Effects of Unemployment Insurance Duration on Nonemployment, Wages, and Health*

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Abstract

Existing research shows that unemployment insurance (UI) subsidizes job search. In this paper, we provide new evidence that these labor market responses vary by gender and that longer UI duration affects workers' welfare outside of the labor market. Specifically, using administrative data for Austrian workers, we show that female workers eligible for 9 additional weeks of UI benefits experience wage gains, fill fewer opioid and antidepressant prescriptions, and are less likely to eventually claim disability. For male workers, extending UI duration does not lead to improvements in wages or health but increases the likelihood of early retirement and disability filing.

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1. Introduction

It is well-documented that unemployment insurance (UI) increases unemployment duration (Card, Chetty, and Weber, 2007b). While on its face, this result implies distortionary effects of the program, recent evidence indicates unemployed workers use benefits to actively improve job match, leading to higher wages, on average (Nekoei and Weber, 2017). However, given that there exist gender gaps in the labor market in terms of hours worked, wages, job search, and occupational choice, these average effects may mask important heterogeneous responses to UI that vary by gender (Blank and Shierholz, 2006; Erosa, Fuster, Kambourov, and Rogerson, 2017; Blau and Kahn, 2017). In this paper we address three fundamental unanswered questions: (i) Do male and female workers respond differently to changes in UI duration in the labor market?; (ii) What could be driving any observed gender differences?; and, (iii) How does UI duration affect not only workers' economic trajectories, but also their overall health and well-being?

To answer these questions, we investigate which workers are most likely to be affected by an extension in UI benefits by estimating effects on job match, wages, early retirement, and disability claims by gender. Because male and female workers may face different constraints and stressors as they explore job opportunities, we then go beyond existing work by measuring differential effects of UI duration on physical and mental health—-a relatively understudied aspect of UI with substantial policy implications. Lastly, we explore potential mechanisms, including time use during unemployment and occupational switches, to better understand how UI can differentially affect worker behavior.

Using administrative data for nearly 400,000 Austrian workers from 2003–2013, we exploit an existing policy in Austria that extends UI benefits for workers aged 40 and older from 30 to 39 weeks. Using a regression discontinuity (RD) approach, we first show that more generous UI time limits lead to average increases in nonemployment duration, consistent with previous research (Nekoei and Weber, 2017). Next, we estimate effects on job match by gender and show that female workers drive the previously observed increases in time spent unemployed and average wage gains. Moreover, we find that female workers eligible for an additional 9 weeks of UI benefits are less likely to return to physically demanding jobs and less likely to eventually claim disability than their counterparts. Male workers eligible for an additional 9 weeks of UI benefits also experience longer unemployment duration but are less likely to switch occupations and do not match to higher-paying jobs. Male workers are instead *more* likely to stay in physically demanding jobs and are more likely to eventually claim early retirement and/or disability. Given that these labor market effects persist over time, our findings suggest that UI subsidizes search for female workers, but not male workers, and has important welfare implications.

Motivated by these differential labor market impacts by gender, we then use linked administrative data on prescriptions and health care utilization for unemployed 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. These secondary effects of UI are especially relevant given that existing research shows that job displacement, early retirement, and conditional cash transfers (CCTs) affect health and risky behavior, with women *more* likely to engage in healthier behaviors and men *less* likely to engage in such behaviors (Kohler and Thornton, 2012; Black, Devereux, and Salvanes, 2015; Lindo, Schaller, and Hansen, 2018; Fitzpatrick and Moore, 2018).[1] Additionally, recent evidence indicates that workers in physically demanding occupations experience more rapidly declining health status, suggesting that gender differences in occupational changes driven by UI duration may be an important avenue to explore differential changes in worker health (Case and Deaton, 2005).

Theoretically, 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. For example, If male workers face more internal pressure than female workers to return to the labor market more quickly, we would expect that any differential labor market effects would translate into differential health effects that vary by gender. On the other hand, additional search time could provide workers with additional chances to invest in healthy behaviors and/or preventative care for themselves or their children. Moreover, if workers experience physical stressors on the job, unemployment may provide temporary pain relief, and extended UI duration could result in workers matching to a less painful job, leading to reduced pain or dependence on pain medication in the future.

Estimates from our age-based RD approach indicate that female 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

[1]Moreover, in the CCT literature, there are a number of papers showing that transfers to women, and mothers in particular, improve nutrition and health outcomes for their children (Schady and Rosero, 2008; Angelucci and Attanasio, 2013; Armand, Attanasio, Carneiro, and Lechene, 2016). Similarly, when looking at the effect of CCTs on risky behavior, Kohler and Thornton (2012) perform a RCT in Malawi granting individuals financial incentives for one year to abstain from risky sexual behavior. They find that men who received the cash transfer were 9 percentage points more likely and women were 6.7 percentage points less likely to engage in risky sex.

to bandwidth selection or functional form.

In comparison, when analyzing effects for male workers, we find that those marginally eligible for an additional 9 weeks of UI benefits are more likely to use heart medications, like beta blockers, and are 0.05 percentage points more likely to experience a heart attack in the 9 months following unemployment as compared to marginally ineligible unemployed male workers. We also find some evidence that male workers increase antidepressant use. In line with previous research on job loss and risky behaviors, we posit that this increase in cardiac events and disability claims for male workers may be due to additional mental stress, physical job stressors, and/or increased smoking behavior as a result of increased time unemployed and job match. Lastly, we provide additional statistical results paired 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.

We 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).[2] Third, 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.[3] Importantly, these data track individuals over time, allowing

[2]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).

[3]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,

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.[4,5]

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).[6] 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.[7] We note that any findings on 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

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).

[4]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`.

[5]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).

[6]Specifically, Elison and Storrie (2006) look at plant closures in Sweden in the late 1980s and find negative effects on mortality for men, whereas Browning, Dano, and Heinesen (2006) use Danish data and find no stress-related health effects of unemployment. However, for Danish men with strong labor attachment, Browning and Heinesen (2012) find that job loss increases overall mortality, alcohol-related diseases, and mental illness. Bloemen, Hochguertel, and Zweerink (2015) analyze Dutch plant closures and find a 0.60 percentage point increase in mortality in the following five years. Böckerman and Ilmakunnas (2009) use Finnish survey data from the European Community Household Panel and find that workers that become unemployed have a lower baseline level of health, implying that unemployment itself does not affect worker health. Kuhn, Lalive, and Zweimüller (2009) study the effects of plant closures in Austria from 1998–2002 and find that job loss reduces the mental health of men.

[7]Although supplementary private health insurance is available in Austria (it covers very specific inpatient services, e.g., free physician choice and the right to stay in a double room), we find no evidence of unemployment leading to reductions in public insurance coverage. Importantly, 99 percent of people living in Austria have full health care coverage regardless of job status (Hofmarcher and Quentin, 2013).

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.[8] 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 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.[9]

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 and baseline eligibility of 20 weeks.[10,11] 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

[8]Relatedly, Rege, Telle, and Votruba (2009) find that both men and women are likely to receive disability insurance following a plant closing, while Savych, Neumark, and Lea (2018) documents that longer-term opioid prescribing for lower back pain increases the duration of temporary disability.

[9]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).

[10]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.

[11]To qualify for baseline benefits, workers must have contributed at least one out of the last two years.

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.[12] Although baseline UI duration is 20 weeks, 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.[13]

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, and meet the experience criterion of having worked at least 6 of the last 10 years.[14]

For information on past fertility, prescriptions, and hospitalizations, we use data containing informa-

[12]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.

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

[14]We emphasize that we employ different panel data, as compared to Nekoei and Weber (2017). While Nekoei and Weber (2017) use a panel for all Austrian workers from 1998–2011, which contain only employment and wage outcomes, we use data on Upper Austrians linked to health outcomes for workers and their children from 2003–2013.[15] Our data additionally contains information on individuals that are out of the labor force, as well as retirement and disability outcomes. For comparison, due to the inability to link health data for all Austrians, our estimates are based on approximately 380,000 observations, compared to 1.7 million observations in Nekoei and Weber (2017).

tion 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).[16] 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. In doing so, we are able to analyze effects of an additional 9 weeks of benefit eligibility on child health care utilization.[17]

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 diagnoses using Anatomical Therapeutic Chemical (ATC) code N medications ("nervous system") and ICD-10 code F diagnoses ("mental and behavioral disorders").[18] 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. 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.[19] There are no prescription refills in Austria, which allows us to capture all possible prescriptions during our sample period.

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 cardiac events, such as heart attacks or strokes. 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

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

[17] In the following analyses 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. Moreover, we only have information on children born in Austria. We note that childlessness in Austria is 35 percent for females aged 30–39 and 18 percent for those aged 45–49.

[18] N02A are opioid analgesics, including fentanyl, N06 contain antidepressants, and N07BC are medications used for opioid dependence like methadone, morphine, and buprenorphine. For reference on ATC codes, see `https://www.whocc.no/atc_ddd_index`.

[19] This data feature allows us to focus on more serious forms of pain treatment. In Austria it is common to prescribe milder pain drugs, such as tramadol and codeine, which are substitutes to Tylenol. Therefore, we also consider effects on prescriptions for "weak" opioids below.

fixed effects. In particular, female workers are more likely to take pain medications and antidepressants, are more likely to visit and spend money on doctor's visits, and are less likely to experience cardiac events. These findings suggest that if UI benefit extensions do affect health, we should expect male and female workers to respond differently, which motivates our empirical approach.

Additionally, to analyze 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.[20]

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 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

[20]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.

strategy by estimating the following OLS models:

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

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 cardiac events, 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, α_t, to control for any cylicality or economic trends in unemployment over time.[21] We highlight estimates from a specification that uses a one-sided bandwidth of 10 years, following Nekoei and Weber (2017), although we additionally present 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

[21]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 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.

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, below 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 2.36 percent of female workers and 2.06 percent of male workers fully exhaust their benefits.[22,23] Therefore, our below analysis investigates to what extent the *opportunity* to receive benefits for an additional 9 weeks affects the ability of workers to match to a higher-paying job or 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 while we present our analyses for the pooled sample as well as for female and male workers separately, we

[22] We find no discontinuity in share of workers who exhaust benefits at the eligible cutoff. For a distribution of an individual's unemployment spell, in days, see Figure A2. Importantly, a large majority of workers return to work within the first quarter of unemployment.

[23] This is consistent with recent survey evidence from Germany showing that while unemployed workers increase search effort as UI benefit length wanes, they do not time the start of new employment with the end of their UI benefits (DellaVigna, Heining, Schmieder, and Trenkle, 2020).

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

Before presenting our estimated effects on health, we first analyze how the discrete 9-week increase in UI benefit duration for workers aged 40 and older affects benefit take-up and corresponding labor market outcomes. In Figure 1, we plot means of individual-level UI benefit and nonemployment duration, using 6-month age bins, for workers meeting the experience criterion unemployed near the age 40 cutoff. We display quadratic fits for the individual-level UI benefit duration, in days. Workers that become unemployed above the age of 40, shown to the right of the vertical line, are eligible for the 39-week UI benefit duration, while those to the left of the vertical line are ineligible and receive benefits lasting a maximum of 30 weeks. In the bottom right corner, we display the coefficient on the main variable of interest (β_1) from Equation (1) and the corresponding standard error.

The top panel of Figure 1 shows the first-stage effect of eligibility of prolonged UI benefits on benefit duration for all workers. We define benefit duration as the number of days in which a worker receives UI benefits. Overall, we estimate a statistically significant increase in UI benefit take-up duration by approximately 2 days for those just over the age threshold, suggesting that an extension in UI duration eligibility, but not generosity, incentivizes workers to claim benefits and/or remain jobless longer.[24]

Furthermore, because a worker may remain unemployed longer than benefit duration and/or choose not to take up UI benefits for the full period, in the bottom panel of Figure 1 we present effects on nonemployment, or the time, in days, of a worker's unemployment spell.[25] Estimates indicate a 4-day increase in nonemployment.

These findings are generally consistent with previous work suggesting 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. For example, male workers may be more likely to experience negative psychosocial effects of unemployment, which may hasten their return to work, as compared to female workers (Hussam, Kelley, Lane, and Zahra, 2021). Moreover,

[24]Importantly, we find no evidence that benefit amounts change discontinuously over the age eligibility threshold; estimates indicate a statistically insignificant increase in UI benefits amounting to 0.45 percent.

[25]This includes the time in days a worker spends out of the labor force. An unemployment spell can end with subsequent employment, retirement, or disability retirement. Importantly, this variable can be larger than UI benefit duration if a worker fully exhausts benefits or chooses not to claim UI benefits due to the conditional aspects of the cash transfer, like job search requirements. This latter condition accounts for 43 percent of the sample, and is consistent with similar evidence on UI take-up in Nekoei and Weber (2017).

because UI replaces only 60% of an individual's income, on average, we may expect to observe differences in time spent out of the labor force if male workers are likely to be solo or primary earners. Although our dataset does not contain information on which households have dual earners and, although we cannot connect married workers to their partners, we do observe some gender differences in work behavior. In our sample, males are much more likely than females to be employed and, according to survey data, are more likely to self-report being the primary household earner (EVS, 2017).

In Figure 2, 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.

Although inducing workers to remain out of the labor force for merely 2–8 days seems relatively small compared to the 9 week eligibility threshold, these effects mirror previous findings for Austria workers showing that this length of time unemployed can affect worker search behavior and job match, potentially changing workers' economic trajectories (Nekoei and Weber, 2017).[26] If male and female workers have different behavioral responses to labor market policies and/or CCTs, we may also expect to find meaningful differences in terms of occupational changes, job match, wages, and/or effects outside the labor market.

In Figure 3 we present evidence to support the notion that UI duration does affect job match, as measured by daily log wages of the first new job after an unemployment spell, and note that this is driven

[26] In the US context, there is less evidence to support the notion that longer benefit duration leads to improved job match (Card, Chetty, and Weber, 2007a).

primarily by female workers. Specifically, we find no changes in wages for male workers, on average. Female workers receive 2 percent higher wages, corresponding to an additional 1 Euro per day, or 371 Euros per year, on average.[27]

Because few workers use the full 39 weeks to search, and there is heterogeneity in how long workers take to reenter the labor force, in Table 4, we investigate these wage effects further by estimating effects by quartiles of nonemployed days.[28] We find that for unemployed females who match to a job within the first 93 days, wages increase slightly, by 0.5–0.8 percent. For female workers that take near the entire 39 weeks, there is no statistically significant change in wages. In contrast, male workers do not experience this similar increase in wages, and face a small wage penalty for claiming UI past the 14-week window.

Moreover, we note that while over three-quarters of female workers in our sample choose to change industries, only half of male workers opt to do so, which could help to explain this gender difference in wage outcomes. Indeed, in Appendix Figure A3 we provide evidence that the wage increase for female workers is driven by those that choose to change industry.

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. These findings suggest that while many workers choose not to spend a full 39 weeks claiming UI benefits, the opportunity to do so increases nonemployment duration and affects worker wages, as compared to unemployed workers with only 30 weeks of benefit eligibility. These findings are 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). Next, we analyze whether this time extension also affects the physical and mental health of unemployed workers and their children.

6. Effects on Early Retirement and Disability Claims

Next, we explore whether the extension of UI benefit duration affects labor market outcomes in the longer run. For example, to the extent that longer nonemployment duration leads to more workers matching to or

[27]These magnitudes are larger, but overall consistent with Nekoei and Weber (2017) who use a search model to show that the discontinuity in UI benefit duration induces Austrian workers to seek higher-wage jobs, but reduces wages by lengthening time unemployed. In particular, Nekoei and Weber (2017) find an increase of 0.00459 log points at age 40. For comparison, our estimates amount to 0.017 log points for female workers and -0.035 log points for male workers. In other words, we find that wages for female workers increase by 4.4 percent of a standard deviation, while wages for male workers fall by 9 percent of a standard deviation.

[28]We acknowledge that this outcome is differentially affected by UI duration and this test requires us to condition on a variable of interest. Nevertheless, given the wide ranges of number of days for our quartiles combined with small average first-stage effects, we believe this is still a useful exercise.

staying in occupations with high rates of injury, these individuals may be more likely to claim disability as a result.[29] Alternatively, if workers are able to match to a safer job and/or a job with higher earnings in perpetuity, extended UI time limits could prolong working behavior and could reduce incentives for disability or early retirement filings (Böckerman and Ilmakunnas, 2020). We explore these possibilities in Figures 4 and Figure 5. Specifically, we first test whether unemployed workers eligible for extended UI benefit duration retire at an earlier age than their counterparts and then test whether these workers are more or less likely to claim disability before retirement. We present these results separately by gender.

Figure 4 displays differences in the probability of early retirement.[30] In Austria early retirement implies that workers forfeit pension benefits to retire before the regular retirement age, which is 60 years for females and 65 for males. We estimate a small, positive effect for male workers. Estimates for female workers are statistically insignificant, suggesting that matching to a higher-paying job does not induce female workers to exit the labor market earlier. Therefore, these results also support the notion that extending UI benefit duration for female workers leads to higher lifetime wages, on average.[31]

In Figure 5, 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.[32] To explore this notion further, in Figure A4 we present event study analogues from an age-based difference-in-differences analysis, comparing male workers to female workers.[33] 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, essentially shifting the administrative costs. Given that we find significant differential labor market responses and longer-run trajectories by male and female workers, below, we investigate

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

[30]This outcome is especially relevant given the recent evidence that early retirement increases mortality among male workers, but not female workers (Kuhn, Staubli, Wuellrich, and Zweimüller, 2009).

[31]We similarly analyze changes in retirement age, and do not estimate any statistically significant effects for eligible workers.

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

[33]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.

whether these changes can be explained by short-run changes in job demands and worker health.

7. 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.[34] We do so in an attempt better understand the relationship between UI, occupational demands, wages, and well-being. We first present results for all unemployed workers in our sample, then further explore how these effects vary by gender, family status, and occupation.

7.1. Opioid Prescriptions

We first 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.[35] 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).[36]

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.[37] 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 6 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). In particular, we include prescribing data for the 9 months (i.e., 39 weeks) following an unemployment event for all workers between ages 30 and 50. Given that a majority of Austrian workers are male, and that we find a differential effect in UI benefit duration by gender, we separately display binned means and quadratic fits for male and female workers. Figure 6 presents suggestive evidence that both male and female workers are less likely to use opioids when benefits are extended from 30 to 39 weeks, with larger effects for

[34]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 A5.

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

[36]Carpenter, McClellan, and Rees (2017) analyze the use of prescription pain relievers and hallucinogens increases when people face substantial shocks during economic downturns, while Dobkin and Puller (2007) focus on effects from a cash transfer program.

[37]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).

female workers.

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. However, we 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. We also note that all regressions are based on the underlying individual-level data, not the age bins themselves, which should provide more reassurance that these observations are not driving the reported decline in opioid prescriptions. Similarly, when we omit observations in the upper five percentiles, estimates are statistically similar to our main result. 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.[38]

In Table 5 Column 1, we present the regression discontinuity estimates from Equation (1) for the pooled sample (Panel (a)) as well as separate estimates for male and female workers (Panels (b) and (c), respectively), which mirrors our estimates from Figure 6. Below each estimate, we present the sample mean for unemployed workers, ages 30–50. Specifically, estimates indicate that female workers are 0.5 percentage points, or 33.3 percent, less likely to use opioids within 9 months of being unemployed, and these estimates drive the decrease in the overall sample. These estimates correspond to approximately 500 fewer opioid prescriptions each year. 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.[39] Moreover, estimates for male and female workers are statitically different at the 1 percent level.

Because female workers are prescribed opioids at a higher rate, and because we are analyzing results separately by gender, in Appendix Table A1, 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 A1

[38]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. However, we find some evidence that unemployed women to the left of the cutoff are more likely to remain in and switch into physically demanding occupations, and we discuss this as a potential driver in greater detail below.

[39]In Section 8 we additionally conduct sensitivity analyses and discuss how these estimates vary across bandwidths and functional form.

Panel (b) Column 1 reinforce the results from Table 5—namely, that extending UI benefits reduces opioid prescriptions for female, but not male, workers.

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 A2, Column 1, we present estimates of extended UI benefit duration on opioid prescriptions within 3, 6, 9, 12, 15, and 18 months after job loss, respectively. Estimates indicate that reductions in opioid 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.

Next, we analyze dynamic effects of longer UI duration, which may be important for several reasons. First, the nature of some health outcomes, like opioid 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 A8 and A9 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 present quarter relative to a worker's UI spell on the x-axis, and RD coefficients on the y-axis. Estimates indicate that opioid prescriptions decline in the quarters following unemployment for female workers, with large temporary reductions lasting 4 quarters. For male workers we estimate small, statistically insignificant effects for opioid prescriptions during this period, with some evidence of an increase in prescription take-up 6 quarters after an unemployment spell.

