The Economic Burden of Burnout

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Abstract

We study work-related stress using linked Swedish administrative and survey data. Stress symptoms emerge, intensify over a year, and culminate in diagnosed burnout. Post-burnout earnings losses are large, persistent, and similar across genders, despite women's threefold higher incidence. Spousal earnings, especially wives', also fall, as do children's educational outcomes, particularly in less-educated families. In aggregate, these losses prove substantial. But burnout is predictable: stressful tasks increase risk, disproportionately among stress-intolerant workers, and frequent stress surveys improve prediction further, enabling targeted prevention. Beyond burnout, severe stress precedes lower earnings even among undiagnosed workers, highlighting the broader economic burden of work-related stress.

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Introduction

Stress is a salient feature of today's jobs. Recent workforce surveys reveal an alarming prevalence of work-related stress.[1] In one survey, 44 percent of workers worldwide reported feeling stressed for much of the previous day—53 percent among workers in the U.S. and 36 percent in Sweden, the focus of our study (Gallup, 2023).[2]

Evidence from psychological experiments and neurobiology suggests that while moderate stress may improve performance on some tasks, intense stress more often impairs it—an inverted-U relationship known as the Yerkes-Dodson law in psychology and as hormesis in biomedicine.[3] When stress responses are sustained or repeatedly activated without adequate recovery, they can produce cumulative physiological wear and tear—termed allostatic load—and alter stress-sensitive brain regions with adverse consequences for memory and cognitive control.[4] In the case of work-related stress, half a century of research in psychology and medicine has documented one consequence of prolonged exposure: *burnout*, a syndrome characterized by exhaustion, mental distancing from or cynicism toward one's work, and reduced professional efficacy (Freudenberger, 1974; Maslach et al., 2001; Maslach and Leiter, 2016; WHO, 2019).[5] In its clinical form, the syndrome extends beyond exhaustion to measurable cognitive impairments—most consistently in executive function, attention and processing speed, and working and episodic memory—together with emotional dysregulation (irritability, anxiety, loss of emotional control) and behavioral problems (interpersonal conflict, social withdrawal) (Van Dam, 2021; Gavelin et al., 2022). These symptoms may persist for years despite treatment, underscoring the lasting impact of burnout and the primacy of prevention as a more effective remedy (Glise et al., 2020).

In response to the rising prevalence of work-related stress and growing experimental evidence of its negative consequences, nine European countries—including Sweden—have, since 2000, established medical diagnostic criteria for burnout and integrated the syndrome into their social security and healthcare systems (Lastovkova et al., 2018). In 2019, the World Health Organization officially recognized burnout as a syndrome caused by chronic work stress in the revised International Classification of Diseases. As of May 2024, 132 countries are at various stages of implementing the new classification (WHO, 2019, 2024).

Despite extensive research, mounting evidence, and widespread policy attention, the economic burden of burnout remains elusive—both at the societal level and for individuals. Understanding its aggregate cost requires first establishing its prevalence and identifying risk factors. Yet most existing evidence remains confined to specific sectors, raising questions about whether the findings generalize to the broader labor force.[6] A second and more challenging task is to understand and quantify the micro-level toll burnout

[1] We use "work stress" and "work-related stress" interchangeably. The literature also uses "occupational stress," "job stress," and "workplace stress"; all terms are indexed under a single subject heading by the U.S. National Library of Medicine (National Library of Medicine, 2018).

[2] Gallup estimates for the U.S. align closely with Maestas et al. (2017), while those for Sweden match our own estimates from the Swedish Work Environment Survey (Appendix Figure A.6a). Global work-related stress rates have gradually risen from 31 to 44 percent between 2009 and 2022 (Appendix Figure A.1). Additional evidence appears in two surveys by the American Psychological Association—*Stress in America* and *Work in America* (APA, 2023a,b)—the *European Working Conditions Survey* (Eurofound, 2007, 2016), and ILO (2016).

[3] See Yerkes and Dodson (1908); Broadhurst (1957); Teigen (1994) for the former and Calabrese and Baldwin (2002); Calabrese (2008); Mattson (2008) for the latter.

[4] See McEwen (1998, 2007) and Lupien et al. (2009).

[5] Two historical precedents are neurasthenia and industrial fatigue, both of which emerged in the decades around 1900 (Rabinbach, 1990; Schaufeli, 2017; Blayney, 2019). The former attributed mental exhaustion among professionals to depleted nervous energy; the latter emphasized the physiological limits among industrial workers—dramatized in Chaplin's *Modern Times*.

[6] For instance, burnout has been widely studied among public health employees, focusing on its prevalence (Robins

exacts on individuals and their families—an area that remains largely unexplored. Closing these gaps is the central aim of this study.

This paper documents how the accumulation of work-related stress leads to burnout, quantifies its prevalence, identifies its risk factors, and assesses its consequences for the entire Swedish labor force. We then explore how our findings may help reduce the economic burden of burnout. We define burnout as a clinical diagnosis of a stress-related illness followed by an extended sick leave. More precisely, Sweden's mandatory sickness insurance combines two weeks of employer-paid sick leave with subsequent state benefits at 80 percent of earnings, subject to physician diagnosis. In the data, we focus on sick-leave spells carrying a stress-reaction diagnosis (ICD-10 code F43).[7] Sweden's early adoption of clinical burnout diagnosis presents a rare opportunity to trace the long-term impacts of work-related stress across the population.

We begin by showing that self-reported work-related stress symptoms—such as insomnia due to work and intrusive work-related thoughts—strongly predict future burnout, whereas other job-related ailments, like back or shoulder pain, do not. Burnout risk escalates nonlinearly with each additional symptom, implying that stressors accumulate rather than act in isolation. Stress symptoms begin to escalate a year before diagnosis and intensify steadily, peaking just before a clinical burnout diagnosis.

Some jobs are more stressful, and some workers are better equipped to handle stress. We study this dual heterogeneity. To capture this heterogeneity, we combine two unique data sources: O*NET, which offers expert ratings of the stress-tolerance requirements for each occupation based on its core tasks, and military draft records, which provide psychologist-assessed stress-tolerance scores for men at age 18, prior to labor market entry. Burnout rates are systematically higher in high-stress occupations for all workers except those in the top quintile of the stress-tolerance distribution. Within high-stress occupations, workers with low stress tolerance exhibit a threefold higher burnout rate than their more stress-tolerant peers. In contrast, the gap is significantly diminished in low-stress jobs. Reflecting this complementarity, stress-intolerant individuals sort into low-stress occupations. However, sorting is quantitatively modest and insufficient to fully equalize burnout risk.

Beyond stress tolerance, gender stands out as the single most influential risk factor for burnout. Women are three times more likely to be diagnosed with burnout than men, at 1.85 percent annually compared to 0.53 percent. The gender gap in burnout almost entirely persists even after accounting for occupation, demographics, and work characteristics. In fact, gender alone explains nearly one-third of the cross-sectional variance captured by a rich set of variables. Moreover, single mothers and female breadwinners in low-income households face the highest risk of burnout. Beyond single-variable associations, a Shapley decomposition reveals that career and professional-life information contribute more than twice as much to predicting burnout as family and private-life factors.

We next assess the economic burden of burnout. By clinical definition, and as we document in the data, burnout arises from persistent work-related stressors, with family events also contributing. Thus, the causal effect of burnout does not reflect the effect of burnout as a treatment separable from its antecedents, but the economic impact of a bundle of stressors that culminate in a clinical diagnosis. We employ three complementary designs, each exploiting a distinct source of variation and isolating a different component

et al., 2023; U.S. Department of Health and Human Services, 2019; Rotenstein et al., 2018), risk factors (Hallsten et al., 2002; Norlund et al., 2010; Purvanova and Muros, 2010; Artz et al., 2022), and burden (Han et al., 2019; Muir et al., 2022). As we will show, burnout rates in this sector are high—though not the highest—and the consequences are equally relevant across other parts of the workforce.

[7] Because reliable diagnostic subcodes are unavailable, this measure pools exhaustion disorder with acute and other stress reactions. We use self-reported symptoms and spell duration to mitigate this data limitation and interpret our estimates as the burden associated with severe, clinically recorded stress episodes.

of this bundle. No single design identifies the causal effect of burnout, and each rests on its own identifying assumptions, which we state explicitly. Agreement across designs would not establish a causal effect, but it would make it less likely that the estimates are driven by any single source of confounding.

Our primary empirical design is a one-to-one matched differences-in-differences estimator that compares individuals who experience burnout with observationally similar peers who never do.[8] This method parallels the approach in the job displacement literature (e.g. Schmieder et al., 2023) and in other contexts (e.g. Adams-Prassl et al., 2024; Jäger et al., 2025). The analogy to job displacement is deliberate: both burnout and layoffs constitute pivotal work-related tipping points with substantial consequences for workers. Our second design compares workers who all eventually experience burnout but at different times, thereby implicitly matching on persistent unobserved stressors and individual characteristics such as stress tolerance.[9] Our third design exploits industry-level variation: changes in the leave-one-out burnout rate among peers in the same industry, excluding the own firm. This design shifts the identifying variation away from person- and family-specific events and own-firm shocks toward time-varying conditions shared across workers within the industry.

The estimates are remarkably consistent across designs. The alignment of estimates indicates that similar post-burnout changes in outcomes emerge whether the variation reflects the full spectrum of stressors, temporal fluctuations in stress, or industry-specific fluctuations. While this alignment does not establish a definitive causal effect of any stressor, it makes it less likely that baseline estimates are driven solely by person- or family-specific events or by persistent differences between workers who do and do not experience burnout.

Burnout is followed by a large and enduring loss in labor income—a pattern comparable in magnitude and persistence to earnings declines following layoffs (Davis and Von Wachter, 2011). A year in, annual earnings fall by nearly 15 percent, driven primarily by sick leave (median: 55 days). Yet the income differential is long-lasting: seven years later, earnings remain 12 percent lower, stemming from transitions to part-time positions and non-employment, with minimal wage effects—ruling out promotion loss as a key mechanism. While women are more likely to burn out, the size and persistence of the earnings losses are similar across genders. Social insurance and a progressive tax system cushion the impact, yet disposable income remains over 6 percent lower in the long run.

Burnout is also followed by a disruption of spousal careers. When a male spouse experiences burnout, his partner's income immediately drops and remains persistently 4.4 percent lower—this is about 40 percent of the drop seen after her own burnout. In contrast, when a female spouse experiences burnout, her partner's income declines by only 1.1 percent. Hence, women not only face a three-times higher risk of burning out, but their careers are also more vulnerable when their partners burn out. In addition, burnout leaves a gender-biased demographic imprint: post-burnout, fertility falls permanently for women, whereas it rises for men.

The consequences of burnout may extend beyond the first generation. To examine this possibility, we use our fourth design, which considers the timing of parental burnout relative to a child's schooling: we compare children whose parent experiences burnout before their exams or college decision with those whose parent experiences burnout only afterward, after first removing cohort trends based on matched children whose parents never experience burnout. In our analysis, children exposed to parental burnout during their schooling years have a 1.9 percentage point (5.3 percent) lower probability of achieving a median GPA and a 2.5 percentage point (8.1 percent) lower probability of enrolling in college. These

[8] To address potential confounding from labor demand effects on both stress and earnings, we conduct a secondary matching within narrowly defined industries.

[9] For similar designs, see (e.g. Hilger, 2016; Fadlon and Nielsen, 2021; Nekoei and Seim, 2023).

patterns do not vary by gender and are less pronounced among children of college-educated parents, suggesting that burnout may contribute to inequality and intergenerational mobility.[10]

The macroeconomic implications of our findings are substantial. The high incidence of burnout and its pronounced gender gap indicate that burnout is far from a niche phenomenon: by age 40, one in seven women and one in twenty men have experienced such a clinical episode. The social cost of burnout can be gauged by aggregating its various channels—direct losses through sick leave, permanent career setbacks for affected individuals, and spillovers to their families. We project that burnout would reduce aggregate labor income by 3.2 percent in a steady state if 2019 conditions persisted. The largest share stems from scarring effects, but spillovers are as consequential as the direct costs of sick leave. Comparing the aggregate economic burden of burnout to its prevalence implies that each burnout event imposes a total burden equivalent to three years of average income.

The burden of burnout motivates policy efforts to prevent and mitigate it. Evidence indicates that organizational-level interventions can reduce burnout (Aust et al., 2023), although important questions remain about designing and implementing effective preventive programs (Bouskill et al., 2022; Demerouti et al., 2021). We explore a path toward prevention in two steps. First, using machine learning, we correctly predict higher burnout risk in 81 percent of pairs comparing a burned-out worker to a non-burned-out peer (AUC = 0.813). This accuracy approaches benchmarks for mortality and health cost prediction (Einav et al., 2018; Handel et al., 2023). Second, we combine this prediction model with our cost estimates to optimize the scope and targeting of a hypothetical prevention program. A cost-benefit analysis reveals that incorporating survey-based work-related stress measures alongside basic demographic information shrinks the optimal program size by about a quarter while doubling net gains. Importantly, a handful of self-reported stress measures rivals the predictive power of the full breadth of Swedish administrative data.[11] The predictive power of self-reported stress fades over time, mirroring our finding of the gradual build-up of stress before burnout. Taken together, our results suggest that high-frequency surveys can monitor evolving risk in real time and substantially improve the effectiveness of burnout prevention efforts.

The external validity of these findings depends on how the sick leave system affects selection into and the consequences of burnout. Observed burnout cases arise from the interplay between underlying work-related stress and the generosity of social insurance—much like layoffs reflect both firm distress and unemployment insurance generosity (Jäger et al., 2023), and disability claims combine worker health with the availability of disability benefits (Autor and Duggan, 2003). Sweden combines generous sick-leave insurance with work-related stress levels below the global average. These features push recorded burnout in opposite directions, complicating direct cross-country comparisons. To provide quantitative insight into one mechanism, we make use of a kink in the sick-leave benefit schedule. When extrapolating the estimates to a scenario with no benefits, the analysis suggests that recorded burnout incidence would be about two-thirds lower. However, this does not necessarily imply that underlying illness or its societal cost would fall proportionally: in the absence of compensated leave, costs could instead manifest as presenteeism, reduced productivity, or worsening health.

Looking beyond clinically diagnosed burnout, we examine the broader labor-market footprint of work-related stress. The data reveal a sharply nonlinear relationship between self-reported stress and subsequent earnings: moderate stress is not linked to lower future earnings—and may even coincide with modest earnings gains—but earnings decline steeply at high stress levels. In matched comparisons, earnings and

[10] In Sweden, Swedish students can attend higher education tuition-free and access public grants and subsidized loans (Chen et al., 2022).

[11] Whether this private signal could generate enough adverse selection to unravel insurance markets remains an open question we leave for future work. See Hendren (2017) for such an argument in the case of unemployment.

employment trajectories for high-stress workers increasingly diverge from those of otherwise similar lower-stress workers, a pattern that persists even when excluding individuals later diagnosed with burnout. These findings indicate that clinically diagnosed burnout represents only a small, visible portion of the overall burden: a substantial share of earnings loss related to severe stress falls below the diagnostic threshold, remains undocumented in sick-leave registers, and is nonetheless detectable through brief survey instruments. This perspective expands both the estimated economic burden of work-related stress and the utility of survey-based monitoring, even in environments lacking a formal burnout diagnosis.

Our paper contributes to various strands of literature. First, we add to a nascent body of work in economics that studies stress and its labor market consequences. Postel-Vinay and Jolivet (2024) examine the interplay of work-related stress, health, and job dynamics, while Nagler et al. (2023) elicit willingness to pay to avoid stressful jobs.[12] Relatedly, Blackburn et al. (2023) study burnout among health professionals and find that it increases turnover and lowers productivity and patient satisfaction. Our study complements the existing medical and psychological literature, which has primarily focused on burnout symptoms (Van Dam, 2021) and the health consequences of stress (O'Connor et al., 2021).

Second, we contribute to the literature studying long-run career effects of mental illness (e.g. Bartel and Taubman, 1986; Biasi et al., 2021) and, more broadly, to an extensive literature studying the adverse effects of health shocks on labor income and spousal labor supply (e.g. McClellan, 1998; Fadlon and Nielsen, 2021). In particular, the magnitude and persistence of our estimated effect on labor and disposable income align closely with those reported for general sick leave—both physical and mental—in Kolsrud et al. (2020). Finally, our findings provide individual-level evidence linking economic conditions and mental health. This relates to prior work documenting how unemployment (Paul and Moser, 2009), firm reorganization (Dahl, 2011), and corporate mergers (Bach et al., 2023) affect employee mental health.[13]

The paper unfolds as follows. Section 1 describes clinical burnout, its symptoms and diagnoses, and how we measure it in administrative data. Section 2 identifies burnout symptoms in the data and documents how stress symptoms accumulate in the lead-up to burnout. Section 3 analyzes heterogeneity in burnout risk, focusing on the interaction between job demands and individual stress tolerance, as well as demographic and labor market characteristics. Section 4 quantifies the individual, familial, and macroeconomic consequences of burnout. Section 5 develops a prediction model for burnout and evaluates the design of preventive interventions. Section 6 discusses the external validity of our findings. Section 7 concludes. We relegate additional background material and auxiliary analyses to an online appendix.

1 Burnout: Measurement and Data

Burnout is a syndrome of chronic stress in which an individual's physical, cognitive, and emotional resources are progressively depleted (Maslach et al., 2001; WHO, 2019). Unlike acute stress, whose effects are transient, burnout develops over time, reaches a tipping point, and results in lasting impairment of work capacity (McEwen, 1998; Van Dam, 2021; Glise et al., 2020; The National Board of Health and Welfare, 2003). This contrast between transient and persistent stress is central to how we measure burnout and interpret the estimates.

[12] Earlier work using panel data has yielded mixed results regarding the existence of compensating wage differentials for stressful work (Brown, 1980; Duncan and Holmlund, 1983).

[13] There is also a growing body of research exploring how treating mental health conditions affects economic outcomes in developing countries, e.g., see Lund et al. (2022).

1.1 Measurement

We observe burnout cases that are severe enough to cause a sick-leave spell exceeding 14 days. The 14-day threshold follows from an institutional rule: Sweden's mandatory sickness insurance combines two weeks of employer-paid sick leave with subsequent state benefits at 80 percent of earnings, subject to physician certification and periodic re-assessment (for more details, see Appendix A.5).

Clinical burnout corresponds to *Exhaustion disorder (utmattningssyndrom)*. The Swedish National Board of Health and Welfare introduced exhaustion disorder as code F43.8A in ICD-10-SE to standardize diagnostic criteria in 2005. F43.8A is a sub-category of "*Reaction to severe stress and adjustment disorders*", F43 in ICD-10.[14] A diagnosis of F43.8A requires physical and psychological symptoms of fatigue that have developed as a result of one or more identifiable stressors present for at least six months, together with at least four of the following symptoms every day for a minimum of two weeks: memory impairment, reduced ability to cope with time pressure, emotional irritability, sleep disturbance, physical weakness, and somatic symptoms. These must cause clinically significant impairment at work, socially, or in other important respects.[15]

We measure burnout using F43 rather than its subcategory F43.8A for several reasons.[16] First, detailed coding was introduced only after 2010, when the Social Insurance Agency instructed physicians to report subcategories (Försäkringskassan, 2020). Second, detailed sick-leave codes remain unreliable even after 2010 (Riksrevisionen, 2018, see Appendix A.6 for details). As a result, researchers often do not receive the subcategories. Although these codes are unreliable and unavailable at the individual level, aggregate information has been provided in a few instances; we use it to assess how pooling within F43 affects our analysis (See Appendix A for details).

The two largest F43 subcategories are exhaustion disorder and acute stress reaction. Together, they account for about three-fifths of F43 diagnoses. The residual consists of adjustment disorder (5 percent), post-traumatic stress disorder (2 percent), and unspecified categories (about one-third) (see Appendix Table A.1 for details). Acute stress reaction is, by diagnostic definition, transient: it captures responses to sudden stressors such as natural disasters, serious accidents, or the death of a loved one, and does not persist beyond four weeks (WHO, 1992). Exhaustion disorder, by contrast, requires stressors to have been present for at least six months (The National Board of Health and Welfare, 2003). The difference is visible in spell lengths: a median of just over one month for acute stress reaction against roughly six months for exhaustion disorder (Försäkringskassan, 2020). We will show how our results vary by spell length, emphasizing that the lion's share of our effects are from exhaustion disorder. Post-traumatic stress disorder and adjustment disorder are more infrequent, but capture events such as serious illness in the family (WHO, 1992), a possibility we investigate later.

The Swedish sick-leave system shapes our measurement in ways that bear on the interpretation of our estimates. Several considerations suggest that our estimates are attenuated. First, paid sick leave may incentivize some individuals to seek a diagnosis earlier and at a less severe stage of exhaustion, which would attenuate the average effect we estimate relative to a setting without such coverage. Second, sick

[14] ICD-10-SE is Sweden's national modification of ICD-10, the WHO's international classification of diseases (See Appendix A).

[15] The criteria are set out in The National Board of Health and Welfare (2003) and summarized in Appendix A.

[16] We do not use Z73.0 (*utbrändhet*, burnout) as part of our measure for a few reasons. Unlike exhaustion disorder (F43.8A), it codes a health problem rather than a clinical diagnosis in ICD-10. It has no entry in Socialstyrelsen's sick-leave decision support (Socialstyrelsen, 2026) and is not a certifiable illness for sickness benefit purposes (Försäkringskassan, 2025). Adherence is not perfect in practice (Riksrevisionen, 2018) and Z73-coded spells appear but are rare among sick leave spells—roughly 2 percent of F43 cases. See Appendix A for details.

leave may buffer the consequences of burnout by facilitating recovery that would not occur in its absence, making the measured condition less severe than clinical burnout in settings without comparable social insurance (The National Board of Health and Welfare, 2003). At the same time, other considerations push in the opposite direction. A sick-leave system might disrupt the careers of individuals who would otherwise have ultimately managed their stress load without passing the tipping point. Evidence presented in Section 2 (Figure 1) shows that even among individuals with severe stress, only about 5 percent go on sick leave due to burnout. We return to this issue and evaluate its implications in Section 6.

1.2 Data and Descriptive Statistics

Our main data are the sick leave register, which covers the start and end dates of all sick leave spells registered at the Social Insurance Agency together with the ICD-10 code of the certified diagnosis. Data are available consistently from 2006 to 2020. Diagnosis codes are recorded for 98–99 percent of sickness spells (Inspektionen för socialförsäkringen, 2014). We match the sick leave register with seven other administrative data sets: (i) the universe of matches between employers and employees; it includes information on earnings and employment spells; (ii) LISA contains individual-level characteristics, including demographic variables; (iii) the Unemployment register from the Public Employment Service with exact duration of unemployment spells; (iv) the Wage Survey (*Lönestrukturstatistiken*) with information on occupations and hours; (v) firms' balance sheets register; (vi) enlistment data from the Military Archives; and (vii) the Swedish Work Environment Survey (AMU) with information on workplace conditions and worker's occupational health.

We describe the Wage Survey, enlistment data, and AMU in further detail. We draw workers' occupations from the Wage Survey, a large-scale administrative survey of employers. We observe occupations of 58 percent of the workforce each year, with large firms and the public sector being over-represented.[17]

We measure individuals' skills, including their stress tolerance, using tests administered at military enlistment. The Swedish Military Archives provide these test results for 1969 to 2010. During our sample period, almost all men were drafted at age 18 or 19. Enlistment scores are available for roughly 80 percent of men in each cohort subject to the draft (Fredriksson et al., 2018). The evaluation process includes standardized tests to assess cognitive skills across four dimensions and interviews conducted by a trained psychologist to evaluate personality traits (non-cognitive skills) across four dimensions.

Data on working conditions comes from AMU, a biannual supplement to the Labor Force Survey. It includes around 157 questions on work arrangements, workers' perceptions of their workplace, and work-related health problems. Importantly, the survey does not affect sick leave administration, and employers are not notified of employees' participation. Therefore, respondents face no repercussions for reporting truthfully. Around 7,000 to 9,000 employees are surveyed in each wave. Our analysis covers waves 2005 to 2019, yielding a sample of 61,121 workers whose responses can be linked to other administrative data.

To assess the relationship between workplace stress and burnout, we use data on occupational stress tolerance requirements from the O*NET (Occupational Information Network) (Peterson et al., 1999). It provides detailed descriptions, including skill and knowledge requirements, for over 970 occupations derived from workers and "occupation analysts" surveys. We use the Stress Tolerance requirement variable, which captures the importance of "accepting criticism and dealing calmly and effectively with high-stress

[17] Firms in the private sector are chosen using stratified sampling from 530 strata: 83 industries × seven size groups. The survey includes all firms with more than 500 employees. As a result, the survey covers 40 percent of private sector employees. For the public sector, coverage is complete (Mediation Office, 2022).

situations" for an occupation.

Table 1 presents descriptive statistics for the population, two samples of individuals experiencing burnout, and the estimation sample used in our matched difference-in-differences analysis. It shows that workers who experience burnout differ systematically from other workers: they are disproportionately female, more likely to hold a college degree, and earn slightly less. Burnout is also more prevalent in the education and health sectors. We return to these patterns in Section 3. A comparison of columns (3) and (4) further shows that matched individuals are, on average, slightly younger and more educated.

2 What Is Burnout?

Burnout is medically defined as a condition caused by intense, prolonged work-related stress, as discussed in the previous section. We investigate and validate this link empirically by addressing three questions. First, which working conditions and symptoms are most strongly associated with burnout? Second, do symptoms interact and exacerbate one another? Third, over what period do symptoms accumulate before burnout onset?

To address the first question, we regress burnout on working conditions, physical symptoms, and stress symptoms reported in AMU, all measured in the final quarter of the preceding calendar year. As described in Section 1, AMU respondents have no reason to misreport, as their responses are neither connected to the sick leave system nor disclosed to employers. To maximize sample size, we restrict the analysis to questions available consistently throughout the sample period (see Appendix C for exact wording and translations). For each question, we define an indicator equal to one for responses above the median. With assistance from a large language model, we rank conditions and symptoms by the strength of their documented association with burnout in the medical literature (see Appendix C for details).[18]

Figure 1a shows the results. The most significant coefficients correspond to the same three work-related stress symptoms included in the diagnostic criteria for burnout defined by the Swedish National Board of Health and Welfare: inability to detach thoughts from work, inability to sleep due to work, and perceiving the job as mentally stressful. These three symptoms are also the most closely related to burnout in the medical literature. The four largest positive coefficients correspond to these three stress-related symptoms and headaches, the final item in the core diagnostic criteria for burnout (see Appendix A for details). In contrast, all other work-related conditions show weaker, statistically insignificant associations with burnout once we account for stress symptoms.

Having established the link between burnout and work-related stress symptoms, we examine how interactions among these symptoms contribute to burnout risk. We focus on the subset of AMU questions that capture the core diagnostic criteria for burnout and are also the questions most strongly correlated with burnout, as shown in Figure 1a.[19] We use these four questions to construct a stress index. For each symptom, we assign a score of 1 to workers reporting the highest intensity (e.g., being unable to sleep due to work every day of the week), -1 to workers reporting the lowest intensity (e.g., never being unable to sleep due to work), and zero otherwise. The stress index sums these scores across the four symptoms and ranges from -4 (no symptoms) to 4 (all symptoms at maximum severity); see Appendix D for details.

Figure 1b shows that workers reporting no stress symptoms have a near-zero probability of burnout in the following year. As reported symptoms increase, burnout risk rises at an accelerating rather than

[18] We validate this association in Section 5 by comparing their predictive power relative to other information.

[19] Section 5 provides complementary validation of this reduced question set, showing that these four items outperform nearly all other four-question combinations in predicting burnout. In addition, Appendix Figure A.6 plots the relationship between burnout and each stress symptom separately.

linear rate. Among workers reporting all four symptoms, the likelihood of burnout in the following year reaches approximately 5 percent, a strikingly high annual incidence. Stress symptoms compound rather than contribute additively, leading to the nonlinear association between burnout and stress. This pattern resembles the inverted-U dose–response relationship long recognized in psychology (Yerkes and Dodson, 1908) and biomedicine (Calabrese and Baldwin, 2002).

We next ask whether burnout results from sustained, chronic stress or from a rapid accumulation of stress culminating in a tipping point. To investigate this, we trace the evolution of stress symptoms preceding burnout. We use a benchmarking approach akin to a difference-in-differences design, matching workers who experience burnout to observationally similar workers who do not based on demographic characteristics and pre-burnout labor income deciles (see Section 4 for details of the matching procedure).

Stress symptoms rise sharply in the year before burnout, peak in the quarter when sick leave begins, and then decline to levels comparable to those one year before burnout (Figure 1c).[20] As we show later, this decline is partly driven by transitions to less demanding jobs and reductions in work intensity following burnout. These patterns suggest that burnout is best understood as a tipping-point phenomenon, triggered by chronic pressure that builds over the preceding year.

3 Who is at Risk of Burning Out?

The previous section showed how work-related stress accumulates and culminates in burnout. We now examine how burnout risk varies across occupations and workers.

3.1 Job Stress Requirements and Individual Stress Tolerance

Occupations differ in the stress tolerance they require, and individuals differ in their capacity to tolerate stress. We first quantify variation along each dimension and then ask whether the two are complementary: are less stress-tolerant workers more prone to burnout in any job, or does their risk rise disproportionately in high-stress occupations? Answering these questions requires separate measures of work-related stress requirements and individual stress tolerance.

Our first measure captures an occupation's stress-tolerance requirement and comes from O*NET (Peterson et al., 1999). A key advantage of O*NET is that it characterizes occupations by the tasks and work contexts they entail, rather than by the characteristics of the workers who hold them. The measure therefore does not systematically reflect how workers are sorted across occupations. Applying O*NET to Sweden may nevertheless introduce two sources of measurement error. First, O*NET's assessments reflect the U.S. labor market and may not reflect working conditions in Sweden.[21] Second, imperfect mappings between the U.S. and Swedish occupational classification systems may introduce additional error. Both sources are likely to attenuate the estimated relationship between work-related stress requirements and burnout. We therefore interpret the observed relationship as lower bounds.

Our second measure captures individual stress tolerance. It comes from assessments conducted during Swedish military enlistment, which was compulsory for nearly all men around age 18 in the relevant cohorts.[22] As part of a comprehensive evaluation of cognitive and non-cognitive skills, trained

[20] The pattern is similar under alternative measures of work-related stress (Appendix Figure A.7).

[21] Because our analysis uses an occupation's rank in the distribution of stress tolerance requirements, only ordinal—not cardinal—differences between Sweden and the U.S. matter.

[22] A key limitation is that the measure is available only for men, whereas burnout is substantially more prevalent among women, as we document below. We considered imputing women's stress tolerance from that of their brothers.

psychologists assessed each conscript's stress tolerance. The measure captures the "ability to control and channel nervousness, tolerance of stress, and disposition of anxiety" (Mood et al., 2012). Scores range from 1 to 5, with a score of 3 corresponding to a "normally functioning eighteen-year-old male".

Figure 2a shows higher burnout rates among Swedish workers in occupations with greater stress-tolerance demands, as measured by O*NET. The figure also illustrates occupations spanning the distribution of these requirements. Psychiatric nurses, midwives, and preschool teachers rank near the upper end, whereas construction machine operators and mining workers rank near the lower end.

Notably, no occupation near the bottom of the O*NET stress-tolerance distribution exhibits a high burnout rate in the Swedish data. This pronounced occupational gradient supports a role for work-related stress in burnout. Were burnout driven primarily by stress outside work, such a systematic pattern across occupations would be difficult to explain.[23] Below we compare the relative importance of workplace and private-life stressors directly.

If workers observe, albeit imperfectly, both their own stress tolerance and occupations' stress requirements, and if work-related stress is an important job attribute, standard sorting logic predicts positive assortative matching along this dimension. Figure 2b shows that workers with greater stress tolerance are, on average, employed in occupations with higher stress-tolerance requirements.[24] Yet sorting is far from complete: the average occupational stress-requirement rank is approximately 60 among the most stress-tolerant workers, compared with about 45 among the least stress-tolerant workers. Under perfect sorting, the corresponding averages would be 92.7 and 0.08, respectively. This limited degree of sorting may reflect imperfect information about worker-job fit, or simply that stress considerations receive limited weight relative to other determinants of occupational choice.

Figure 2c reveals a pronounced interaction between occupational stress requirements and individual stress tolerance. Workers with low stress tolerance face higher burnout risk than their more tolerant peers, and this gap widens sharply as occupational stress requirements rise.[25] In the highest-stress occupations, burnout among the least stress-tolerant workers is roughly three times that among the most stress-tolerant. By contrast, among highly stress-tolerant workers, burnout varies little with occupational stress requirements. This asymmetric gradient is consistent with complementarity in worker-job fit: stress tolerance is most valuable in demanding occupations.[26]

3.2 Gender, Family, and Career

Burnout risk varies systematically with the stressfulness of jobs and individual stress tolerance. The occupational gradient is present for both genders, but we can study the role of individual stress tolerance only among men because of data limitations. We now document that gender is another important determinant of burnout risk. Several mechanisms may underlie this disparity. First, gendered mental health stigma may lead to differential reporting or recognition of burnout symptoms (Bharadwaj et al., 2015). Second, men and women may sort into different occupations or take on different responsibilities

However, previous work documents substantial heterogeneity in stress tolerance even among brothers (Almgren, Kramer, and Sigurdsson, 2025), making such an imputation unreliable. We therefore do not pursue this approach.

[23] The gradient holds separately for men and women, and appears within workers who change occupation (Appendix Figure A.33).

[24] Figure A.12 reports the full distribution of occupational stress requirements at each level of individual stress tolerance.

[25] Appendix Figure A.11 shows that the negative relationship between stress tolerance and the likelihood of burnout is robust to controlling for other cognitive and non-cognitive skills.

[26] Noise in both measures likely attenuates these contrasts and helps explain why burnout remains positive across all cells.

within similar jobs (Goldin, 2014; Cortes and Pan, 2018). Finally, family responsibilities may place an additional burden on women, exacerbating work-related stress. In what follows, we focus on the latter two explanations.

Figure 3a plots burnout rates among men and women, further partitioned into four groups by marital and parental status. The sample consists of all prime-age (25-60) Swedish workers between 2006 and 2020 who were employed full-time the prior year.

Women are at much greater risk of burnout than men. The average burnout rate among women is 1.85 percent, three times higher than the average rate of 0.53 percent among men. This salient gender difference is present across all family types. Among both men and women, single parents stand out as particularly vulnerable, rendering single mothers the demographic group most at risk of burnout. For men, other family types exhibit virtually no heterogeneity in burnout rates. Among women, however, burnout risk follows a clear gradient: after single mothers, singles without children have the highest rates, followed by married women with children, and finally, married women without children have the lowest rates. Strikingly, among the group of women with the lowest risk of burnout—married without a child—burnout is still twice as likely as among single fathers, the group of men at the highest risk.

While a relatively small fraction of the Swedish workforce experiences burnout in any given year, a significant share of workers experience burnout over their lifetime. For the cohort born in 1985, we can observe each individual's sick leave history between ages 25 and 40. By age 40, around 14 percent of women and 5 percent of men in this cohort have diagnosed burnout, suggesting that burnout is not confined to a small subset of the population.

As emphasized above, a potential explanation for the gender disparity in burnout risk is that women and men differ systematically along career dimensions that affect the likelihood of burnout—such as industries and occupations in which they work. For instance, female-dominated professions like nursing and teaching are associated with relatively high burnout rates (see Figure 2a).

To investigate this issue, Table 2 presents the OLS regression of burnout on key individual characteristics in our data. Column (1) replicates the key pattern in Figure 3a, showing the unconditional gender gap in burnout. Comparing columns (1) to (3), observed characteristics explain about 25 percent of the gender difference: the coefficient declines from 1.33 to 1.01, implying that the full set of controls reduces the gap by about a third of a percentage point, based on the gender difference in burnout rates. Notably, this reduction occurs entirely before occupation is accounted for: the coefficient is already 1.00 in column (2), and adding occupation fixed effects in column (3) leaves it unchanged at 1.01, so the gender gap is present within occupations rather than reflecting sorting across them. Comparing columns (4) and (5) for women and columns (6) and (7) for men in Table 2 highlights the significant explanatory power of occupation.[27] Comparing columns (5) and (7) suggests that female burnout is more strongly linked to observable characteristics than that of men.

To further isolate the role of gender, we conduct a variance decomposition analysis.[28] The results are reported in Figure 3a. The decomposition implies that gender alone accounts for one-third of the explained variance. All other demographics and work-related factors contribute 42.5 percent. The remaining 24.3 percent can be attributed to the correlation of gender with other observed predictors of burnout, highlighting the importance of the interaction of gender and both family and work characteristics.

What characteristics explain burnout? For female workers, being foreign-born or married is associated

[27] Occupation has a stronger explanatory power than industry and all other characteristics in this table together (see Appendix Table A.3).

[28] This regression model is an extended version of Table 2, column (3), where we add information about the number and age of children.

with lower burnout, whereas these characteristics have no significant association for male workers. Across both genders, single parenthood shows a meaningful association with burnout even when controlling for income and age. Burnout follows a hump-shaped profile over the life cycle, peaking around age 40 for both male and female workers. Conditional on age, industry, and occupation, burnout declines steeply with income—similar to the unconditional relationship shown in Appendix Figure A.5. Notably, that figure also demonstrates that burnout is more evenly distributed across the income distribution than other health conditions or unemployment, which are much more regressive. Education is positively associated with burnout, especially among male workers, but this relationship largely disappears once we control for occupation, suggesting the education gradient operates primarily through occupational sorting.

