	(0.0377)
Elasticity mean	0.258	0.258	0.258	0.258	0.258	0.258
Mean SE	0.457	0.457	0.457	0.457	0.457	0.457
Share sig. 5%	0.164	0.164	0.164	0.164	0.164	0.164
Panel (b) Elasticity of UI receipt duration						
Age	0.022**	0.008	0.021*	0.008	0.020*	0.010
	(0.0103)	(0.0093)	(0.0105)	(0.0092)	(0.0099)	(0.0094)
Years contributed in last 3	-0.006	-0.256**				
	(0.0832)	(0.0996)				
Years contributed in last 5			0.029	-0.071		
			(0.0404)	(0.0465)		
Years contributed in last 7					0.032	-0.010
					(0.0249)	(0.0211)
Elasticity mean	0.650	0.650	0.650	0.650	0.650	0.650
Mean SE	0.498	0.498	0.498	0.498	0.498	0.498
Share sig. 5%	0.442	0.442	0.442	0.442	0.442	0.442
Cells	314	314	314	314	314	314
Regime fixed effects	✓	✓	✓	✓	✓	✓
Covariates	✓	✓	✓	✓	✓	✓
PBD level		✓		✓		✓

Notes: The table presents meta regression results, where the outcomes are the estimated elasticity of nonemployment duration (panel a) and UI receipt duration (panel b) w.r.t. potential benefit duration. Observations are age-by-contribution time cells that satisfy the validity criteria described in Section 4.2. RD estimates are based on nonparametric local linear regression for age cells, and difference-in-means with linear spline in contribution for contribution cells. All meta regressions use inverse-variance weights winsorized at the 10th and 90th percentiles. Standard errors (in parentheses) are clustered by cells' age group (in 5-year bands), contribution time group (in 4-month bands) and cutoff type. Composition variables are share of females, non-German, residence in East Germany, secondary education, higher education, and last job part-time.

Table 3: Meta Regression of Duration Elasticity Estimates -- Estimates Using Different Cell Aggregation Levels, and Validity Criteria

	(1) Valid cells split by year	(2) All cells by year	(3) All cells by regime	(4) Valid cells by regime	(5) Valid cells biannual	(6) Consistent sample of spells
Panel (a) Elasticity of nonemployment duration						
Age	-0.016	-0.007	-0.007	-0.007	-0.016	-0.034
	(0.0121)	(0.0090)	(0.0112)	(0.0155)	(0.0149)	(0.0362)
Years contributed in last 3	-0.306*	-0.280**	-0.291*	-0.565	-0.365*	-0.742***
	(0.1625)	(0.1027)	(0.1402)	(0.3314)	(0.1813)	(0.2156)
Elasticity mean	0.258	0.280	0.261	0.239	0.256	0.370
Mean SE	0.457	0.457	0.198	0.198	0.347	0.559
Share sig. 5%	0.164	0.164	0.375	0.375	0.237	0.183
Panel (b) Elasticity of UI receipt duration						
Age	0.008	0.009	0.005	0.018	0.009	0.054
	(0.0093)	(0.0075)	(0.0085)	(0.0133)	(0.0135)	(0.0327)
Years contributed in last 3	-0.256**	-0.192**	-0.302	-0.513**	-0.167	-0.125
	(0.0996)	(0.0906)	(0.1838)	(0.1894)	(0.1855)	(0.1295)
Elasticity mean	0.650	0.694	0.660	0.608	0.635	0.743
Mean SE	0.498	0.498	0.209	0.209	0.397	0.570
Share sig. 5%	0.442	0.442	0.738	0.738	0.535	0.362
Cells	314	434	80	47	137	195
Regime fixed effects	✓	✓	✓	✓	✓	✓
Covariates	✓	✓	✓	✓	✓	✓
PBD level	✓	✓	✓	✓	✓	✓

Notes: The table presents meta regression results, where the outcomes are the estimated elasticity of nonemployment duration (panel A) and UI receipt duration (panel B) w.r.t. potential benefit duration. Observations are age-by-contribution time cells. RD estimates are based on nonparametric local linear regression for age cells, and difference-in-means with a linear spline for contribution cells. All meta regressions use inverse-variance weights winsorized at the 10^{th} and 90^{th} percentiles. Standard errors (in parentheses) are clustered by cells' age group (in 5-year bands), contribution time group (in 4-month bands), and cutoff type. Composition variables include the share of females, non-Germans, residents in East Germany, individuals with secondary education and higher education, and individuals whose last job was part-time. Column (1) presents results based on valid cells split by year that satisfy the criteria described in Section 4.2. Column (2) uses all cells split by year. Column (3) uses all cells, with cells split by regime. Column (4) uses the subset of valid cells split by regime. Column (5) uses valid cells split biannually. Column (6) uses the sample of unemployment spells where the potential benefit duration was consistently imputed based on age and contribution time.

Table 4: Meta Regression of Duration Elasticity Estimates -- Estimates Using Different Subsamples and Specifications

	(1) Non-round contribution	(2) Before 2005	(3) After 2005	(4) Year fixed effects
Panel (a) Elasticity of nonemployment duration				
Age	-0.008	-0.018	-0.001	-0.012
	(0.0110)	(0.0110)	(0.0201)	(0.0126)
Years contributed in last 3	-0.271	-0.360**	-0.337	-0.352*
	(0.1598)	(0.1649)	(0.2231)	(0.1766)
Elasticity mean	0.423	0.254	0.282	0.258
Mean SE	0.459	0.457	0.457	0.457
Share sig. 5%	0.200	0.164	0.164	0.164
Panel (b) Elasticity of UI receipt duration				
Age	0.008	0.006	0.025	0.015
	(0.0097)	(0.0098)	(0.0202)	(0.0107)
Years contributed in last 3	-0.388*	-0.239*	-0.295	-0.177
	(0.2194)	(0.1291)	(0.3008)	(0.1138)
Elasticity mean	0.715	0.644	0.676	0.650
Mean SE	0.491	0.498	0.498	0.498
Share sig. 5%	0.463	0.442	0.442	0.442
Cells	226	261	53	314
Regime fixed effects	✓	✓		✓
Covariates	✓	✓	✓	✓
PBD level	✓	✓	✓	✓

Notes: The table presents meta regression results, where the outcomes are the estimated elasticity of nonemployment duration (panel A) and UI receipt duration (panel B) w.r.t. potential benefit duration. Observations are age-by-contribution time cells. RD estimates are based on nonparametric local linear regression for age cells, and difference-in-means with a linear spline for contribution cells. All meta regressions use inverse-variance weights winsorized at the 10$^{\text{th}}$ and 90$^{\text{th}}$ percentiles. Standard errors (in parentheses) are clustered by cells' age group (in 5-year bands), contribution time group (in 4-month bands), and cutoff type. Composition variables include the share of females, non-Germans, residents in East Germany, individuals with secondary education and higher education, and individuals whose last job was part-time. All estimations use valid cells split by year that satisfy the criteria described in Section 4.2. Column (1) uses the subsample of spells with imputed contribution time within four days of a multiple of 365 days. Column (2) and (3) use pre-2005, and post-2005 spells, respectively, i.e. before the reform of unemployment assistance. Column (4) is as (1) but uses year instead of regime fixed effects.

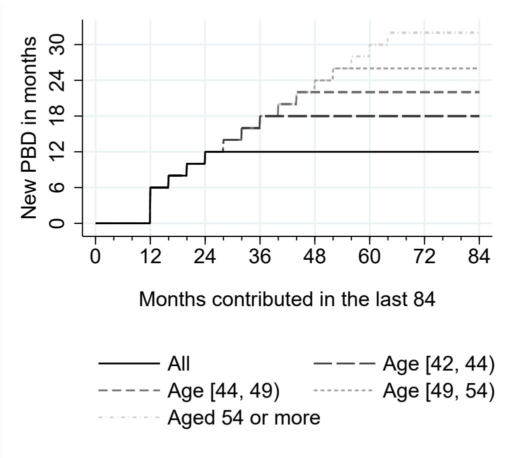
Table 5: Meta Regression of Duration Elasticity Estimates -- Estimates from Alternative Specifications

	(1)	(2)	(3)	(4)	(5)
Panel (a) Elasticity of nonemployment duration					
Age	-0.012		-0.013	-0.011	-0.004
	(0.0105)		(0.0115)	(0.0113)	(0.0114)
Years contributed in last 3		-0.271*	-0.246		
		(0.1550)	(0.1793)		
Years contributed in last 5				-0.033	
				(0.0805)	
Years contributed in last 7					0.059
					(0.0455)
Full contribution last 7 years			-0.212**	-0.231*	-0.310**
			(0.0990)	(0.1134)	(0.1272)
Elasticity mean	0.258	0.258	0.258	0.258	0.258
Mean SE	0.457	0.457	0.457	0.457	0.457
Share sig. 5%	0.164	0.164	0.164		0.164
Panel (b) Elasticity of UI receipt duration					
Age	0.010		0.007	0.008	0.010
	(0.0094)		(0.0097)	(0.0097)	(0.0101)
Years contributed in last 3		-0.273***	-0.260**		
		(0.0943)	(0.1081)		
Years contributed in last 5				-0.075	
				(0.0502)	
Years contributed in last 7					-0.011
					(0.0245)
Full contribution last 7 years			0.019	0.023	0.006
			(0.0908)	(0.0967)	(0.1048)
Elasticity mean	0.650	0.650	0.650	0.650	0.650
Mean SE	0.498	0.498	0.498	0.498	0.498
Share sig. 5%	0.442	0.442	0.442		0.442
Cells	314	314	314	314	314
Regime fixed effects	✓	✓	✓	✓	✓
Covariates	✓	✓	✓	✓	✓
PBD level	✓	✓	✓	✓	✓

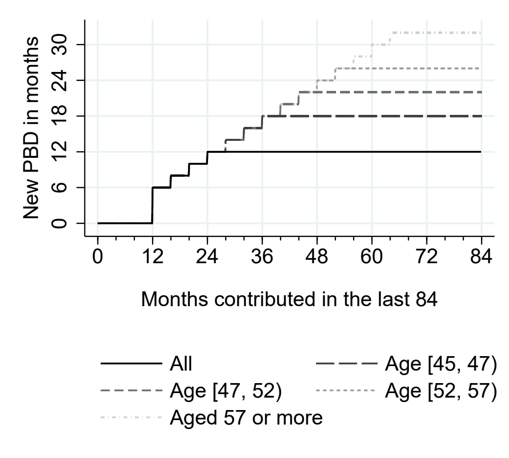
Notes: The table presents meta regression results, where the outcomes are the estimated elasticity of nonemployment duration (panel a) and UI receipt duration (panel b) w.r.t. potential benefit duration. Observations are age-by-contribution time cells that satisfy the validity criteria described in Section 4.2. RD estimates are based on nonparametric local linear regression for age cells, and difference-in-means with linear spline in contribution for contribution cells. All meta regressions use inverse-variance weights winsorized at the 10^{th} and 90^{th} percentiles. Standard errors (in parentheses) are clustered by cells' age group (in 5-year bands), contribution time group (in 4-month bands) and cutoff type. Composition variables are share of females, non-German, residence in East Germany, secondary education, higher education, and last job part-time.

Figure 1: Potential Benefit Duration as a Function of Age and Contribution Time at Entry into Unemployment