Overall, these differential effects by gender motivate the idea that male and female workers face different demands on the job and in the household. Two potential explanations uphold these findings: (i) female workers use opioids while employed due to existing physical stressors and/or (ii) unemployment provides temporary pain relief. Alternatively, if extending UI duration allows women needed time to match to a less painful job, starting a new position itself may reduce reliance on opioids. As shown in Table A3, 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.

We have also analyzed whether these effects may be explained by substitution to other less-addictive pain medication, and present evidence supporting this hypothesis in Figure A10. Specifically, we find weak evidence that women substitute to non-opioid analgesics in the 9 months following unemployment. When pooling months together, and/or observing quarterly data, as shown in Figure A8, 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.[40] Therefore, these findings support the idea that some female workers may take low-potency opioids to perform at their jobs, and joblessness allows for a reduction in the use of such drugs.

Furthermore, we note that opioid use may vary depending on a worker's level of education, lifestyle, and occupation type. To further analyze effects on opioid use, in the first column of Table 6 we investigate additional heterogeneous effects of UI extensions on opioid prescriptions across female worker subgroups.[41] 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 this subgroup.[42,43]

In Table 6 Column 1 Panel (a) we present evidence that female workers with children drive our main results. Estimates indicate that women with children experience a up to a 0.9 percentage point, or 60.0 percent, reduction in opioid prescriptions when eligible for an additional 9 weeks of UI benefits.[44] While this reduction is relatively large, we note that only 1.5 percent of female workers fill an opioid prescription each year.

Next, in the first column of Table 6 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

[40]These effects fade after 3 months, and estimates after 9 months shown in Table 5 Column 2 are statistically insignificant.

[41]For completeness, subgroup estimates are presented in Table A4 for male workers.

[42]Importantly, fathers are only recorded if the child is born in wedlock, which may bias our estimates for male workers.

[43]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.

[44]We have also analyzed whether workers that fully exhaust benefits before returning to work are driving our results. Overall, our results are concentrated in female and male workers that return to work before the end of the 39-week eligibility period, although we note that the sample of workers that fully exhaust benefits represent a smaller sample, and these estimates may be underpowered.

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.[45] 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.

Importantly, this effect may be largely driven by the types of jobs workers match to when given a 9-week extension in benefits. In the previous section, we show that, conditional upon finding a new job, female workers take an additional 8 days, on average, to search for their next position. We also find that average wages increase for female workers eligible for this extension. Next, we analyze whether the conditions of the next job can explain the reduction in opioid use shown in Table 6. In Table 7, 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 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.[46] This estimate corresponds to nearly 1,000 fewer female workers in jobs with hardship, 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.

We also note that we find some evidence that male workers do not match to a less physically strenuous occupation when given an additional 9 weeks of UI benefits. Alternatively, these eligible unemployed male workers are slightly *more* likely to stay in a physically demanding job, and male workers that exhaust their UI benefits match to a lower-paying job. Therefore, our findings imply that male workers may not be reducing opioid use, on average, due to the existing physical job stressors that female workers no longer face when given an extension in UI benefits.

Overall, these findings have stark implications for the adverse health conditions that many workers face. Female workers, especially mothers, are less likely to use opioids when they experience extended UI benefit eligibility, and these effects are concentrated for low-skilled workers in industries imposing a large

[45]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.

[46]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.

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, as well as evidence that male workers do not switch away from a physically demanding job when granted additional time to search for a new job (Krueger, 2017; Serdarevic, Striley, and Cottler, 2018). Our findings therefore speak to distinct differences in worker behavior and opioid 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). In the next section, we further discuss prescription drug usage to analyze effects of UI benefit duration on mental health and/or drug and alcohol dependence.

7.2. 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, 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 results in consumption of goods like drugs, alcohol, or other risky behaviors, anxiety or depression may worsen. Similarly, if there is societal or family pressure to remain unemployed longer due to the extension in UI benefits, workers that do feel a sense of meaning when employed may experience more adverse mental health consequences.

In Figure 7 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 5. Overall, we find that female workers eligible for an additional 9 weeks of UI benefits experience decreases in antidepressant prescriptions following unemployment.[47] In particular, estimates indicate that extending UI benefits reduces antidepressant prescriptions by 8.7 percent for female workers. As shown in Table 6 Column 3, effects are largest for full-time workers, low-educated workers, and workers in low-skill occupations.

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 Tables A5 and A6, we investigate the effects of longer UI duration on changes in the level of prescriptions. Table A5

[47]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 or consistent across bandwidths.

reports results for the total number of packages prescribed, including zeroes, while Table A6 provides estimates for the number of packages prescribed, conditional on receiving a prescription. These estimates are largely insignificant, but imply that longer UI duration does affect patients' decisions to start or stop taking a prescription drug.[48,49]

7.3. 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.[50]

In Figure 8 and Table 8 we consider the average effects of extending UI benefits by 9 weeks on 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, and are statistically similar for male and female workers at the 10 percent level.[51,52] We note that 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.

For male workers, we find some evidence that extending UI benefit duration reduces inpatient days by 12 percent. However, we note that effects on in-patient days for unemployed male workers is not always significant across specifications, and is not statistically significant in any one quarter after unemployment, casting doubt on whether these particular estimates on all aggregated diagnoses represent true causal effects. Below, we further investigate what types of acute illnesses may be more likely to be affected by

[48]Additionally, for opioid prescriptions, estimates indicate that changes in the extensive margin drives our main result; that is, having access to a longer period of UI benefits greatly reduces the probability that more female workers start taking opioids.

[49]We have also tested whether an employee eligible for 9 additional weeks of UI benefits is more likely to seek treatment for alcohol or opioid dependence. However, these occurrences are relatively rare. Estimates for alcohol addiction and opioid addiction treatment are statistically insignificant and we can only rule out up to a 39 percent decrease in opioid- and alcohol-dependence prescriptions overall.

[50]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).

[51]Similarly, we estimate no increases in physician fees or hospital fees billed or the number of physician visits.

[52]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 A11. Similarly, we find no discontinuous effect on workers choosing to have a baby after unemployment (i.e. Figure A12), nor do we find any evidence of discontinuities in birth complications for unemployed women.

unemployment specifically and focus our attention primarily on cardiac events.

7.4. Cardiac Events

In this section, we present estimated effects of UI duration on the prevalence of heart attack or stroke, using individual-level data on hospitalizations from the UAHIF. Despite the fact that cardiac events are relatively rare, we focus on these outcomes due to the existing evidence suggesting that unemployment leads to negative effects on cardiovascular health, due to increases in adverse health behaviors, like smoking and/or increases in stress due to job search (Vogli and Santinello, 2005; Black, Devereux, and Salvanes, 2015).[53] While we cannot focus on smoking behavior directly, this possible explanation is especially plausible and important for Austria, which maintains the highest smoking rate for teenagers and ranks 4$^{\text{th}}$ for adults in OECD countries (OECD, 2019).

Figure 9 shows the mean counts of heart attack or stroke within 9 months after job loss for male and female workers separately just above the UI extension eligibility cutoff. We present our main regression-based estimates in Table 9. Estimates indicate that male workers are 0.05 percentage points, or 33.3 percent, more likely to experience such an event within 9 months. These effects are driven by a 0.03 percentage point, or 41.7 percent, increase in the likelihood of a heart attack.[54] We find no such effect for female workers, despite the fact that female workers are only marginally less likely to experience cardiac events, as shown in Table A1.

To put these estimates into context, tobacco cessation interventions have been shown to reduce cardiac events by 3–5 percentage points (Centers for Disease Control and Prevention, 2017), while job loss has been shown to lead to a 5–6 percent increase in daily smoking for Norwegian workers in their 40s (Black, Devereux, and Salvanes, 2015). If 6 percent of male workers in our sample started smoking daily as a result of prolonged time out of the labor force, that would lead to a 1.8 percent increase in total daily smokers, corresponding to an expected 66 additional smoking-related heart attacks, based on calculations from the existing medical literature (Woloshin, Schwartz, and Welch, 2008).[55] Given that 20–33 percent of heart attacks are linked to smoking, our estimates account for approximately 48–79

[53]Specifically Black, Devereux, and Salvanes (2015) estimate a dynamic difference-in-differences model and find that job displacement in Norway for workers in their early 40s led to a decline in cardiovascular health, driven by increase in smoking behavior, although they do not document any other significant health effects. Vogli and Santinello (2005) find that changes in smoking and excessive drinking behaviors are a result of the psychosocial stress suffered by the unemployed.

[54]For heart disease that is less severe, we may also expect to see an increase in prescriptions for heart medications. Indeed, we find that prescriptions for all heart medications, including beta blockers and cholesterol drugs, increase for male workers when they are eligible for 9 additional weeks of UI benefits. We find no such effects for the placebo sample, male workers unemployed near the age 40 cutoff that are not eligible for the extension in benefits.

[55]This figure is calculated using the 30 percent base smoking rate for adults in Austria and corresponds to nearly 440 additional daily smokers in Upper Austria per year (Bank, 2020).

additional heart attacks due to increased smoking behavior (CDC, 2010). Therefore, our estimates are well in line with previous research and provide suggestive evidence that increases in smoking behavior among male workers may be largely responsible for these estimated effects.

We present the dynamic effects of such acute illness in Figure A9, following Black, Devereux, and Salvanes (2015), and we find that these effects for heart attacks for male workers are largest in the 1–2 quarters (i.e., 4–9 months) after job loss, while effects for stroke peak 12–15 months after job loss.[56] These slightly delayed effects of extended UI duration for male workers may be unsurprising given that heart disease triggered by exertion and stress develop slowly, and individuals can have warning signs and symptoms of chest pain weeks in advance. Moreover, these findings mirror estimated short-run increases in prescriptions for cholesterol drugs and beta blockers for male workers. Importantly, none of these effects are present prior to unemployment, providing additional support for the idea that these cardiac events are related to unemployment and not preexisting anomalies of the data.[57]

When we investigate how these effects differ across worker types, estimates in Table A7 indicate that the average increases in cardiac events are driven by parents (Panel (a)), men working full-time jobs (Panel (d)), and men *not* in low-skilled or physically demanding occupations (Panels (b) and (c)).[58] These findings support the idea that male workers experiencing adverse health consequences when UI duration is extended are working stressful office jobs. This is in contrast to effects we find for female workers, which seem to be driven by those in jobs prior to unemployment that are low-skill and require physical pain mitigation.[59] Furthermore, estimates from a specification using an expanding 6-month post-period window, as shown in Table A8, indicate that these cardiac health effects are not driven by any particular sample selection window.

8. 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 unemployment on health if firms hire and fire different types of workers based on their knowledge of the age 40 cutoff. Importantly,

[56]Conversely, as shown in Figure A8 the probability of a female worker experiencing a cardiac event decreases over time.

[57]Although these estimates may seem at odds with the *decrease* in in-patient days for male workers, which is statistically significant at the 10 percent level and is described in the above section, we note that hospitalizations for cardiac events are relatively rare compared to all types of hospitalizations, but may be most related to stress-inducing job shocks.

[58]While effects for parents are positive and statistically significant across all cardiac outcomes, because we lack full birth certificate information on fathers, this particular panel may represent effects for a biased sample, as described above in Section 3.

[59]Moreover, when we estimate effects for female workers, estimates indicate that some women, namely those without children and those in less physically demanding jobs, have a *lower* probability of experiencing a cardiac event when eligible for 9 additional weeks of UI benefits, suggesting that the extension in job search time may benefit certain types of female workers.

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 11 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 12, and formal estimates are presented in Table A9. 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.[60]

To further test whether these health effects are simply an artifact of the data, in the top panel of Table 10 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 criteria to receive 39 weeks of UI benefits (namely, the experience criterion). 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 10 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.[61] Similarly, male workers are not more likely to experience cardiac events prior to unemployment.[62]

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,

[60]Similarly, when we test whether the compositions of our defined subgroups from Table 6 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.

[61]When estimating effects for eligible workers, using a difference-in-RD approach with the ineligible unemployed workers as a control groups, estimates are similar to these baseline results and indicate reductions in opioid prescriptions, antidepressant prescriptions, and inpatient expenditures.

[62]Although we estimate some small effects on prescriptions for male workers, generally, antidepressant and health care utilization results for male workers are inconsistent across samples and bandwidths.

Lindo, and Waddell, 2016; and Carpenter and Dobkin, 2009). In Figure A13 we show RD estimates for a sample without female workers who become unemployed within one quarter before and after their 40th birthday.[63] These estimates are similar to the baseline results, which mitigates concerns that other events interfere with our identification strategy.[64]

Finally, we provide evidence that our effects are not sensitive to various functional forms or bandwidths in Tables 11 (female workers) and 12 (male workers). 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.[65] 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 11 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 11 Panel (b) are similar to the main results for female workers across specifications for all outcome variables and indicate reductions in opioid prescriptions ranging from 20.0–53.3 percent and reductions in antidepressant prescriptions ranging from 8.5–9.4 percent. P-values once accounting for multiple hypothesis testing range from 0.002–0.27. Estimates in Panels (a) and (b) for male workers (Table 12) do not indicate any wage gains or reductions in opioid prescriptions; if anything, wages for male workers decline.

In Panel (c) of Tables 11 and 12 we present estimates for health care utilization. Estimates indicate some declines in outpatient expenditures for both female and male workers, although estimates for male workers are not consistent across models and may pick up existing trends (i.e. see Figure A9). Therefore, we rely less on these aggregate estimates to represent true causal effects. Finally, estimates for cardiac events and heart attacks (Table 12 Panel (d)) for male workers estimates are positive and similar in magnitude across columns and indicate effects ranging from 20–35 percent, although accounting for multiple hypothesis testing reduces the p-value to be statistically insignificant at conventional levels. We estimate no statistically significant effects on cardiac events for female workers.

[63]Estimates for other outcome variables and for male workers are also statistically similar to main results at the 1 percent level.

[64]We also present age-based histograms for the main outcome variables for all Upper Austrians, regardless of employment status, in Figure A14 to show that there is no bunching in prescription take-up around the age 40 cutoff.

[65]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.

Lastly, in Figures A15–A18 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.[66]

9. Analyzing Within Household Spillovers

Next, we use matched birth certificate data to analyze how a change in a mother's UI benefit length can affect the health of their children.[67] 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 13 based on their parent's age of unemployment.[68] 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).[69]

When investigating this further, we find that these effects are driven primarily by both lower physician 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.[70]

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

[66]In Tables A10–A12 we also provide evidence that the inclusion of various fixed effects does not have a meaningful effect on our main estimates. Estimates are statistically similar across columns, suggesting that the inclusion of fixed effects does not drive our results.

[67]We focus on mothers because of the fact that there may be some nonrandom selection of fathers listed on birth certificates.

[68]RDD figures for children of female workers are presented in Figure 10.

[69]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.

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

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 13, 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.

Taken with our previous results, our findings suggest that when mothers 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 improvements in health for young children. Below, we discuss possible mechanisms to explain these results.

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. Relaxation of Time Constraints

First, we ask: how much of our findings are explained by the increase in leisure time as a result of unemployment? This is akin to asking to what extent are female and male workers differently 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 *Gender & Gender Survey* (GGS).[71] 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.[72] We present simple correlations from OLS models in Table A13.

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.[73] Moreover, in Figure A19 we present evidence that longer unemployment duration is weakly positively correlated with childcare obligations for females but not for males, consistent with the other evidence showing that, across households, women report spending more time on childcare responsibilities. Finally, we find that working females are 3.3 percentage points more likely to report finding it difficult to concentrate at work due to family responsibilities than males. This descriptive evidence implies that allowing female workers the additional time to search for a new job could lessen stressors at home as well as relieving the time pressure from work, which could explain our estimated health effects, including the reduction in antidepressant prescriptions.

Indeed, given that female workers are more likely to work part-time, earn less income, on average, and are more likely to be a secondary earner, it is possible that the increase in UI duration leads male workers to be feel more pressure to spend longer out of the work force in an effort to find a higher-paying job, leading to more stress.[74] This story could explain the observed increase in antidepressants for male workers shown in Table 5. Moreover, existing evidence shows that male workers engage in more risky behavior when leisure time increases, potentially explaining the increases in cardiac events for these workers (Mullahy and Sindelar, 1996). In Section 7.4 we provide back-of-the-envelope calculations showing that if job loss leads to increases in smoking behavior in Austria at the same documented rate as workers in other European countries, this change in behavior could account for much of the estimated 0.05 percentage point increase in cardiac events for male workers.

More formally, we have also considered how our coefficients change if we reweight the sample by

[71]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.

[72]In this survey, we can tell if a worker is unemployed but do not know whether they are claiming UI benefits.

[73]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 A14 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.

[74]For example, in the Austrian Census, only 255 women report being a sole earner in the household, as compared to 23,418 men.

individual characteristics, like parental status. Therefore, in an attempt to more clearly compare effects for females and males, 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. In doing so, we 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 present estimates from this reweighting exercise in Figure A20. 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, while if more male workers were parents, the effects on cardiac events would be slightly larger. These estimates additionally reinforce our descriptive statistics on the differential mental loads carried by female and male workers and predict that lessening parental burdens on female workers would further reduce prescription take-up, while placing greater household stress on male workers would exacerbate the increase in cardiac events even more.

10.2. Reducing Physical Demands

One striking result from our main analysis is that female workers reduce their dependence on opioid prescriptions. 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 7, 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.

10.3. Changes in Income

Lastly, 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.[75] Finally, as shown in Figure A20, smaller UI benefit generosity is associated with a greater probability of antidepressant prescription take-up, indicating that replacing income during unemployment can have positive effects on mental health.

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, cardiac events, 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 remain unemployed longer, are less likely to use opioids, less likely to use antidepressants, and less likely to claim disability as compared to ineligible female workers. 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.

[75]See Table A15, which presents are results for female workers with a wage increase and wage decrease, separately.

We find that these positive health effects for mothers reduce health expenditures for their children under the age of 6.

We find that male workers eligible for a 9-week extension in UI benefits also remain out of the labor force longer, but are not more likely to switch industries or find a higher-paying job. Consequently, male workers do not experience any health gains; these workers are more likely to experience a heart attack, and more likely to eventually claim disability retirement. Across physical and mental health outcomes, effects are largest for low-skill workers and parents, and we note that our results can possibly be explained by a combination of existing household burdens and parental duties, stress, smoking behavior, and income effects.

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.[76] 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. In this paper, 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. Moreover, 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.

On the contrary, we estimate costs for male workers, driven by those that do exhaust the additional 9 weeks of benefits. For these workers, our effects correspond to 170 additional in-patient visits per year for cardiac-related events, totaling approximately 1.3 million Euros (Bachner, Bobek, Habimana, Ladurner, Lepuschütz, Ostermann, Rainer, Schmidt, Zuba, Quentin, and Winkelmann, 2018).[77] We argue that the magnitudes we calculate are in line with previous studies showing that job loss for men is associated with increases in stress and smoking behavior (Kuhn, Lalive, and Zweimüller, 2009; Browning and Heinesen, 2012; Black, Devereux, and Salvanes, 2015; Fu and Liu, 2019).

Moreover, although we estimate some increases in antidepressant use for male workers, this is more than offset by the significant and persistent reductions in antidepressant use for female workers,

[76]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).

[77]This figure is based on the fact that 18 percent of total health care costs are paid by the patient out-of-pocket, and we estimate an average in-patient cost of 970,000 Euros per year for heart attack or stroke diagnoses, based on our Upper Austrian administrative data.

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). Taken together with the evidence that net disability expenditures do not change much as a result of extended UI, we find that the benefits far exceed the costs of offering workers an additional 9 weeks of potential benefits.

Lastly, we note that 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.