While we cannot rule out innate gender differences in stress tolerance, we find evidence that differences in family responsibilities, interacting with and exacerbating work-related stress, account for part of the gender gap in burnout rates. The differences in burnout rates between single and married parents—for both men and women—provide suggestive evidence in support of this interpretation. To investigate this interaction further, we examine how burnout relates to couples' incomes and women's relative position within the household. Figure 3b plots a heatmap of burnout rates among married and cohabiting women against the labor incomes of each of the spouses within the couple.[29] The x-axis represents the labor income of the male spouse (in 10K SEK), while the y-axis represents the labor income of the female spouse (also in 10K SEK), i.e., their own income. We use a two-dimensional moving average of the burnout rate given that observations are non-uniformly distributed (see Appendix Figure A.8). More precisely, we report the average rate of 38,416 observations in the circular vicinity of each point. This number of observations is based on a power calculation for the binomial distribution and is sufficient to detect statistical significance for differences of size 10^{-4}. This can be viewed as a simple version of a variable kernel estimator. Labor incomes are rank-adjusted to 2020 Swedish krona (SEK) to render incomes comparable across years. More specifically, an individual's adjusted income in each year is the income in SEK of a person holding the same income rank in 2020.[30] This approach is equivalent to a non-parametric wage inflation adjustment.[31] The adjustment renders individual labor incomes comparable over time but does not affect nominal income growth rates.[32]

Darker shades of red depict higher burnout rates among women. Two patterns stand out. First, the dominant gradient in the figure is vertical: burnout rates are highest among women with own annual labor incomes of roughly 200–300k SEK and decline steeply with own income, largely independent of the spouse's income. This horizontal band is consistent with the income gradient documented in Table 2 and Appendix Figure A.5. Second, conditional on her own income, a woman's relative position within the household matters. We overlay a line marking the median couple's total income. Burnout rates are particularly high among women in households with earnings below the median who earn more than their spouses, as indicated by the dark area above the diagonal. That is, in couples where the woman is the primary breadwinner and household income is below the median, the average burnout rate for women is as high as 2.19 percent — a result that echoes the strikingly high burnout rates of single mothers, who are by definition the breadwinners in their households. The rate drops to 1.29 percent for primary-earner women in couples with above-median income, and burnout rates are lower still in households where women earn

[29] Appendix Figure A.9a presents the corresponding figure for married and cohabiting men.

[30] Throughout the paper, we report all nominal values (income) in 10 kSEK (thousand Swedish kronor), roughly equivalent to 1,000 USD/Euro (exchange rate in January 2020: 9,64 to USD and 10,55 to Euro).

[31] We also adjust for labor income changes due to parental leave, using data on the number of days on leave.

[32] In order to remain consistent with our event-study analysis in Section 4, we restrict the sample to workers ages 25 to 55 for whom we observe income in the previous year ($t-1$) and sick leave outcomes next year ($t+1$) (see Appendix B for details on the sample).

less than their husbands.

Having established the connection between burnout and women's relative labor income position within the household, we now study how burnout relates to their career progress. We measure career progress through the growth in labor income between two consecutive years. An individual's labor income in year t is calculated using her rank-adjusted income in year $t-1$ multiplied by the growth rate in her nominal income between years t and $t-1$.

Figure 3c plots the burnout rate of women against their labor income growth. This figure uses a two-dimensional moving average and rank-adjusted income, both following the procedures described above. Two key patterns emerge. First, the lighter-shaded diagonal indicates that women with stable labor income exhibit the lowest burnout rates among full-time employed women. Second, burnout risk rises with deviations from the diagonal in either direction—that is, with income changes of either sign. This pattern is intuitive once income changes are read as markers of labor-market transitions, each bundling its own stressors. Above the diagonal, rising income typically reflects promotions, job changes, or expanded responsibilities; consistent with this interpretation, promotion to a managerial position raises subsequent burnout risk (Appendix Figure A.17, panel a), and income accelerates in the years preceding burnout (Section 4).[33] Below the diagonal, falling income reflects reduced hours, spells of absence, or transitions to less demanding positions—adjustments that themselves may be responses to accumulating strain. Risk rises more steeply above the diagonal than below it, indicating that career advancement, rather than setbacks, is the stronger correlate of subsequent burnout.

Workplace and family events both relate to burnout risk, but in different ways. Panel (a) in Figure 4 shows that the likelihood of burnout increases most after severe illness of a spouse, followed by severe illness of an adult child. Among workplace events, the largest increase follows sexual harassment and is comparable in magnitude to the increase after child illness. Manager changes and industry shocks are substantially more frequent, but are followed by smaller increases in burnout risk. Overall, the figure reveals that rare family shocks coincide with sharp increases in burnout, whereas common workplace shocks are associated with smaller risk increases per event.

Because family shocks are rare, they precede far fewer burnouts than workplace shocks. In the year before burnout, 21.1 percent of first-burnout cases experienced a workplace event, compared with 4.9 percent for a family event; including the year of burnout, the shares are 31.9 and 15.8 percent (Appendix Figure A.39).[34]

Panel (b) shows that career and workplace variables consistently contain more information about next-year burnout than family and private-life variables. Across alternative orderings of the predictor groups, their marginal contribution to predictive accuracy is 1.9 to 4.1 times as large; averaging over all possible orderings yields a Shapley-value ratio of 2.37. Thus, workplace information contributes more than twice the predictive power of family information, although this comparison is predictive rather than causal.

4 The Economic Burden of Burnout

This section examines how the lives of workers and their families change after an episode of diagnosed burnout and quantifies the resulting loss in aggregate income.

[33] The pattern is similar for men, and among workers who stayed with the same employer throughout (Appendix Figure A.10).

[34] Industry shocks account for most of the workplace share, and the death of a parent is the most common family event (Appendix Figure A.40).

4.1 Labor Market Consequences for Affected Workers

As we discussed and demonstrated above, burnout results from a bundle of accumulated stressors that culminates in a burnout episode. To quantify the economic burden of these episodes, we use a set of complementary designs, each built on a different comparison group and drawing its variation from a different part of the stressor bundle. We interpret the resulting estimates as conditional post-episode differences—associations with the stressor bundle culminating in the episode—rather than as the effect of burnout holding that bundle fixed.

Our primary design is a one-to-one matched differences-in-differences estimator, in the spirit of recent applications (e.g., Jäger et al., 2025; Adams-Prassl et al., 2024). It compares workers at the time they go into burnout to observationally similar individuals, matched on demographics and pre-burnout income and employment histories, who never experience burnout. This design nets out confounding from observable differences in stress exposure and earnings trajectories.[35]

Even conditional on these observables, individuals who burn out may differ from those who do not along persistent unobserved dimensions—such as susceptibility to stress or life-cycle earnings profiles (Section 3)—that independently shape their outcomes. We therefore complement our primary design with a timing-of-treatment approach. That is, among those who burn out, we compare those who burn out in year t to observationally similar individuals who instead burn out in year $t + \delta$. We refer to this difference-in-differences estimator as the *fixed-delta* method (Hilger, 2016; Fadlon and Nielsen, 2019; Nekoei and Seim, 2023).

Because both the matched and fixed-delta comparison groups eventually differ from the treated group only in the timing or occurrence of burnout, the identifying assumption in each case is that, absent the differential accumulation of stressors that leads the treated group to reach burnout at the observed date, treated and comparison incomes would have continued to evolve in parallel. Under this assumption, the estimated post-burnout divergence reflects the economic consequences of the stressor bundle culminating in burnout, rather than an effect of burnout independent of its antecedents.

As a further diagnostic check, we use an industry-level design where we instrument individual burnout with changes in the burnout rate among other workers in the same five-digit industry, excluding the individual and their firm. The rationale is that idiosyncratic private-life shocks—such as divorce—average out at the industry level, so shifts in industry-level burnout rates instead reflect conditions shared across employers in an industry.. This design therefore places greater weight on variation shared across an industry and reduces sensitivity to person-specific events and shocks confined to the individual's employer. Because industry-level conditions could also affect labor-market outcomes —e.g., income, hours, or job security— directly, however, we do not treat this design as independently causal. Comparing them with our main estimates assesses whether the negative relationship persists when identifying variation is less sensitive to idiosyncratic private-life shocks. Appendix E provides details of the estimation procedure, drawing on the grouped-instrumental-variables approach of Angrist (1991).

We first describe the procedure underlying the matched difference-in-differences design, and then describe the fixed-delta method. The estimation sample is a balanced panel of individuals whom we observe for twelve years. We select the control group from a candidate pool of individuals who have never experienced burnout and satisfy the sample selection criteria previously listed in Section 3 (see Appendix B for details). We perform one-to-one exact matching without replacement of burned-out individuals to controls based on the year of birth, education, gender, income percentile in the year prior

[35] A potential concern is that burnout coincides with a negative labor demand shock. To address this, we will refine the matching procedure to include industry, ensuring treated and control individuals operate within the same sector.

to treatment within this demographic group, and their employment in the four years prior to treatment. Of all individuals who experience a burnout event, 99.34 percent can be matched with an observationally similar control. The matched treated group consists of a balanced panel of 150,834 individuals.[36]

Figure 5a plots average labor income for workers who burn out at event time zero and their matched never-treated controls. Earnings follow broadly similar paths before treatment, although they grow slightly faster among workers who subsequently burn out. At the onset of burnout, treated workers' earnings fall sharply and then recover only from a lower level, while control-group earnings continue to rise.

Building on the income drop descriptively shown in Figure 5a, we estimate a difference-in-differences regression. It compares outcomes for workers who experience burnout with matched control observations. The coefficients of interest are α_t in our estimation equation:

$$Y_{i,t} = \phi_{G_i,T_i} + \delta_{G_i,t} + \sum_{s=-4,\, s\neq -1}^{7} \mathbb{1}_{s=t}\alpha_s T_i + \varepsilon_{i,t}. \tag{1}$$

where $Y_{i,t}$ is the outcome of interest for individual i at event time t, T_i is the treatment indicator, and G_i is the observation group used in matching that individual i belongs to. The regression includes both group-treatment status fixed effects, ϕ_{G_i,T_i}, and group-time fixed effects, $\delta_{G_i,t}$. Standard errors are clustered at the individual level.

Figure 6a presents the patterns of labor income around burnout based on equation (1). In the years before burnout, the estimates exhibit a small upward trend in earnings. This is consistent with Figure 3c, which shows that burnout is associated with prior income growth, potentially reflecting promotions or firm changes. Labor income falls by roughly 10 percent in the year of burnout and by almost 15 percent in the following year. The loss remains 12.1 percent seven years after burnout. The magnitude of the income loss is similar to, but slightly exceeds, the approximately 10 percent loss following physical and mental health shocks that lead to sick leave (Kolsrud et al., 2020). Burnout therefore appears to generate a somewhat larger earnings scar than the average health shock. The losses are comparable to the long-run effects of job displacement, which range from 10 to 20 percent depending on macroeconomic conditions (Davis and Von Wachter, 2011).

In the year of the first burnout episode, sick leave due to burnout amounts to 82 days, or 22.5 percent of the year (Figure A.15b), whereas labor income falls by only 9.6 percent (Figure 6a); this discrepancy is explained by deferred payments and by supplementary sick-pay top-ups from employers and collective agreements, which are recorded as labor income. Reassuringly, the two estimates align in the following year, when 56 days of sick leave (15 percent of the year) correspond to a 14.3 percent income loss. By year 7, sick leave has fallen to 11 days (3 percent of the year) while labor income remains 12.1 percent below its counterfactual level, implying that only about a quarter of the long-run earnings loss is attributable to sick leave.

Figure 6c shows how the income loss varies with the duration of the initial sick-leave spell. Two features of this pattern are noteworthy. First, the long-run loss is far less dispersed than the initial absence. Whereas mean spell length varies by more than a factor of twenty across groups, the loss seven years after burnout varies by only a factor of 2.5. Even the shortest spells, in which the initial absence amounts to a few weeks, are followed by a persistent loss of over 8 percent. This points to a substantial component of the long-run loss that is common to all burnout cases and unrelated to the duration of absence itself.[37] Second, as

[36] Appendix Figure A.31 compares the age distribution of the estimation sample with that of all burnout spells.

[37] Whereas sick leave in the year of the first episode exceeds the corresponding income loss and the two are aligned by year 1, by year 7 the income loss persists at a level well above what the remaining sick leave can explain. This pattern

discussed in Section 1, the diagnosis code pools exhaustion disorder with acute and other stress reactions. Because acute stress reactions typically resolve within weeks, they concentrate in short spells, whereas long spells consist predominantly of burnout proper. The heterogeneity in Figure 6c therefore partly reflects diagnostic composition rather than severity alone, and the baseline estimate of 12 percent is best read as a lower bound on the loss from burnout proper, for which the 21 percent loss among spells of six months or more provides a closer indication.

Results are robust to matching within industry to account for potential negative labor demand shocks (Appendix Table A.5), indicating that sectoral shocks do not drive our findings. The industry-level estimate reported in Appendix E likewise implies a 13.8 percent earnings loss two years after burnout, similar in magnitude to the difference-in-differences estimate. This similarity makes it less likely that the baseline earnings decline is driven solely by person- or family-specific events that coincide with burnout. We also address this issue directly: dropping matched pairs in which either individual experiences a severe illness of a child or spouse, or the death of a parent, leaves the estimated loss no smaller, and for women somewhat larger (Appendix Figure A.35).

We complement our analysis with another design to address concerns about the potential influence of unobserved characteristics of individuals who experience burnout. It also addresses the possibility that the estimated income loss might be conflated with the pattern of earnings growth prior to the onset of burnout, which might attenuate the estimates (Figure 3c). The complementary design evaluates the effects compared to a control group that also experiences burnout but δ years later.

Figure 5b plots average labor income for workers who burn out at event time zero and matched controls who first burn out five years later, so that $\delta = 5$. The two groups exhibit similar earnings growth before event time zero. Their earnings diverge when the treated group burns out, and the gap begins to narrow when the comparison group experiences its own burnout event at $t = 5$. This pattern motivates using variation in burnout timing as a complement to comparing workers who ever and never experience burnout.[38]

The estimated earnings drop at impact is similar under both designs, suggesting that unobserved characteristics play a negligible role. Moreover, the estimated long-term differences is similar but slightly larger than using the never-treated control group, estimated at 14.9 percent (Appendix Table A.5). The pre-burnout acceleration for the control group creates a divergence of income over time in the fixed-delta method, in contrast to the stagnant effect when the control group consists of individuals who never burn out. These patterns are robust to the choice of the window, δ, showing that income life-cycle patterns are the primary source of identification, similar to the case of inheritance in Nekoei and Seim (2023).

Do individuals experiencing burnout face income reductions because they receive fewer promotions in their current job, or do they transition to lower-paying positions? Alternatively, are income declines driven by reductions in working hours or labor force withdrawal? And how do these mechanisms evolve over time? To address these queries, conventional static analysis of either intensive or extensive margins is insufficient because it fails to capture the dynamic interplay between labor supply adjustments, job transitions, and wage trajectories over time. We therefore decompose average post-burnout income loss into its underlying components. Before the decomposition and as a first step, we conduct a descriptive analysis of changes in months worked, full-time employment, and turnover before and after burnout (Appendix Figure A.14). We observe a slight upward pre-trend in months worked, consistent with more work in the run-up to burnout, and a sharp drop in months worked when they go into burnout. On average,

is similar to what we saw in aggregate.

[38] Appendix Figure A.13 presents the corresponding estimates for values of δ ranging from two to seven years and compares them with the baseline estimate in Figure 6a.

workers lose permanently about one month of work per year. Full-time employment also exhibits a sudden and persistent drop of about 10 percentage points. Among burned-out workers who remain employed in the following years, job-to-job mobility increases by around 3.1 percent for men and 2 percent for women. Labor force exit and job-to-job mobility combined imply substantial turnover. Two years after their first burnout incident, 48.5 percent of workers in the treated group have separated from their original employer versus 39.8 percent in the control group.

Our decomposition approach measures the dynamic quantitative importance of each channel. It is grounded in the idea that for any sample partition, stable or dynamic, the average treatment effect can be broken down into the contribution of each respective partition.[39] To formalize this, we denote the time-varying indexing function associated with a partition P by $\pi_{i,t}$, identifying the set to which individual i belongs at time t. Moreover, $c(i)$ denotes the match of individual i in the control group. Thus, for any outcome $Y_{i,t}$, $Y_{c(i),t}$ denotes its counterpart in the control group. To estimate the contribution of a set $p \in P$, we use as outcome, $Y^p_{i,t}$, that takes the control value if individual i does not belong to p,

$$Y^p_{i,t} \equiv Y_{i,t}\mathbb{1}\left(\pi_{i,t} = p\right) + Y_{c(i),t}\mathbb{1}\left(\pi_{i,t} \neq p\right) \tag{2}$$

We can thus decompose the individual treatment effect as the contribution of each set of the partition:

$$Y_{i,t} - Y_{c(i),t} = \sum_{p \in P} Y^p_{i,t} - Y^p_{c(i),t} \tag{3}$$

The last equation implies that the average treatment effect can be decomposed in the same way, and that we can calculate the contribution of the partitions by:

$$\sum_{p \in P} \frac{\mathbb{E}(Y^p_{i,t} - Y^p_{c(i),t})}{\mathbb{E}(Y_{i,t} - Y_{c(i),t})} = 1 \tag{4}$$

where each fraction measures the contribution of each partition at time t.

The strength of this decomposition lies in its dynamic nature; the indexing function changes over time. This feature is particularly valuable in labor market analyses, where partitions are inherently dynamic, such as the distinction between employed and unemployed statuses. We implement this decomposition by partitioning workers into four categories. The initial division of worker states differentiates between the extensive and intensive margins. The extensive margin quantifies the income loss from burned-out workers ceasing work or transitioning to part-time employment. Conversely, the intensive margin arises from reduced income among those who return to full-time work after a burnout episode, further broken down into within-firm and between-firm contributions: it captures the contribution of individuals who remain with the same firm where the burnout occurred and those who switch firms thereafter.

Figure 6, panel (b), presents the outcomes of our dynamic decomposition, in which we reclassify workers each event year. Most lasting post-burnout income loss is attributable to the extensive margin, with workers either not working or, more significantly, shifting to part-time roles. A minor fraction of the income loss can be ascribed to stalled career advancement, reflecting lower earnings among workers who remain with their pre-burnout employer.[40] Workers who switch firms after burnout experience smaller

[39] To the best of our knowledge, this type of decomposition has not been explored in prior work, and we are therefore unable to cite direct precedents.

[40] Appendix Figure A.32 reports the share of the sample in each category by event-year. Because the categories are defined by post-burnout labor market status, the decomposition allocates the total effect across margins rather than comparing causally identified subgroups. The results are quantitatively similar across genders as shown in Appendix

income losses. If firms compensate workers for the work-related stress that leads to burnout, then leaving such a firm should mean forgoing a wage premium and hence a larger loss. We find the opposite, which suggests that stressful work is not, in practice, compensated.

In fact, workers move to less stressful jobs after experiencing burnout. We focus on firm switchers and study the evolution of their industry-level burnout rates. After a burnout episode, workers tend to exit high-risk industries for those with lower burnout risk (Appendix Figure A.37). Two years after burnout, individuals exiting their pre-burnout employer move to industries with 0.027 percentage points lower burnout rates, a reduction equal to 4.5 percent of the standard deviation across firm movers in the control group.[41] Taken together, Appendix Figure A.37 and Figure 6, panel (b), show that firm switchers move toward lower-risk industries while the switcher component mitigates the earnings loss.

Our measurement of burnout is directly linked to the receipt of social insurance claims. In addition to paid sick leave, Sweden maintains a generous social insurance system through disability insurance and progressive taxation. Figure 6d asks the extent to which public insurance buffers the earnings loss following burnout. In the short run, sick pay compensates burned-out workers for a large share of their lost earnings. The buffer fades quickly, however: the median burnout sick-leave spell lasts less than two months, and eligibility was generally capped at 914 days (see Appendix Figures A.15 and A.30 and Appendix A.5). In the long run, increases in other public transfers compensate for the reduction in sick leave benefits. Yet despite these social insurance mechanisms, disposable income seven years after the first burnout is still 6.1 percent lower than in the control group. Interestingly, the long-term impact of burnout on disposable income is comparable in magnitude to the five percent long-term decrease in *consumption* following both physical and mental health shocks estimated in Kolsrud et al. (2020).

4.2 Gender Differences, Spousal Labor Market Outcomes, and Family Outcomes

In Section 3, we documented that women are three times more likely to burn out than men. In Figure 7a, we examine whether the consequences of burnout differ by gender. Interestingly, the earnings losses are rather similar across genders: 11.9 percent for women and 13.5 percent for men.[42] Taken together, these results suggest that while the incidence of burnout varies substantially by gender, the severity of its economic consequences is more uniform.[43]

We now turn to spousal labor market outcomes. The motivation for analyzing intra-household spillovers is twofold. First, spousal labor supply can act as a private insurance mechanism against earnings losses, which has implications for the optimal design of public insurance (Cullen and Gruber, 2000; Fadlon and Nielsen, 2019; Autor et al., 2019). At the same time, burnout symptoms are severe enough to require caregiving by family members, potentially reducing their labor supply.[44]

To perform our event study for spousal earnings, we focus on workers who were married or cohabiting

Figure A.16. Transitions to part-time explain the largest share of the earnings loss among women, whereas exit from the labor force constitutes the main adjustment margin for men.

[41] Appendix Figure A.29 reports the underlying reallocation across nine broad industry groups following burnout. Both men and women move out of manufacturing and out of finance and insurance, and into professional and administrative services.

[42] As a comparison, the displacement literature finds larger earnings losses for women than for men (Illing et al., 2024).

[43] Appendix Figure A.38 shows that men and women employed in the same sector before burnout experience nearly identical earnings losses. Losses are larger in the private sector, where men are more concentrated, which accounts for their somewhat larger pooled loss.

[44] For similar care-giving results in the context of elderly parents, see (Løken et al., 2017; Massner and Wikström, 2024)

in the year prior to burnout. We then follow spouses over time regardless of whether they separate in subsequent periods, and study separation as an outcome. We require that spouses satisfy the same sample restrictions we impose for workers in our baseline analysis, i.e., a balanced panel of individuals whom we observe for twelve years. We perform the same matching procedure as in the baseline analysis, except that we match at the spouse level so treated and control spouses are born in the same year. Our estimation sample includes 57,441 spouses married to workers experiencing burnout.

Figure 7b depicts the evolution of spousal earnings. For male spouses, earnings begin to decline in the periods leading up to their wives' burnout and then remain broadly flat thereafter. By contrast, female spouses experience an immediate and persistent earnings drop that closely mirrors the own-earnings losses documented in Section 4.1. Seven years after the burnout event, female spouses earn 4.4 percent less than observationally similar women in the control group.

This gender asymmetry is consistent with caregiving norms that disproportionately burden women (Anand et al., 2022). The pre-burnout decline in male spouses' income raises concerns that spousal incomes were already diverging from those of the matched controls before burnout occurred. We therefore re-estimate the spousal event study using the fixed-δ method in Appendix Figure A.21 and the industry-variation design in Appendix Table A.6. Results suggest that the income falls of wives are large and permanent in contrast to smaller and more transient loss of income for husbands. Because industry shocks may affect spouses directly, we treat this estimate as corroborating the direction of the spillover rather than as a separately identified causal effect. Appendix Figure A.34 decomposes the spousal earnings loss into sickness or disability, unemployment, and a residual category. A substantial share operates through the spouse's own sickness or disability—which caregiving alone would not generate—and the channel runs in both directions, since a spouse's severe illness is associated with the largest increase in own burnout risk among the events in Appendix Figure A.17. Taken together, these findings imply that intra-family spillovers constitute a meaningful component of the aggregate cost of burnout.

Burnout may undermine workers' well-being not only by affecting professional lives but also by disrupting private lives. Moreover, changes in family circumstances can heighten overall stress levels and compound the burden of occupational stress, as discussed in Section 3.2. Appendix Figure A.21, Panels (a) and (b) investigate how couple stability evolves around a burnout episode. The outcome variable is an indicator of whether the individual has the same spouse as at $t = -4$. Individuals who experience burnout are generally more likely to separate than the controls. In the year of burnout, separations jump by 4 percentage points, about a 50 percent increase in the annual rate. Fixed-$delta$ estimations show similar patterns.[45] Panels (c) and (d) of Appendix Figure A.21 present how fertility evolves around a burnout. They show a permanent reduction in fertility among women.[46] Men, in contrast, have fewer children in the short run but more in the long run. Appendix Figure A.22 shows that the decline among women also appears on the extensive margin, while the corresponding estimate for men is small and statistically indistinguishable from zero. Women's burnout is also preceded by an increased rate of childbirth in the year before, with no such pattern for men. The similar results from fixed-δ design indicate that they are tied to the timing of burnout rather than to persistent differences across workers. Childbirth may itself contribute to burnout among women.

[45] Appendix E presents the corresponding industry-level estimate (Appendix Table A.6), which is similar in magnitude.

[46] Appendix E presents the corresponding industry-level estimate (Appendix Table A.6), which is negative but not statistically different from zero. This estimate pools men and women for statistical power. Estimated separately, the industry-level estimates qualitatively align with the difference-in-differences estimates.

4.3 Children's Human Capital

Parental burnout may affect children through several channels, including reduced parental time, attention, and emotional support. To assess these potential channels, we examine children's school performance and educational attainment. Unlike the worker-level event studies in the preceding subsections, which follow outcomes around the worker's own burnout, this analysis exploits whether parental burnout occurs before or after the child's educational outcome is measured. We therefore conduct the analysis separately by the child's age at the time of parental burnout.[47]

Estimates use a timing-based difference-in-differences design, similar in spirit to the fixed-delta design. We first match children whose parent experiences burnout to children with the same birth cohort, gender, and sibling order whose parents never experience burnout. We subtract the matched control-group mean from each outcome to remove cohort-specific differences in educational outcomes. We then compare these adjusted outcomes across children whose parent burns out before and after the outcome is measured. Identification requires that, conditional on the included parent and child characteristics and absent anticipation, adjusted potential outcomes would not vary systematically with the timing of parental burnout. Formally, child i's adjusted outcome is $\hat{y}_i = y_i - \bar{y}_i^c$, where $\bar{y}_i^c$ is the mean outcome among the matched controls assigned to child i. We estimate

$$\hat{y}_i = \sum_k \beta_k \mathbb{I}(a_i = k) + X_i + \varepsilon_i, \tag{5}$$

where $\mathbb{I}(a_i = k)$ indicates that the first parental burnout episode occurs when child i is age k. The vector X_i includes indicators for the parent's birth cohort and gender and the child's birth cohort, gender, and sibling order. Standard errors are clustered at the parent level.

We examine children's human capital using two outcomes. The first is academic achievement, measured by test scores on national exams at the end of compulsory schooling. All Swedish students—typically age 16—complete them in 9th grade. We define a threshold indicator for achieving a total score of 240 or higher, corresponding to an average grade of C (15) across 16 subjects and close to the national median. These exams are high-stakes: the score determines access to selective secondary programs and influences college admission (see, e.g., Ramstedt, 2005, for further discussion and details).[48] The second outcome is educational attainment, measured by an indicator for college enrollment at ages 19, 20, or 21.[49]

Figure 8a plots the coefficients from equation (5) for grade-9 test scores by the child's age at parental burnout. The coefficients therefore compare the control-adjusted outcomes of children exposed before the examination with those of children whose parent burns out afterward, at age 17. For presentation, we add the matched control-group mean back after estimating these differences, so the plotted series is expressed in outcome levels. On average, children whose parent burns out between ages 10 and 16 are 1.9 percentage points less likely to achieve an average grade of C or higher than children whose parent burns out at age 17. This corresponds to a 5.3 percent reduction relative to the control-group mean. Because parental burnout

[47] We measure age at parental burnout as the age at the first observed burnout episode of either the mother or the father. Our results are similar when restricting the analysis to maternal burnout, which constitutes the largest share of burnout events.

[48] The sample for this outcome comprises 352,891 children whose parents experience burnout during our sample period and who turn 16 by the end of it. The youngest age at parental burnout in this sample is therefore ten.

[49] We measure college enrollment by age 21 since many students take longer to complete college, so completion would limit the number of cohorts available for the analysis. This leaves 297,668 children of burned-out parents who turn 21 by the end of the sample period, for whom the youngest age at parental burnout is seven. Appendix Figure A.18 shows similar results when using college enrollment by age 24 as the outcome.

at age 17 or later occurs after the grade-9 examination, the corresponding estimates provide placebo tests: future parental burnout cannot causally affect an outcome already realized. We find no effect on school grades when parental burnout occurs at ages 17 to 25.

Figure 8c presents the corresponding estimates for college enrollment. Parental burnout between ages 7 and 18 reduces college enrollment by 2.5 percentage points, or 8.1 percent relative to the control-group mean. The estimates are somewhat smaller when burnout occurs after the child reaches college age. The estimates for ages 7–18 are statistically indistinguishable, although the point estimates are slightly larger for children exposed at younger ages. Because parental burnout at ages 22 to 25 occurs after college enrollment is measured, the corresponding estimates provide placebo tests and are not statistically different from zero.

Figures 8b and 8d show that the effects are concentrated among children of less-educated parents, implying that parental burnout widens educational disparities across family backgrounds and reduces intergenerational educational mobility.[50]

Parental burnout may coincide with other events in the life of the parent, child, or family. To shift the identifying variation away from person- and family-specific events, we instrument parental burnout with the burnout rate in the parent's industry, as in our analysis of workers' income. Appendix Table A.7 shows that estimates using industry-variation are nearly identical to the difference-in-differences estimates.

This agreement suggests the results are not driven solely by person- or family-specific events and remain unchanged when we isolate variation to parental industry. A causal interpretation would nevertheless require that changes in the parent's industry-level burnout rate affect children's outcomes only through parental burnout. This exclusion restriction could fail if the underlying industry shocks also alter parental earnings or work schedules, affecting household resources and parental availability independently of burnout. Changes in these factors caused by parental burnout are legitimate mediating channels; changes arising directly from industry conditions are not. We therefore interpret the agreement as a diagnostic check, not as establishing causality.

We benchmark these magnitudes against prior studies of parental job loss and parental death.[51] Our 1.9-percentage-point difference in the probability of reaching an average grade of C corresponds to about 0.05 standard deviations of the total test score. This is about three-quarters of the effect of paternal job loss in Rege et al. (2011), close to the effect of maternal job loss on children exposed two to four years before graduation in Mörk et al. (2020), and close to the 0.06-standard-deviation reduction in school grades following parental death in Liu et al. (2022). The educational differences we document are therefore of the same order of magnitude as those following parental job loss and parental death.

4.4 Aggregate Labor Income Loss

We are now equipped to calculate the aggregate loss of labor income post-burnout across four channels: current sick leave, own-income scarring, spousal spillovers, and children's education.

$$\text{Share of Aggregate Income Lost} = \frac{\sum_i \left(\sigma_i \hat{y}_i + \alpha^o \frac{y_i^o}{1-\alpha^o} + \alpha^s \frac{y_i^s}{1-\alpha^s} + \alpha^c \frac{y_i^c}{1-\alpha^c} \right)}{\sum_i \left(\hat{y}_i + \frac{y_i^o}{1-\alpha^o} + \frac{y_i^s}{1-\alpha^s} + \frac{y_i^c}{1-\alpha^c} \right)} \tag{6}$$

[50] The gradient is not driven by the parent's own income loss, which is nearly identical across education groups (Appendix Figure A.20). Appendix Figure A.19 examines heterogeneity by maternal and paternal burnout and for boys and girls. The similarity between maternal and paternal effects is surprising given our earlier finding that wives are themselves substantially affected by their husbands' burnout.

[51] Estimates from settings where households finance education directly—such as Hilger (2016) for the United States and Chen et al. (2009) for Taiwan—are not directly comparable, see footnote 10.

where $\hat{y}_i$ is individual i's counterfactual annual income absent burnout, σ_i is the share of the year spent on burnout-related sick leave. The terms y_i^o, y_i^s, and y_i^c denote income for individuals exposed to burnout directly, through a spouse, and through a parent, respectively. The terms α^o, α^s, and α^c are the proportional income losses associated with these forms of exposure, estimated in Figures 6a, 7b, and 8c. Appendix Section F provides the details of these calculations.

Figure 9 implies a 2019 loss of 2.09 percent of aggregate labor income, comprising 0.49 percentage points from current sick leave, 1.35 from persistent own-income losses, 0.21 from spousal spillovers, and 0.04 from children's education.[52]

Because burnout diagnoses are observed only from 2006 onward, this calculation understates accumulated long-run losses. To overcome this shortcoming, we calculate the loss in a hypothetical steady state. Specifically, we assume the burnout rate in Sweden stays constant at its 2019 level, so we can compute survival rates as a function of age, as is common in life expectancy studies.

Holding the 2019 burnout process fixed, the estimated steady-state loss is 3.20 percent: 0.49 percentage points from current sick leave, 2.29 from own-income scarring, 0.26 from spousal spillovers, and 0.16 from children's education. To put the aggregate loss in perspective, we divide it by the incidence of burnout in the population. This calculation implies that each case of burnout is associated with a loss equivalent to about three years of average income ($3.20/1.12 = 2.86$). Adjusting for this difference yields a loss equivalent to just over three years of their income ($3.20/1.12 \times 325/303 = 3.06$). The scale of this economic burden motivates our analysis of prevention policy in the next section.

5 Predicting and Preventing Burnout

The substantial costs of burnout we have documented suggest that prevention may yield substantial gains. Preventive programs can be effective (Tetrick and Winslow, 2015; Aust et al., 2023), but are themselves costly. We combine our cost estimates with a burnout prediction model to evaluate these costs and benefits and study the optimal scope and targeting of a preventive program.

5.1 Predicting Burnout Using Administrative and Survey Data

As shown in Section 3, individuals' observable characteristics are highly correlated with burnout onset, suggesting that work histories and demographics may be predictive. Yet burnout remains relatively uncommon even in high-stress occupations, highlighting the limits of administrative data alone in identifying the workers most likely to burn out. Comparing Figures 1b and 2a suggests that self-reported stress symptoms may predict burnout better than occupation. We systematically compare these predictors. To leverage the high-dimensional data, we employ an Extreme Gradient Boosting algorithm (Chen and Guestrin, 2016), a sequential ensemble that iteratively constructs decision trees and flexibly incorporates interactions. Appendix G provides details on the prediction procedure.

We predict burnout in the *following* calendar year, using six models trained on two samples and different information sets. The two samples are the AMU survey sample and the entire Swedish population. For the AMU sample, we construct four information sets: (i) the information available on a standard CV; (ii) CV plus survey responses; (iii) a comprehensive set of administrative data available to us, the "kitchen sink";

[52] Hassard et al. (2018) systematically review estimates of the cost of work-related stress from across the literature. They find that productivity-related losses account for 70–90 percent of total costs, while healthcare and medical expenses account for the remaining 10–30 percent. Although their cost categories differ from ours, the predominance of productivity losses is broadly consistent with our estimates.

and (iv) the administrative data plus survey responses. For the full population, where survey responses are unavailable, we use sets (i) and (iii). The CV set contains gender, age, citizenship, and education, measured in 348 categories combining level and field (e.g., trained cardiologist, biology). The administrative data add marital status, duration since marriage or divorce, children's ages, spouse's income rank, occupation, labor income, employment, and sick leave over the past five years, firm-specific information such as industry and turnover, and, for men, cognitive and non-cognitive skills assessed during military enlistment. We measure predictive performance with the area under the Receiver Operating Characteristic (ROC) curve, that is, the true positive rate against the false positive rate.

Table 3 reports the results. In the AMU sample, the parsimonious model using only basic demographics yields an AUC of 0.655. Adding survey responses raises the AUC substantially to 0.725. By contrast, adding the full set of administrative records (the "kitchen sink" specification) raises the AUC only to 0.712. Thus, survey responses add more predictive value than the full set of administrative records. The combined survey-administrative model performs best (AUC of 0.746), highlighting that subjective assessments add value even to rich administrative and medical data.[53]

Our findings suggest that targeted surveys eliciting workers' own assessments of their work experience provide substantial information for predicting burnout that administrative data do not capture. A key feature of AMU is that responses are neither communicated to employers nor used in sick-leave administration, limiting concerns about the consequences of truthful reporting. This institutional separation distinguishes AMU from employer-administered stress surveys, which are widespread: 44 percent of European establishments with more than twenty employees have surveyed staff about work-related stress in the past three years (Howard et al., 2022).[54] We argue that, when designed to be incentive compatible, such surveys can serve as effective tools for identifying workers at risk and targeting preventive interventions.[55]

Given the cost of large-scale surveys, we use our prediction framework to study two dimensions of survey design relevant for cost-effective burnout prevention. First, we assess how frequently surveys must be administered to remain informative about burnout risk. Second, we ask whether restricting the survey to a core set of questions preserves predictive performance.

To assess how frequently surveys must be administered, we use a two-year prediction horizon in column (3) of Table 3. Although self-reported stress improves one-year-ahead prediction, it adds little predictive value at a two-year horizon relative to administrative data alone. This pattern is consistent with Figure 1c, which shows that stress rises sharply in the year before burnout. Thus, surveys capture acute, short-run signals, whereas administrative variables—particularly slow-moving characteristics such as occupation—are more informative about longer-run risk.