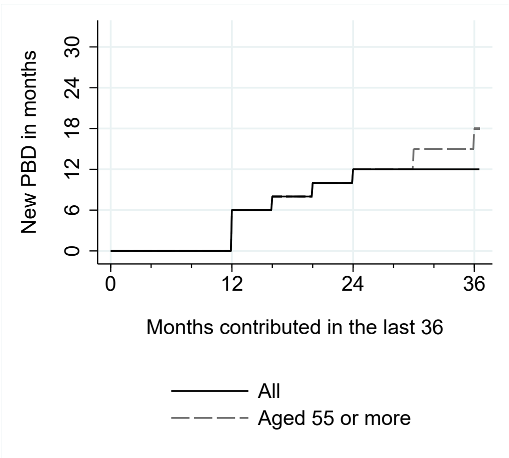
(a) Regime 1, July 1987--March 1997



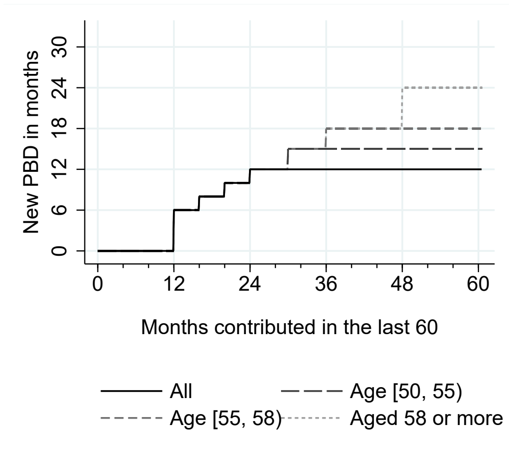
(b) Regime 2, April 1997--January 2006



(c) Regime 3, February 2006--December 2007

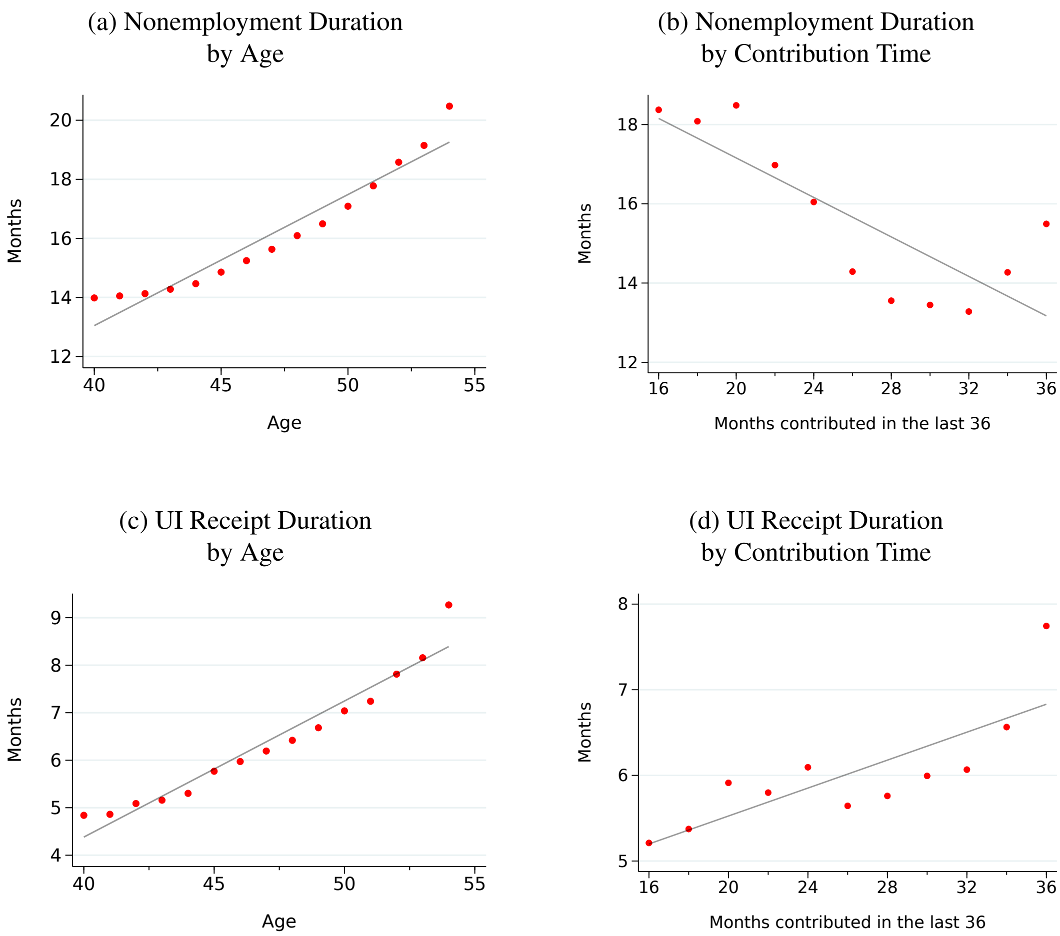


(d) Regime 4, January 2008--June 2020



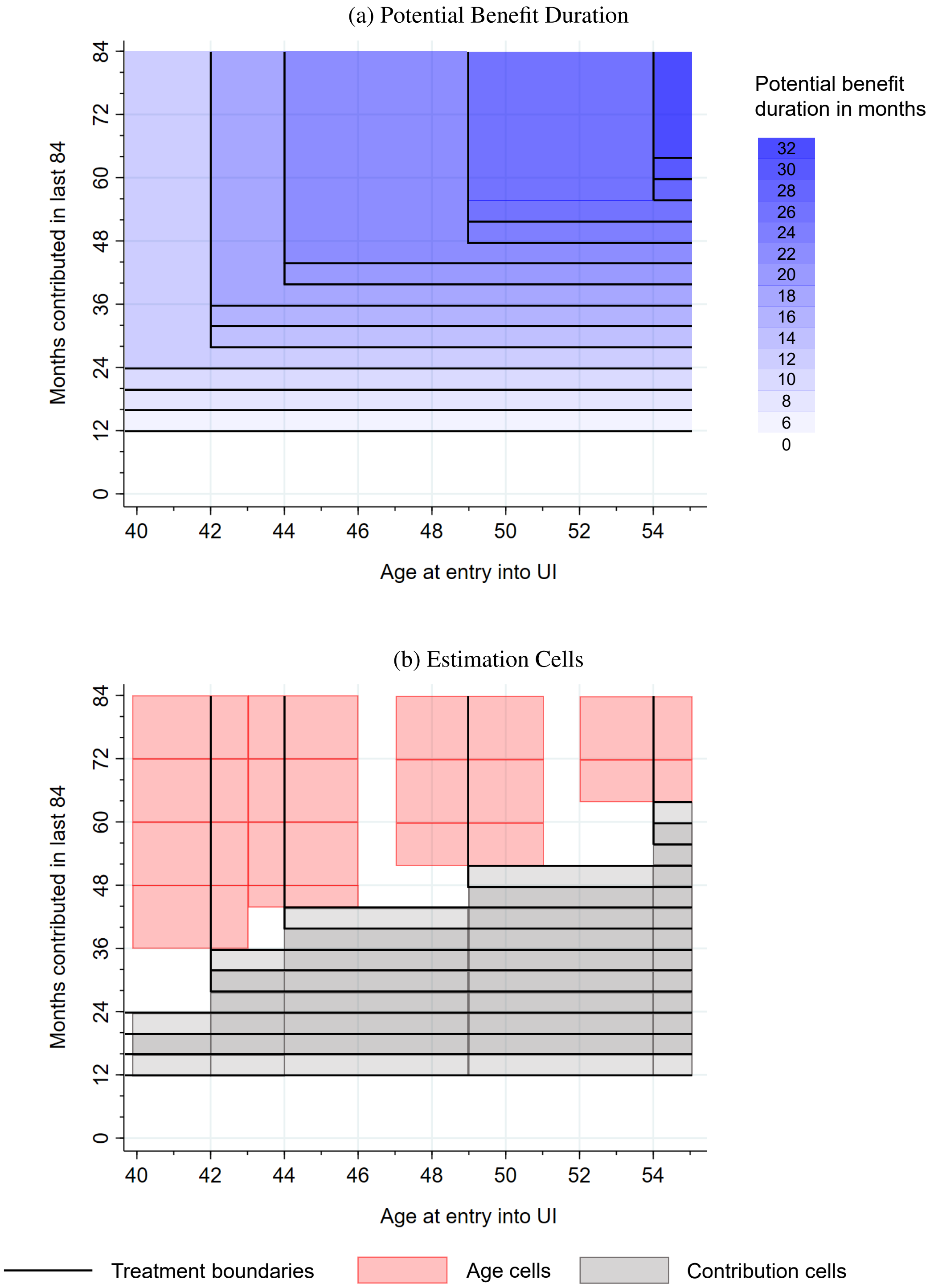
Notes: The figures display the potential benefit duration for new unemployment benefit claims as a function of age in years and contribution time in months measured at job loss across regimes that overlap with our study period. Sources: *Arbeitsförderungsgesetz*, and *Sozialgesetzbuch III*.

Figure 2: Duration Outcomes as a Function of Age and Contribution Time



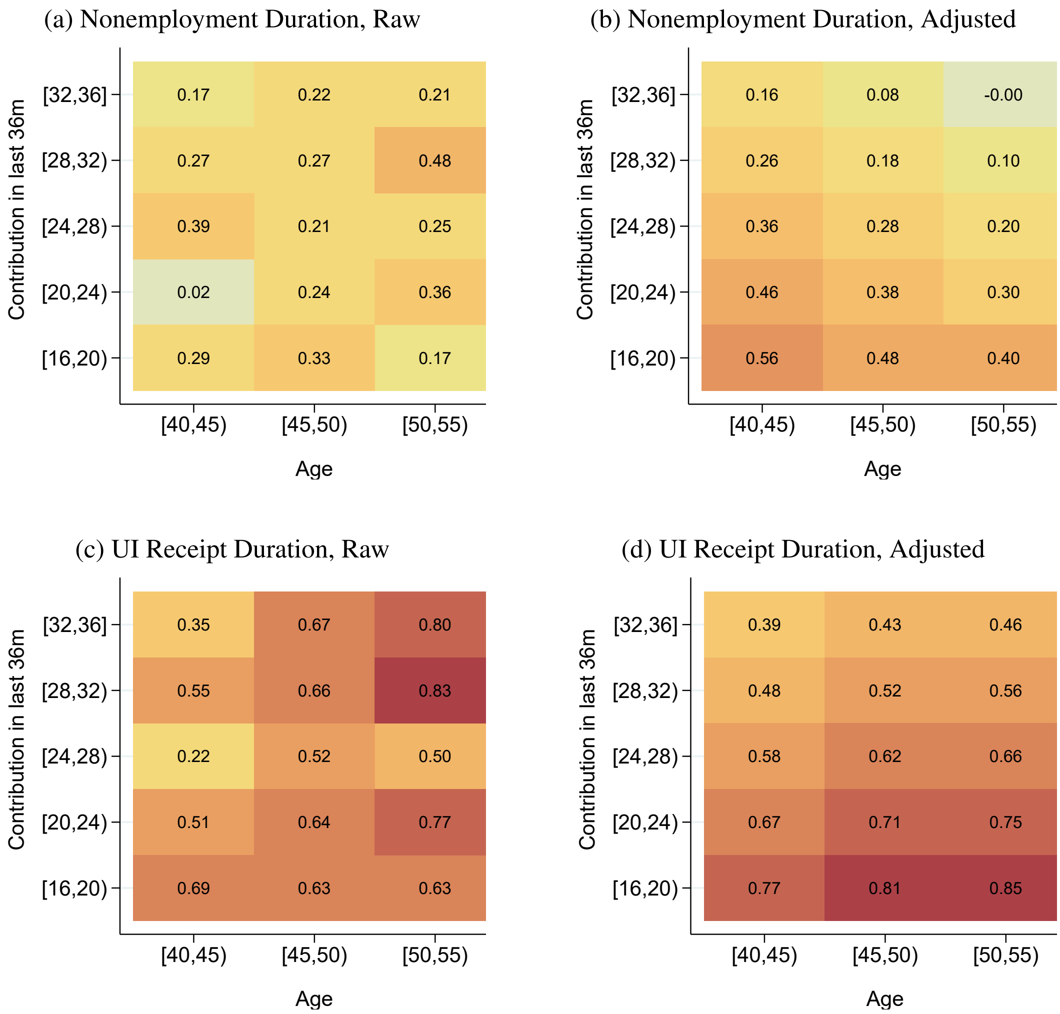
Notes: The figures plot unadjusted averages of the nonemployment duration and UI benefit receipt duration (in months) by 1-year bins of age, and 4-month bins of contribution time using the full sample of unemployment spells. The grey line is a linear fit.

Figure 3: Treatment Plane in Age and Contribution Time



Notes: The figure illustrates the treatment boundaries (solid black lines) in age and contribution time for regime 1 (the years 1994 to 1997 in our data), and the corresponding PBD level in Panel (a). Panel (b) illustrates the construction of the disjoint estimation cells along the treatment boundaries in which we estimate RD effects, with cells at age cutoffs in red, and at contribution cutoffs in grey.

Figure 4: Elasticities by Age and Contribution Time

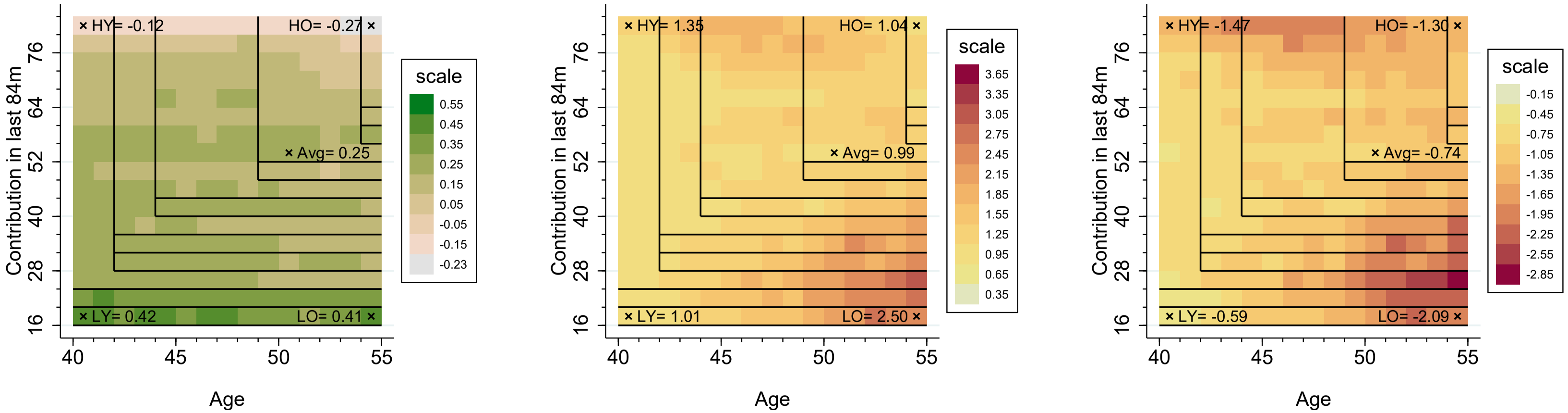


Notes: The figure displays elasticity estimates, taking cells that pass the RD validity criteria. The left-hand side panel show raw averages of the estimates by age and contribution time bins. The right-hand side panel shows adjusted values from the meta regression (12) where the estimate is taken as the outcome, and regressed on age, contribution time, potential benefit duration below the cutoff, regime fixed effects, and sample composition.

Figure 5: Welfare Effects of a Potential Benefit Duration Extension with a Uniform Tax, and $\gamma = 2$

Panel A. Regime 1 (January 1994–March 1997)

(a) Social Value $\gamma = 2$ (b) Behavioral Cost (c) Welfare Derivative



Panel B. Regime 2 (April 1997–January 2006)

(d) Social Value $\gamma = 2$ (e) Behavioral Cost (f) Welfare Derivative

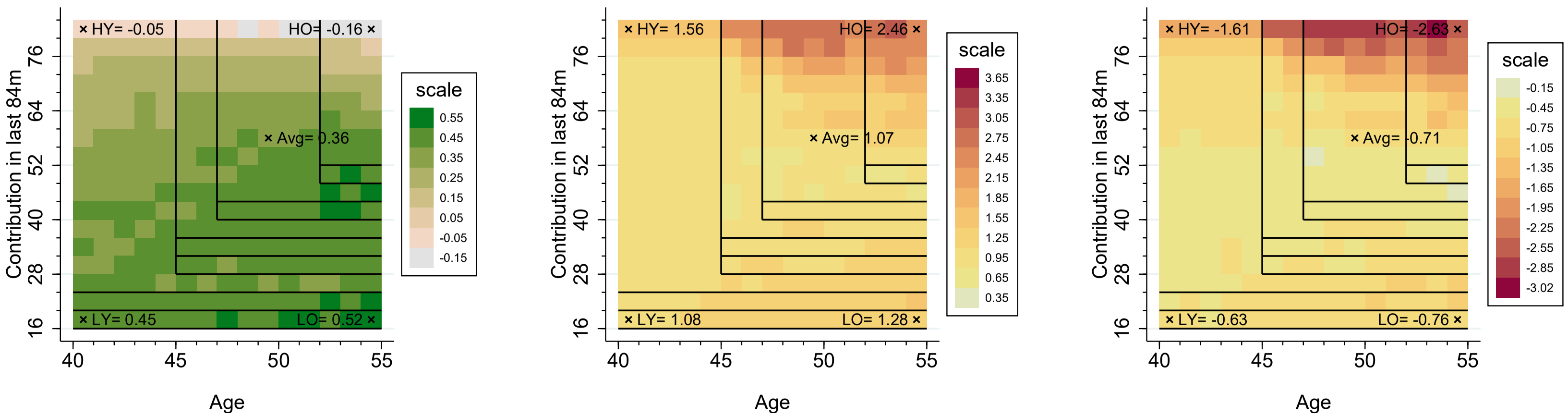
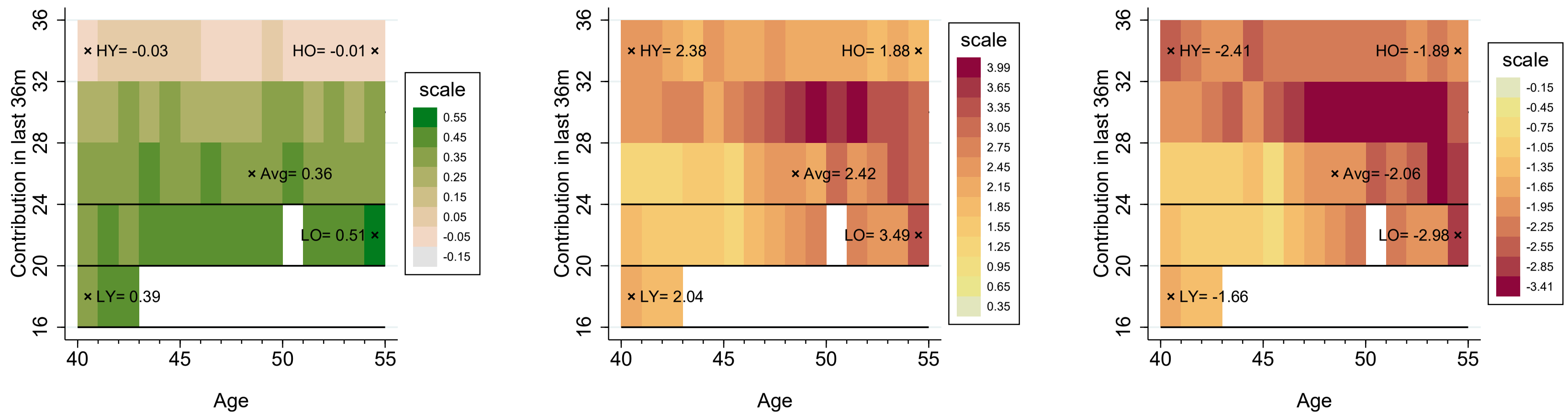


Figure 5: Welfare Effects of a Potential Benefit Duration Extension with a Uniform Tax, and $\gamma = 2$ (Cont.)

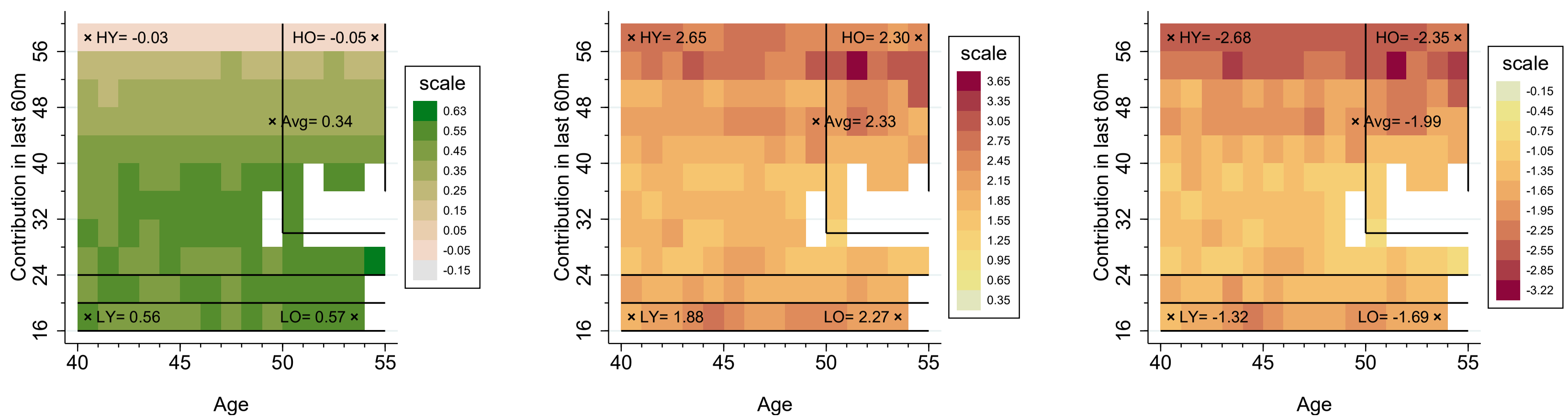
Panel C. Regime 3 (February 2006–December 2007)

(a) Social Value $\gamma = 2$ (b) Behavioral Cost (c) Welfare Derivative



Panel D. Regime 4 (January 2008–December 2010)

(d) Social Value $\gamma = 2$ (e) Behavioral Cost (f) Welfare Derivative



Notes: The figure presents the estimated social value (SV) with a homogeneous coefficient of relative risk aversion $\gamma = 2$ (left side), behavioral cost (BC, middle), and welfare derivative (right side) of PBD extensions for group x. The implementation uses a uniform tax, as in equation 7. Groups x are bins of age (1-year bins) and contribution time (4-month bins) in each regime in our observation period. The black lines denote treatment boundaries where the potential benefit duration increases by half of the additional months contributed. Abbreviations: LY: Low contributors, young; HY: High contributors, young; LO: low contributors, old; HO: High contributors, old.

