# Effects of Unemployment Insurance Duration on Mental and Physical Health*

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**Abstract**

Using administrative data for Upper Austrian workers from 2003–2013, we show that a 9-week extension in unemployment insurance (UI) duration increases nonemployment length and impacts worker physical and mental health. These effects vary by gender. Specifically, we find that female workers eligible for an additional 9 weeks of UI benefits fill fewer opioid and antidepressant prescriptions and experience a lower likelihood of filing a disability claim. Moreover, we find some evidence of beneficial within-household spillovers for young children. For male workers, we find no health effects of extending UI benefit duration. We posit that these differential effects are driven by a combination of income and occupational changes that also vary by gender.

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# 1. Introduction

Unemployment Insurance (UI) programs are a critical part of the safety net of many countries, providing a large buffer against income shocks (East and Simon, 2020). Yet, although the labor market effects of UI benefits are well-documented, the broader effects of the program are less understood.[1]

One such understudied aspect of UI, with substantial importance for policymaking, is the potential impact on health. For example, the replacement of income due to UI and increase in potential search time could affect mental health by reducing the time pressure of the job search and related stress and anxiety. Moreover, if workers experience physical stressors on the job, unemployment may provide temporary pain relief and the opportunity to match to a less painful job in the future.

In this paper, we test whether longer UI duration leads to changes in worker mental and physical health outcomes in an effort to measure the more comprehensive effects of UI. To do so, we exploit a policy in Austria that extends UI benefits for workers aged 40 and older from 30 to 39 weeks but does not change benefit levels. We first show that these more generous UI time limits lead to increases in nonemployment duration for all workers, with female workers more likely to spend additional time out of the labor force, switch occupations, and match to higher-paying jobs. Then, we estimate the extent to which the changes in occupational outcomes and wages additionally drive changes in outcomes outside of the labor market.

To analyze effects on worker health, we use linked administrative data on UI claims, hospitalizations, prescriptions, and disability claims for nearly 400,000 unemployed Upper Austrian workers and their children.[2] From our regression discontinuity (RD) approach, we first show that more generous UI time limits lead to average increases in nonemployment duration that vary by gender for Upper Austrian workers. Motivated by the disproportionate labor market impacts for female workers, we then use linked administrative data on prescriptions and health care utilization for unemployed female workers and their children to estimate the extent to which more generous UI benefit duration affects physical and mental health and/or generates spillovers within households. In doing so, we provide support for the notion that these gender differences may also translate into differences in long-run economic trajectories and worker well-being.

Estimates from an age-based regression discontinuity (RD) approach indicate that female workers

[1]For a review of this extensive literature on how UI extends nonemployment duration and affects job match, see Card, Chetty, and Weber (2007).

[2]Health data is available only for Upper Austria, a state in Austrian containing 1.5 million individuals. Therefore, unlike Nekoei and Weber (2017), which use data for all Austrian workers to estimate labor market effects, our analyses will focus on health effects for this smaller subset of workers.

just eligible for longer UI benefit duration are 0.5 percentage points (33.3 percent) less likely to be prescribed opioids and 0.9 percentage points (8.7 percent) less likely to be prescribed antidepressants in the 9 months following job loss, as compared to their female counterparts. We show that female workers in physically demanding and low-skill jobs drive this increase in job quality and subsequent reduction in prescription use. We also present evidence of spillovers within the household. In particular, young children under the age of 6 of unemployed eligible mothers experience reduced child health expenditures. Estimates are not sensitive to bandwidth selection or functional form. Below, we pair additional findings with survey evidence to discuss the different household demands and expectations that unemployed male and female workers face and show that effects are likely driven by a combination of occupational changes and changes in income.

These findings contribute to the related literature in a number of ways. First, we note that the existing literature primarily focuses on the health effects of job loss and/or UI benefit amounts, and there is much less evidence on how UI *duration* affects worker outcomes. While many studies have analyzed the effects of unemployment on health more broadly, these findings often rely either on widespread macroeconomic shocks (Ruhm, 2000, 2015; Hollingsworth, Ruhm, and Simon, 2017; Musse, 2020), or shocks common to small, local areas, like plant closures, to identify effects (Ruhm, 1991; Elison and Storrie, 2006; Sullivan and von Wachter, 2009; Browning and Heinesen, 2012; Venkataramani, Bair, O'Brien, and Tsa, 2020).[3] Second, while many recent studies focus on the impact of UI generosity on health in the US, US data on health outcomes and well-being is often self-reported, drawing concerns over whether employees systematically report poorer health when they temporarily lose health insurance coverage (Schaller and Stevens, 2015; Cylus, Glymour, and Avendano, 2015; Kuka, 2020; Fu and Liu, 2019).

To overcome these limitations, we use exogenous sources of variation across individuals using a large sample of workers and objective measures of health in the months following job loss in a setting in which workers cannot manipulate their UI eligibility, do not lose health insurance, and are not granted more generous benefits due to a recession.[4] Importantly, these data track individuals over time, allowing

[3]In particular, while Ruhm (2000) shows that unfavorable health conditions follow macroeconomic growth, Ruhm (2015) suggests that total mortality has shifted away from being strongly pro-cyclical to being unrelated to macroeconomic shocks, with the exception of some conditions, like deaths from cardiovascular events. However, Hollingsworth, Ruhm, and Simon (2017) show that rising unemployment rates increase opioid-related deaths, primarily among White individuals, which is consistent with Case and Deaton (2015), who show that deterioration in economic conditions corresponds to increases in "deaths of despair". Other recent work estimates the elasticity of labor shocks on opioid use and finds that during economic expansions the demand for pain relief medication increases and is related to jobs in high injury industries (Musse, 2020).

[4]This latter point is especially important, given the relative stickiness of wages that has been well-documented in the Austrian labor market (Dickens, Goette, Groshen, Holden, Messina, Schweitzer, Turunen, and Ward, 2007). For example, Jäger, Schoefer, and Zweimüller (2019) exploit changes in UI benefit levels in Austria in the 1980s and 1990s and find that wages are relatively unresponsive to UI generosity. This insensitivity holds even among low-wage earners, frequent job switchers, and those with high predicted nonemployment duration (Jäger, Schoefer, Young, and Zweimüller, 2019).

us to observe trends in health conditions, hospitalization, disability, and prescription take-up prior to and following unemployment. By comparing unemployed workers that are similar on all observed characteristics but vary by UI duration eligibility, these data allow us to get a better sense of how UI duration affects an individual's physical and mental health.

Our findings build on work documenting the adverse health consequences of unemployment and UI, and extend these findings beyond mortality, self-reported health, and mental health effects (Elison and Storrie, 2006; Sullivan and von Wachter, 2009; Kuhn, Lalive, and Zweimüller, 2009). Furthermore, unlike many existing studies which focus only on men, we measure effects for female workers and their children during a period when female labor force participation is at an all-time high and in an era where Austrian women report spending more time on childcare and housework.[5]

Our analysis focuses on UI benefits in a European context, where previous work on job loss and health has shown mixed results in terms of mortality and mental health (Elison and Storrie, 2006; Kuhn, Lalive, and Zweimüller, 2009; Böckerman and Ilmakunnas, 2009; Browning, Dano, and Heinesen, 2006; Browning and Heinesen, 2012; Bloemen, Hochguertel, and Zweerink, 2015). However, we note that Austria is more similar to the US than Scandinavia in terms of work hours and views of traditional gender roles, implying that our findings can inform policy in many different settings and countries (EVS, 2017). Moreover, we are able to isolate health effects for a set of workers whose health insurance coverage is unaffected by job loss. We note that any findings on null or adverse health consequences of longer UI duration will appear in *spite* of Austria's universal health care system, yielding important policy implications for discussions on optimal UI duration determination in the presence of relatively generous safety net programs.

Finally, because we test the effects of UI duration on prescription drug use, our findings can speak to programs that may affect opioid misuse. This is especially important, given both the magnitude and reach of the ongoing US opioid crisis, and also the unclear causal channel between employment and drug use. For example, Krueger (2017) finds that the increase in opioid prescriptions spanning 1999–2015 could account for up to 43 percent of the decline in US labor force participation for men during that time. Alternatively, for workers that need pain medication to perform the daily functions of their jobs, unemployment may lessen opioid prescriptions and the probability of misuse, while extending UI benefit

[5]In particular, Austrian women's total paid and unpaid working time exceeds men's total work by 21 minutes per day, on average. This average is identical to the difference in men and women's reported time usage in the US. For information on time spent in paid and unpaid work, by county and by sex, see https://stats.oecd.org/index.aspx?queryid=54757. Unlike some European countries, Austria does not offer free public childcare for children under the age of 6, and there exists considerable excess demand for subsidized childcare. Less than 20 percent of Austrian children under the age of 3 participated in center-based early childhood education and care (ECEC) in 2017, below the EU average of 33 percent (European Commission, 2019).

duration may allow workers to match to a new job that is associated with less physical pain. Given that Austria leads the world in per capita morphine consumption (United Nations, 2018), these findings are especially relevant in our context.[6]

Our findings have several implications for policy. The magnitudes of the estimates indicate that extending UI benefit duration eligibility by 9 weeks does not induce all workers to take up benefits for the fully extended time, although it does incentivize workers to spend more time matching to their next job. This additional time out of the labor force leads to long-lasting changes in occupation and wages for female workers, but not male workers, which corresponds to economically meaningful changes in physical and mental health. Therefore, our findings suggest differential labor market and health costs of UI on men and women and have important implications for addressing gaps in labor force participation.

## 2. Unemployment Insurance in Austria

Austria's unemployment insurance program is compulsory, with workers paying a 6 percent payroll tax. UI benefits are related to previous after-tax earnings, with a 55 percent minimum replacement rate.[7] Similar to the UI system in the US, applicants for UI benefits must be willing to accept reasonable employment or undergo retraining, and must be able to prove that they are frequently applying for new jobs. Benefits for laid-off workers are payable immediately upon entry into unemployment; for job quitters there is a one-month waiting period.[8]

The total duration for UI benefits increases discontinuously with age. For workers up to 39 years old, the maximum baseline UI benefit period is 30 weeks, for workers aged 40–49 years old, benefits are extended to 39 weeks, conditional on a sufficient contribution period. To qualify, workers must meet an experience requirement of having worked at least 6 out of the last 10 years. After age 50, benefits are extended up to a year, although, in practice, this threshold does not result in a discontinuous change in eligibility.[9]

[6]While the rate of opioid overdose deaths in Austria is low compared to countries like the US and the UK, Austria ranks above Switzerland, Germany, and France in terms of drug-related deaths, with a drug-related mortality rate of 37 per million population (United Nations Office on Drugs and Crime, 2019). Opioid prescribing behavior is one factor contributing to these statistics; estimates from a large randomized control trial indicated that the mortality risk of opioid treatment in Austria is 4.5 times that of the general population with the same age and gender distribution (European Monitoring Centre for Drugs and Drug Addiction, 2019).

[7]Replacement wages are calculated using the last six months' income. Maximum and minimum benefit levels are adjusted annually. Total UI replacement rates cannot exceed 60 percent for single claimants without dependents, or 80 percent for a claimant with dependents. See http://www.oecd.org/els/soc/29725351.PDF for more information.

[8]In our sample, only 9.4 percent of workers are job quitters. We include these workers in an attempt to show more conservative baseline estimates.

[9]See Figure A1. Specifically, for workers up to age 39, UI benefits can span 30 weeks only after 156 weeks (3 years) of work in 5 years. For those over 40, workers must have contributed for 6 of the last 10 years to have UI benefits for 39 weeks. UI benefit duration is 52 weeks for workers over the age of 50 with a 9 out of 15 years contribution record, although older workers

In this paper, we focus on the jump in UI benefit duration from 30 to 39 weeks at age 40. We do so for three main reasons. First, this age group gives us a large sample of workers with a high density around the age cutoff. Second, the eligibility extension at age 50 does not often represent a sharp change in benefit duration eligibility for workers receiving UI benefits. Third, the other potential UI duration extension in Austria (from 20 to 30 weeks) is not binding at a particular age, limiting our ability to compare workers in a causal framework. Below, we further discuss the extent to which focusing on this cutoff affects both internal and external validity.

## 3. Data

To analyze the effects of UI benefit duration on health, we use administrative data on all workers in Upper Austria spanning 2003–2013. Upper Austria is a state in northern Austria, containing approximately 1.5 million, or 17 percent, of the total inhabitants of Austria. These data include information on an employee's age, which is critical to the research design, as well as their gender, migrant status, and residence location. Because of the existence of another UI cutoff at age 50, described above, we follow Nekoei and Weber (2017) and include only workers that are between 30–50 years old upon entering unemployment. In our main analysis we also restrict our sample to those workers that meet the experience criterion of having worked at least 6 of the last 10 years, although we later relax this assumption to perform sensitivity checks.

For information on past fertility, prescriptions, and hospitalizations, we use data containing information on both workers and nonworkers from the Upper Austrian Health Insurance Fund (UAHIF) database linked to social security records from the Austrian Social Security Database (ASSD).[10] The UAHIF is the main statutory health insurance provider in Upper Austria, covering 99 percent of the total population. Importantly, unemployed workers continue to be insured with the UAHIF, irrespective of their former employment. To address the potential for within-household spillovers, we additionally use birth certificate data to link workers to their children. We focus primarily on mother-child linkages, as we do not have full matching information on fathers if they are not present for the birth, which may lead to selection bias.

Prescription data include the names and doses of every medication which requires a prescription in Austria. These data include the universe of Upper Austrian prescriptions, including both inpatient and outpatient prescriptions. Specifically, we analyze antidepressants (ATC code N06A), opioids (N02A and

may also qualify for a special benefit scheme to top up benefits by up to 25 percentage points.

[10] Zweimüller, Winter-Ebmer, Lalive, Kuhn, Wuellrich, Ruf, and Büchi (2009) provide a detailed description of these data.

N01AH), and non-opioid painkillers (N02B).[11] The data do not contain information on over-the-counter drugs, implying that any estimates on drug use may be understated. However, we note that many drugs typically sold over the counter in the US, like Acetaminophen, are commonly prescribed by a physician in Austria. There are no prescription refills in Austria, which allows us to capture all possible prescriptions during our sample period. Diagnosis codes are available if an individual has either an inpatient hospital stay or a sick leave, which excludes doctor's visits where no sick leave is certified. Therefore, while we have information on outpatient visits and expenditures, we will not be able to analyze outpatient diagnoses.

Hospitalization data from the UAHIF contain individual-level information on inpatient and outpatient visits, including information on total physician visits and fees paid, and occurrence of acute health events. These data will allow us to track whether unemployed workers experience more serious health conditions or spend more on physician visits after job loss. Hospital data do not include information on emergency department visits.

When we analyze these health data for all Upper Austrian workers, including those that have never experienced job loss, we note that there are existing differences in health status that vary by gender. We present these residual differences for a 10 percent sample of workers in Table 1, adjusting for age and time fixed effects. In particular, female workers are more likely to take pain medications and antidepressants and are more likely to visit and spend money on doctor's visits. These findings suggest that if UI benefit extensions do affect health, we should expect male and female workers to respond differently, which further motivates our empirical approach.

Additionally, to estimate longer-run effects of UI duration, we use administrative data on individual-level disability claims. These data allow us to track whether a worker files a disability claim prior to or following job loss. We consider a disability claim to be active if a worker has filed for disability prior to December 31, 2018, which is the latest sample date we can observe labor market status. Importantly, filing a disability claim in Austria is a form of retirement, we therefore refer to disability claims as "disability retirement" throughout.[12]

Summary statistics for our main sample—that is, Upper Austrian workers aged 30–50 that meet the experience criteria and suffered job loss between 2003–2013—are shown in Table 2. We present

[11] For reference on ATC codes, see https://www.whocc.no/atc_ddd_index.

[12] Workers bear the burden of proof of inability to work. In Austria, disability pension is paid for an assessed loss of more than 50 percent of earning capacity for workers with at least 60 months of paid contributions. Although the claimant has the burden of proving inability to work due to a physical or mental impairment, there need not be direct medical evidence of subjective events like chronic pain (Federal Ministry Republic of Austria, 2018). See https://www.ssa.gov/policy/docs/progdesc/ssptw/2008-2009/europe/austria.html for more information on the interworkings of the disability pension system.

descriptive statistics for the pooled set of workers (Columns 1–2) and also present these means by gender (Columns 3–4). In Column 5 we present estimates from a $t$-test showing whether the means for female and male workers are statistically different for each outcome. Notably, unemployed workers aged 30–50 in Upper Austria are more likely to be male and have 17 years of job experience, on average. Splitting these descriptive statistics by gender, female workers are more likely than male workers to visit a physician and are more likely to have an opioid and/or antidepressant prescription, mirroring our descriptive statistics from the full population in Table 1. Male workers, on the other hand, earn approximately 26.5 Euros more per day, and become employed again 18 days earlier than female workers.

## 4. Regression Discontinuity Design

Our empirical strategy exploits the discontinuous jump in UI benefit duration from 30 to 39 weeks at age 40. This regression discontinuity design (RDD) is motivated by the idea that characteristics of unemployed workers related to behaviors and outcomes of interest are likely to vary smoothly through the age threshold; that is, any discontinuity in prescription drug use, health care utilization, or disability claims can be reasonably attributed to the change in benefit length. We operationalize this identification strategy by estimating the following OLS models:

$$y_i = \beta_0 + \beta_1 UIextend + f(age_i) + \alpha_t + \eta_i, \tag{1}$$

where $y_i$ represents the main outcome variables of interest such as individual-level prescriptions for opioids and other painkillers and antidepressants as well as hospitalizations and whether a worker $i$ ever claimed disability retirement. $f$ represents some smooth function of our running variable, worker age. $UIextend$ is a binary indicator variable for whether a worker is at least 40 years old at the time of layoff. To construct our preferred estimates, we adopt a quadratic specification for the function of our running variable and allow the slope term to be flexible on each side of the UI eligibility threshold, although we additionally fit models where the running variable enters the equation linearly and cubically. In our preferred specifications we also include quarter-year fixed effects, $\alpha_t$, to control for any cylicality or economic trends in unemployment over time.[13] We highlight estimates from a specification that uses a one-sided bandwidth of 10 years, following Nekoei and Weber (2017), although we additionally present

[13]This is especially important in light of the fact that our data from 2003–2013 span the years of the global financial crisis. We note that changes in Austrian unemployment rates were relatively modest during this time, compared to surrounding countries, and the government did not change UI benefit generosity or duration, opting instead to invest in retraining programs and expand short-term work allowances (Hofer, Weber, and Winter-Ebmer, 2013). Omitting 2007–2009 from our analysis to account for the Great Recession yields estimates that are statistically similar to our baseline estimates at the 1 percent level.

results from a wide range of bandwidths, including a MSE-optimal bandwidth, as suggested by Calonico, Cattaneo, Farrell, and Titiunik (2016). Because we analyze several different health outcomes, for some specifications we additionally present $p$-values from models that correct for multiple hypothesis testing. Standard errors are clustered on the running variable; worker age bin. Estimates from this reduced-form specification represent intent-to-treat effects.

In all specifications, we estimate effects using information for unemployed workers only. Our approach therefore compares unemployed workers that are under the age of 40 and are just-ineligible for the 9-week UI benefit extension to those that become unemployed just after turning 40 and are eligible for the additional UI benefit weeks. Below, we additionally consider comparisons restricting our sample to just female workers on either side of this cutoff and just male workers on either side of this cutoff separately. The identification assumption underlying this model is that no other income transfers, employment shocks, or other related events occur concurrently at the age-40 benefit extension eligibility threshold. The fact that individuals have no control over their age alleviates potential selection concerns. However, hiring and firing powers are held with the firm, which may be aware of an individual's birth date and may be incentivized to discharge workers just before (or just after) this UI extension cutoff.

UI benefits in Austria are not experience-rated, implying that there is no strategic advantage to the firm to either delay or speed up layoffs, based on the UI system. Moreover, firms report the date of layoff, so workers cannot delay claims to UI benefits just after they turn 40. Nonetheless, we provide formal evidence that there are no discontinuities in worker unemployment at age 40, and provide support that gender, education, urbanicity, migrant status, job experience, parental status, and prior job characteristics do not drive the discontinuities we observe in nonemployment duration or health outcomes.

Moreover, with any age-based design, it is critical to consider any other treatments at age 40 that may also affect the outcomes of interest. One such example is if health providers recommend certain preventative care treatments at the age of 40 (e.g., mammographies) and we believe that individuals schedule these appointments near or on their birthdays, leading to an increase in diagnoses or prescriptions. Another such example is birthday celebrations. If an individual decides to engage in risky behaviors, like opioid use, on their $40^{\text{th}}$ birthday, our estimates will be biased upward. We can address this issue primarily by estimating a "donut RD" which omits observations near the age cutoff, as suggested by Barreca, Guldi, Lindo, and Waddell (2011). Additionally, by analyzing subgroups more prone to opioid use, or opioid prescription potency, we can get a better sense of which types of short-lived behaviors are more likely to be age-related and thus related to turning a year older (i.e., celebratory events or actions due to a "midlife crisis") and which are likely to be sustained as a result of job loss. Furthermore, we note that no other

Austrian cash or in-kind transfer schemes use this same age threshold.

We primarily focus on effects within 9 months of unemployment, which corresponds to the maximum benefit duration of 39 weeks, noting that only approximately 2 percent of workers fully exhaust their benefits. Therefore, our below analysis investigates to what extent the *opportunity* to receive benefits for an additional 9 weeks affects the ability of workers alters their health. We note that health effects during the period right after unemployment and those occurring once a majority of workers are back to work may vary. To track individual outcomes over time, we additionally estimate the above equation for quarters and months prior to and after unemployment separately. This allows us to check whether the discontinuities we observe in health after job loss are attributed to the timing of unemployment or preexisting anomalies of the data and whether health effects persist after workers have matched to a new job. Finally, we note that much of the discussion of the paper is focused on female workers; however, we present our analyses for the pooled sample of workers and present effects for male workers separately. Moreover, we show additional results from a reweighting approach in an attempt to more clearly compare effects across gender, in the spirit of Hainmueller (2012).

## 5. Effects on Nonemployment Duration, Job Match, and Wages

It is well-documented that longer UI duration causes longer unemployment (Card, Lee, Pei, and Weber, 2015; Nekoei and Weber, 2017). However, these average effects may hide important gender differences in job search behavior. Using data on the universe of Austrian workers from 2003–2013, we show that female workers drive previously measured wage gains, which then motivates our study of health outcomes by gender.

In Figure 1, we address the notion that the impact of UI benefit duration on nonemployment is likely to vary by gender. Blue circles represent binned means for female workers, while gray diamonds represent binned means for male workers. We display quadratic fits for each group separately. Estimates indicate that both female and male workers eligible for an additional 9 weeks of benefits take up UI benefits and remain unemployed for a longer period of time than noneligible workers, although effects are larger for female workers.