To assess the role of survey length, we focus on the four questions comprising the stress index introduced in Section 2; their selection was guided by the medical literature. We compare a classifier trained on these responses with classifiers trained on every other four-question combination drawn from the twenty-five questions with the highest individual AUC. The stress-index specification outperforms 94.4 percent of these alternatives, providing a complementary, data-driven validation of the index (Appendix Figure A.25a). The 5.6 percent of four-question combinations that outperform the stress index typically

[53] Appendix Figure A.26 evaluates the statistical precision of the AUC estimates and shows they are close to the median across 1,000 random sample partitions.

[54] The share of establishments conducting such surveys is highest in the Nordic countries, reaching 84 percent in Sweden. Yet establishments rarely follow these surveys with preventive interventions, despite evidence of their effectiveness (West et al., 2014; Linzer et al., 2015).

[55] See Chassang and Zehnder (2024), who show how secure survey design can improve information elicitation when respondents fear retaliation.

replace one question from the stress index with an alternative, such as the number of subordinates and reluctance to go to work.

The four-question stress index raises the AUC from 0.66 to 0.71, compared with a baseline using only basic demographics. The model using the full survey yields an AUC of 0.725 (Appendix Figure A.25a). Thus, the stress index captures 79.6 percent of the full survey's incremental predictive gain.[56] Using a richer set of administrative data as the baseline raises this share to 85.4 percent. Together, these results show that a parsimonious survey focused on a small set of early-warning symptoms adds substantial predictive value for identifying individuals at high risk of burnout.

We then examine how predictive performance varies across samples. Unlike survey responses, administrative records cover the full population. In this population, basic demographics yield an AUC of 0.73; the full set of administrative records raises it to 0.81.[57] An AUC of 0.81 means that, for a randomly drawn pair of individuals—one who experiences burnout and one who does not—the model assigns higher predicted risk to the former with 81 percent probability. For comparison, Einav et al. (2018) report an AUC of 0.87 for mortality prediction.[58]

5.2 Optimal Scope and Targeting of a Preventive Program

This section shows how our cost estimates and prediction model can guide the optimal scope and targeting of a preventive program. We then assess the incremental value of incorporating a stress survey.

5.2.1 Cost-Benefit Analysis: Theoretical Framework

We begin by characterizing theoretically the economic costs and benefits of a preventive program.[59] The program has two stages. First, screening (triage) identifies individuals at high risk. Screening costs p and has a true-positive rate α and a false-positive rate β. Second, those identified as high risk receive preventive treatment, which costs P per individual and has a success rate θ. The treatment cost is weighed against the cost of burnout, C.[60]

Consider a planner—an employer or government agency—that chooses the share x of workers to select for screening based on burnout risk predicted using gender, citizenship, age, and education. Let b denote the share of workers who would experience burnout absent the program. Individuals selected are either true positives at $\pi(x)$—correctly identified as high-risk—or false positives at $\eta(x)$ —mistakenly flagged by the prediction model. Thus,

$$x = b \underbrace{\pi(x)}_{\text{true-positive rate}} + (1-b) \underbrace{\eta(x)}_{\text{false-positive rate}} . \tag{7}$$

The cumulative-gains curve in Figure 10a estimates $\pi(x)$.

[56] The number of questions ranges from 67 in the earlier survey waves to 100 in the more recent waves.

[57] Figure 10b shows that adding the "kitchen-sink" predictors shifts the population cumulative-gains curve outward and also smooths it.

[58] A larger sample improves predictive performance. Appendix Figure A.24b shows that training on the full population and evaluating on the AMU survey sample, as in (Mueller and Spinnewijn, 2024), further increases predictive power, especially when using all administrative variables.

[59] Our cost-benefit calculation is not a full welfare analysis because it omits utility costs associated with work, burnout, program participation, and risk exposure.

[60] The success rate θ denotes the expected proportion of burnout costs avoided through treatment, encompassing both prevention and reductions in symptom severity. The burnout cost C includes immediate and persistent income losses, medical costs, and spillovers. The economically important participation condition assumed is $\theta C > P$.

The program's benefits accrue only from the true positives. False positives, by contrast, impose treatment cost P without generating any gain. The planner trades off these and chooses the share x of workers targeted for the program to maximize per capita net benefits:

$$W(x) = (\theta C - P) \underbrace{\alpha b \pi(x)}_{\text{true positives}} - P \underbrace{\beta(1-b)\eta(x)}_{\text{false positives}} - px. \tag{8}$$

Differentiating $W(x)$ and using (7) to eliminate $\eta'(x)$ yields the first-order condition for an interior optimum:

$$\frac{\partial \pi(x^*)}{\partial x} = \frac{p + \beta P}{\kappa}, \tag{9}$$

where $\kappa := b\,[\alpha(\theta C - P) + \beta P]$. [61]

If $W(1) > 0$, either universal implementation or implementation in a random subsample is cost-effective. Targeting may still produce substantially greater net benefits, but it is not necessary. We focus on $W(1) < 0$, where any cost-effective positive program must rely on targeting. The first-order condition then implies $\pi'(x^*) > 1$, i.e., at an interior optimum, the marginal worker targeted must have above-average burnout risk.

The program's per capita net benefit at the optimum is

$$W(x^*) = \kappa\, I(\pi), \tag{10}$$

where $I(\pi) \equiv \pi(x^*) - x^* \frac{\partial \pi(x^*)}{\partial x}$ is the vertical intercept of the tangent to the cumulative-gains curve at x^*. Thus the proportional increase in optimal net benefits from an improved prediction model equals the proportional increase in this intercept.

Now suppose the planner augments the demographic predictors with a stress survey. Let $\pi_s(x)$ denote the resulting detection rate and σ the survey's per capita cost. The optimal program size x_s^* satisfies the analogue of (9), yielding

$$W_s(x_s^*) = \kappa\, I(\pi_s) - \sigma, \tag{11}$$

The survey weakly raises optimal benefits before paying for the survey. But it raises net benefits only when the value of improved targeting exceeds the survey cost, $I(\pi_s) - I(\pi) > \sigma/\kappa$. Conducting a stress survey will therefore yield a positive net gain if the survey cost is sufficiently low relative to the gains from improved detection and the cost reduction associated with a decrease in the optimal program size.[62]

5.2.2 Cost-Benefit Analysis: Numerical Calculations

We combine the theoretical framework with the estimated cumulative-gains curves and our estimates of burnout incidence and cost. We set triage sensitivity to $\alpha = 0.8$ and its false-positive rate to $\beta = 0.1$. The annual burnout risk is $b = 0.0112$. Dividing the steady-state aggregate labor income loss of 3.20 percent in Figure 9 by this risk gives $C = 2.86$, measured in units of average annual labor income. We set treatment

[61] The first-order condition characterizes the global maximum because $\frac{\partial \pi(x)}{\partial x}$—the marginal worker's burnout probability relative to the population base rate—weakly declines as coverage expands. This holds in our application, as in many others, because workers enroll in order of prediction score, and true burnout risk weakly increases in that score.

[62] Adding the survey has an ambiguous effect on the optimal scope of the program. It reduces optimal coverage only if survey's predictive gains are sufficiently concentrated among the highest-risk workers.

effectiveness to $\theta = 0.3$ and treatment cost to one month of average labor income, $P = 1/12$. [63] Valuing time at average hourly labor income and assuming 2,250 work hours per year, we set the triage cost p to five hours of work.

Under this calibration, equation (9) implies a common marginal-detection threshold of 1.5 for the slope of each gains curve. When the prediction is only based on basic demographics, this optimal slope implies that the optimal size of the triage group is 31 percent of the population and the intercept of the tangent to the curve is 8.5 percent (Figure 10a). Equation (10) then gives a per capita net gain of 0.060 percent of average annual labor income. Applying the same intervention to a randomly selected group of equal size would instead generate a 0.109 percent loss. Thus, even basic demographic targeting converts a loss into a gain.

Adding survey responses shifts the gains curve outward. The same marginal threshold yields $x_s^* = 0.23$ and a tangent intercept of 0.182. A key finding is that $x_s^* < x_d^*$ in our application: the survey's predictive gains are concentrated among those at high risk of burnout. We assume that the four-question survey takes ten minutes to complete. After deducting this population-wide survey cost, equation (11) gives a per capita net gain of 0.120 percent of average annual labor income. Therefore, the program's net benefit is approximately twice as large when complemented by a survey.

The baseline calibration values only labor income losses. We conclude by discussing how a more comprehensive measure of the cost of burnout—which includes the disutility of experiencing burnout—might affect our results. Suppose instead that workers' willingness to pay to avoid burnout implies a broader cost $C^W > C$. A higher cost lowers the marginal-detection threshold and, with concave gains curves, and expands optimal coverage. Consequently, the net gain from the program, as captured by equation (10), would be amplified through two channels: higher prevention benefits and an expanded optimal scope. The same logic applies to the survey specification (equation (11)).

However, the relative gain from including the survey may be larger or smaller than we have estimated above. On the one hand, the gain in prediction from including the survey is relatively less important, given the already extensive scope of the program. On the other hand, the net cost of the survey is smaller because the prevention gain is larger. In sum, as our baseline cost estimates underestimate the willingness to pay to avoid burnout, our estimated program gain represents a lower bound, but the incremental gain from the survey need not be.

6 Discussion

We have shown that chronic stress leads to burnout, with consequences that extend beyond individuals' careers to affect their spouses' earnings and their children's human capital. Consequently, work-related stress—via burnout—contributes to a substantial loss in aggregate labor productivity in Sweden. We conclude by taking up two questions that bear on the interpretation and generality of these findings. First, how do our estimates—obtained in a country with generous social insurance and a formal burnout diagnosis—travel to other institutional settings? Second, what does burnout, the clinically visible culmination of stress, imply about the broader cost of work-related stress?

[63] Meta-analyses—primarily involving healthcare workers—and a recent quasi-experimental study of 60 nurses suggest that individual, organizational, and combined interventions may reduce self-reported burnout-related scores, particularly emotional exhaustion(Lee and Cha, 2023; Bes et al., 2023; Othman et al., 2023; Zhang et al., 2020; Salvado et al., 2021). Because these studies primarily estimate effects on symptom scales rather than burnout incidence, we set $\theta = 0.3$ as an illustrative calibration.

6.1 External Validity: Stress, Institutions, and Diagnosed Burnout

To assess the external validity of our findings, it is crucial to recognize that burnout arises from the interaction between work-related stress and institutional context—particularly the generosity of the welfare state. More generous sick leave policies increase the likelihood that workers will take leave after periods of stress. At the same time, more progressive tax systems amplify the income loss and scarring effects associated with burnout.[64] Evaluating the extent to which our results generalize, therefore, requires careful consideration of both stress exposure and the social safety net.

Indeed, Sweden stands out on both fronts. In international comparison, workforce surveys suggest that work-related stress in Sweden is well below the global average (Gallup, 2023). For example, stress levels in the U.S. are about 40 percent higher than in Sweden (Appendix Figure A.1). Moreover, Sweden maintains an extensive welfare state with paid sick leave, similar to other European countries, whereas the United States has no paid sick leave program. Sweden is also one of nine countries that have established medical diagnosis criteria for burnout and one of five that have integrated them into their sick leave systems (Lastovkova et al., 2018).

To disentangle the effects of stress and the social insurance system, the ideal experiment would compare similar individuals exposed to the same degree of work-related stress, with one residing in a country with paid sick leave and another in a country without. In the absence of such a comparison, we study the effect of varying the replacement rate, estimating the sensitivity of burnout-related sick leave take-up with respect to daily benefit levels.[65] More precisely, we exploit a kink in the benefit schedule generated by a cap in sick leave payments and estimate the change in sick leave take-up due to burnout at the kink. For workers earning below this threshold, sick pay is a fixed proportion of income, whereas above the threshold, it becomes a fixed amount.

Appendix Figure A.27 illustrates the benefit schedule—the daily sick leave benefit level as a function of income—and the burnout rate around the threshold. Our regression kink design estimates imply that a 1 SEK increase in daily sick pay benefits increases the likelihood of burnout-related sick leave take-up by 0.0014 percentage points. Given that the average daily benefit associated with take-up over the sample period was 509 SEK, the implied elasticity suggests that eliminating sick pay entirely would lower the rate of burnout-related sick leave take-up to 0.41 percent, compared to the sample average of 1.12 percent.

Our estimates suggest that if Sweden abolished its generous paid sick leave system, burnout-related sickness absence would shrink to one-third of its current level.[66] However, this does not imply that the total cost of burnout would decline proportionally. As we show below, work-related stress depresses earnings and employment even among workers who never take burnout-related sick leave, suggesting that much of the cost reflects diminished work capacity rather than the availability of benefits. Moreover, reduced eligibility for sick leave benefits could also worsen health outcomes, creating additional societal costs (Gelber et al., 2023; Black et al., 2024).

Another aspect of external validity of our estimates to other European countries with similar sick leave programs based on ICD-10 but without a comparable diagnosis of burnout. We can assess this external

[64] An extensive literature has studied whether sickness insurance affects work absence behavior (e.g. Henrekson and Persson, 2004; Johansson and Palme, 2005). Moreover, for evidence on the effect of disability insurance benefit receipt on earnings, see Maestas et al. (2013), French and Song (2014), and Autor et al. (2019).

[65] This design enables us to identify the extensive margin response of sick leave take-up. Given that Sweden allows for sick leave to be taken at partial levels—at 25, 50, 75 or 100 percent—our analysis may miss potential response at the intensive margin.

[66] Sickness absence does not fall to zero in this counterfactual because the sick leave system comprises two components: the right to take leave when sick and the provision of income support during leave.

validity using the introduction of burnout in 2005 in Sweden. What followed admits two interpretations, with different implications for the external validity. Under the first, the new code relabeled absences already occurring: severely exhausted workers were certified as unable to work before 2005 under other diagnoses, and the code changed the label attached to those spells rather than the set of people receiving them. Under the second, it expanded eligibility, drawing in sick leave workers who previously would not have qualified.

The direct test—comparing the diagnostic composition of sick leave before and after 2005—is infeasible, since diagnosis information is incomplete before 2005. We instead use total sick-leave uptake, recorded consistently throughout, and ask whether its relationship to underlying stress changed. Extending the AMU sample of Section 2 back to 1997 and linking respondents to the sick-leave register, we regress uptake in the year after interview on the stress index, which captures the four core diagnostic criteria for burnout and strongly predicts subsequent diagnosis (Figure 1b).

Uptake fell substantially overall. This decline reflects stricter administrative practice and two reforms aimed at long-term absence. From January 2005, employers co-financed full-time sickness benefit, a change intended to strengthen their incentives to prevent absence, facilitate rehabilitation, and speed return to work (Government of Sweden, 2004). From July 2008, the rehabilitation chain tightened eligibility through fixed assessments of work capacity (Hägglund and Skogman Thoursie, 2010; Hägglund, 2013). Yet uptake rose relatively among high-stress respondents: at the top of the index, post-2005 uptake is indistinguishable from its pre-2005 level (Figure A.3). Against a falling baseline, this relative preservation is consistent with the new diagnosis extending or preserving sick-leave access among severely stressed workers. Because the relevant post-2005 counterfactual without the diagnosis is unobserved, however, the figure cannot distinguish such an expansion from the relabeling of absences that would otherwise have been recorded under other diagnoses.

6.2 Beyond Burnout: The Cost of Stress

Throughout the paper, we have measured the economic burden of work-related stress at the point where it becomes clinically visible: a diagnosis of burnout followed by extended sick leave, leaving a trace in administrative registers. Yet burnout is the culmination of the phenomenon we are ultimately interested in—chronic work-related stress—rather than the phenomenon itself. If stress erodes earnings capacity even when it never crosses the diagnostic threshold, the burden documented above, however large, understates the economic cost of stress. In this final analysis, we therefore step back from the clinical event and relate self-reported stress directly to subsequent labor market outcomes, without conditioning on any diagnosis or sick leave.

We return to the stress index constructed in Section 2 and ask how labor income evolves after workers report stress symptoms. Figure 11, panel (a), projects cumulative labor income over the three years following the survey, normalized by income in the survey year, on the level of the stress index. The resulting dose–response relationship in earnings mirrors the burnout-risk gradient of Figure 1b.[67] Low and moderate stress carry no earnings penalty—if anything, point estimates are mildly positive—an earnings-based counterpart to the inverted-U relation between stress and productivity (Yerkes and Dodson, 1908; Calabrese and Baldwin, 2002). Beyond the midpoint of the index, however, the profile turns steeply negative: workers reporting nearly all symptoms at their highest intensity subsequently forgo about 15 percent of a year's earnings over the following three years. Similar to burnout incidence, the cost of stress is highly convex, concentrated in the chronically stressed tail of the distribution.

[67] One rare empirical example of this non-linearity has been documented among professional tennis players (Paserman, 2023).

Panels (b) and (c) trace out the dynamics behind this cross-sectional gradient using a pseudo-event-study design: respondents whose stress index exceeds its midpoint are matched to lower-index respondents on interview wave, demographics, and pre-interview earnings. Before the interview, the two groups show little evidence of differential trends in earnings or employment. Afterward, high-stress workers' earnings fall by 1.4 percent per year on average over the following three years, accompanied by a similar decline in employment. The central result, however, is the comparison with estimates that exclude every respondent who subsequently receives a burnout diagnosis. The estimates barely move: excluding these workers reduces the estimated earnings loss only from 1.4 to 1.2 percent, and leaves the employment response unchanged. The bulk of the earnings losses following high stress thus accrues to workers who never enter the sick leave register with burnout. As with our burnout estimates, we read these patterns as the labor market footprint of the bundle of stressors that elevated symptoms reveal, not as the causal effect of stress as a separable treatment: workers are not randomly assigned stress, and self-reports may partly reflect adverse circumstances at work or at home. With this caveat in mind, the results carry three implications.

First, diagnosed burnout is the tip of the iceberg. Our estimate that burnout reduces aggregate labor income by 3.2 percent in steady state captures only the losses channeled through a clinical episode; Figure 11 shows that most stress-related earnings losses accrue below the diagnostic threshold and are therefore invisible in sick leave data. The aggregate burden of work stress accordingly exceeds the burden of burnout, plausibly by a wide margin.[68] Moreover, the size of the visible tip is itself institutional. Sweden has a formal burnout diagnosis, a sick-leave system that records it, and benefits generous enough to be used; our estimate of the recorded burden is therefore, perhaps, close to a best case for measurement. Where those institutions are weaker, the same underlying stress leaves a smaller administrative trace, but not a smaller economic cost.

Second, this reasoning completes the external-validity argument made earlier. Our kink estimates imply that abolishing sick pay would cut burnout-related sick leaves by two-thirds. But much of the loss in Figure 11 never runs through the sick leave system, and it would persist in its absence. Combined with the substantially higher stress levels reported in the United States, this suggests that the economic cost of work-related stress there is not lower than in Sweden, but largely unrecorded.

Third, the stress-survey questions shown in Section 5 to predict burnout also predict earnings losses that never culminate in a burnout diagnosis. The returns to survey-based monitoring of workplace stress are thus larger than our cost–benefit analysis, which values only averted burnout, suggests—and they extend to settings where no burnout diagnosis exists.

7 Conclusion

A structural transformation has reshaped the labor market in recent decades. First, jobs have changed. While average working hours have declined, an increasing share of roles now require workers to be "always on", eroding the boundaries between professional and personal life (Gerstel and Clawson, 2018). Physical demands have eased, but mental demands have intensified (Autor et al., 2003). Second, institutional shifts (Peoples, 1998) and globalization (Autor et al., 2013) have intensified competition and led to an expansion of non-standard work (Katz and Krueger, 2019). Third, dual-earner households have become more prevalent, creating intertwined career–family tradeoffs for partners (Goldin, 2006). Perhaps as a consequence of these

[68] For context, roughly 1 percent of workers experience a burnout episode in a given year, and an episode is followed by a permanent income loss of about 12 percent. High self-reported stress is far more common—12 percent of surveyed workers—and is associated with an income loss of 1.2 percent.

shifts, worker stress has been rising.[69] In our setting, a stark manifestation of this growing work stress is that each year, more than one percent of the population experiences severe work-related stress and takes extended sick leave due to burnout.[70]

In this paper, we provide a comprehensive analysis of work stress, particularly the economics of burnout, drawing on rich Swedish administrative data that link workers' labor market and family outcomes to medical diagnoses of sick leave. Burnout has severe and lasting consequences—not only for individuals' careers, but also for their spouses' earnings and their children's human capital. We show that the risk of burnout can be accurately predicted, especially when objective worker characteristics are complemented by self-reported stress symptoms. We argue that such surveys can help identify at-risk workers and expand access to preventive support, provided they are incentive compatible: confidential, voluntary, and separate from personnel and benefit decisions.

We emphasize that our effort to understand this multifaceted issue invites further research into the economics of work-related stress and burnout. In our view, several key questions remain open. First, what role do firms and employers play in shaping exposure to and management of workplace stress? Second, beyond the first evidence offered here, what are the full economic costs—and potential benefits—of stress in the workplace, including impacts on productivity, innovation, and long-term outcomes? Third, what is the compensating wage differential for stressful jobs? Fourth, how do social insurance and progressive taxation affect wage compensation, and how can they help workers cope with stress on the job? We aspire to answer some of these important questions in future work.

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[69] Appendix Figure A.1 shows the share of workers reporting stress during much of the previous day, based on Gallup's *State of the Global Workplace* survey since 2008 (Gallup, 2023).

[70] The exact connection between those technological, institutional and demographic changes and work stress remains a topic for future work.

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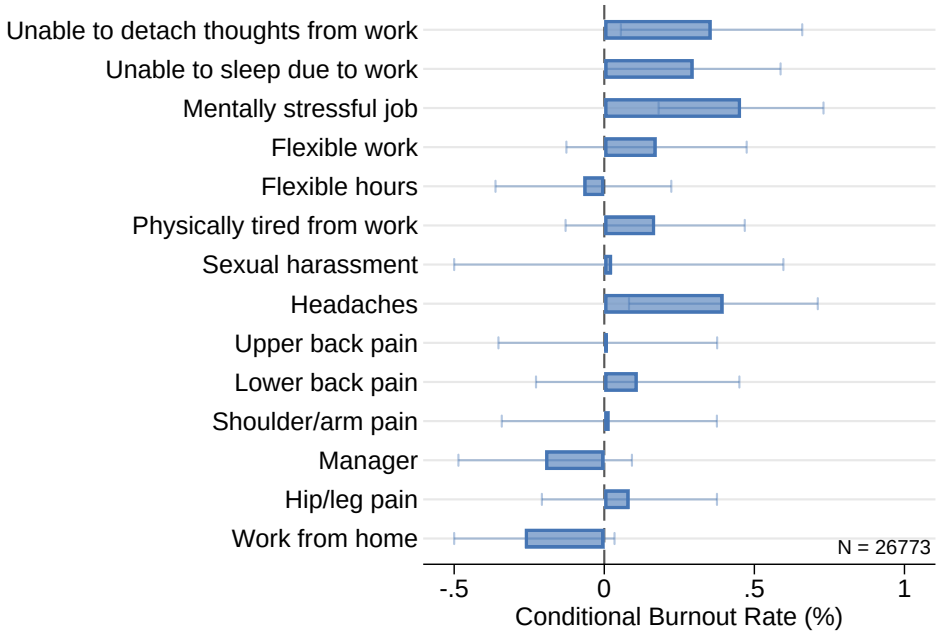
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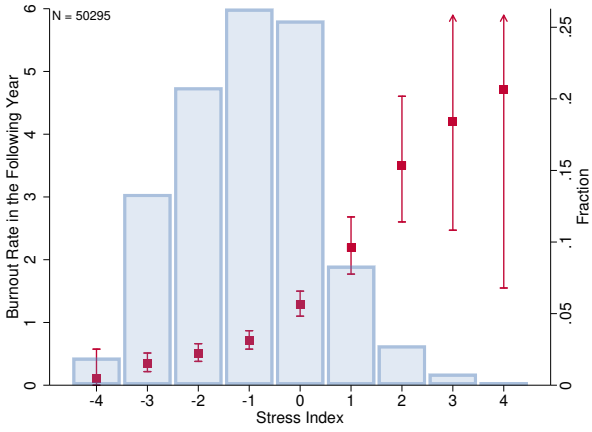
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Figure 1: What is Burnout?

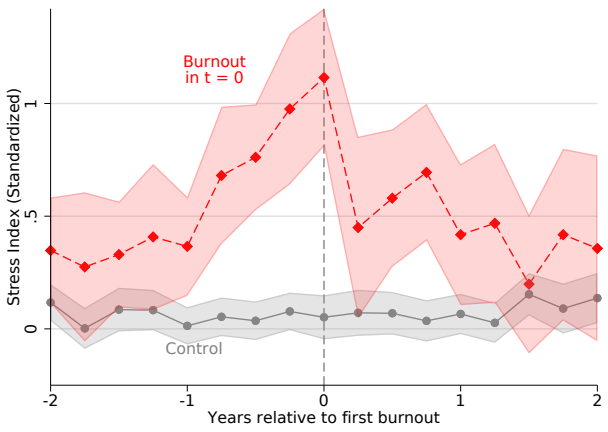
(a) Work Conditions and Burnout (multivariate regression)



(b) Stress Symptoms and Burnout Following Year



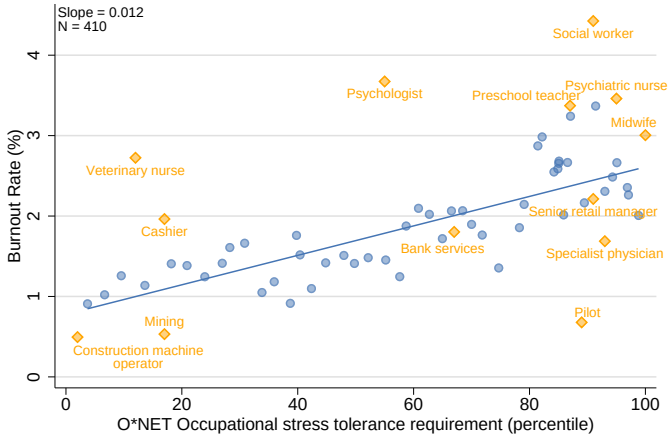
(c) Evolution of Stress Symptoms around Burnout



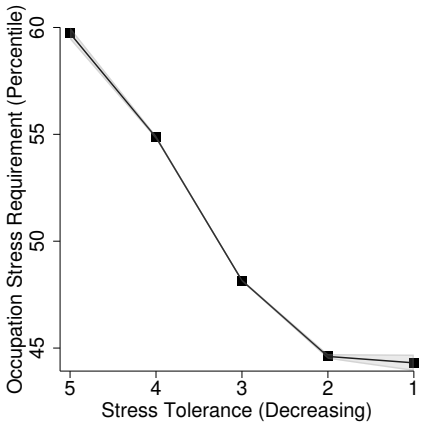
Notes: The figure documents the relationship between burnout and work conditions measured in two independent sources: administrative sick leave data and the Work Environment survey (AMU). **Panel (a)** plots the coefficients from a regression of a burnout indicator on self-reported work conditions in the previous calendar year, controlling for gender × education × age × family-type fixed effects and year fixed effects. We order work conditions by their relative association with burnout according to medical literature using an LLM (See Appendix C). Each work condition is coded as an indicator relative to the median. **Panel (b)** shows the relationship between a stress index and the burnout rate of a worker in the following year. Whiskers are 95-percent Clopper-Pearson confidence intervals, truncated from above. The stress index is constructed from self-reported conditions in panel (a), which are symptoms of burnout: inability to sleep due to work, a mentally stressful job, inability to detach thoughts from work, and headaches (See Appendix D). **Panel (c)** shows the evolution of the stress index (z-score) around the time of burnout. We match workers diagnosed with burnout at $t = 0$ to observationally similar workers who do not burn out based on demographic characteristics and the pre-burnout labor income decile. See Section 4 for details of the matching procedure.

Figure 2: Who is Affected by Burnout? Work-Related Stress & Individual Stress Tolerance

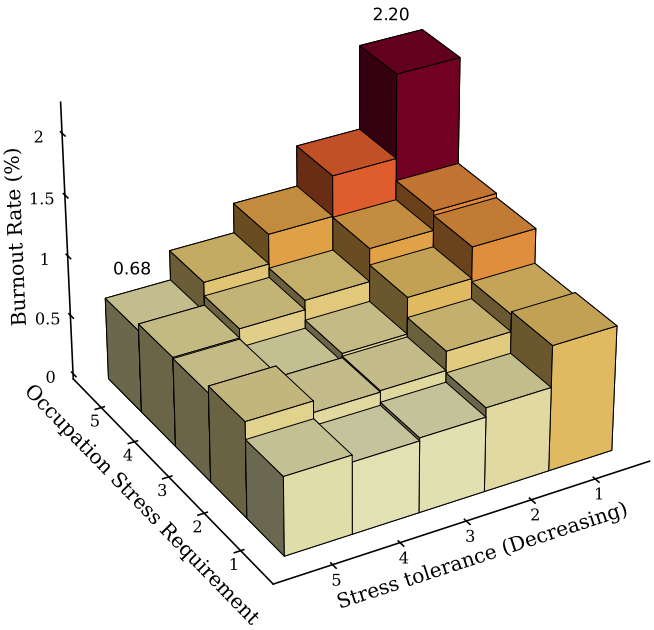
(a) Occupational Stress Tolerance Requirements



(b) Sorting by Individual Stress Tolerance



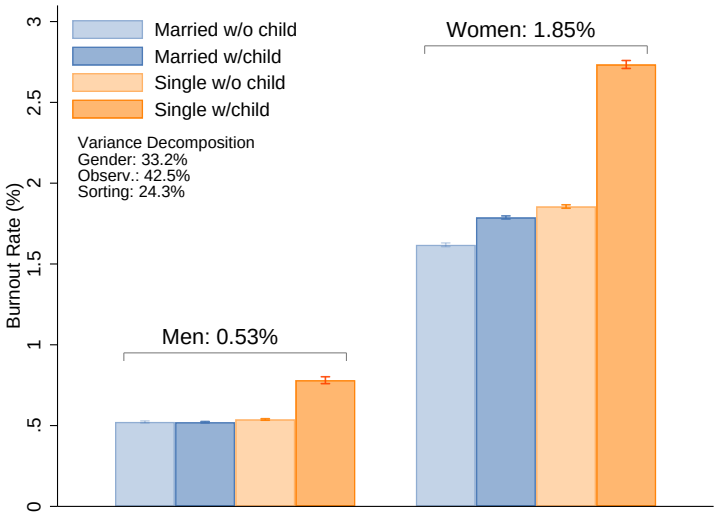
(c) Burnout by Occupational Requirements and Workers' Tolerance



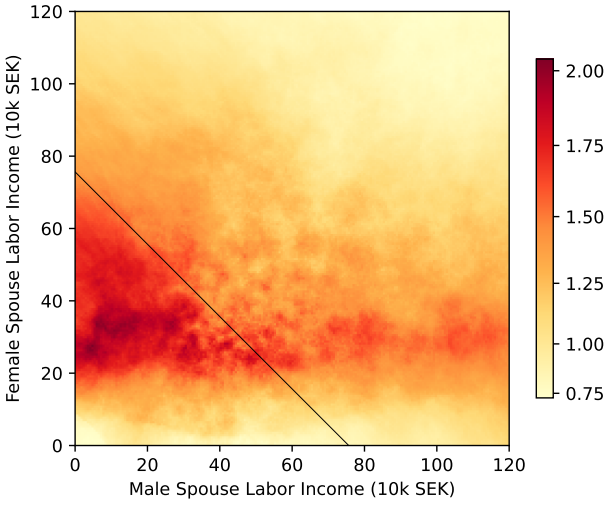
Notes: **Panel (a)** plots a binned scatterplot of workers' burnout rate against the stress-tolerance requirement of their occupation according to O*NET. Orange diamonds show a selected subset of occupations. **Panel (b)** displays the sorting of stress-tolerant workers across occupations with varying stress-requirement levels. **Panel (c)** reports burnout rates for each combination of workers' individual stress tolerance and the stress-tolerance requirement of their occupation. Occupational stress tolerance requirement is measured as the degree to which "Job requires accepting criticism and dealing calmly and effectively with high-stress situations." Psychologists assess individual stress tolerance at age 18 as part of Swedish military conscription. Panel (a) includes both men and women, while panels (b) and (c) focus on men because individual stress-tolerance scores are available only for them.

Figure 3: Who is Affected by Burnout? Gender, Family, & Career

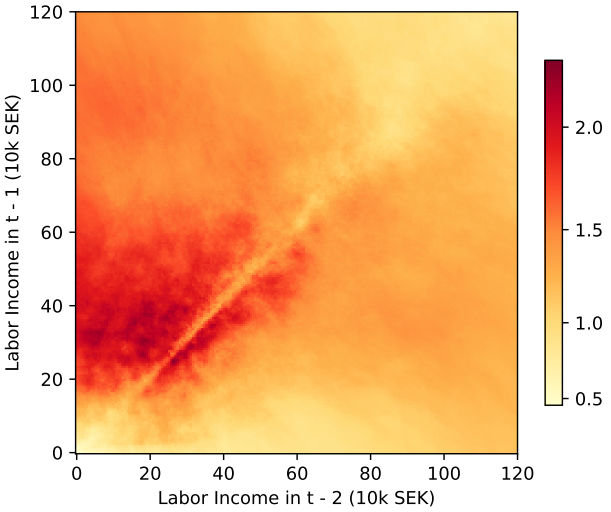
(a) Burnout Rate by Gender & Family Type



(b) Women: Burnout Rate by Couple Incomes



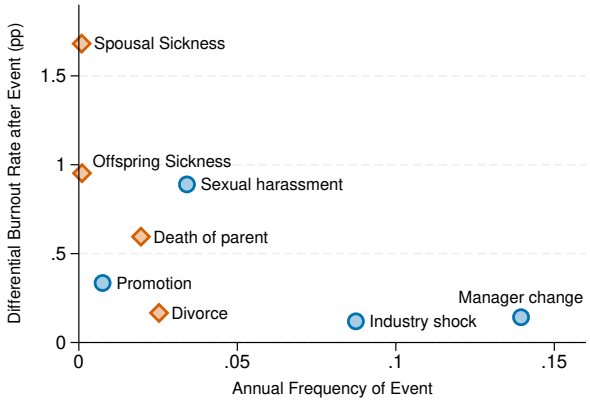
(c) Women: Burnout Rate by Income Growth



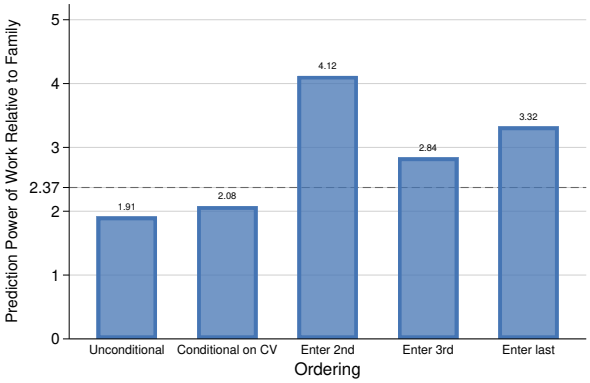
Notes: **Panel (a)** displays the annual burnout rate by marital and parental status and by gender, with an average of 1.12% for the entire employed population (20.0 million women and 24.9 million men). The respective shares in the four groups are 24%, 37%, 31%, and 8% for women, and 19%, 41%, 37%, and 3% for men. Pearson chi-square tests reject the null hypothesis of independence of burnout and family type among men ($\chi = 787$) and women ($\chi = 8.7 \cdot 10^3$), as well as joint independence of burnout and gender interacted with family type ($\chi = 1.8 \cdot 10^5$). The dependent variable of variance decomposition is a binary indicator for burnout one year ahead. In addition to gender and family type, the explanatory variables include native status, education, age, number of children and their age, labor income, and fixed effects for the calendar year, 5-digit industry, and 4-digit occupation. **Panel (b)** shows women's burnout rate over the joint distribution of annual labor incomes of 11,008,512 couple-year observations. The line marks the median couple's total income of 756k SEK. Income is winsorized at 1,200k, corresponding to the P97 of men and the P99 of women. **Panel (c)** reports burnout rates of 39,119,278 women against their own labor income histories in the past two years. **Panels (b) and (c)** use (i) two-dimensional moving averages of burnout rate: the average rate of approximately 40,000 individuals in the circular vicinity, leading to the statistical significance of differences of size 10^{-4} (See Section 4); (ii) rank-adjusted incomes to 2020 SEK. In all panels, the sample consists of individuals aged 25 to 55 without prior burnout in the period 2006 to 2020. Appendix Figure A.8 shows the underlying population distributions for Panels (b) and (c). All nominal values (incomes) are reported in 10 kSEK (ten thousand Swedish kronor), roughly equivalent to 1,000 USD/Euro (exchange rate in January 2020: 9,64 to USD and 10,55 to Euro).