Table 6: Comparison of the Welfare Effects Relative to the Average Worker's

	(1) Social value $\gamma = 2$		(2) Behavioral cost		Welfare derivative	
	Difference	SE	Difference	SE	Difference	SE
Panel (a) Regime 1						
Average worker (own estimate)	0.25	0.00	0.99	0.06	-0.74	0.06
Diff. High contributors, age 40	-0.37	0.00	0.37	0.07	-0.73	0.07
Diff. Low contributors, age 40	0.17	0.00	0.02	0.08	0.15	0.08
Diff. High contributors, age 54	-0.52	0.00	0.05	0.07	-0.57	0.07
Diff. Low contributors, age 54	0.16	0.00	1.51	0.17	-1.35	0.17
Panel (b) Regime 2						
Average worker (own estimate)	0.36	0.00	1.07	0.06	-0.71	0.06
Diff. High contributors, age 40	-0.41	0.00	0.49	0.06	-0.90	0.06
Diff. Low contributors, age 40	0.09	0.00	0.01	0.06	0.08	0.06
Diff. High contributors, age 54	-0.53	0.00	1.39	0.08	-1.91	0.08
Diff. Low contributors, age 54	0.16	0.00	0.21	0.10	-0.04	0.10
Panel (c) Regime 3						
Average worker (own estimate)	0.36	0.00	2.42	0.22	-2.06	0.22
Diff. High contributors, age 40	-0.39	0.00	-0.04	0.29	-0.35	0.29
Diff. Low contributors, age 40	0.02	0.00	-0.38	0.28	0.40	0.28
Diff. High contributors, age 54	-0.37	0.00	-0.54	0.25	0.17	0.25
Diff. Low contributors, age 54	0.15	0.00	1.06	0.56	-0.92	0.56
Panel (d) Regime 4						
Average worker (own estimate)	0.34	0.00	2.33	0.13	-1.99	0.13
Diff. High contributors, age 40	-0.36	0.00	0.32	0.20	-0.69	0.20
Diff. Low contributors, age 40	0.22	0.00	-0.46	0.23	0.67	0.23
Diff. High contributors, age 54	-0.39	0.00	-0.03	0.16	-0.36	0.16
Diff. Low contributors, age 54	0.24	0.00	-0.06	0.31	0.30	0.31

Notes: The table presents estimates of $d\tilde{W}_0/dP_x - d\tilde{W}_0/dP_{\bar{x}}$, the difference in the welfare derivative for the corner groups x highlighted in Figure 5 and the average worker $\bar{x}$. SV_x denotes the social value, and BC_x the behavioral cost of a marginal potential benefit duration (PBD) extension. These estimates allow evaluating the differentiation of the PBD for group x relative to $\bar{x}$. A positive (negative) estimate indicates that the return to an additional EUR of transfers to group x is higher (lower) than an equivalent transfer to $\bar{x}$ at their existing PBD levels. Standard errors are bootstrapped.

Appendix for Online Publication

Unemployment Insurance with Policy Differentiation

Conny Wunsch Véra Zabrodina

This version: September 18, 2024.

A Existing Literature

Table A.1: Studies on the Effect of Unemployment Insurance Based on RD Designs

Study	Setting	Threshold	PBD extension	Key sample restrictions
Caliendo et al. (2013)	Germany	Age 45	from 12 to 18 months	Age 44 to 46, employed at least 36 months in the last 7 years
Card et al. (2007)	Austria	36 months of contribution in previous 5 years	from 20 to 30 weeks	Age 20 to 50, tenure of at least 1 year of the past 5 years (at their last firm)
Johnston and Mas (2018)	Missouri, United States	Cohorts eligible for the maximum PBD	reduction from 73 to 57 weeks	Tenure of 14.5 quarters with previous employer
Lalive (2007)	Austria	Age 50	from 39 to 52 weeks, and from 39 to 209 weeks	Men aged 46 to 53, employed at least 312 weeks in the last 10 years (below cutoff), and 468 weeks over last 15 years (above cutoff)
Le Barbanchon (2016)	France	8 months of employment in the previous year	from 7 to 15 months	Age below 50, employed at most 12 months in the last 2 years
Lalive (2008)	Austria	Age 50 and geographical border cutoff	from 30 to 209 weeks	Age 46 to 53, employed at least 9 years in the last 15 years
Nekoei and Weber (2017)	Austria	Age 40	from 30 to 39 weeks	Age 30 to 50, employed 3 (or 6) years in the last 5 (or 10) years
Schmieder et al. (2012)	Germany	Age 42, 44 and 49	from 12 to 18 months, from 18 to 22 months, and from 22 to 26 months	40 to 49, employed at least 36 (44 and 52, respectively) months in the last 7 years
Schmieder et al. (2016)	Germany	Age 42, 44	from 12 to 18 months, and from 18 to 22 months	Age 40 to 46, employed at least 36 (44, respectively) months in the last 7 years

Notes: The table presents the key design features and sample restrictions of recent papers using regression discontinuity designs to evaluate the effect of UI generosity.

B Derivation of Theoretical Results

B.1 Worker's Problem

Consider the worker's problem described in Section 2. The life-time value of utility if a person finds a job at the beginning of period t is

$$V_{x,t}(A_{x,t}) = \max_{A_{x,t+1} \geq A_{x,L}} \left(v_x(\underbrace{A_{x,t} - A_{x,t+1} + (1-\tau)w_{x,t}}_{c^e_{x,t}}) + V_{x,t+1}(A_{x,t+1}) \right), \tag{14}$$

The value for a person who does not find a job at the beginning of a period is

$$U_{x,t}(A_{x,t}) = \max_{A_{x,t+1} \geq A_{x,L}} \left(u_x(\underbrace{A_{x,t} - A_{x,t+1} + b_{x,t}}_{c^u_{x,t}}) + J_{x,t+1}(A_{x,t+1}) \right), \tag{15}$$

where $u_x(c^u_{x,t})$ is the flow utility while unemployed. The value of job search in period t is

$$J_{x,t}(A_{x,t}) = \max_{s_{x,t}} \left(s_{x,t} V_{x,t}(A_{x,t}) + (1 - s_{x,t}) U_{x,t}(A_{x,t}) - \psi_x(s_{x,t}) \right), \tag{16}$$

where $s_{x,t}$ is job search effort expressed in terms of the job finding rate and $\psi_x(s_{x,t})$ is the differentiable, increasing, and convex cost of job search. Under the assumption that $U(\cdot)$ is concave, optimal search intensity in each period is implicitly defined by

$$V_{x,t}(A_{x,t}) - U_{x,t}(A_{x,t}) = \psi'_x(s_{x,t}). \tag{17}$$

B.2 Proof of PROPOSITION 1

Let $\bar{W} \equiv \sum_{x \in X} N_x (T_x - D_x) w_x$ denote total lifetime earnings that serve as the tax base for financing UI and $\bar{B} \equiv \sum_{x \in X} N_x B_x b_x$ total expenditures on UI such that $\tau = \bar{B}/\bar{W}$. Differentiating the government budget constraint (2) yields:

$$\frac{d\tau}{dP_x}\bar{W} + \tau \sum_{x' \in X} w_{x'} \left(\frac{dN_{x'}}{dP_x}(T_{x'} - D_{x'}) - \frac{dD_{x'}}{dP_x} N_{x'} \right) = b_{x'} \left(\frac{dN_{x'}}{dP_x} B_{x'} + \frac{dB_{x'}}{dP_x} N_{x'} \right) \tag{18}$$

Rearranging then yields:

$$\frac{d\tau}{dP_x} = \frac{1}{\bar{W}} \sum_{x' \in X} \frac{dN_{x'}}{dP_x} \left[B_{x'} b_x - (T_{x'} - D_{x'}) w_{x'} \tau \right] + N_{x'} \left(\frac{dD_{x'}}{dP_x} w_{x'} \tau + \frac{dB_{x'}}{dP_x} b_{x'} \right) \tag{19}$$

Replacing τ with $\bar{B}/\bar{W}$ yields the result in PROPOSITION 1.

B.3 Welfare Derivative

Social welfare at time $t=0$ aggregates welfare over all groups accounting for their size:

$$W_0 = \sum_{x\in X} N_x W_{x,0} \tag{20}$$

$$W_{x,0} = s_{x,0}V_{x,0}(P_x,\tau)+(1-s_{x,0})U_{x,0}(P_x,\tau)-\psi_x(s_{x,0}). \tag{21}$$

To be able to work with derivatives with respect to P_x, we follow Schmieder et al. (2012) and assume that P_x can be increased by a fraction of 1, meaning that a fraction of the period $int(P_x)$ is covered by the higher benefit level b_x if P_x is not an integer number. Thus, $b_{x,t}$ can change within a period and equals the fraction that is covered times b_x. In that case, a marginal change in P_x normalized by b_x is the same as a marginal change in b_{x,P_x}, where P_x is the period after benefits are exhausted since we start at time 0. Hence, the welfare derivative is given by

$$\frac{dW_0}{dP_x}\frac{1}{b_x} = \frac{dW_0}{db_{x,P_x}} = \sum_{x'\in X} N_{x'}\frac{dW_{x',0}}{db_{x,P_x}} + \sum_{x'\in X}\frac{dN_{x'}}{db_{x,P_x}}W_{x,0}. \tag{22}$$

Under the assumption that workers cannot manipulate the group they belong to, $\frac{dN_{x'}}{dP_x}=0$ for all groups $x'\in X$, the second sum on the right-hand side of (22) is zero. The remaining first term on the right-hand side of (22) sums over the group-specific welfare derivatives. For group x that directly benefits from the increase in transfers, it is given by

$$\frac{dW_{x,0}}{db_{x,P_x}} = (1-s_{x,0})\frac{\partial U_{x,0}}{\partial b_{x,P_x}} - \left((1-s_{x,0})\frac{\partial U_{x,0}}{\partial w_x}+s_{x,0}\frac{\partial V_{x,0}}{\partial w_x}\right)w_x\frac{d\tau}{dP_x}\frac{1}{b_x}. \tag{23}$$

The first term on the right-hand side is the utility gain from increasing PBD for group x. The second term is the utility loss from reduced consumption due to the higher tax payed when employed. For group $x'\neq x$, the welfare derivative only comprises the utility loss from lower consumption, because the higher taxes are being collected from *all* groups to finance UI:

$$\frac{dW_{x',0}}{db_{x,P_x}} = -\left((1-s_{x',0})\frac{\partial U_{x',0}}{\partial w_{x'}}+s_{x',0}\frac{\partial V_{x',0}}{\partial w_{x'}}\right)w_{x'}\frac{d\tau}{dP_x}\frac{1}{b_x} \quad \forall\, x'\neq x. \tag{24}$$

Following the derivations in Schmieder et al. (2012), we get

$$(1-s_{x,0})\frac{\partial U_{x,0}}{\partial b_{x,P_x}} = S(P_x)u_x'(c^u_{x,P_x}) \tag{25}$$

$$(1-s_{x,0})\frac{\partial U_{x,0}}{\partial w_x}+s_{x,0}\frac{\partial V_{x,0}}{\partial w_x} = (T_x-D_x)E_{0,T_x-1}[v_x'(c^e_{x,t})] \tag{26}$$

where $S_x(P_x)=\prod_{i=0}^{P_x}(1-s_{x,i})$ is the UI exhaustion rate of group x and

$$(T_x-D_x)E_{0,T_x-1}[v'(c^e_{x,t})] = s_{x,0}T_x v'(c^e_{x,0}) + \sum_{t=1}^{T_x-1}\left[\prod_{i=1}^{t-1}(1-s_{x,i})\right]s_{x,t}(T_x-t)v'(c^e_{x,t}). \tag{27}$$

The total welfare derivative with respect to P_x is then given by

$$\frac{dW_0}{dP_x} = \frac{dW_0}{db_{x,P_x}} b_x = N_x b_x \left[S_x(P_x) u'_x(c^u_{x,P_x}) - \frac{d\tau}{dP_x} \sum_{x' \in X} \bar{W}_{x'} E_{0,T'_x-1}[v'_{x'}(c^e_{x',t})] \right], \tag{28}$$

where $\bar{W}_{x'} \equiv N_{x'}(T_{x'} - D_{x'}) w_{x'}$ is expected lifetime earnings of group x'. Plugging the tax derivative (53) into (28) and rearranging yields

$$\frac{dW_0}{dP_x} = N_x b_x \left[S_x(P_x) u'_x(c^u_{x,P_x}) - \left(\frac{dB_x}{dP_x} + \frac{dD_x}{dP_x} \frac{\bar{B}}{\bar{W}} \frac{w_x}{b_x} \right) \sum_{x' \in X} \frac{\bar{W}_{x'}}{\bar{W}} E_{0,T'_x-1}[v'_{x'}(c^e_{x',t})] \right]. \tag{29}$$

As Schmieder et al. (2012), we use the approximation that $E_{0,T_{x'}-1}[v'_{x'}(c^e_{x',t})] \approx v'_{x'}(c^e_{x',P_x})$. This approximates expected marginal utility while employed over the remaining working life in group x' with marginal utility at time $t = P_x$ in the unemployment spell where group x would exhaust UI. This is reasonable if nonemployment durations are short relative to lifetime employment, or if the people with shorter durations than P_x who have lower $v'_x(c^e_{x',t})$ are outweighed by individuals with longer durations. Using this approximation, we get

$$\frac{dW_0}{dP_x} = N_x b_x \left[S_x(P_x) u'_x(c^u_{x,P_x}) - \left(\frac{dB_x}{dP_x} + \frac{dD_x}{dP_x} \frac{\bar{B}}{\bar{W}} \frac{w_x}{b_x} \right) \sum_{x' \in X} \frac{\bar{W}_{x'}}{\bar{W}} v'_{x'}(c^e_{x',P_x}) \right]. \tag{30}$$

Using $\bar{v}'(c^e_{P_x}) \equiv \sum_{x' \in X} \frac{\bar{W}_{x'}}{\bar{W}} v'_{x'}(c^e_{x',P_x})$ yields the welfare derivative (B.3).

B.4 Proof of PROPOSITION 2

Note that

$$\frac{dB_x}{dP_x} = S_x(P_x) + \sum_{t=0}^{P_x-1} \frac{dS_x(t,x)}{dP_x}. \tag{31}$$

Using this, we get

$$\frac{dW_0}{dP_x} = N_x b_x \left[S_x(P_x)[u'_x(c^u_{x,P_x}) - \bar{v}'(c^e_{P_x})] - \left(\sum_{t=0}^{P_x} \frac{dS_x(t,x)}{dP_x} + \frac{dD_x}{dP_x} \frac{\bar{B}}{\bar{W}} \frac{w_x}{b_x} \right) \bar{v}'(c^e_{P_x}) \right]. \tag{32}$$

Dividing the welfare derivative by N_x, b_x, $S_x(P_x)$ and $\bar{v}'(c^e_{P_x})$ yields

$$\frac{d\tilde{W}_0}{dP_x} \equiv \frac{dW_0}{dP_x} \Big/ \left(N_x b_x S_x(P_x) \bar{v}'(c^e_{P_x}) \right) \tag{33}$$

$$= \frac{u'_x(c^u_{x,P_x}) - \bar{v}'(c^e_{P_x})}{\bar{v}'(c^e_{P_x})} - \frac{1}{S_x(P_x)} \left(\sum_{t=0}^{P_x} \frac{dS_x(t,x)}{dP_x} + \frac{dD_x}{dP_x} \frac{\bar{B}}{\bar{W}} \frac{w_x}{b_x} \right). \tag{34}$$

We obtain the expression in PROPOSITION 2 by rewriting the duration derivatives in terms of the elasticities using $\sum_{t=0}^{P_x} \frac{dS_x(t,x)}{dP_x} = \varepsilon_{B,x} \frac{B_x}{P_x}$ and $\frac{dD_x}{dP_x} = \varepsilon_{D,x} \frac{D_x}{P_x}$, where the elasticities are defined as $\varepsilon_{Y,P_x} = \frac{dY}{dP_x} \frac{P_x}{Y}$ for $Y \in \{B_x, D_x\}$.

B.5 Budget-Neutral Changes in PBD

A budget-neutral change in the PBD schedule $\{\Delta P_x\}_{x \in X}$ can be defined as

$$d\tau \overset{!}{=} 0 \quad = \quad \sum_{x \in X} \frac{d\tau}{dP_x} \Delta P_x = \frac{N_x}{\bar{W}} \left(\frac{dD_x}{dP_x} w_x \frac{\bar{B}}{\bar{W}} + \frac{dB_x}{dP_x} b_x \right) \Delta P_x, \tag{35}$$

where ΔP_x denotes the change in PBD of group x. Welfare-increasing changes in PBD for group x satisfy

$$sign(\Delta P_x) = sign\left(\frac{d\tilde{W}_0}{dP_x} \right) \Leftrightarrow \frac{d\tilde{W}_0}{dP_x} \Delta P_x > 0. \tag{36}$$

Thus, a necessary condition for the existence of budget-neutral changes in PBD that improve overall welfare is that the welfare derivative is positive for at least one group $x \in X$ and negative for at least one other group $x' \neq x$. In this case, PBD should increase for the former and decrease for the latter. A change in the PBD schedule $\{\Delta P_x\}_{x \in X}$ that satisfies budget neutrality (35) and (36) will increase total welfare if

$$\sum_{x \in X} \frac{dW_0}{dP_x} \frac{1}{b_x \bar{v}'(c^e_{P_x})} \Delta P_x = \sum_{x \in X} N_x S_x(P_x) \frac{d\tilde{W}_0}{dP_x} \Delta P_x > 0. \tag{37}$$

This will depend on the group sizes N_x and benefit exhaustion rates S_x of all groups $\sum_{x \in X}$ for which the welfare derivative is not zero.