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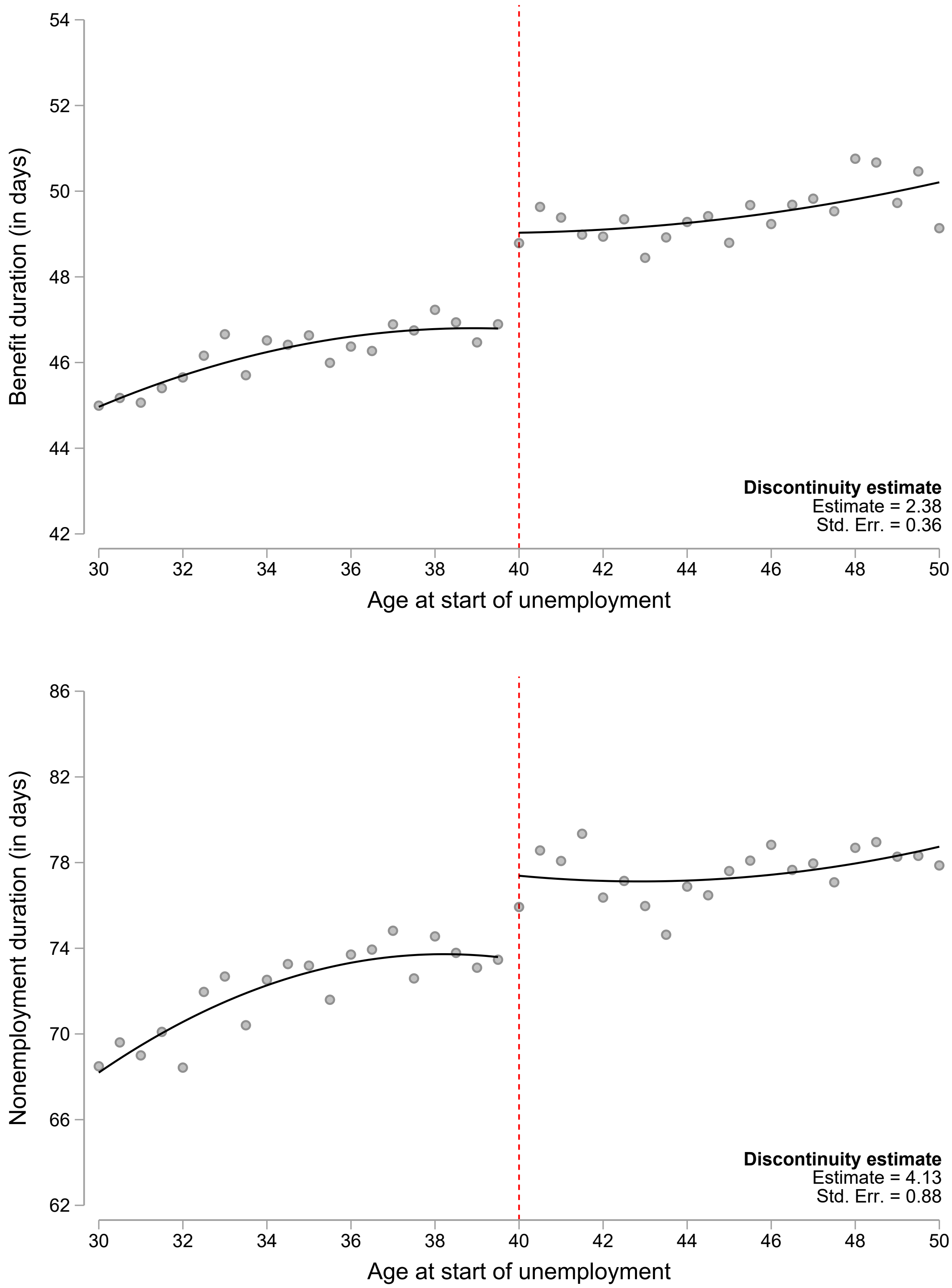
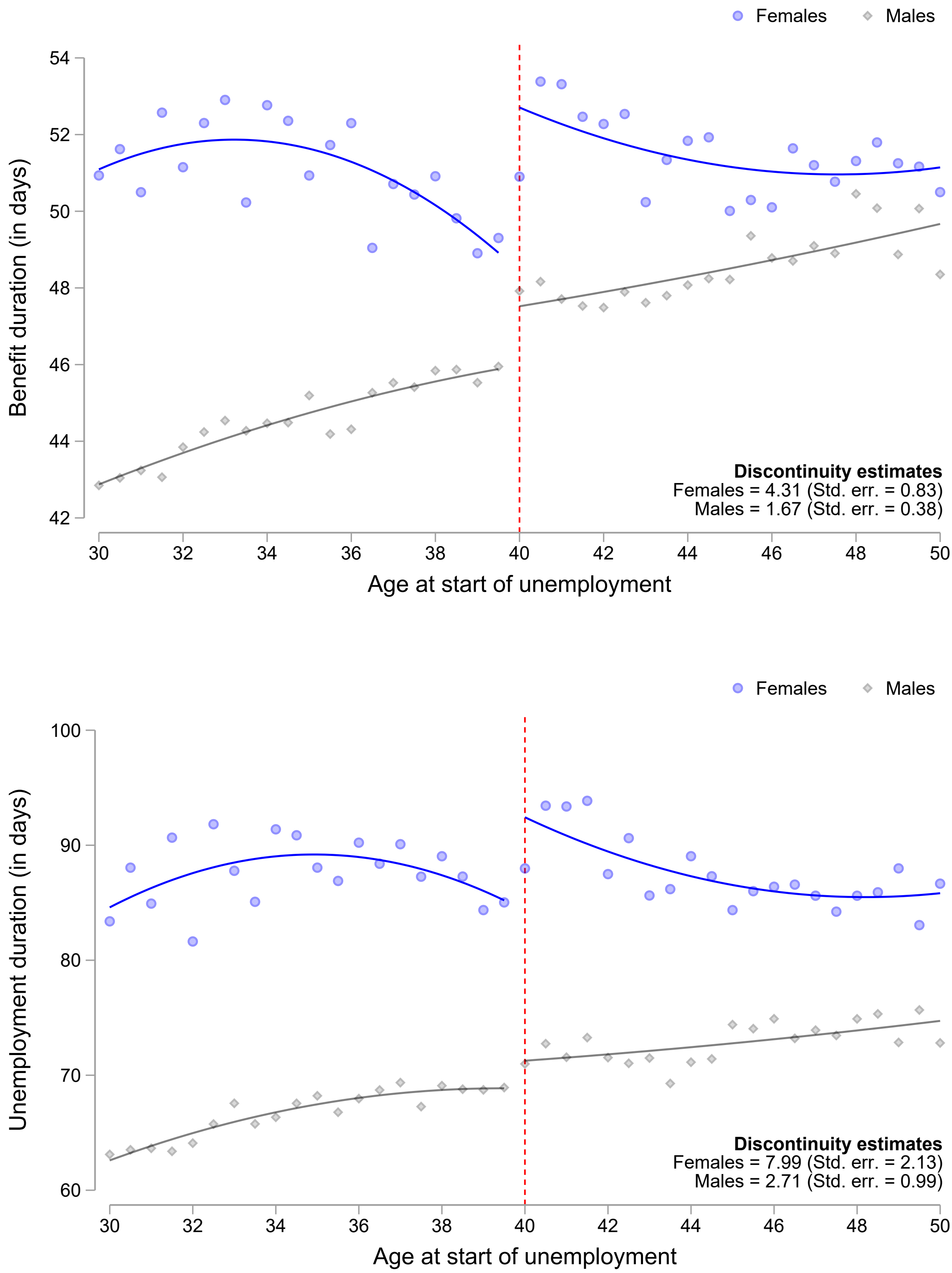
12. Figures and Tables

Figure 1 — Effects of UI Extensions on Benefit and Nonemployment Duration



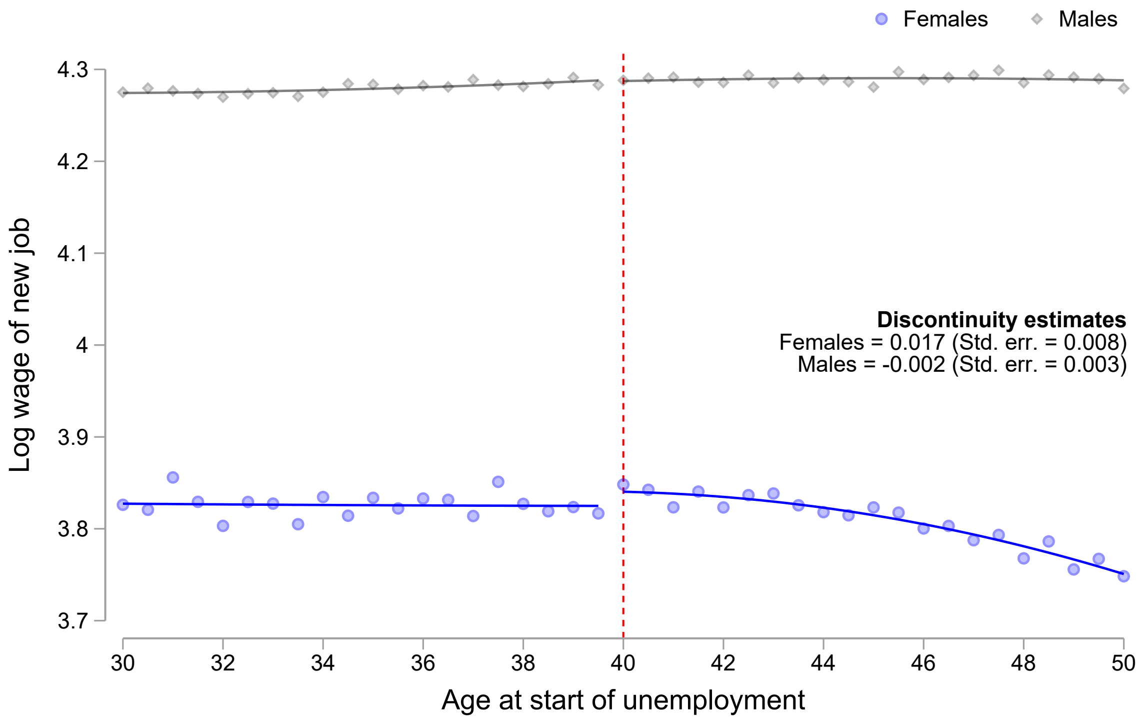
Notes: Individual-level data on unemployment insurance health events is from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. Scatters represent the mean residual of the listed outcome variable net of quarter-year fixed effects for 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.

Figure 2 — Effects of UI Extensions on Benefit and Nonemployment Duration by Gender



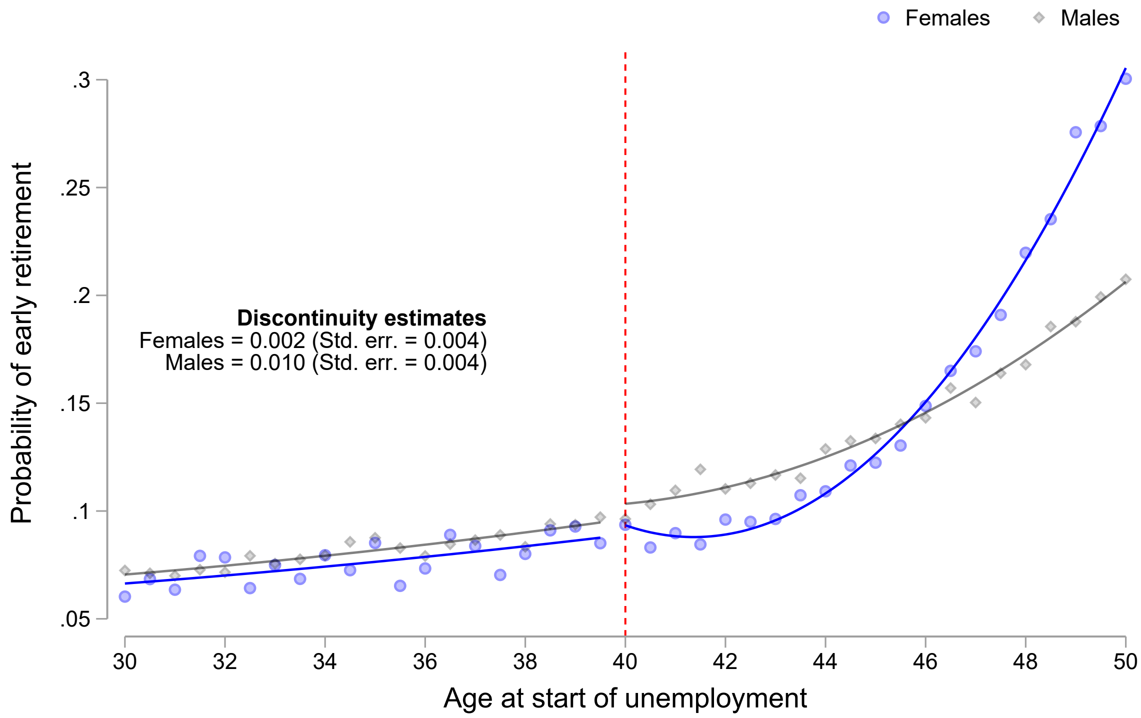
Notes: Individual-level data on unemployment insurance health events is from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. Scatters represent the mean residual listed outcome variable net of quarter-year fixed effects for each 6-month 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 3 — Effects of UI Extensions on Changes in Log Wages



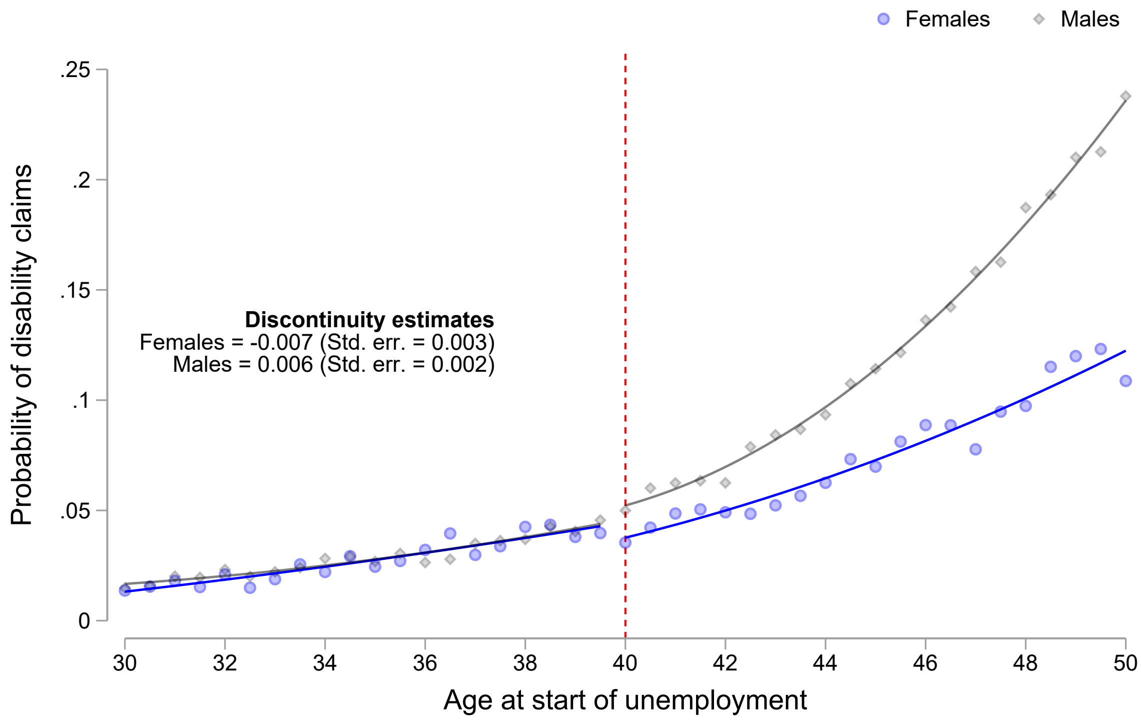
Notes: Individual-level data on unemployment insurance health events is from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. Scatters represent the mean residual of the listed outcome variable (log wage of the first job after an unemployment 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 4 — Effects of Extended UI Benefit Duration on the Probability of Early Retirement



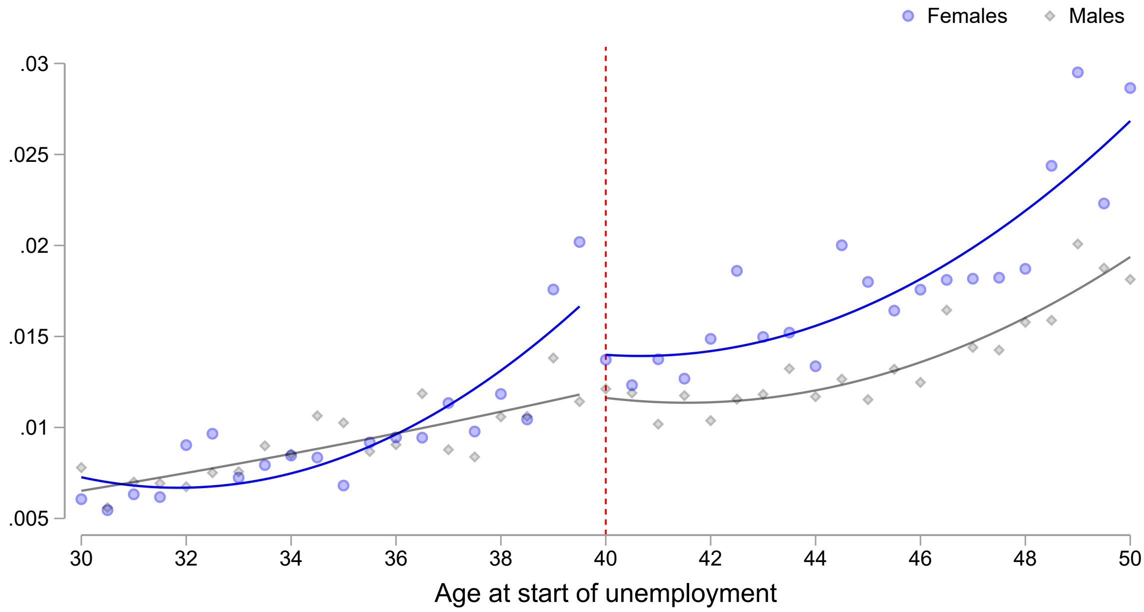
Notes: Individual-level data on unemployment insurance health events is from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. The vertical line represents the age at which workers are eligible for an additional 9 weeks of UI benefits. 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 retires before the "normal retirement age" set by the Social Security Administration between the time unemployed and the end of our sample, December 31, 2018, and zero otherwise. 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 5 — Effects of Extended UI Benefit Duration on the Probability of Disability Claims



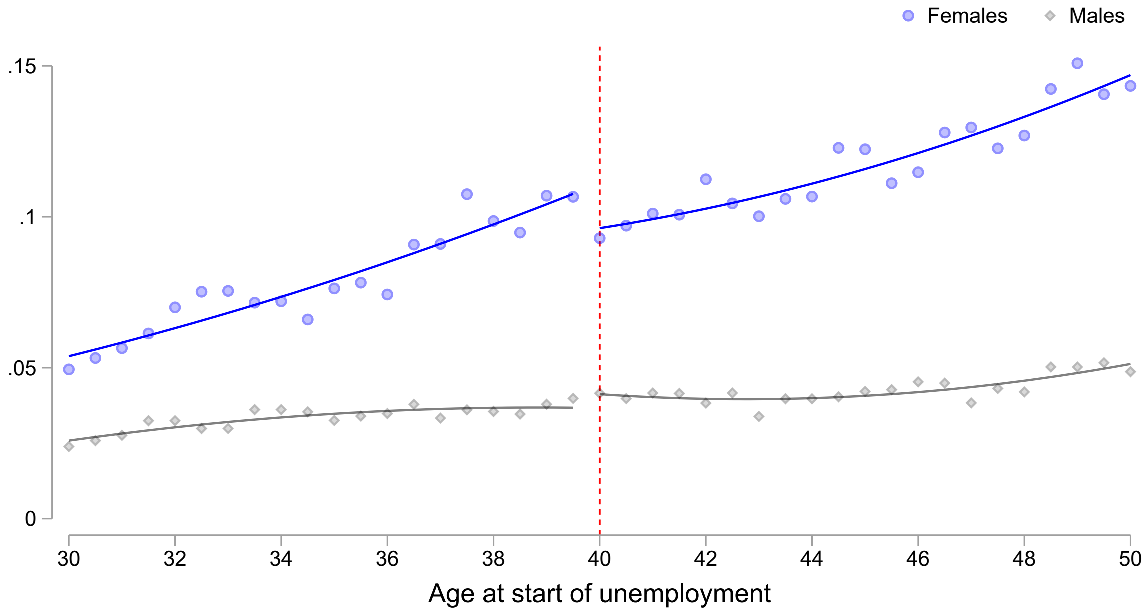
Notes: Individual-level data on unemployment insurance health events is from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. The vertical line represents the age at which workers are eligible for an additional 9 weeks of UI benefits. 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 6 — Effects of UI Extensions on Opioid Prescriptions



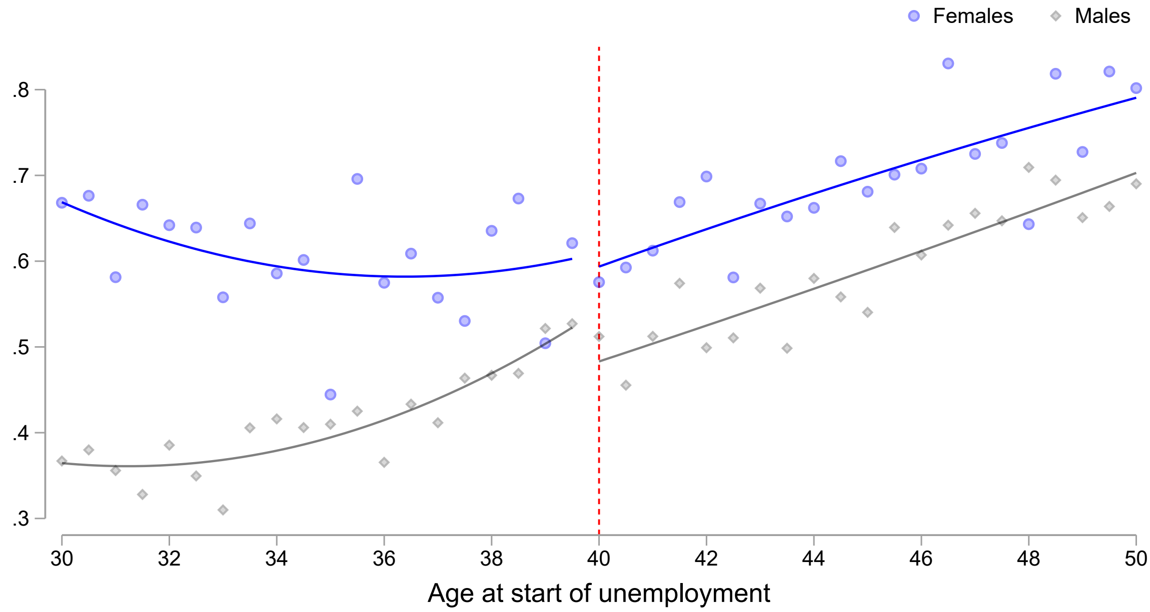
Notes: Individual-level data on unemployment insurance health events is from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. Scatters represent the mean residual of the listed outcome variable (whether a worker received an opioid 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.