Figure 4: Determinants of Burnout: Work vs. Family

(a) Career vs. Family Events

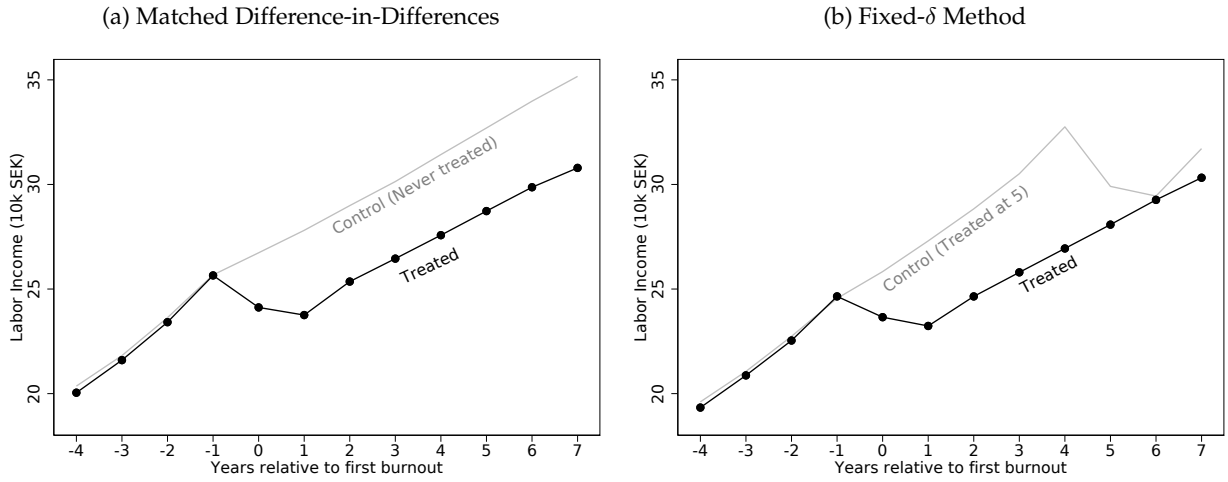


(b) Workplace vs. Family Prediction Power



Notes: The figure compares workplace and family determinants of burnout. **Panel (a)** plots matched difference-in-differences estimates of the differential burnout rate in three years after selected career and family events against their frequencies. Appendix Figure A.17 contains the figure behind each point estimate and the exact definition of each event with two exceptions: divorce is shown in Appendix Figure A.23, and the industry shock is described in Appendix Section E. **Panel (b)** compares the predictive power of career and family variables for future burnout, following the Shapley value logic. Predictors are grouped into own medical history, family, career, and CV (information usually available in a CV: gender, age, and education). See Appendix Section G.2 for details. The bars report the ratio of the marginal AUC contribution of career variables to that of family under alternative permutations: "Unconditional" each group first, "Conditional on CV" adds it after CV, and the remaining bars average over permutations in which each group enters second, third, or last. The dashed line reports the ratio of their Shapley values. Appendix Figure A.36 plots the underlying marginal contributions. Appendix Figure A.39 reports how often first burnouts are preceded by these events: 21.1 percent of first-burnout cases follow a workplace event in the preceding year, compared with 4.9 percent for a family event. Including the year of burnout, the shares are 31.9 and 15.8 percent. Workplace shares sum across event types. Appendix Figure A.40 reports each event separately.

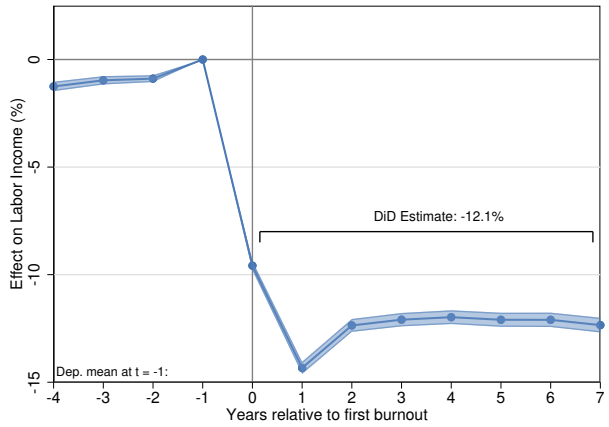
Figure 5: Two Empirical Designs



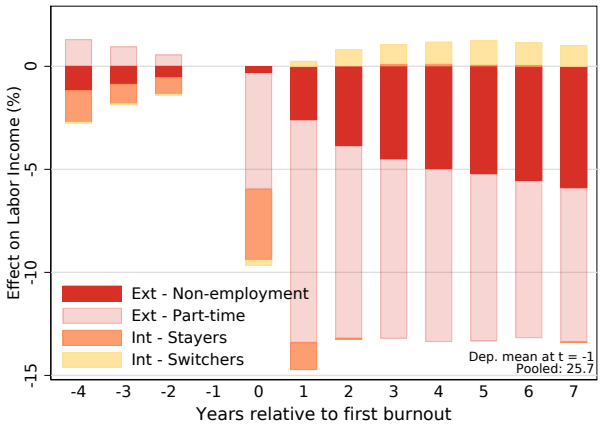
Notes: This figure illustrates two of our research designs. In both panels, the estimation sample is a balanced panel of treated workers whose first burnout occurs between 2006 and 2013, at ages 29–53. This restriction ensures we observe all outcomes during prime working age (25–60). **Panel (a)** plots average labor income for treated workers and matched controls who never experience burnout. We match workers one-to-one on birth year, education, gender, income percentile within the corresponding demographic group in the year before burnout, and employment history through that year. The resulting sample contains 150,834 matched treated-control pairs. **Panel (b)** plots average labor income for treated workers and matched controls who experience burnout five years later. We use the same matching variables, except we match on income deciles rather than percentiles to increase the number of treated workers for whom we can find a control. The resulting sample contains 99,861 matched treated-control pairs. Labor income is nominal and measured in units of SEK 10,000, approximately USD/EUR 1,000 at January 2020 exchange rates (SEK 9.64 per USD and SEK 10.55 per EUR).

Figure 6: Burnout and Labor Income

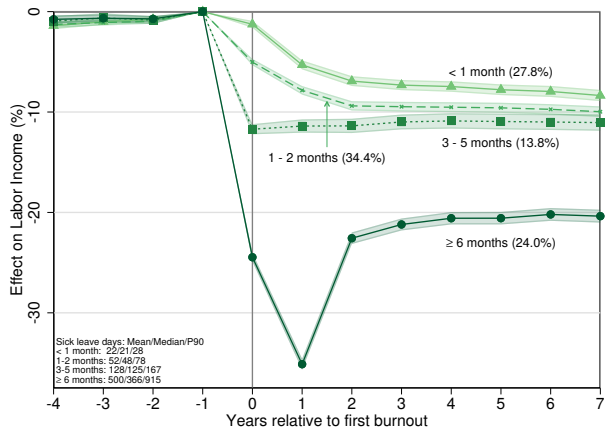
(a) Scarring Effect on Labor Income



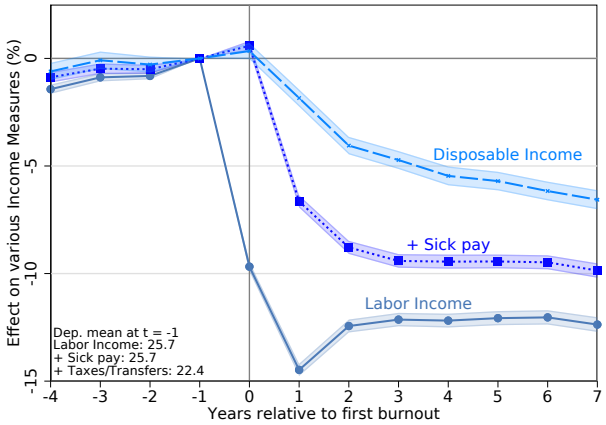
(b) Dynamic Decomposition of Labor Income Effect



(c) Labor Income Effect by Duration



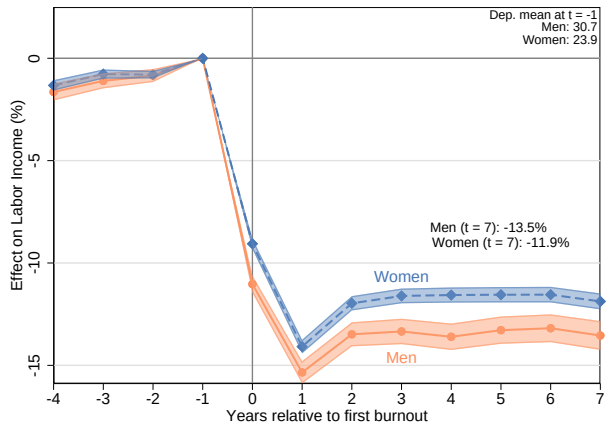
(d) Cushioning Effect of Social Insurances



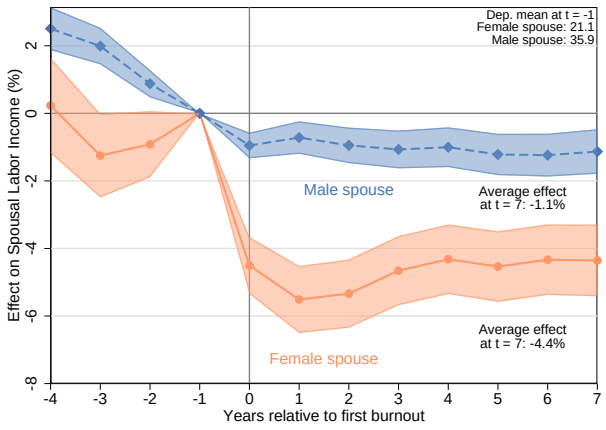
Notes: This figure investigates the evolution of labor income around burnout using the dynamic matched difference-in-differences model, equation (1). **Panel (a)** shows the proportional loss after burnout, **Panel (b)** decomposes the loss according to equation (2) into the extensive margin——ceasing work or transitioning to part-time——and the intensive margin——changes in income for individuals remaining with the same firm where the burnout occurred (stayers) and for those who transition to a new job (switchers). **Panel (c)** shows income loss by the duration of the initial burnout spell. The relative frequency of each category among treated workers is reported in parentheses. **Panel (d)** compares the labor income loss with labor income plus sick pay, and labor income adjusted for all taxes and transfers (disposable income). All results here are based on the dynamic matched difference-in-differences model, equation (1). The shaded area is the 95 percent confidence interval based on individual-level-clustered standard errors.

Figure 7: Gender Differences in Own and Spousal Income

(a) Own Labor Income

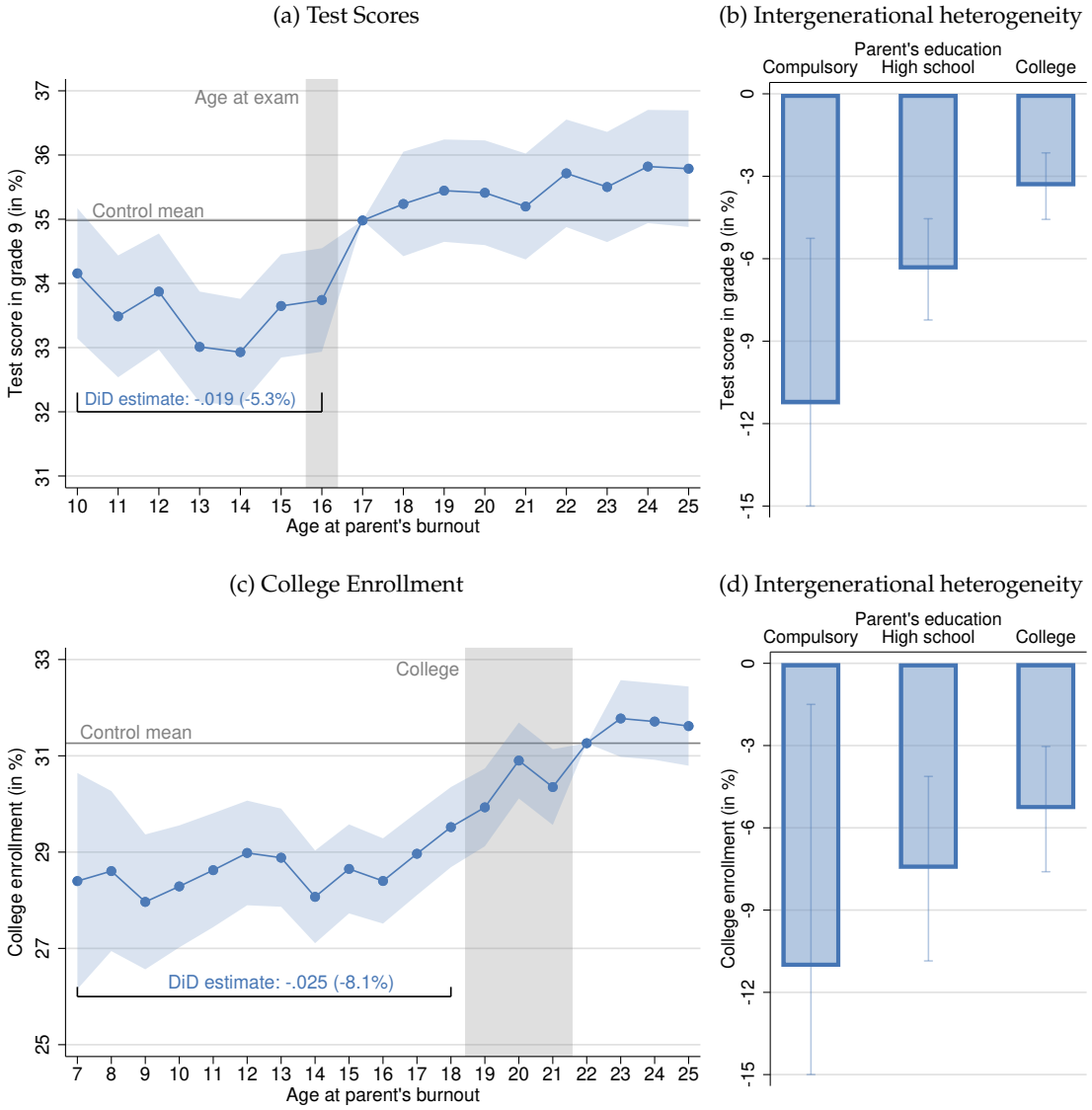


(b) Spousal Labor Income



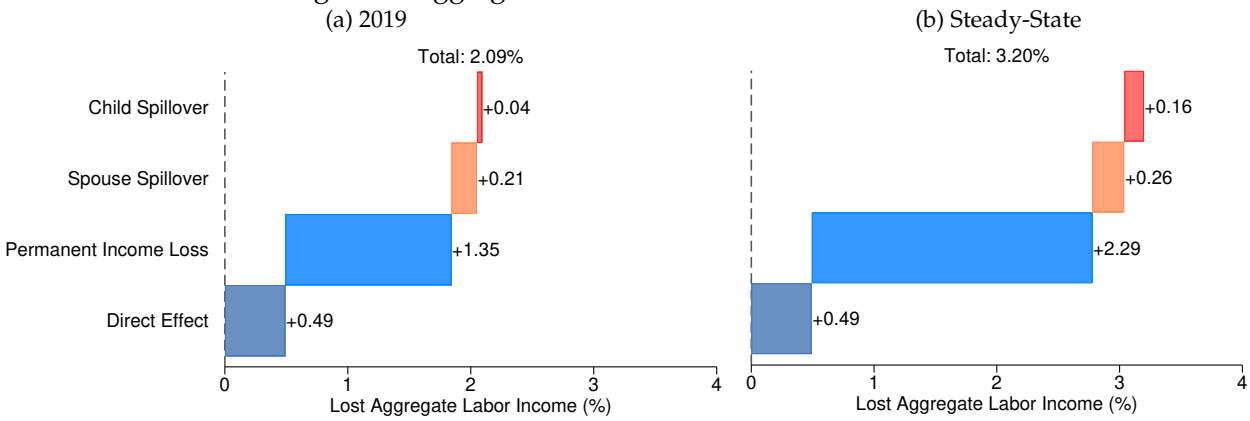
Notes: **Panel (a)** plots the proportional effect of burnout on individuals' own labor income, similar to previous Figure 6, but now by gender. **Panel (b)** plots the proportional effect of burnout on the labor income of 57,441 spouses (married/cohabiting partners in the year prior to burnout), irrespective of the current marital status.

Figure 8: Parental Burnout and Children's Human Capital



Notes: The figure uses a difference-in-differences design. The outcomes are grade-9 test scores (**Panel (a,b)**), and college enrollment measured at ages 19, 20, or 21 (**Panel (c,d)**). Test score is an indicator of an average grade of C across all subjects—roughly the median in our sample. Heterogeneous effects by parental education are reported in **Panels (b)** and **(d)**. The figure plots the coefficients on the child's age at the parent's first burnout from equation (5), which controls for the parent's birth cohort and gender and the child's birth cohort, gender, and sibling order. The reference group consists of children whose parent burns out after the education outcomes are measured: at age 17 for test scores and age 22 for college enrollment. "DiD estimate" reports the average effect for ages 10–16 for test scores and ages 7–18 for college enrollment. In Panels (b) and (d), we control for the parent's birth cohort and the child's birth cohort, gender, and sibling order. We measure parental education for the parent who experiences burnout. Panels (a) and (b) include 352,891 children; Panels (c) and (d) include 297,668 children. The shaded areas and whiskers show 95 percent confidence intervals based on robust standard errors clustered at the parent level.

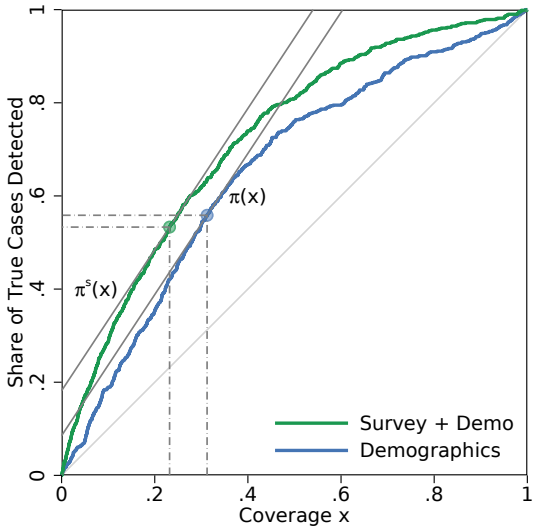
Figure 9: Aggregate Loss in Income Due to Burnout



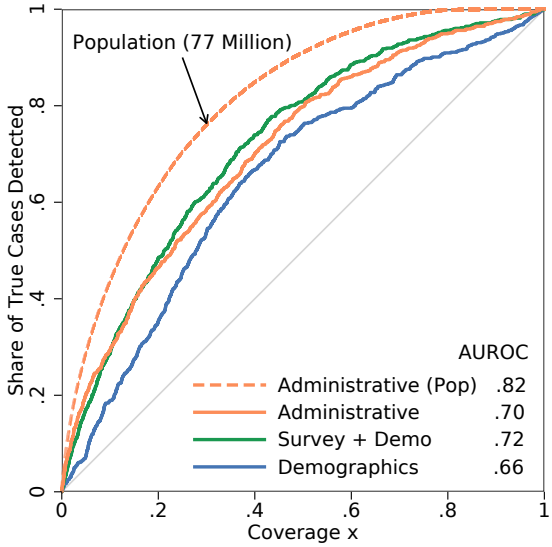
Notes: The figure presents our estimates of the loss of aggregate labor income due to burnout. Panel (a) presents estimates for the year 2019, whereas panel (b) presents steady-state estimates assuming that the 2019 conditions are permanent. The aggregate loss is calculated using equation (6) and has four components: i) lost days of work due to sick leave with burnout diagnoses, ii) scarring effects on labor income, reported in Figure 6a, iii) spillover effects on spousal earnings, reported in Figure 7b, and iv) spillovers on children's college enrollment, reported in Figure 8c.

Figure 10: Predicting Burnout in the Following Calendar Year

(a) Surveys vs. Basic Demographic



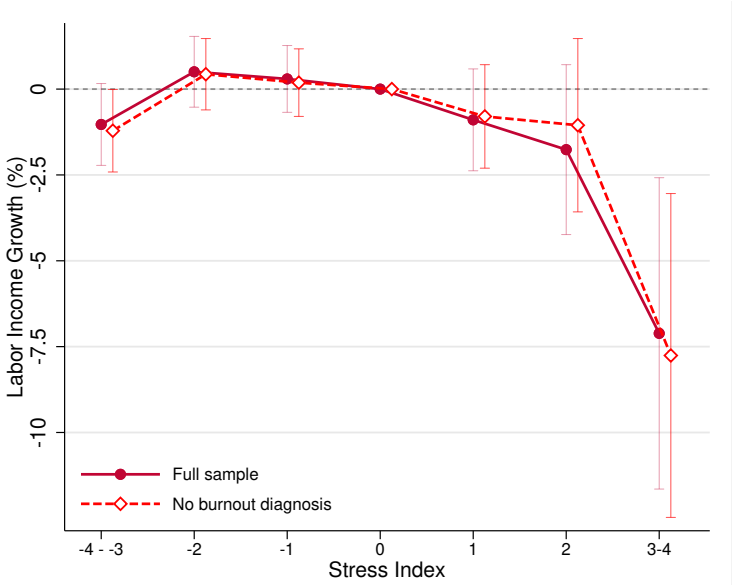
(b) Survey vs. Admin data



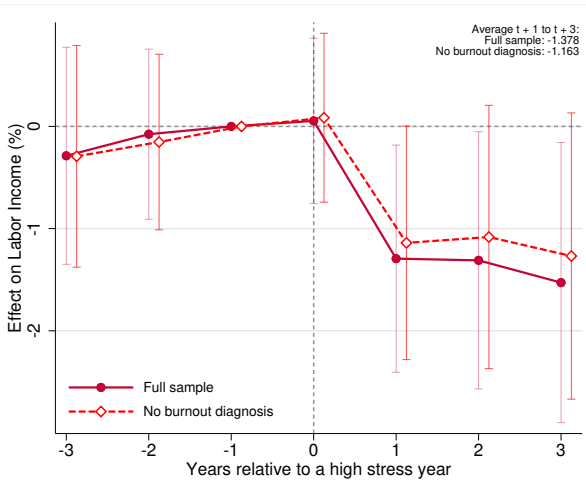
Notes: The figure shows the Cumulative Gains Chart for prediction models of burnout in the subsequent calendar year using Extreme Gradient Boosting. It depicts the share of positives discovered at a given level of coverage. **Panel (a)** compares the prediction power of adding questions about work conditions from the Work Environment Survey (AMU) to basic demographics (gender, age, native status, and detailed educational qualification). The figure also plots the optimal tangent lines, indicating the optimal program size for each prediction (Equations 10 and 11). **Panel (b)** tests the prediction gain once the model includes all relevant administrative data available to us (yellow lines). The sample consists of 61,121 individual-year observations from the AMU survey, except for the dotted yellow line, which extends to all 77,138,798 observations in the administrative data. See Appendix Table A.9 for a detailed list of predictors.

Figure 11: Work-related Stress and Labor Market Outcomes

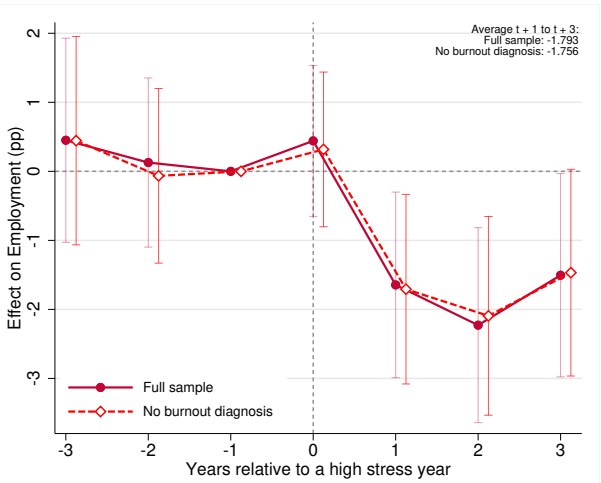
(a) Stress Levels and Subsequent Labor Income



(b) Labor Income Dynamics



(c) Employment Dynamics



Notes: This figure illustrates the evolution of labor market outcomes by self-reported stress. **Panel (a)** reports estimates from a regression of cumulative labor income over the three post-interview years, scaled by interview-year income, on the stress index based on self-reported stress (See Figure 1, Sections 2, and Appendix Section D). Controls include pre-interview earnings and fixed effects for interactions of interview year, gender, education, and 5-year age bins. Because the tails contain few observations, we pool extreme index values. **Panels (b) and (c)** report difference-in-differences estimates comparing full-time workers with a stress index exceeding 0, the index midpoint, with their less stressed peers. The one-to-one matching is based on interview year, gender, education, 5-year age bins, and within-wave earnings quartile. The hollow markers series excludes respondents who subsequently receive a burnout diagnosis. We cluster standard errors at the individual level.

Table 1: Descriptive Statistics

	Population 2006-2020 (1)	Burnout 2006-2020 (2)	Burnout 2006-2013 (3)	Matched sample (4)
	a) Individual-level characteristics			
Female	0.49	0.76	0.75	0.74
Age	42.03	43.08	43.39	41.21
Native	0.7	0.86	0.86	0.85
Married	0.47	0.52	0.53	0.56
Education				
Compulsory	0.11	0.07	0.08	0.07
Upper secondary	0.4	0.43	0.44	0.44
College	0.42	0.5	0.47	0.49
Labor Income in t - 1				
$\mathbb{E}[Y\|Y>0]$	325.1	303.0	266.3	264.7
$\mathbb{P}[Y>0]$	0.71	0.96	0.95	0.97
	b) Firm-level information			
Establishment size	546	714	770	766
Industry shares (%)				
Manufacturing	9.6	7.5	8.5	9.3
Construction	4.9	2.8	2.5	2.7
Public administration	4.5	7.7	6.9	6.6
Education	8.3	17.2	16.6	15.9
Health	12.6	26.5	26.3	24.8
Other	34.1	35.7	35.1	36.9
Missing	26.1	2.7	4.0	3.8
Number of individuals	7,380,543	526,108	220,715	150,900
Number of individual-years	79,463,491	655,917	247,943	150,900

Notes: The table reports key descriptive statistics across samples. Column (1) includes averages for the entire Swedish population aged 25 to 60 from 2006 to 2020. Column (2) restricts the burnout subpopulation: individuals who experience burnout between 2006 and 2020. Column (3) further restricts the sample to burnout cases between years 2006 and 2013. Column(4) considers the estimation sample underlying our difference-in-differences design, which is a subset of column (3) restricted to individuals' *first* burnout incidents. Section 4 describes how we construct the estimation sample. Appendix Table A.4 shows how different sample restrictions affect the estimation sample size. In columns (2) and (3), the discrepancy between the number of burnout incidents and afflicted individuals arises because individuals can be observed with multiple burnout incidents. Natives marks individuals born in Sweden. Married refers to both legally married and cohabiting couples with children. Appendix Table A.2 reports more granular information on the industry composition of the sample.

Table 2: Burnout Risk Factors

	Pooled			Women		Men	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	1.329	1.003	1.013				
	(0.003)	(0.004)	(0.024)				
Native		0.199	0.130	0.372	0.276	0.026	-0.023
		(0.005)	(0.022)	(0.009)	(0.030)	(0.004)	(0.028)
Married		-0.117	-0.128	-0.279	-0.297	-0.007	0.011
		(0.005)	(0.020)	(0.009)	(0.036)	(0.005)	(0.021)
Familytype							
Married with children		-0.001	0.021	-0.010	0.013	-0.042	-0.035
		(0.005)	(0.020)	(0.010)	(0.034)	(0.005)	(0.021)
Single parent		0.625	0.656	0.750	0.703	0.192	0.299
		(0.008)	(0.053)	(0.013)	(0.066)	(0.010)	(0.095)
Labor Income							
P25 - P50		-0.161	-0.279	-0.254	-0.422	-0.092	-0.123
		(0.005)	(0.028)	(0.008)	(0.039)	(0.005)	(0.041)
P50 - P75		-0.279	-0.421	-0.519	-0.692	-0.188	-0.197
		(0.005)	(0.031)	(0.009)	(0.048)	(0.005)	(0.042)
P75 - P90		-0.355	-0.536	-0.747	-0.903	-0.218	-0.275
		(0.006)	(0.034)	(0.011)	(0.062)	(0.005)	(0.042)
P90 - P99		-0.485	-0.678	-1.084	-1.219	-0.302	-0.367
		(0.007)	(0.038)	(0.015)	(0.068)	(0.006)	(0.046)
P99+		-0.700	-0.774	-1.789	-1.422	-0.488	-0.484
		(0.017)	(0.075)	(0.050)	(0.333)	(0.013)	(0.055)
Education							
Upper secondary		-0.028	-0.002	0.159	0.017	-0.012	-0.016
		(0.006)	(0.026)	(0.014)	(0.055)	(0.005)	(0.028)
College		0.061	-0.022	0.525	0.064	0.069	-0.100
		(0.007)	(0.030)	(0.014)	(0.064)	(0.005)	(0.029)
Age							
31 - 35		0.240	0.277	0.465	0.477	0.135	0.167
		(0.007)	(0.034)	(0.014)	(0.068)	(0.006)	(0.034)
36 - 40		0.364	0.362	0.720	0.675	0.198	0.197
		(0.007)	(0.031)	(0.014)	(0.064)	(0.006)	(0.033)
41 - 45		0.351	0.375	0.706	0.624	0.217	0.262
		(0.007)	(0.038)	(0.014)	(0.066)	(0.006)	(0.048)
46 - 50		0.293	0.343	0.631	0.662	0.204	0.173
		(0.007)	(0.037)	(0.013)	(0.081)	(0.006)	(0.030)
51 - 55		0.244	0.294	0.593	0.534	0.167	0.184
		(0.007)	(0.036)	(0.013)	(0.075)	(0.006)	(0.033)
56 - 62		0.179	0.206	0.503	0.412	0.141	0.113
		(0.007)	(0.029)	(0.014)	(0.060)	(0.006)	(0.029)
Year Fixed-Effects	✓	✓	✓	✓	✓	✓	✓
Industry Fixed-Effects		✓	✓	✓	✓	✓	✓
Occupation Fixed-Effects			✓		✓		✓
Mean Dependent Var.	1.137	1.137	1.330	1.879	1.965	0.543	0.595
N (Millions)	42.3	42.3	22.5	18.8	12.1	23.5	10.4
R^2	0.4955	0.6254	0.8044	0.2908	0.6337	0.0721	0.3692

Notes: The table reports estimates from linear-probability models of burnout, either pooled across genders or estimated separately for men and women. The estimation sample comprises all Swedish individuals aged 25–60 who were alive between 2006 and 2020, except in columns (3), (5) and (7), which include occupation fixed effects and are restricted to respondents in the wage register. In those columns, we weight estimates by sampling weights. Standard errors are shown in parentheses.

Table 3: Predicting Burnout

Outcome: Burnout in	t + 1	t + 1	t + 2
CV	0.664	0.727	0.630
CV + AMU	0.724		0.652
Admin	0.703	0.813	0.665
Admin + AMU	0.742		0.668
Sample	AMU	Population	AMU
Sample Size	61,121	77,138,798	53,710

Notes: The table presents AUC values for predicting burnout in the next calendar year (columns 1 and 2) and two years ahead (column 3). AUC (Area Under the ROC Curve) measures the accuracy of binary classifiers. Columns 1 and 3 use the AMU sample for alternate years from 2005 to 2019; column 2 covers the full Swedish prime-age population over the same period. Each row uses a fixed set of training variables: *CV* includes gender, native status, age, and education; *Admin* includes nearly all relevant and available administrative variables (see Section 5). The second and fourth rows incorporate AMU survey.

Online Appendix of:

The Economic Burden of Burnout

Arash Nekoei, Jósef Sigurdsson, and Dominik Wehr
October 14, 2026

Appendix Contents

A Burnout: Concept, Diagnosis, and Clinical Course **A4**
A.1 The Concept of Burnout . . . A4
A.2 From Concept to Clinical Diagnosis . . . A4
A.3 Diagnostic Criteria for Exhaustion Disorder . . . A6
A.4 Clinical Course and Symptoms . . . A6
A.5 The Swedish Sick-Leave System . . . A7
A.6 F43 and its Subcategories . . . A8

B Sample Selection **A12**

C Questions in the Work Environment Survey **A12**

D Stress Index **A14**

E Industry-Level Design **A15**
E.1 Design and Interpretation . . . A15
E.2 Labor-Market and Family Outcomes . . . A16
E.3 Children's Human Capital . . . A16

F Technical Details for Section 4.4 **A17**

G Prediction and Prevention **A17**
G.1 Construction of Burnout Prediction and Evaluation . . . A17
G.2 Basic Demographic and Administrative Data . . . A18

H Supplementary Figures and Tables **A19**

Appendix Figures

A.1 Increase in Self-Reported Stress Levels . . . A19
A.2 Evolution of Burnout Rates over Time . . . A20
A.3 Institutional Reform, Stress Levels and Sick Leave . . . A21
A.4 Evolution of F43 Subcategories over 2010-2022 . . . A22
A.5 Incidence Across Income Distribution . . . A23
A.6 Components of Stress Index . . . A24
A.7 Evolution of Alternative Stress Indices Around Burnout . . . A25
A.8 Distribution of Labor Income Histories . . . A26
A.9 Burnout Rate of Men: Couple Incomes & Career . . . A27
A.10 Burnout and Labor Income Histories (Stayers) . . . A28
A.11 Individual's stress tolerance and burnout . . . A29
A.12 Sorting into Occupations . . . A29
A.13 Effect of Burnout on Labor Income: Baseline vs. Fixed-Delta Method . . . A30
A.14 Labor Income around Burnout: Extensive vs. Intensive Margins . . . A31
A.15 Evolution of Work and Sick-Leave around Burnout . . . A32
A.16 Decomposition of the Impact of Burnout on Labor Income: Men vs. Women . . . A33
A.17 Workplace and Family Determinants of Burnout . . . A34
A.18 Effect of Parental Burnout on Child's College Enrollment . . . A35
A.19 Heterogeneity of Effects of Parental Burnout on Child's Human Capital . . . A36
A.20 Heterogeneity of Burnout Effects by Education . . . A37
A.21 Burnout Effect on Spousal Labor Income . . . A38
A.22 Burnout Effect on the Probability of Ever Having a Child . . . A39
A.23 Burnout vs. Separation and Fertility . . . A40
A.24 Predicting Burnout . . . A41
A.25 Prediction Performance of Stress Index Components . . . A42
A.26 Prediction—Robustness of Model Performance to Test-Train Split . . . A43
A.27 Effect of Benefits on Burnout-Related Sickleave Take-Up . . . A44
A.28 Instrumental-Variable First Stage . . . A45
A.29 Industry Mobility Following Burnout . . . A46
A.30 Sick Leave Spell Durations . . . A47
A.31 Age at First Burnout: Event-Study Sample and All Spells . . . A47
A.32 Partition Size for Earnings Decomposition . . . A48
A.33 Occupational Stress and Burnout . . . A49
A.34 Decomposition of Spousal Earnings Losses . . . A50
A.35 Burnout Effects on Labor Income Excluding Family Health Shocks. . . . A51
A.36 Importance of Work and Family for Burnout Prediction . . . A52
A.37 Avoiding Future Stress After Burnout . . . A53
A.38 Effect of Burnout on Labor Income by Gender and Sector . . . A53
A.39 Adverse Work and Family Events Preceding Burnout . . . A54
A.40 Adverse Work and Family Events Preceding Burnout – Disaggregated . . . A55

Appendix Tables

A.1 Distribution of F43 subcategories among women and men, by age A9
A.2 Descriptive Statistics – Industry Composition A56
A.3 Burnout Risk Factors A57
A.4 Sample Selection and Matching Results A58
A.5 Estimates of Burnout Effect on Income A58
A.6 Instrumental Variable Estimates of Burnout Effects A59
A.7 Effects of Parental Burnout on Children's Outcomes A59
A.8 Burnout Prediction A60
A.9 Variables used for burnout prediction A61

A Burnout: Concept, Diagnosis, and Clinical Course

This appendix provides background on the concept of burnout, its development into a clinical diagnosis, and the diagnostic criteria used in Sweden. Section A.1 describes the psychological construct and its measurement; Section A.2 traces its recognition as a medical condition; Section A.3 reproduces the diagnostic criteria of the Swedish National Board of Health and Welfare; Section A.4 describes the clinical course and symptoms; Section A.5 describes the Swedish sick-leave system; and Section A.6 provides details on the the F43 diagnosis category and it subcategories.

A.1 The Concept of Burnout

The term *burnout* originates in American social and work psychology.[71] It was first used in the early 1970s by Herbert Freudenberger, a practicing American psychologist, to describe the gradual emotional depletion, loss of motivation, and reduced commitment he observed among clinic volunteers in New York (Freudenberger, 1974). Since then, the concept and its diagnosis have developed within psychology.

The conceptualization of burnout on the basis of Conservation of Resources (COR) theory—a general theory of psychological stress (Hobfoll, 1989)—is that burnout reflects a state of depletion of physical, cognitive, and emotional resources (Hobfoll et al., 2000). Burnout therefore reflects a combination of physical fatigue, cognitive weariness, and emotional exhaustion. COR theory describes how people are motivated to obtain, retain, and protect their resources, and emphasizes that stress has a central environmental, social, and cultural basis in the demands placed on people. According to the theory, work-related stress occurs when individuals fail to maintain their resources. Stress is thus not a single event but an unfolding process, leading to burnout when resources are depleted (Shirom, 2003).[72]

Several established measures of burnout exist. The Shirom-Melamed Burnout Questionnaire (SMBQ) (Melamed et al., 1992) is based on COR theory and has been used in Sweden to identify potential clinical cases of burnout (Lundgren-Nilsson et al., 2012). Another widely used assessment tool is the Maslach Burnout Inventory (MBI) (Maslach and Jackson, 1981).[73] Despite some dissimilarities, all measures of burnout emphasize the role of exhaustion as a key component of the construct (Schaufeli and Enzmann, 1998).