C Model Extensions

C.1 Group-Specific Tax Rates: Proof of PROPOSITION 3

Assume that the government budget needs to be balanced within group:

$$(T_x - D_x) w_x \tau_x = B_x b_x \qquad \forall\, x \in X. \tag{38}$$

Differentiating this budget constraint with respect to P_x yields:

$$\frac{d\tau_x}{dP_x}(T_x - D_x) w_x \;=\; \frac{dB_x}{dP_x} b_x + \frac{dD_x}{dP_x} w_x \tau_x = b_x \left(\frac{dB_x}{dP_x} + \frac{dD_x}{dP_x} \frac{B_x}{T_x - D_x} \right). \tag{39}$$

Note that with group-specific tax rates, other groups do not matter for the fiscal externality such that inflow effects on group size and spillover effects across groups are absent by construction.

The groups-specific welfare derivatives are

$$\frac{dW_{x,0}}{db_{x,P_x}} \;=\; (1 - s_{x,0}) \frac{\partial U_{x,0}}{\partial b_{x,P_x}} - \left((1 - s_{x,0}) \frac{\partial U_{x,0}}{\partial w_x} + s_{x,0} \frac{\partial V_{x,0}}{\partial w_x} \right) w_x \frac{d\tau_x}{dP_x} \frac{1}{b_x}. \tag{40}$$

$$\frac{dW_{x',0}}{db_{x,P_x}} \;=\; 0 \quad \forall\, x' \neq x. \tag{41}$$

For group x, the only difference is that the tax derivative is now group-specific. However, all groups $x' \neq x$ are now unaffected by the change in P_x because only the tax in group x is raised to finance this change. The total welfare derivative then becomes

$$\frac{dW_0}{dP_x} = N_x b_x \left[S_x(P_x) u_x'(c^u_{x,P_x}) - \left(\frac{dB_x}{dP_x} + \frac{dD_x}{dP_x} \frac{B_x}{T_x - D_x} \right) E_{0,T_x-1}[v_x'(c^e_{x,t})] \right]. \tag{42}$$

Following the same steps to replace $\frac{dB_x}{dP_x}$ as before, dividing by N_x, b_x, $S_x(P_x)$ and $E_{0,T_x-1}[v_x'(c^e_{x,t})]$, and using the approximation that $E_{0,T_x-1}[v_x'(c^e_{x,t})] \approx v_x'(c^e_{x,P_x})$, we get

$$\frac{d\tilde{W}_0}{dP_x} \;\equiv\; \frac{dW_0}{dP_x} \Big/ \left(N_x b_x S_x(P_x) v_x'(c^e_{x,P_x}) \right) \tag{43}$$

$$\;=\; \frac{u_x'(c^u_{x,P_x}) - v_x'(c^e_{x,P_x})}{v_x'(c^e_{x,P_x})} - \frac{1}{S_x(P_x)} \left(\sum_{t=0}^{P_x} \frac{dS_x(t,x)}{dP_x} + \frac{dD_x}{dP_x} \frac{B_x}{T_x - D_x} \right). \tag{44}$$

Rewriting the duration derivatives in terms of elasticities then yields the result in PROPOSITION 3.

C.2 Inflow and Spillover Effects

The general model allows for manipulation of group size and spillover effects across groups. Using the approximation that $E_{0,T_x-1}[v_x'(c^e_{x,t})] \approx v_x'(c^e_{x,P_x})$, the welfare derivative rescaled by average marginal utility of the employed, $\bar{v}'(c^e_{P_x})$, is given by

$$\frac{dW_0}{dP_x}\frac{1}{\bar{v}'(c^e_{P_x})} = \underbrace{\sum_{x'\in X}\frac{dN_{x'}}{dP_x}\frac{W_{x,0}}{\bar{v}'(c^e_{P_x})}+N_x b_x S_x(P_x)\frac{u'_x(c^u_{x,P_x})}{\bar{v}'(c^e_{P_x})}}_{\substack{\text{Social value } SV_x \\ \text{of 1 EUR add. transfer}}} \quad (45)$$

$$\underbrace{-\sum_{x'\in X}\frac{dN_{x'}}{dP_x}\left(B_{x'}b_{x'}-(T_{x'}-D_{x'})w_{x'}\frac{\bar{B}}{\bar{W}}\right)+N_{x'}\left(\frac{dD_{x'}}{dP_x}w_{x'}\frac{\bar{B}}{\bar{W}}+\frac{dB_{x'}}{dP_x}b_{x'}\right)}_{\substack{\text{Behavioral cost } BC_x \\ \text{of 1 EUR add. transfer}}}.$$

Rewriting the derivatives in terms of elasticities yields

$$\begin{aligned}\frac{dW_0}{dP_x}\frac{1}{\bar{v}'(c^e_{P_x})} &= \sum_{x'\in X}\varepsilon_{N,x'}\frac{N_{x'}}{P_x}\frac{W_{x',0}}{\bar{v}'(c^e_{P_x})}+N_x b_x S_x(P_x)\frac{u'_x(c^u_{x,P_x})}{\bar{v}'(c^e_{P_x})} \\ &\quad -\sum_{x'\in X}\varepsilon_{N,x'}\frac{N_{x'}}{P_x}\left(B_{x'}b_{x'}-(T_{x'}-D_{x'})w_{x'}\frac{\bar{B}}{\bar{W}}\right) \\ &\quad -\sum_{x'\in X}N_{x'}\left(\varepsilon_{D,x'}\frac{D_{x'}}{P_x}w_{x'}\frac{\bar{B}}{\bar{W}}+\varepsilon_{B,x'}\frac{B_{x'}}{P_x}b_{x'}\right),\end{aligned} \quad (46)$$

where the first term on the right-hand side is the social value and the two other terms together comprise the behavioural cost. In addition to the duration responses of group x, $\varepsilon_{D,x}$ and $\varepsilon_{D,x}$ that need to be estimated in the restricted model, assessing the welfare effects of changing PBD in group x in the general model would require quantifying the inflow effects for all $x'\in X$, $\varepsilon_{N,x'}$, the group-specific welfare levels for all $x'\in X$, $W_{x',0}$, as well as the spillover effects in terms of duration responses of all remaining groups $x'\neq x$, $\varepsilon_{D,x'}$ and $\varepsilon_{D,x'}$.

C.3 Heterogeneous Welfare Weights

Let $\gamma_x \geq 0$ denote the welfare weight the planner gives to group x. Social welfare at time $t=0$ is then given by

$$W_0 = \sum_{x\in X}\gamma_x N_x W_{x,0}. \quad (47)$$

If $\gamma_x = 1$ group size N_x fully determines the total weight of group x in the welfare function. If $\gamma_x > 1$, group x receives an over-proportional weight, and if $\gamma_x < 1$ an under-proportional weight. It is easy to see that the normalized per capita welfare derivative is unchanged in this case except that the normalization includes dividing by γ_x:

$$\frac{d\tilde{W}_0}{dP_x} \equiv \frac{dW_0}{dP_x}\Big/\left(\gamma_x N_x b_x S_x(P_x)\bar{v}'(c^e_{P_x})\right) \quad (48)$$

$$= \underbrace{\frac{u'_x(c^u_{x,P_x})-\bar{v}'(c^e_{P_x})}{\bar{v}'(c^e_{P_x})}}_{\substack{\text{Social value } SV_x \\ \text{of 1 EUR add. transfer}}} - \underbrace{\frac{1}{S_x(P_x)}\left(\varepsilon_{B,x}\frac{B_x}{P_x}+\varepsilon_{D,x}\frac{D_x}{P_x}\frac{\bar{B}}{\bar{W}}\frac{w_x}{b_x}\right)}_{\substack{\text{Behavioral cost } BC_x \\ \text{of 1 EUR add. transfer}}}. \quad (49)$$

However, the total welfare derivative is affected by both group size and the welfare weight, such that conclusions about the overall welfare effects of changing PBD for any group x can change if the planner gives over- or under-proportional weight to certain groups:

$$\frac{dW_0}{dP_x}\frac{1}{b_x\bar{v}'(c^e_{P_x})} = \gamma_x N_x S_x(P_x)\frac{d\tilde{W}_0}{dP_x} = \gamma_x N_x S_x(P_x)(SV_x - BC_x). \tag{50}$$

C.4 Wage Effects of Changing PBD

Let $w^e_{x,t}$ denote the worker's wage when finding a job in period t after the beginning of unemployment, which may be affected by UI generosity. The life-time value of utility if a person finds a job at the beginning of period t is

$$V_{x,t}(A_{x,t}) = \max_{A_{x,t+1}\geq A_{x,L}} \left(v_x(\underbrace{A_{x,t} - A_{x,t+1} + (1-\tau)w^e_{x,t}}_{c^e_{x,t}}) + V_{x,t+1}(A_{x,t+1})\right) \tag{51}$$

in this case. While the wage w^e_x may change upon reemployment, we assume that it stays constant over the remaining working life. The government budget constraint is

$$\tau \sum_{x\in X} N_x(T_x - D_x)w^e_x = \sum_{x\in X} N_x B_x b_x. \tag{52}$$

Under the assumptions of no manipulation of group size and no spillover effects across groups, differentiating the budget constraint yields

$$\frac{d\tau}{dP_x} = \frac{N_x}{\bar{W}}\left(\frac{dD_x}{dP_x}w^e_x\frac{\bar{B}}{\bar{W}} + \frac{dB_x}{dP_x}b_x - \frac{dw^e_x}{dP_x}(T_x - D_x)\frac{\bar{B}}{\bar{W}}\right), \tag{53}$$

where the last term is the wage effect of changing PBD. If higher PBD improves job match quality in terms of the wage, this reduces the fiscal externality. If, instead, human capital depreciation dominates and reduces the reemployment wage, the fiscal externality is larger than in the absence of wage effects (Nekoei and Weber, 2017).

Plugging the tax derivative into the welfare derivative (28), using the approximation that $E_{0,T_x-1}[v'_x(c^e_{x,t})] \approx v'_x(c^e_{x,P_x})$ and rearranging yields

$$\frac{dW_0}{dP_x} = N_x b_x\left[S_x(P_x)u'_x(c^u_{x,P_x}) - \left(\frac{dB_x}{dP_x} + \frac{dD_x}{dP_x}\frac{\bar{B}}{\bar{W}}\frac{w_x}{b_x} - \frac{dw^e_x}{dP_x}(T_x - D_x)\frac{\bar{B}}{\bar{W}}\right)\bar{v}'(c^e_{P_x})\right]. \tag{54}$$

Normalizing the welfare derivative as before and rewriting the duration and wage derivatives in terms of elasticities yields the final welfare formula

$$\frac{d\tilde{W}_0}{dP_x} \equiv \frac{dW_0}{dP_x} / \left(N_x b_x S_x(P_x) \bar{v}'(c^e_{P_x}) \right) \tag{55}$$

$$= \underbrace{\frac{u'_x(c^u_{x,P_x}) - \bar{v}'(c^e_{P_x})}{\bar{v}'(c^e_{P_x})}}_{\substack{\text{Social value } SV_x \\ \text{of 1 EUR add. transfer}}} \tag{56}$$

$$\underbrace{- \frac{1}{S_x(P_x)} \left[\varepsilon_{B,x} \frac{B_x}{P_x} + \left(\varepsilon_{D,x} \frac{D_x}{P_x} - \varepsilon_{w^e,x} \frac{T_x - D_x}{P_x} \right) \frac{\bar{B}}{\bar{W}} \frac{w^e_x}{b_x} \right]}_{\substack{\text{Behavioral cost } BC_x \\ \text{of 1 EUR add. transfer}}}.$$

The behavioral cost now includes the wage effect of changing PBD, while the rest of the formula remains unchanged. The wage elasticity $\varepsilon_{w^e,x}$ can be measured with the same reduced-form approach we employ to estimate the duration elasticities. We obtain estimates that are very small and not statistically significant at conventional levels.

D Details on the Institutional Setting, Data and Variables

D.1 Unemployment Insurance Regimes in Germany

We conducted a systematic review of the relevant legal provisions and changes therein for the years 1994 to 2016 — our observation window. We begin in January 1994 because the UI replacement rate has been unchanged since then, at 60% without and 67% with dependent children, respectively. This allows us to focus on changes in the duration rather than the level of benefits. The *Arbeitsförderungsgesetz* (AFG) was in effect until 1998, and the *Drittes Buch Sozialgesetzbuch* (SGB III) afterwards, with several revisions. As shown in Table D.1, we split our study period in 4 regimes. We summarise the main regulations and what can be observed in the data in this Appendix. The main relevant differences are in the PBD schedule, as well as the time horizons used to determine eligibility and the PBD.

Note that transition rules applied between some regime changes. In the transition between regimes 1 and 2, the SGB III reform was implemented gradually between 1997 and 1999, so that those workers who contributed at least one year in the three years before 1 April 1997 fell under the old rules until 1 April 1999. We assign the concerned workers to regime 1. In the transition between regimes 3 and 4, workers who were unemployed at the time of the reform had their PBD prolonged retroactively. We exclude them as we cannot infer their initial PBD from the data.

Table D.1: PBD Schedule Regimes in Germany

Regime	Start date	End date	Eligibility determination time horizon	PBD determination time horizon
1	1 July 1987	31 March 1997	36	84
2	1 April 1997	31 January 2006	36	84
3	1 February 2006	31 December 2007	24	36
4	1 January 2008	30 June 2020	24	60

Notes: Time horizons in months of 30 calendar days, from the start date of UI benefits payment. PBD: Potential benefit duration. Sources: *Arbeitsförderungsgesetz* (AFG), and *Drittes Buch Sozialgesetzbuch* (SGB III).

Eligibility. The key elements for UI eligibility and PBD determination rules remained constant over the study period. We focus on spells which constituted a new claim, such that the unemployed is eligible for a new PBD rather than the leftover, if any. The key requirements for a new claim are: (i) Being below the statutory retirement age at entry into unemployment; (ii) job loss (in case of a voluntary separation, a waiting penalty of up to 3 months applies); (iii) having contributed to social security at least 12 months within the last 36 months (24 after 2006), or since the last UI spell. One month is 30 calendar days, so that one year is 360 calendar days.

PBD determination rules. Conditional on eligibility, the key ingredients for the determination of the new PBD are the exact age at entry into UI and the months contributed to social security within the PBD determination time horizon (see Figure 1). We impute the second variable from past social security spells (see below). The total PBD at the beginning of the spell includes leftover PBD from past unemployment spells that is added up to the new PBD, up to the age-specific maximum. This is the case if the new claim arises less than 7 years (5 and 4 in regimes 3 and 4, respectively) after accrual of the old claim. If there is no new claim within this period, old unused claims expire 4 years after their accrual.

PBD imputation. Each spell in the unemployment records (LEH) contains information on the leftover PBD from the total at the beginning of the spell (equal to 0 if benefits are exhausted). The start and end dates of the spell capture the time of actual receipt of benefits, since unemployed workers are deregistered from unemployment at benefit exhaustion. Adding the duration of the spell to the leftover PBD allows recovering the beginning PBD P^{begin} as

$$P^{begin} = \min\{P^{max}(a), D + R\} \tag{57}$$

where $P^{max}(a)$ is the age-specific maximum, D is the duration of UI receipt, and R is the leftover PBD of this spell. A similar approach is adopted by Price (2019). It is possible that the PBD is updated while the worker is unemployed, giving rise to a new spell in the data. We correct for this by regrouping all UI spells one day apart, and compute the initial PBD at entry into UI using the duration and the remaining PBD from the first spell in the group.

Our treatment of interest is extensions in new PBD at the threshold. Furthermore, for the estimation of RD effects at the cutoffs, we select spells where the new PBD falls onto a specific step (see Section 3.2). To compute new PBD, we take the beginng PBD and subtract the leftover from the previous UI spell (if any within the carry-over horizon). Note that the new PBD cannot be computed for spells with total PBD equal to the age-specific maximum due to the capping in (57). The PBD may be adjusted during the course of the spell, e.g., due to penalties for not accepting a suitable job. Our step-based approach should eliminate these cases.

D.2 Details on Unemployment Spell Selection

In the unemployment record data, we delete duplicates, correct the spells for overlap by truncating the later spell, and regroup spells with end and start dates one day apart due to corrections or ex-post changes in benefits.

For the sample at the age cutoffs (*age sample*), we take workers aged at most 2 years from the closest age cutoff, who satisfy the minimum contribution requirement to be eligible for the age-specific maximum above that cutoff. As for sample at the contribution cutoffs (*contribution sample*), we select spells with a new PBD equal to given steps of the schedule (e.g., 10, 12 months). This restricts the sample to workers eligible for a new UI claim.

The sample excludes spells with no previous employment at all, as well as spells with no regular employment nor contribution-relevant social security records since the last UI spell or in the last 3 years. We also exclude inflows occurring in transition periods between regimes, in particular spells starting within 2 months before any regime change, and spells that cross January

1, 2008, for which the PBD might have been prolonged retroactively.