FIGURE 7 — Effects of Extended UI Benefit Duration on the Probability of Being Prescribed Drugs for Depression



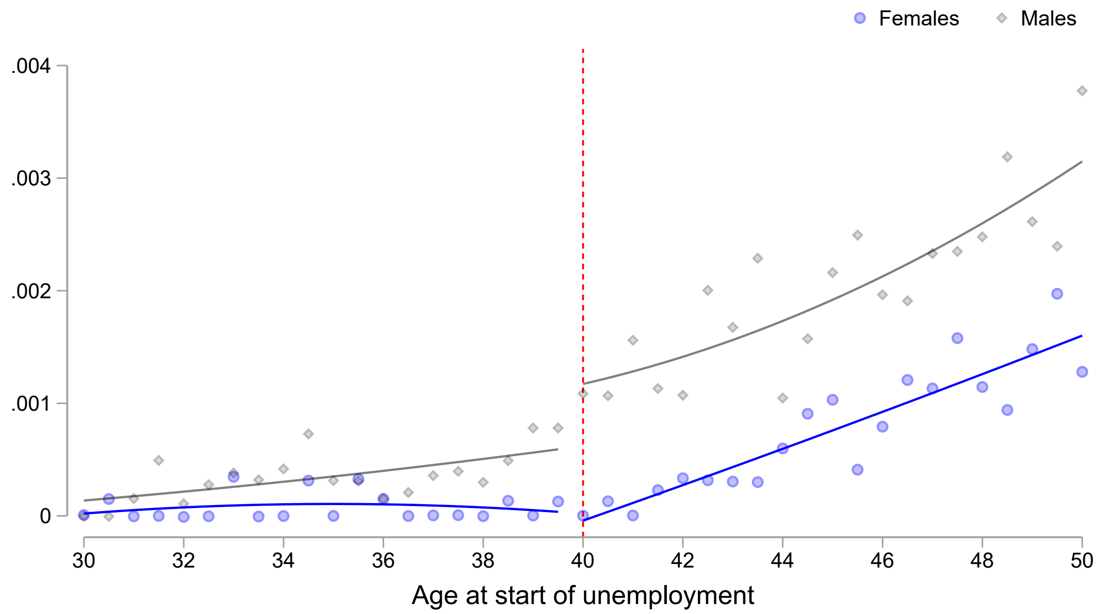
Notes: See notes for Figure 6. Prescription categories are defined by ATC codes, where N06 indicates antidepressants. For a full list of ATC code N medications, see https://www.whocc.no/atc_ddd_index.

Figure 8 — Effects of Extended UI Benefit Duration on Health Care Utilization



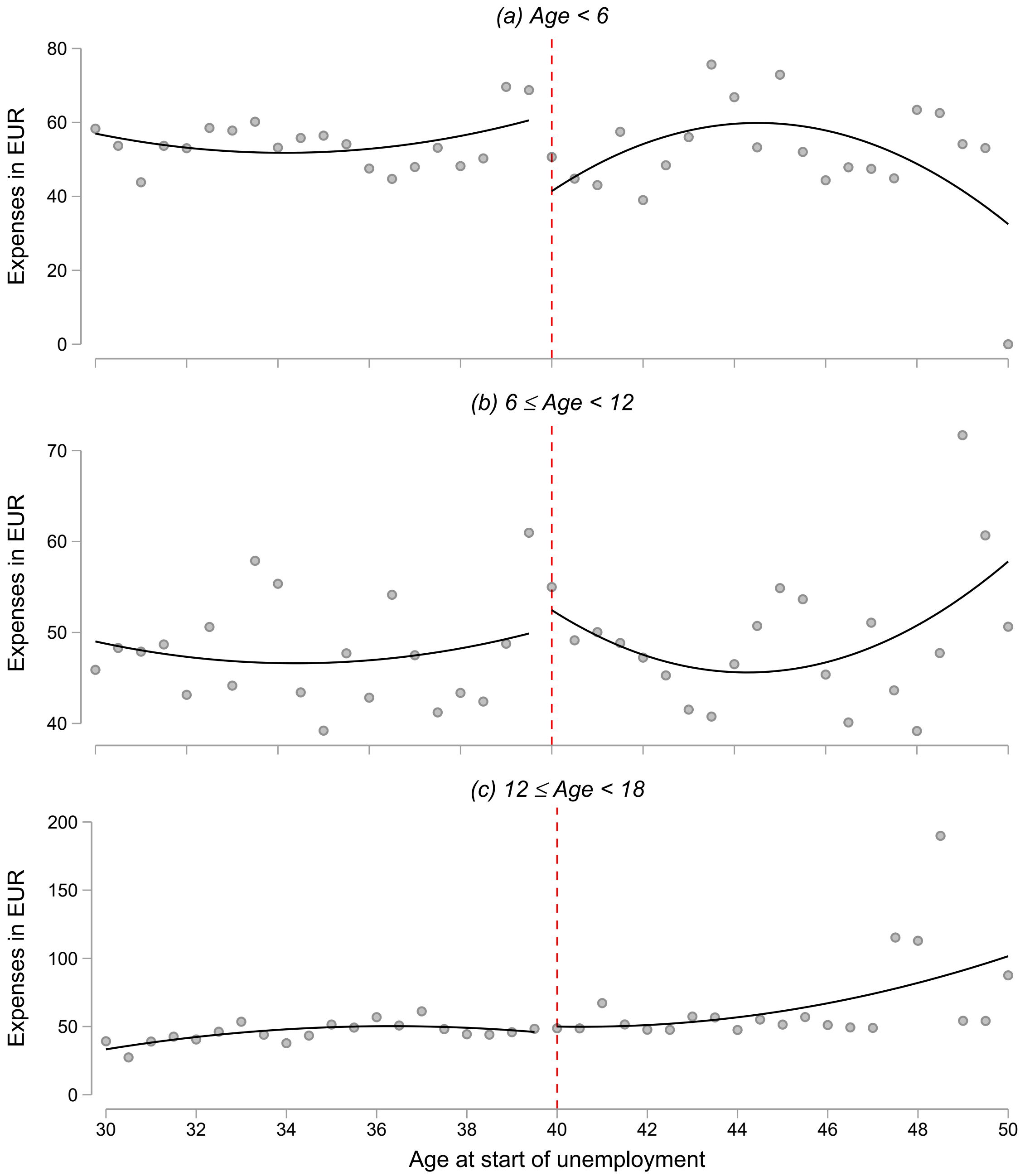
Notes: See notes for Figure 6. The outcome is the total number of inpatient hospital days for unemployed workers within 9 months of job loss.

FIGURE 9 — Effects of Extended UI Benefit Duration on Cardiac Events



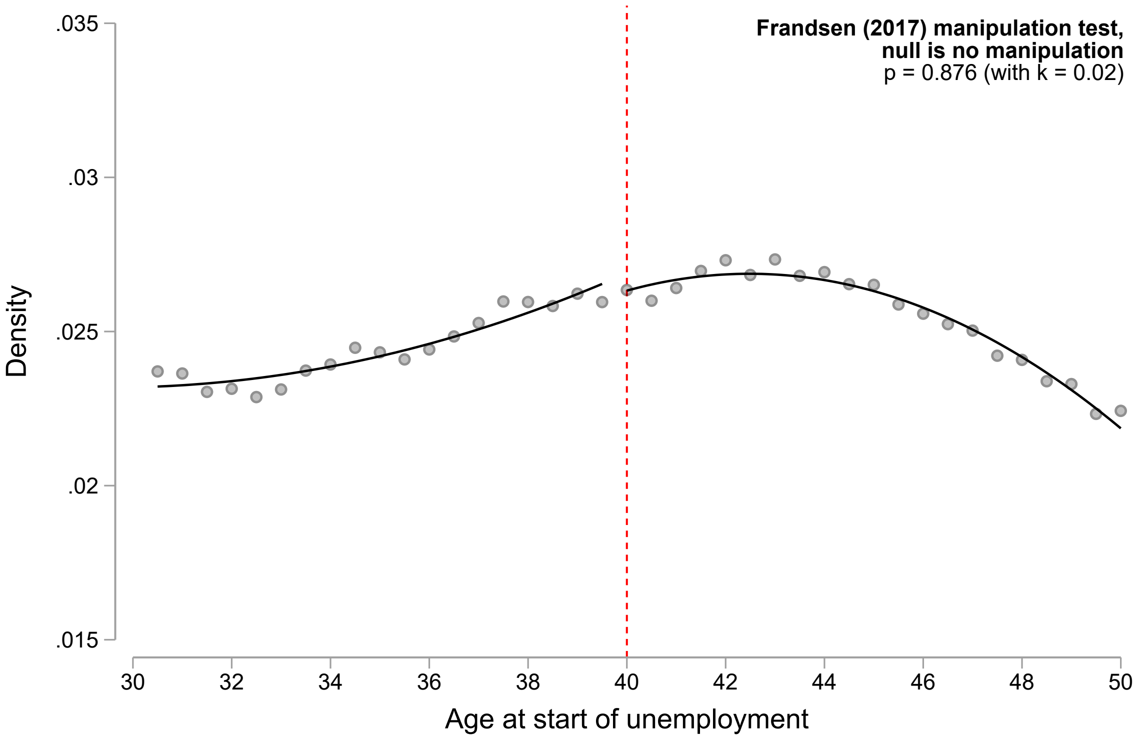
Notes: See notes for Figure 6. Cardiac events include heart attack and stroke.

Figure 10 — Effects on Outpatient and Drug Expenditure for Children of Unemployed Female Workers, by Child Age



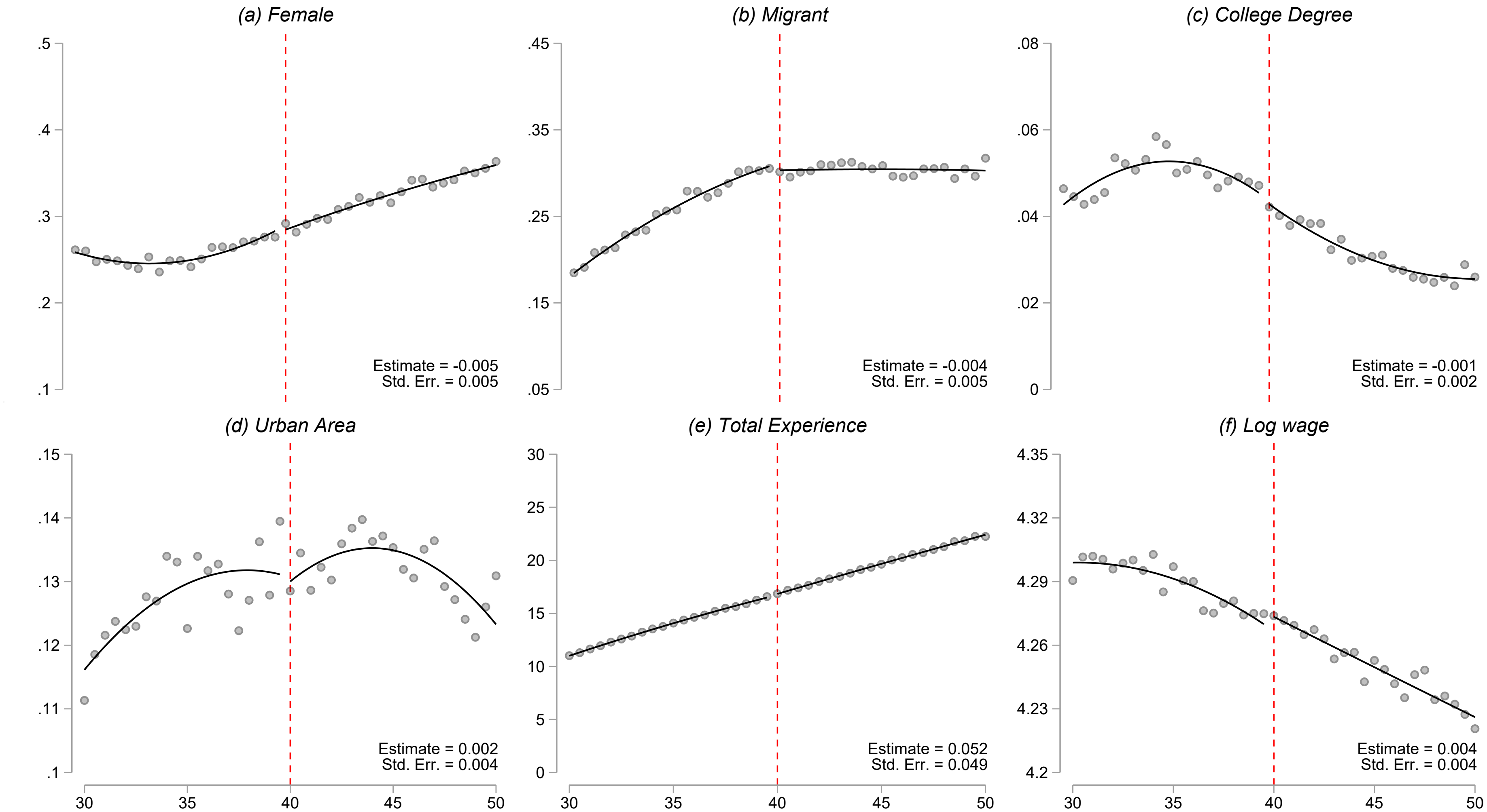
Notes: Individual-level data on unemployment insurance health events is from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. The vertical line represents the age at which workers are eligible for an additional 9 weeks of UI benefits. Age is calculated based on month of birth. Scatters represent the average residual of outpatient expenditures for each listed age group net of quarter-year fixed effects for each 6-month age bin.

Figure 11 — 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, which suggests that there is no manipulation at the cutoff.

FIGURE 12 — 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			
	Opioids	Non-opioid Painkillers	Antide-pressants
Female	0.009***	0.007***	0.039***
	(0.001)	(0.000)	(0.001)
Age fixed effects	Yes	Yes	Yes
Quarter-year fixed effects	Yes	Yes	Yes
Sample mean	0.021	0.010	0.059
(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
(c) Cardiac Events			
	Any Cardiac Event	Heart Attack	Stroke
Female	−0.0017***	−0.0017***	0.0000
	(0.0002)	(0.0002)	(0.0001)
Age fixed effects	Yes	Yes	Yes
Quarter-year fixed effects	Yes	Yes	Yes
Sample mean	0.0028	0.0019	0.0010

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 θ 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					
Opioids	0.012	0.111	0.015	0.011	−0.004***
Non-Opioid Painkillers	0.006	0.077	0.008	0.005	−0.003***
Antidepressants	0.058	0.233	0.104	0.038	−0.066***
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***
Cardiac Events					
Any Cardiac Event	0.0013	0.0361	0.0008	0.0015	0.0007***
Heart Attack	0.0010	0.0315	0.0005	0.0012	0.0007***
Stroke	0.0003	0.0178	0.0003	0.0003	0.0000
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 male and female workers separately. In Column (5), we provide the difference in means of the respective variable between females and males 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 (1)	Nonemployment (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 — Wage Effects, by Nonemployment Duration Quartiles

	Quartile 1 (1–22 Days) (1)	Quartile 2 (23–50 Days) (2)	Quartile 3 (50–93 Days) (3)	Quartile 4 (94–273 Days) (4)
(a) Females				
Discontinuity	0.025***	0.018*	0.028***	0.008
	(0.010)	(0.009)	(0.010)	(0.009)
Sample mean	3.858	3.856	3.819	3.784
(b) Males				
Discontinuity	−0.004	0.007	0.007*	−0.017***
	(0.004)	(0.004)	(0.004)	(0.005)
Sample mean	4.277	4.297	4.295	4.242

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. Columns 1–4 present separate estimates for workers' nonemployment days in quartile bins. 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 Prescriptions within 9 Months of Job Loss

	Opioids (1)	Non-opioid Painkillers (2)	Antide-pressants (3)
(a) Pooled			
Discontinuity	−0.002**	0.0004	−0.0005
	(0.0008)	(0.0005)	(0.002)
Sample mean	0.009	0.005	0.046
Observations		380,634	
(b) Females			
Discontinuity	−0.005**	0.002	−0.009*
	(0.002)	(0.001)	(0.005)
Sample mean	0.010	0.006	0.081
Observations		112,214	
(c) Males			
Discontinuity	−0.0006	−0.0002	0.003*
	(0.0009)	(0.0006)	(0.002)
Sample mean	0.009	0.004	0.033
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. Panel (a) presents estimates for all workers experiencing an unemployment spell, Panel (b) presents estimates for the sample of unemployed female workers, and Panel (c) 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 6 — Effects of Extending UI Benefits on Health Outcomes within 9 Months of Job Loss, by Subgroup (Female Workers)

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

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 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 7 — 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. 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 8 — 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 5. "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 9 — Effects of Extending UI Benefits on Cardiac Events within 9 Months of Job Loss

	Any Cardiac Event (1)	Heart Attack (2)	Stroke (3)
(a) Pooled			
Discontinuity	0.0004**	0.0003**	0.0001
	(0.0002)	(0.0002)	(0.00009)
Sample mean	0.0004	0.0003	0.0001
Observations		380,634	
(b) Females			
Discontinuity	0.0001	−0.00008	0.0002
	(0.0002)	(0.0001)	(0.0001)
Sample mean	0.0002	0.0001	0.0001
Observations		112,214	
(c) Males			
Discontinuity	0.0005**	0.0005**	0.00007
	(0.0002)	(0.0002)	(0.0001)
Sample mean	0.0005	0.0004	0.0001
Observations		268,420	

Notes: See notes for Table 5. Cardiac events include recorded hospitalizations for heart attacks and strokes.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10 — Placebo Tests

	Opioids	Non-opioid Painkillers	Antide-pressants	Inpatient Days	Cardiac Event
	(1)	(2)	(3)	(4)	(5)
Sample: 3 Months Prior to Job Loss					
Females					
Discontinuity	0.0009	0.001	−0.008	−0.03	0.0005
	(0.002)	(0.002)	(0.007)	(0.074)	(0.000)
Males					
Discontinuity	0.002	−0.0002	0.005*	0.01	0.0003
	(0.001)	(0.001)	(0.002)	(0.043)	(0.000)
Sample: Non-eligible Unemployed Workers					
Females					
Discontinuity	0.003	0.00006	0.005	−0.01	0.0001
	(0.002)	(0.001)	(0.004)	(0.05)	(0.0003)
Males					
Discontinuity	0.003	0.0001	−0.004	−0.06	0.0001
	(0.002)	(0.001)	(0.003)	(0.04)	(0.0006)

Notes: See Table 5. 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 11 — Testing Alternative Specifications (Female Workers)