A.2 From Concept to Clinical Diagnosis

Burnout was first recognized as a condition in the United States during the 1970s, with its acknowledgment spreading to Western Europe in the 1980s. Within Europe, burnout transitioned from a psychological concept to a formally diagnosed medical condition. This evolution was shaped by the social security systems of countries such as Sweden and the Netherlands, which cover sick leave payments for both

[71] For an overview of the historical and conceptual development of burnout, see, e.g., Maslach and Schaufeli (2018). For an overview of research on burnout within psychology and medicine, see, e.g., Maslach et al. (2001) and Grossi et al. (2015).

[72] Other definitions of burnout are conceptually similar. The Dictionary of Psychology defines burnout as exhaustion—physical, emotional, or mental—accompanied by reduced motivation, weaker performance, and negative attitudes toward oneself and others, arising from sustained high-level performance under prolonged exertion or excessive workload (American Psychological Association, n.d.). The World Health Organization characterizes burnout as a syndrome resulting from chronic workplace stress that has not been successfully managed, comprising energy depletion or exhaustion, increased mental distance from or cynicism toward one's job, and reduced professional efficacy (WHO, 2019).

[73] Other burnout scales include the Burnout Measure (BM) (Pines and Aronson, 1988), the Copenhagen Burnout Inventory (CBI) (Kristensen et al., 2005), and the Oldenburg Burnout Inventory (OLBI) (Demerouti and Bakker, 2008).

physical and mental health conditions and require a medical diagnosis for insurance benefits. Nine European Union countries—Denmark, Estonia, France, Hungary, Latvia, the Netherlands, Portugal, Slovakia, and Sweden—recognize burnout as an occupational illness (Lastovkova et al., 2018). Diagnosis is therefore central to accessing both healthcare and sick-leave compensation.

The definition of clinical burnout usually follows the criteria for work-related neurasthenia in the ICD-10. These comprise (i) persistent and distressing complaints of increased fatigue after mental effort, or persistent and distressing complaints of bodily weakness and exhaustion after minimal effort; (ii) at least four additional symptoms from among insomnia, cognitive deficits, pain, palpitations, gastroenteric problems, and sensitivity to sound and light. These complaints and symptoms (iii) must be present nearly every day for at least two weeks; (iv) must be due to psychosocial stressors present for at least six months before diagnosis; and (v) must lead to clinically significant distress or impairment (Grossi et al., 2015; Van Dam, 2021).

In many countries, clinicians nonetheless lack clear consensus on which ICD-10 classification corresponds to clinical burnout (Grossi et al., 2015). To clarify the diagnostic criteria, the Swedish National Board of Health and Welfare introduced "exhaustion disorder" (*utmattningssyndrom*) into the Swedish version of the ICD-10 (ICD-10-SE) in 2005.[74] Elsewhere, special clinical guidelines have been introduced instead: the Royal Dutch Medical Association, for example, issued guidelines for assessing and treating stress-related disorders in occupational and primary health care in 2000 (Van Der Klink and Van Dijk, 2003).

Background on ICD-10 The International Statistical Classification of Diseases and Related Health Problems, Tenth Revision (ICD-10), is the World Health Organization's standard nomenclature for the classification of diseases, injuries and causes of death, providing the alphanumeric framework within which morbidity and mortality data are recorded and compared across countries. Within Chapter V (Mental and behavioral disorders, F00–F99), category F43 designates *Reaction to severe stress, and adjustment disorders*, a group defined not by symptom profile alone but by the aetiological requirement that an identifiable stressor—an acute traumatic event or a sustained adverse life circumstance—be a necessary causal condition of the disorder. F43 comprises acute stress reaction (F43.0), post-traumatic stress disorder (F43.1), adjustment disorders (F43.2), and two residual codes: F43.8, Other reactions to severe stress, which captures clinically significant stress reactions not meeting criteria for the preceding categories, and F43.9, the unspecified variant. In the WHO base classification F43.8 is a terminal, non-subdivided code.

The Swedish adaptation of ICD-10 Sweden applies a national modification, ICD-10-SE, issued and maintained by Socialstyrelsen (the National Board of Health and Welfare), which replaced the earlier Swedish edition KSH97 on 1 January 2011 and is mandatory for reporting to the national health registers. Consistent with WHO rules permitting national extension below the four-character level, ICD-10-SE adds detail through a fifth-position letter (a *fördjupningskod*) while leaving the international structure intact. F43.8 is subdivided accordingly into two codes: F43.8A: *Utmattningssyndrom* (exhaustion disorder) and F43.8W: other specified reactions to severe stress than exhaustion disorder.

F43.8A was proposed by a Swedish psychiatric research group in a 2003 report, approved by the National Board of Health and Welfare two years later, and entered into the Swedish version of ICD-10; it is used only in Sweden.[75] It therefore constitutes a nationally bounded diagnostic construct rather than an ICD-10 category, with two consequences for register-based work: Swedish prevalence estimates for

[74] This was preceded by a pronounced increase in sick leave due to stress-related illness beginning in the 1990s, particularly among women (Persson et al., 2006; Försäkringskassan, 2020).

[75] See Svenaeus (2025).

stress-related disorder are not directly comparable with those derived from WHO-coded or ICD-10-CM data, and cross-national harmonisation requires collapsing F43.8A and F43.8W back to the four-character parent F43.8, which necessarily discards the distinction the modification was created to record.

A.3 Diagnostic Criteria for Exhaustion Disorder

The Swedish criteria for exhaustion disorder follow The National Board of Health and Welfare (2003). All of the following must be met for the diagnosis to be made, with **E** and **F** particularly important for a correct diagnosis.

A. Physical and psychological symptoms of fatigue for at least two weeks. The symptoms developed as a result of one or more identifiable stressors present for at least six months.

B. Significant lack of mental energy or stamina dominates the picture.

C. At least four of the following symptoms have been present virtually every day for at least two weeks:

1. Difficulty concentrating or memory impairment
2. Markedly reduced ability to cope with demands or to do things under time pressure
3. Emotional lability or irritability
4. Sleep disturbance
5. Marked physical weakness or fatigue
6. Physical symptoms such as aches, chest pains, palpitations, abdominal pain, dizziness, or sensitivity to sound

D. The symptoms cause clinically significant suffering or impairment at work, socially, or in other important respects.

E. The exhaustion is not due to the direct physiological effects of any substance (e.g., drug of abuse, medication) or any somatic disease or injury (e.g., hypothyroidism, diabetes, infectious disease).

F. If the criteria for major depression, dysthymia, or generalized anxiety disorder are simultaneously met, exhaustion disorder is listed as an additional specification to the current diagnosis.

A.4 Clinical Course and Symptoms

Exhaustion disorder is a characteristic reaction to prolonged stress—usually psychosocial, occasionally physical—without the possibility of adequate recovery (Åsberg et al., 2010). It typically progresses in three phases. The first is a prodromal phase characterized by physical and psychological stress symptoms, often episodic. Most people perceive physical symptoms as a warning and attempt to reduce the burden. If they do not succeed, an acute phase may follow, characterized by pronounced physical and mental fatigue and an inability to recover. The acute phase often begins suddenly, with alarming physical and cognitive symptoms; the cognitive problems are usually episodic, such as acute difficulty in recollection, sudden memory impairment, or a temporary aphasia-like inability to find the right word in normal conversation. The recovery phase is characterized by a gradual reduction of symptoms, but with marked sensitivity to stress and a tendency to relapse. A full-blown exhaustion disorder is a severe and long-lasting condition that results in total or partial loss of work capacity for an extended period, and the majority of patients appear to retain heightened stress sensitivity after referral, which continues to affect their work capacity.

The symptoms of chronic stress and burnout can be separated into physical symptoms, cognitive problems, and emotional and behavioral problems (see, e.g., Van Dam, 2021).

Physical symptoms. Stress affects the immune, cardiovascular, digestive, endocrine, and reproductive systems. Chronic stress can therefore cause a variety of physical symptoms in burnout patients, including headaches, intestinal problems, muscle tension or pain, chest pain, fatigue, changes in sex drive, stomach upset, and heightened vulnerability to disease.

Cognitive problems. Chronic stress affects cognitive performance. Clinical burnout impairs attention, concentration, and working memory (Deligkaris et al., 2014). The impairments observed in burnout patients appear to affect complex, higher-order cognitive processes such as executive functioning more than simpler processes (Deligkaris et al., 2014). Specific symptoms include difficulty thinking clearly and learning new things at work, forgetfulness and absent-mindedness, indecisiveness, poor memory, attention and concentration deficits, and trouble staying focused (Linden et al., 2005; The National Board of Health and Welfare, 2003). Because executive control is crucial for tasks requiring planning, control, evaluation, adaptation, and problem solving, these impairments are likely to hamper job performance (Bakker et al., 2008; Taris, 2006).

Emotional and behavioral problems. Stress reduces the capacity to regulate emotions (Raio et al., 2013). Chronic stress therefore leads to emotional instability, manifested in intense emotional reactions. Specific symptoms include frustration and anger at work, irritability, anxiety and panic, overreacting, and feeling unable to control one's emotions at work. Because of the cognitive impairments and increased emotional lability, burnout patients experience more interpersonal conflict. Other behavioral problems relate to the consumption of food, alcohol, and medication.

A.5 The Swedish Sick-Leave System

Sweden introduced a mandatory, government-financed national sickness insurance system in 1955 (Henrekson and Persson, 2004; Adlercreutz and Nyström, 2021). Employees need to provide a physician's certificate from day 8 of a sickness spell, and employers pay *sjuklön* through day 14, after which Försäkringskassan assesses *sjukpenning* eligibility from day 15. To trigger this transition, the employer is required to submit a *sjukanmälan* to Försäkringskassan — an administrative notice that the *sjuklön* period is ending and *sjukpenning* may be needed — with day 15 as the target and day 21 as the statutory deadline (Sveriges riksdag, 1991, § 12). It is this *sjukanmälan* that records the diagnosis registered by the Agency.

Sickness benefit from Försäkringskassan replaces about 80 percent of covered earnings up to a cap. Many collective agreements top these payments up by around 10 percent, and sick leave payments are taxable. Sick leave may also be taken at partial rates of 25, 50, 75 or 100 percent, so a spell need not imply full absence from work.

The rules governing benefit duration changed twice around our sample period. Before July 2008, benefits were paid at this rate with no upper limit on the total duration of a spell. The 2008 "rehabilitation chain" reform introduced fixed assessment points at 90 and 180 days—at which the Social Insurance Agency re-assesses individuals' eligibility based on their ability to return to work at their previous employer (any employer)—tightened access to disability insurance, and created a two-tier benefit structure: at most 364 days at the normal level within a rolling 450-day window, followed by up to 550 days at a continuation level of about 75 percent, for a maximum of 914 days (Government of Sweden, 2008). This cap was abolished on 1 February 2016, since then continuation-level benefit can be paid without a fixed maximum (Government of Sweden, 2015).[76] Individuals whose work capacity is permanently reduced are eligible for disability

[76] One further change falls immediately before our sample period: a 2005 reform requiring employers to co-finance

insurance, which requires that rehabilitation options have been exhausted and therefore normally follows an extended period of sick leave (Sveriges riksdag, 2010, ch. 33).

Despite providing a broad-based system for sick leave, the share of the population having work-related health problems resulting in sick leave is at the lower end within Europe (Spasova et al., 2016).

A.6 F43 and its Subcategories

This section reviews the subcategories of F43 and what is known about their distribution and durations. It first defines the subcategories that together constitute code F43, then reports prevalence estimates for each from two independent sources, which permits an assessment of how consistent the available figures are, and finally compares the duration of F43.0 episodes with that of F43.8A.

A.6.1 Definition of Subcategories

F43 denotes adjustment disorders and reactions to severe stress, a group of stress-related conditions that differ in the nature and duration of the stressor, symptom profiles, timing of onset, and course.

F43 category includes the following subcategories:[77]

- F43.0 is acute stress reaction, a transient reaction to exceptional physical or psychological stress. It arises in close temporal connection with a traumatic event and usually subsides within a few days. Dissociative symptoms, such as detachment, emotional numbing, or a sense of observing the event from outside oneself, may occur. Although the prognosis is generally good, the condition may develop into post-traumatic stress disorder, depression, or another psychiatric or somatic disorder.
- F43.1 is post-traumatic stress disorder, a delayed or prolonged reaction to an exceptionally threatening or catastrophic traumatic event. The diagnosis is ordinarily applied from four weeks after the trauma, although symptoms may begin after a longer symptom-free interval. Characteristic features include intrusive re-experiencing through flashbacks or nightmares, avoidance of reminders of the trauma, persistent tension or arousal, and impaired affect regulation. The prognosis is generally better when the condition is identified and treated early, but it may become chronic in a minority of cases.
- F43.2 is adjustment disorder, involving difficulty or delay in adapting to changed life circumstances or a burdensome life situation, such as a bereavement or other personal crisis. Symptoms commonly include anxiety, depressive symptoms, or psychosomatic complaints without meeting the diagnostic criteria for an anxiety disorder or major depression. Distress may persist after a severe crisis, but functioning is generally restored relatively quickly and the prognosis is usually good.
- F43.8 is other specified reactions to severe stress, excluding exhaustion disorder, which is reported separately as F43.8A. For definitional purposes, this residual row is interpreted using the later Swedish code F43.8W: an identifiable exposure to stress is present and produces clear symptoms, substantial distress, and impaired functioning, but the clinical picture does not unequivocally meet the criteria for exhaustion disorder. This interpretation harmonizes the older table label with the newer Swedish coding terminology but does not recode the underlying observations.

long full-time absences, repealed at the end of 2006. Together with the 2008 reform, it has been linked to the substantial decline in Swedish sickness absence over this period (Hägglund, 2013).

[77] Diagnostic definitions are adapted from (Socialförsäkringsutskottet, 2024, pp. 15–16).

- F43.8A is exhaustion disorder, characterized by pronounced physical and psychological exhaustion following prolonged exposure to stress. The acute phase may be preceded by several years of fluctuating symptoms and may be followed by a prolonged recovery phase with residual symptoms and marked intolerance to stress. The clinical picture commonly includes substantial and functionally impairing cognitive difficulties, affective symptoms approaching depression or anxiety, and various somatic symptoms.

A.6.2 Prevalence in 2018 Based on Försäkringskassan (2020)

Table A.1: Distribution of F43 subcategories among women and men, by age

ICD-10	Diagnosis	20–24	25–34	35–44	45–54	55–69	Total
Panel A: Women							
F43.0	Acute stress reaction	33.8	27.1	23.0	25.0	29.2	26.1
F43.1	Post-traumatic stress disorder	5.2	2.6	1.6	1.3	0.9	1.9
F43.2	Adjustment disorder	6.1	5.7	4.9	4.6	4.8	5.1
F43.8	Other specified reactions to severe stress	8.4	10.1	11.8	11.6	10.9	11.0
F43.8A	Exhaustion disorder	22.2	31.0	36.1	34.0	29.2	32.5
F43.9	Reaction to severe stress, unspecified	24.3	23.5	22.6	23.5	25.0	23.4
Total		**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**
Panel B: Men							
F43.0	Acute stress reaction	38.3	30.6	25.1	23.7	26.2	26.9
F43.1	Post-traumatic stress disorder	3.2	2.3	1.8	1.9	2.0	2.0
F43.2	Adjustment disorder	6.8	5.7	4.7	4.6	4.4	5.1
F43.8	Other specified reactions to severe stress	9.7	10.4	11.9	12.7	12.3	11.8
F43.8A	Exhaustion disorder	19.4	27.2	32.8	32.5	29.8	30.0
F43.9	Reaction to severe stress, unspecified	22.6	23.8	23.7	24.6	25.3	24.2
Total		**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**

Note: The table covers sickness spells among women and men that lasted more than 14 days and began in 2018–2019. F43 denotes adjustment disorders and reactions to severe stress, which the report treats as stress-related mental ill-health characterized by the importance of external causes.
F43.0 is acute stress reaction, generally associated with sickness absence lasting just over one month.
F43.1 is post-traumatic stress disorder, which may substantially reduce work capacity and is associated with sickness absence lasting nearly 200 days.
F43.2 is adjustment disorder, generally associated with shorter sickness absence.
F43.8 is other specified reactions to severe stress; in this table it excludes F43.8A, which is reported separately.
F43.8A is exhaustion disorder, associated with prolonged work incapacity and sickness absence lasting approximately half a year.
Source: Calculations based on Försäkringskassan (2020), Tables 3–4 and pp. 15, 19, and 48–50.

The calculation of F43.8A share is based on Försäkringskassan (2020). Tables 3–4 and 14–15 imply approximately 92,224 F43 cases at ages 25–60, of which 30,083 are F43.8A. Women account for about 75.4% of these F43 cases and men 24.6%; the corresponding weighted F43.8A shares are approximately 33.3% and 30.8%. Using the full age-cell weights rather than these rounded figures gives: F43.8A share $= 30{,}083/92{,}224 = 32.62\% \approx 32.6\%$.

The weighted estimate contains approximately 21,760 F43.9 cases, or 23.6% of all F43 cases. Removing them changes only the denominator: F43.8A share among specified F43 $= 30{,}083/(92{,}224 - 21{,}760) = 30{,}083/70{,}464 = 42.69\%$. Because the report groups ages 55–69 together, the 55–60 component is approximated using the finer age distribution in Table 5.

A.6.3 Prevalence in 2010-22 based on Socialförsäkringsutskottet (2024)

Based on the number of newly commenced sick-leave spells (*påbörjade sjukfall*) by specific stress-related diagnosis, exhaustion disorder (F43.8A, *utmattningssyndrom*) accounted for roughly 3,400 of approximately 14,300 F43 spells in 2010 and roughly 20,500 of approximately 69,300 in 2022, corresponding to a simple share of about 24 % and 30 %, respectively. However, this apparent increase of some six percentage points is largely attributable to the relative contraction of the unspecified residual category (F43.9, *reaktion på svår stress, ospecificerad*); once F43.9 is excluded from the denominator, the share of F43.8A is nearly constant at approximately 35 % in 2010 and 38 % in 2022. Appendix Figure A.2 reports the corresponding burnout rate in our estimation sample over 2006–2019.

A.6.4 Duration of F43.0 vs. F43.8A

Two major subcategories of F43 are F43.0 (acute stress reaction) and F43.8A (exhaustion disorder, a Swedish-specific ICD-10-SE diagnosis introduced in 2005; Lindsäter et al., 2022). Swedish administrative evidence shows a stark contrast in sickness-absence duration between F43.0 and F43.8A.

Försäkringskassan's nationwide MiDAS duration analysis included all 656,236 sickness spells lasting more than 14 days that began in 2018–2019 among employed people aged 20–69: the median duration for F43.0 was 38 days for both women ($N = 19{,}832$) and men ($N = 6{,}770$), whereas the corresponding medians for F43.8A were 180 days for women ($N = 24{,}775$) and 170 days for men ($N = 7{,}546$), implying approximately 4.5–4.7 times longer spells; by comparison, the medians were 49 days across all diagnoses and nearly 90 days for psychiatric diagnoses overall (Försäkringskassan, 2020, p. 70 and Tables 13–15).

These observed medians are unadjusted and should be distinguished from Socialstyrelsen's clinical guidance: sick leave should generally be avoided for mild F43.0 and may be prescribed for up to four weeks in moderate cases, while exhaustion syndrome may justify up to six months in the acute phase and one year or longer when cognitive difficulties persist (Socialstyrelsen, 2017a,b).

In Riksrevisionen's selected audit of employed individuals with psychiatric sickness spells exceeding 60 days, spells ending in F43.8A had a mean duration above 300 days and a median around 250 days, figures that describe the long-duration tail rather than the population distribution (Riksrevisionen, 2018, pp. 27 and 39). Two caveats are important: spells lasting 14 days or less are excluded from the MiDAS analysis, although the duration of included spells is measured from the initial sickness-report date (Försäkringskassan, 2020, pp. 15 and 70), and the principal diagnosis changed in approximately half of audited long psychiatric spells, with F43.0 frequently ending as depression or F43.8A, making estimates based solely on the initial diagnosis difficult to interpret (Riksrevisionen, 2018, pp. 27–29).

A.6.5 A note on Z73.0

We exclude Z73.0 from our analysis. In ICD-10 it falls under Chapter XXI, "Factors influencing health status and contact with health services" (Z00–Z99), which records reasons for contact with care and circumstances affecting health rather than diseases. It is therefore not a clinical diagnosis. Exhaustion disorder (*utmattningssyndrom*, F43.8A), by contrast, is the diagnosis under which burnout is certified in Sweden.

This distinction carries through directly into how Swedish sick leave is administered: the National Board of Health and Welfare's (*Socialstyrelsen*) medical insurance decision-support (*försäkringsmedicinska beslutsstödet*)—the diagnosis-specific sick-leave guidance that physicians and Swedish Social Insurance Agency (*Försäkringskassan*) caseworkers are instructed to follow—lists dedicated recommended sick-leave

durations for F43.8A and the other F43 stress diagnoses, but has no corresponding entry for Z73 anywhere in its diagnosis list (Socialstyrelsen, 2026). Z73 therefore does not carry a certifiable illness (*sjukdom*) of the kind Försäkringskassan requires for sickness benefit (*sjukpenning*) eligibility, which the agency determines based on assessed reduction in work capacity due to illness rather than the diagnosis code itself (Försäkringskassan, 2025).

This guideline gap does not, however, guarantee clean administrative practice. Sweden's National Audit Office (*Riksrevisionen*) found that Försäkringskassan caseworkers sometimes cite the beslutsstöd's guidance even for diagnoses it does not cover: in a reviewed sub-sample of 240 sickness benefit cases, 47 carried a diagnosis with no diagnosis-specific recommendation in the tool, and in 17 of these the caseworker's own notes nonetheless stated the sick-leave duration was "supported by" the beslutsstöd (Riksrevisionen, 2018). This shows that the formal coverage boundary is not always tracked precisely in practice—relevant to any diagnosis lacking a clinical reference, Z73 included—though we are not aware of evidence that this occurs specifically or disproportionately for Z73-coded cases rather than other uncovered diagnoses generally.

In addition, in the sick-leave data, sick-leave spells coded under Z73 are rare in any case—roughly a thousand cases per year, or about 2 percent of F43 cases—consistent with Z73 functioning as an occasional administrative or self-report label rather than a route into the formal sick-leave system.

A.6.6 Gender Differences Across Diagnoses

We compare the gender gap in F43 sickness absence to the gender gap in other diagnoses. Women's excess risk of sickness absence is present across diagnostic categories but is larger for stress-related psychiatric diagnoses than for sickness absence overall. The female-to-male relative risk is 1.25 for all diagnoses, 1.31 for psychiatric diagnoses, 1.41 for F43, and 1.42 for exhaustion disorder (F43.8A) specifically (Försäkringskassan, 2020). The diagnostic composition of psychiatric sickness absence also differs by gender: F43 accounts for 57.1 percent of women's psychiatric sickness spells, compared with 45.0 percent of men's (Försäkringskassan, 2020). The gender gap in sickness absence is therefore not unique to burnout, but it is more pronounced for F43, and most pronounced for exhaustion disorder.

B Sample Selection

Event-Study Estimation Sample This section describes the construction of our estimation sample used in Section 4. Appendix Table A.4 reports the sample size after each sample selection step. To build our treated sample, we start with 201,714 burnout cases, with their first burnout incident occurring from 2006 to 2013. We chose this time frame since 2006 is the first year where our data has complete information on diagnoses, and 2013 since we follow individuals for seven years after their burnout, and our last year of data is for 2020. We focus on the first incidence so that prior burnouts do not influence pre-trends. We restrict the sample to individuals between the ages 29 to 53 for whom we can observe labor market trajectories during prime age (25-60). This results in a sample of 153,218 first burnout cases. We drop 1,349 individuals who die within seven years after treatment. We then dropped 117 observations with missing education information. After matching treatment group contains 150,900 observations. When performing the fixed-delta method, the matched sample is substantially smaller containing between 75,197 for $\delta = 7$ and 62,993 for $\delta = 2$ treated individuals.

Career Progress Sample We restrict our sample of workers in several ways when studying how burnout relates to career progress in Sections 3 and 4. Starting with the overall population, we restrict the sample work workers ages 25 to 55 for whom we observe income in the previous period ($t-1$) and sick leave outcomes in the next period ($t+1$). We start with a sample of 79,094,577 individual-year observations between 2005 and 2019, for whom we can reliably measure burnout-related sick leave in the following year. Restricting to workers of ages 25 to 55, dropping individuals for whom we cannot observe the last lag of labor income ($t-1$) and sick leave outcomes in $t+1$, and restricting to individuals who have not had a burnout-related sick leave spell up to t results in 63,851,447 observations. Within this sample, we drop 21,513,853 observations, which have no recorded employer in $t-1$. We then drop all observations where the worker is enrolled in college or is self-employed, defined as working in a firm with a single employer, in t or $t-1$. The final sample contains 38,349,547 individual-year observations.

C Questions in the Work Environment Survey

In Section 2 we study the relationship between work-related stress and burnout, studying what work conditions are associated with burnout. We use self-reported measures of work conditions from the Work Environment Survey (AMU). We choose questions to maximize our sample size, accounting both for our sample period and not all questions in AMU being consistently asked in all years. This gives us a set of 16 questions. We combine two of these questions into one for the purpose of our analysis. Below is the list of questions, including the original question in Swedish.

1. Do you have any direct subordinates?
    - *Antal direkt underställda*
2. Do you experience headaches after work?
    - *Har du under de senaste 3 månaderna haft huvudvärk*
3. Do you feel physically exhausted after work?
    - *Händer det att du, när du kommer hem i från arbetet är uttröttad i kroppen?*

4. Do you experience lower back pain after work?
    - *Har efter arbetet ont i nedre delen av ryggen?*
5. Can you decide for ourself your own work pace?
    - *Har du möjlighet att själv bestämma din arbetstakt?*
6. Do you experience upper back or neck pain after work?
    - *Har du efter arbetet ont i övre delen av ryggen eller nacken?*
7. Do you perceive your work as mentally demanding or calm?
    - *Upplever du att ditt arbete är psykiskt påfrestande eller lugnt och behagligt?*
8. Have you experienced sexual harassment at your workplace?
    - *Är du utsatt för sexuella trakasserier från andra personer på din arbetsplats (t ex patienter, kunder, klienter, passagerare)?*
    - *Är du utsatt för sexuella trakasserier på din arbetsplats från chefer eller arbetskamrater?*
9. Do you experience pain in your hips, legs, knees, or feet after work?
    - *Har du efter arbetet ont i höfter, ben, knän eller fötter?*
10. Is disconnecting from thoughts about work during your time off difficult?
    - *Händer det att du inte kan koppla av tankarna från arbetet när du är ledig?*
11. Can you decide for yourself when different work tasks should be performed?
    - *Kan du delvis själv bestämma när olika arbetsuppgifter skall göras (tex genom att välja att jobba lite fortare vissa dagar?*
12. Do you experience pain in your shoulders, arms, wrists, or hands after work?
    - *Har du efter arbetet ont i axlar eller armar?*
    - *Har du efter arbetet ont i handleder eller händer?*
13. What proportion of your regular working hours do you typically work from home?
    - *Hur stor del av din ordinarie arbetstid arbetar du vanligtvis i hemmet?*
14. Have you experienced difficulties sleeping because thoughts about work have kept you awake?
    - *Har du under de senaste 3 månaderna haft svårigheter att sova, därför att tankar på jobbet hållit dig vaken?*

With the help of AI, we order these work conditions by their relation to burnout according to the medical literature. More precisely, we give ChatGPT the above questions and ask it to order them accordingly. We gave it the following prompt:

> *You are an academic psychologist, expert on burnout. Below, you find a list of 14 work conditions. Can you rank them with their relation with burnout according to medical literature? Please rank all 14 conditions. Don't add any additional text. Take your time.*

We performed this 10 times. Below is the rank of questions we received from ChatGPT each time:

1. 10,7,14,8,5,11,3,1,2,6,4,12,9,13
2. 10,14,7,5,11,8,3,1,2,4,6,12,9,13
3. 7,10,14,5,11,8,3,2,4,6,12,9,1,13
4. 10,14,7,5,11,8,3,2,6,4,12,9,1,13
5. 10,14,7,3,5,11,8,2,1,13,6,12,4,9
6. 10,14,7,3,11,5,8,2,6,4,12,9,1,13
7. 14,10,7,5,11,8,3,2,6,12,4,9,1,13
8. 7,10,14,3,5,11,8,2,6,12,4,9,1,13
9. 10,7,14,3,8,5,11,2,6,4,12,9,1,13
10. 10,14,7,5,11,8,3,2,6,4,12,9,13,1

Based on these 10 sequences, we calculate the rank of questions:

- Questions: 10, 14, 7, 5, 11, 3, 8, 2, 6, 4, 12, 1, 9, 13
- Average rank: 1.3, 2.3, 2.4 , 4.7 , 5.5, 5.8, 6, 8.2, 9.6, 10.4, 11.2, 11.7, 12.4, 13.5

D Stress Index

We construct an index of stress symptoms building on the diagnosis criteria for burnout; see Appendix A. Assume there exists a set of questions Q. Each question has a set of (ordered) responses Y_q. For each individual i, we observe response y_{qi} on question q. We first transform individual responses as follows

$$d_{qi} = \begin{cases} -1 & \text{if} \quad y_{qi} = \min\{Y_q\} \\ 1 & \text{if} \quad y_{qi} = \max\{Y_q\} \\ 0 & \text{Otherwise} \end{cases}$$

The stress index is then constructed by aggregating over all questions

$$S_i = \sum_{q \in Q} d_{qi}$$

We use questions from the AMU survey that best map into stress symptoms for burnout. The questions we use for the construction of the index are: i) "Do you find your job mentally stressful or calm?", ii) "Can you not disengage your thoughts from work in your free time?", iii) "Are you unable to sleep due to thoughts about work?", iv) "Did you experience headaches during the previous three months?". The index therefore ranges from -4 for those who do not show any symptoms to 4 for those who show all symptoms.

E Industry-Level Design

The matched difference-in-differences design controls for permanent differences between treated individuals and their matched controls, but a remaining concern is that contemporaneous private-life events—such as divorce or illness in the family—may both precipitate burnout and affect the outcomes we study. To separate such person-level shocks from work-related variation, we complement the main design with an industry-level design based on changes in burnout rates within narrow five-digit industries. The rationale is that idiosyncratic private-life events should largely average out across workers in an industry, whereas changes in working conditions and sector-specific stress may raise burnout risk more broadly. We therefore instrument individual burnout with the burnout rate among other workers in the same industry, following the grouped-data approach of Angrist (1991).[78] This exercise does not fully isolate exogenous work-related stress, because time-varying industry shocks may affect the outcomes through channels other than an individual's burnout. It nevertheless provides a useful diagnostic of whether the baseline estimates persist when the variation predicting burnout shifts away from person- and family-specific events and toward industry-level variation. As we show below, the resulting estimates are similar in direction and magnitude to the difference-in-differences estimates. We interpret this similarity as evidence that the baseline results are not driven solely by person- or family-specific events that coincide with burnout.

E.1 Design and Interpretation

For individual i, we construct the instrument from the annual burnout rate among other workers in the individual's five-digit industry. We exclude individual i and every worker employed at i's firm. Leaving out the individual prevents a mechanical relationship between the diagnosis and the instrument. Leaving out the firm reduces the influence of firm-specific shocks that could directly affect earnings, employment, or family outcomes. We assign the industry based on the individual's employment in the year before treatment and include industry fixed effects. The identifying variation therefore comes from changes in burnout risk within five-digit industries over time, rather than from permanent differences across industries.

As in the event-study, T_i denotes the treatment status (burnout indicator) of individual i, who belongs to matched group G_i. Let t_i denote the treatment year of the matched pair, and J_i the sector in which individual i was employed prior to treatment (at $t_i - 1$).[79] We estimate the following first-stage regression:

$$T_i = \beta B_i + \phi_{J_i} + \psi_{G_i} + \epsilon_i, \tag{12}$$

where B_i is the leave-one-out industry-level burnout rate for sector J_i at time t_i, and ϕ_{J_i} and ψ_{G_i} denote industry-origin and group-time fixed effects, respectively.[80] The coefficient β reflects the pass-through of industry-level burnout rates to individual burnout propensities. The inclusion of industry-origin fixed effects implies that the identifying variation comes from changes in industry-level burnout rates at the individual level—generated either by changes over time in the industry-level burnout rate or by individuals moving between industries. Industry-origin fixed effects absorb variation from sorting across industries.

The second stage replaces T_i in the relevant outcome equation with its fitted value from equation (12).

[78] For applications of this method to estimate wage elasticity of labor supply, see, e.g., Angrist (1991) and Blau and Kahn (2007).

[79] For connection to our notation before, note that $k = t - t(i)$, where t is calendar time.

[80] We construct the groups by pooling all treated individuals with the same treatment year, as well as their matched controls. Thus, by construction, our matched group takes into account the calendar time of treatment, so ψ_{G_i} could be denoted as $\psi_{G_{i,t_i}}$.

For the children's outcomes, we use the corresponding age-window specification described in Section 4, instrument parental burnout with the leave-one-out industry-level burnout rate, and retain the child and family controls used in that specification.

The exclusion restriction requires that, conditional on the fixed effects and controls, changes in the leave-one-out industry burnout rate affect an outcome only through the individual's burnout. This condition may not hold. For example, a decline in industry demand could raise stress and burnout while directly reducing earnings. Industry-level changes in hours, work organization, or job security could also affect spouses or children through channels other than the diagnosed parent's burnout. Excluding the individual's firm reduces the influence of firm-specific shocks, while industry fixed effects absorb persistent differences across sectors. These adjustments do not, however, remove time-varying shocks shared across firms within an industry. We therefore acknowledge the limits of the design and interpret the IV results primarily as a diagnostic comparison with the difference-in-differences estimates.

Appendix Figure A.28 plots the relationship between individual burnout and the leave-one-out burnout rate among other workers in the same five-digit industry. The sample is the matched sample used in the baseline labor-market analysis; by construction, half of these workers experience burnout and half are matched controls who do not. The relationship is positive and approximately linear. The first-stage F-statistic is 173.8, indicating a strong first stage. The outcome-specific first-stage statistics for the family and children's samples are reported in Appendix Tables A.6 and A.7, respectively.

E.2 Labor-Market and Family Outcomes

Appendix Table A.5 compares the IV estimate for the worker's labor income with the estimates from the three difference-in-differences designs. For labor income two years after burnout, the IV estimate is a loss of 13.79 percent. This is close to the baseline matched difference-in-differences estimate of 12.36 percent, the fixed-delta estimate of 14.85 percent, and the estimate of 12.47 percent obtained when matching within industry. This suggests that estimated effects are not driven by other private-life events coinciding with burnout.

Appendix Table A.6 reports the IV estimates for the other family outcomes. The estimates point to a 21.2 percent decline in spousal earnings, a 10.8 percent decline in fertility, and a 95.7 percent increase in divorce. The fertility estimate is not statistically distinguishable from zero, and the estimate for divorce is imprecise. The corresponding first-stage F-statistics are 47.4, 44.5, and 173.8. Given both the uncertainty and the possibility that industry shocks directly affect household outcomes, we view these estimates as descriptive evidence on whether the family patterns survive this alternative source of variation, not as separately identified causal effects.

E.3 Children's Human Capital

We next apply the IV design to the two measures of children's human capital studied in Section 4: college enrollment by age 21 and the probability of earning at least 240 points on the grade-9 test. For college enrollment, the treatment indicator equals one when a parent experiences burnout while the child is between ages 7 and 18. For grade-9 performance, it equals one when parental burnout occurs while the child is between ages 10 and 16, before the exam. We instrument these indicators with the lagged leave-out burnout rate in the parent's five-digit industry. The regressions retain the age-window controls from the difference-in-differences specification and include child-cohort, child-gender, sibling-order, and industry fixed effects. Standard errors are clustered at the parent level.

Appendix Table A.7 compares the IV estimates with the headline difference-in-differences estimates. Parental burnout is associated with a 2.53 percentage-point decline in college enrollment in the difference-in-differences specification and a 2.77 percentage-point decline in the IV specification. For the grade-9 threshold, the two estimates are nearly identical: declines of 1.86 and 1.85 percentage points, respectively. In both cases, the IV estimates are similar in magnitude to the difference-in-difference estimates, suggesting that impact on children from a burnout resulting from work environment and similar to that of events in private life.

F Technical Details for Section 4.4

We calculate the aggregate loss for the year 2019, the last year in our data not impacted by the COVID-19 pandemic.

For individuals experiencing burnout in 2019, $\hat{y}_i$ represents their income in the most recent year without burnout, while σ_i denotes the proportion of the year they were on sick leave due to burnout. In the last case, we refrain from using 2019 income data, acknowledging its distortion by the scarring effects of burnout. The cases affected by burnout through several other channels, e.g., the individual and her spouse both experienced burnout, are not quantitatively important.

For the effect on children's income, we convert the college-enrollment loss, estimated in Figure 8, to an income loss using estimates of returns to college in Sweden from Sinn (2024). The income terms in equation (6) are assigned to their corresponding exposure groups and set to zero otherwise. Cases affected through more than one channel are quantitatively negligible.