D.3 Imputation of Contribution Time

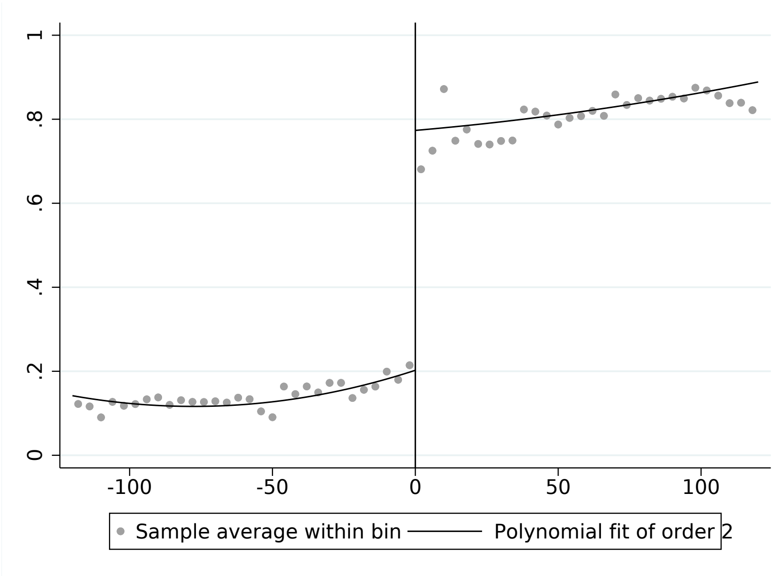
Counting days of contribution. Contribution time is not directly recorded in our data. We use daily social security records to impute this variable. First, for each unemployment spell in the initial sample, we identify all observed recorded past spells that count towards social security contribution time (regular employment, employment programs, employment with zero wages up to 4 weeks, and certain types of education). We correct these spells for overlap by truncating those with the earliest starting date to end one day before the next spell. We also truncate spells overlapping with unemployment benefit receipt, prioritizing the latter. Second, we count the distinct days of contribution over the eligibility and the PBD determination time horizons. We then convert this into months, where 1 month equals 30 calendar days.

Third, we use past contribution records to exclude individuals subject to special rules, and non-standard UI incentives. These special groups include seasonal workers, who are subject to lower eligibility requirements (e.g., 6 months of work for 3 months of UI, excluded automatically since we exclude spells with less than 6 months of new PBD); participants in certain vocational training programs that reduced the PBD; recipients of Unterhaltsgeld (UHG), which altered applicable contribution time horizons.

Measurement error. There are several potential sources of mismeasurement in contribution time. Certain events that affect contribution time or the relevant time horizon are unobserved in the data (e.g., penalties for not accepting a suitable job, sick leave, parental leave, self-employment). There can also be imprecisions in the recording of spells, especially early in the observation period (e.g., overlapping spells, gaps in the labor market history, waiting times, misreporting of employment durations by firms for short-term contracts).

Figure D.1 shows that there is a first-stage discontinuity in the *true* treatment status as a function of imputed contribution time centered at the closest cutoff. This check provides evidence that not all the observations are contaminated by measurement error in our sample. We then compare the PBD imputed based on imputed contribution time, with the PBD obtained from the reliably-recorded leftover PBD. We define as *consistent* the spells where the imputed PBD equals the observed one. Table D.2 shows that the share of consistent spells lies between 60 and 78 percent across regimes.

Figure D.1: True Treatment Probability as a Function of Imputed Contribution



Notes: The figure displays the true treatment probability (based on the PBD) as a function of centered imputed contribution time (in days) using the contribution sample.

Table D.2: Share of Samples among All Available Unemployment Spells

	Regime 1	Regime 2	Regime 3	Regime 4
Age maximum PBD	0.437	0.406	0.519	0.508
No new claim (PBD $<$ 6 mths)	0.087	0.125	0.169	0.131
Classified to PBD step	0.164	0.207	0.123	0.152
Age sample	0.261	0.208	0.016	0.145
Contribution sample	0.105	0.124	0.063	0.092
Consistent	0.783	0.737	0.601	0.736
Observations	423974	663331	92483	210486

Notes: The table shows shares of given samples in the initial sample of drawn unemployment spells. Age maximum PBD: Spells with the age-specific maximum potential benefit duration (PBD), which include the spells entering in the age sample. No new claim: Spells with observed PBD below 6 months (i.e., not eligible for a new claim, but a residual unemployment claim from a previous spell only). Age sample: Spells used in the estimations based on age cutoffs. Contribution sample: Spells used in the estimations based on age cutoffs (see Section 3.2). Consistent: Spells for which we correctly impute the PBD in the analysis sample.

D.4 Variables and Descriptive Statistics

This appendix provides additional details on the construction of covariates and outcome variables. We code missing values of categorical variables as separate categories if their share exceeds 5% of the initial sample, and to the highest mode otherwise. Missing education information for each unemployment spell is filled up using information from past employment spells or corresponding ASU spells if available, following the procedure in Fitzenberger et al. (2005). Last-job characteristics are based on the last non-zero wage job before UI entry. Tenure is computed as the duration between the start and the end date of this job, regrouping spells that are at most 14 days apart and carry the same firm identifier. Following existing studies (Schmieder et al., 2012; Price, 2019), the first job at reemployment is identified as the first regular employment spell after unemployment. This way, we do not consider small or mini jobs used to top-up UI benefits, but rather employment subject to regular social security contributions, that is more likely to reflect a stable reintegration into the labor market. Tenure in the first job at reemployment is computed as for the last job.

Table D.3: Summary Statistics for the Analysis Sample of Unemployment Spells

	(1)		(2)		(3)	
	Pooled sample		Age sample		Contribution sample	
Panel (a) Observable characteristics						
Age	47.77	(4.06)	47.74	(4.03)	47.84	(4.13)
Female	0.42	(0.49)	0.41	(0.49)	0.45	(0.50)
Non-German	0.08	(0.27)	0.07	(0.26)	0.10	(0.30)
Residence in East Germany	0.21	(0.40)	0.20	(0.40)	0.23	(0.42)
Residence missing	0.30	(0.46)	0.32	(0.47)	0.27	(0.44)
Secondary schooling (ref.)	0.88	(0.32)	0.88	(0.32)	0.88	(0.33)
No secondary schooling	0.08	(0.27)	0.08	(0.28)	0.08	(0.27)
Schooling missing	0.04	(0.19)	0.03	(0.18)	0.04	(0.20)
Vocational training (ref.)	0.71	(0.45)	0.73	(0.44)	0.68	(0.47)
Without vocational training	0.20	(0.40)	0.18	(0.39)	0.23	(0.42)
Academic degree	0.05	(0.23)	0.06	(0.23)	0.05	(0.22)
Degree missing	0.04	(0.19)	0.03	(0.18)	0.04	(0.20)
Last job part-time	0.16	(0.36)	0.14	(0.34)	0.20	(0.40)
Last job tenure	42.43	(46.89)	53.80	(51.82)	19.59	(20.97)
Contribution in last 36 mths	30.16	(7.58)	33.41	(4.50)	23.65	(8.27)
Contribution in last 84 mths	63.77	(21.97)	74.53	(11.95)	42.14	(21.57)
UI in last 84 mths	4.68	(6.94)	2.50	(4.59)	9.06	(8.59)
New PBD	11.42	(4.08)	.	(.)	11.42	(4.08)
Monthly UI benefits	948.08	(419.26)	1,008.79	(433.89)	826.10	(358.37)
Panel (b) Labor market outcomes						
Nonemployment duration (capped at 36m)	17.34	(14.50)	17.08	(14.57)	17.85	(14.34)
Nonemployment duration capped	0.31	(0.46)	0.31	(0.46)	0.32	(0.47)
UI receipt duration	7.89	(6.98)	8.29	(7.66)	7.09	(5.28)
Exhausted UI benefits	0.16	(0.37)	0.12	(0.33)	0.24	(0.43)
First job observed	0.85	(0.36)	0.84	(0.37)	0.86	(0.35)
Unemployed again within 36 months	0.30	(0.46)	0.29	(0.45)	0.31	(0.46)
Wage at reemployment	1,870.47	(934.76)	1,984.03	(957.22)	1,646.19	(845.02)
Log(First wage) - Log(Last wage)	-0.10	(0.53)	-0.13	(0.52)	-0.05	(0.55)
First job tenure	29.57	(43.60)	32.59	(46.31)	23.66	(37.05)
First job part-time	0.18	(0.38)	0.16	(0.36)	0.22	(0.41)
Cum. earnings within 60m	52.73	(56.30)	58.28	(59.62)	41.57	(47.04)
Observations	420448		280716		139732	

Notes: The table shows sample averages with standard deviations in parentheses. Column (1) pools all spells entering the RD analysis (Section 4) for the years 1994–2010. Columns (2) and (3) uses the subset of spells at age and contribution cutoff, respectively. All durations are in months. The new potential benefit duration (PBD) cannot be imputed for spells with PBD at the age-specific maximum, as the PBD at the beginning of the spell (new plus leftover from the last spell) is capped. Nonemployment duration is the time between the first and the last job, capped at 36 months. UI benefits, wages and earnings are in EUR from 2010. UI benefits and wages are monthly. Cumulated earnings are in kEUR. All figures based on the first job at reemployment use the subsample of individuals who find a job within 6 years after job loss.

Table D.4: Summary Statistics for the Analysis Sample of Unemployment Spells by Regime

	(1) Regime 1 1994-1997	(2) Regime 2 1997-2006	(3) Regime 3 2006-2008	(4) Regime 4 2008-2010
Panel (a) Observable characteristics				
Age	47.39	46.96	46.93	47.12
Female	0.41	0.41	0.41	0.40
Non-German	0.10	0.08	0.08	0.09
Residence in East Germany	0.05	0.30	0.28	0.25
Residence missing	0.86	0.02	0.00	0.00
Secondary schooling (ref.)	0.89	0.88	0.88	0.88
No secondary schooling	0.07	0.08	0.10	0.10
Schooling missing	0.04	0.03	0.02	0.02
Vocational training (ref.)	0.69	0.70	0.74	0.73
Without vocational training	0.22	0.21	0.18	0.19
Academic degree	0.05	0.05	0.06	0.06
Degree missing	0.04	0.03	0.02	0.02
Last job part-time	0.13	0.18	0.19	0.18
Last job tenure	32.10	32.89	32.81	31.25
Contribution in last 36 mths	26.93	25.95	26.68	27.53
Contribution in last 84 mths	55.13	57.41	62.87	61.05
UI in last 84 mths	6.69	7.54	8.28	7.58
New PBD	4.69	4.41	2.29	2.78
Monthly UI benefits	1031.96	885.63	887.86	862.93
Panel (b) Labor market outcomes				
Nonemployment duration (capped at 36m)	17.01	16.72	12.64	13.12
Nonemployment duration capped	0.31	0.30	0.22	0.21
UI receipt duration	7.00	6.48	4.32	5.10
Exhausted UI benefits	0.22	0.24	0.14	0.13
First job observed	0.83	0.87	0.90	0.90
Unemployed again within 36 months	0.35	0.35	0.39	0.23
Wage at reemployment	1916.32	1801.43	1764.23	1737.74
Log(First wage) - Log(Last wage)	-0.09	-0.08	-0.02	-0.02
First job tenure	25.55	25.84	26.58	23.47
First job part-time	0.17	0.18	0.17	0.20
Cum. earnings within 60m	50.53	48.57	60.63	61.75
Observations	423974	663331	92483	210486

Notes: The table shows sample averages by regime for the full sample of unemployment spells for the years 1994–2010. Columns (2) and (3) uses the subset of spells at age and contribution cutoff, respectively. All durations are in months. Nonemployment duration is the time between the first and the last job, capped at 36 months. UI benefits, wages and earnings are in EUR from 2010. UI benefits and wages are monthly. Cumulated earnings are in thousands of euros. All figures based on the first job at reemployment use the subsample of individuals who find a job within 6 years after job loss.

Table D.5: Means of Observable Characteristics for IEB and GSOEP Samples, 2010

	(1) Full sample	(2) RD sample	(3) Consistent sample	(4) GSOEP unemployed	(5) GSOEP employed
Age	47.28	50.09	50.61	44.16	44.00
Female	0.40	0.43	0.44	0.44	0.52
Non-German	0.09	0.08	0.07	0.09	0.08
Residence in East Germany	0.23	0.24	0.23	0.41	0.37
Secondary schooling (ref.)	0.88	0.87	0.87	0.83	0.80
No secondary schooling	0.10	0.10	0.11	0.16	0.18
Vocational training (ref.)	0.73	0.73	0.74	0.73	0.73
Without vocational training	0.19	0.18	0.17	0.13	0.10
Academic degree	0.06	0.06	0.07	0.14	0.16
Last job white collar	0.27	0.29	0.31	0.24	0.42
Earnings above EUR 1800	0.47	0.47	0.49	0.23	0.33
Tenure longer than two years	0.35	0.41	0.49	0.50	0.41
Any unemployment observed in last 5 years	0.59	0.38	0.30	0.53	0.37
Observations	61004	14914	11957	285	500

Notes: The table first displays means from the IEB data for the year 2010 from the full sample of unemployment spells (column 1), the analysis sample used for the regression discontinuity design (column 2), and the sample of spells for which the potential benefit duration is imputed consistently (column 3). Columns (4) and (5) show means for the GSOEP samples of unemployed and employed workers from 2010.

E Estimation Cells and Validity Criteria

E.1 Cell Construction

Age cells. We assign observations within a bandwidth of 2 years from the closest cutoff C_i^a in the applicable regime, up to the midpoint to the adjacent cutoff for non-extreme cutoffs. We then split the age boundary into 12-month contribution bands to allow for effect heterogeneity in contribution time. These bands are comparable to the ones in contribution cells. We impose minimum contribution time requirements such that workers would be eligible for a higher PBD. We thus exclude corner cases that would need an increase in both running variables for a PBD extension, and avoid overlap in spells across types of cutoff.

Contribution cells. We select spells lying on adjacent 4-month steps at contribution boundaries C_i^h (Le Barbanchon 2016 uses similar bandwidths). We split the boundary by age group in 5-year bands. We only consider individuals older than 40 to have common support over the treatment plane. The lowest age boundary lies at 42, whereby we use a 2-year bandwidth. Furthermore, workers over 40 have typically participated long enough in the labor market to be able to reach any contribution cutoff. For both types of cells, our main implementation computes separate estimates by calendar year of the spell start date allow for heterogeneity in time, due to e.g., economic conditions or policy changes. We present versions with alternative aggregation levels.

Recall that we cannot directly infer the new PBD in spells with PBD at the beginning of the spell equal to the age-specific maximum. In our estimations using adjacent PBD steps, we drop observations in the control group with leftover PBD such that they would reach the age-specific maximum with the new PBD of the treated group. This ensures that all observations face the same potential change in PBD at the cutoff, i.e., there is a sharp change in treatment status at the cutoff.

E.2 Description of Validity Criteria

We create a set of validity criteria to flag cells that display evidence of selection around the cutoff. Flags are defined to be equal to 1 if the sample fails the corresponding criterion. We exclude ex ante all cells with fewer than 250 spells.

Common support in covariates.[46] We flag the sample if any of the covariates in the sample has an average smaller than the 1$^{\text{st}}$ or greater than the 99$^{\text{th}}$ percentile of the distribution of sample averages. This allows excluding cells with very particular subpopulations.

Sorting in covariates. We take covariates as outcomes, and estimate the RD effect between treated and control groups within each estimation sample. We do so by taking a simple difference-in-means, as well as an RD estimator for each type of cutoff. We use the latter to select our main set of valid cells, as the flags from the two approaches are highly correlated. We flag the sample if the share of covariates with a jump significant at the p level exceeds a share x of all considered covariates. This criterion identifies cells which display evidence of systematic selection around

[46] Covariates are female, non-German, residence in East Germany, secondary education, higher education, and last job part-time.

the cutoff in terms of observable characteristics.

Manipulation of the running variable (age cells only).[47] We perform a density discontinuity test to check for evidence of manipulation of the running variable around the cutoff using the method in Cattaneo et al. (2018). We flag cells where the test statistic is significant at the p level and which show evidence of precise manipulation of the timing of entry into UI at the cutoff. Notice that the density plots in Figure E.1 show no evidence for local manipulation at the age cutoffs.

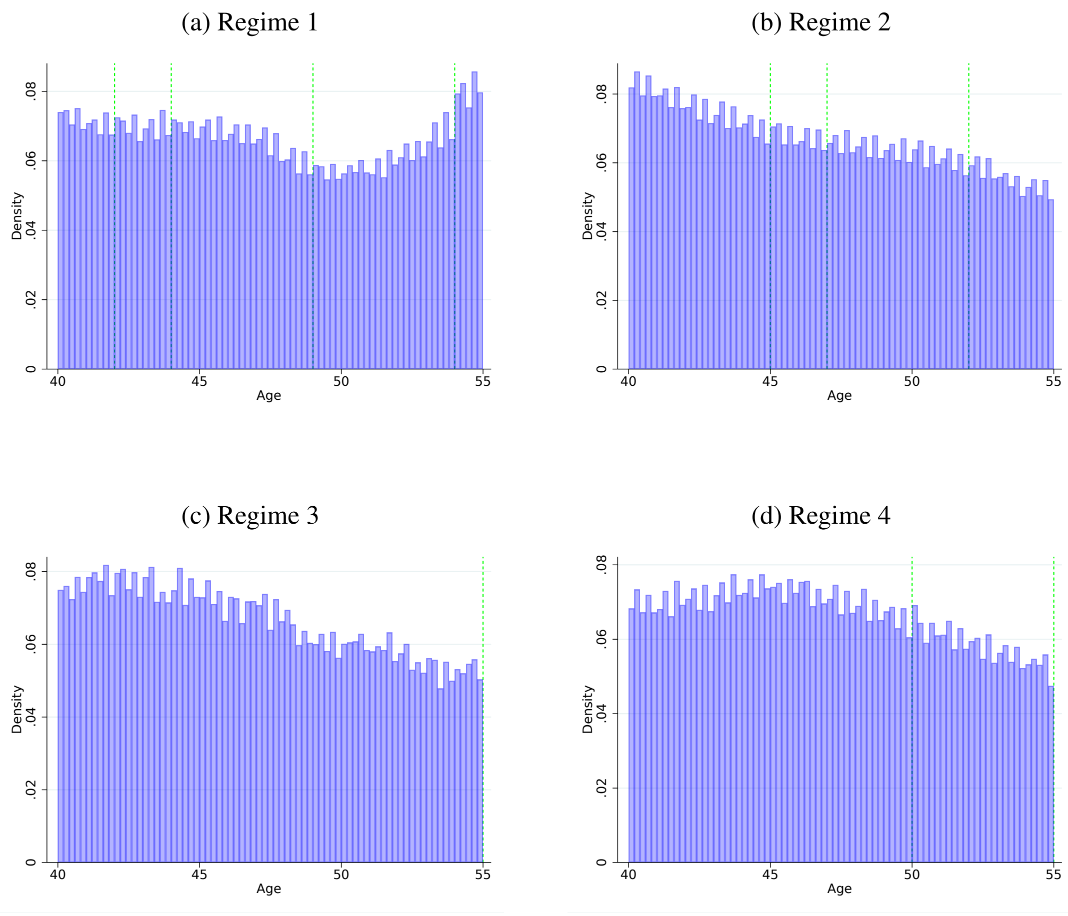
Flatness of potential outcomes (contribution cells only). We regress nonemployment duration on the days in the main activities subject to social security contributions,[48] separately within control and treated groups. We exclude the sample if the share of activities with a slope significant at the p level jointly in the control and the treated group exceeds a share x of all considered activities. This criterion is meant to exclude cells with potentially steep and nonlinear potential outcome functions.