	Different polynomials		Robust CIs		MHT-adjusted
	Quadratic (Baseline)	Linear	Triangular kernel	Optimal bandwidth	p-values
	(1)	(2)	(3)	(4)	(5)
(a) Wages					
Log Daily Wage	0.017**	0.022***	0.023***	0.022***	0.002
	(0.008)	(0.003)	(0.004)	(0.005)	
(b) Prescriptions					
Opioids	−0.005**	−0.004***	−0.004***	−0.006***	0.002
	(0.002)	(0.001)	(0.001)	(0.001)	
Non-Opioid Painkillers	0.002	0.0005	0.001	0.0009	0.270
	(0.001)	(0.001)	(0.001)	(0.001)	
Antidepressants	−0.009*	−0.01***	−0.01***	−0.01***	0.026
	(0.005)	(0.002)	(0.002)	(0.003)	
(c) Health Care Utilization					
Outpatient Expenditure	−0.3	−8.4***	−4.3*	−2.7	0.922
	(6.542)	(2.017)	(2.637)	(4.154)	
Outpatient Visits	0.3	−0.3	0.005	−0.2	0.718
	(0.250)	(0.184)	(0.144)	(0.228)	
Inpatient days	−0.03	0.02	−0.0002	−0.03	0.898
	(0.053)	(0.029)	(0.032)	(0.045)	
(d) Cardiac Events					
Any Cardiac Event	0.0001	−0.0001	0.000002	0.0003*	0.898
	(0.000)	(0.000)	(0.000)	(0.000)	
Stroke	0.0002	0.000007	0.0001	0.0003**	0.602
	(0.000)	(0.000)	(0.000)	(0.000)	
Heart Attack	−0.00008	−0.0001	−0.0001	−0.00009	0.898
	(0.000)	(0.000)	(0.000)	(0.000)	

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 12 — Testing Alternative Specifications (Male Workers)

	Different polynomials		Robust CIs		MHT-adjusted
	Quadratic (Baseline)	Linear	Triangular kernel	Optimal bandwidth	p-values
	(1)	(2)	(3)	(4)	(5)
(a) Wages					
Log Daily Wage	−0.001	−0.005***	0.000	0.003	0.904
	(0.003)	(0.002)	(0.002)	(0.003)	
(b) Prescriptions					
Opioids	−0.0006	−0.002***	−0.002***	−0.002**	0.896
	(0.001)	(0.000)	(0.001)	(0.001)	
Non-Opioid Painkillers	−0.0002	−0.0003	−0.0002	−0.0003	0.904
	(0.001)	(0.000)	(0.000)	(0.001)	
Antidepressants	0.003*	−0.002**	0.0007	0.002	0.122
	(0.002)	(0.001)	(0.001)	(0.001)	
(c) Health Care Utilization					
Outpatient Expenditure	−1.8	−3.4***	−2.0*	−3.2*	0.758
	(2.500)	(1.075)	(1.145)	(1.616)	
Outpatient Visits	0.1	0.04	0.1**	0.2**	0.544
	(0.084)	(0.060)	(0.055)	(0.087)	
Inpatient days	−0.06*	−0.02	−0.04*	−0.05*	0.158
	(0.033)	(0.017)	(0.019)	(0.026)	
(d) Cardiac Events					
Any Cardiac Event	0.0005**	0.0003**	0.0004**	0.0003	0.222
	(0.000)	(0.000)	(0.000)	(0.000)	
Stroke	0.00007	−0.00006	−0.000005	0.0001	0.904
	(0.000)	(0.000)	(0.000)	(0.000)	
Heart Attack	0.0005**	0.0004***	0.0004***	0.0003*	0.174
	(0.000)	(0.000)	(0.000)	(0.000)	

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

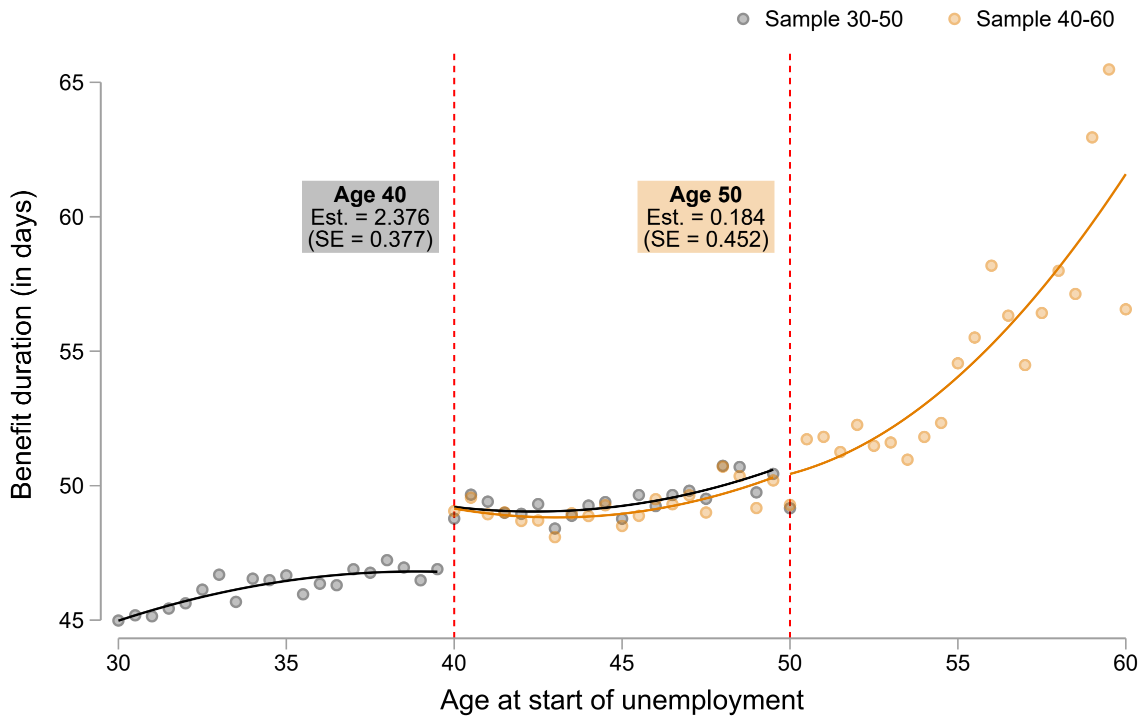
Table 13 — Effects of Extending UI Benefits on Child Health

	Outpatient Expenditure	Outpatient Visits	Inpatient Days	Disentangling Outpatient Expenditure: Preventative	Disentangling Outpatient Expenditure: Curative
	(1)	(2)	(3)	(4)	(5)
(a) Mothers					
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		
(b) Fathers					
Child Age < 6	−0.020	0.143	0.003	−0.074	0.055
	(0.549)	(0.134)	(0.003)	(0.051)	(0.525)
Sample mean	3.14	0.22	0.01	0.29	2.85
Observations			48,840		
6 ≤ Child Age < 12	−1.034*	−0.103	−0.001	−0.001	−1.033*
	(0.551)	(0.107)	(0.006)	(0.001)	(0.551)
Sample mean	3.68	0.21	0.01	0.00	3.68
Observations			82,423		
12 ≤ Child Age < 18	−0.440	−0.056	0.016*	−0.051	−0.389
	(0.609)	(0.045)	(0.008)	(0.037)	(0.606)
Sample mean	5.93	0.39	0.02	0.04	5.89
Observations			58,642		

Notes: See notes for Table 5. Panel (a) presents estimates for the sample of children with unemployed mothers, while Panel (b) presents estimates for the sample of children with unemployed fathers. Estimates are from separate regressions for each listed child age group. "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.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

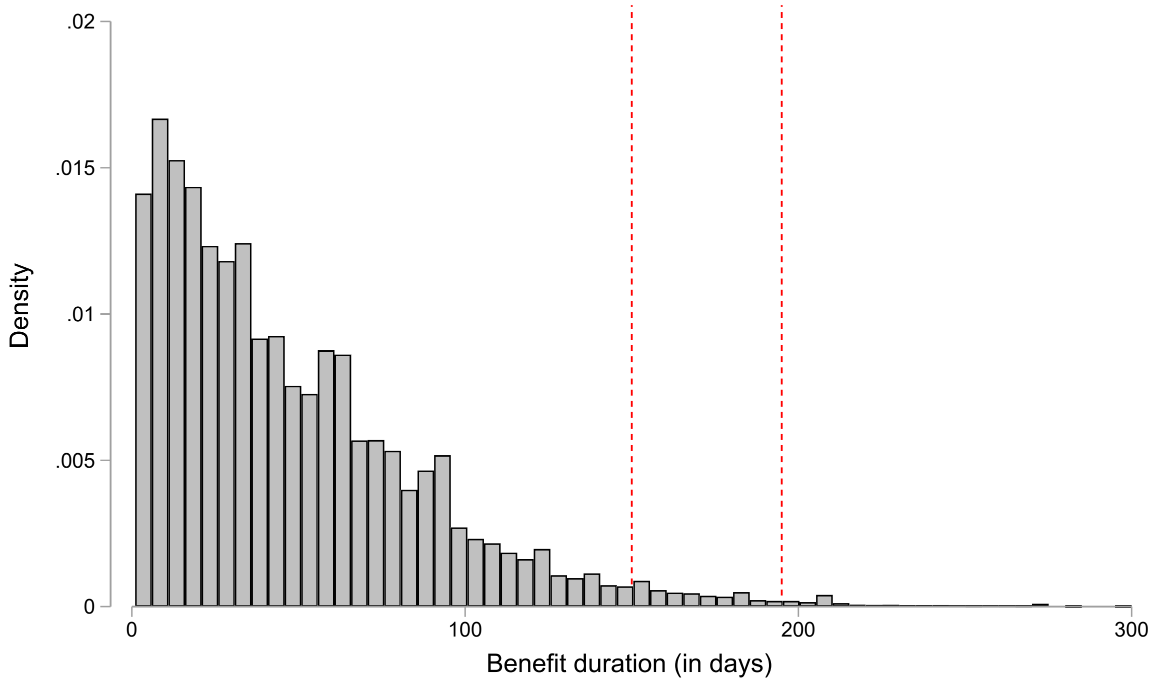
Appendix

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



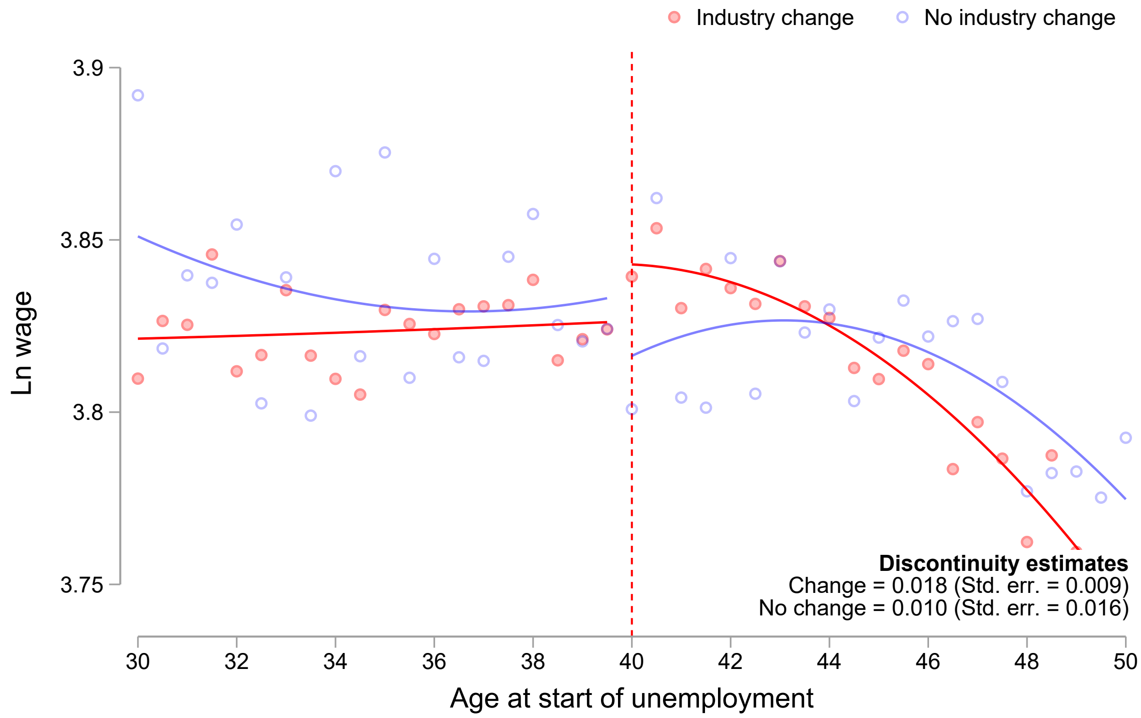
Notes: Individual-level data on unemployment insurance health events is from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. We build two samples, each being symmetric around the respective discontinuity at age 40 (our defined treatment 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 — Density of UI Benefit Duration Length, in Days



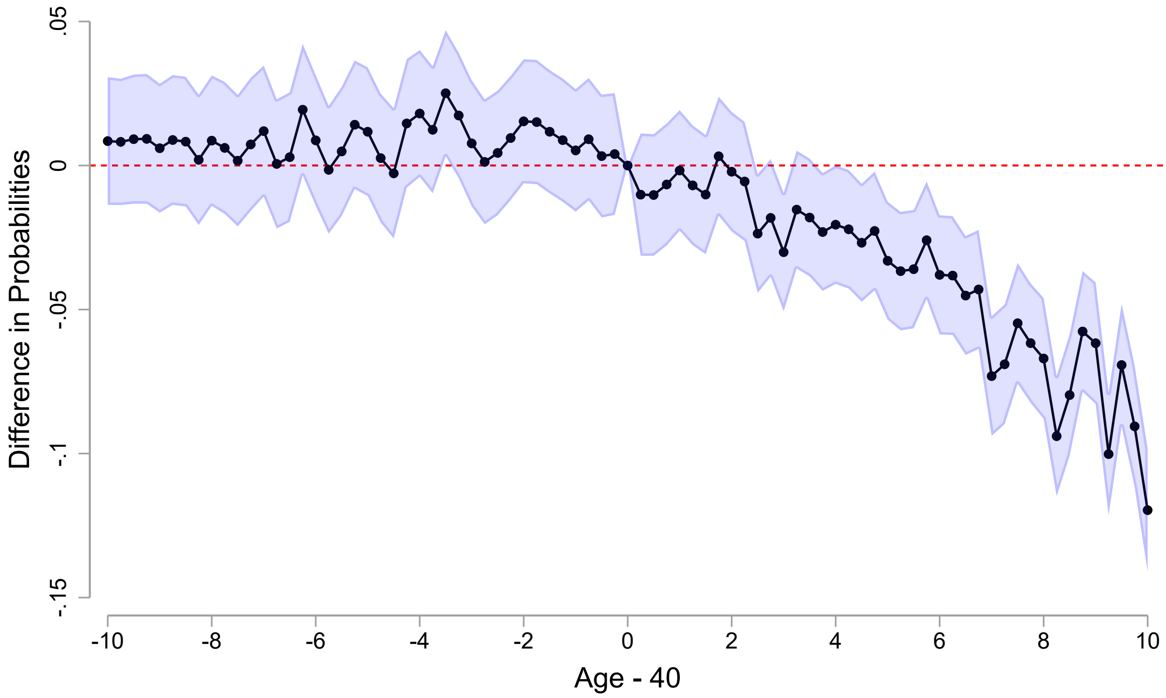
Notes: Individual-level data on unemployment insurance health events is from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. Bars represent the frequency of UI benefit duration, in days, for the full sample of unemployed workers. The vertical lines represent 30 and 39 weeks of UI benefits (paid 5 days per week).

Figure A3 — Wage Effects by Industry Change (Female Workers)



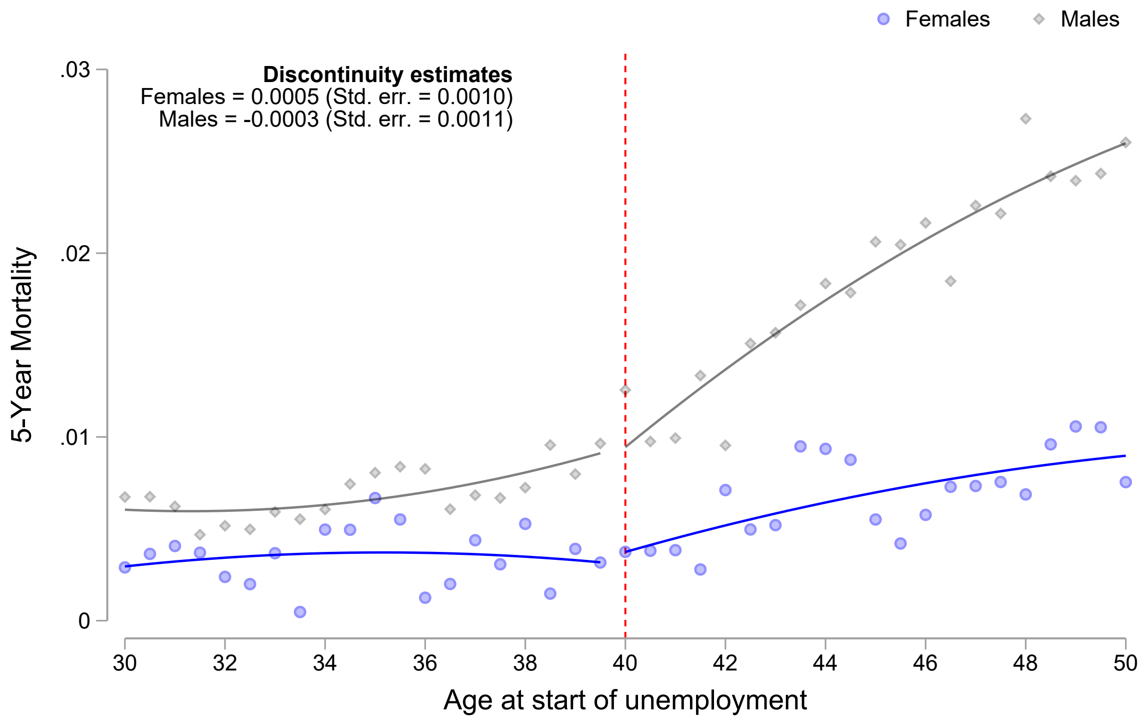
Notes: Individual-level data on unemployment insurance health events is from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. Scatters represent the mean residual of the listed outcome variable (log wage of the first job after an unemployment 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 A4 — Differences in Probabilities of Filing a Disability Claim, by Age and Gender



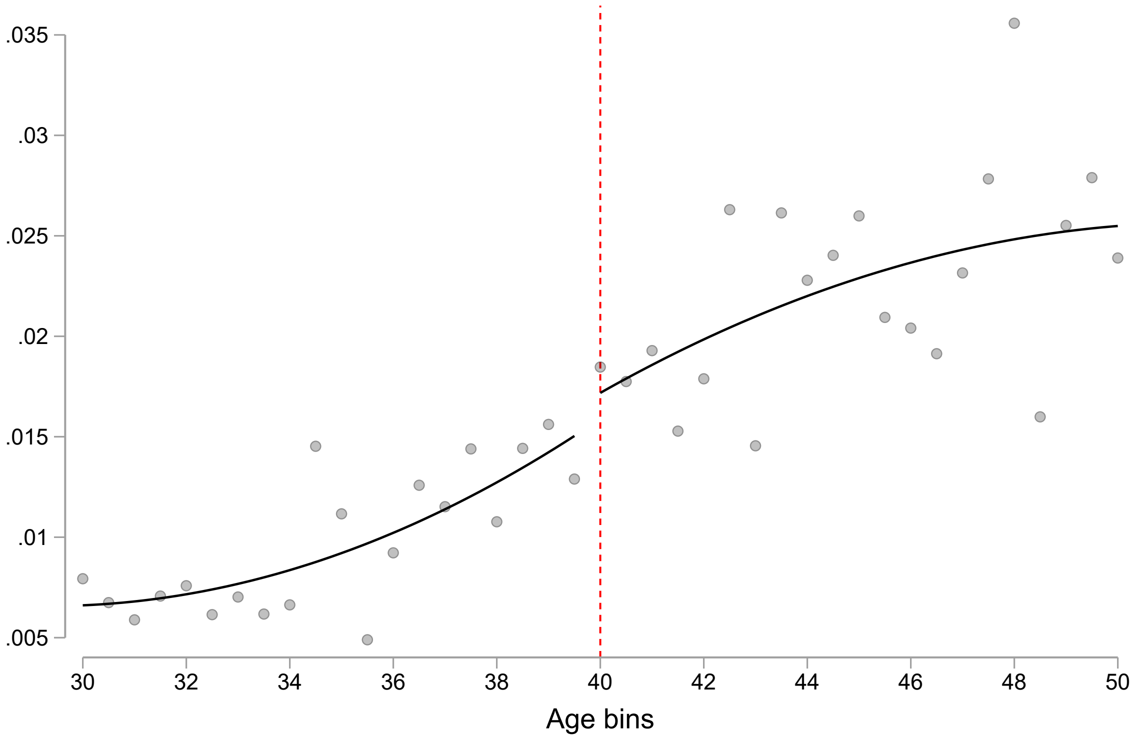
Notes: Event study coefficients and their respective 95% confidence intervals are generated from the following regression estimated using OLS: $y_i = \sum_{k=-10|t\neq-1}^{10} \beta_k(female_i \times age_k) + female_i + \sum_k age_k + \epsilon_{ik}$, where y represents the outcome “filing for disability 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 A5 — Effects on Mortality, Within 5 years of Receiving UI Benefits