Table 3 formalizes these estimates based on the model described in Equation (1). In Column 1 we present estimates for UI benefit duration for the pooled sample of workers, as well as for male and female workers separately. Estimates largely reinforce the conclusions that can be drawn from the figures—longer UI benefit eligibility leads to longer time spent unemployed, and these effects are larger for female

workers. Specifically, estimates indicate a statistically significant increase in UI benefit duration by 2.4 days, with average effects of 1.7 days for male workers and 4.3 days for female workers. Moreover, estimates in Column 2 indicate that female workers eligible for 9 additional weeks of benefits remain unemployed 8 days longer than ineligible female workers, while male workers remain unemployed 3 days longer. Estimates for both outcomes are statistically different across gender at the 1 percent level.

In Figure 2 we present evidence that UI duration does affect job match, as measured by daily log wages of the first new job after an unemployment spell. Estimates indicate that female workers eligible for an additional 9 weeks of benefits match to higher paying jobs, and we show that these effects are driven by workers that switch industries (e.g., Figure A2). Female workers receive 2 percent higher wages, corresponding to an additional 1 Euro per day, or 371 Euros per year, on average. Male workers, on the other hand, reenter the labor force more quickly, are much less likely to switch industry, and do not experience wage gains, on average.

Importantly, these findings imply that granting workers an additional 9 weeks to look for their next job allows some female workers the ability to place in a higher-paying position than they would otherwise, even if they do not use the full UI allowance. Therefore, while many workers choose not to spend a full 39 weeks claiming UI benefits, the opportunity to do so increases nonemployment duration and affects female worker wages, as compared to unemployed workers with only 30 weeks of benefit eligibility. This result is consistent with recent work suggesting that some workers overestimate their ability to find a new and/or higher paying job, and allowing additional search time can yield better outcomes (Mueller, Spinnewijn, and Topa, 2020). Below, we analyze whether this time extension also affects the physical and mental health of unemployed workers and their children.

## 6. Effects on Worker Health

In this section, we test to what extent prolonged UI benefit duration affects physical and mental health, health care utilization, and drug expenditures.[14] We do so in an attempt better understand the relationship between UI, occupational demands, wages, and well-being.

### 6.1. Mental Health

Unemployment is often associated with increased stress, depression, and deteriorated mental health (Kuhn, Lalive, and Zweimüller, 2009; Classen and Dunn, 2012). This could be due to financial insecurity,

[14]We have also analyzed effects on the most serious health outcome—mortality. We find no evidence of effects of longer UI duration on mortality for either gender ($p > 0.61$). See Figure A3.

changed plans or expectations, or perceived loss of purpose. Extending UI duration could lead to improved mental health if employees take more time to relax and rest or find a job with better wages. On the other hand, if prolonged joblessness compounds this mental stress, or if there is unwanted societal or family pressure to remain unemployed longer due to the extension in UI benefits, workers may experience more adverse mental health consequences.

In Figure 3 we analyze the effects of UI duration on the uptake of prescription drugs for stress and depression, namely antidepressants. We present our formal RD estimates for these health outcomes in Table 4. Overall, we find that female workers eligible for an additional 9 weeks of UI benefits experience decreases in antidepressant prescriptions following unemployment. In particular, estimates indicate that extending UI benefits reduces antidepressant prescriptions by 11.1 percent for female workers.[15]

One remaining question is whether prescribing behavior is changing most for those with existing prescriptions or for those who previously did not have a prescription for antidepressants. In the first column of Tables A1 and A2, we investigate the effects of longer UI duration on changes in the level of prescriptions. Table A1 reports results for the total number of packages prescribed, including zeroes, while Table A2 provides estimates for the number of packages prescribed, conditional on receiving a prescription. Estimates in Table A2 are largely insignificant, but Table A1 provides some evidence that longer UI duration does affect female patients' decisions to start or stop taking a prescription drug.[16]

Next, we analyze dynamic effects of longer UI duration, which may be important for several reasons. First, the nature of some health outcomes, like prescription misuse or acute illness may take time to develop, suggesting that these effects may become more apparent and/or grow after job loss. Second, given that a majority of individuals find new jobs within 6 months, looking at the development of short-lived effects and their persistence can more directly speak to the changes in health behavior associated with the stress of unemployment and/or the relief of finding a new job. Third, by presenting estimates of effects in the months prior to unemployment, we can test whether any estimated health effects represent existing trends in behaviors of laid-off workers.

In Figures A4 and A5 we display RD coefficients from Equation (1) for the main outcomes of interest separately by quarter for the quarter prior to and the 6 quarters following the start of UI benefits. We

[15]Estimates for male and female workers are statistically different at conventional levels. We find some evidence that male workers increase use of antidepressants when eligible for longer UI duration. However, this effect is not statistically significant across bandwidths and other alternative specifications.

[16]We also consider how these effects evolve within different time windows after unemployment, to test whether average effects fade or remain stable when including observations in the longer run. In Table A3, Column 1, we present estimates of extended UI benefit duration on antidepressant prescriptions within 3, 6, 9, 12, 15, and 18 months after job loss, respectively. Estimates indicate that reductions in antidepressant prescriptions for female workers are similar to our main results within the 18 month-window after job loss. This finding also implies that our 9-month sample window is not driving the main result.

present quarter relative to a worker's UI spell on the $x$-axis, and RD coefficients on the $y$-axis. Estimates indicate that antidepressant prescriptions decline in the quarters following unemployment for female workers, with large reductions lasting 6 quarters.

One natural follow-up question to these findings is: Do these effects vary by observable worker characteristics? To further analyze effects on opioid use for female workers, in the first column of Table 5 we investigate additional heterogeneous effects of UI extensions on antidepressant prescriptions across female worker subgroups. First, we consider the idea that female workers may face more pain while unemployed due to a combination of physical work demands and within-household stressors. These challenges may be even greater for households with children. To explore this possibility, we create an indicator for whether a female worker gave birth before the age of 44 or whether a male worker has been registered as a father before the age of 44, and analyze whether effects are stronger for parents.[17]

In the first column of Table 5 Panels (b)-(e) we present estimates by occupation type and education to explore whether low-skill, low-educated, or low-income female workers are more likely to experience large gains in health when UI benefits are extended. In particular, we consider effects based on whether a female worker works in a designated "low-skill" occupation, works in a job that is physically taxing, works part-time, and/or has less than a college education, respectively.[18] Estimates indicate that female workers in full-time and low-skill jobs are more likely to reduce antidepressant use in the 9 months following unemployment.

## 6.2. Physical Health

### *6.2.1. Opioid Prescriptions*

To estimate effects of UI duration on physical health, we first turn to a key indicator of health tied to work: pain. We estimate the effects of workers receiving an additional 9 weeks of UI benefits on opioid prescriptions, a proxy for opioid use, using the universe of prescription data for Upper Austria from 2003–2013. We do so given the expansive and growing literature suggesting that opioid prescriptions and opioid misuse is related to job performance and/or unemployment.[19] Moreover, there is existing evidence that income shocks affect consumption of prescription pain relievers and hallucinogens (Carpenter, McClellan, and Rees, 2017) and illicit drugs and alcohol (Dobkin and Puller, 2007).

[17]For mothers, we define motherhood by age 44 due to data restrictions. Birth register information is available only until 2007. Thus, females who are 50 years old (the maximum age in our baseline sample) in 2013 (the last year of our sample) were only 44 years of age in 2007. Therefore, we can only observe completed fertility up to age 44 for every mother in our main sample.

[18]Because not all variables are recorded for all workers in all years, sample sizes vary across panels, although remain relatively similar in size, with no notable systematic non-reporting.

[19]See, for example, Krueger (2017), Hollingsworth, Ruhm, and Simon (2017), and Musse (2020).

In our context, average daily per capita opioid use in Austria ranks among the top five countries in the world, and Austria leads the world in per capita morphine consumption.[20] On average, 1.2 percent of our full sample has a prescription for opioid analgesics. Female workers are prescribed opioids at 1.3 times the rate for male workers.

First, Figure 4 shows the probability of being prescribed an opioid for workers just above the UI extension eligibility cutoff for all years in our sample period (2003–2013). We include prescribing data for the 9 months (i.e., 39 weeks) following an unemployment event for workers between ages 30 and 50. Figure 4 presents suggestive evidence that female workers are less likely to use opioids when benefits are extended from 30 to 39 weeks, with larger effects for female workers.[21]

These estimates correspond to approximately 500 fewer opioid prescriptions each year, and the estimated declines in opioid use for female workers are consistent when increasing the outcome window and when analyzing effects over time (Table A3 and Figure A4). Estimates for male workers are statistically insignificant and are precise enough to rule out more than a 11.6 percent decrease in the likelihood of being prescribed opioids. In Section 9 we additionally conduct sensitivity analyses and discuss how these estimates vary across bandwidths and functional form.[22]

Importantly, this effect may be largely driven by the types of jobs workers match to when given a 9-week extension in benefits. We analyze whether the conditions of the next job can explain the reduction in opioid use shown in Table 5 Column 2. Estimates indicate that female workers in physically demanding jobs, low-skill jobs, and workers with lower education levels are more likely to reduce opioid use in the 9 months following unemployment. In Table 6, we present estimates from Equation (1) and additionally include an interaction term for whether an individual experienced occupational hardship prior to job loss. Occupational hardships are considered and noted in the data for jobs that expose workers to hazardous materials, like acids or gases, include physical demands, like freight or construction workers, and/or

[20]The top four countries, in order of per capita opioid use, are the United States, Canada, Germany, and Denmark, with average days of opioid use per resident per year spanning 8.3–17.4 (United Nations, 2018).

[21]We note that, based on this figure, there are apparent increases in average opioid prescription take up for women aged 38–40. This may imply that unemployed women just under age 40 may differ in an important, unobserved way as compared to unemployed women just over the age of 40. Importantly, this small relative increase in opioid prescriptions for unemployed women aged 38–39 is not driven by systematic or differential means in injuries, hospitalizations, or childbirth complications. We also present evidence in Figures A6 and A7 that this perceived "jump" is not present in the sample of female workers that do not meet the experience criteria, and therefore are ineligible for the UI extension, nor is this trend present in the full population of workers, implying that, in the absence of the UI duration extension, we would have expected the upward trend in opioid prescriptions through the cutoff. Below we provide more sensitivity checks to support the notion that our estimated reduction is not reliant on functional form and holds even when omitting observations close to the cutoff.

[22]Because female workers are prescribed opioids at a higher rate, and because we are analyzing results separately by gender, in Appendix Table A4, we additionally present results from a model analogous to Equation (1) that includes a dummy variable equal to one if a worker is female (0 otherwise), and an interaction term of this variable with our main variable of interest, $UIextend$. Estimates in Table A4 Panel (b) Column 1 reinforce the results from Table 4—namely, that extending UI benefits reduces opioid prescriptions for female workers.

require working nights and weekends, like heavy truck drivers and cooks.

Estimates indicate that female workers laid off from a physically demanding job are 1.3 percentage points, or 7.4 percent less likely to match to a physically demanding job during their next employment spell when eligible for additional weeks of UI benefits.[23] This estimate corresponds to nearly 1,000 fewer female workers in jobs with hardship per year, which is twice the estimated reduction in opioid prescriptions. Since over one-third of opioid users in our sample work a physically demanding job, we note that these findings may have important implications for how work conditions affect pain and prescription take-up.

These findings also suggest that female workers use opioids while employed due to existing physical stressors and/or that unemployment provides temporary pain relief. If extending UI duration allows female workers needed time to match to a less painful job, starting a new position itself may reduce reliance on opioids. We provide more evidence for this story in Figure 5 and Table A5.

In Figure 5, we present estimates of the probability of receiving an opioid based on previous occupation. In the left panel, we show that the decrease in opioid take-up is driven by female workers that were previously in a physically demanding job (i.e. a job with hardship). Estimates do not indicate any change in opioid use for female workers in other occupations. Because female workers in jobs with hardship are also disproportionately switching away from such occupations when eligible for an additional 9 weeks of UI benefits, these findings suggest that the drop in opioid use is a result of women pivoting towards a different, and less physically demanding job.

Additionally, in Table A5 we show that our main estimates are driven by a decrease of “weak," or low-potency opioids prescribed to female workers, including opioids in ATC categories N02AX, like tramadol, or codeine and dihydrocodeine, versus higher-potency opioids, like morphine or oxycodone. Indeed, these weaker opioids are most likely to be associated with everyday pain, rather than traumatic events or serious injuries, suggesting that this reduction corresponds to relatively lower levels of chronic pain for unemployed female workers eligible for an additional 9 weeks of UI benefits.

### *6.2.2. Other Pain Medication*

We have also analyzed whether our estimated effects may be explained by substitution to other less-addictive pain medication, and present evidence supporting this hypothesis in Figure 6. Specifically, we find weak evidence that female workers are prescribed more non-opioid analgesics in the 9 months

[23] We note that there is much persistence in job type over time. Female workers unemployed from a physically demanding job are 40 percent more likely to work in a physically demanding job during their next employment spell, as compared to workers in other occupations.

following unemployment. When pooling months together, and/or observing quarterly data, as shown in Figure A4, we find a large and statistically significant positive effect of non-opioid pain prescriptions for female workers in the first quarter (i.e. first 3 months) after unemployment.[24] Lastly, in Tables A1 and A2, estimates indicate that changes in the extensive margin drives our main result; that is, having access to a longer period of UI benefits greatly increases the chances that a female workers completely stops taking opioids. Therefore, these findings support the idea that some female workers may take low-potency opioids to perform at their jobs, and joblessness or occupational switching allows for a temporary substitution of other pain medication with eventual terminated use of such drugs.

Altogether, the effects on prescription usage have stark implications for the adverse health conditions that many workers face. Female workers are less likely to use antidepressant and opioid prescriptions when they experience extended UI benefit eligibility, and these effects are concentrated for low-skilled workers in industries imposing a large physical toll. Low-skilled male workers, on the other hand, experience no change in the probability of being prescribed opioids following unemployment, which is consistent with previous findings suggesting a strong complementary between leisure and opioid use for men but not women (Krueger, 2017; Serdarevic, Striley, and Cottler, 2018). These conclusions are also consistent with the above findings that male workers do not switch away from a physically demanding job when granted additional time to search for a new job Our findings therefore speak to distinct differences in worker behavior and prescription use across gender, especially during a time when women are contributing to high rates of female labor force participation but also report engaging in more housework and childcare than their partners (OECD, 2020).

### *6.2.3. Health Care Utilization*

In this section, we test the relationship between UI duration and health care utilization. To the extent that UI benefit duration affects risky behaviors, we may observe changes in the number of and/or the intensity of interactions with the health care system. Importantly, Austrian workers do not lose health care coverage after job loss, implying no effects on the intensive or extensive margins of health care utilization due to changes in out-of-pocket costs. Therefore, any observed effects on hospitalizations, doctor's visits, or prescriptions are likely due to changes in worker health.[25]

In Figure 7 and Table 7 we consider the average effects of extending UI benefits by 9 weeks on

[24] These effects fade after 3 months, and estimates after 9 months shown in Table 4 Column 2 are statistically insignificant.

[25] UI benefit duration may also affect a worker's leisure time, leading to more doctor's visits and/or prescriptions for previously untreated ailments. However, in Austria, many workers participate in sick leave insurance, which compensates workers for lost earnings due to illness, and by law employers must grant time off to see a doctor during working hours (Ahammer, 2018).

in-patient hospital days within 9 months after job loss. Overall, we find some evidence for reductions in outpatient expenditures, although estimates are relatively imprecise. We estimate no increases in physician fees or hospital fees billed or the number of physician visits.[26] This result may be unsurprising since health care coverage does not change at job loss and workers have access to sick leave when suffering from an acute illness; however, given that all prescriptions in Austria have a small, but required fee of six Euros, these findings also indicate that expanding a conditional cash transfer does not adversely affect uptake of health care services. Notably, when observing hospitalizations at the intensive margin, conditional on being hospitalized, female workers spend, on average, 1 fewer day in the hospital, which could indicate that these workers are able to visit the hospital at an earlier stage in an illness.

## 7. Estimating Within Household Spillovers

In this section, we analyze whether a female worker's change in health outcomes due to extended UI duration could also create within household spillovers. This is especially important, given that marginal value of public funds (MVPF) of public expenditure programs have been shown to increase dramatically when taking into consideration the effects on children (Bailey, Hoynes, Rossin-Slater, and Walker, 2020). To analyze whether a change in a mother's UI benefit length also affects the health of their children, we use birth certificate data. There are two arguments that reinforce the idea that child health will improve with longer UI duration: (i) more leisure time for women could lead to more scheduled and attended well-visits and/or (ii) longer UI leading to a "better match" job with higher wages may allow for less stress within the household and/or a better affordability of complements to health, like more nutritious food.

We present estimates on proxies for child health separately by child age in Table 8 based on their parent's age of unemployment. In Columns 1 and 2 we present estimates for outpatient expenditures and visits, respectively, and in Column 3 we present estimates for a count of total inpatient days. We find that when workers are eligible for longer UI assistance, children under the age of 6 experience decreases in outpatient expenses, amounting to approximately 16 Euros per year (30.1 percent).[27]

When investigating this further, we find that these effects are driven primarily by both lower physician

[26] We also consider the possibility that at age 40 women are more likely to go to the doctor for a mammogram. However, we find no evidence that extending UI insurance changes behavior on this margin. See Figure A8. Similarly, we find no discontinuous effect on workers choosing to have a baby after unemployment (i.e. Figure A9), nor do we find any evidence of discontinuities in birth complications for unemployed women.

[27] We have additionally explored whether the presence of siblings differentially impacts children of unemployed mothers. Estimates indicate that our main effects are driven by children under the age of 6 with no siblings at the time of mother's job loss; however, estimates for children with siblings are relatively imprecise and cannot rule out greater than a 27.7 percent decline in outpatient expenditures.

expenses and fewer drug expenses. Estimates for outpatient visits (Column 2) are statistically insignificant for all ages. Similarly, estimates for inpatient days, shown in Column 3, are statistically insignificant at the 5 percent level, suggesting that there are little effects of UI benefits on total hospitalizations for children. These estimates provide some support for the notion that when parents are unemployed longer, they spend less on their child's health but do not neglect doctor's visits.[28]

In Columns 4 and 5, we additionally present separate estimated effects based on types of outpatient expenditures. In Column 4, we analyze effects of longer UI duration on preventative care visits for children. This includes all screenings, including mother/child well visits. Notably, well visits for young children have a financial incentive for all mothers in Austria, regardless of household income. Therefore, perhaps unsurprisingly, we find no change in the probability that a child will complete a preventative care doctor's visit.

Nonetheless, even if the total number of visits is unchanged, we may be interested in any changes observed as a part of the visits that occur before and after unemployment. In Column 5 of Table 8, we analyze effects on "curative" health expenditures. Again, estimates are statistically significant for children under the age of 6, and suggest lower expenditures of approximately 31.3 percent, similar to the decline in overall health care expenditures. One possible explanation is when parents have access to an additional 9 weeks of UI benefits, they can make time to see the doctor earlier and do not let a child's illness progress to a stage that may be more costly. Notably, across columns and panels we see little to no effects on children above the age of 6. If anything, we see an increase in expenditures for children aged 12–17 (significant at the 10 percent level) which may indicate that either these children are old enough to know when they are sick and can stay home by themselves from school even if their parents are working, or are better able to articulate to their parents what their needs are.

## 8. Effects on Disability Claims

Lastly, to get a better sense of the broader effects of extended UI duration over a worker's lifetime, we explore whether extending UI benefit duration could affect labor market and health outcomes in the longer run. In particular, we estimate effects of a 9-week extension in UI eligibility on disability claims. Given that for female workers we show that longer nonemployment duration leads to more workers matching away from occupations with high rates of injury, these individuals may be less likely to claim disability as a result. And, if these workers are able to match to a safer job and/or a job with

[28] Unfortunately, our data do not contain information on vaccines, as they are not covered by public health insurance.

higher earnings in perpetuity, extended UI time limits could prolong working behavior and could reduce incentives for disability filings (Böckerman and Ilmakunnas, 2020). Alternatively, male workers who are more likely to stay in a physically demanding job may experience more adverse health conditions and more disability claims.[29] We explore these possibilities in Figure 8, using an extended panel from 2003–2018. Specifically, we test whether unemployed workers eligible for extended UI benefit duration are more or less likely to claim disability before retirement.

In Figure 8, we test whether workers eligible for the UI extension are more likely to claim disability retirement, which is a longer-term outcome that is more directly linked with health and working conditions. We find that unemployed female workers eligible for extended UI benefits are 0.7 percentage points less likely to claim disability, while unemployed male workers are 0.6 percentage points *more* likely to claim disability. These effects increase as workers near age 50. This is consistent with work by Sullivan and von Wachter (2009), which suggests that older workers who become unemployed may be close enough to retirement that they fill in the gap of unemployment and retirement with disability.[30] To explore this notion further, in Figure A10 we present event study analogues from an age-based difference-in-differences analysis, comparing male workers to female workers.[31] Estimates indicate that the disability filing wedge between female and male workers is more than 10 percent for workers becoming unemployed at age 50. These results correspond to 700 additional disability claims for male workers, but 700 *fewer* cases for females each year. Given that approximately 1,000 eligible unemployed female workers are switching away from physically demanding jobs each year, these magnitudes are in line with the idea that occupational demands affect worker health and allowing workers more time to search for a job in their 40s can help mitigate physical pain in the longer run.

Taken with our previous results, our findings suggest that when female workers are eligible for 9 additional weeks of UI benefits, they are less likely to be prescribed antidepressants and opioids, and are able to find a higher paying, less physically demanding job, potentially leading to long-term improvements in health. Below, we discuss possible mechanisms to explain these results.

[29] See Savych, Neumark, and Lea (2018) for recent work on the effects of opioid prescriptions on disability, which motivates this analysis.

[30] In related work, Mueller, Rothstein, and von Wachter (2016) find that the expiration of UI benefits does not induce workers to file for disability.

[31] This estimation model takes the form $y_i = \sum_{k=-10|t\neq-1}^{10} \beta_k (female_i \times age_k) + female_i + \sum_k age_k + \varepsilon_{it}$, where $y$ represents the outcome "filing for disability retirement" for individual $i$, $female$ is an indicator variable taking the value 1 if a worker is female, and $age$ is the age at unemployment.