We conservatively define a sample as valid if it does not fail any of the criteria above, using $p = 0.05$ for the level of significance and $x = 0.2$ for the share of covariates that has to be significant. Table E.1 displays summary statistics for sample characteristics and validity. Overall, 314 of the 434, i.e., 73% of cells satisfy all the criteria. The average sample size of about 1,100 spells is similar for the valid cells, with contribution cells smaller on average. The share of treated observations in each sample is around 0.46 on average. The share of cells with significant selection in covariates is around 13%, with larger shares using difference-in-means estimators. The average share of contribution activities with significant slope is of 10%.

[47] This test relies on precise measurement of the running variable and cannot be implemented directly in contribution cells.

[48] Considered activities are regular employment, zero-wage employment (capped at 4 weeks) and some forms of education, mini jobs, UI benefit receipt, and participation in contribution-relevant active labor market programs. These are measured within the regime-specific contribution horizon or up to the last UI spell (time in UI is measured over last 7 years).

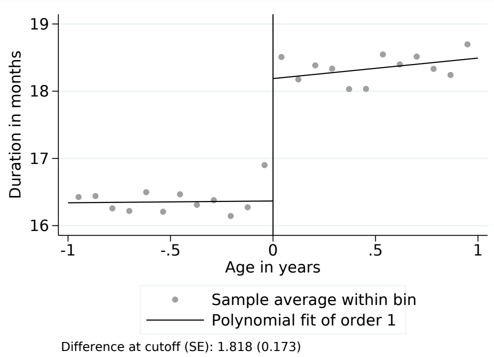
Figure E.1: Density of Age at Unemployment



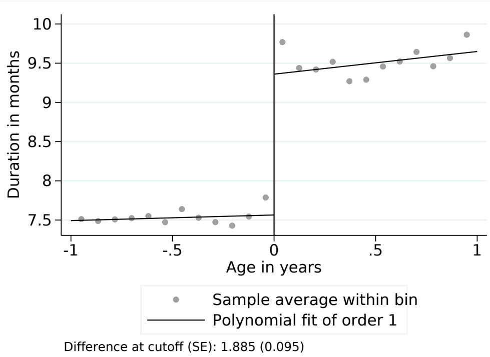
Notes: The figures plot the density of age at unemployment using inflows into unemployment insurance. Vertical green lines mark age cutoffs where potential benefit duration increases sharply.

Figure E.2: Regression Discontinuity Plots Pooling All Age Cutoffs

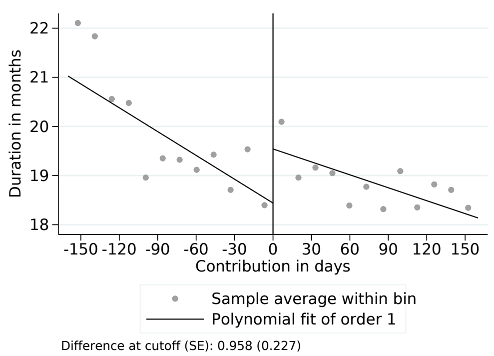
(a) Nonemployment Duration,
Age Cutoffs



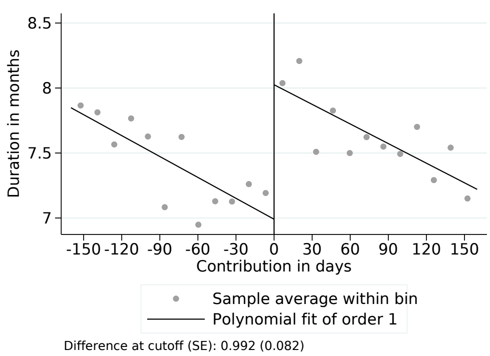
(b) UI Receipt Duration,
Age Cutoffs



(c) Nonemployment Duration,
Contribution Cutoffs

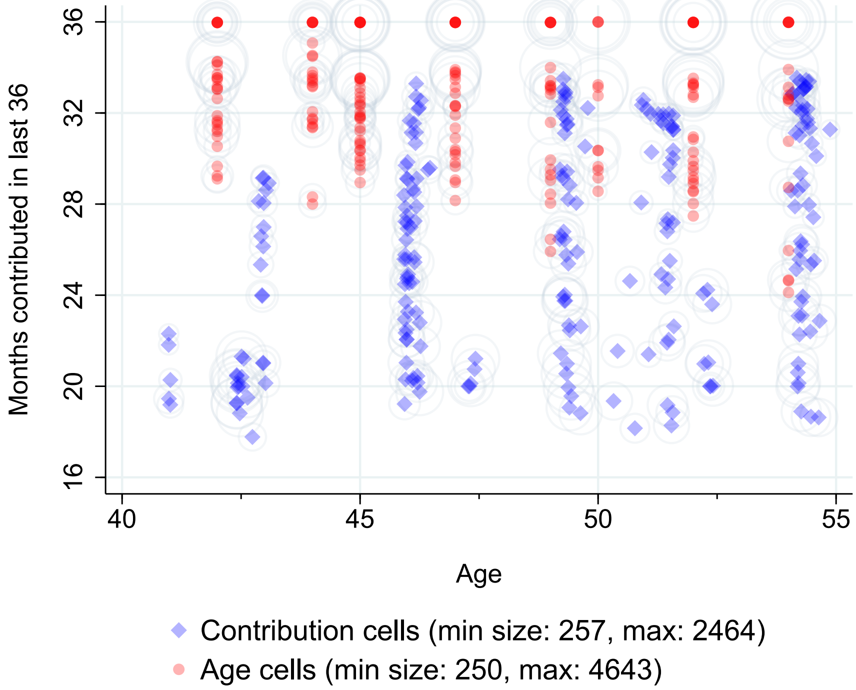


(d) UI Receipt Duration,
Contribution Cutoffs



Notes: In the upper half, the figure plots the average for the respective outcomes by age at entry into UI (in 1-month bins), pooling all age cutoffs in the age sample. In the lower half, the figure plots the average for the respective outcomes by contribution time at entry into UI (in 2-week bins, measured within the regime-specific time horizon for PBD determination), pooling all contribution cutoffs in the contribution sample. The solid lines mark linear fits on each side of the cutoff.

Figure E.3: Cells in the Age and Contribution Time Treatment Plane



Notes: The figure displays the cells in the treatment plane (age cells in red and contribution ones in blue). The value of age, contribution time respectively, is defined as the value of the cutoff, or the sample average. Grey circles are proportional to the underlying number of unemployment spells.

Table E.1: Summary Statistics of Sample Validity Criteria

	(1)		(2)		(3)	
	Pooled		Age cells		Contribution cells	
	Mean	(SD)	Mean	(SD)	Mean	(SD)
Panel (a) Yearly cells						
Spells in sample	1,112	(785)	1,460	(934)	830	(483)
More than 500 spells	0.76	(0.43)	0.85	(0.36)	0.69	(0.46)
Share treated	0.46	(0.12)	0.46	(0.16)	0.45	(0.08)
Passes RD validity criteria	0.72	(0.45)	0.72	(0.45)	0.72	(0.45)
Cells	434		194		240	
Panel (b) Cells pooling years within regimes						
Spells in sample	6,100	(4,440)	8,158	(5,056)	4,499	(3,107)
More than 500 spells	1.00	(0.00)	1.00	(0.00)	1.00	(0.00)
Share treated	0.46	(0.11)	0.47	(0.15)	0.46	(0.08)
Passes RD validity criteria	0.59	(0.50)	0.66	(0.48)	0.53	(0.50)
Cells	80		35		45	
Panel (c) Yearly cells, using consistent spells only						
Spells in sample	1,200	(933)	1,460	(934)	400	(134)
More than 500 spells	0.69	(0.46)	0.85	(0.36)	0.22	(0.42)
Share treated	0.46	(0.14)	0.46	(0.16)	0.45	(0.08)
Passes RD validity criteria	0.76	(0.43)	0.77	(0.42)	0.71	(0.46)
Cells	257		194		63	

Notes: The table shows summary statistics for the sample characteristics and validity criteria described in this appendix. Observations are estimation cells along the treatment boundaries. Panel (a) uses cells constructed as explained in Section 4. Panel (b) uses cells pooling years within regimes, and Panel (c) is as (a) but uses spells from the consistent sample only. The criteria are defined to equal 1 if the sample fails them. Valid cells are those that pass all the validity criteria. The significance level underlying the tests is 5%.

Table E.2: Meta Regression of the Indicator for a Cell Being Valid

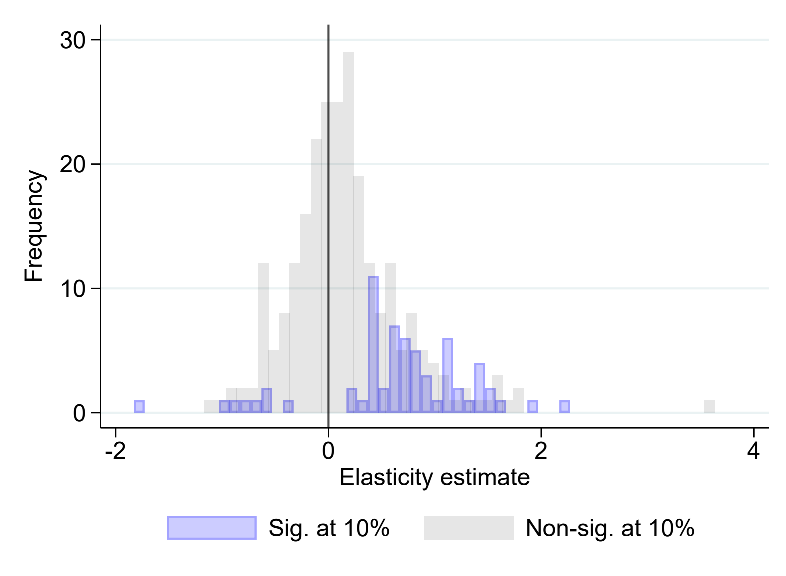
	(1)	(2)	(3)
Age	0.0021	0.0024	0.0016
	(0.0077)	(0.0083)	(0.0085)
Years contributed in last 3	0.1185		
	(0.0976)		
Years contributed in last 5		0.0406	
		(0.0764)	
Years contributed in last 7			0.0094
			(0.0390)
PBD level	-0.0046	-0.0037	-0.0013
	(0.0069)	(0.0082)	(0.0090)
Cells	434	434	434
Outcome mean	0.7235	0.7235	0.7235

Notes: The table presents the full results of the meta regression where the outcome is the indicator for a cell satisfying all RD validity criteria (Section 4.2). Observations are estimation cells. Standard errors (in parentheses) are clustered by cells' age group (in 5-year bands), contribution time group (in 4-month bands), and cutoff type.

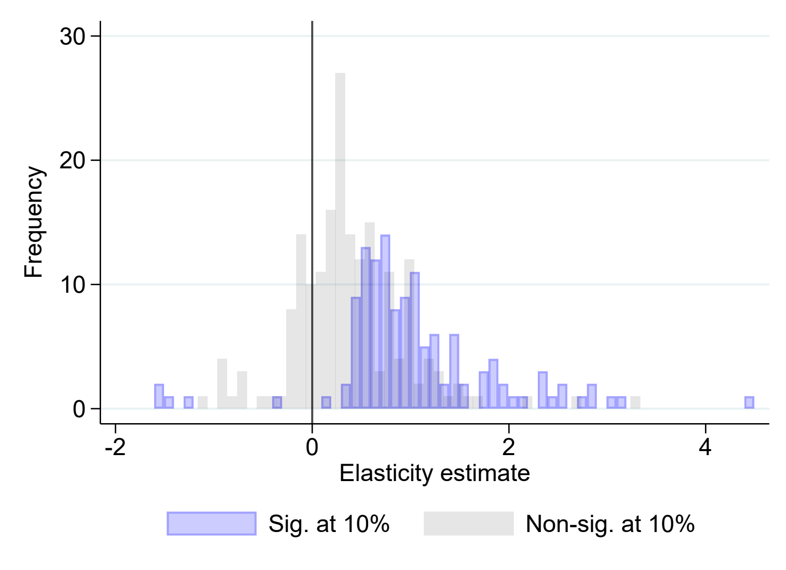
F Reduced-Form Elasticity Estimates

Figure F.1: Distribution of Elasticity Estimates

(a) Elasticity of Nonemployment Duration



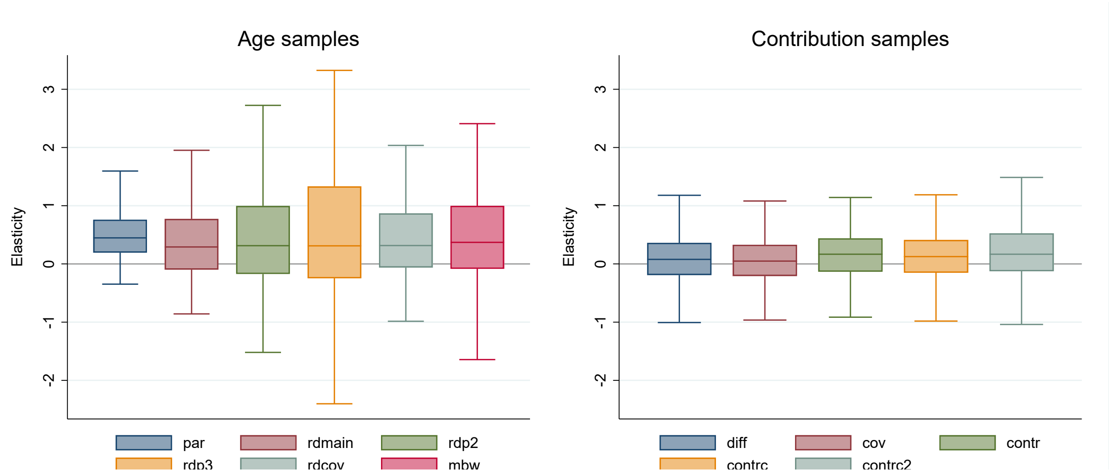
(b) Elasticity of UI Receipt Duration



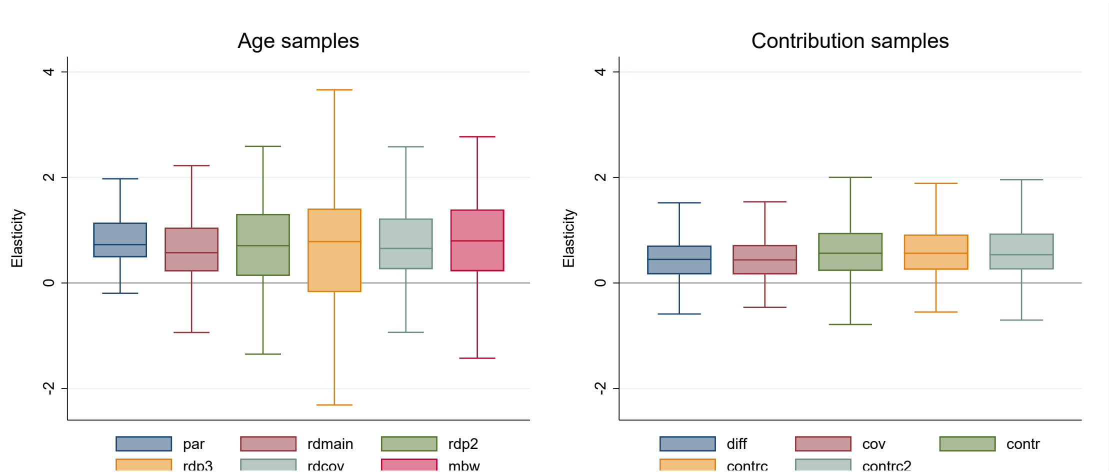
Notes: The figures display histograms of the respective elasticity estimates, separately for estimates statistically significant (in blue), and nonsignificant (in grey) at the 10% level. The underlying observations are valid estimation cells.