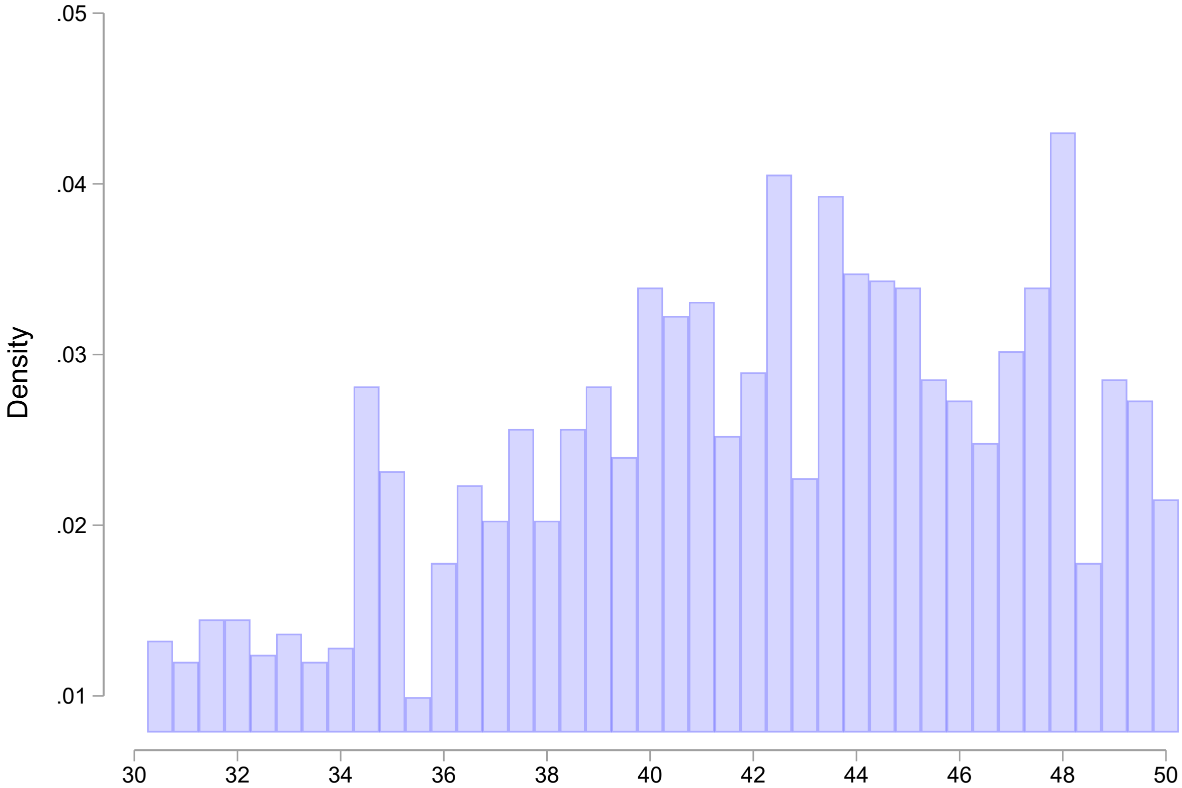
Notes: See notes for Figure 6. The outcome variable is whether a worker dies within five years of receiving UI payments.

Figure A6 — Probability of Having an Opioid Prescription, Ineligible Sample (Female Workers)



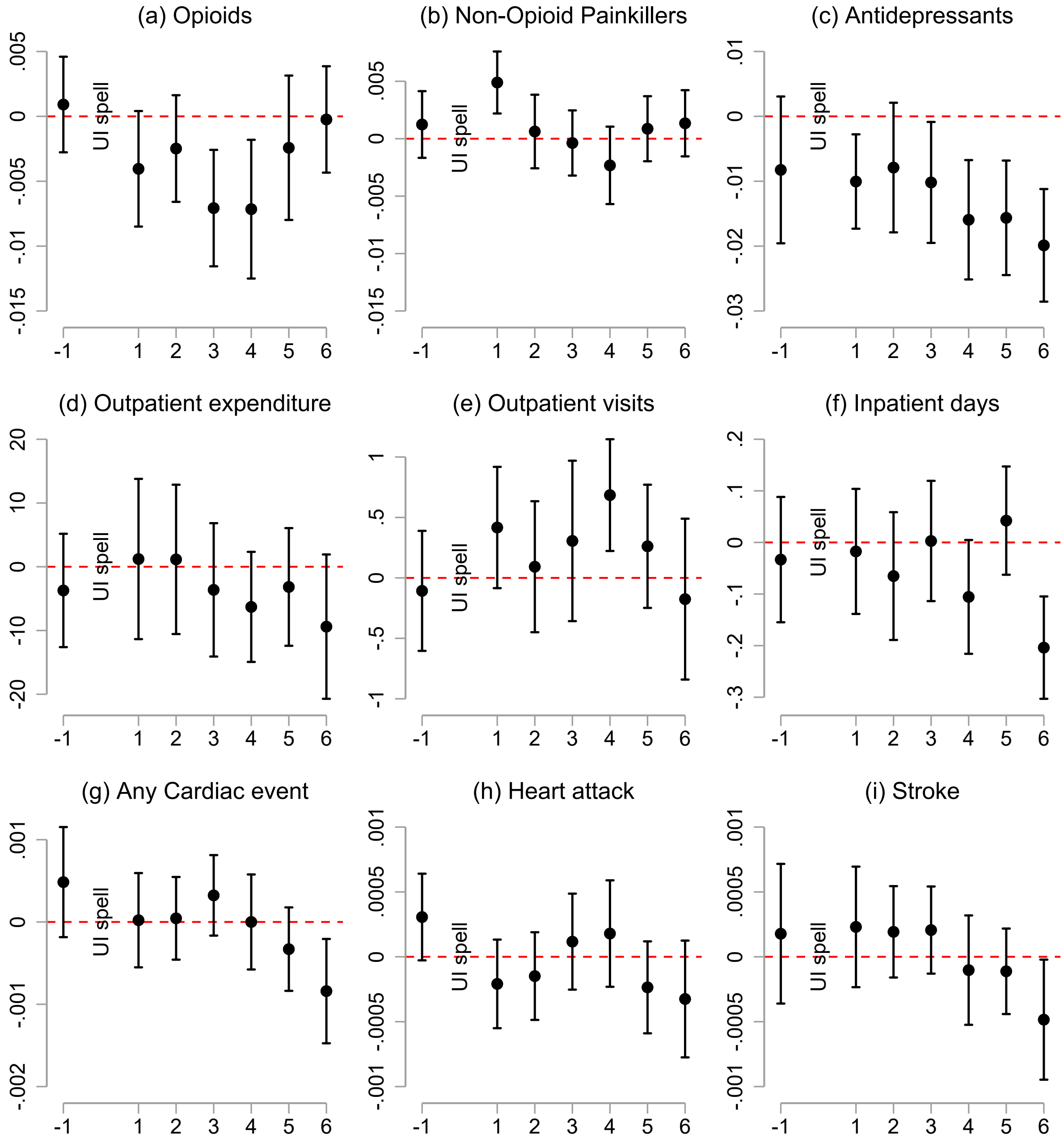
Notes: See notes for Figure 6. The outcome variable is an indicator variable equal to one if a worker received an opioid prescription within 9 months after job loss. The sample includes only female workers that are ineligible for the UI extension, as determined by the experience criterion.

Figure A7 — Age Distribution of All Female Opioid Users



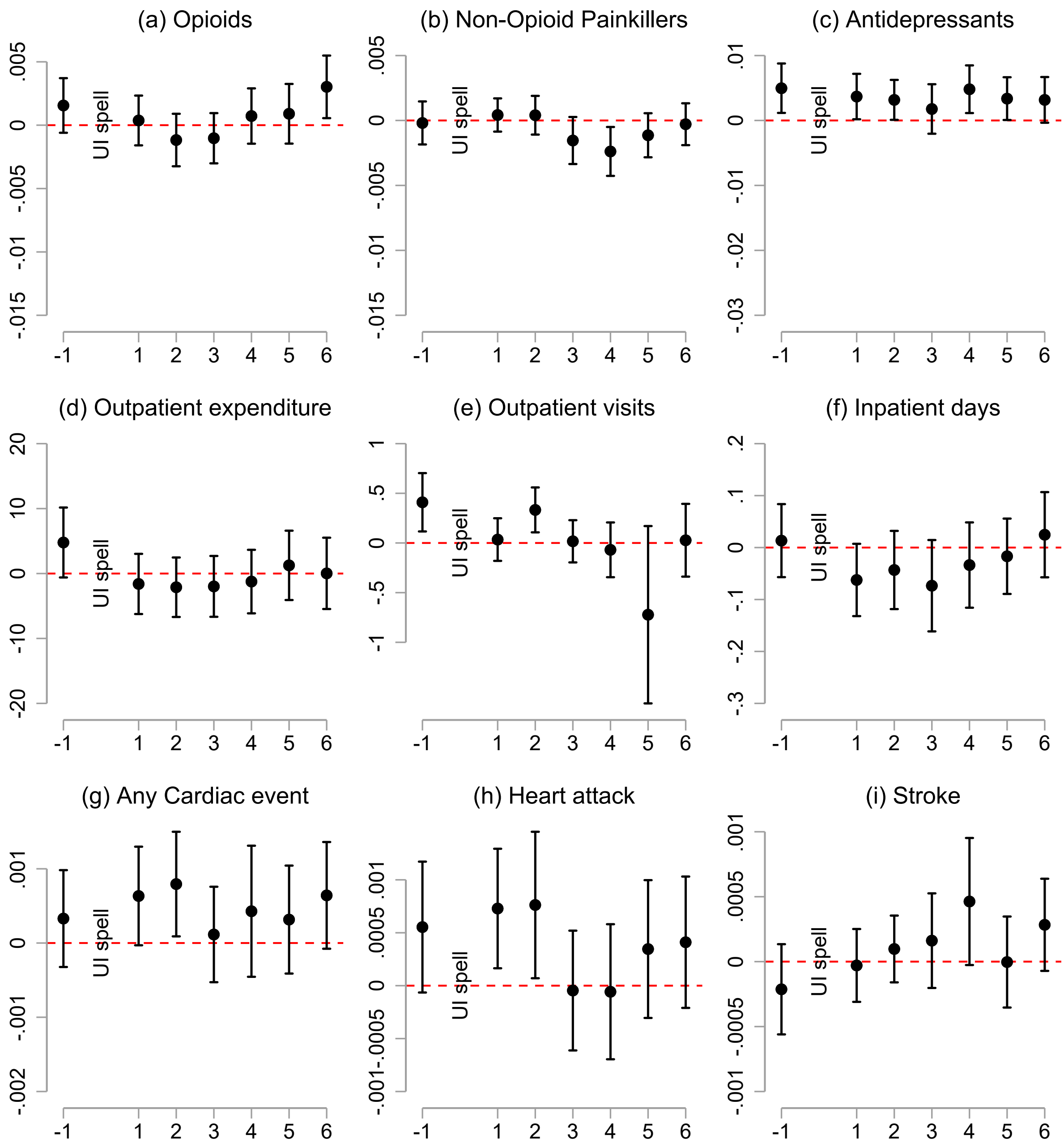
Notes: Individual-level data on unemployment insurance health events is from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. The y-axis displays the frequency of opioid prescriptions, by age. The sample includes all female workers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

Figure A8 — Effects of UI Extensions on Health Outcomes By Quarter Relative to Job Loss (Female Workers)



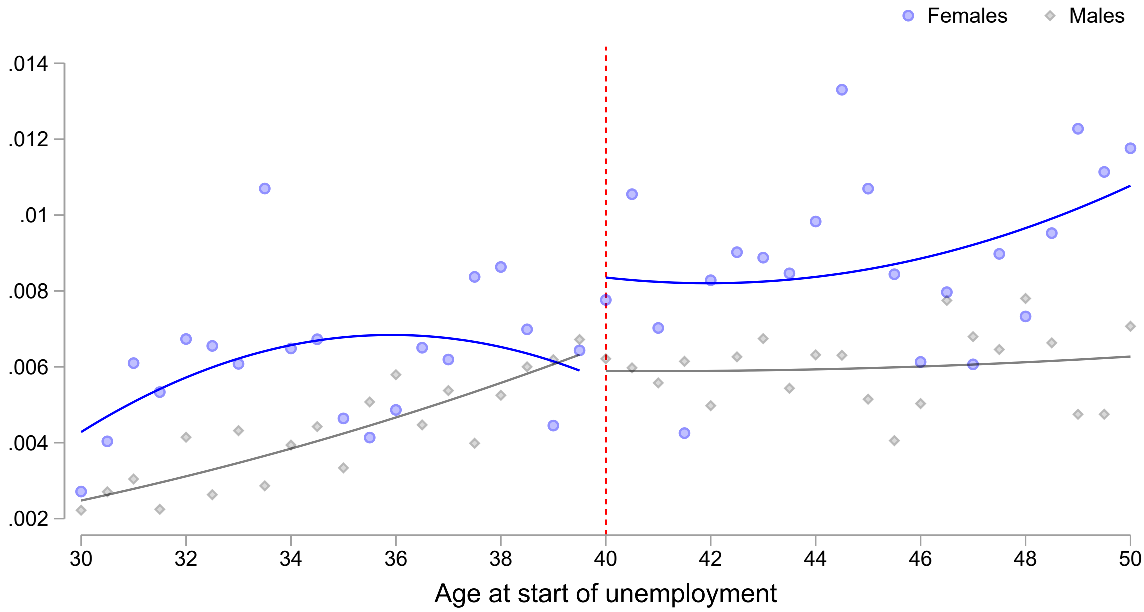
Notes: Individual-level data on unemployment insurance health events is from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. Each scatter represents a coefficient of the main variable of interest from Equation (1), using quarterly data. The vertical lines represent corresponding 95% confidence intervals based on age-bin clustered standard errors. An x-axis value of "i" where $i = -1, 0, 1, \ldots 6$ 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 A9 — Effects of UI Extensions on Health Outcomes By Quarter Relative to Job Loss (Male Workers)



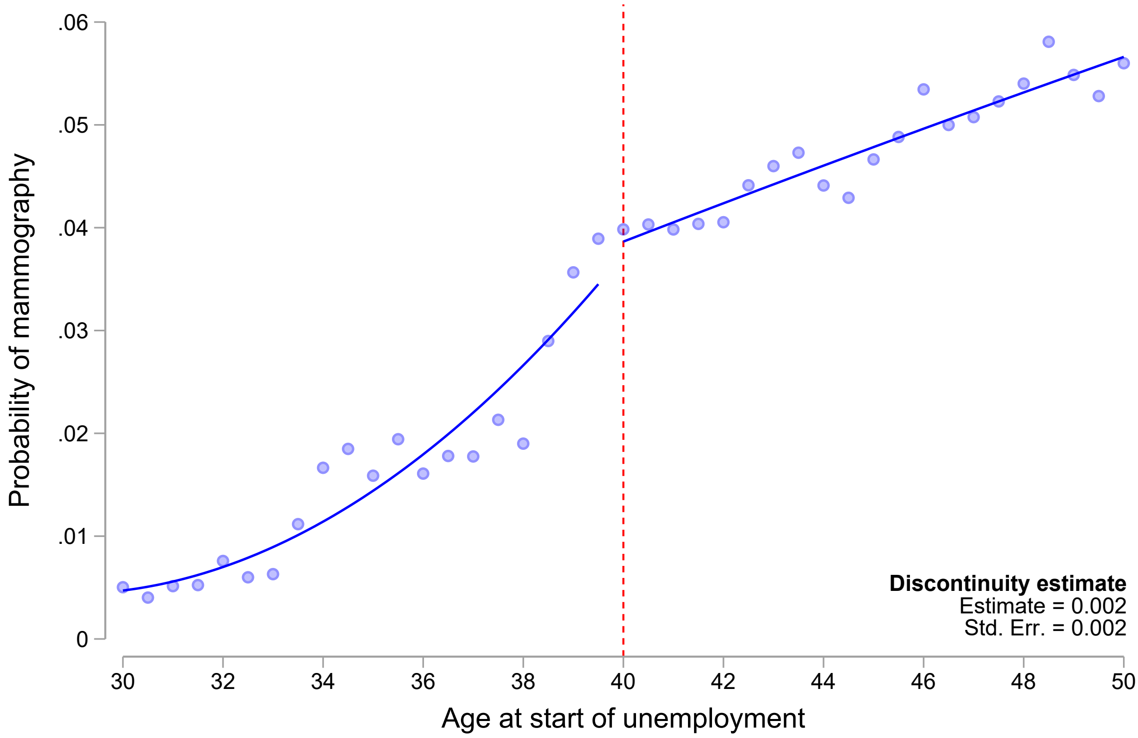
Notes: Individual-level data on unemployment insurance health events is from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. Each scatter represents a coefficient of the main variable of interest from Equation (1), using quarterly data. The vertical lines represent corresponding 95% confidence intervals based on age-bin clustered standard errors. An x-axis value of "i" where $i = -1, 0, 1, \ldots 6$ 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 A10 — Effects of Extended UI Benefit Duration on the Probability of Being Prescribed Non-Opioid Pain Drugs



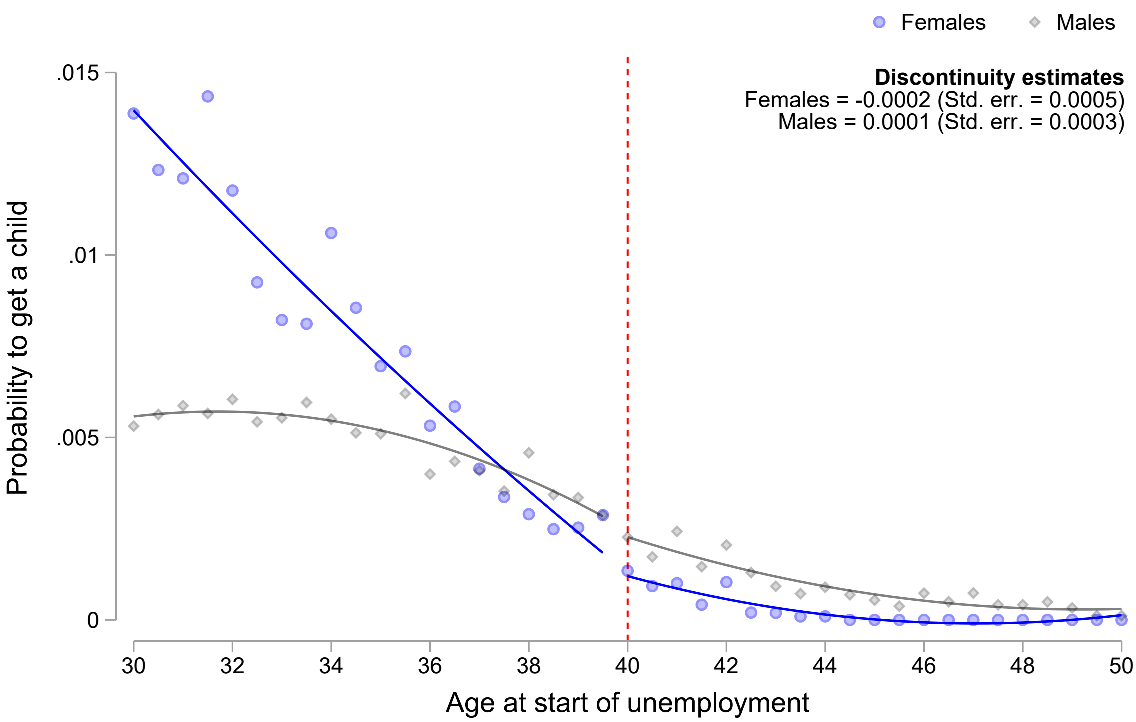
Notes: See notes for Figure 6. Non-opioid analgesics include non-habit-forming pain medication such as nonsteroidal anti-inflammatory drugs and acetaminophen. For a full list of ATC code N medications, see `https://www.whocc.no/atc_ddd_index`.