## 9. Testing the Sensitivity of the Estimates

In this section, we explore the sensitivity of our estimates to functional form and various threats to identification. First, we note that our findings may overstate the true effects of UI duration on health if firms hire and fire different types of workers based on their knowledge of the age 40 cutoff. Importantly, firms do not receive any type of penalty or reward based on this threshold, and Austrian UI benefits are not experience-rated. Nonetheless, in Figure 9 we present an age distribution of unemployed workers and estimated discontinuity in the number of jobless workers near this cutoff. We find no lumpiness in this age distribution, implying there is no manipulation of the eligibility cutoff in layoff decisions.

Next, we explore whether there exist discontinuities in other types of observable characteristics, including gender, as well as urbanicity, migrant status, education, experience, and log wage. Graphical evidence is presented in Figure 10, and formal estimates by gender are presented in Table A6. Across all outcomes these estimates are statistically insignificant at the 1 percent level, providing additional support that workers on either side of the UI extension eligibility threshold are similar on measurable characteristics.[32]

To further test whether these health effects are simply an artifact of the data, in the top panel of Table 9 we present effects for the three months prior to unemployment. This is especially important if certain types of workers with physical or mental illness are more likely to be laid off work. All estimates prior to job loss are statistically insignificant at the 5 percent level, providing additional support for the notion that unemployed workers eligible for the UI extension are comparable to unemployed workers that are just below the age cutoff and do not become unemployed due to existing physical or mental health ailments that would be observed even in the absence of the benefit extension.

Additionally, we test whether workers that do not meet the experience criterion and are thus ineligible for the benefit extension experience similar health effects. As discussed above, this eligibility provision requires that workers have worked at any job for at least 6 out of the last 10 years. In particular, in the bottom panel of Table 9 we show our baseline effects for both female and male workers compared to workers that are laid off at age 40 but *not* eligible for the extension in benefits. We find that female workers eligible for the program are driving the main results, which provides further evidence that the extension in benefits, and not unemployment itself, is responsible for changes in physical and mental health.[33]

[32]Similarly, when we test whether the compositions of our defined subgroups from Table 5 change differentially across the threshold, we estimate no discontinuities at the eligibility cutoff in whether a worker is a parent, part-time worker, low education, or working with hardship or in a low-skill occupation.

[33]When estimating effects for eligible workers, using a difference-in-RD approach with the ineligible unemployed workers as

Then, to verify that our estimates are not driven by a few points near the cutoff, we test whether omitting observations in a small neighborhood around the age cutoff (i.e., a "donut") affects our results, as is practice in other age-based designs (e.g., Barreca, Guldi, Lindo, and Waddell, 2011; Barreca, Guldi, Lindo, and Waddell, 2016; and Carpenter and Dobkin, 2009). In Figure A11 we show RD estimates for a sample without female workers who become unemployed within one quarter before and after their 40$^{th}$ birthday. These estimates are similar to the baseline results, which mitigates concerns that other events interfere with our identification strategy.[34]

Finally, we provide evidence that our effects are not sensitive to various functional forms or bandwidths in Tables 10 and 11. In Column 1 we replicate our baseline results from Equation (1). In Column 2 we present results from a specification that allows the running variable to vary linearly.[35] Column 3 presents estimates from Equation 1 using triangular kernel instead of uniform kernel weighting. Column 4 shows estimates from a model using a smaller MSE-driven bandwidth, instead of our preferred one-sided bandwidth of 10 years. In Column 5 we report Romano-Wolf $p$-values for each outcome in an effort to test whether our estimates are sensitive to multiple hypothesis testing.

Estimates on wages for female workers (Table 10 Panel (a)) are positive and statistically significant across columns, indicating approximately a 1 Euro increase in daily wages, or 370 Euros per year, for female workers eligible for a 9-week UI extension. Estimates in Table 10 Panel (b) are similar to the main results for across specifications for all outcome variables and indicate reductions in antidepressant prescriptions ranging from 8.5–9.4 percent and reductions opioid prescriptions ranging from 20.0–53.3 percent. $p$-values once accounting for multiple hypothesis testing range from 0.004–0.23. In Panel (c) of Table 10 we present estimates for health care utilization. Estimates indicate some suggestive, but not definitive, declines in outpatient expenditures. Estimates for male workers (Table 11) are inconsistent across columns and indicate no beneficial health or wage effects of extending UI duration.

Lastly, in Figures A13–A15 we present coefficients and their respective 95% confidence intervals across a wide range of bandwidths, highlighting the MSE-optimal bandwidth for comparison. Estimates are relatively consistent across bandwidths and estimates relying on the MSE-optimal bandwidth reinforce our main findings.[36]

a control groups, estimates are similar to these baseline results and indicate reductions in opioid prescriptions, antidepressant prescriptions, and inpatient expenditures.

[34]We also present age-based histograms for the main outcome variables for all Upper Austrians, regardless of employment status, in Figure A12 to show that there is no bunching in prescription take-up around the age 40 cutoff.

[35]We do not present estimates from models including higher-order polynomials given that Gelman and Imbens (2019) suggest these models as these estimates are more likely to be noisy and lead to poor inference.

[36]In Tables A7 and A8 we also provide evidence that the inclusion of various fixed effects does not have a meaningful effect on our main estimates.

# 10. Potential Mechanisms

Our above results indicate that extending UI benefit duration leads to moderate changes in job search time translating into large positive health and economic benefits for female workers but has some adverse consequences for male workers. In this section, we tie together the interpretations of our findings, investigate whether the marginal changes in time spent unemployed can fully explain these health effect magnitudes, and explore potential mechanisms that explain these gender differences. While each mechanism described below cannot alone justify the entirety of our findings, together the pieces tell a cohesive story.

### 10.1. Reducing Physical Demands

One striking result from our main analysis is that female workers reduce their dependence on opioid prescriptions and are less likely to eventually claim disability retirement. In particular, we estimate approximately 500 fewer females using an opioid prescription each year as a result of the UI benefit extension. Above, we present evidence showing that the period of unemployment (i.e., the 1–2 months after job loss) correspond to a short-term substitution to non-opioid painkillers. However, the reduction in opioids is persistent even after female workers find a new job.

One remaining question is whether the magnitude of our estimates can be explained by the number of women matching to jobs that no longer require physical demands. Indeed, as shown in Table 6, we estimate that over 1,000 unemployed eligible female workers previously in physically demanding occupations match to occupations without physical hardship, as compared to ineligible female workers. Therefore, the additional search time granted to women over the age of 40 reasonably explains the estimated reduction in pain medications. These findings suggest that many female workers use opioids due to the physical demands of their job and would switch to non-addictive alternatives or use no pain medication if in a different occupation.

Interestingly, we don't observe these same changes in occupation for male workers that we observe for female workers; on the contrary, unemployed male workers over the age of 40 are more likely to switch to a physically demanding job. This likely explains why we do not see a drop in opioid prescriptions for these workers and may explain the corresponding offsetting gender effects in disability retirement, if jobs with hardship are more likely to lead to physical injury over time.

### 10.2. Changes in Income

Next, we attempt to better understand how changes in nonemployment duration lead to improvements in job match, which may affect a worker's ability to better invest in their health and well-being. In particular, we note the large gains we find for female workers in terms of wages. We do not find the same gains for male workers; if anything, we find decreases in wages for males that exhaust, or nearly exhaust, their UI benefits. While, on average, gains in wages total 371 Euros per year, we note that for some workers, this wage increase is much larger. Moreover, we find that our main health effects are largest for female workers experiencing an increase in wages, which does indicate that persistent changes in health are due, at least partially, to an income effect.[37] Finally, as shown in Figure A16, the effects on antidepressant and opioid use would be much smaller if females had the same UI benefit levels as men. Since men, on average, have higher UI benefits than females, this indicates that replacing income during unemployment can have positive effects on mental and physical health.

### 10.3. Relaxation of Time Constraints

Lastly, we ask: how much of our findings for women and their children are explained by the increase in leisure time as a result of unemployment? This is akin to asking to what extent are female workers are burdened by other tasks, like household chores and childcare, which may impede a worker's ability to invest in their health. To investigate the relationship between unemployment and time spent on household chores, we use data from the 2018 Austrian Census and Austrian respondents in the *Generations & Gender Survey* (GGS).[38] These survey data contain information on Austrian households, including information on age, gender, household size, household responsibilities, whether a worker is unemployed, and their unemployment duration. We present simple correlations from OLS models in Table A10.

We find that longer unemployment duration is positively correlated with being married for females. This suggests that in two-earner households, female workers spend longer looking for their next job, potentially due to a smaller change in household income.[39] We also find that female workers continue childcare obligations during unemployment, which may explain our estimated reduction in child health expenditures, if when mothers are out of work longer they are more likely to notice or treat an illness

[37] See Table A9, which presents are results for female workers with a wage increase and wage decrease, separately.

[38] The GGS is a cross-country panel on families, life course trajectories, and gender relations administered by the *Generations and Gender Programme*. We use data on all Austrian respondents from both wave 1 and wave 2.

[39] Indeed, this is consistent with our administrative dataset; when we attempt to classify workers as "married" or "unmarried", based on available tax information, effects are primarily driven by married workers. See Table A11 for a replication of our main results for married female and male workers. We note that we can identify only half of all married Upper Austrian workers based on tax status alone and do not have data on this characteristic directly.

before it becomes more serious.

More formally, we have also considered how our coefficients change if we reweight the sample by individual characteristics, like parental status. Therefore, in an attempt to more clearly address the fact that any gender differences in health behavior may arise from the fact that female and male workers differ in a variety of measurable ways, including education levels, existing health, and different levels of UI benefit generosity, we use an entropy balancing approach as suggested by Hainmueller (2012). Using this procedure, we construct balancing weights for observable characteristics, including race/ethnicity, hardship occupation status, health expenditures in year $t-1$, and parental status, to recalculate our RD estimates. This approach thus creates samples where male and female workers have the same covariate distributions.

We present estimates from this reweighting exercise in Figure A16. Estimates are generally similar in sign and magnitude to our main results. This suggests that baseline differences in demographics cannot explain much of the gender differential in our estimates. However, estimates from the balanced sample do indicate that if fewer female workers were parents, on average, the reduction in opioid prescriptions would be much smaller and statistically insignificant. These estimates additionally reinforce our descriptive statistics on the differential mental loads carried by female workers and predict that lessening parental burdens on female workers would further reduce prescription take-up.

## 11. Discussion and Conclusion

In this paper we study the effects of increased UI benefit duration on worker health. In particular, we exploit a feature of the Austrian UI system, namely that workers between the ages of 40 and 50 are eligible for an additional 9 weeks of UI benefits, and analyze effects of UI duration on benefit duration and nonemployment duration, opioid and antidepressant use, health care utilization, and disability retirement. We find that extending UI benefit duration significantly impacts time spent out of the labor force, physical health, and prescription purchases, and that these effects vary by gender. Specifically, we find that unemployed female workers eligible for a 9-week extension in UI benefits are less likely to use antidepressants, less likely to use opioids, and less likely to claim disability. We show that these effects do not hold for unemployed workers of the same age that are ineligible for the benefits extension, and posit that effects are driven by an improved match to less physically demanding, higher-paying jobs for female workers. We find that these positive health effects for mothers reduce health expenditures for their children under the age of 6. Across physical and mental health outcomes, effects are largest for low-skill

workers and parents.

Despite the fact that economic theory suggests that UI should be allocated at the amount where the direct and moral hazard costs equal the beneficial effects of consumption smoothing, we note that existing calculations will be misspecified given the spillover effects to workers themselves.[40] Importantly, only two percent of Austrian workers exhaust their UI benefits, implying that any effects that we estimate are simply a result of the relaxed search time constraint and not a result of prolonged government expenditures.

We provide new evidence that unemployed female workers achieve higher lifetime wages as a result of increased UI duration, implying large benefits for this sector of the workforce, totaling approximately 42 million Euros each year. Given the reduction in opioid prescriptions and the number of female workers that switch away from physically demanding jobs, our results suggest large positive benefits in terms of pain mitigation and reductions in the likelihood of potential opioid addiction. Moreover, estimates indicate significant and persistent reductions in antidepressant use for female workers, suggesting large positive net benefits in terms of productivity and attendance (Centre for Mental Health, 2010; Greenberg, Kessler, Birnbaum, Leong, Lowe, Berglund, and Corey-Lisle, 2003). We estimate no wage gains or positive health benefits for male workers. In terms of costs, eligible workers claim benefits for an additional three days, on average, with a mean claim of 29 Euros. Therefore, the costs of extending UI by 9 weeks is approximately 19.6 million Euros per year. Taken together, these findings imply that the benefits far exceed the costs of offering workers an additional 9 weeks of potential benefits.

Lastly, our main effects are driven by parents, low-skill workers, and workers in physically strenuous jobs, which sheds some light on the relationships between economic circumstances, occupational demands, and worker health, and the role that pain medication takes in everyday life. Given that UI has been shown to be a critical and responsive part of the social safety net during economic downturns (Bitler and Hoynes, 2016; East and Simon, 2020), these findings are especially relevant as countries continue to address the ongoing pandemic and/or face new declines in life expectancy for young men as a result of the opioid crisis.

[40]For work on optimal UI payments and inefficiency, see, for example, Chetty (2008); Lalive, Landais, and Zweimüller (2015); Kroft and Notowidigdo (2016); Landais, Michaillat, and Saez (2018).

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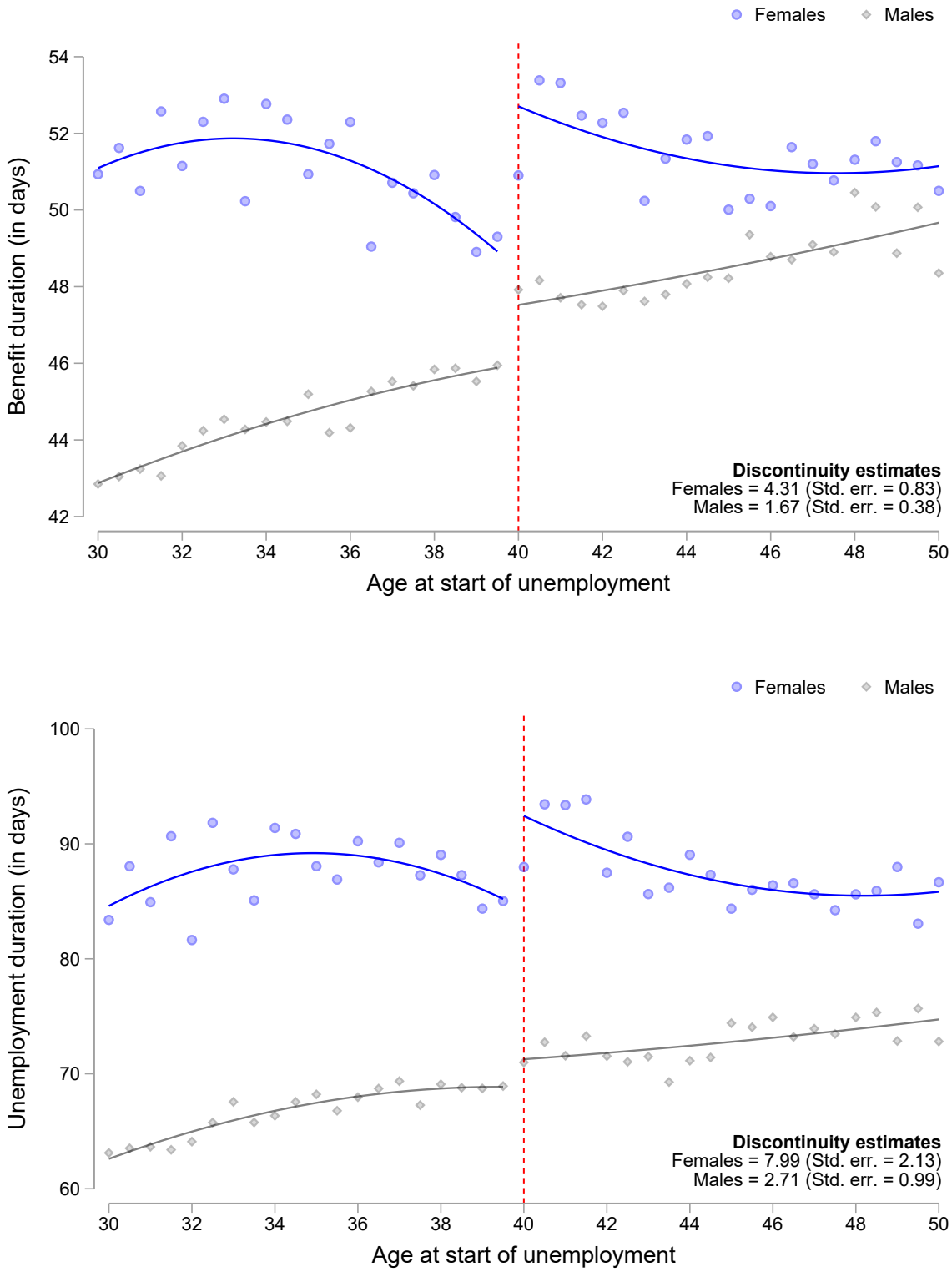
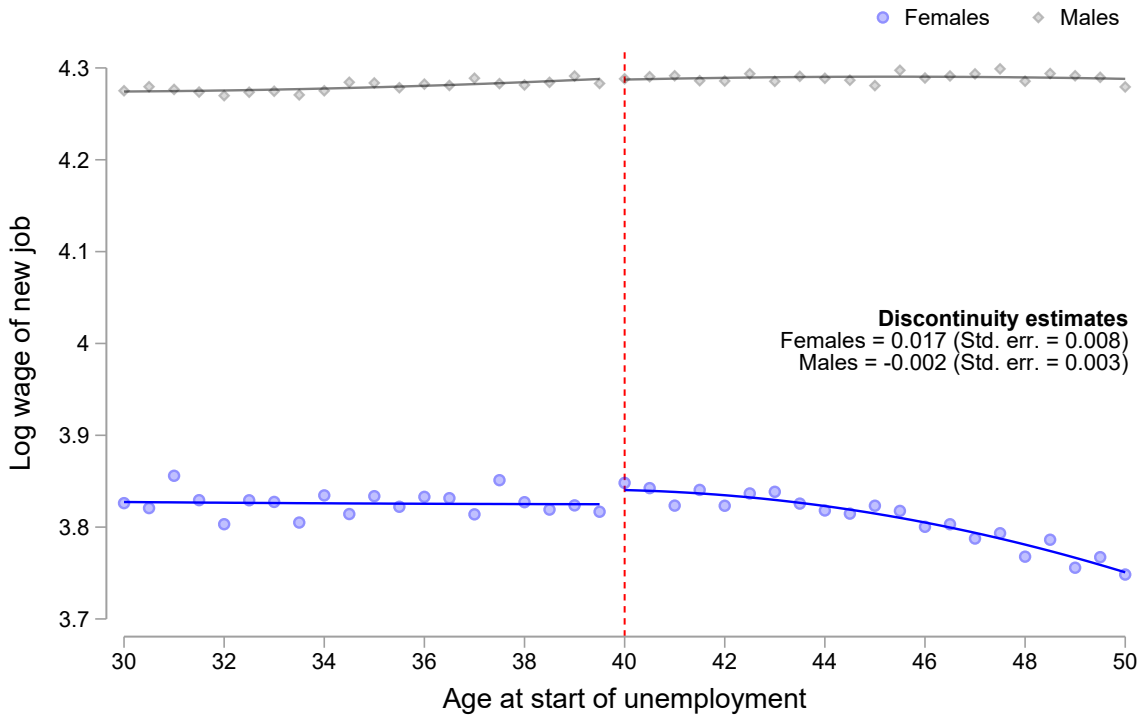
## 12. Figures and Tables

FIGURE 1 — Effects of UI Extensions on Benefit and Nonemployment Duration by Gender



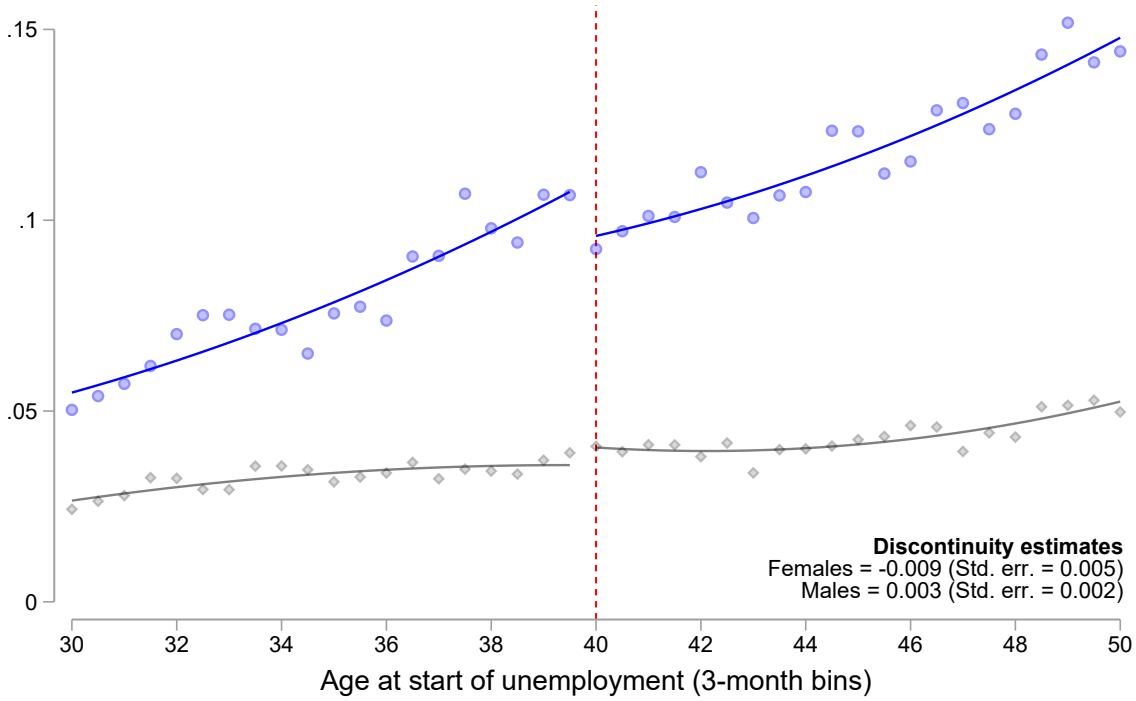

Notes: Individual-level data on unemployment insurance health events is from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. Scatters represent the mean residual listed outcome variable net of quarter-year fixed effects for each 6-month age bin. The top panel presents estimates for UI benefit duration and the bottom panel presents estimates for nonemployment duration. The vertical line represents the age at which workers are eligible for an additional 9 weeks of UI benefits. On either side of the cutoff, we display quadratic fits. Age is calculated based on month of birth. Circles represent averages for female workers, while diamonds represent averages for male workers.