Figure F.2: Distribution of Elasticity Estimates Across RD Estimators

(a) Nonemployment Duration



(b) UI Receipt Duration



Notes: The figures display box plots of the distribution of elasticity estimates across RD estimators. The underlying observations are valid estimation cells. Estimators for age cells.— *par*: Difference-in-means of outcomes between treated and control. *rdmain*: Nonparametric local linear regression with a triangular kernel. *rdp2*: Quadratic polynomial. *rdp3*: Cubic polynomial. *rdcov*: Controlling for covariates. *mbw*: Manually chosen 1-year bandwidth. Estimators for contribution cells.— *diff*: Difference-in-means of outcomes between treated and control. *cov*: Difference-in-means controlling for covariates. *contr*: Allowing for a linear effect of imputed contribution time. *contrc*: Additionally controlling for covariates. *contrc*: Quadratic polynomial.

G Robustness Checks for the Meta Regression

Table G.1: Meta Regression of the Elasticity Estimates -- Fully-Adjusted Specifications

	(1) Nonemployment duration	(2) UI receipt duration
Age	-0.016	0.008
	(0.0121)	(0.0093)
Years contributed in last 3	-0.306*	-0.256**
	(0.1625)	(0.0996)
PBD level	0.035**	0.036**
	(0.0129)	(0.0148)
Regime 2	0.160	0.004
	(0.1282)	(0.1298)
Regime 3	0.142	-0.075
	(0.1251)	(0.1701)
Regime 4	0.169	-0.095
	(0.1480)	(0.1807)
Unemployment rate in %	0.005	0.031
	(0.0295)	(0.0216)
% Female	-0.012	-0.014
	(0.0072)	(0.0086)
% Non-German	-0.008	-0.002
	(0.0201)	(0.0158)
% Residence in Eastern Germany	-0.013*	-0.004
	(0.0068)	(0.0052)
% Residence missing	-0.002	-0.001
	(0.0023)	(0.0023)
% Secondary schooling degree	-0.052	0.037
	(0.0384)	(0.0391)
% Without vocational training	-0.012	0.017*
	(0.0102)	(0.0099)
% Academic degree	0.034	0.023
	(0.0501)	(0.0472)
% Last job part-time	0.011	0.004
	(0.0119)	(0.0116)
% spells in 2nd quarter	-0.010	-0.008
	(0.0075)	(0.0075)
% spells in 3nd quarter	-0.003	-0.014
	(0.0084)	(0.0084)
% spells in 4nd quarter	0.003	0.014***
	(0.0030)	(0.0040)
Constant	2.523**	0.171
	(1.0411)	(0.6001)
Elasticity mean	0.258	0.650
Mean SE	0.457	0.498
Share sig. 5%	0.164	0.442

Notes: The table presents the full results of the meta regression from column (2) of Table 2. Observations are age-by-contribution time cells that satisfy the validity criteria described in Section 4.2. RD estimates are based on nonparametric local linear regression for age cells, and a parametric estimation linear spline in contribution for contribution cells. All meta regressions use inverse-variance weights winsorized at the 10^{th} and 90^{th} percentiles. Standard errors (in parentheses) are clustered by cells' age group (in 5-year bands), contribution time group (in 4-month bands) and cutoff type.

Table G.2: Meta Regression of the Elasticities of Alternative Labor Market Outcomes

	(1) Nonempl. duration cap 48mths	(2) Nonempl. duration cap 60mths	(3) Log(first - last wage)	(4) Unemployed again within 36mths	(5) Employed at 80% of past wage within 12mths	(6) First job tenure	(7) First job part-time	(8) Cumulated earnings within 60mths
Age	-0.018	-0.020	-0.001*	-0.012	-0.018	0.009	-0.010	0.012
	(0.0133)	(0.0142)	(0.0004)	(0.0189)	(0.0167)	(0.0169)	(0.0162)	(0.0163)
Years contributed in last 3	-0.355*	-0.402**	0.003	0.096	0.325	-0.241	0.250	0.323
	(0.1770)	(0.1880)	(0.0044)	(0.2060)	(0.2126)	(0.1985)	(0.3581)	(0.2094)
Elasticity mean	0.281	0.297	0.004	-0.330	-0.226	0.325	0.491	-0.199
Mean SE	0.519	0.563	0.029	1.191	1.139	1.214	1.685	0.753
Share sig. pos. 5%	0.150	0.140	0.029	0.013	0.010	0.054	0.029	0.006
Cells	314	314	314	314	314	314	314	314
Regime fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Covariates	✓	✓	✓	✓	✓	✓	✓	✓
PBD level	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The meta regression outcome is the estimated elasticity w.r.t. PBD. Observations are age-by-contribution time cells that satisfy the validity criteria described in Section 4.2. RD estimates are based on nonparametric local linear regression for age cells, and difference-in-means with linear spline in contribution for contribution cells. All meta regressions use inverse-variance weights winsorized at the 10^{th} and 90^{th} percentiles. Standard errors (in parentheses) are clustered by cells' age group (in 5-year bands), contribution time group (in 4-month bands) and cutoff type. Composition variables are share of females, non-German, residence in East Germany, secondary education, higher education, and last job part-time.

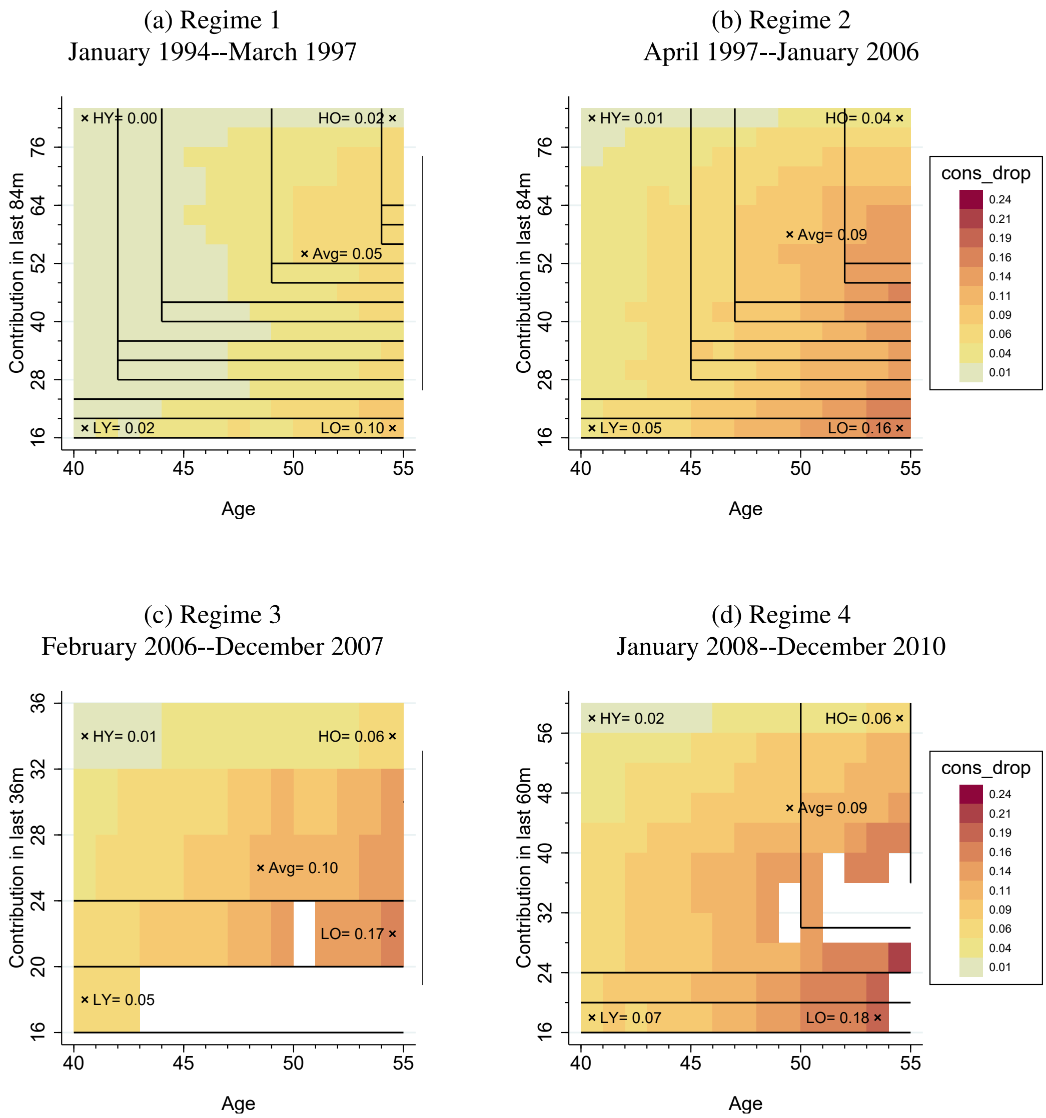
Table G.3: Meta Regression -- Robustness Checks Using Alternative Regression Discontinuity Estimators

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Age cutoff estimator:	Local linear	Local linear	Local linear	With covariates	With covariates	With covariates	Quadratic polynomial	Quadratic polynomial	Quadratic polynomial
Contribution cutoff estimator:	Difference-in means	Linear spline	Quadratic spline	Difference-in means	Linear spline	Quadratic spline	Difference-in means	Linear spline	Quadratic spline
Panel (a) Elasticity of nonemployment duration									
Age	-0.005	-0.016	-0.014	-0.004	-0.015	-0.014	0.003	-0.008	-0.006
	(0.0139)	(0.0121)	(0.0119)	(0.0138)	(0.0121)	(0.0117)	(0.0137)	(0.0122)	(0.0118)
Years contributed in last 3	-0.289*	-0.306*	-0.346**	-0.291*	-0.305*	-0.344*	-0.116	-0.124	-0.158
	(0.1614)	(0.1625)	(0.1640)	(0.1671)	(0.1664)	(0.1682)	(0.2025)	(0.2033)	(0.2075)
Elasticity mean	0.214	0.258	0.288	0.218	0.262	0.291	0.220	0.265	0.294
Mean SE	0.430	0.466	0.480	0.450	0.486	0.500	0.562	0.597	0.611
Share sig. pos. 5%	0.137	0.153	0.166	0.140	0.156	0.169	0.080	0.096	0.108
Panel (b) Elasticity of UI receipt duration									
Age	0.008	0.008	0.009	0.006	0.005	0.007	0.007	0.006	0.007
	(0.0107)	(0.0093)	(0.0099)	(0.0109)	(0.0095)	(0.0103)	(0.0111)	(0.0101)	(0.0108)
Years contributed in last 3	-0.172*	-0.256**	-0.245**	-0.155	-0.239*	-0.229*	-0.125	-0.211	-0.208
	(0.0984)	(0.0996)	(0.1006)	(0.1200)	(0.1218)	(0.1220)	(0.1785)	(0.1863)	(0.1884)
Elasticity mean	0.569	0.650	0.642	0.601	0.682	0.674	0.595	0.676	0.668
Mean SE	0.462	0.506	0.517	0.486	0.530	0.540	0.613	0.657	0.667
Share sig. pos. 5%	0.366	0.398	0.369	0.366	0.398	0.369	0.290	0.322	0.293
Cells	314	314	314	314	314	314	314	314	314
Regime fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Covariates	✓	✓	✓	✓	✓	✓	✓	✓	✓
PBD level	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The table presents meta regression results, where the outcomes are the estimated elasticity of nonemployment duration (panel A) and UI receipt duration (panel B) w.r.t. potential benefit duration. Observations are age-by-contribution time cells. All meta regressions use inverse-variance weights winsorized at the 10$^{\text{th}}$ and 90$^{\text{th}}$ percentiles. Standard errors (in parentheses) are clustered by cells' age group (in 5-year bands), contribution time group (in 4-month bands), and cutoff type. Composition variables include the share of females, non-Germans, residents in East Germany, individuals with secondary education and higher education, and individuals whose last job was part-time. All estimations use valid cells split by year that satisfy the criteria described in Section 4.2. Estimators for age cells.— *rdmain*: Nonparametric local linear regression with a triangular kernel. *rdcov*: Controlling for covariates. *rdp2*: Quadratic polynomial. Estimators for contribution cells.— *cov*: Difference-in-means controlling for covariates. *contrc*: Allowing for a linear effect of imputed contribution time and controlling for covariates. *contrc2*: Quadratic polynomial.

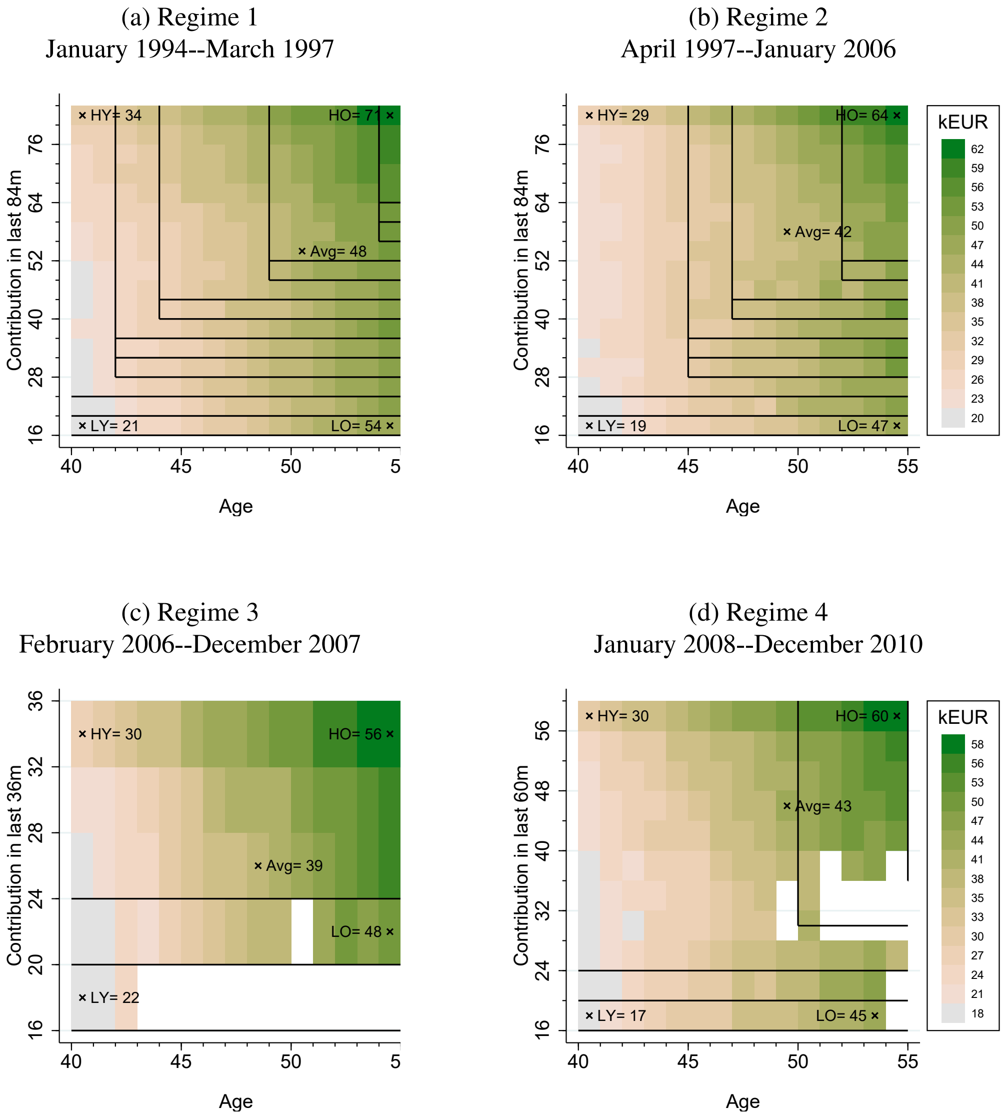
H Welfare Analysis

Figure H.1: Consumption Drop at Unemployment



Notes: The figure presents the estimated consumption drop at unemployment for group *x* relative to the average consumption of all of the employed. The bins are by age (1 year) and contribution time (4 months), separately for each regime in our observation period. The black lines denote treatment boundaries where the PBD increases by half of the additional months contributed.

Figure H.2: Assets Before Job Loss

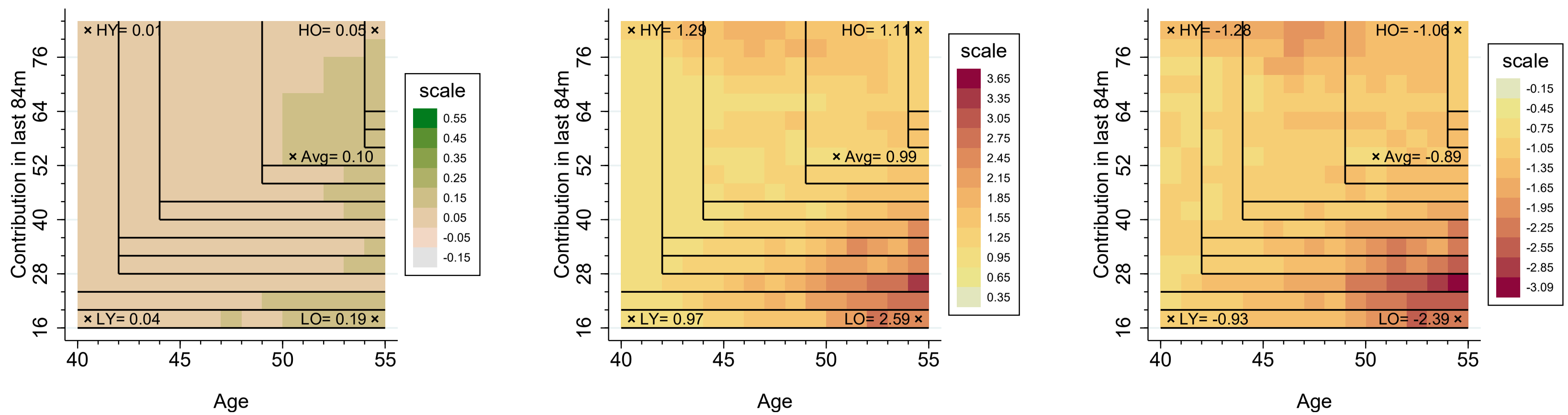


Notes: The figure presents the assets in kEUR before the onset of unemployment by age (1-year bins) and contribution time (4-month bins), separately for each regime in our observation period. The black lines denote treatment boundaries where the PBD increases by half of the additional months contributed.