FIGURE A11 — Probability of Mammography (Female Workers)



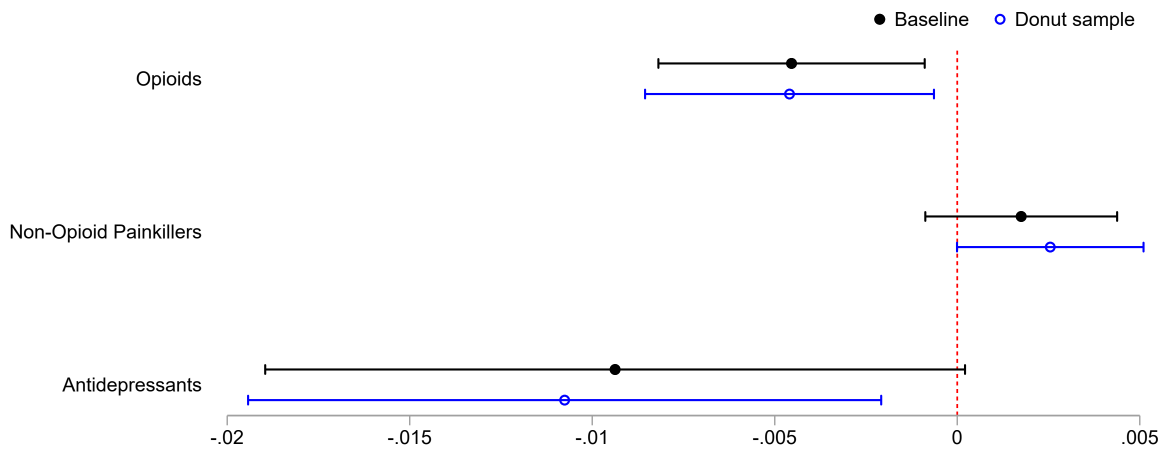
Notes: See Figure 6. Mammographies are recorded in the data and are considered under "screenings", or preventative care. The outcome variable is an indicator variable equal to one if a female worker received a mammography within 9 months after job loss.

FIGURE A12 — Probability of Having a Baby



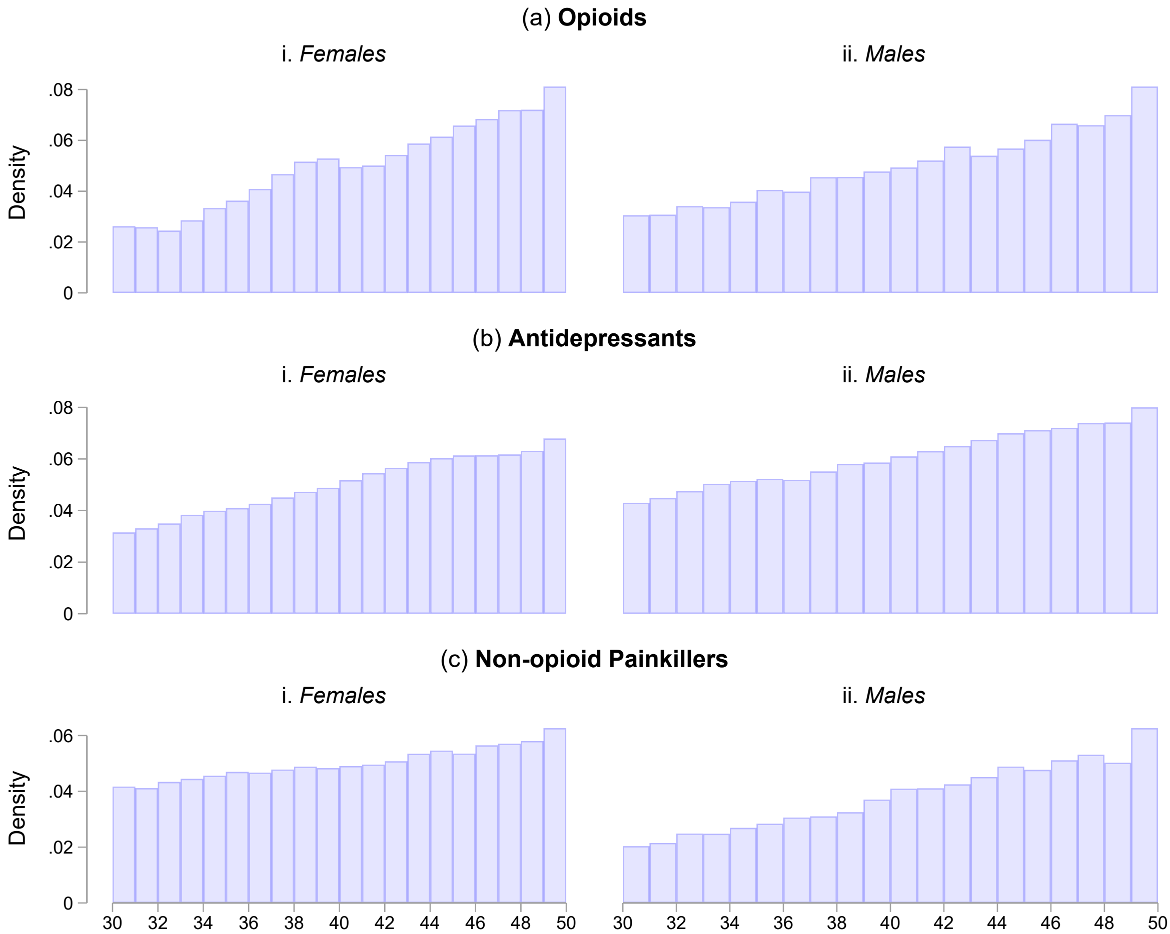
Notes: See Figure 6. The outcome variable is an indicator variable equal to one if a worker (male or female) was registered on newborn's birth certificate within 9 months after job loss.

FIGURE A13 — Difference-in-RD Estimates on Prescriptions Leaving out a Donut Sample (Female Workers)



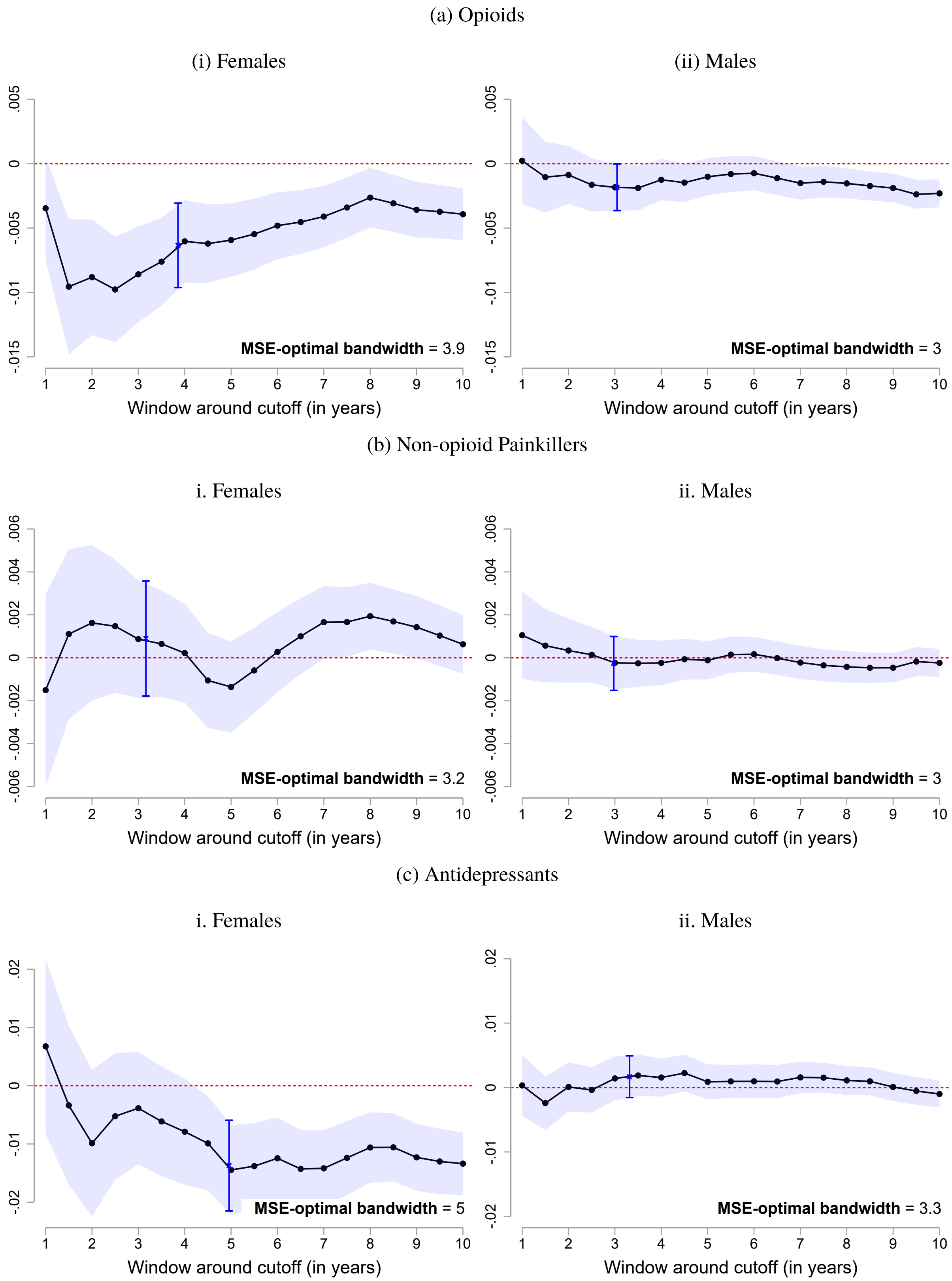
Notes: Individual-level data on unemployment insurance health events is from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. The donut sample omits workers that become unemployed withing a one-quarter-year window around the cutoff. The solid black dots resemble the baseline estimates from Table 5, 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.

Figure A14 — 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 number of observations by age bin. Age is based on date of prescription purchase.

Figure A15 — Estimated Effects on Prescriptions Across Bandwidths

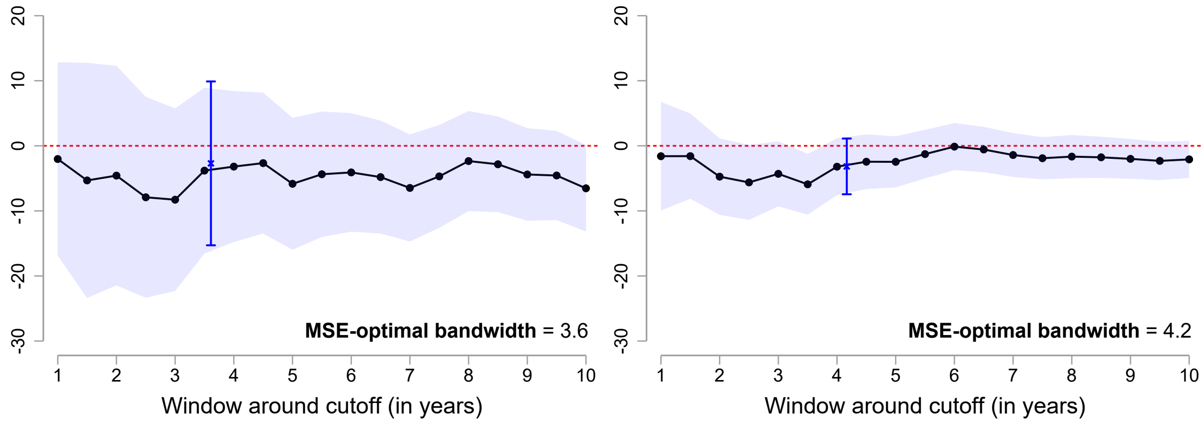


Notes: Individual-level data on unemployment insurance health events is from linked Upper Austrian Health Insurance Fund database files and Austrian Social Security Database files from 2003–2013. Each figure shows estimates and their 95% confidence intervals from our preferred specification (Equation 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 A16 — Estimated Effects on Health Care Utilization Across Bandwidths

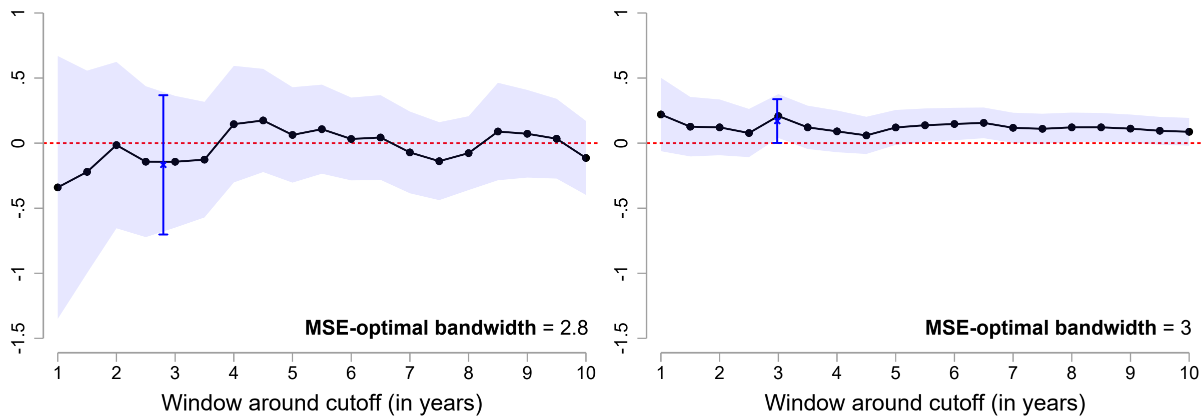
(a) Outpatient Expenditure

i. Females ii. Males



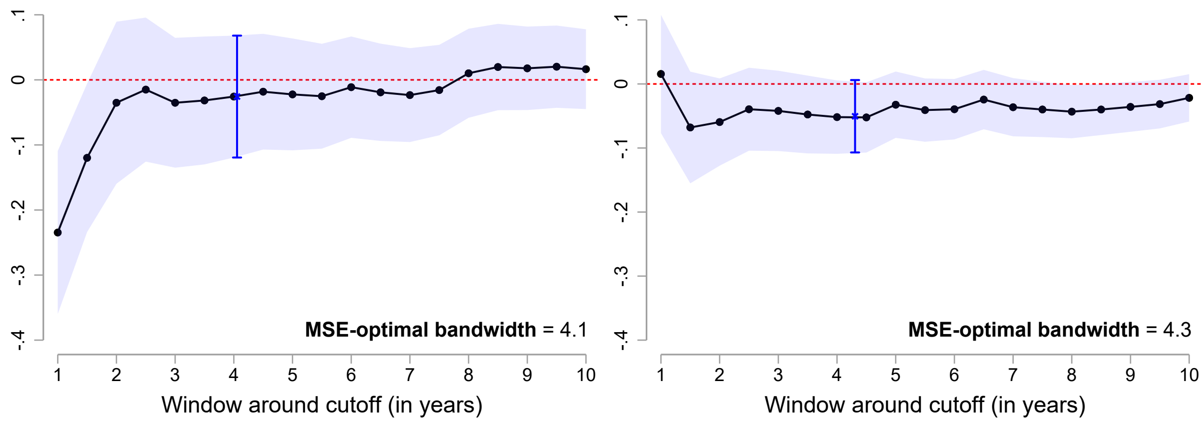
(b) Outpatient Visits

i. Females ii. Males



(c) Inpatient Days

i. Females ii. Males

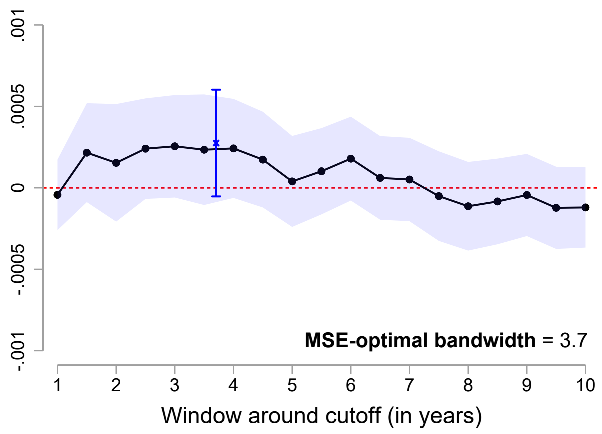


Notes: See notes for Figure A15. “Outpatient Expenditure" denotes the total amount spent, in Euros, on doctor’s visits. “Outpatient Visits" include the number of visits to a physician. “Inpatient Days" include the number of days spent in a hospital.

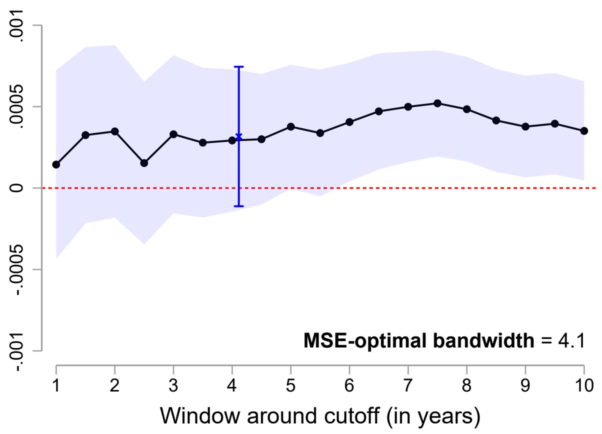
Figure A17 — Estimated Effects on Cardiac Events Across Bandwidths

(a) Any Cardiac Event

i. Females

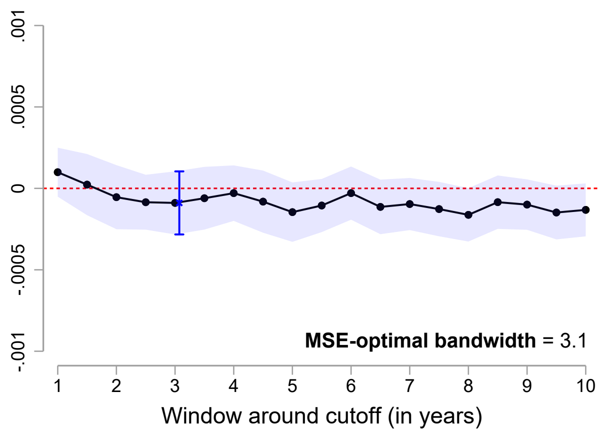


ii. Males

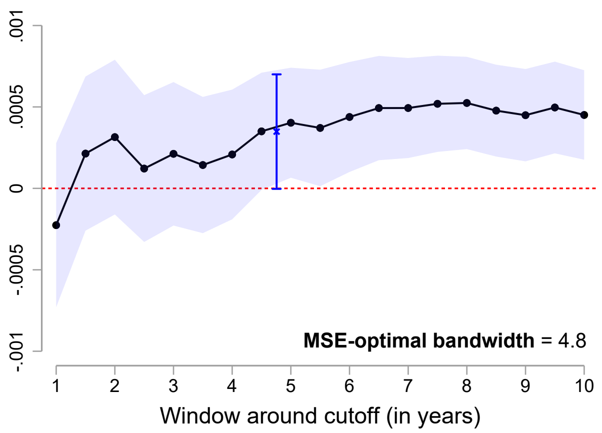


(b) Heart Attack

i. Females

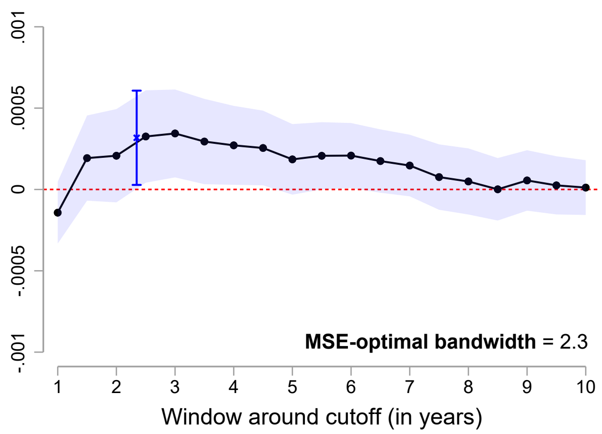


ii. Males

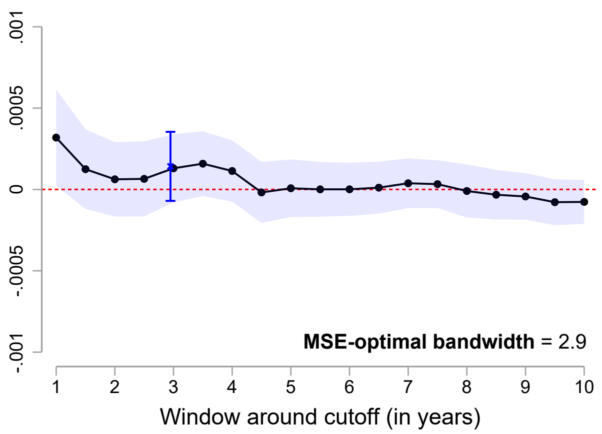


(c) Stroke

i. Females



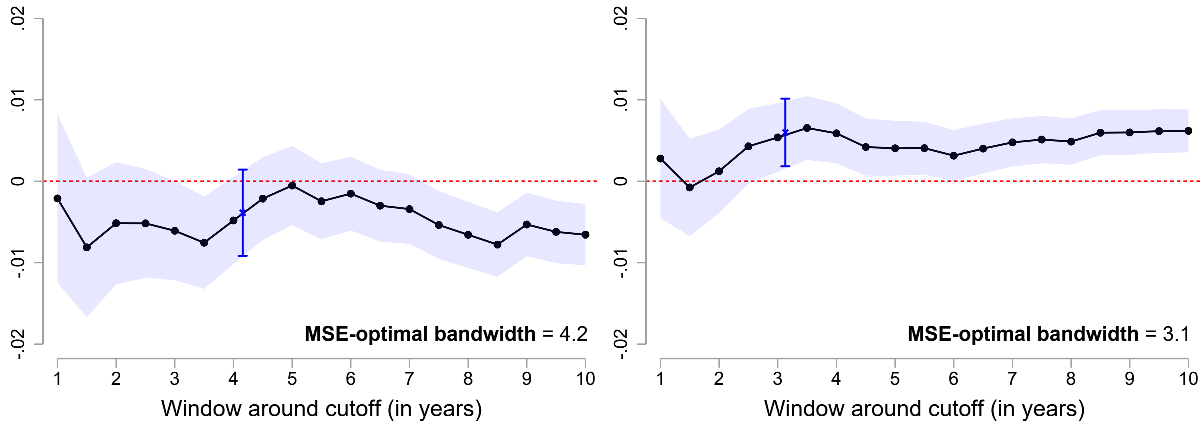
ii. Males



Notes: See notes for Figure A15. Cardiac events include recorded hospitalizations for heart attacks and strokes.