FIGURE 2 — Effects of UI Extensions on Changes in Log Wages



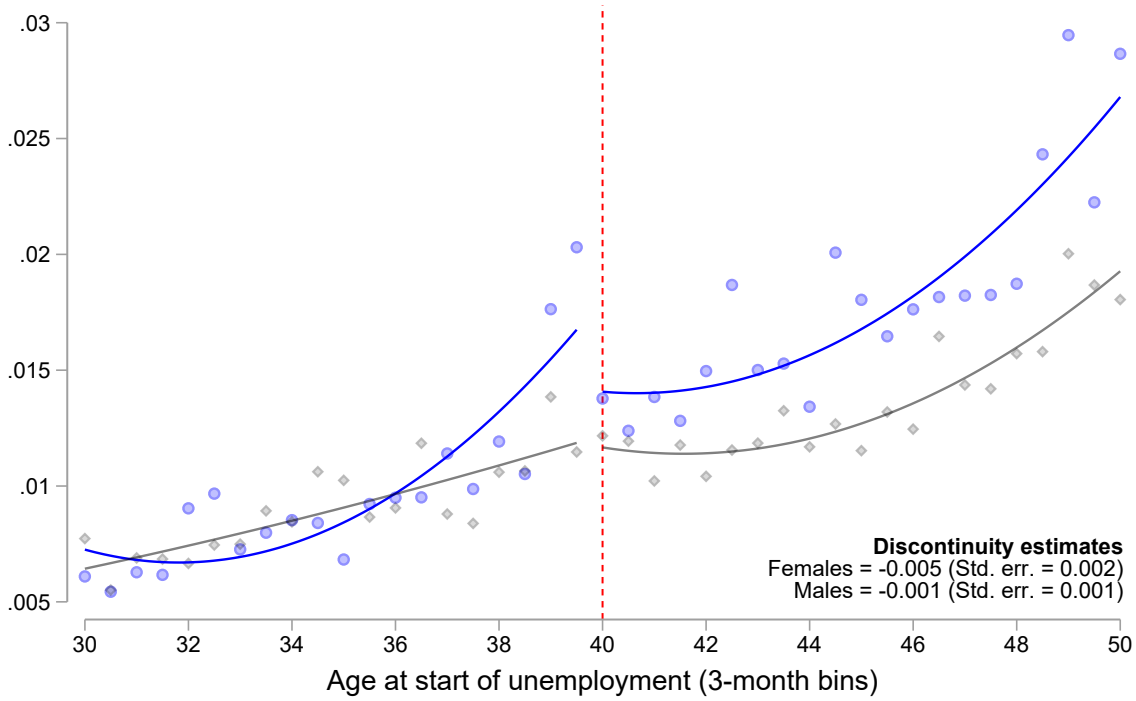

Notes: Individual-level data on unemployment insurance health events is from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. Scatters represent the mean residual of the listed outcome variable (log wage of the first job after an unemployment spell) net of quarter-year fixed effects for each 6-month age bin. The vertical line represents the age at which workers are eligible for an additional 9 weeks of UI benefits. On either side of the cutoff, we display quadratic fits. Age is calculated based on month of birth. Circles represent averages for female workers, while diamonds represent averages for male workers. We present the main estimate and the corresponding standard error, based on our main RD approach described by Equation (1).

FIGURE 3 — Effects of Extended UI Benefit Duration on the Probability of Being Prescribed Drugs for Depression



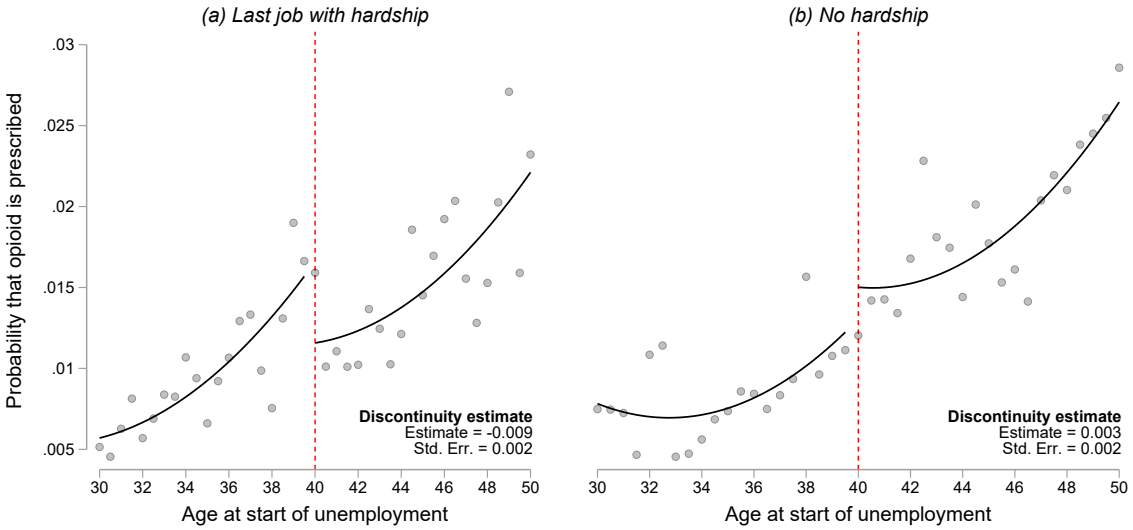

Notes: Individual-level data on unemployment insurance health events is from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. Scatters represent the mean residual of the listed outcome variable (whether a worker received an antidepressant prescription within 9 months after job loss) net of quarter-year fixed effects for each 6-month age bin. The vertical line represents the age at which workers are eligible for an additional 9 weeks of UI benefits. Age is calculated based on month of birth. We present the main estimate and the corresponding standard error, based on our main RD approach described by Equation (1).

FIGURE 4 — Effects of UI Extensions on the Probability of Being Prescribed Opioids



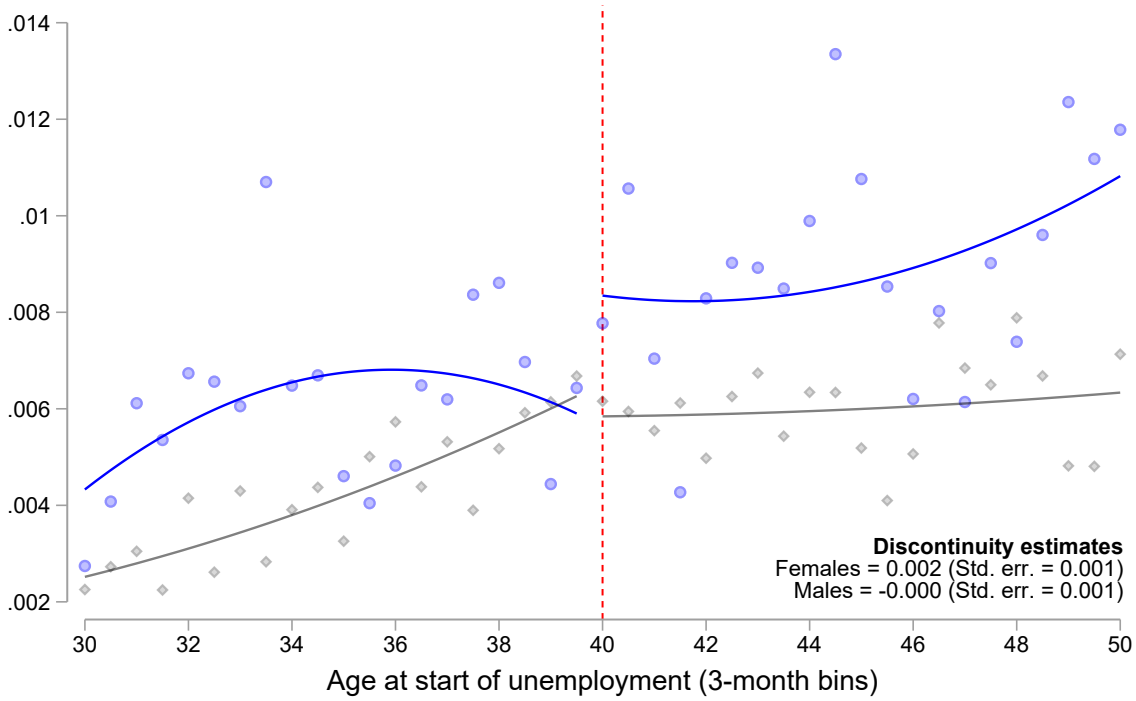

Notes: See notes for Figure 3. Prescription categories are defined by ATC codes, where N02A indicates opioids. For a full list of ATC code N medications, see https://www.whocc.no/atc_ddd_index.

FIGURE 5 — Effects of UI Extensions on Opioid Prescriptions, by Previous Job Hardship Status (Female Workers)



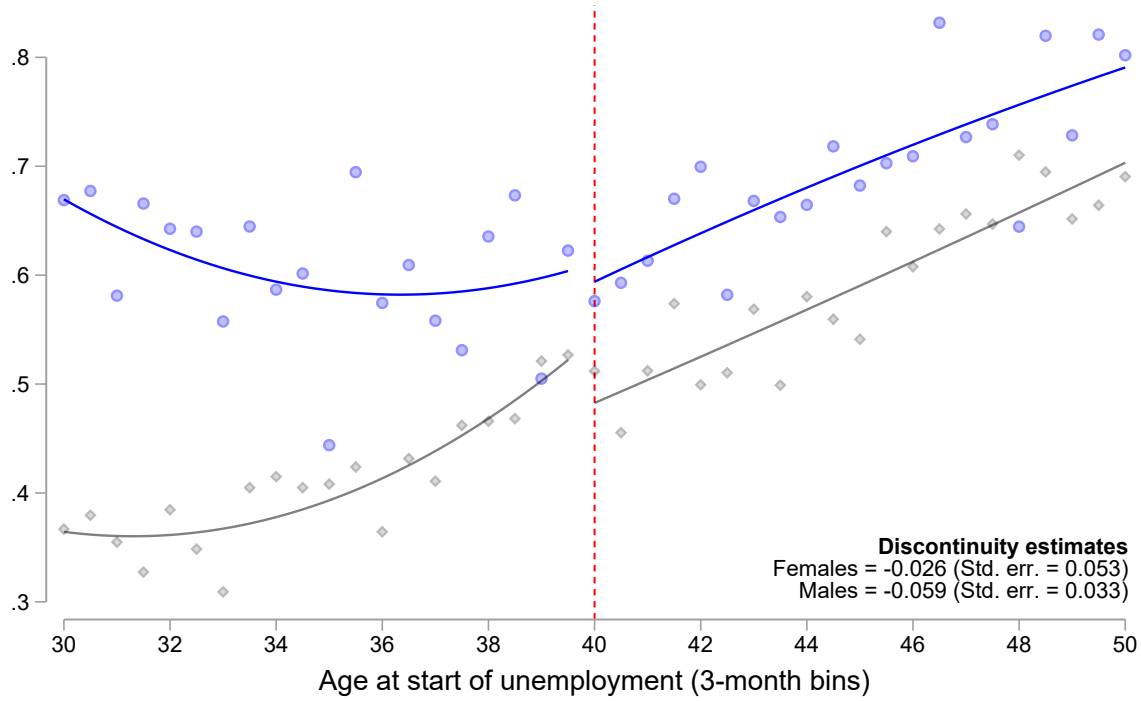

Notes: Individual-level data on unemployment insurance health events is from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. Scatters represent the mean residual listed outcome variable net of quarter-year fixed effects for each 6-month age bin. The left panel presents estimates for whether a female worker received an opioid prescription within 9 months after job loss, condition on the worker's previous job being flagged as a job with hardship. The right panel presents estimates for whether a female worker received an opioid prescription within 9 months after job loss, conditional on working a job that was not considered one with hardship. The vertical line represents the age at which workers are eligible for an additional 9 weeks of UI benefits. On either side of the cutoff, we display quadratic fits. Age is calculated based on month of birth. For each panel, we present the main estimate and the corresponding standard error using each sample restriction, based on our main RD approach described by Equation (1).

FIGURE 6 — Effects of Extended UI Benefit Duration on the Probability of Being Prescribed Non-Opioid Pain Drugs



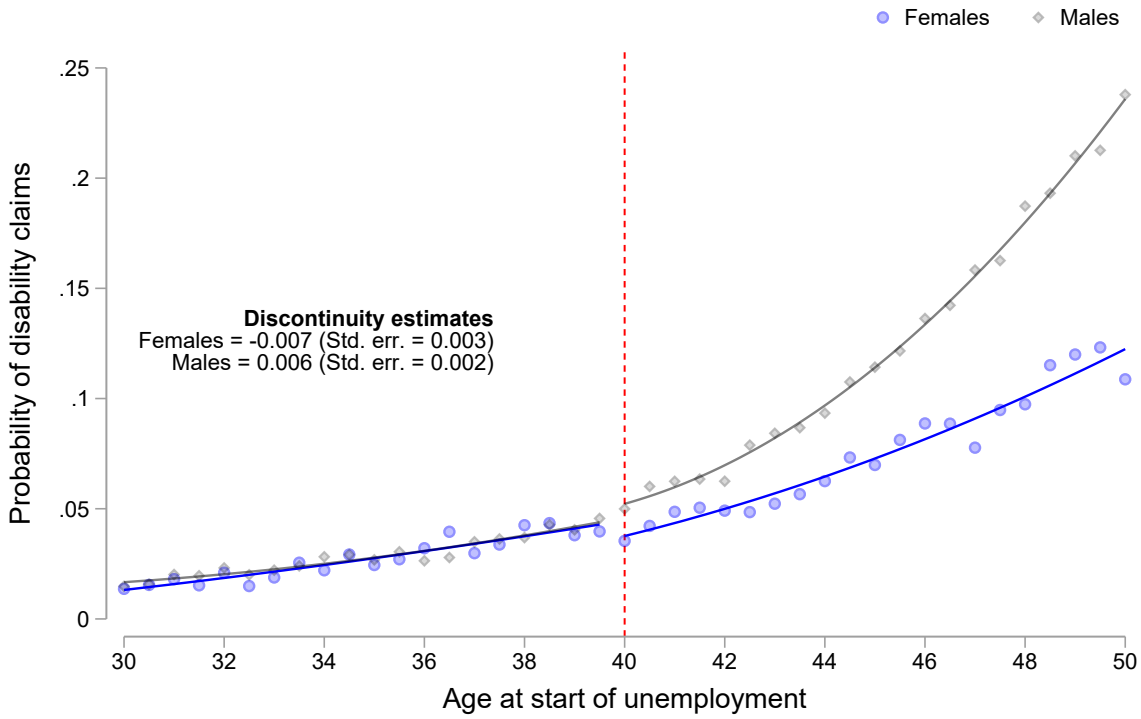

Notes: See notes for Figure 3. Non-opioid analgesics include non-habit-forming pain medication such as nonsteroidal anti-inflammatory drugs and acetaminophen. For a full list of ATC code N medications, see https://www.whocc.no/atc_ddd_index.

FIGURE 7 — Effects of Extended UI Benefit Duration on Health Care Utilization



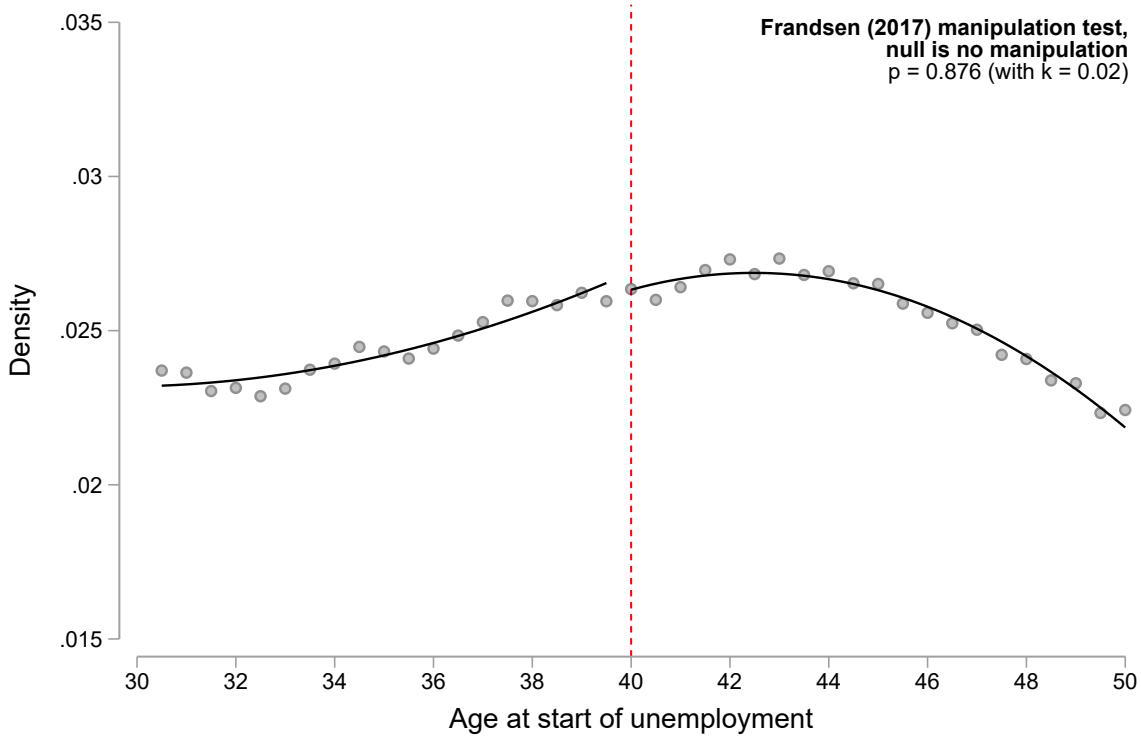

Notes: See notes for Figure 3. The outcome is the total number of inpatient hospital days for unemployed workers within 9 months of job loss.

FIGURE 8 — Effects of Extended UI Benefit Duration on the Probability of Disability Claims



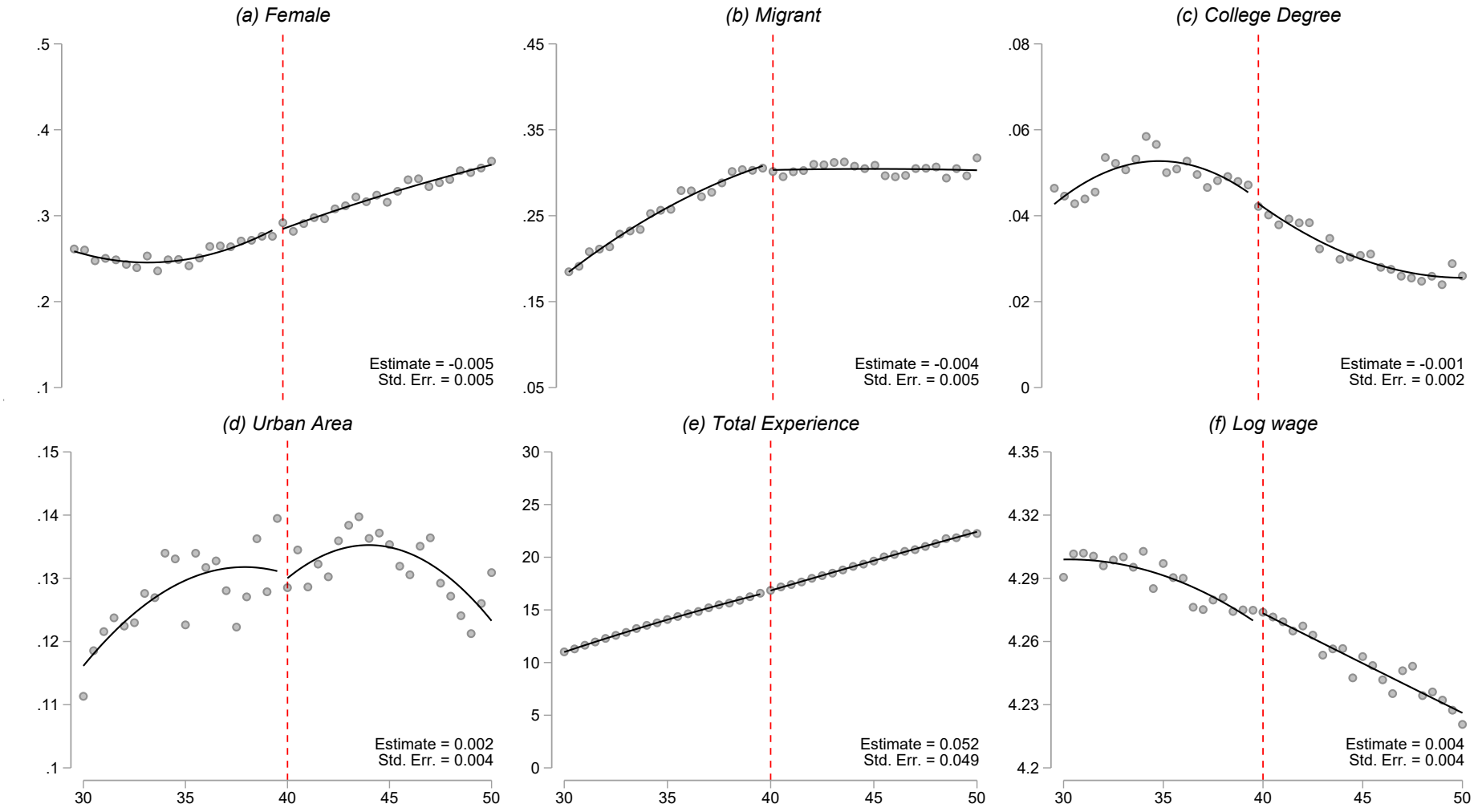

Notes: Individual-level data on unemployment insurance health events is from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. The vertical line represents the age at which workers are eligible for an additional 9 weeks of UI benefits. Age is calculated based on month of birth. Scatters represent the average residual of the listed outcome variable net of quarter-year fixed effects for each 6-month age bin. Circles represent averages for female workers, while diamonds represent averages for male workers. Our main variable of interest is an indicator variable equal to one if a worker claims disability pension between the time unemployed and the end of our sample, December 31, 2018, and zero otherwise. On average, 6.9 percent of workers (5.6 percent of females and 7.4 percent of males) in our sample ever claim disability pension. We present estimates and their respective standard errors for these two samples (female and male workers, respectively), based on our main RD approach described by Equation (1).

FIGURE 9 — Age Distribution




Notes: Individual-level data on unemployment insurance health events is from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. The vertical line represents the age at which workers are eligible for an additional 9 weeks of UI benefits. Age is calculated based on month of birth. Scatters represent the age density for each 6-month age bin. We present the Frandsen (2017) density test for running variables with discrete realizations to test for manipulation at the cutoff.