In steady-state calculation, unavoidably, we must adopt an assumption regarding the data-generating process for the burnout time series. We opt for a simple form, assuming a first-order Markov process. Moreover, we impose that transition probabilities are independent of age, in line with a flat life-cycle profile among prime-age workers in the data.

The following stylized calculation illustrates the intuition behind the magnitudes in our results. A 2.5 percentage point drop in college enrollment, together with a 38% college wage return—equivalent to a 27.5% loss in income from not completing college—yields an expected permanent income loss of approximately 0.7%. While modest in isolation, this loss must be considered alongside the prevalence of exposure to parental burnout. In steady state, the lifetime probability of an individual experiencing burnout is approximately 20%. Given that roughly 80% of the population becomes parents, the likelihood that a child is exposed to at least one episode of parental burnout is around 30%. This implies a back-of-the-envelope estimate of income loss from child spillovers of about 0.2%.

G Prediction and Prevention

G.1 Construction of Burnout Prediction and Evaluation

The sample that we use to predict future burnout includes the entire Swedish population between ages 25 and 60 between 2005 and 2019. We impose no further restrictions on the sample, for example, with regard to data availability or employment status. For this population, we create two sets of information. The first information set contains basic demographic characteristics mirroring the information an employer could easily deduce from a standard CV. This set contains gender, age, citizenship status, and detailed education information. The second information set contains a comprehensive set of variables from

administrative records, detailed in the next section. When evaluating the performance of the work environment survey (AMU), we analyze a much smaller population of 61,121 individual-year observations. Very few individuals appear in two different waves of the survey. We impose no further sample restrictions.

To predict burnout incidence one-year-ahead, we use Extreme Gradient Boosting (Chen and Guestrin, 2016). We choose the hyper-parameters based on conservative priors, setting the learning rate to 0.4, the maximum tree depth to four, and the minimum child weight to six. We obtain the optimal number of trees when training XGBoost on the full-information population sample and fix this parameter for the remaining prediction algorithms.

When working on the full population sample, we test the model using a 20 percent hold-out sample. Given that we are dealing with a low-frequency outcome, we under-sample the majority class, though in practice, we have found that this step had no discernible impact on the prediction results. When predicting using the workplace survey, we work with a smaller sample and evaluate the model using cross-validation with five folds. That is, we draw five random sub-samples without replacement and use each subset as a hold-out sample once, training on the remaining 80 percent of the sample.

G.2 Basic Demographic and Administrative Data

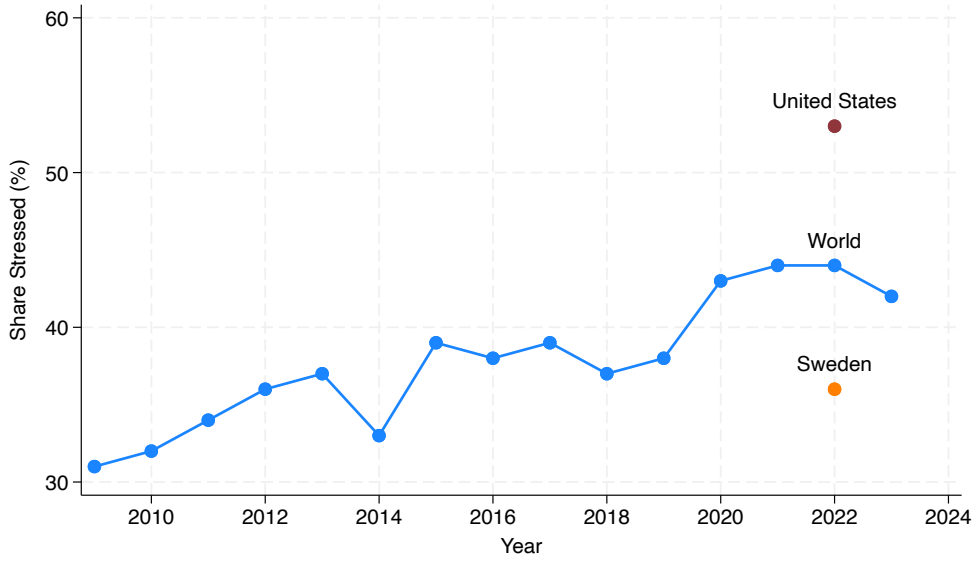
Basic Demographic data contain the following set of predictors: gender, age, citizenship status, education level (3 categories), education field (348 categories), municipality of the employer. For men, we also scores from the military enlistment tests on: inductive reasoning, verbal comprehension, spatial ability, technical understanding, social maturity, psychological energy, intensity and stress tolerance, psychological functional ability, and body height. We include information on marital status in the current year, a flag for cohabitation, the number of years since the last divorce or marriage, the number of children, the ages of the first six children, and the earnings rank of the spouse (within their gender and year cell).

Sick leave records yield the count data for sick leave spells in each past year (up to five years) for the following diagnosis categories: physical and unrelated to pregnancy, physical related to pregnancy, single-episode depression, recurring depression, anxiety, stress-related mental health diagnoses, other mental health diagnoses, missing diagnosis. For each category, we include the total number of spells in the last five years as a predictor.

Work-information includes flags for non-employment-to-employment, employer-to-employer and inter-industry moves, tenure at the given employer, separations, turnover and the change in turnover at the given employer, the cumulative number of cases until that year in an employee's firm or industry, a person's earnings rank, earnings growth in the past four years, flags for full-time employment, unemployment and long-term unemployment in the past four years, the total number of years with full-time employment, unemployment or long-time unemployment in the past four years, the number of days in unemployment and on parental-leave in the last year, 4-digit occupation codes, 5-digit industry codes.

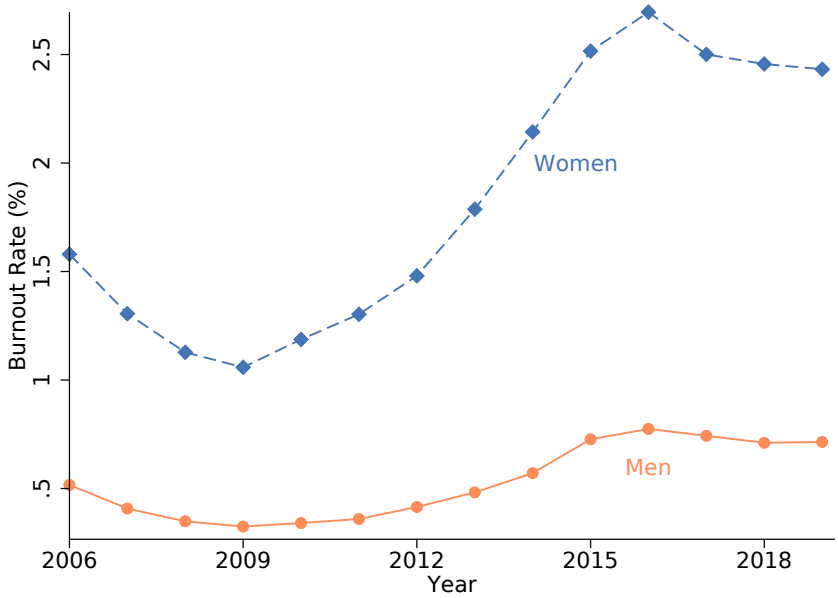
H Supplementary Figures and Tables

Figure A.1: Increase in Self-Reported Stress Levels



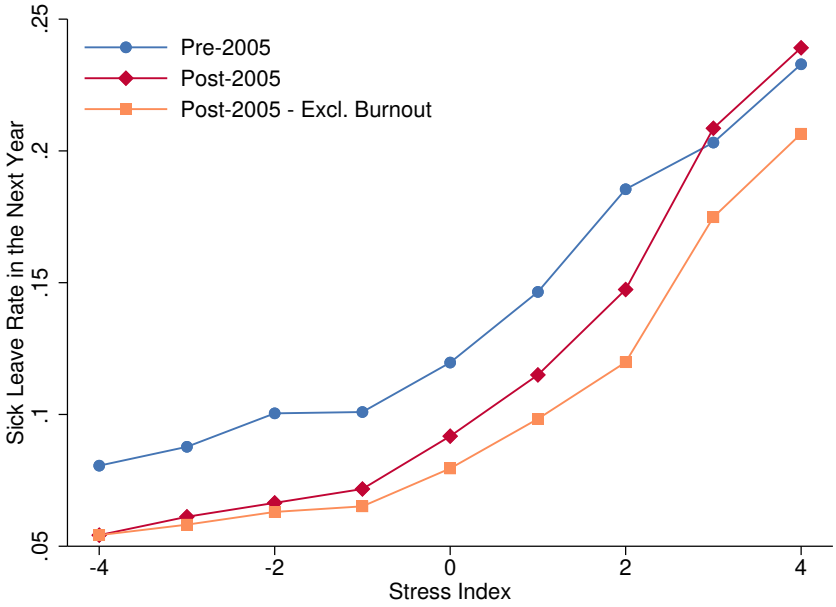
Notes: The figure plots the share of survey respondents who state that they experienced stress during a lot of the previous day in the Gallup State of the Global Workplace Survey. The blue line plots the average across worker worldwide, whereas red and orange dots mark national averages for the United States and Sweden, respectively.

Figure A.2: Evolution of Burnout Rates over Time



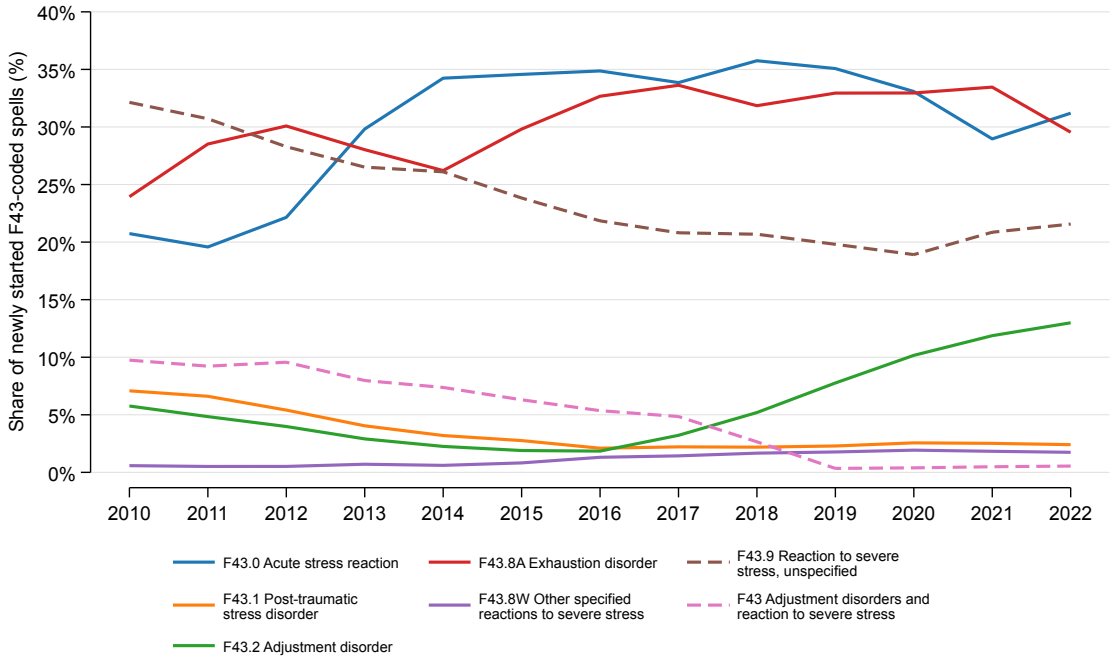
Notes: The figure plots the burnout rate, defined as the share of the population experiencing at least one burnout sick-leave spell in a given year among those full-time employed in the previous year between 2006 and 2019, the years where we have data on sick-leave spells and diagnoses for the full year.

Figure A.3: Institutional Reform, Stress Levels and Sick Leave



Notes: The figure plots sick leave uptake in the subsequent year against stress index. The sample consists of respondents to the Swedish Work Environment Survey (AMU) conducted bi-annually between 1997 and 2019 in the last quarter of each year. The stress index is constructed using self-reported symptoms of burnout: inability to sleep due to work, mentally stressful job, inability to detach thoughts from work, and headaches. For more details on the construction of the index, see Appendix D.

Figure A.4: Evolution of F43 Subcategories over 2010-2022

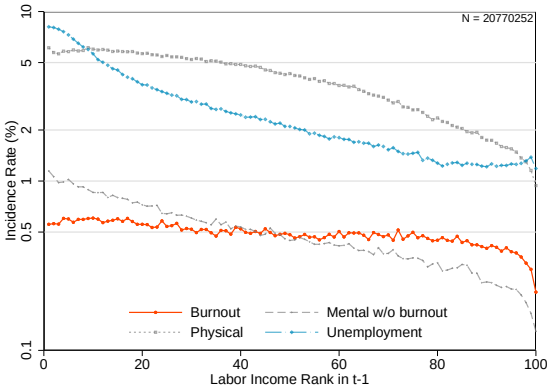


Note: The figure reports the prevalence of F43 subcategories of newly started sickness-absence spells for 2010–2022. F43.9 is a genuine four-character subcategory, generally used temporarily for a stress or crisis reaction when the criteria for F43.0, F43.2, or F43.8 are not met. Following Försäkringskassan's explicit coding convention, the separate series labeled F43 is interpreted as sickness spells recorded only at the three-character level because the more specific four-character diagnosis is missing. F43.9 is a valid four-character diagnosis for an unspecified reaction to severe stress. The separate series labeled F43 should be interpreted here as spells recorded only at the three-character level, without a reported subcategory; the source diagram does not explicitly define this series. This is supported by comparing this figure to Table A.1.

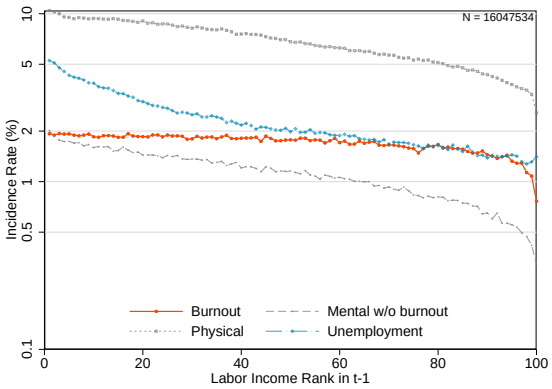
Source: Socialförsäkringsutskottet (2024), Figure 3. The figure reports authors' calculations of each recorded diagnosis code's share of newly started F43-coded sickness spells during 2010–2022. The source diagram reports annual counts; we read these counts from the diagram and divided them by the sum across the displayed F43 categories.

Figure A.5: Incidence Across Income Distribution

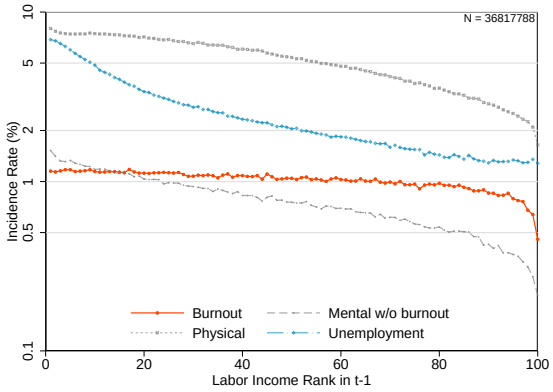
(a) Men



(b) Women



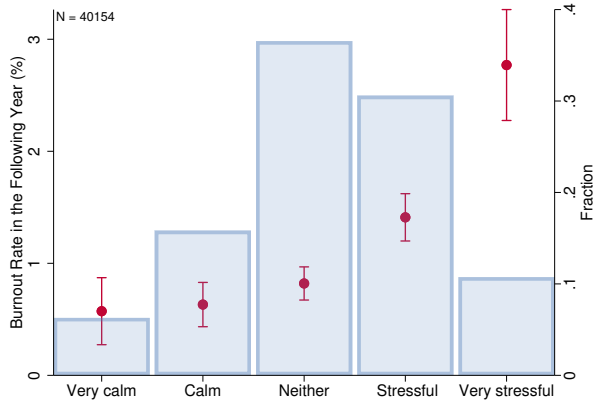
(c) Pooled



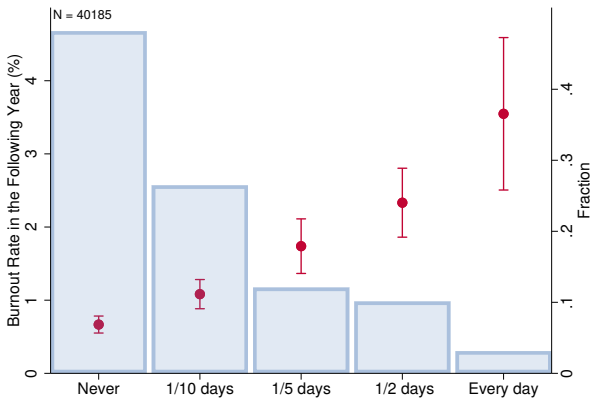
Notes: The figure shows the incidence of unemployment and sick leave due to different diagnoses across the labor income distribution. The sample consists of all prime-age, full-time employed workers in Sweden between 2006 and 2019. To ensure accurate measurement of labor income, we delete all observations with unemployment or sick leave days in a given year, and measure incidence in the subsequent year. The labor income rank is computed within a given year x birth cohort x gender cell.

Figure A.6: Components of Stress Index

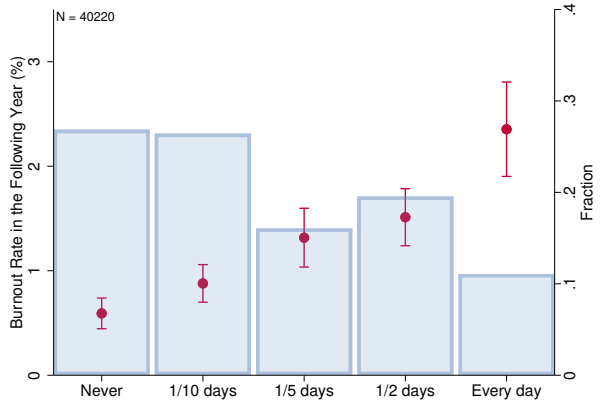
(a) Mentally stressful job



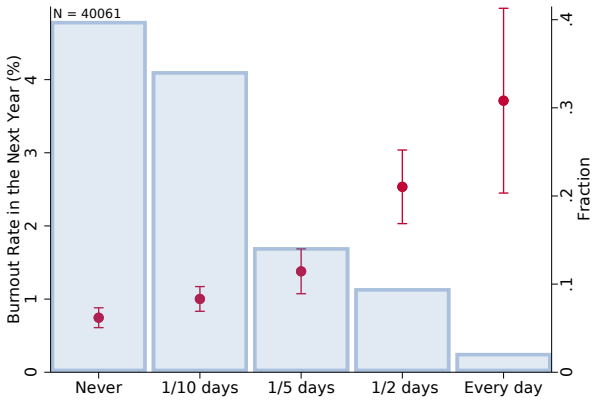
(b) Are you Unable to sleep due to work



(c) Unable to detach thoughts from work

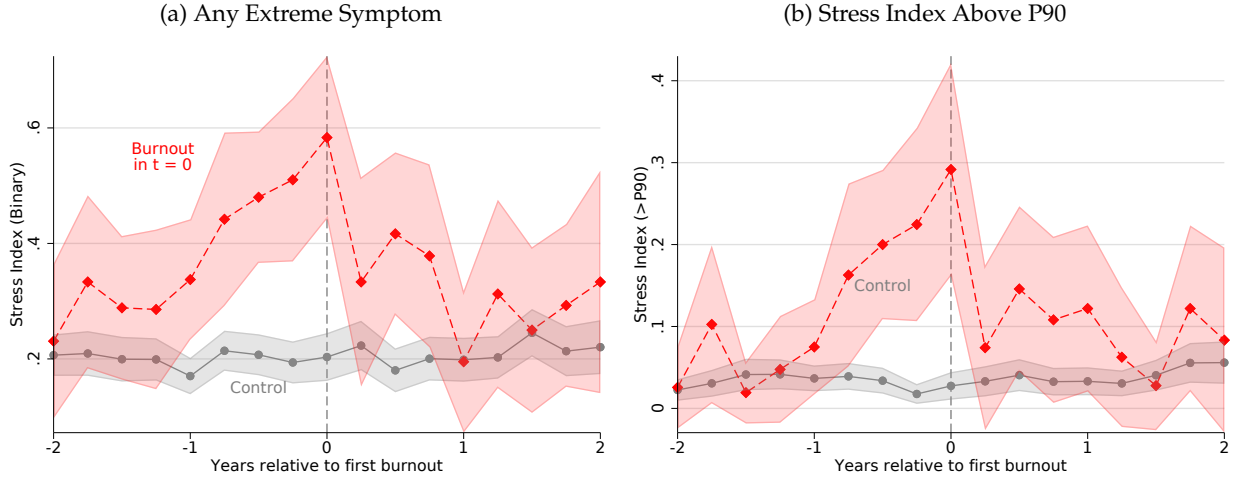


(d) Headaches



Notes: The figure documents the relationship between self-reported work conditions in the Work Environment Survey (right y-axis) and the burnout rate of the same worker in the year after the survey (left y-axis). The four symptoms reported are those used in constructing the stress index (see Appendix D). The exact phrasing of the questions is reported in Appendix C.

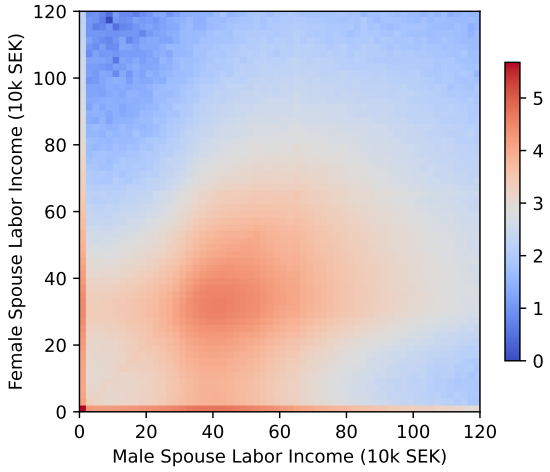
Figure A.7: Evolution of Alternative Stress Indices Around Burnout



Notes: The figure shows the evolution of alternative measures for work-related stress around burnout. In **Panel a)** the outcome is an indicator assuming value one if a respondent gives the highest response to one the four questions about symptoms of burnout used in the construction of the stress index described in Figure 11. In **Panel b)**, the outcome is a binary indicator returning value one if the stress index exceeds the 90th percentile of its cross-sectional distribution for a given respondent.

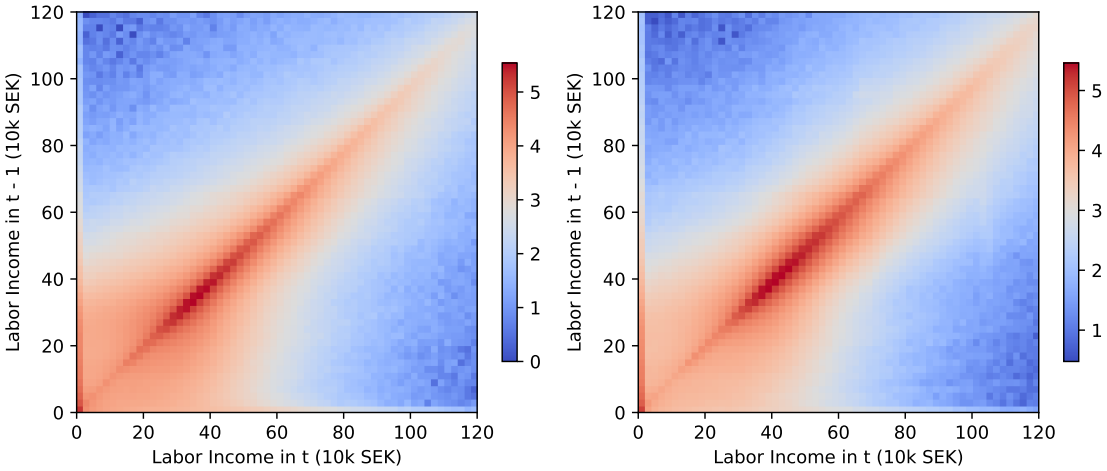
Figure A.8: Distribution of Labor Income Histories

(a) Joint distribution of spousal labor incomes



(b) Income history (Women)

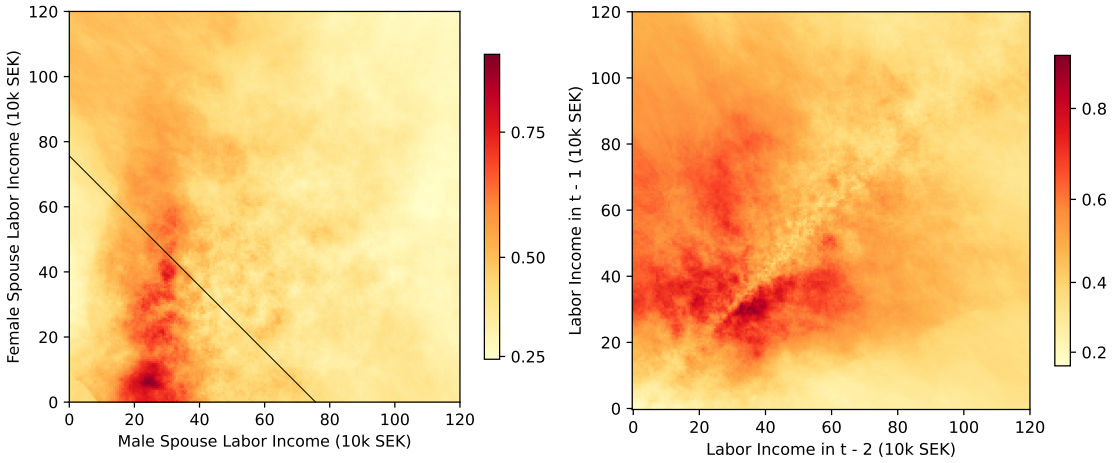
(c) Income history (Men)



Notes: The figure shows the frequency distribution of labor income histories and joint income allocations. We discretize the state space using a grid with 2k SEK increments. The construction of the sample is described in Appendix Section B.

Figure A.9: Burnout Rate of Men: Couple Incomes & Career

(a) Male Spouse Burnout Rate (b) Labor Income Growth

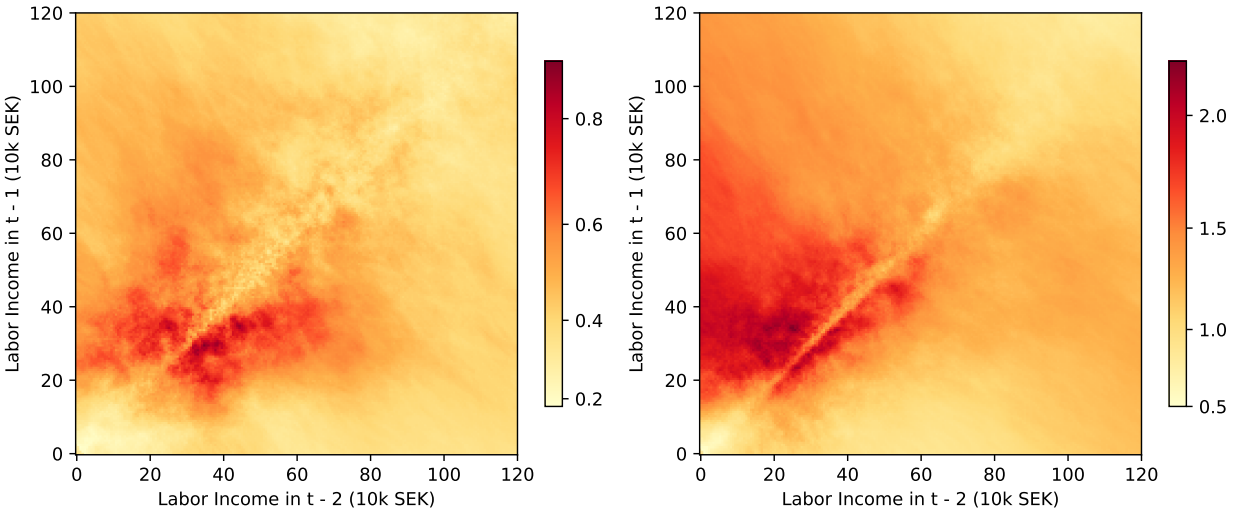


Notes: **Panel (a)** shows burnout rates over the joint distribution of spousal labor incomes for 11,008,512 couple-year observations in each subfigure. The two lines are 45-degree lines and a line marking the median couple's total income of 756k SEK. Annual labor income is winsorized at 1,200k (corresponding to P97 of men and P99 of women) and rank-adjusted to 2020 SEK when the exchange rate was 9,20 to USD and 10,49 to Euro. Two-dimensional moving averages are used so that the burnout rate represents the average rate for approximately 40000 individuals in the circular vicinity of each point. **Panel (b)** reports burnout rates in $t+1$ across individuals' labor income histories. The x-axis reports labor income in $t-1$. The y-axis reports labor income in t. We perform a rank-adjustment to 2020 levels for labor income in $t-1$ and compute income in t using rank-adjusted labor income in the previous year and nominal income growth at the individual level. The sample consists of individuals aged 25 to 55 between the years 2005 and 2019 without prior burnout sick leave. We drop observations within a two-year window of childbirth. See notes in Figure A.8 for a more detailed description of the sample construction.

Figure A.10: Burnout and Labor Income Histories (Stayers)

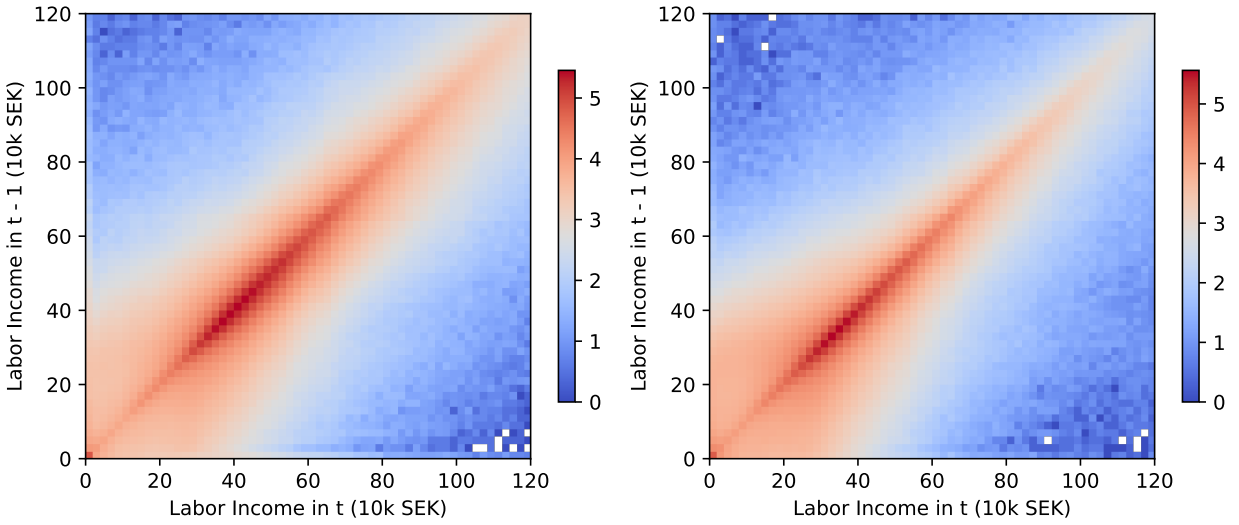
(a) Men: Burnout Rate among Stayers

(b) Women: Burnout Rate among Stayers



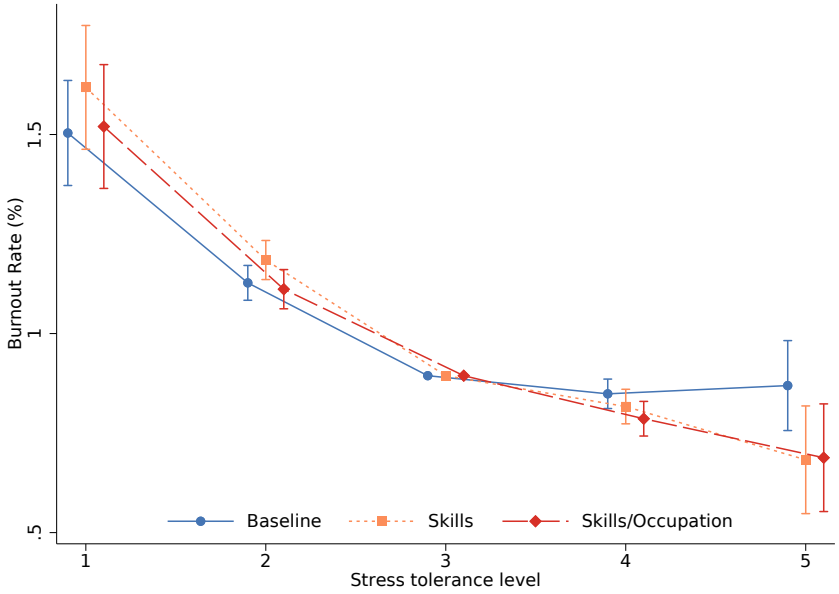
(c) Men: Histogram of Income Histories

(d) Women: Histogram of Income Histories



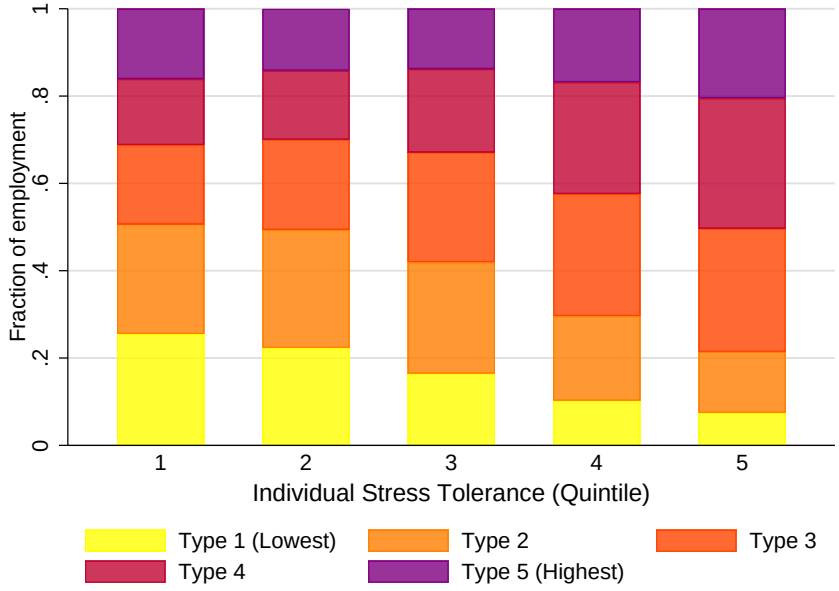
Notes: **Panels (a) and (b)** reports burnout rates by gender among workers staying at the same employer in the past two years against their labor income histories during the same period. The construction of the sample is described in Appendix Section B. Details on the estimation procedure are provided in Section 4. **Panels (c) and (d)** show the corresponding frequency distributions of earnings histories. The state space is discretized using a grid with 2k SEK increments.

Figure A.11: Individual's stress tolerance and burnout



Notes: The figure plots the average individual burnout rates by individual stress tolerance, measured in association with the military draft. Blue circles are averages estimated using a regression where the median group is the reference category. Orange squares are estimates from a similar regression but control for fixed effects for all other skills measured in association with the military draft (cognitive and non-cognitive skills). Red diamonds further add occupation fixed effects to the same regression.

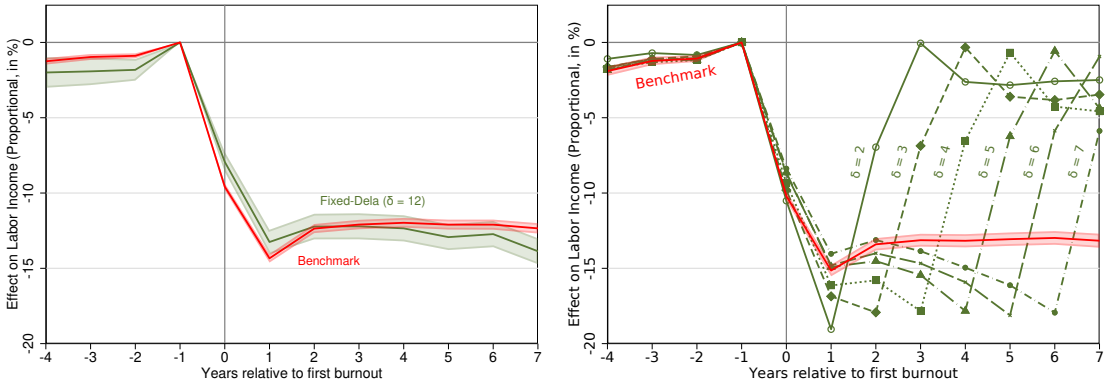
Figure A.12: Sorting into Occupations



Notes: This figure shows the distribution of employment across occupation stress levels conditional on workers stress tolerance in Sweden from 2005 to 2019. The sample space is the same as in panel (b) of Figure 2. The stress tolerance measures used are only available for men.