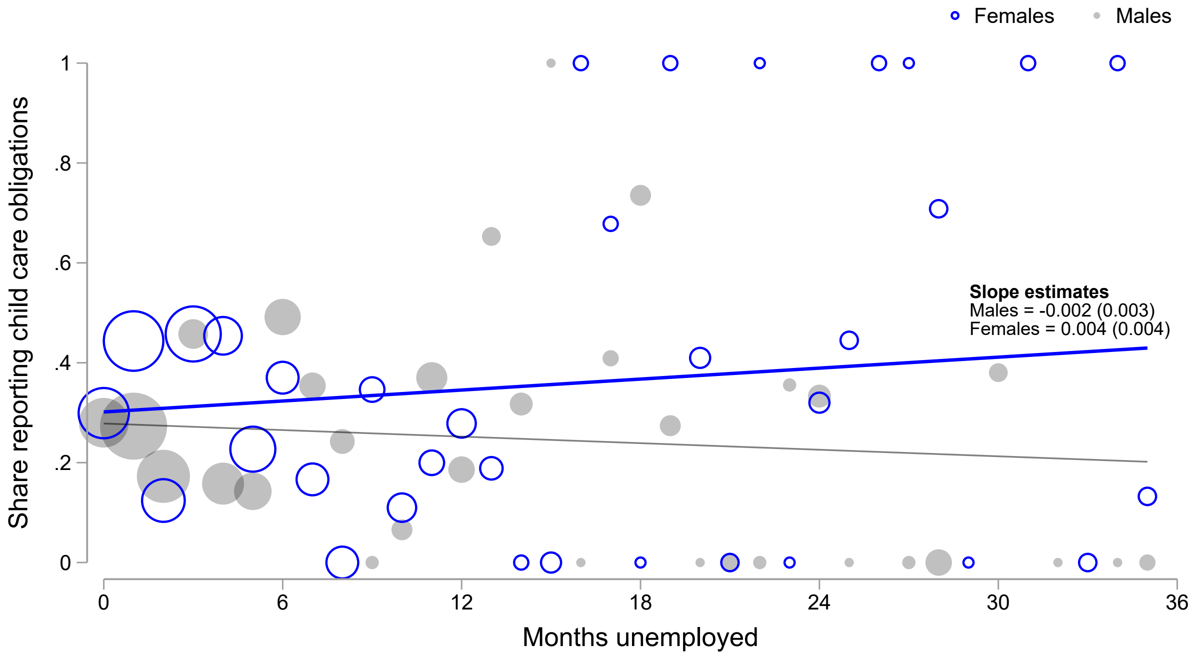
FIGURE A18 — Effects of Extended UI Benefit Duration on the Probability of Disability Claims with Different Bandwidths

(a) Females (b) Males



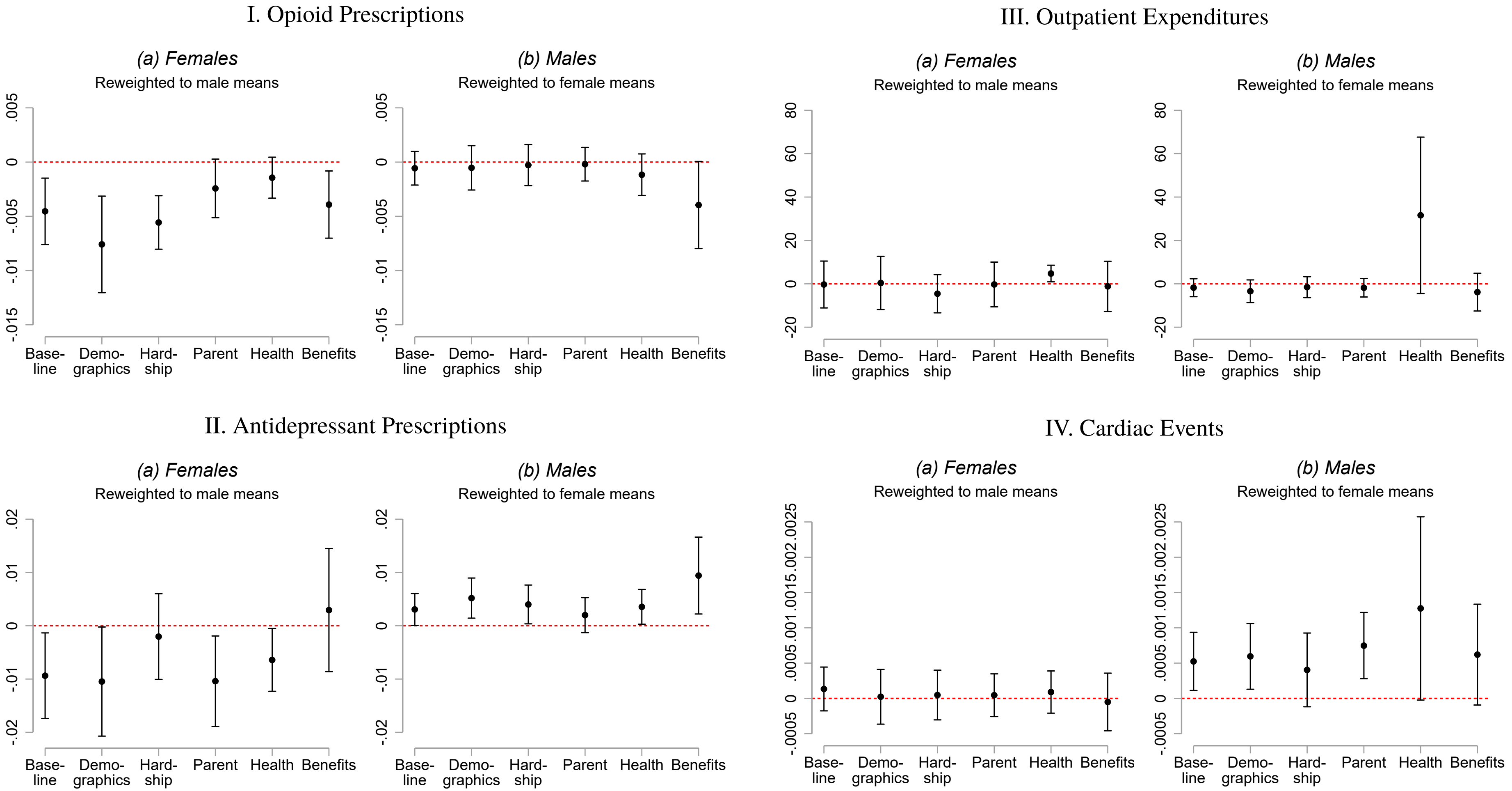
Notes: See notes for Figure A15.

FIGURE A19 — Gender Differences in Childcare Obligations



Notes: Data from the 2018 Austrian Microcensus, only people who participated in the ad hoc module "Reconciliation of work and family" (N = 22,604). Note that participating in the census is mandatory, while answering the ad hoc module is not. This figure plots means for answers to the question "Do you have any childcare obligations?" within unemployment duration bins, weighted by the number of unemployed people in each bin.

Figure A20 — RDD Estimates Based on Across-Gender Balanced Samples



Notes: See Figure 6. 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 opioid 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 Extending UI Benefits on Health, Using a Model with Interaction Terms

	(1)	(2)	(3)
(a) Log Wages			
Discontinuity	−0.0015		
	(0.0034)		
Female	−0.5854		
	(0.3652)		
Discontinuity × female	0.0186**		
	(0.0083)		
(b) Prescriptions			
	Opioids	Non-opioid Painkillers	Antide-pressants
Discontinuity	−0.001	0.000	0.003*
	(0.001)	(0.001)	(0.002)
Female	0.201***	−0.038	−0.007
	(0.069)	(0.055)	(0.214)
Discontinuity × female	−0.004*	0.002	−0.012**
	(0.002)	(0.002)	(0.006)
(c) 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)
(d) Cardiac Events			
	Any Cardiac Event	Heart Attack	Stroke
Discontinuity	0.0005**	0.0005**	0.0001
	(0.0002)	(0.0002)	(0.0001)
Female	−0.0074	−0.0083	0.0009
	(0.0086)	(0.0076)	(0.0049)
Discontinuity × female	−0.0004	−0.0006**	0.0001
	(0.0003)	(0.0003)	(0.0002)

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, β_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, Panel (b) presents estimates for the listed health care utilization variables, and Panel (c) presents estimates for cardiac events. 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 A2 — Effects of Extending UI Benefits on Prescriptions within 3–18 Months of Job Loss

	Opioids (1)	Non-opioid Painkillers (2)	Antide-pressants (3)
(a) Female Workers			
3 Months	−0.004*	0.005***	−0.01**
	(0.003)	(0.002)	(0.004)
6 Months	−0.003*	0.003*	−0.009*
	(0.002)	(0.002)	(0.005)
9 Months	−0.005**	0.002	−0.009*
	(0.002)	(0.001)	(0.005)
12 Months	−0.005**	0.0008	−0.01**
	(0.002)	(0.001)	(0.005)
15 Months	−0.005**	0.0008	−0.01**
	(0.002)	(0.001)	(0.005)
18 Months	−0.004**	0.0009	−0.01***
	(0.002)	(0.001)	(0.005)
(b) Male Workers			
3 Months	0.0004	0.0004	0.004*
	(0.001)	(0.0008)	(0.002)
6 Months	−0.0004	0.0004	0.004*
	(0.001)	(0.0006)	(0.002)
9 Months	−0.0006	−0.0002	0.003*
	(0.0009)	(0.0006)	(0.002)
12 Months	−0.0002	−0.0007	0.004**
	(0.0009)	(0.0006)	(0.002)
15 Months	−0.00002	−0.0008	0.004**
	(0.0009)	(0.0006)	(0.002)
18 Months	0.0005	−0.0007	0.004**
	(0.0009)	(0.0006)	(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. 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, based on an expanded 6-month window after an unemployment spell. 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 A3 — 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 5. “Weak" opioids include opoids 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 A4 — Effects of Extending UI Benefits on Health Outcomes within 9 Months of Job Loss, by Subgroup (Male Workers)

	Prescriptions			Health Care Utilization		
	Opioids	Non-opioid Painkillers	Antide-pressants	Outpatient Expenditure	Outpatient Visits	Inpatient Days
	(1)	(2)	(3)	(4)	(5)	(6)
(a) Parent						
No (n = 146,038)	−0.002	−0.002**	0.006**	−1.9	0.2	−0.05
	(0.001)	(0.001)	(0.003)	(3.442)	(0.138)	(0.051)
Yes (n = 122,382)	0.0007	0.001	−0.00004	−1.8	0.1	−0.06
	(0.001)	(0.001)	(0.003)	(3.336)	(0.128)	(0.038)
(b) Low skilled occupation						
Yes (n = 188,607)	0.0002	0.00003	0.003	0.7	0.2*	−0.07*
	(0.001)	(0.001)	(0.002)	(3.044)	(0.106)	(0.036)
No (n = 79,813)	−0.002*	−0.0006	0.003	−7.4*	0.01	−0.03
	(0.001)	(0.001)	(0.003)	(4.176)	(0.137)	(0.058)
(c) Receives hardship allowance						
Yes (n = 174,642)	0.0002	0.0003	−0.0009	−3.2	0.1	−0.02
	(0.001)	(0.001)	(0.002)	(3.074)	(0.087)	(0.030)
No (n = 70,622)	−0.0007	−0.002	0.008**	−0.05	0.1	−0.1*
	(0.002)	(0.002)	(0.004)	(4.853)	(0.167)	(0.065)
(d) Part-Time						
Yes (n = 31,996)	−0.009**	−0.0002	−0.008	−1.7	−0.5**	−0.2***
	(0.004)	(0.002)	(0.007)	(6.367)	(0.203)	(0.080)
No (n = 213,243)	0.001	−0.0005	0.003	−2.5	0.2**	−0.02
	(0.001)	(0.001)	(0.002)	(2.780)	(0.087)	(0.033)
(e) Low Education						
Yes (n = 224,902)	−0.001	−0.0003	0.0003	−3.8	0.02	−0.07**
	(0.001)	(0.001)	(0.002)	(2.790)	(0.098)	(0.035)
No (n = 36,826)	0.01***	0.006***	0.02***	33.8***	1.4***	0.03
	(0.004)	(0.002)	(0.008)	(9.204)	(0.372)	(0.102)

Notes: See notes for Table 6. Estimates are for the sample of unemployed male workers.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5 — Effects of Longer UI Duration on Total Prescriptions

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

Notes: See Table 5. The outcome variables in each column represent the total number of packages prescribed for each type of drug, including zeroes.

TABLE A6 — Effects of Longer UI Duration on the Number of Packages Prescribed, Conditional on Receiving a Prescription

	Opioids (1)	Non-opioid Painkillers (2)	Antide-pressants (3)
(a) Pooled			
Discontinuity	0.19	0.07	−0.04
	(0.15)	(0.07)	(0.06)
Sample mean	2.20	1.46	2.38
Observations	2,964	1,502	8,035
(b) Females			
Discontinuity	0.26	0.14	−0.04
	(0.27)	(0.16)	(0.07)
Sample mean	2.09	1.53	2.39
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 5. The outcome variables represent marginal effects, conditional on a patient receiving at least one prescription.

Table A7 — Effects of Extending UI Benefits on Cardiac Events within 9 Months of Job Loss, by Subgroup (Male Workers)

	Any Cardiac Event (1)	Heart Attack (2)	Stroke (3)
(a) Parent			
Yes (n = 122,382)	0.001***	0.0007**	0.0005***
	(0.0004)	(0.0004)	(0.0001)
No (n = 146,038)	–0.0002	0.0002	–0.0003
	(0.0003)	(0.0003)	(0.0002)
(b) Low-Skilled Occupation			
Yes (n = 188,607)	0.0004	0.0003	0.0002
	(0.0003)	(0.0003)	(0.0001)
No (n = 79,813)	0.0009	0.001**	–0.0001
	(0.0006)	(0.0005)	(0.0002)
(c) Job with Hardship			
Yes (n = 181,598)	0.0004	0.0002	0.0001
	(0.0003)	(0.0003)	(0.0002)
No (n = 73,021)	0.0004	0.0009*	–0.0003
	(0.0005)	(0.0005)	(0.0003)
(d) Part-Time			
Yes (n = 33,409)	–0.0008	–0.0005	–0.0003
	(0.0007)	(0.0006)	(0.0005)
No (n = 221,180)	0.0006*	0.0006**	0.00004
	(0.0003)	(0.0003)	(0.0001)
(e) Low Education			
Yes (n = 224,902)	0.0005*	0.0004	0.0001
	(0.0003)	(0.0002)	(0.0001)
No (n = 36,826)	0.001	0.002**	–0.0003
	(0.0008)	(0.0008)	(0.0003)

Notes: See notes for Table 6. Estimates are for a sample of unemployed male workers. Cardiac events include heart attacks and strokes.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A8 — Effects of Extending UI Benefits on Cardiac Events within 3–18 Months of Job Loss

	Any Cardiac Event	Heart Attack	Stroke
(a) Female Workers			
3 Months	0.00002	−0.0002	0.0002
	(0.0003)	(0.0002)	(0.0003)
6 Months	0.00004	−0.0002	0.0002
	(0.0002)	(0.0001)	(0.0002)
9 Months	0.0001	−0.00008	0.0002
	(0.0002)	(0.0001)	(0.0001)
12 Months	0.0001	−0.00001	0.0001
	(0.0002)	(0.0001)	(0.0001)
15 Months	0.00003	−0.00005	0.00009
	(0.0002)	(0.0001)	(0.0001)
18 Months	−0.0001	−0.00010	0.000002
	(0.0002)	(0.0001)	(0.0001)
(b) Male Workers			
3 Months	0.0006	0.0007**	−0.00003
	(0.0004)	(0.0003)	(0.0002)
6 Months	0.0007**	0.0007***	0.00003
	(0.0003)	(0.0003)	(0.0001)
9 Months	0.0005**	0.0005**	0.00007
	(0.0002)	(0.0002)	(0.0001)
12 Months	0.0005**	0.0004*	0.0002
	(0.0002)	(0.0002)	(0.0001)
15 Months	0.0005**	0.0004*	0.0001
	(0.0002)	(0.0002)	(0.00010)
18 Months	0.0005**	0.0004*	0.0002*
	(0.0002)	(0.0002)	(0.00009)

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, based on a expanded 6-month window after an unemployment spell. Robust standard errors are clustered on the age bin level and are shown in parentheses. Cardiac events include recorded hospitalizations for heart attacks and strokes.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A9 — Balancing of Socioeconomic Variables

	Samples		
	Pooled (1)	Females (2)	Males (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 A10 — Testing Different Specifications (Prescription Drugs)

	(1)	(2)	(3)	(4)
(a) Females				
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)
Antidepressants	−0.010*	−0.009*	−0.009*	−0.009*
	(0.005)	(0.005)	(0.005)	(0.005)
Year FEs	No	Yes	Yes	No
Quarter FEs	No	No	Yes	No
Year × quarter FEs	No	No	No	Yes
(b) Males				
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)
Antidepressants	0.003*	0.003*	0.003*	0.003*
	(0.002)	(0.002)	(0.002)	(0.002)
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 A11 — 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 A10. "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 A12 — Testing Different Specifications, Cardiac Events

	(1)	(2)	(3)	(4)
(a) Females				
Cardiac Event	0.0001	0.0001	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Heart Attack	−0.0001	−0.0001	−0.0001	−0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Stroke	0.0002	0.0002	0.0002	0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Year FEs	No	Yes	Yes	No
Quarter FEs	No	No	Yes	No
Year × quarter FEs	No	No	No	Yes
(b) Males				
Cardiac Event	0.0005**	0.0005**	0.0005**	0.0005**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Heart Attack	0.0005**	0.0005**	0.0005**	0.0005**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Stroke	0.0001	0.0001	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Year FEs	No	Yes	Yes	No
Quarter FEs	No	No	Yes	No
Year × quarter FEs	No	No	No	Yes

Notes: See Table A10. Cardiac events include heart attacks and strokes.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A13 — 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 A14 — Effects Based on Marriage Status

	(1)	(2)	(3)
(a) Prescriptions			
	Opioids	Non-opioid Painkillers	Antide-pressants
Females	−0.009***	0.006**	0.008
	(0.003)	(0.002)	(0.01)
Males	0.003	0.001	0.005
	(0.002)	(0.002)	(0.004)
(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)
(c) Cardiac Events			
	Any Cardiac Event	Heart Attack	Stroke
Females	0.0008	−0.0001	0.0009**
	(0.0005)	(0.0003)	(0.0004)
Males	0.0006	0.0002	0.0004**
	(0.0005)	(0.0004)	(0.0002)

Notes: See notes for Tables 5, 8, and 9. 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.

Table A15 — Effects Based on Post-UI Wage Change, Female Workers

	(1)	(2)	(3)
(a) Prescriptions			
	Opioids	Non-opioid Painkillers	Antide-pressants
Wage decrease	−0.001	0.002	−0.004
	(0.002)	(0.002)	(0.005)
Wage increase	−0.009**	0.002	−0.02*
	(0.003)	(0.002)	(0.008)
(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)
(c) Cardiac Events			
	Any Cardiac Event	Heart Attack	Stroke
Wage decrease	0.0001	0.00002	0.00010
	(0.0002)	(0.0002)	(0.0002)
Wage increase	0.0001	−0.0002	0.0003
	(0.0003)	(0.0002)	(0.0002)

Notes: See notes for Tables 5, 8, and 9. "Wage decrease (increase)" indicates that an unemployed worker experienced a decrease (increase) in wage levels, conditional on matching to a new occupation.