FIGURE 10 — Testing Discontinuity of Socioeconomic and Labor Market Characteristics




Notes: Individual-level data on unemployment insurance health events is from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. The vertical line represents the age at which workers are eligible for an additional 9 weeks of UI benefits. Age is calculated based on month of birth. Scatters represent the average residuals for each 6-month age bin for the listed outcome variables. In panels (a)–(d) we consider indicator variables equal to one for workers who are female, migrants, have a college degree, live in an urban area and zero otherwise. In panels (e) and (f) we present residualized binned means of worker experience, in years, and worker's daily wage in Euros. In each panel we present discontinuity estimates and standard errors, based on our main RD approach described by Equation (1).

TABLE 1 — Differences in Health by Gender, Using a Random Sample of All Upper Austrian Workers

| | (1) | (2) | (3) |
|---|---|---|---|
| *(a) Prescriptions* | | | |
| | Antide-pressants | Opioids | Non-opioid Painkillers |
| Female | 0.039*** | 0.009*** | 0.007*** |
| | (0.001) | (0.001) | (0.000) |
| Age fixed effects | Yes | Yes | Yes |
| Quarter-year fixed effects | Yes | Yes | Yes |
| Sample mean | 0.059 | 0.021 | 0.010 |
| *(b) Health Care Utilization* | | | |
| | Outpatient Expenditure | Outpatient Visits | Inpatient Days |
| Female | 1.238*** | 0.374*** | –0.008 |
| | (0.379) | (0.023) | (0.005) |
| Age fixed effects | Yes | Yes | Yes |
| Quarter-year fixed effects | Yes | Yes | Yes |
| Sample mean | 13.970 | 0.874 | 0.070 |

Notes: Individual-level data on health events is from linked Upper Austrian Health Insurance Fund database files. Estimates are based on regressions of the following form, $y_{it} = \beta_0 + \beta_1 female_{it} + \theta + \varepsilon_{it}$, where $y$ is the listed outcome variable for individual $i$ in quarter-year $t$ and $female$ is an indicator variable equal to one for a female worker, and zero otherwise, and $\theta$ is a set of age and quarter-year fixed effects. The sample includes a 10% random sample of all workers in a given quarter, 2003–2013. $N$ = 304,860 in each cell.

TABLE 2 — Descriptive Statistics

| | Full Sample | | By Gender | | |
|---|---|---|---|---|---|
| | Mean (1) | Std. dev. (2) | Females (3) | Males (4) | Difference (5) |
| *Prescriptions* | | | | | |
| Antidepressants | 0.058 | 0.233 | 0.104 | 0.038 | −0.066*** |
| Opioids | 0.012 | 0.111 | 0.015 | 0.011 | −0.004*** |
| Non-Opioid Painkillers | 0.006 | 0.077 | 0.008 | 0.005 | −0.003*** |
| *Health Care Utilization* | | | | | |
| Outpatient Expenditure | 95.3 | 259.4 | 134.2 | 79.0 | −55.1*** |
| Outpatient Visits | 5.8 | 18.5 | 9.2 | 4.4 | −4.8*** |
| Inpatient Days | 0.5 | 3.9 | 0.7 | 0.5 | −0.2*** |
| *Disability Claims* | | | | | |
| Disability Pension Claim | 0.069 | 0.253 | 0.056 | 0.074 | 0.018*** |
| *Socioeconomic Information* | | | | | |
| Female | 0.29 | 0.46 | | | |
| Migrant | 0.28 | 0.45 | 0.22 | 0.31 | 0.09*** |
| College Degree | 0.04 | 0.20 | 0.06 | 0.03 | −0.03*** |
| Urban Area | 0.13 | 0.34 | 0.15 | 0.12 | −0.03*** |
| Total Experience (years) | 17.05 | 5.99 | 16.24 | 17.38 | 1.14*** |
| Daily Wage (Euros) | 69.17 | 27.28 | 50.29 | 76.79 | 26.50*** |
| *Unemployment Spell Information* | | | | | |
| Benefit Duration (days) | 47.9 | 40.2 | 51.0 | 46.7 | −4.4*** |
| Nonemployment Duration (days) | 75.0 | 97.5 | 87.5 | 69.8 | −17.7*** |
| UI Claims (Euros) | 29.3 | 7.2 | 24.7 | 31.2 | 6.6*** |

Notes: Individual-level data on unemployment insurance health events is from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files. Descriptive statistics include the means and standard deviations for the listed outcomes from 2003–2013 for all workers and workers split by gender separately, measured in the month of the start of the unemployment spell, with one exception. The outcome variable "Disability Pension Claim" alternatively measures an indicator variable equal to one if we observe a worker claim disability pension prior to December 31, 2018. Columns (1) and (2) present means and standard errors for all workers, respectively, while Columns (3) and (4) present means for female and male workers separately. In Column (5), we provide the difference in means of the respective variable between female and male workers according to a two-sample $t$ test. $N$ = 380,634.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 3 — Effects of Extending UI Benefit Eligibility on Benefit and Nonemployment Duration

| | Benefit | Nonemployment |
|---|---|---|
| | (1) | (3) |
| Pooled | 2.38*** | 4.13*** |
| | (0.36) | (0.88) |
| Females | 4.31*** | 7.99*** |
| | (0.83) | (2.13) |
| Males | 1.67*** | 2.71*** |
| | (0.38) | (0.99) |

Notes: RD estimates are based on individual-level data on unemployment insurance health events from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. Each regression includes quarter-year fixed effects. Benefit duration is defined as the number of days in which a worker receives UI benefits. Nonemployment duration is the time, in days, that the worker remains in the UI system and is considered "unemployed". Robust standard errors are clustered on the age bin level and are shown in parentheses. $N$ = 380,634
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 4 — Effects of Extending UI Benefits on Prescriptions within 9 Months of Job Loss

| | Antide-pressants (1) | Opioids (2) | Non-opioid Painkillers (3) |
|---|---|---|---|
| *(a) Pooled* | | | |
| Discontinuity | −0.0005 | −0.002** | 0.0004 |
| | (0.002) | (0.0008) | (0.0005) |
| Sample mean | 0.046 | 0.009 | 0.005 |
| Observations | | 380,634 | |
| *(b) Females* | | | |
| Discontinuity | −0.009* | −0.005** | 0.002 |
| | (0.005) | (0.002) | (0.001) |
| Sample mean | 0.081 | 0.010 | 0.006 |
| Observations | | 112,214 | |
| *(c) Males* | | | |
| Discontinuity | 0.003* | −0.0006 | −0.0002 |
| | (0.002) | (0.0009) | (0.0006) |
| Sample mean | 0.033 | 0.009 | 0.004 |
| Observations | | 268,420 | |

Notes: RD estimates are based on individual-level data on unemployment insurance health events from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. Each estimate presents separate effects of an additional 9-week eligibility of UI benefits for the 9 months following unemployment for the listed outcome. Each regression includes quarter-year fixed effects. Robust standard errors are clustered on the age bin level and are shown in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 5 — Effects of Extending UI Benefits on Health Outcomes within 9 Months of Job Loss, by Subgroup (Female Workers)

| | Antide-pressants (1) | Opioids (2) | Non-opioid Painkillers (3) |
|---|---|---|---|
| *(a) Parent* | | | |
| Yes ($n$ = 70,301) | −0.006 | −0.009*** | −0.0004 |
| | (0.006) | (0.003) | (0.001) |
| No ($n$ = 41,913) | −0.01 | 0.004 | 0.006*** |
| | (0.008) | (0.003) | (0.002) |
| *(b) Low-Skilled Occupation* | | | |
| Yes ($n$ = 100,022) | −0.009* | −0.004** | 0.002* |
| | (0.005) | (0.002) | (0.001) |
| No ($n$ = 12,192) | −0.01 | −0.006 | −0.004 |
| | (0.017) | (0.004) | (0.002) |
| *(c) Job with Hardship* | | | |
| Yes ($n$ = 45,761) | −0.001 | −0.009*** | 0.0008 |
| | (0.006) | (0.002) | (0.002) |
| No ($n$ = 54,613) | −0.004 | 0.003* | 0.002 |
| | (0.007) | (0.002) | (0.002) |
| *(d) Part-Time* | | | |
| Yes ($n$ = 54,242) | 0.007 | −0.005*** | −0.0005 |
| | (0.006) | (0.002) | (0.002) |
| No ($n$ = 46,118) | −0.02** | 0.001 | 0.004*** |
| | (0.007) | (0.002) | (0.002) |
| *(e) Low Education* | | | |
| Yes ($n$ = 89,512) | −0.01** | −0.006*** | 0.002 |
| | (0.005) | (0.002) | (0.001) |
| No ($n$ = 17,701) | −0.02* | 0.004 | −0.0003 |
| | (0.012) | (0.003) | (0.002) |

Notes: RD estimates are based on individual-level data on unemployment insurance health events from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013, although hardship and part-time indicators are not available for 2013. Each estimate presents separate effects of an additional 9-week eligibility of UI benefits for the 9 months following unemployment for the listed group of female workers. "Parent" is an indicator variable equal to one if a worker has at least one child. "Low-Skilled Occupation" is defined based on the International Standard Classification of Occupations (ISCO) code of an individual's last occupation. "Job with Hardship" is an indicator variable equal to one if a worker receives an allowance due to working a job that is hazardous or otherwise physically demanding. "Part-time Worker" indicates an employee that works less than 35 hours per week. "Low Education" is an indicator equal to one if a worker has not met criteria to attend college. Robust standard errors are clustered on the age bin level and are shown in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 6 — Effects on Jobs with Hardship: Previous vs. Next Job

| | (1) | (2) | (3) |
|---|---|---|---|
| *(a) Females* | | | |
| Last job with hardship | 0.373*** | 0.359*** | 0.373*** |
| | (0.002) | (0.002) | (0.002) |
| Age ≥ 40 | | | −0.001 |
| | | | (0.001) |
| Last job with hardship × age ≥ 40 | | | −0.013*** |
| | | | (0.003) |
| *(b) Males* | | | |
| Last job with hardship | 0.464*** | 0.503*** | 0.464*** |
| | (0.001) | (0.001) | (0.001) |
| Age ≥ 40 | | | −0.006*** |
| | | | (0.001) |
| Last job with hardship × age ≥ 40 | | | 0.039*** |
| | | | (0.002) |

Notes: RD estimates are based on individual-level data on unemployment insurance health events from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013, although hardship indicators are not available for 2013. Each estimate presents separate effects of an additional 9-week eligibility of UI benefits for the 9 months following unemployment for the listed group of workers. "Last job with hardship" is an indicator variable equal to one if a worker receives an allowance due to working a job that is hazardous or otherwise physically demanding prior to job loss. $age \geq 40$ is an indicator variable equal to 1 if an individual is at least 40 years old at the time of layoff, corresponding to the coefficient of interest from Equation 1. Panel (a) presents estimates for the sample of unemployed female workers and Panel (b) presents estimates for the sample of unemployed male workers. Robust standard errors are clustered on the age bin level and are shown in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 7 — Effects of Extending UI Benefits on Health Care Utilization within 9 Months of Job Loss

| | Outpatient Expenditure (1) | Outpatient Visits (2) | Inpatient Days (3) |
|---|---|---|---|
| *(a) Pooled* | | | |
| Discontinuity | −1.3 | 0.2 | −0.05** |
| | (2.5) | (0.09) | (0.03) |
| Sample mean | 82.4 | 4.9 | 0.5 |
| Observations | | 380,634 | |
| *(b) Females* | | | |
| Discontinuity | −0.3 | 0.3 | −0.03 |
| | (6.5) | (0.2) | (0.05) |
| Sample mean | 118.0 | 8.5 | 0.6 |
| Observations | | 112,214 | |
| *(c) Males* | | | |
| Discontinuity | −1.8 | 0.1 | −0.06* |
| | (2.5) | (0.08) | (0.03) |
| Sample mean | 70.0 | 3.7 | 0.4 |
| Observations | | 268,420 | |

Notes: See notes for Table 4. "Outpatient Expenditure" denotes the total amount spent, in Euros, on doctor's visits. "Outpatient Visits" include the number of visits to a physician. "Inpatient Days" include the number of days spent in a hospital.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 8 — Effects of Extending UI Benefits to Mothers on Child Health

| | | | | Disentangling Outpatient Expenditure | |
|---|---|---|---|---|---|
| | Outpatient Expenditure (1) | Outpatient Visits (2) | Inpatient Days (3) | Preventative (4) | Curative (5) |
| Child Age < 6 | −16.184** | −0.053 | −0.002 | −0.515 | −15.669** |
| | (7.355) | (0.254) | (0.074) | (0.331) | (7.332) |
| Sample mean | 53.97 | 3.66 | 0.13 | 3.81 | 50.16 |
| Observations | | | 8,822 | | |
| 6 ≤ Child Age < 12 | −1.824 | −1.177 | −0.161 | 2.027 | −3.851 |
| | (4.486) | (0.776) | (0.135) | (1.469) | (4.363) |
| Sample mean | 47.96 | 2.78 | 0.15 | 0.10 | 47.87 |
| Observations | | | 16,497 | | |
| 12 ≤ Child Age < 18 | 10.321* | 0.115 | 0.043 | 0.216 | 10.106* |
| | (5.539) | (0.302) | (0.032) | (0.330) | (5.581) |
| Sample mean | 48.67 | 3.22 | 0.22 | 0.18 | 48.48 |
| Observations | | | 32,092 | | |

Notes: See notes for Table 4. Estimates are from separate regressions for each listed child age group. Children are matched to unemployed mothers using linked birth certificate data. "Outpatient Expenditure" denotes the total amount spent, in Euros, on doctor's visits. "Outpatient Visits" include the number of visits to a physician. "Inpatient Days" include the number of days spent in a hospital. "Preventative" visits include any type of screening or mother/child well visits, excluding vaccinations (due to data limitations). "Curative" visits include visits to the doctor's office that are not primarily for a sick visit, and do not include any type of preventative care.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 9 — Placebo Tests

| | Antide-pressants (1) | Opioids (2) | Non-opioid Painkillers (3) | Inpatient Days (4) |
|---|---|---|---|---|
| **Sample: 3 Months Prior to Job Loss** | | | | |
| *(a) Pooled* | | | | |
| Discontinuity | −0.0006 | −0.0002 | −0.0002 | 0.03 |
| | (0.002) | (0.001) | (0.001) | (0.026) |
| *Females* | | | | |
| Discontinuity | −0.008 | 0.001 | 0.0009 | −0.03 |
| | (0.007) | (0.002) | (0.002) | (0.074) |
| *Males* | | | | |
| Discontinuity | 0.005* | −0.0002 | 0.002 | 0.01 |
| | (0.002) | (0.001) | (0.001) | (0.043) |
| **Sample: Non-eligible Unemployed Workers** | | | | |
| *(a) Pooled* | | | | |
| Discontinuity | 0.001 | −0.00002 | 0.003* | −0.03 |
| | (0.003) | (0.0009) | (0.002) | (0.03) |
| *Females* | | | | |
| Discontinuity | 0.005 | 0.00006 | 0.003 | −0.01 |
| | (0.004) | (0.001) | (0.002) | (0.05) |
| *Males* | | | | |
| Discontinuity | −0.004 | 0.0001 | 0.003 | −0.06 |
| | (0.003) | (0.001) | (0.002) | (0.04) |

Notes: See Table 4. Estimates in the top panel are from a sample that includes only observations during the three months prior to the unemployment spell. Estimates in the bottom panel are from the sample of workers that do not meet the experience criterion of working 6 out of 10 years prior to unemployment, i.e. workers that are not eligible for the 9-week UI extension. Standard errors clustered at the age-bin level are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 10 — Testing Alternative Specifications (Female Workers)

| | Different polynomials | | Robust CIs | | MHT-adjusted $p$-values |
|---|---|---|---|---|---|
| | Quadratic (Baseline) | Linear | Triangular kernel | Optimal bandwidth | |
| | (1) | (2) | (3) | (4) | (5) |
| *(a) Wages* | | | | | |
| Log Daily Wage | 0.017** | 0.022*** | 0.023*** | 0.022*** | 0.004 |
| | (0.008) | (0.003) | (0.004) | (0.005) | |
| *(b) Prescriptions* | | | | | |
| Antidepressants | −0.009* | −0.01*** | −0.01*** | −0.01*** | 0.014 |
| | (0.005) | (0.002) | (0.002) | (0.003) | |
| Opioids | −0.005** | −0.004*** | −0.004*** | −0.006*** | 0.004 |
| | (0.002) | (0.001) | (0.001) | (0.001) | |
| Non-Opioid Painkillers | 0.002 | 0.0005 | 0.001 | 0.0009 | 0.226 |
| | (0.001) | (0.001) | (0.001) | (0.001) | |
| *(c) Health Care Utilization* | | | | | |
| Outpatient Expenditure | −0.3 | −8.4*** | −4.3* | −2.7 | 0.924 |
| | (6.542) | (2.017) | (2.637) | (4.154) | |
| Outpatient Visits | 0.3 | −0.3 | 0.005 | −0.2 | 0.684 |
| | (0.250) | (0.184) | (0.144) | (0.228) | |
| Inpatient days | −0.03 | 0.02 | −0.0002 | −0.03 | 0.848 |
| | (0.053) | (0.029) | (0.032) | (0.045) | |

Notes: RD estimates are based on individual-level data on unemployment insurance health events from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. Each regression includes quarter-year fixed effects. The sample includes only unemployed female workers. Column 1 replicates the baseline estimates for workers experiencing an unemployment spell, Column 2 presents estimates from specifications that allow the running variable to vary linearly, and Column 3 presents the baseline estimates using triangular kernel instead of uniform kernel weighting. Column 4 shows estimates from a model using a smaller MSE-driven bandwidth, instead of our baseline one-sided bandwidth of 10 years. Robust standard errors are clustered on the age bin level and are shown in parentheses. Column 5 presents Romano-Wolf adjusted $p$-values for our baseline estimates.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

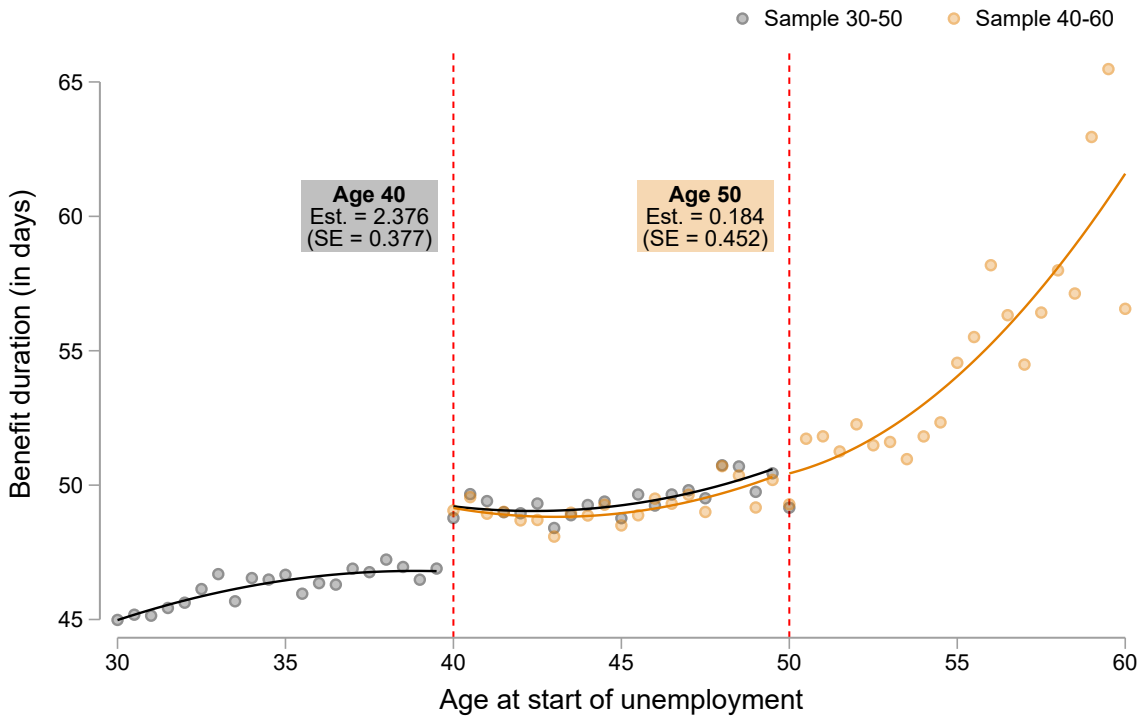
TABLE 11 — Testing Alternative Specifications (Male Workers)

| | Different polynomials | | Robust CIs | | MHT-adjusted $p$-values |
|---|---|---|---|---|---|
| | Quadratic (Baseline) | Linear | Triangular kernel | Optimal bandwidth | |
| | (1) | (2) | (3) | (4) | (5) |
| *(a) Wages* | | | | | |
| Log Daily Wage | −0.001 | −0.005*** | 0.000 | 0.003 | 0.824 |
| | (0.003) | (0.002) | (0.002) | (0.003) | |
| *(b) Prescriptions* | | | | | |
| Antidepressants | 0.003* | −0.002** | 0.0007 | 0.002 | 0.112 |
| | (0.002) | (0.001) | (0.001) | (0.001) | |
| Opioids | −0.0006 | −0.002*** | −0.002*** | −0.002** | 0.824 |
| | (0.001) | (0.000) | (0.001) | (0.001) | |
| Non-Opioid Painkillers | −0.0002 | −0.0003 | −0.0002 | −0.003 | 0.824 |
| | (0.001) | (0.000) | (0.000) | (0.001) | |
| *(c) Health Care Utilization* | | | | | |
| Outpatient Expenditure | −1.8 | −3.4*** | −2.0* | −3.2* | 0.710 |
| | (2.500) | (1.075) | (1.145) | (1.616) | |
| Outpatient Visits | 0.1 | 0.04 | 0.1** | 0.2** | 0.494 |
| | (0.084) | (0.060) | (0.055) | (0.087) | |
| Inpatient days | −0.06* | −0.02 | −0.04* | −0.05* | 0.132 |
| | (0.033) | (0.017) | (0.019) | (0.026) | |

Notes: RD estimates are based on individual-level data on unemployment insurance health events from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. Each regression includes quarter-year fixed effects. The sample includes only unemployed male workers. Column 1 replicates the baseline estimates for workers experiencing an unemployment spell, Column 2 presents estimates from specifications that allow the running variable to vary linearly, and Column 3 presents the baseline estimates using triangular kernel instead of uniform kernel weighting. Column 4 shows estimates from a model using a smaller MSE-driven bandwidth, instead of our baseline one-sided bandwidth of 10 years. Robust standard errors are clustered on the age bin level and are shown in parentheses. Column 5 presents Romano-Wolf adjusted $p$-values for our baseline estimates.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