Figure H.3: Welfare Effects of a Potential Benefit Duration Extension with Group-Specific Taxes, and $\gamma = 2$

Panel A. Regime 1 (January 1994–March 1997)

(a) Social Value $\gamma = 2$ (b) Behavioral Cost (c) Welfare Derivative



Panel B. Regime 2 (April 1997–January 2006)

(d) Social Value $\gamma = 2$ (e) Behavioral Cost (f) Welfare Derivative

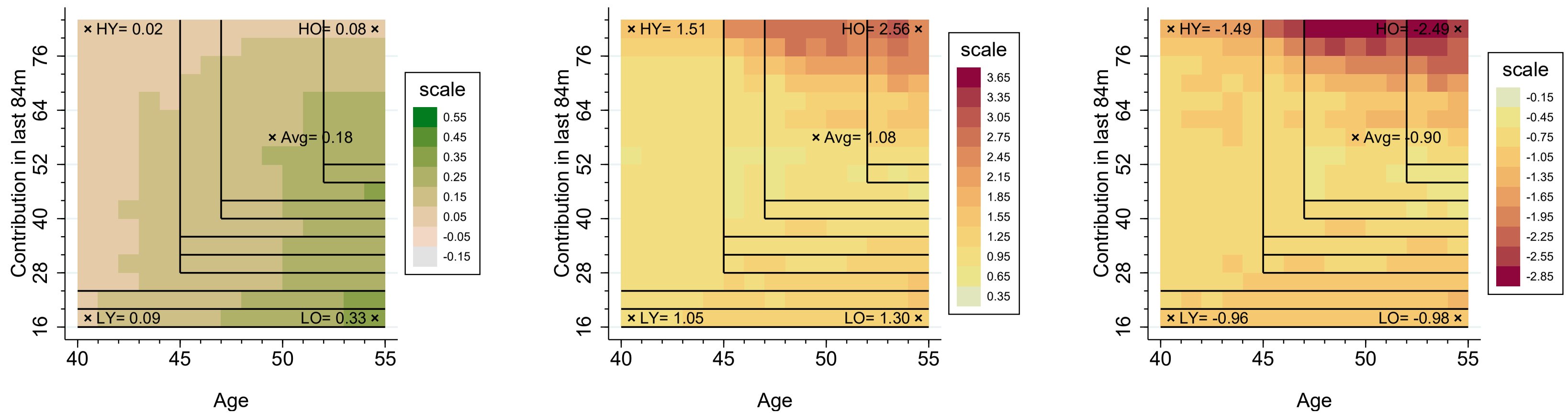
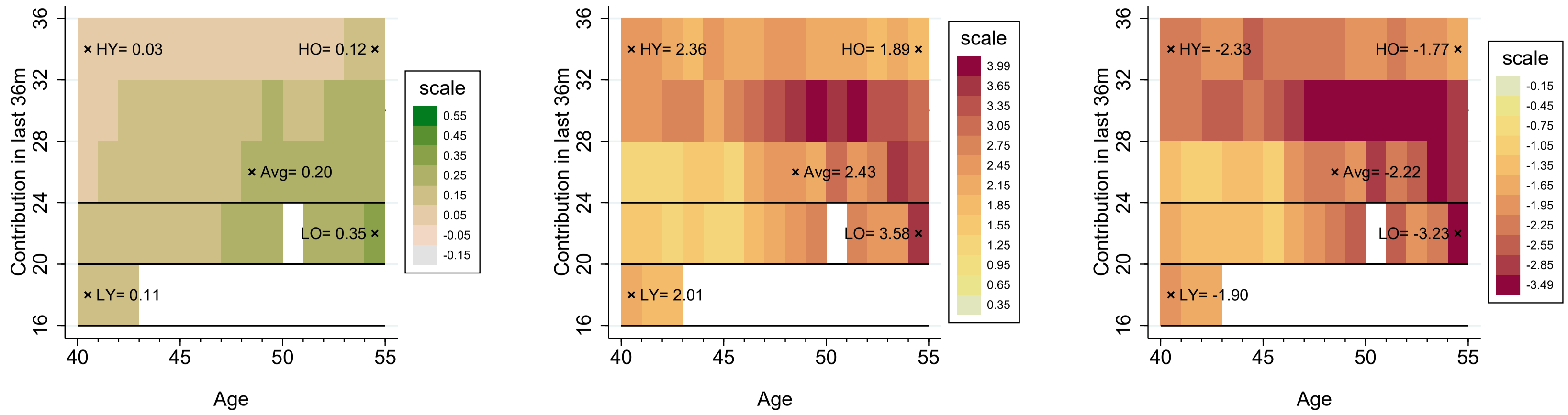


Figure H.3: Welfare Effects of a Potential Benefit Duration Extension with Group-Specific Taxes, and $\gamma = 2$ (Cont.)

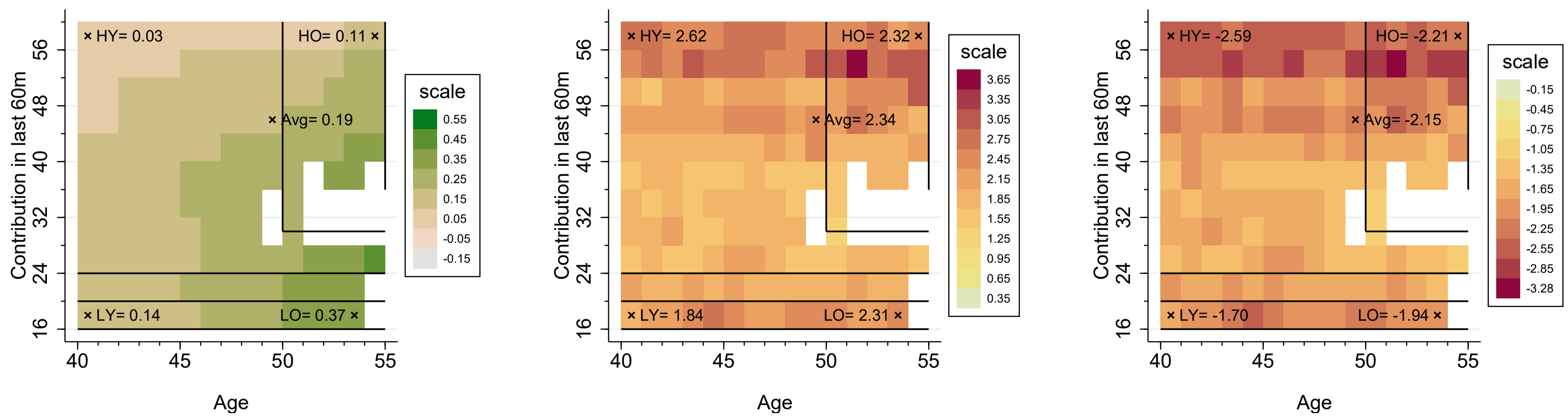
Panel C. Regime 3 (February 2006–December 2007)

(a) Social Value $\gamma = 2$ (b) Behavioral Cost (c) Welfare Derivative



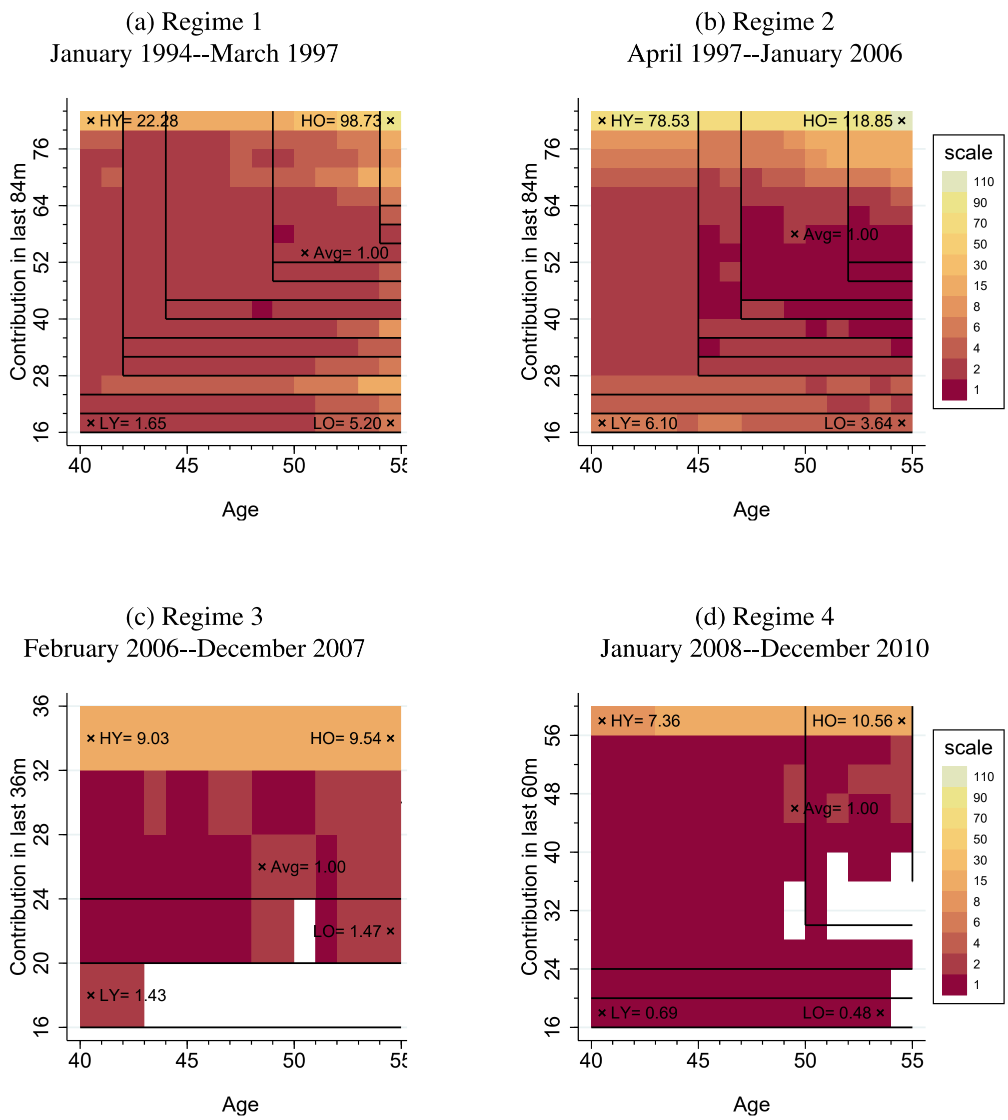
Panel D. Regime 4 (January 2008–December 2010)

(d) Social Value $\gamma = 2$ (e) Behavioral Cost (f) Welfare Derivative



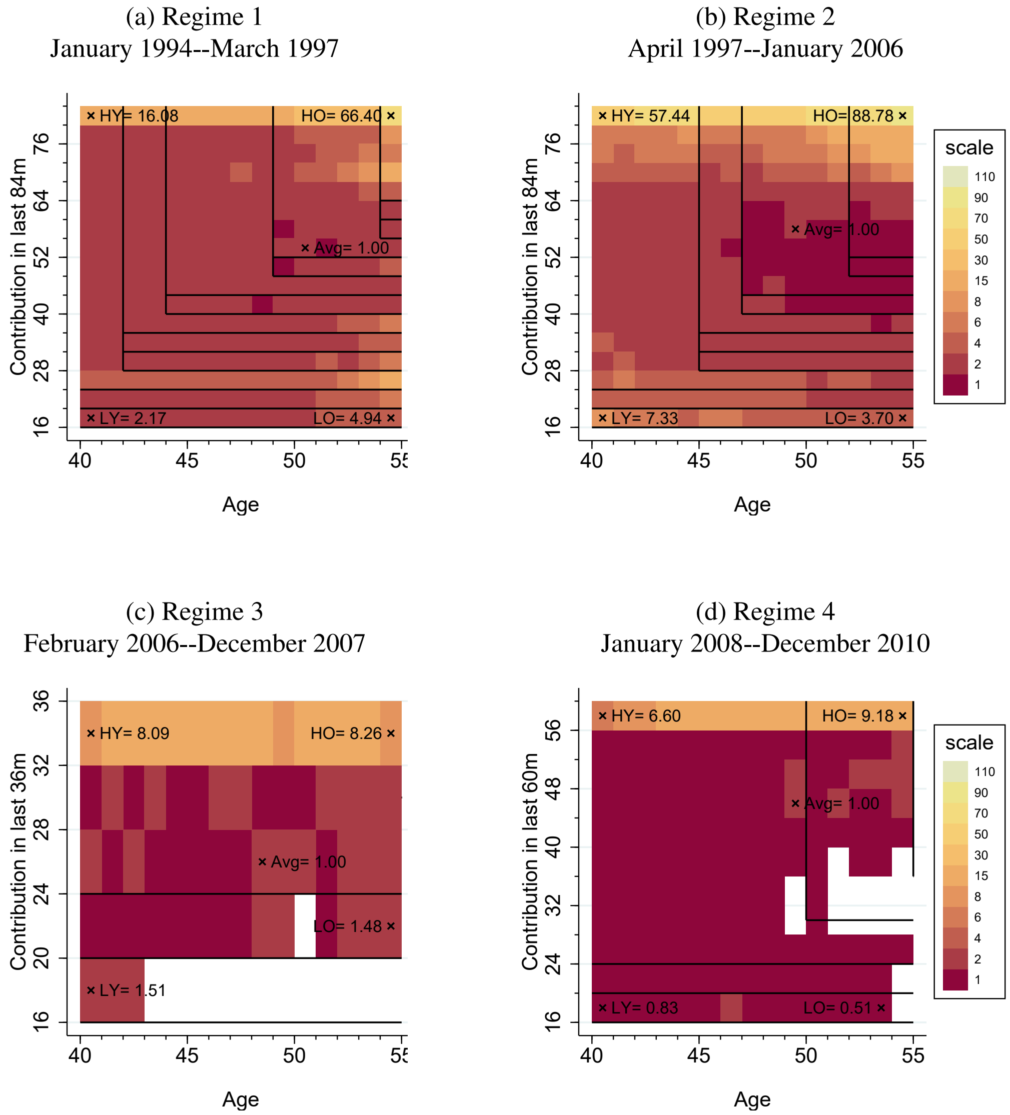
Notes: The figure presents the estimated social value (SV) with a homogeneous coefficient of relative risk aversion $\gamma = 2$ (left-hand side), behavioral cost (BC, middle), and welfare derivative (right-hand side) of PBD extensions for group x. The implementation uses group-specific taxes, as in equation 9. Groups x are bins of age (1-year bins) and contribution time (4-month bins) in each regime in our observation period. The black lines denote treatment boundaries where the potential benefit duration increases by half of the additional months contributed. Abbreviations: LY: Low contributors, young; HY: High contributors, young; LO: low contributors, old; HO: High contributors, old.

Figure H.4: Ratio of Welfare Derivatives, Accounting for Group Size and Benefit Exhaustion Rate, with a Uniform Tax



Notes: The figure presents the ratios of the welfare derivative, accounting for the sizes of the population entering each group. Groups x are bins of age (1-year bins) and contribution time (4-month bins) in each regime in our observation period. Each bin shows the estimate of $N_x S_x(P_x) d\tilde{W}_0/dP_x / (N_{\bar{x}} S_{\bar{x}}(P_{\bar{x}}) \tilde{W}_0/dP_{\bar{x}})$, where $\bar{x}$ is the average worker. The implementation uses a uniform tax rate and assumes a homogeneous coefficient of relative risk aversion. The black lines denote treatment boundaries where the potential benefit duration increases by half of the additional months contributed. Abbreviations: LY: Low contributors, young; HY: High contributors, young; LO: low contributors, old; HO: High contributors, old.

Figure H.5: Ratio of Welfare Derivatives, Accounting for Group Size and Benefit Exhaustion Rate, with a Group-Specific Tax



Notes: The figure presents the ratios of the welfare derivative, accounting for the sizes of the population entering each group. Groups x are bins of age (1-year bins) and contribution time (4-month bins) in each regime in our observation period. Each bin shows the estimate of $N_x S_x(P_x) d\tilde{W}_0/dP_x/(N_{\bar{x}} S_{\bar{x}}(P_{\bar{x}})\tilde{W}_0/dP_{\bar{x}})$, where $\bar{x}$ is the average worker. The implementation uses a group-specific tax rate and assumes a homogeneous coefficient of relative risk aversion. The black lines denote treatment boundaries where the potential benefit duration increases by half of the additional months contributed. Abbreviations: LY: Low contributors, young; HY: High contributors, young; LO: low contributors, old; HO: High contributors, old.