Figure A.13: Effect of Burnout on Labor Income: Baseline vs. Fixed-Delta Method

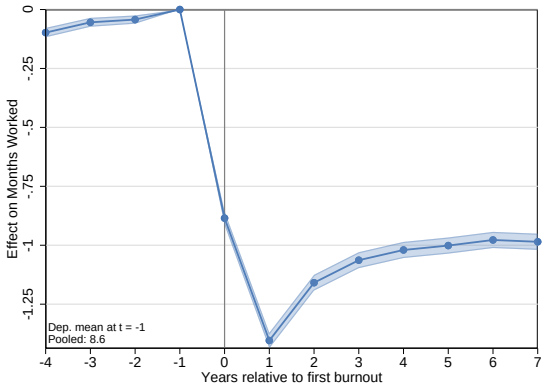
(a) Long-Run Effects (b) Robustness to Choice of δ



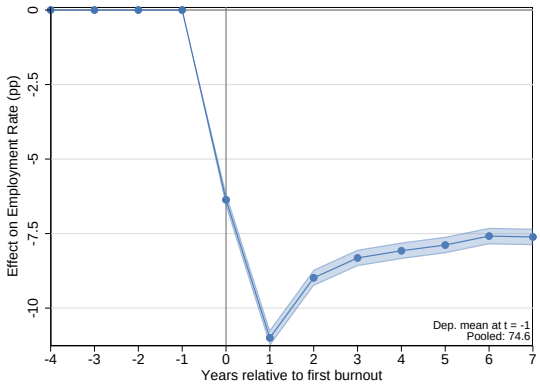
Notes: The figure shows the proportional effect of burnout on labor income as estimated with different matched control groups. The red line labeled *Benchmark* depicts the estimated effects when never-treated individuals are used as a control (Figure 6a). The control group in the remaining lines are individuals who burn out δ periods after the treatment group (the fixed-delta method). In both cases, we match treated and control individuals on the year of birth, gender, education, and earnings percentile within their demographic cell. When applying the fixed-delta method, we deviate from the benchmark matching procedure by not matching on employment history. Throughout, we maintain a balanced sample and require that treated individuals experience their first burnout incident in the years 2006 to 2013 at ages 29 to 53. For the benchmark model with never-treated as controls, we report standard errors clustered at the individual-level.

Figure A.14: Labor Income around Burnout: Extensive vs. Intensive Margins

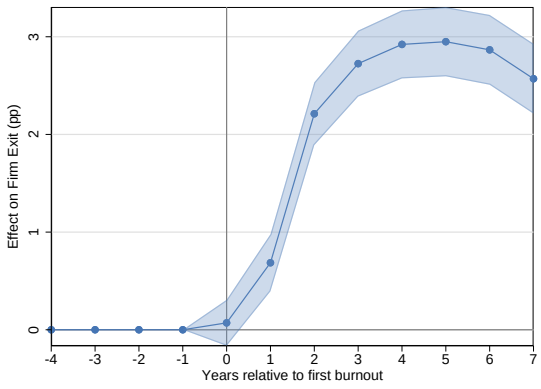
(a) Months worked



(b) Employment Rate



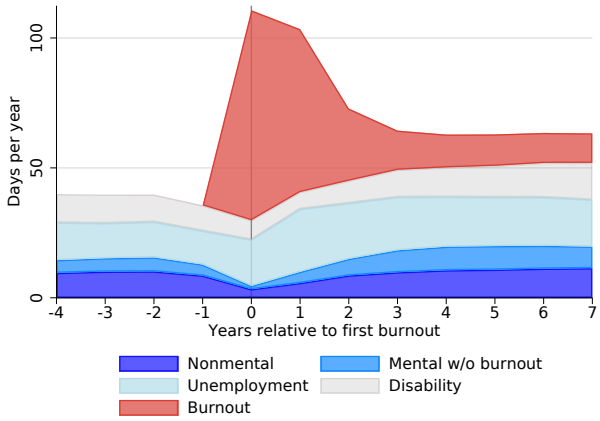
(c) Firm Switching



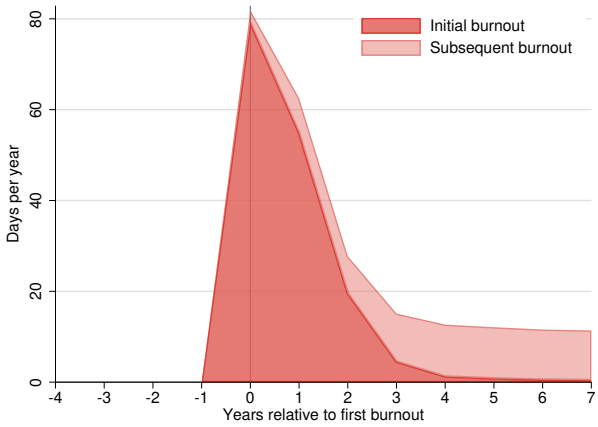
Notes: **Panels (a-c)** plot the coefficients on event-time fixed effect interacted with an indicator for burnout, and their standard error, from the dynamic difference-in-difference model in equation (1) for various labor market outcomes. **Panel (a)** reports the coefficients when the model is estimated with months of employment as the dependent variable. **Panel (b)** shows the dynamic response of employment rates following burnout. Employment rates are equalized across treatment and control group in -4 through -1 by design. **Panel (c)** shows the effect on firm exit. The outcome is a dummy which assumes one if an individual is not recorded as an employee at her main employer in the month coinciding with the beginning of her burnout sick leave spell. All values prior to 0 are set to zero by design.

Figure A.15: Evolution of Work and Sick-Leave around Burnout

(a) Days of Work Absence

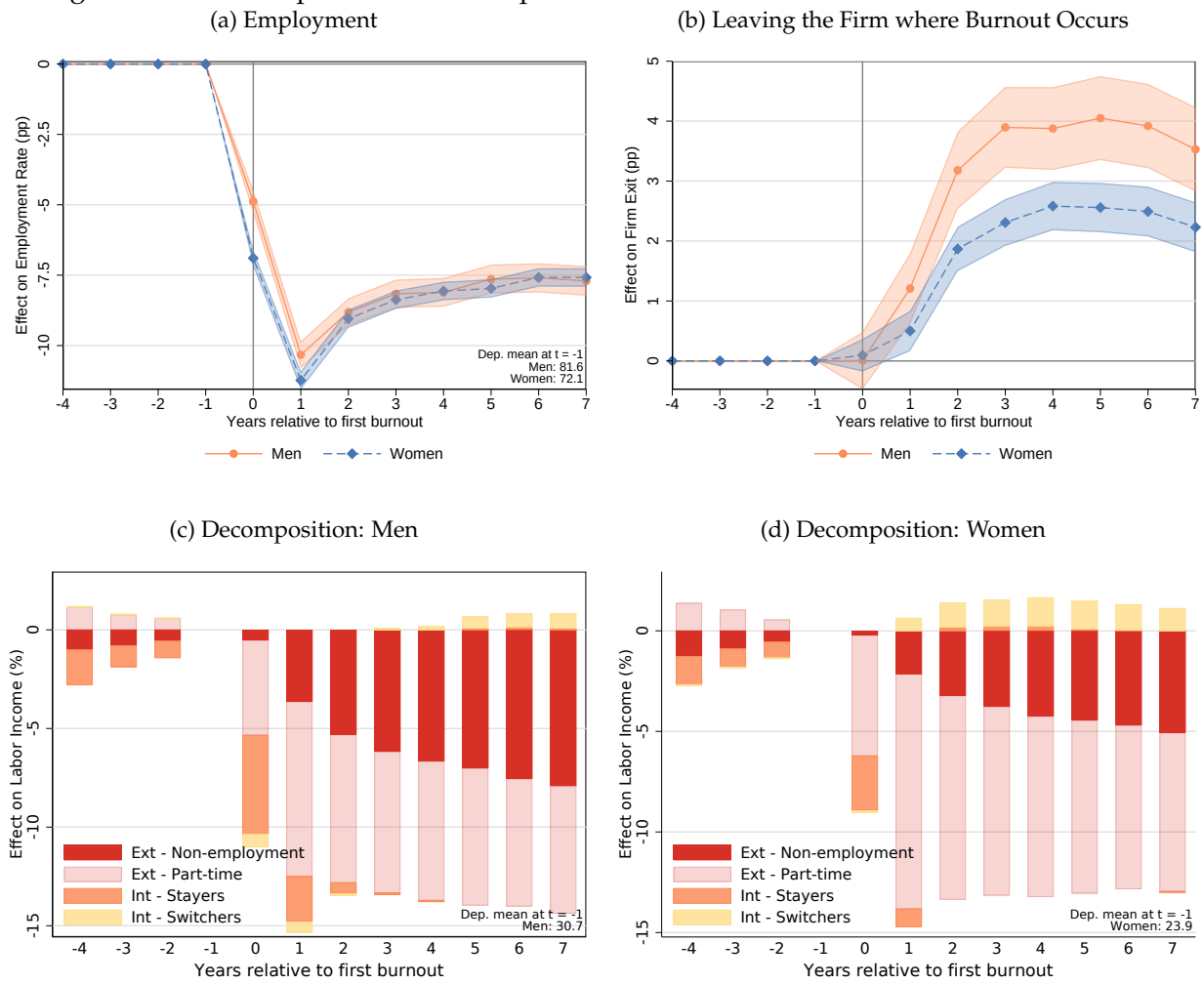


(b) Burnout Sickleave Days



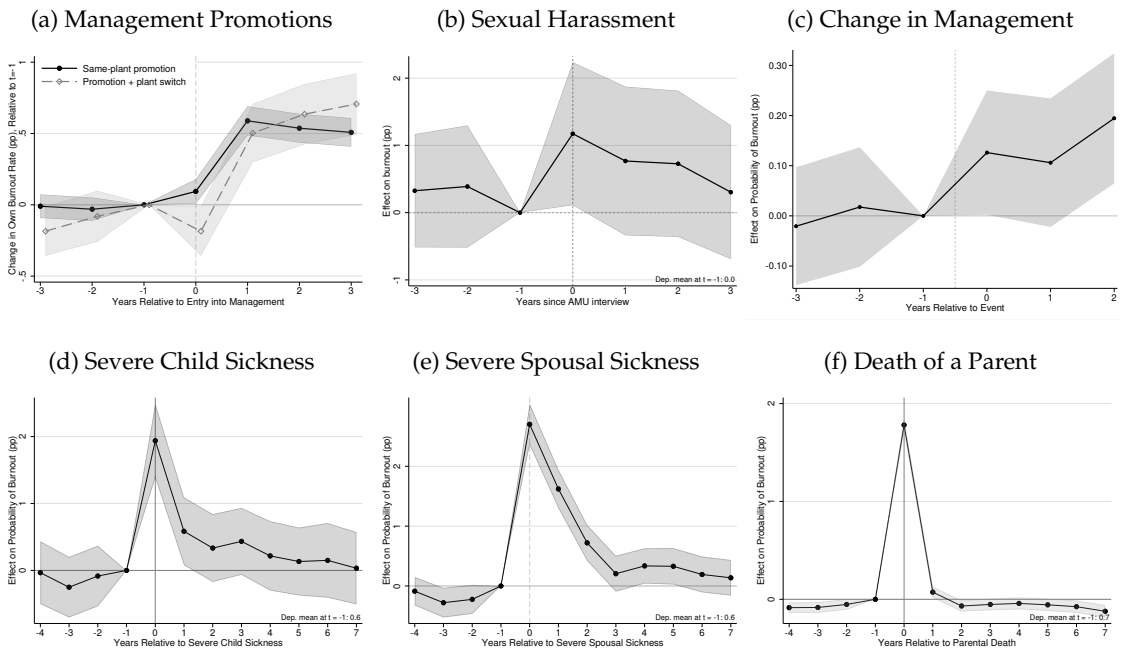
Notes: **Panel (a)** presents estimation results of the dynamic difference-in-difference model for days on sick leave by diagnosis category, as well as days in unemployment and on disability. **Panel (b)** further decomposes sick leaves due to burnout into initial and later spells.

Figure A.16: Decomposition of the Impact of Burnout on Labor Income: Men vs. Women



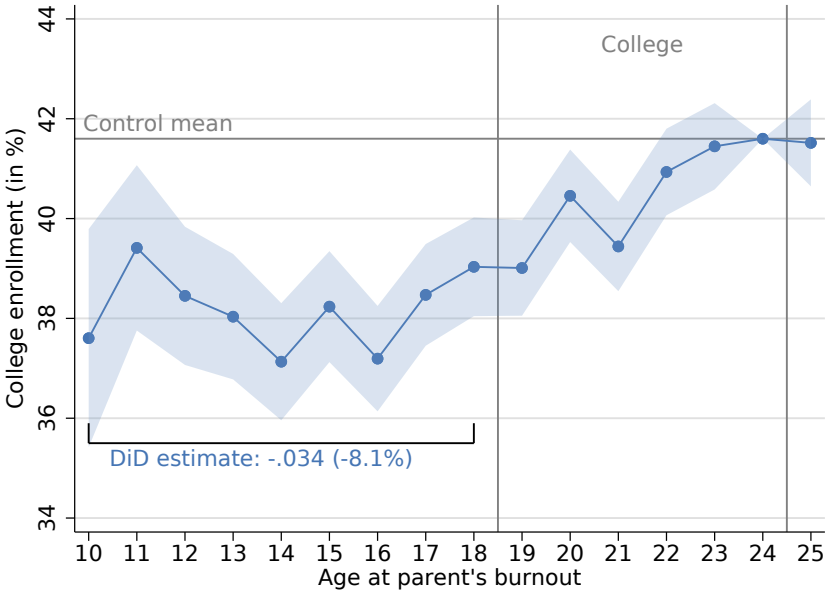
Notes: This figure shows margins of labor market adjustment to burnout and their contribution to earnings dynamics separate by gender. The decomposition follows equations (4) and (2). Treated individuals and controls are matched based on year-of-birth, gender, education and the earnings percentile in the year prior to treatment. The 95 % confidence intervals are based on standard errors clustered at the individual level.

Figure A.17: Workplace and Family Determinants of Burnout



Notes: The figure shows the dynamic evolution of burnout around workplace or family events. The top row shows results for events at the workplace. **Panel a)** plots the change in burnout risk associated with an occupation change from non-managerial to a managerial occupation. The figure separately reports transitions into management occurring within the same establishment and transitions that coincide with a change of establishment. **Panel b)** reports the change in burnout risk around self-reported exposure to sexual harassment. Control observations are matched based on survey year, gender, education at $t = -1$, and employment status at $t = -1$. Regressions include individual and calendar-year fixed effects. **Panel c)** shows the change in burnout risk around a change in an establishment's management. We restrict the analysis to small establishments with between ten to thirty employees. We then identify the manager as the highest earner in three consecutive years. A manager change takes place in $t = 0$ if the highest earner leaves the firm. To avoid time aggregation, we require that they receive no income in $t = 0$ from their previously managed plant. We match treated establishments to control units which do not experience a manager change in $t = 0$ based on three broad size bins. The bottom row shows results for family events. **Panel d)** shows the change in burnout around the time of adult child's (age 20-30) diagnosis of a severe sickness according to sick leave records. We classify ICD-10 codes C, D, and E as severe sicknesses that are unlikely to suffer from reverse causality. These diagnoses span cancer (C), other neoplasms, blood and immune disorders (D), endocrine, nutritional and metabolic conditions such as diabetes (E). We focus on the first diagnosis due to one of the above diagnoses to define the event. **Panel e)** shows the change in burnout risk around the time of a spouse being diagnosed with a severe condition, based on sick leave records. **Panel f)** shows the effect of parental death. In the family events studies in Panels e) to f), control observations are chosen from observationally similar individuals who are potentially at risk of being exposed to the event. For example, in the event-study around an adult child's sickness, controls are required to have an adult child between ages 20 and 30. In a similar manner, we require controls to have a spouse in Panel e), and at least one living parent in Panel f). We select controls using coarsened exact matching on year of birth, education, gender, and earnings percentile in the cohort distribution in $t-1$. Confidence intervals are based on standard errors clustered at the individual level.

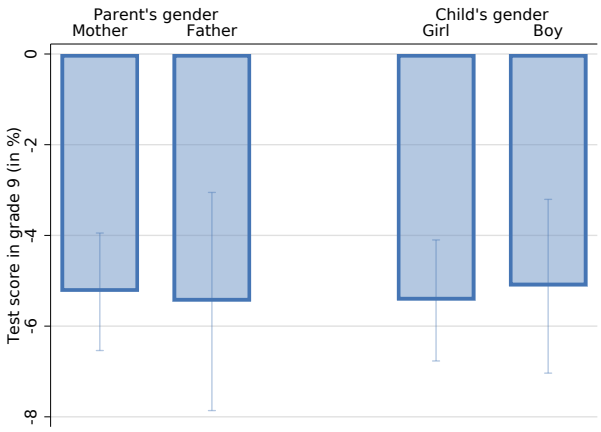
Figure A.18: Effect of Parental Burnout on Child's College Enrollment



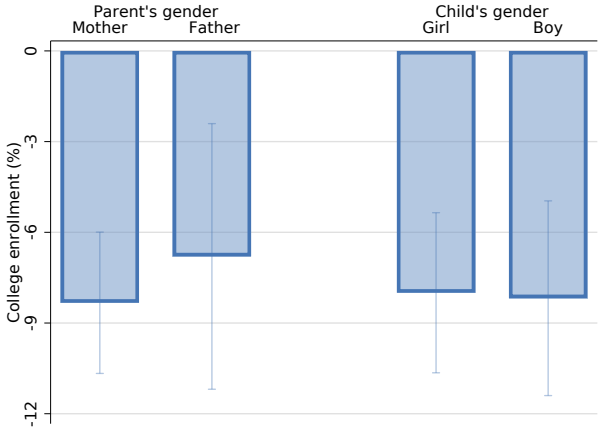
Notes: The figure plots the effect of parental burnout on children's college enrollment measured at some age 19 to 24. To identify deviations in the treated group from potential cohort-specific trends in college enrollment, we demean the outcome with the mean outcome of a control group with the same birth cohort, gender, and sibling order but whose parents never burn out. The figure plots the coefficients on the child's age at parent's burnout in regression (5) that includes controls for the parent's birth cohort and gender and the child's birth cohort, gender, and sibling order. The coefficient estimates measure college enrollment of children by their age at the time of first parental burnout relative to those whose parents burn out at age 24, i.e., difference-in-differences, scaled by adding the mean college enrollment of the control group. The shaded area reflects 95% confidence intervals based on robust standard errors clustered at the parent level. "DiD estimate" reports the average effect for ages 10-18.

Figure A.19: Heterogeneity of Effects of Parental Burnout on Child's Human Capital

(a) School Grades



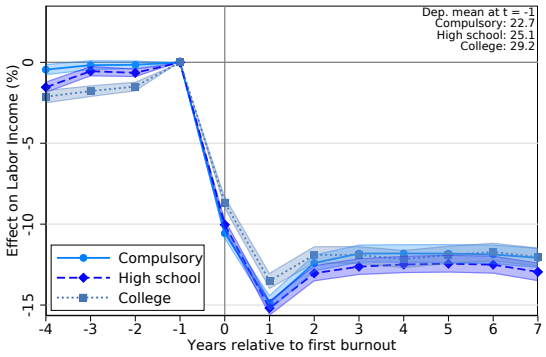
(b) College Enrollment



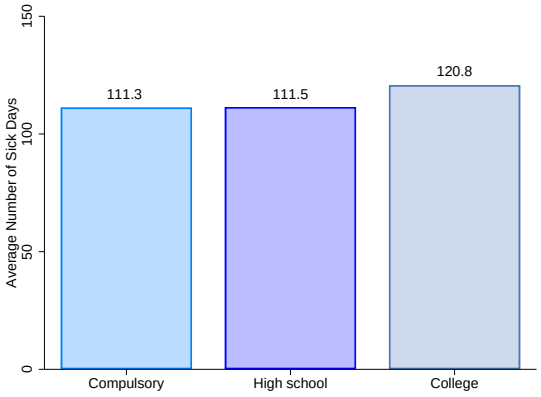
Notes: The figure plots the effect of parental burnout on children's performance (GPA) in national-level tests at the end of 9th grade around age 16 (**Panel (a)**), and on college enrollment measured at ages 19, 20, or 21 (**Panel (b)**) by gender of parent that burns out and gender of children studied. We match children whose parent experiences burnout to a control group of children in the same birth cohort, gender, and sibling order but whose parents never experience burnout. Since the only role of the control group is to identify deviations in the treated group from potential (group-specific) trends in college enrollment, we demean the outcome with the control-group mean. In panel (a), the bars measure the average test score of children whose parents burn out at age 10-16 compared to those whose parents burn out when children are at age 17, estimate with regression (5). In panel (b), the bars measure the average college enrollment of children whose parents burn out at age 7-18 compared to those whose parents burn out when children are at age 22, estimate with regression (5). In both panels, the coefficient estimates are scaled by dividing by the average outcome for the control group. In the regression, we include controls for the parent's birth cohort and the child's birth cohort, gender, and sibling order. The whiskers are 95 percent confidence intervals where standard errors are clustered at the parent level.

Figure A.20: Heterogeneity of Burnout Effects by Education

(a) Labor Income



(b) Days on Sick Leave



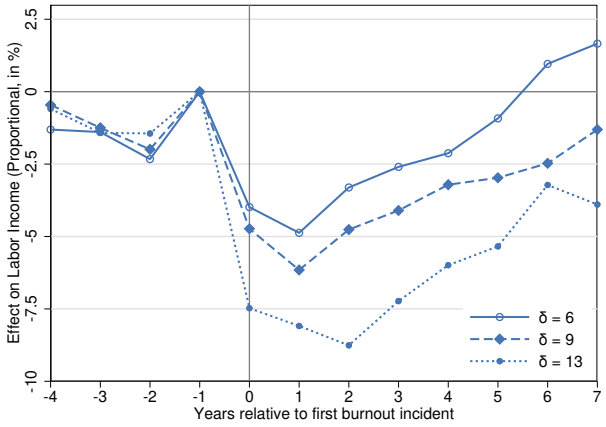
Notes: **Panel (a)** plots the proportional effect of burnout on the labor income by education. It plots the coefficients on event-time fixed effect interacted with an indicator for burnout and their 95 percent confidence interval based on individual-level-clustered standard errors from the dynamic matched difference-in-difference model in equation (1). **Panel (b)** plots the average number of sick leave days due to burnout in the treated group by education. We winsorize the number of days at 365 days.

Figure A.21: Burnout Effect on Spousal Labor Income

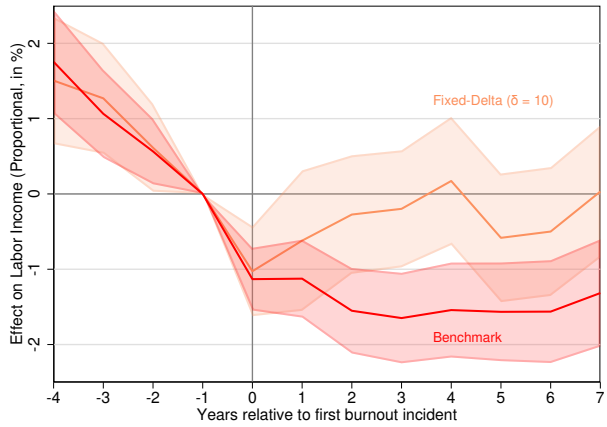
(a) Fixed-δ Estimates: Female Spouse



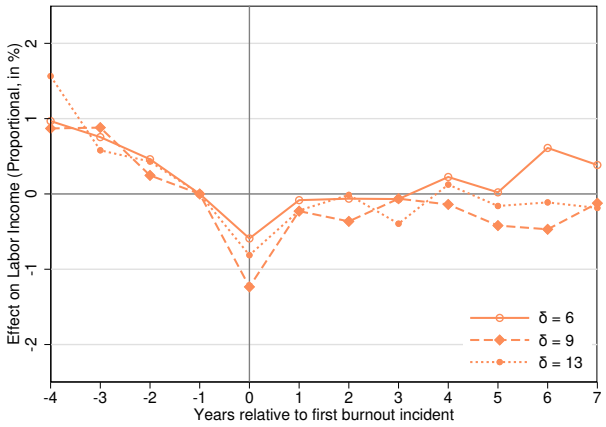
(b) Robustness to choice of δ: Female Spouse



(c) Fixed-δ Estimates: Male Spouse

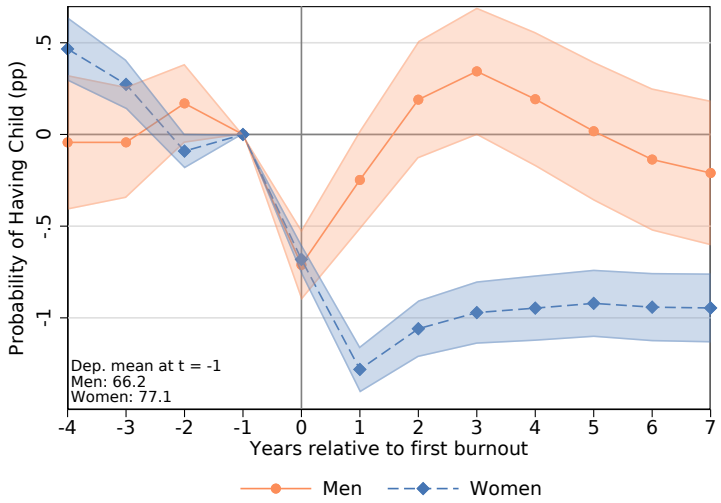


(d) Robustness to choice of δ: Male Spouse



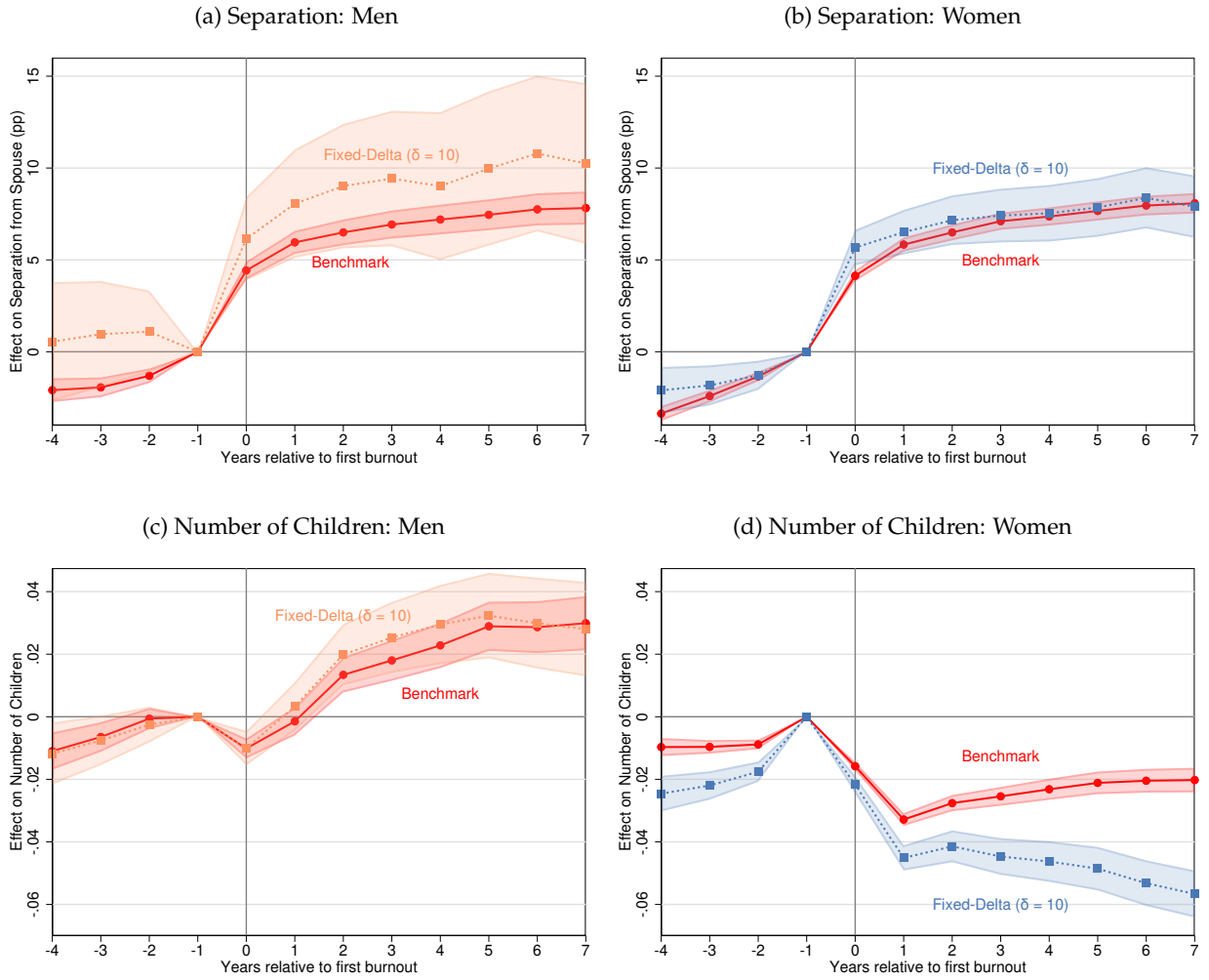
Notes: The figure re-estimates the effect of burnout on spousal labor income using control groups that themselves experience burnout later, and compares them with the benchmark estimates in Figure 7, panel (b). The sample is the 57,441 spouses (married or cohabiting partners in the year prior to burnout) used throughout, followed irrespective of how marital status evolves thereafter. **Panels (a)** and **(b)** report results for female spouses; **panels (c)** and **(d)** for male spouses. Panels (a) and (c) plot the benchmark estimates, in which controls never experience burnout, against the fixed-δ estimates with $\delta = 10$; shaded areas are 95 percent confidence intervals. Figure 7. Panels (b) and (d) plot the fixed-δ estimates for δ equaling six, nine or thirteen years, where the control group consists of spouses of workers who first burn out δ years after the treated worker. Throughout, we plot the coefficients on event-time fixed effects interacted with an indicator for burnout from the dynamic matched difference-in-differences model in equation (1), with standard errors clustered at the individual level. Matching is at the spouse level, on year of birth, gender, education, and earnings percentile within the demographic cell. Pre-burnout paths are flat under the fixed-δ design, and the post-burnout decline among female spouses is similar in magnitude to the benchmark.

Figure A.22: Burnout Effect on the Probability of Ever Having a Child



Notes: The figure plots the effect of burnout on the probability of ever having a child based on matched difference-in-differences, as described by equation (1). It plots the coefficients on event-time fixed effects interacted with an indicator for burnout and their individual-level-clustered standard errors from the dynamic matched difference-in-differences model in equation (1). The estimation sample is a balanced panel of 150,834 treated individuals whose first burnout between 2006 and 2013, aged 29 to 53. The control group consists of individuals who never experienced burnout and meet the same sample selection criteria. We match treated and control individuals one-to-one on the year of birth, education, gender, income percentile within these demographic groups in the year before treatment, and their employment history up to that year.

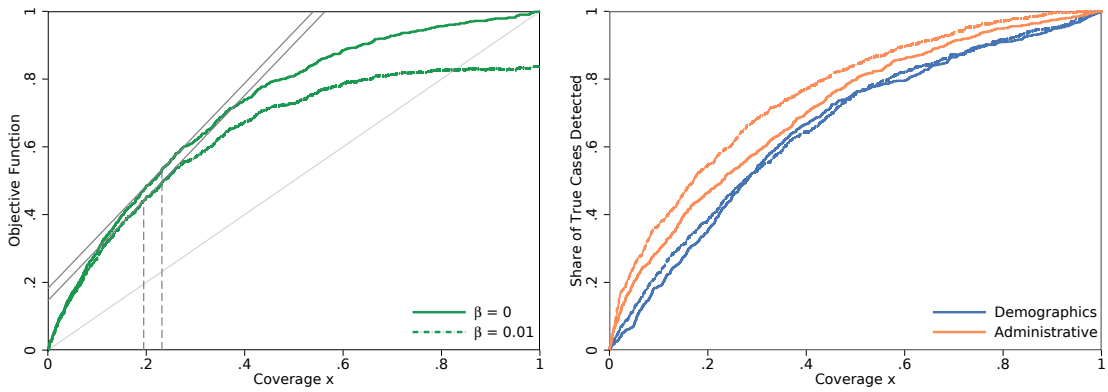
Figure A.23: Burnout vs. Separation and Fertility



Notes: The figure shows the association of burnout with fertility and separation from spouse estimated with three difference-in-differences estimators. Blue and orange colors represent the estimates implied by the fixed-δ method, under which treated individuals are matched to individuals who burn out ten years later. Red lines represent results implied by the baseline design with never-treated individuals as controls. Solid red lines indicate estimates obtained when the sample is aligned between the $\delta = 10$ design and the baseline design. Dashed red lines indicate estimates obtained on the larger baseline sample. **Panels (a) and (b)** plot the effect of burnout on the marital status of individuals who were married to or cohabiting with a partner in the year prior to burnout, irrespective of current marital status. Separation is defined as no longer being married to/cohabiting with the pre-burnout (t=-4) spouse. The figures plot the coefficients on event-time fixed effects interacted with an indicator for burnout, and their 95 percent confidence intervals based on individual-level-clustered standard errors, from the dynamic matched difference-in-differences model in equation (1). **Panels (c) and (d)** plot the effect of burnout on the Number of Children, using the baseline matched sample without additional restrictions regarding marital status/presence of a spouse.

Figure A.24: Predicting Burnout

(a) Surveys vs. Basic Demographic (b) Survey vs. Admin data



Notes: The figure shows the additional results for burnout prediction. **Panel a)** shows the welfare gain of the preventive program outlined in Section 5.2 excluding screening costs under different assumptions for the effectiveness of the triage. Formally, the function is defined as

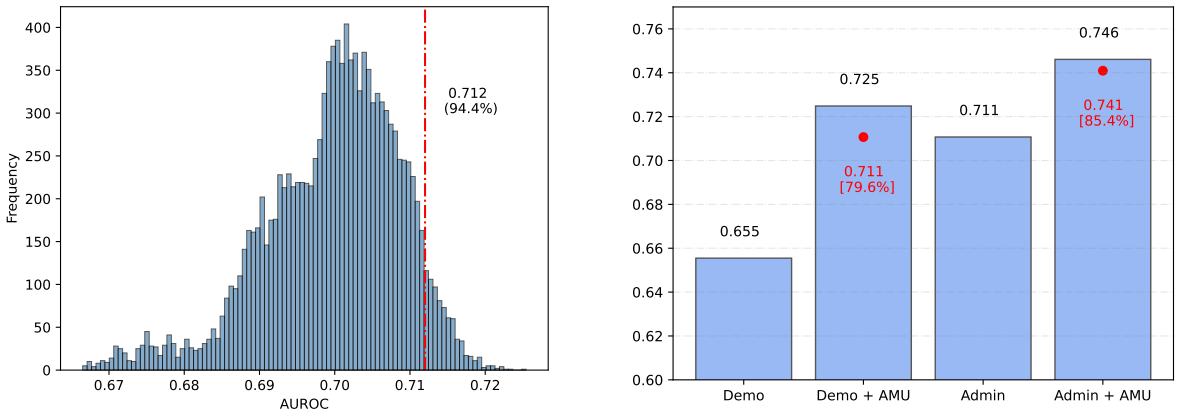
$$\widetilde{W}_\beta(x) = \pi(x) - \frac{\beta P(1-b)}{\alpha b(\theta C - P)}\eta(x),$$

where $\pi(x)$ is the true-positive rate and $\eta(x)$ is the false-positive rate. The solid line presents the objective function when the screening generates no false positives, that is when the Type I error rate is set to zero. The dashed line presents the case when the Type I error rate is set to $\beta = 0.01$. The prediction uses both basic demographic information as well as information from the AMU. **Panel b)** shows the Cumulative Gains curves generated on the AMU sample under different prediction models. We consider two sets of features: i) basic demographics, and ii) a large set of administrative data. The solid lines present the prediction when the model is trained on the AMU sample and evaluated using cross-validation. The dashed lines present the prediction when the model is trained on the entire population, and evaluated on the AMU sample.