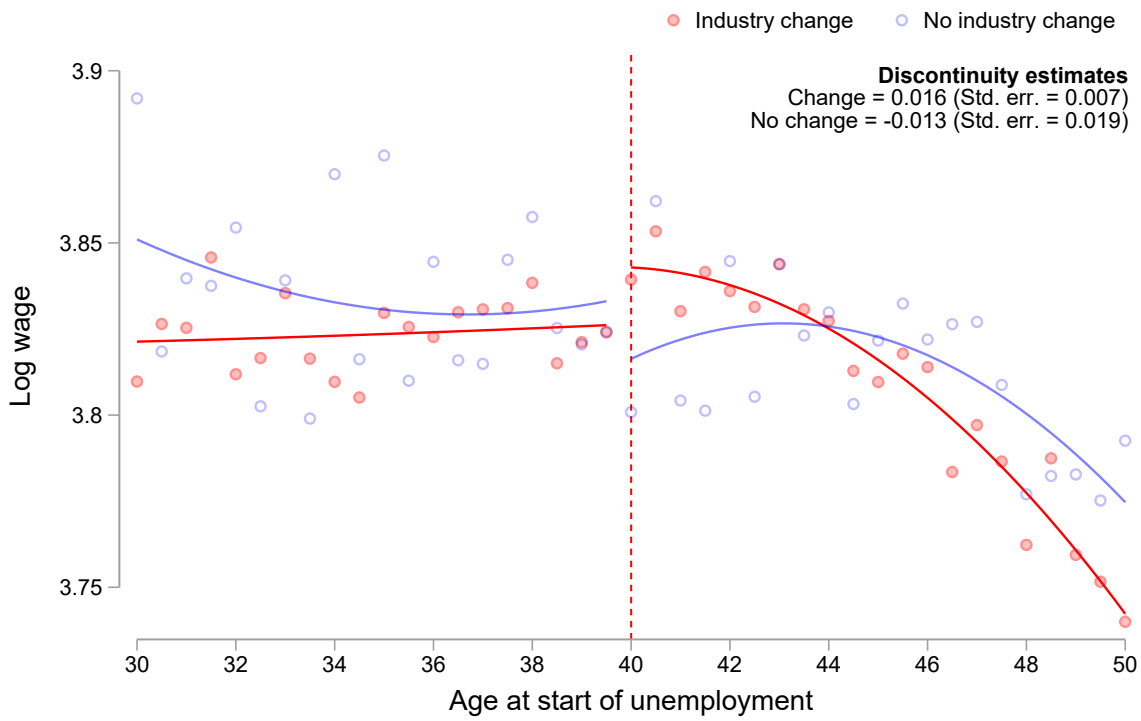
# Appendix

FIGURE A1 — Testing an Alternative Discontinuity at Age 50 on UI Benefit Duration, in Days



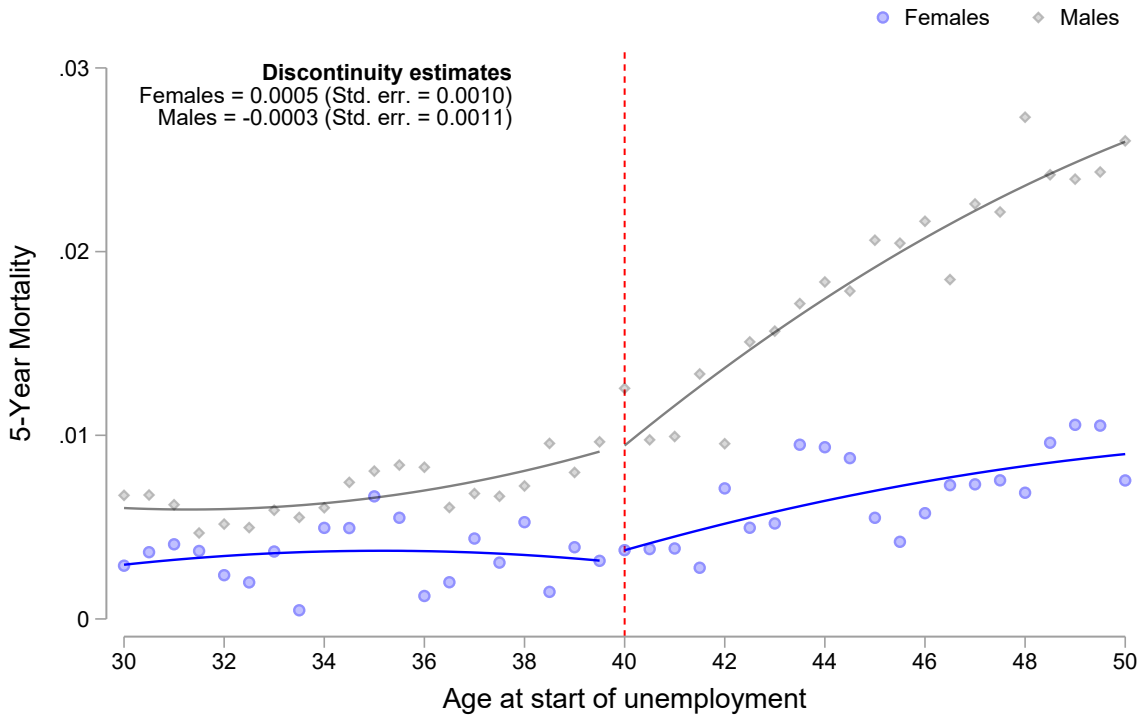

Notes: Individual-level data on unemployment insurance health events is from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. We build two samples, each being symmetric around the respective discontinuity at age 40 (our defined treatment cutoff) and age 50 (an alternative cutoff). For each cutoff we present estimates and their respective standard errors for these two samples, based on our main RD approach described by Equation (1).

FIGURE A2 — Wage Effects by Industry Change



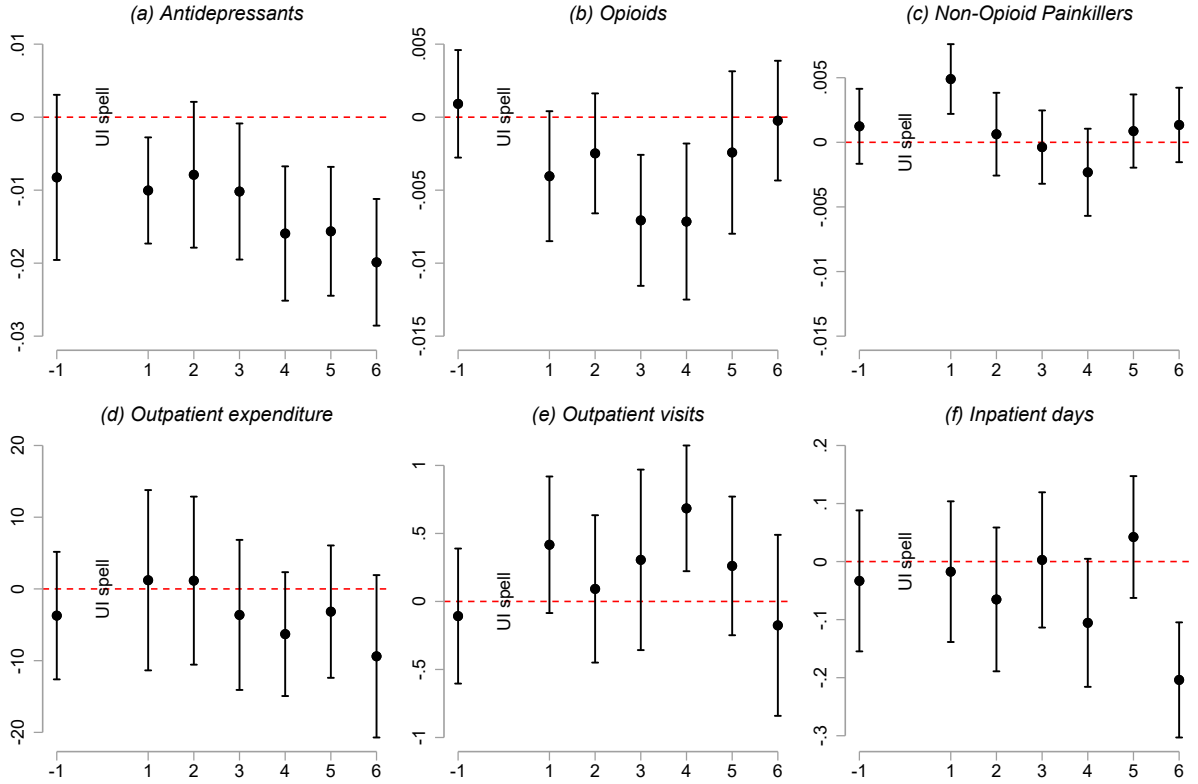

Notes: Individual-level data on unemployment insurance health events is from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. Scatters represent the mean residual of the listed outcome variable (log wage of the first job after an unemployment spell) net of quarter-year fixed effects for each 6-month age bin. The vertical line represents the age at which workers are eligible for an additional 9 weeks of UI benefits. On either side of the cutoff, we display quadratic fits. Age is calculated based on month of birth. Hollow circles represent averages for female workers that experienced a change in industry code at their first job after the unemployment spell, while shaded circles represent averages for female workers that did not change industries. We present the main estimate and the corresponding standard error, based on our main RD approach described by Equation (1).

FIGURE A3 — Effects on Mortality, Within 5 years of Receiving UI Benefits



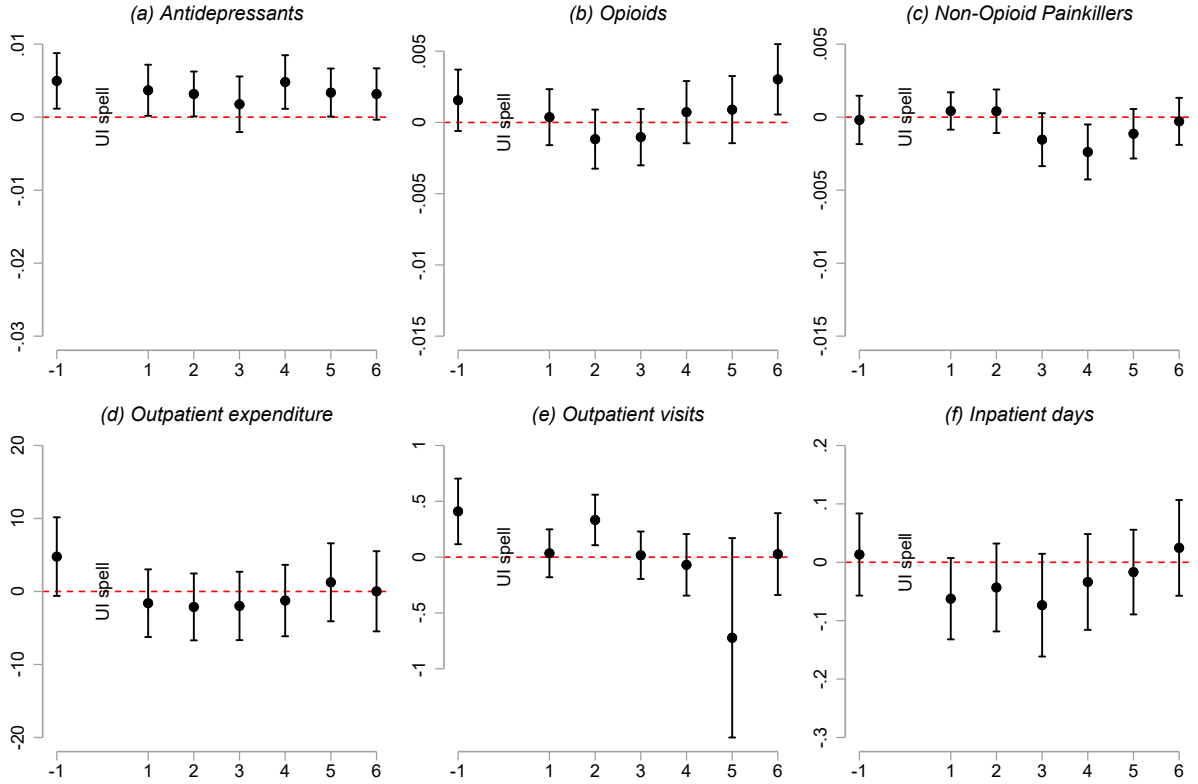

Notes: See notes for Figure 3. The outcome variable is whether a worker dies within five years of receiving UI payments.

FIGURE A4 — Effects of UI Extensions on Health Outcomes by Quarter Relative to Job Loss (Female Workers)



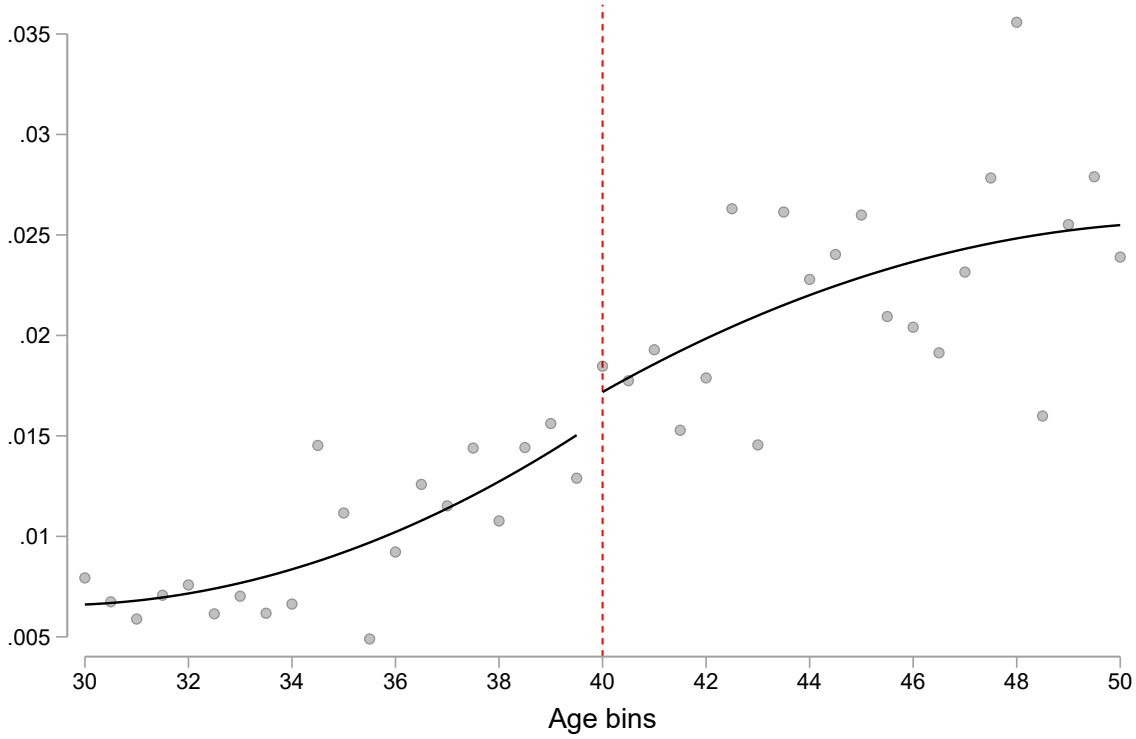

Notes: Individual-level data on unemployment insurance health events is from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. Each scatter represents a coefficient of the main variable of interest from Equation (1), using quarterly data. The vertical lines represent corresponding 95% confidence intervals based on age-bin clustered standard errors. An x-axis value of "$i$" where $i = -1, 0, 1, ...6$ indicates an estimate from our main RD analysis comparing the listed outcome for unemployed workers around the UI eligibility threshold for quarter $i$ only, where $i = 0$ represents the quarter of unemployment, $i = 1$ represents one quarter after unemployment, and so on. Each panel displays estimates for the listed outcome variable of interest using a sample of only female workers.

FIGURE A5 — Effects of UI Extensions on Health Outcomes by Quarter Relative to Job Loss (Male Workers)



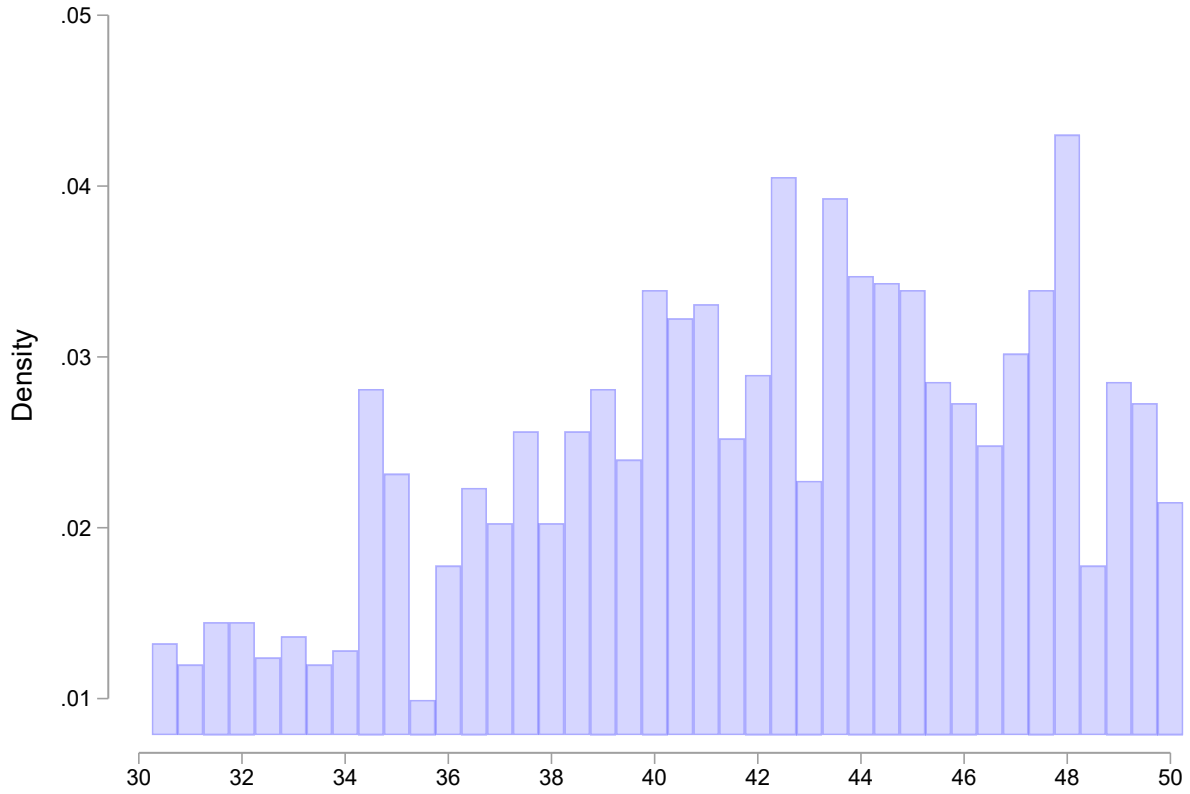

Notes: Individual-level data on unemployment insurance health events is from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. Each scatter represents a coefficient of the main variable of interest from Equation (1), using quarterly data. The vertical lines represent corresponding 95% confidence intervals based on age-bin clustered standard errors. An x-axis value of "$i$" where $i = -1, 0, 1, ...6$ indicates an estimate from our main RD analysis comparing the listed outcome for unemployed workers around the UI eligibility threshold for quarter $i$ only, where $i = 0$ represents the quarter of unemployment, $i = 1$ represents one quarter after unemployment, and so on. Each panel displays estimates for the listed outcome variable of interest using a sample of only male workers.

FIGURE A6 — Probability of Having an Opioid Prescription, Ineligible Sample



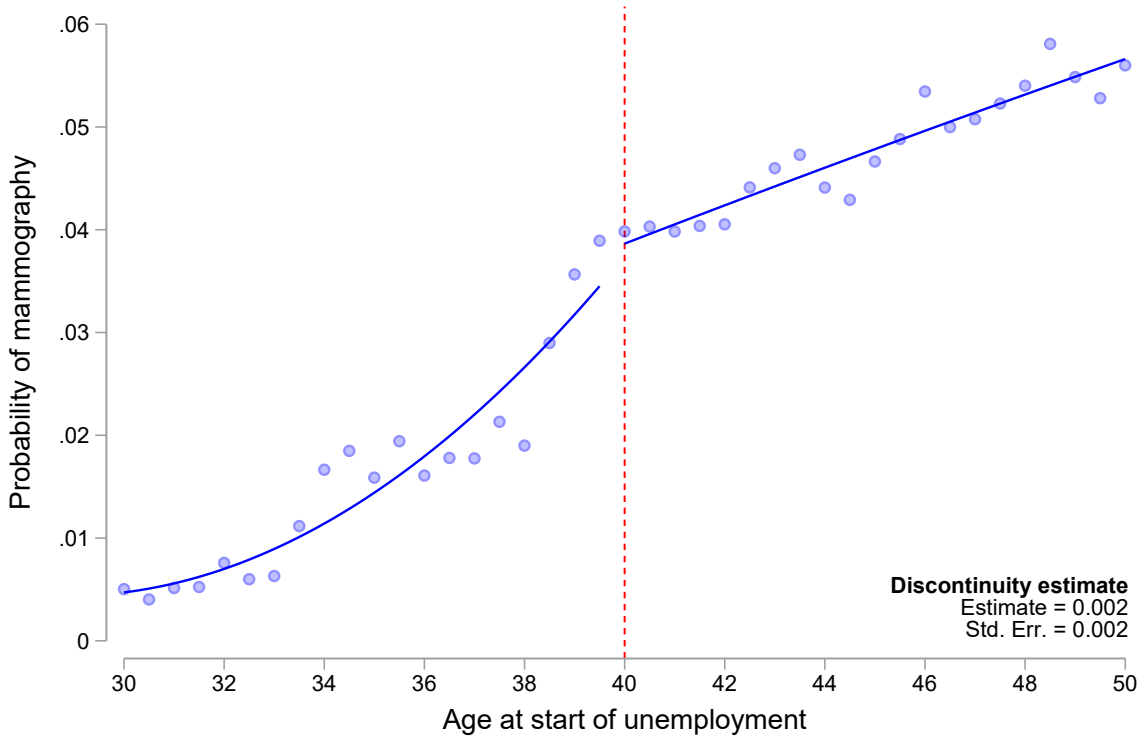

Notes: See notes for Figure 3. The outcome variable is an indicator variable equal to one if a worker received an opioid prescription within 9 months after job loss. The sample includes only female workers that are ineligible for the UI extension, as determined by the experience criterion (i.e. working 6 out of the last 10 years).

FIGURE A7 — Age Distribution of All Female Opioid Users



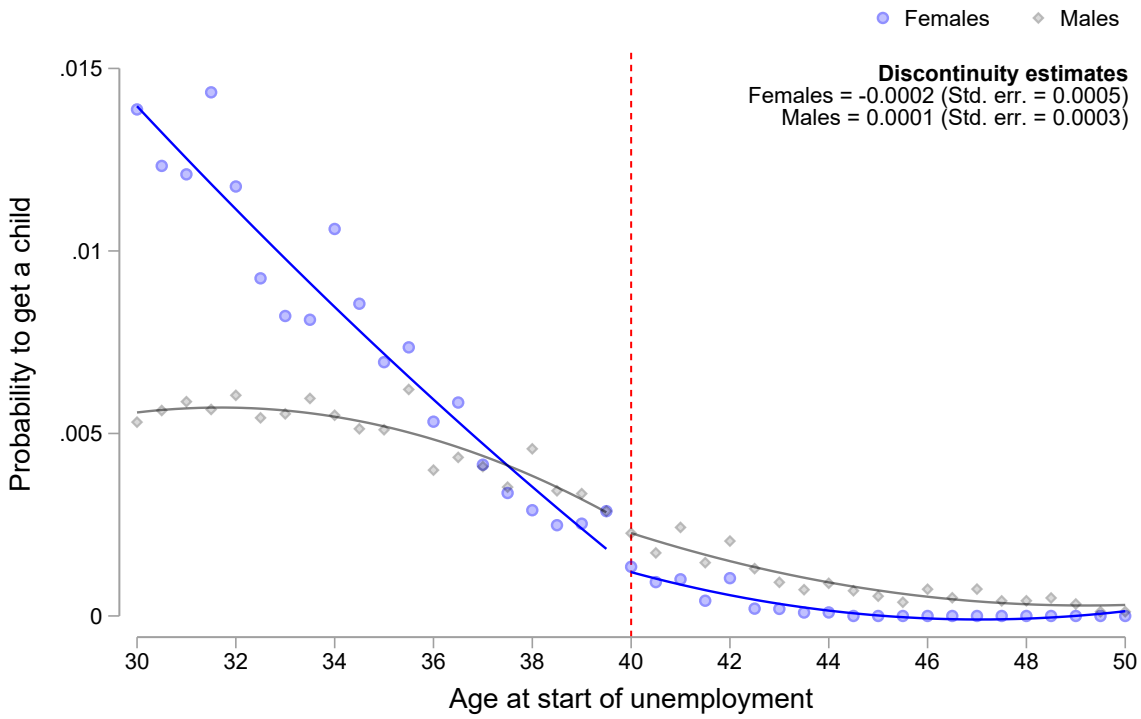

Notes: Individual-level data on unemployment insurance health events is from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. The y-axis displays the frequency of opioid prescriptions, by age. The sample includes all female workers with an opioid prescription (e.g. unemployed and employed workers).

FIGURE A8 — Probability of Mammography



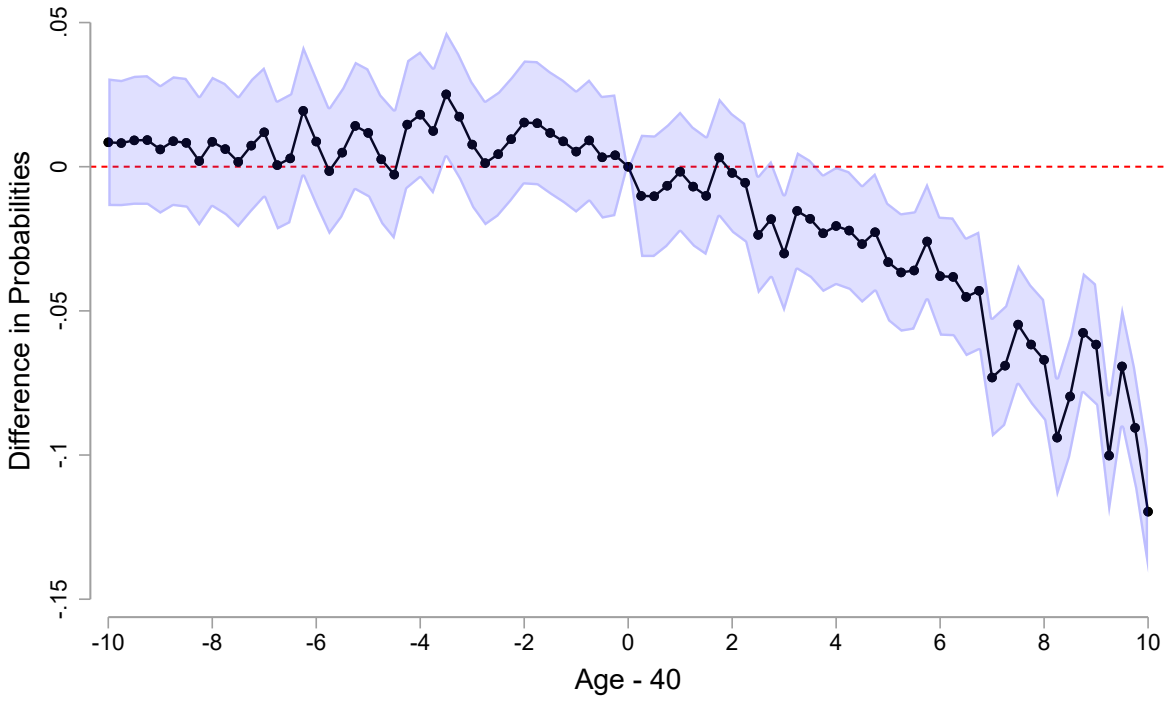

Notes: See Figure 4. Mammographies are recorded in the data and are considered under "screenings", or preventative care. The outcome variable is an indicator variable equal to one if a female worker received a mammography within 9 months after job loss.

FIGURE A9 — Probability of Having a Baby



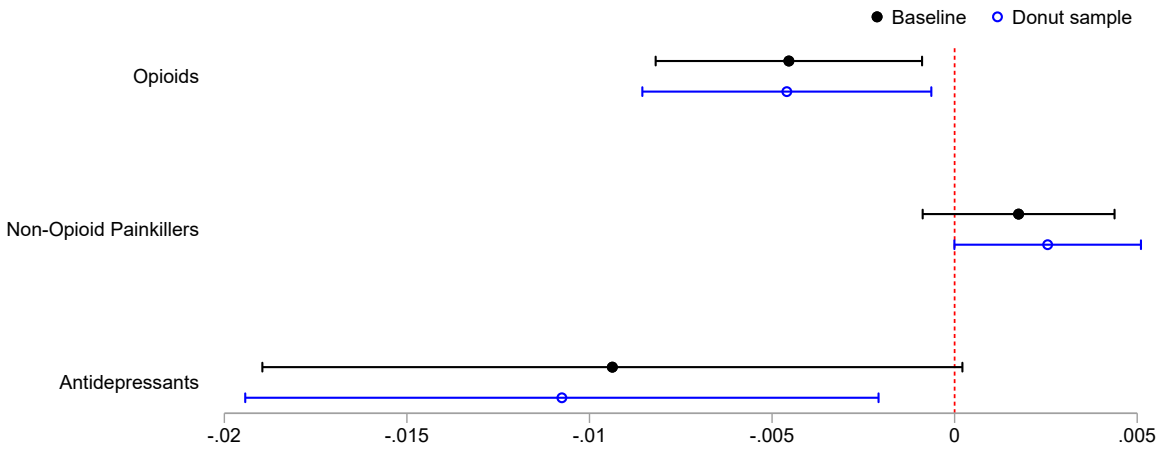

Notes: See Figure 4. The outcome variable is an indicator variable equal to one if a worker was registered on a newborn's birth certificate within 9 months after job loss.

FIGURE A10 — Differences in Probabilities of Filing a Disability Claim, by Age and Gender



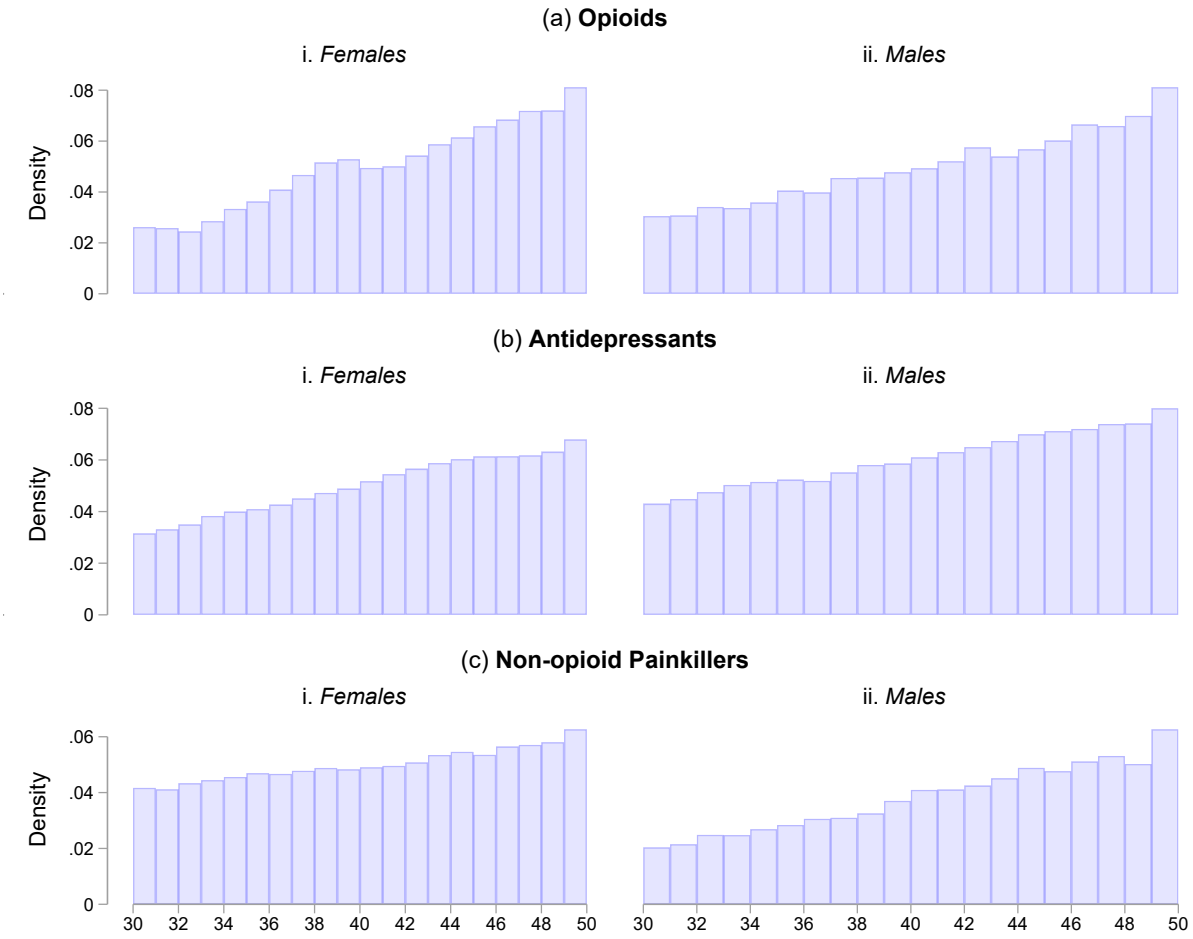

Notes: Event study coefficients and their respective 95% confidence intervals are generated from the following regression estimated using OLS: $y_i = \sum_{k=-10|t\neq-1}^{10} \beta_k(female_i \times age_k) + female_i + \sum_k age_k + \epsilon_{ik}$, where $y$ represents the outcome "filing for disability retirement" for individual $i$, and $female$ is an indicator variable taking the value 1 if a worker is female, and $age$ is the age the worker becomes unemployed, centered around 40. Our main variable of interest is an indicator variable equal to one if a worker claims disability pension between the time unemployed and the end of our sample, December 31, 2018, and zero otherwise.

FIGURE A11 — RD Estimates on Prescriptions Leaving out a Donut Sample




Notes: Individual-level data on unemployment insurance health events is from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. The donut sample omits workers that become unemployed within a one-quarter-year window around the cutoff. The solid black dots resemble the baseline estimates from Table 4, panel (b). The hollow blue dots are RD estimates based on the donut sample. Each regression includes quarter-year fixed effects. Bars indicate 95% confidence intervals. The sample includes only female workers.

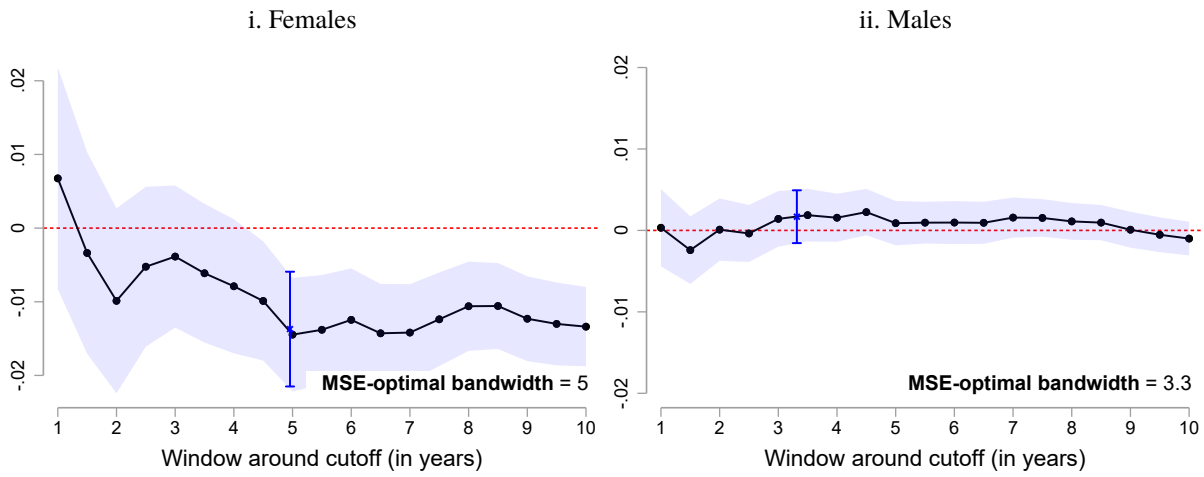
FIGURE A12 — Testing the Density of Yearly Age Bins



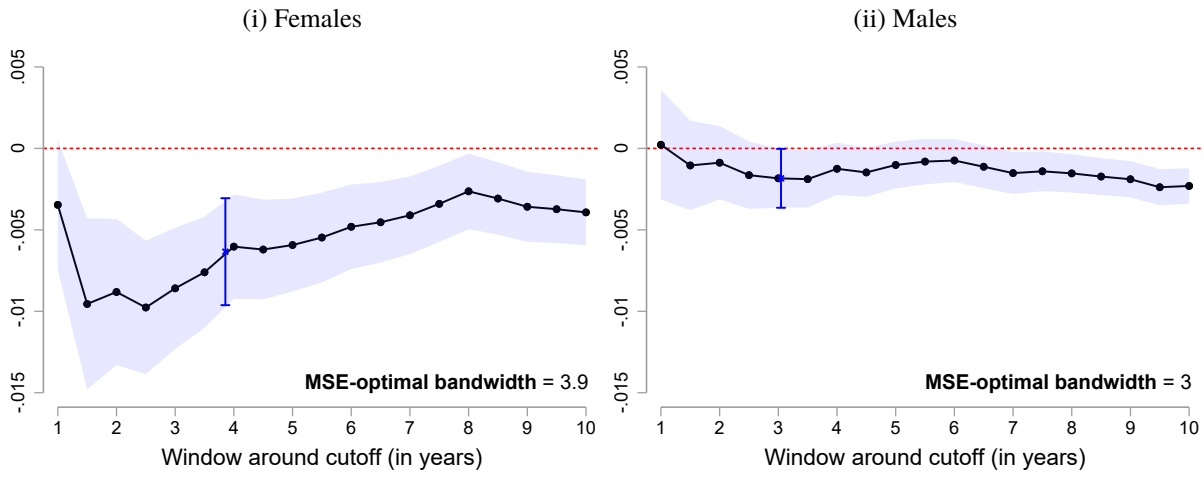

Notes: Individual-level data on Upper Austrian Health Insurance Fund database files from 2003–2013. Each bar represents the density of observations by age bin. Age is based on date of prescription purchase.

FIGURE A13 — Estimated Effects on Prescriptions Across Bandwidths

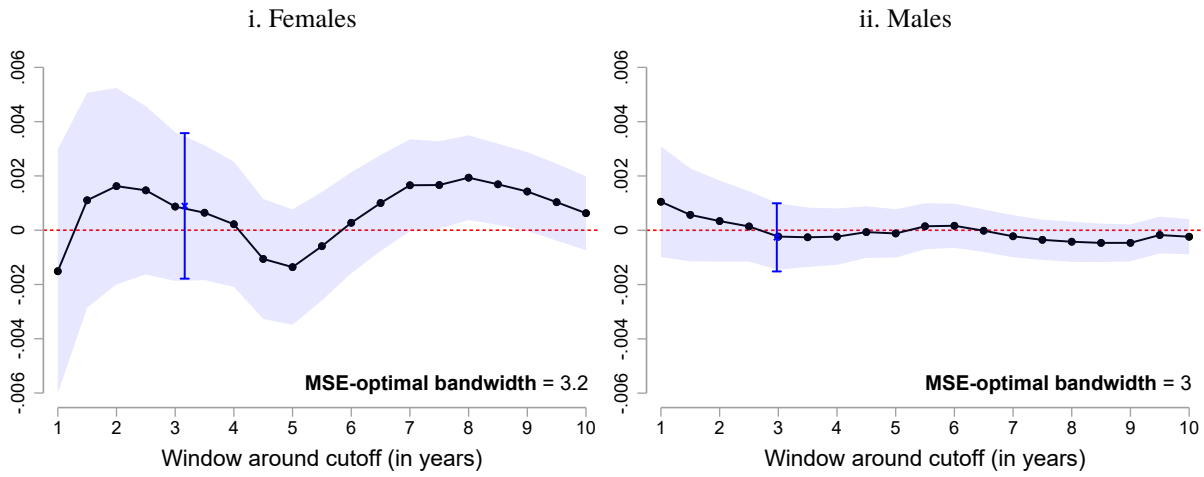
(a) Antidepressants




(b) Opioids



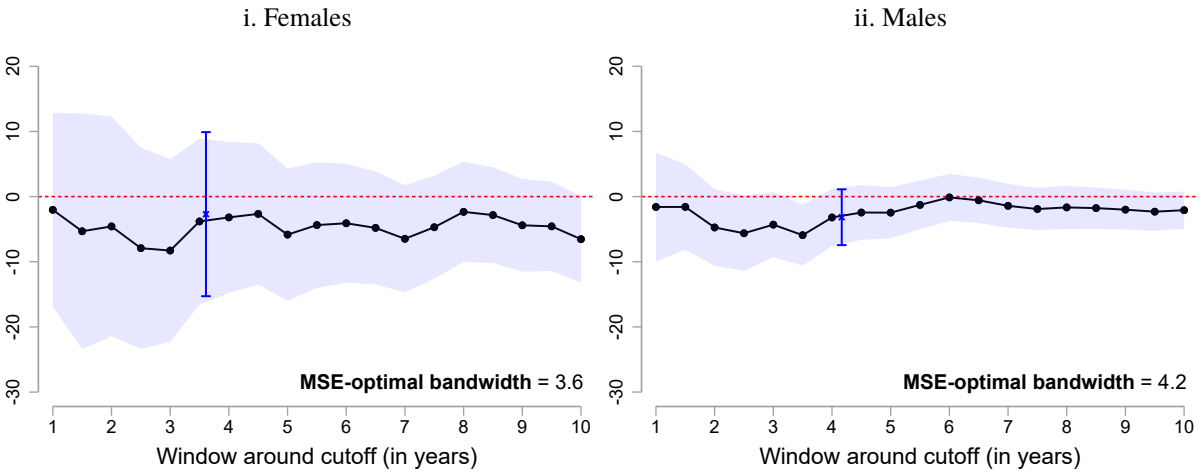

(c) Non-opioid Painkillers



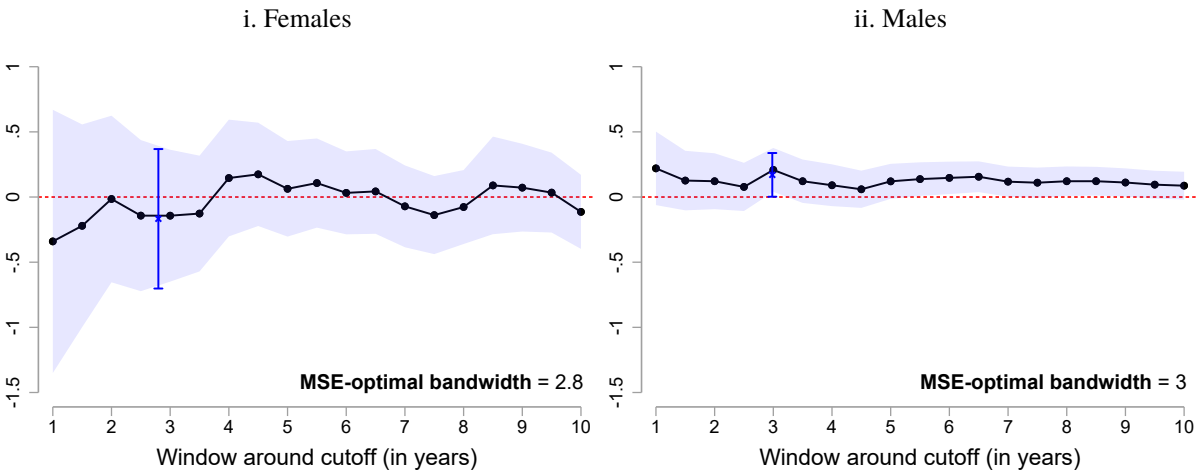

Notes: Individual-level data on unemployment insurance health events is from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. Each figure shows estimates and their 95% confidence intervals from our preferred specification (Equation 1) using a uniform kernel for a range of bandwidths. The vertical line shows the estimate and corresponding confidence interval using the MSE-optimal bandwidth.

FIGURE A14 — Estimated Effects on Health Care Utilization Across Bandwidths

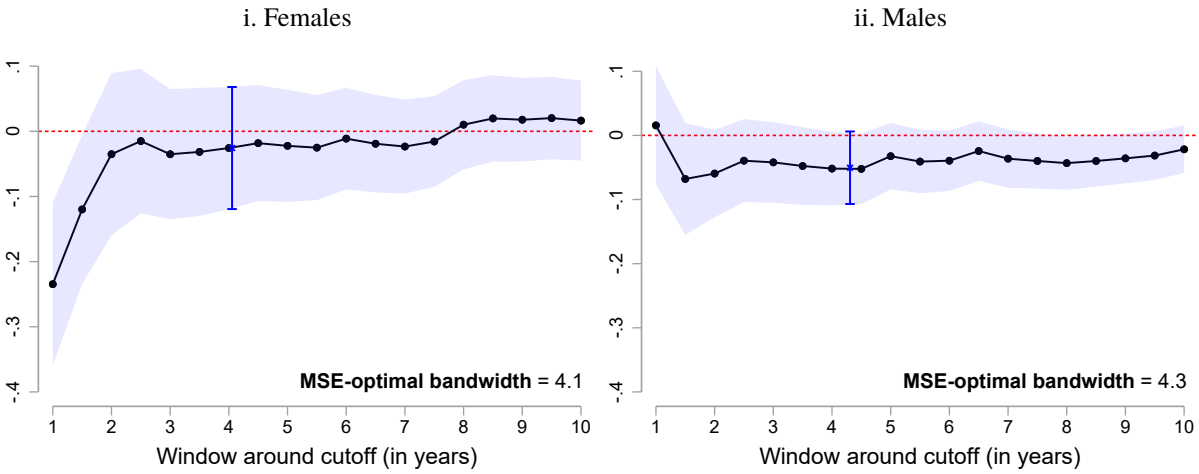
(a) Outpatient Expenditure




(b) Outpatient Visits

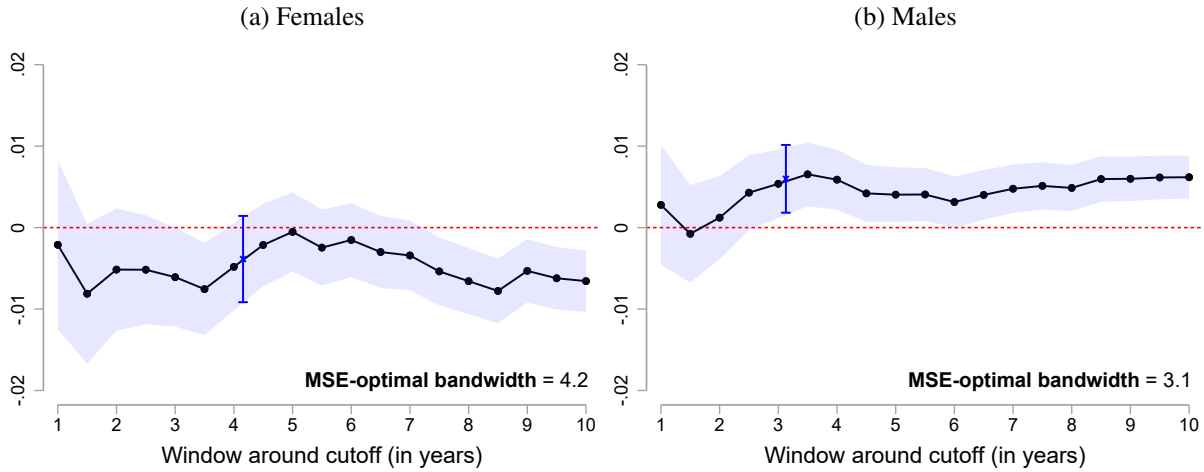



(c) Inpatient Days



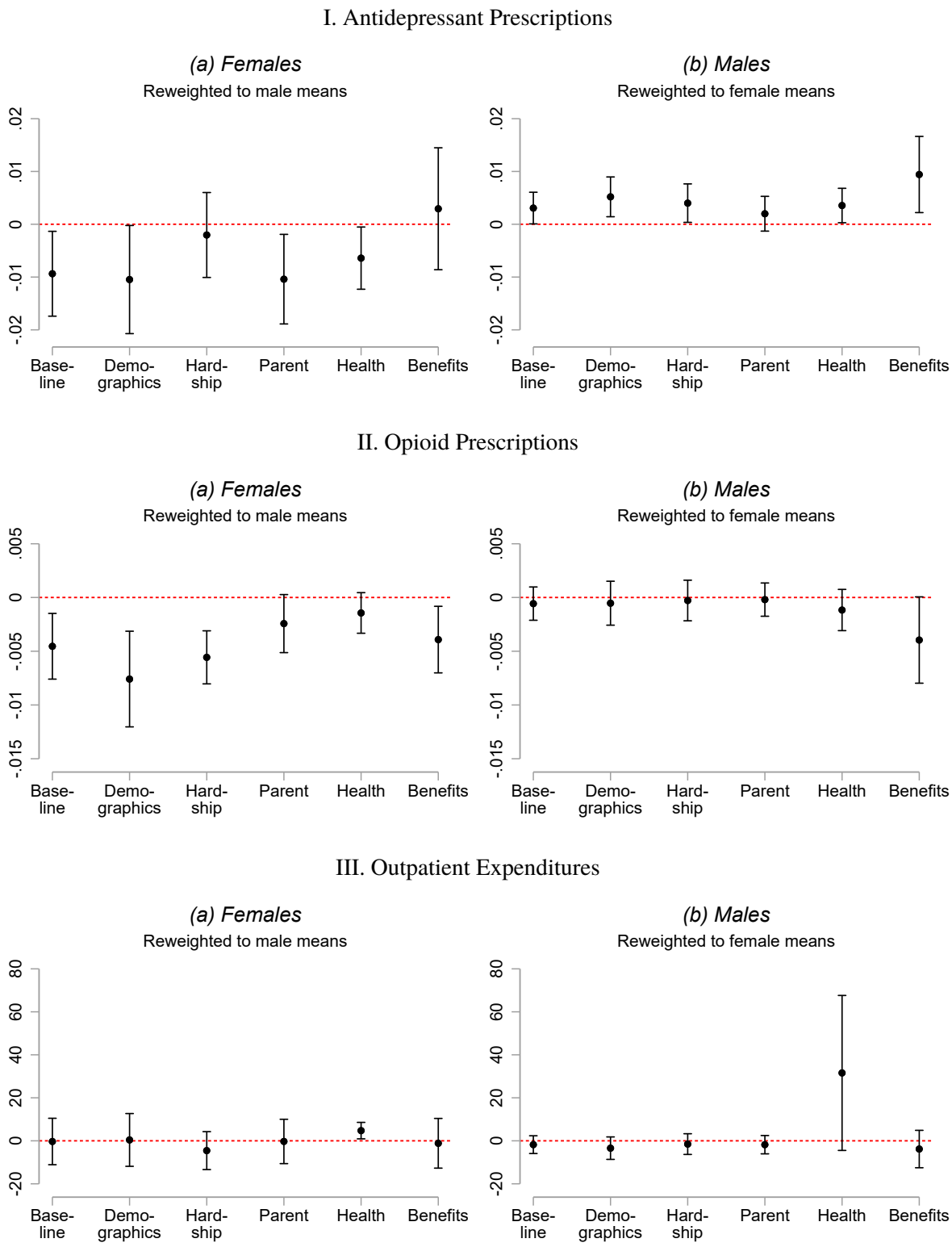

Notes: See notes for Figure A13. "Outpatient Expenditure" denotes the total amount spent, in Euros, on doctor's visits. "Outpatient Visits" include the number of visits to a physician. "Inpatient Days" include the number of days spent in a hospital.

FIGURE A15 — Effects of Extended UI Benefit Duration on the Probability of Disability Claims with Different Bandwidths




Notes: See notes for Figure A13. Our main variable of interest is an indicator variable equal to one if a worker claims disability pension between the time unemployed and the end of our sample, December 31, 2018, and zero otherwise.

FIGURE A16 — RDD Estimates Based on Across-Gender Balanced Samples




Notes: See Figure 4. We follow the entropy balance procedure from Hainmueller (2012). Panel (a) presents results for female workers and Panel (b) presents results for male workers for each listed outcome. Each estimate and its 95% confidence interval represents the RDD estimate from Equation (1), using a sample reweighted by the listed control variables for the opposite gender. For example, the estimate for "Parent" in Panel (I.a) of the top row displays the RDD coefficient on antidepressant prescription take up for female workers, after reweighting the sample such that females are parents with the same likelihood as males. Demographic weights include a categorical variable for education, a citizenship variable, equal to one for citizens, zero otherwise, and a dummy variable equal to one for individuals living in an urban area. "Hardship" and "Parent" represent dummy variables equal to one if an individual is in a job with hardship or one if a worker is a parent, respectively. Occupational weights includes a blue-collar dummy variable and a low-skilled job dummy variable, as categorized by occupational codes. Health weights include a measure of standardized total healthcare expenditures in the two quarters prior to becoming unemployed. Benefits represent the level of income received from UI payments.

TABLE A1 — Effects of Longer UI Duration on Total Prescriptions

| | Antide-pressants (1) | Opioids (2) | Non-opioid Painkillers (3) |
|---|---|---|---|
| *(a) Pooled* | | | |
| Discontinuity | −0.003 | −0.0001 | 0.001 |
| | (0.006) | (0.002) | (0.0009) |
| Sample mean | 0.108 | 0.020 | 0.007 |
| Observations | | 380,634 | |
| *(b) Females* | | | |
| Discontinuity | −0.03* | −0.004 | 0.005* |
| | (0.02) | (0.005) | (0.002) |
| Sample mean | 0.194 | 0.020 | 0.010 |
| Observations | | 112,214 | |
| *(c) Males* | | | |
| Discontinuity | 0.006 | 0.001 | 0.00004 |
| | (0.005) | (0.003) | (0.0009) |
| Sample mean | 0.079 | 0.019 | 0.006 |
| Observations | | 268,420 | |

Notes: See Table 4. The outcome variables in each column represent the total number of packages prescribed for each type of drug, including zeroes.

TABLE A2 — Effects of Longer UI Duration on the Number of Packages Prescribed, Conditional on Receiving a Prescription

| | Antide-pressants (1) | Opioids (2) | Non-opioid Painkillers (3) |
|---|---|---|---|
| *(a) Pooled* | | | |
| Discontinuity | −0.04 | 0.19 | 0.07 |
| | (0.06) | (0.15) | (0.07) |
| Sample mean | 2.38 | 2.20 | 1.46 |
| Observations | 8,035 | 2,964 | 1,502 |
| *(b) Females* | | | |
| Discontinuity | −0.04 | 0.26 | 0.14 |
| | (0.07) | (0.27) | (0.16) |
| Sample mean | 2.39 | 2.09 | 1.53 |
| Observations | 1,105 | 551 | 4,106 |
| *(c) Males* | | | |
| Discontinuity | 0.18 | 0.05 | −0.03 |
| | (0.18) | (0.08) | (0.08) |
| Sample mean | 2.24 | 1.42 | 2.37 |
| Observations | 1,861 | 951 | 3,940 |

Notes: See Table 4. The outcome variables represent marginal effects, conditional on a patient receiving at least one prescription.

TABLE A3 — Effects of Extending UI Benefits on Prescriptions within 3–18 Months of Job Loss

| | Antide-pressants (1) | Opioids (2) | Non-opioid Painkillers (3) |
|---|---|---|---|
| *(a) Female Workers* | | | |
| 3 Months | −0.01** | −0.004 | 0.005*** |
| | (0.004) | (0.003) | (0.002) |
| 6 Months | −0.009* | −0.003* | 0.003* |
| | (0.005) | (0.002) | (0.002) |
| 9 Months | −0.009* | −0.005** | 0.002 |
| | (0.005) | (0.002) | (0.001) |
| 12 Months | −0.01** | −0.005** | 0.0008 |
| | (0.005) | (0.002) | (0.001) |
| 15 Months | −0.01** | −0.005** | 0.0008 |
| | (0.005) | (0.002) | (0.001) |
| 18 Months | −0.01*** | −0.004** | 0.0009 |
| | (0.005) | (0.002) | (0.001) |
| *(b) Male Workers* | | | |
| 3 Months | 0.004* | 0.0004 | 0.0004 |
| | (0.002) | (0.001) | (0.0008) |
| 6 Months | 0.004* | −0.0004 | 0.0004 |
| | (0.002) | (0.001) | (0.0006) |
| 9 Months | 0.003* | −0.0006 | −0.0002 |
| | (0.002) | (0.0009) | (0.0006) |
| 12 Months | 0.004** | −0.0002 | −0.0007 |
| | (0.002) | (0.0009) | (0.0006) |
| 15 Months | 0.004** | −0.00002 | −0.0008 |
| | (0.002) | (0.0009) | (0.0006) |
| 18 Months | 0.004** | 0.0005 | −0.0007 |
| | (0.002) | (0.0009) | (0.0006) |

Notes: RD estimates are based on individual-level data on unemployment insurance health events from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. Each estimate presents separate effects of an additional 9-week eligibility of UI benefits for the 3–18 months following unemployment for the listed group of workers. Each regression includes quarter-year fixed effects. Panel (a) presents estimates for female workers, while Panel (b) presents estimates for male workers. Robust standard errors are clustered on the age bin level and are shown in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A4 — Effects of Extending UI Benefits on Health, Using a Model with Interaction Terms

*(a) Prescriptions*

| | Antide-pressants | Opioids | Non-opioid Painkillers |
|---|---|---|---|
| Discontinuity | 0.003* | −0.001 | 0.000 |
| | (0.002) | (0.001) | (0.001) |
| Female | −0.007 | 0.201*** | −0.038 |
| | (0.214) | (0.069) | (0.055) |
| Discontinuity × female | −0.012** | −0.004* | 0.002 |
| | (0.006) | (0.002) | (0.002) |

*(b) Health Care Utilization*

| | Outpatient Expenditure | Outpatient Visits | Inpatient Days |
|---|---|---|---|
| Discontinuity | −1.8 | 0.1 | −0.1* |
| | (2.5) | (0.1) | (0.0) |
| Female | 194.4 | 7.3 | 1.2 |
| | (253.8) | (13.7) | (2.3) |
| Discontinuity × female | 1.5 | 0.1 | 0.0 |
| | (7.0) | (0.3) | (0.1) |

Notes: RD estimates are based on individual-level data on unemployment insurance health events from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. Each estimate presents separate effects of an additional 9-week eligibility of UI benefits for the 9 months following unemployment for the listed outcome. Each regression includes quarter-year fixed effects. Each estimate is from an equation analogous to Equation 1 that includes an indicator variable for gender, equal to one for female workers and zero otherwise, interacted with the full model. Above we present the discontinuity estimate, $\beta_1$, as well as the coefficient and standard errors for the gender indicator variable and the interaction term. Panel (a) presents estimates for prescription take-up and Panel (b) presents estimates for the listed health care utilization variables. Robust standard errors are clustered on the age bin level and are shown in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A5 — Effects of UI Extensions on Opioid Prescribing, by Potency

| | Opioid Potency | |
|---|---|---|
| | Low | High |
| | (1) | (2) |
| *(a) Pooled* | | |
| Discontinuity | −0.0013* | −0.0002 |
| | (0.0008) | (0.0002) |
| Sample mean | 0.0114 | 0.0010 |
| Observations | 356,684 | |
| *(b) Females* | | |
| Discontinuity | −0.0025** | −0.0002 |
| | (0.0012) | (0.0006) |
| Sample mean | 0.0091 | 0.0007 |
| Observations | 104,558 | |
| *(c) Males* | | |
| Discontinuity | −0.0008 | −0.0002 |
| | (0.0009) | (0.0002) |
| Sample mean | 0.0086 | 0.0006 |
| Observations | 252,126 | |

Notes: See Table 4. "Weak" opioids include opioids in ATC categories N02AX, like tramadol, and "strong" opioids, including those categorized by N02AA, like morphine or oxycodone (but not codeine and dihydrocodeine, which are also in N02AA, but we classify as "weak").
$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A6 — Balancing of Socioeconomic Variables

| | Samples | | |
|---|---|---|---|
| | Pooled | Females | Males |
| | (1) | (2) | (3) |
| *Socioeconomic variables* | | | |
| Female | −0.007 | | |
| | (0.005) | | |
| Migrant | −0.006 | −0.004 | −0.007 |
| | (0.005) | (0.008) | (0.006) |
| College degree | 0.000 | 0.003 | −0.001 |
| | (0.002) | (0.004) | (0.002) |
| Urban area† | 0.002 | −0.005 | 0.006 |
| | (0.004) | (0.007) | (0.004) |
| *Labor market variables* | | | |
| Total experience† | 0.059 | 0.012 | 0.061 |
| | (0.050) | (0.089) | (0.057) |
| Log wage† | 0.372 | 0.588 | −0.029 |
| | (0.337) | (0.502) | (0.393) |

Notes: Individual-level data on unemployment insurance health events is from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. The listed socioeconomic and labor market variables are measured in the year prior to the start of the unemployment spell. Standard errors in parentheses are clustered on the age bin level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A7 — Testing Different Specifications (Prescription Drugs)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *(a) Females* | | | | |
| Antidepressants | −0.010* | −0.009* | −0.009* | −0.009* |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| Opioids | −0.005** | −0.005** | −0.005** | −0.005** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Non-opioid Painkillers | 0.002 | 0.002 | 0.002 | 0.002 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Year FEs | No | Yes | Yes | No |
| Quarter FEs | No | No | Yes | No |
| Year × quarter FEs | No | No | No | Yes |
| *(b) Males* | | | | |
| Antidepressants | 0.003* | 0.003* | 0.003* | 0.003* |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Opioids | −0.001 | −0.001 | −0.001 | −0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Non-opioid Painkillers | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Year FEs | No | Yes | Yes | No |
| Quarter FEs | No | No | Yes | No |
| Year × quarter FEs | No | No | No | Yes |

Notes: RD estimates are based on individual-level data on unemployment insurance health events from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. Each estimate presents separate effects of an additional 9-week eligibility of UI benefits for the 9 months following unemployment. Column 1 includes no fixed effects, Column 2 includes only year fixed effects, Column 3 includes year and quarter fixed effects, and Column 4 includes year-by-quarter fixed effects. Panel (a) presents estimates for unemployed female workers and Panel (b) presents estimates for unemployed male workers.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A8 — Testing Different Specifications (Health Care Utilization)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *(a) Females* | | | | |
| Outpatient Expenditure | −0.63 | −0.18 | −0.21 | −0.32 |
| | (6.59) | (6.53) | (6.54) | (6.54) |
| Outpatient Visits | 0.25 | 0.28 | 0.28 | 0.28 |
| | (0.25) | (0.25) | (0.25) | (0.25) |
| Inpatient Stays | −0.03 | −0.03 | −0.03 | −0.03 |
| | (0.05) | (0.05) | (0.05) | (0.05) |
| Year FEs | No | Yes | Yes | No |
| Quarter FEs | No | No | Yes | No |
| Year × quarter FEs | No | No | No | Yes |
| *(b) Males* | | | | |
| Outpatient Expenditure | −1.53 | −1.69 | −1.81 | −1.79 |
| | (2.53) | (2.51) | (2.50) | (2.50) |
| Outpatient Visits | 0.16* | 0.14* | 0.13 | 0.13 |
| | (0.09) | (0.08) | (0.08) | (0.08) |
| Inpatient Stays | −0.06* | −0.06* | −0.06* | −0.06* |
| | (0.03) | (0.03) | (0.03) | (0.03) |
| Year FEs | No | Yes | Yes | No |
| Quarter FEs | No | No | Yes | No |
| Year × quarter FEs | No | No | No | Yes |

Notes: See Table A7. "Outpatient Expenditure" denotes the total amount spent, in Euros, on doctor's visits. "Outpatient Visits" include the number of visits to a physician. "Inpatient Days" include the number of days spent in a hospital.
$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A9 — Effects Based on Post-UI Wage Change

| | (1) | (2) | (3) |
|---|---|---|---|
| *(a) Prescriptions* | | | |
| | Antide-pressants | Opioids | Non-opioid Painkillers |
| Wage decrease | −0.004 | −0.001 | 0.002 |
| | (0.005) | (0.002) | (0.002) |
| Wage increase | −0.02* | −0.009** | 0.002 |
| | (0.008) | (0.003) | (0.002) |
| *(b) Health Care Utilization* | | | |
| | Outpatient Expenditure | Outpatient Visits | Inpatient Days |
| Wage decrease | 4.8 | 0.3 | −0.02 |
| | (4.7) | (0.3) | (0.07) |
| Wage increase | −6.7 | 0.2 | −0.03 |
| | (12.4) | (0.4) | (0.09) |

Notes: See notes for Tables 4 and 7. "Wage decrease (increase)" indicates that an unemployed worker experienced a decrease (increase) in wage levels, conditional on matching to a new occupation.

TABLE A10 — Compatibility of Job and Household Responsibilities

| | Too tired for chores after work | Too tired at work due to HH responsibilities | Difficulty concentrating due to family responsibilities |
|---|---|---|---|
| Female | 0.094*** | –0.005 | 0.033** |
| | (0.018) | (0.010) | (0.014) |
| Age | 0.031*** | –0.002 | 0.042*** |
| | (0.012) | (0.007) | (0.009) |
| $Age^2$ | 0.000*** | 0.000 | –0.001*** |
| | (0.000) | (0.000) | (0.000) |
| Living with partner | 0.004 | –0.028** | –0.037** |
| | (0.019) | (0.011) | (0.015) |
| Intercept | –0.010 | 0.176 | –0.506*** |
| | (0.211) | (0.124) | (0.162) |
| Sample mean | 0.56 | 0.09 | 0.18 |
| Number of observations | 3,192 | 3,191 | 3,190 |

Notes: Data are from Austrian households in both waves of the *Generations & Gender Survey*. Listed outcomes are binary variables equal to 1 if the respondent answers anything else than "never" to the question. Responses include survey weights. Coefficients are from a simple OLS model where each column is a separate regression.

TABLE A11 — Effects Based on Marriage Status

| | (1) | (2) | (3) |
|---|---|---|---|
| *(a) Prescriptions* | | | |
| | Antide-pressants | Opioids | Non-opioid Painkillers |
| Females | 0.008 | –0.009*** | 0.006** |
| | (0.01) | (0.003) | (0.002) |
| Males | 0.005 | 0.003 | 0.001 |
| | (0.004) | (0.002) | (0.002) |
| *(b) Health Care Utilization* | | | |
| | Outpatient Expenditure | Outpatient Visits | Inpatient Days |
| Females | 1.4 | 1.3* | 0.1 |
| | (9.9) | (0.7) | (0.1) |
| Males | –4.8 | 0.3 | 0.09** |
| | (3.8) | (0.2) | (0.04) |

Notes: See notes for Tables 4 and 7. We are able to identify approximately half of all married Upper Austrians, based on data limitations. We identify a worker as "married" based on tax status, including whether a worker claims a deduction based on being an earner living in a household with children.