Figure A.25: Prediction Performance of Stress Index Components

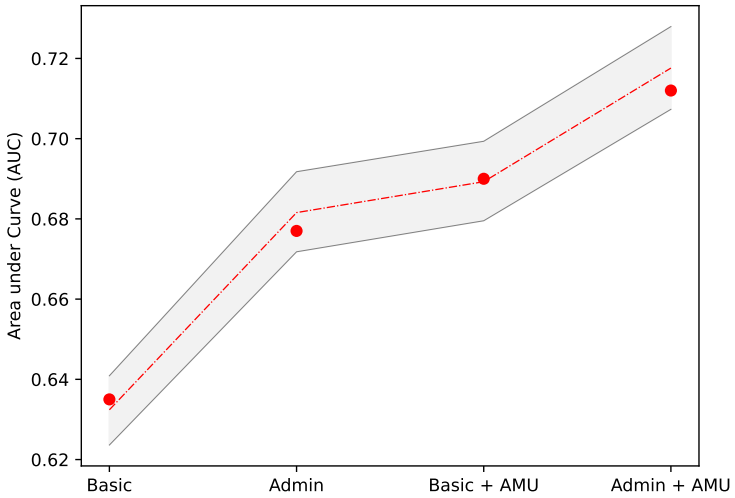
(a) Permutations

(b) Comparison with Complete Questionnaire



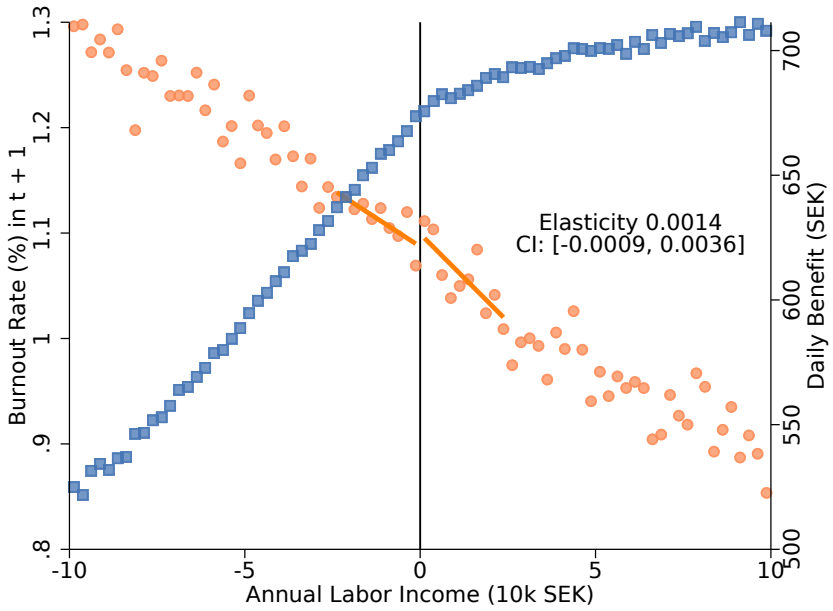
Notes: The figure demonstrates the predictive performance of the four burnout symptoms included in the stress index: lack of sleep, inability to relax, mental stress and headaches. **Panel a)** shows the distribution of the area-under-curve performance metric among alternative combinations of four AMU questions together with a basic set of demographics (age, gender, education). In order to generate these permutations, we restrict the set of questions to those that generate the highest AUCs when added individually to demographics characteristics. For each question ever recorded in the AMU, we train the model using this question and demographic information and evaluate it via cross-validation. We keep only the twenty-five questions with the highest AUC. While we did not force the components of the stress index to lie in this set of twenty-five best predictors, it turns out that they are always included. The dashed red line marks the AUC implied by the four questions included in the stress index. The associated percentile is reported in brackets. **Panel b)** compares the predictive performance of a model trained on a base set of observables (either demographics, or a large set of administrative data) and the four stress index components against models trained on the base set, or the base set together with the full AMU questionnaire. The bars represent the AUC obtained by evaluating each model using cross-validation. Red dots mark the AUC associated with the base set and only the four stress index components. In brackets we report the difference between the four component prediction and the base set prediction over difference between the full AMU prediction and the base set prediction.

Figure A.26: Prediction—Robustness of Model Performance to Test-Train Split



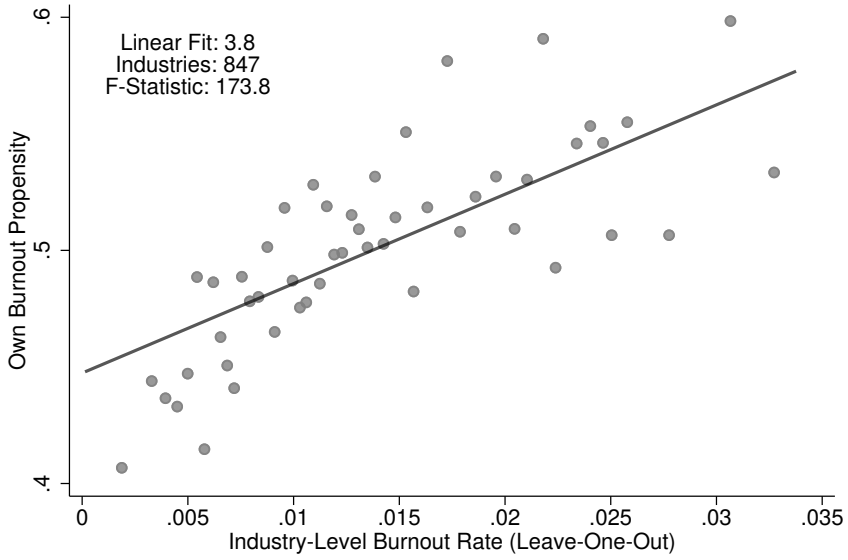
Notes: The figure illustrates the sensitivity of the model performance for burnout prediction to draws of test-trains splits underlying cross-validation. The red dots mark the results reported in Table 3 for burnout prediction using the AMU sample and various information sets. The partition underlying these results was chosen using a random number generator, setting the seed equal to the first four digits of the youngest co-author's birthday. To probe the robustness of these results, we then draw 1,000 random partitions of the sample and retrieve the AUC using cross-validation. The dashed red lines mark the median of each set of AUCs. The gray shaded area indicates the range of AUCs between the 2.5th and 97.5th quantile.

Figure A.27: Effect of Benefits on Burnout-Related Sickleave Take-Up



Notes: The figure shows mean burnout-related sickleave take-up and daily sick leave benefits as a function of annual labor income in 10k SEK around the replacement threshold. Annual labor income is measured using earnings in the previous year. Daily benefits are computed from sickleave spells starting and ending in full eligibility in the first quarter of a given year for workers full-time employment throughout the previous year and without unemployment days. Moreover, we drop spells without a diagnosis classification. Take-up in the next year is computed among full-time employed workers without unemployment days. The sample period is 2005 to 2019. We set the width of each bin to 2,500 SEK. Orange lines represent the fitted local linear regressions on both sides of the replacement threshold. The optimal bandwidth is chosen following Calonico et al. (2014) for the first stage. We report the elasticity of take-up with respect to daily benefits, and the associated 95% confidence intervals.

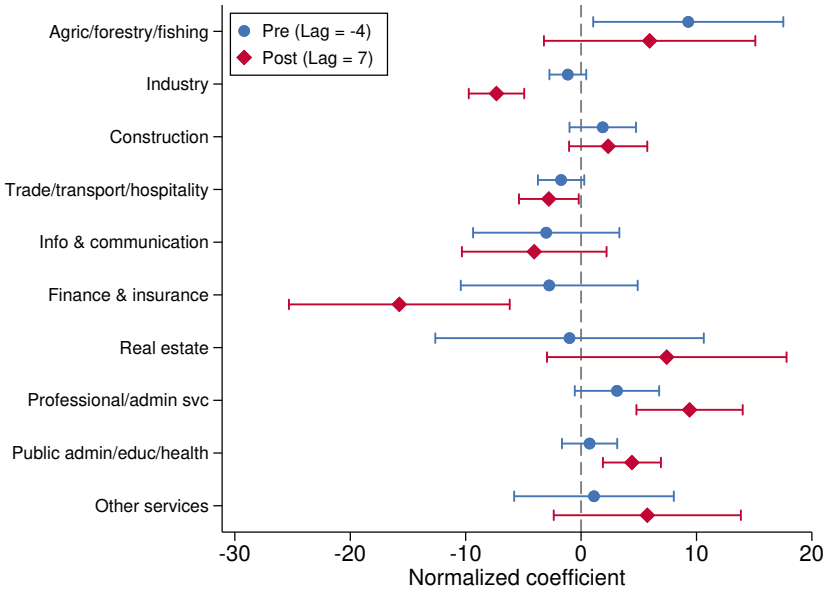
Figure A.28: Instrumental-Variable First Stage



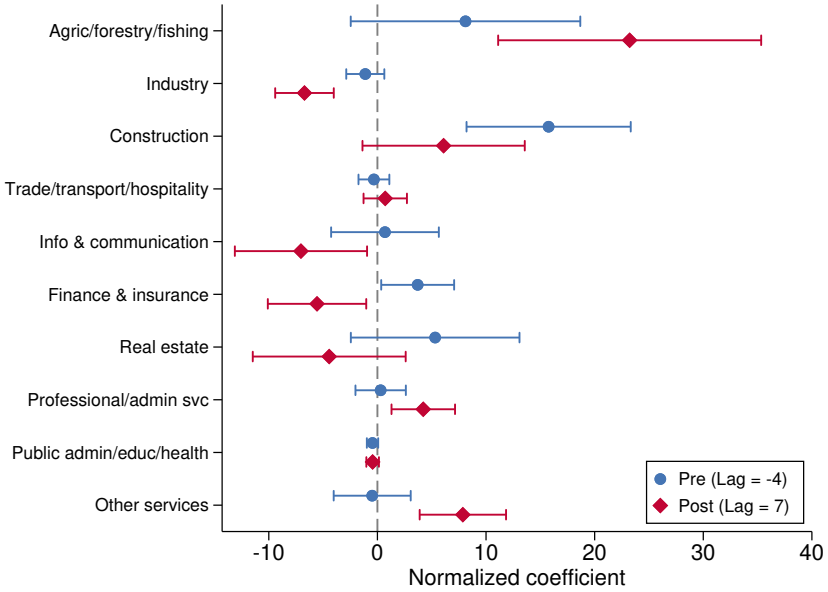
Notes: The figure presents a binned scatter plot of individual burnout against the burnout rate among other workers in the same five-digit industry. The sample is the matched worker sample used in the baseline labor-market analysis. Industry burnout rates are calculated in the full population of workers, excluding the focal worker and all workers at the focal worker's firm. The regression includes industry-origin and group-time fixed effects. The first-stage F-statistic is 173.8.

Figure A.29: Industry Mobility Following Burnout

(a) Men

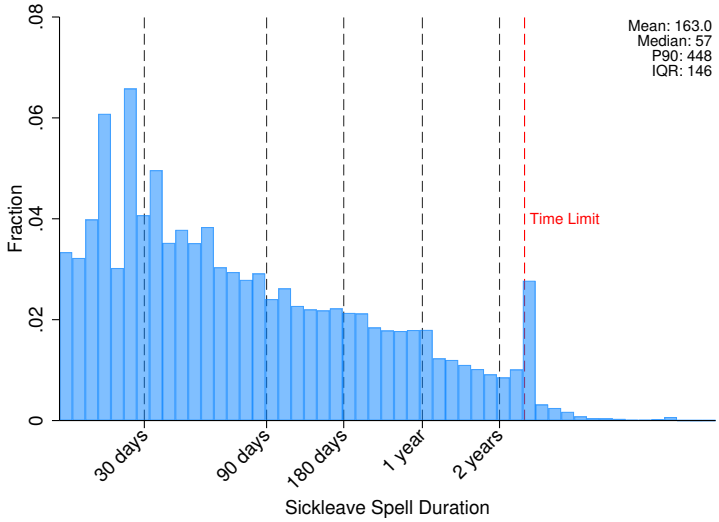


(b) Women



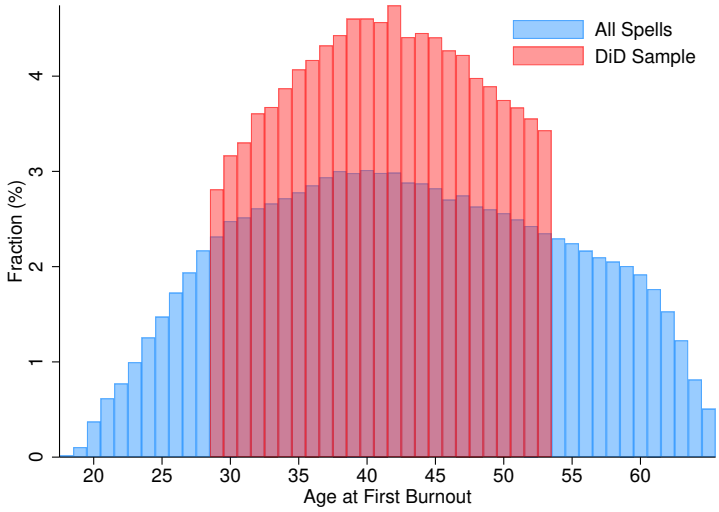
Notes: The figure presents results on workers' selection into industries around the first burnout diagnosis. For each one out of ten broad industry groups, we observe whether a worker is employed at an employer affiliated with that industry, and then estimate the event-study in equation (1) with this binary indicator as the outcome. The figure sheds light on the selection into burnout by plotting the event-study coefficient for event-time $t = -4$. Moreover, it shows the long-run effect on industry affiliation seven years after the first burnout diagnosis. Event-studies are estimated separately by gender. **Panel a)** shows the results for men. **Panel b)** shows the results for women. Standard errors clustered at the individual level are reported in parentheses.

Figure A.30: Sick Leave Spell Durations



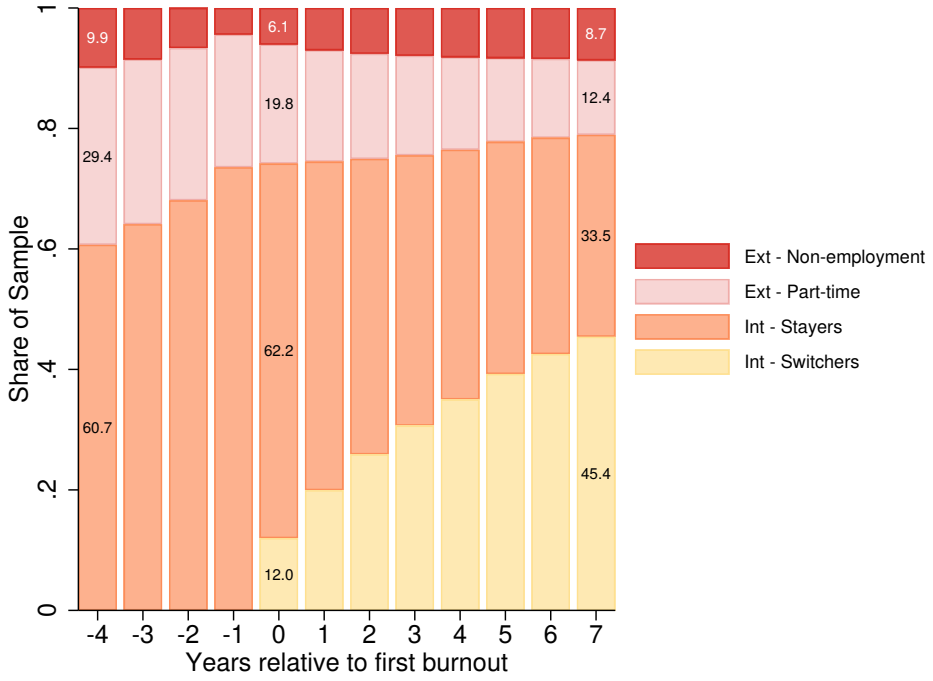
Notes: The figure shows the distribution of sick-leave spell durations among treated individuals in the estimation sample underlying the dynamic difference-in-differences estimator in (1). The red dotted line marks the upper time limit (*bortre tidsgränsen*). Until 2016, individuals on sick leave received 80 percent of their sickness-benefit qualifying income for the first 364 days, and a reduced replacement rate of 75 percent for the next 550 days, resulting in a total benefit duration of 914 days. After 914 days, individuals would ordinarily cease to receive sickness benefits and be offered participation in the labor-market introduction program (*Arbetslivsintroduktion*), which lasted for at most three months. In exceptional cases, benefits could be extended beyond 914 days. The 2016 reform removed the 914-day limit, so that individuals no longer automatically lost eligibility, while periodic assessments of work capacity remained (Socialdepartementet, 2015).

Figure A.31: Age at First Burnout: Event-Study Sample and All Spells



Notes: The figure compares the age distribution of the event-study sample underlying the dynamic difference-in-differences estimator in (1) with the age distribution of all burnout-related sick-leave spells between 2006 and 2020. The event-study sample requires a first burnout between 2006 and 2013 at ages 29 to 53, so that outcomes are observed over a twelve-year window during prime working age.

Figure A.32: Partition Size for Earnings Decomposition

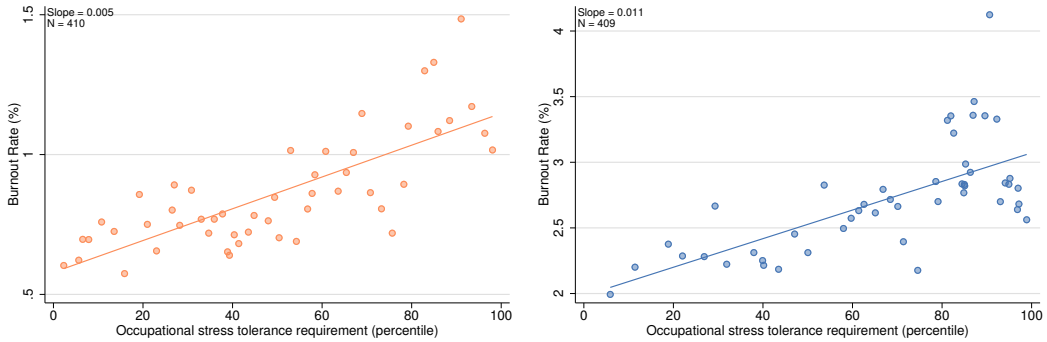


Notes: The figure shows the relative group size of the dynamic decomposition of labor income loss according to equation (2) into the extensive margin—ceasing work or transitioning to part-time—and the intensive margin—changes in income for individuals remaining with the same firm where the burnout occurred (stayers) and for those who transition to a new job (switchers). Since the partition assigns each observation to one of four categories, the four group sizes stack up to one at any point in time. The decomposition results are shown in Figure 6b.

Figure A.33: Occupational Stress and Burnout

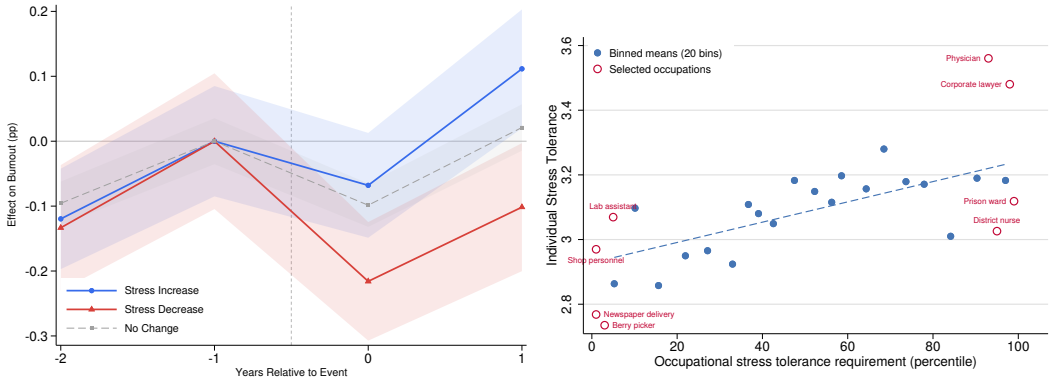
(a) Stress Requirements and Burnout – Men

(b) Stress Requirements and Burnout – Women



(c) Changes in Stress Requirements

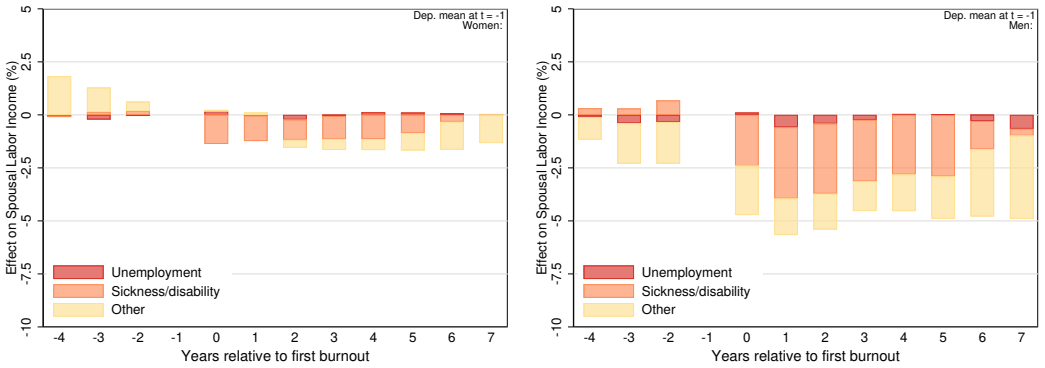
(d) Stress Requirements and Stress Tolerance



Notes: The figure shows the relationship between burnout, occupational stress tolerance requirements and individual stress tolerance. **Panel a)** and **Panel b)** shows a binned scatter plot of occupation-level burnout rate against occupational stress-tolerance requirement from O*NET, separately for men and women. **Panel c** shows changes in burnout risk around occupation changes depending on the induced change in occupational stress requirements. The sample consists of workers who work in the same occupation for two consecutive years before switching to and remaining in another occupation for two years. We then classify the move into three categories based on O*NET's occupational stress requirements for the origin and destination occupation. If the occupational stress tolerance requirement increases (decreases) by one, we classify the move as a stress increase (decrease). We retain all moves that result in a smaller absolute change in the stress tolerance requirement as a third category. Shaded areas depict 95 percent confidence intervals. Standard errors are clustered at the individual level. **Panel d)** shows a binned scatter plot of stress tolerance among male workers as a function of their current occupation's stress tolerance requirement. Red dots mark selected occupations with very high or low stress tolerance requirements.

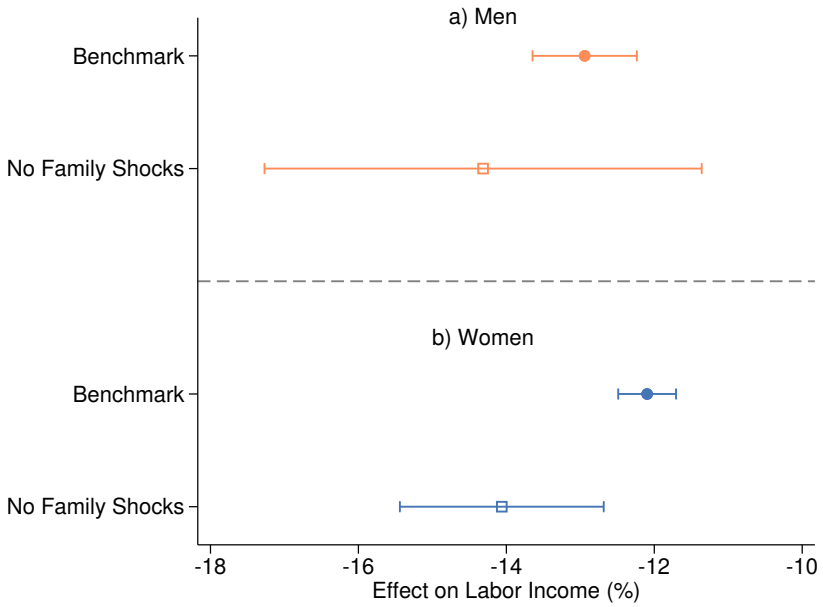
Figure A.34: Decomposition of Spousal Earnings Losses

(a) Decomposition: Men (b) Decomposition: Women



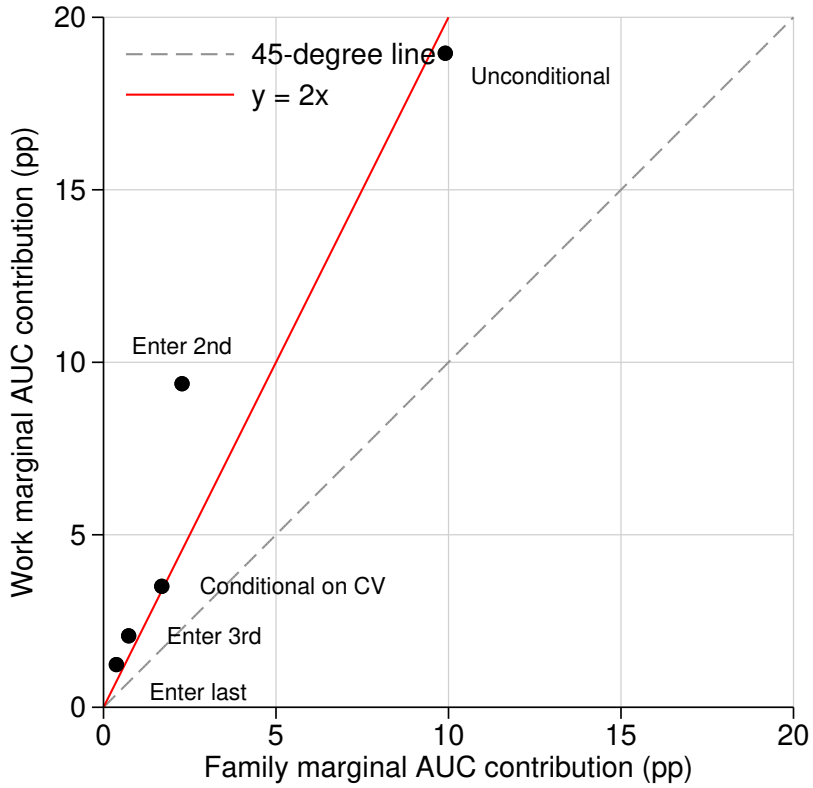
Notes: The figure shows the dynamic decomposition of spousal labor income losses according to equation (2) into unemployment, sickness or disability, and a residual category for individuals neither unemployed nor on paid sick leave or disability insurance. The sample consists of 57,441 spouses (married/cohabiting partners in the year prior to burnout), which are included irrespective of how marital status evolves prior to or following the event. **Panel a)** shows the results for men. **Panel b)** shows the results for women.

Figure A.35: Burnout Effects on Labor Income Excluding Family Health Shocks.



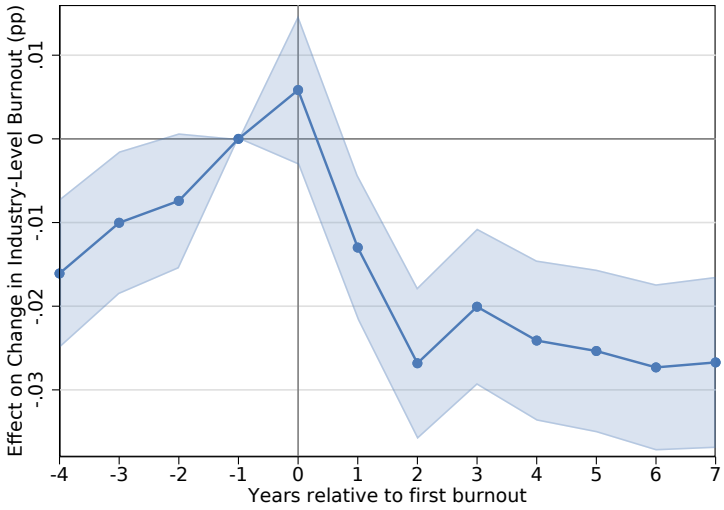
Notes: The figure shows the long-term effect of burnout on labor income under different sample restrictions. Each point represents a seven year lag coefficient estimated from a dynamic matched difference-in-differences model as in equation (1). Benchmark refers to main analysis of burnout events sample used throughout the paper. "No Family Shocks" excludes matched pairs in which either individual experiences a sickness-absence or disability event of a biological child or spouse, or the death of a parent, during the event-study window. Whiskers represent the 95 percent confidence interval based on individual-level-clustered standard errors.

Figure A.36: Importance of Work and Family for Burnout Prediction



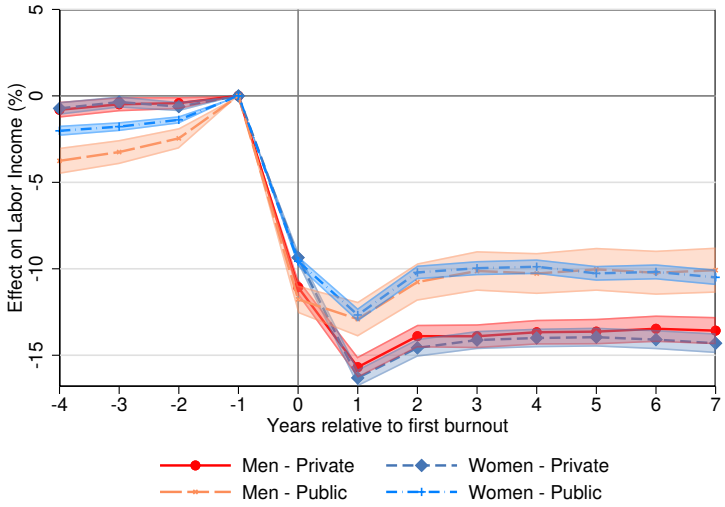
Notes: The figure compares the predictive power of work and family variables for future burnout, following the Shapley value logic. Predictors are grouped into own medical history, family, career, and CV (information usually available in a CV: gender, age, and education). See Appendix Section G.2 for details. Each dot plots the marginal AUC contribution of career variables against the contribution of family under alternative permutations: "Unconditional" each group first, "Conditional on CV" adds it after CV, and the remaining bars average over permutations in which each group enters second, third, or last. The dashed line marks the 45 degree line. The red line marks the line along which the contribution of work variables is twice as large the contribution of family variables.

Figure A.37: Avoiding Future Stress After Burnout



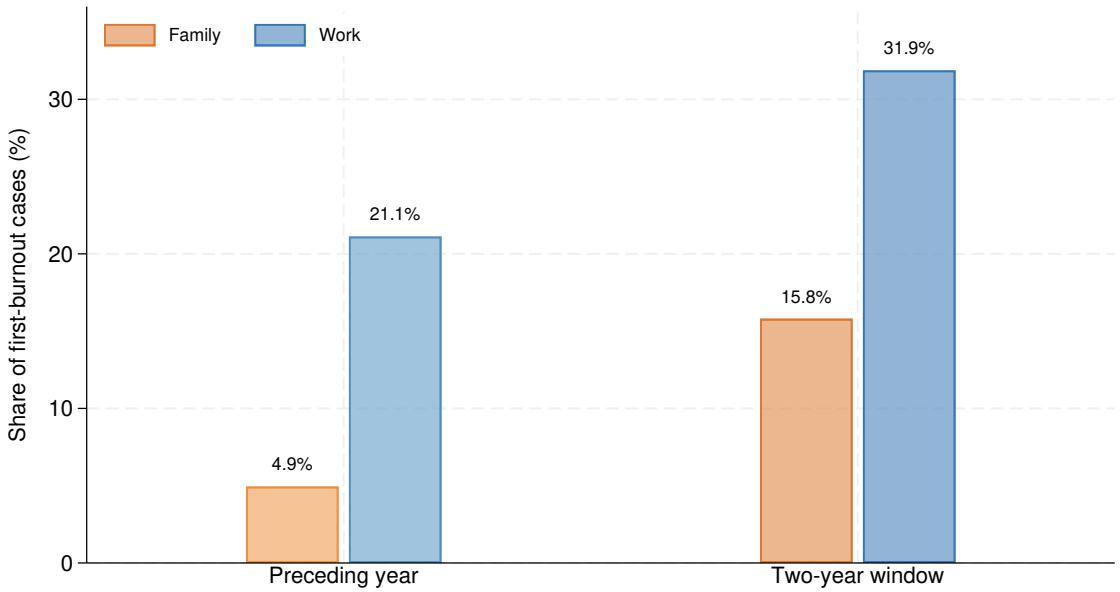
Notes: The figure focuses on workers who switch firms following burnout and reports the effect of burnout on the change in the burnout rate of their industry—the difference between the burnout rate in their current industry and in the industry in which they worked in the year prior to burnout. Negative values therefore indicate moves toward industries with lower burnout rates. Given the small number of firm switchers, we perform one-to-many matching to aid with the precision of the estimated treatment effects. The shaded area is the 95 percent confidence interval based on standard errors clustered at the individual level. The sample pools men and women.

Figure A.38: Effect of Burnout on Labor Income by Gender and Sector



Notes: The figure shows the proportional effect of burnout on labor income separately for men and women, by whether the treated worker is employed in the public or the private sector in $t = -1$. Estimates use the baseline matched difference-in-differences design, and treated individuals and controls are matched on year of birth, gender, education, and the earnings percentile in the year prior to treatment. Estimates are normalized to $t = -1$. The 95 percent confidence intervals are based on standard errors clustered at the individual level.

Figure A.39: Adverse Work and Family Events Preceding Burnout



Notes: The figure shows the frequency of adverse family events and workplace-related events in the year preceding and the year of burnout. We collect all individuals experiencing their first recorded burnout spell in calendar year t and record whether an event occurred in the preceding year ($t-1$), or in either the same year or the preceding year (t or $t-1$). For each window, we estimate the conditional probability that an event took place conditional on observing the first burnout event: $\Pr(\text{event} \mid \text{first burnout in } t)$. Family events comprise severe sickness, as measured by the start of a recorded sick-leave spell with ICD-10 codes C, D, or E, disability, and death, among spouses, children, or parents. An individual is counted once per window if any linked relative experiences any one of the events specified above. Workplace-related events comprise a transition from a non-managerial to a managerial occupation, sexual harassment reported in the AMU, and an industry shock, defined as an annual increase of at least one standard deviation in the leave-one-out industry burnout measure. For plotting, we sum the three workplace-event probabilities rather than compute the probability of experiencing any one of them, due to the small sample size of the AMU. Individuals experiencing more than one type of workplace event therefore contribute more than once. For industry shocks, we focus on burnout cases occurring between 2008 and 2020. For health events, we focus on cases starting in 2007, since ICD-10 codes are reliably recorded starting in 2006. For the remaining work events, we count all cases from 2006 onwards.

Figure A.40: Adverse Work and Family Events Preceding Burnout – Disaggregated



Notes: The figure shows the frequency of adverse family events and workplace-related events in the years surrounding burnout. We collect all individuals experiencing their first recorded burnout spell in calendar year t and record whether an event occurred in the preceding year ($t-1$), the year of burnout (t), or either year ($t-1$ or t). For each event and window, we estimate the conditional probability that the event took place among individuals experiencing their first burnout, $\Pr(\text{event} \mid \text{first burnout in } t)$, conditional on the relevant information being observed. Family events comprise severe sickness, measured by the start of a recorded sick-leave spell with ICD-10 codes C, D, or E, disability, and death among spouses, children, or parents. Each event is reported separately for each relative group. Workplace-related events comprise a transition from a non-managerial to a managerial occupation, sexual harassment reported in the AMU, and an industry-level burnout shock, defined as an annual increase in the leave-one-out industry burnout measure exceeding the mean annual change by at least one standard deviation. Each workplace-related event is reported separately, using the sample for which the respective event is observed. For industry shocks, we consider first-burnout cases occurring between 2008 and 2020. For family events, the preceding-year and two-year-window estimates use cases from 2007 onwards, using family-event records starting in 2006. For the remaining workplace events, we consider cases from 2006 onwards.

Table A.2: Descriptive Statistics – Industry Composition

Industry shares (%)	Population 2006-2020 (1)	Burnout 2006-2020 (2)	Burnout 2006-2013 (3)	Matched sample (4)
Agricultural	1.0	0.4	0.4	0.4
Mining	0.1	0.1	0.1	0.1
Manufacturing	9.6	7.5	8.5	9.3
Utilities	0.8	0.8	0.8	0.8
Construction	4.9	2.8	2.5	2.7
Retail	8.6	9.3	9.1	9.7
Transport	3.7	3.4	3.8	3.8
Financial services	1.6	1.9	2.0	2.1
Non-financial services	12.4	13.5	13.2	13.8
Public administration	4.5	7.7	6.9	6.6
Education	8.3	17.2	16.6	15.9
Health	12.6	26.5	26.3	24.8
Entertainment	1.4	1.5	1.6	1.6
Other	34.1	35.7	35.1	37.0
Missing	26.1	2.7	4.0	3.8
Number of individuals	7,380,543	526,108	220,715	150,834
Number of individual-years	79,463,491	655,917	247,943	150,834

Notes: The table reports the industry composition of the overall Swedish population and our sample of burned out workers. Column (1) include the entire Swedish population who are between the ages of 25 and 60 in the period from 2006 to 2020. Column (2) includes only observations with at least one burnout spell in a given year, between 2006 and 2020. Column (3) restricts the sample to burnout cases between years 2006 and 2013. Column (4) considers the estimation sample underlying our difference-in-difference design. Section 4 describes the construction of the estimation sample. Appendix Table A.4 shows the sample size under different sample restrictions. Since our event-study design studies the effect of the first burnout incident, there is only one burnout incident per treated individual in the matched sample, so that the number of individuals we observe equals the number of individual-years. In columns (2) and (3), the discrepancy between the number of burnout incidents and afflicted individuals arises because individuals can be observed with multiple burnout incidents.

Table A.3: Burnout Risk Factors

	Men			Women		
	(1)	(2)	(3)	(4)	(5)	(6)
Native	0.026	0.052	0.011	0.377	0.350	0.237
	(0.004)	(0.005)	(0.008)	(0.009)	(0.009)	(0.012)
Education						
Upper secondary	0.071	0.012	-0.006	0.241	0.182	0.111
	(0.004)	(0.004)	(0.007)	(0.008)	(0.008)	(0.012)
College	0.107	-0.038	-0.094	0.498	0.296	0.097
	(0.004)	(0.005)	(0.009)	(0.009)	(0.010)	(0.015)
Familytype						
Single w/child	0.109	0.108	0.138	0.482	0.468	0.528
	(0.010)	(0.010)	(0.016)	(0.014)	(0.014)	(0.018)
Married w/o child	-0.034	-0.022	-0.006	-0.384	-0.369	-0.350
	(0.005)	(0.005)	(0.008)	(0.010)	(0.010)	(0.012)
Married w/child	-0.140	-0.131	-0.132	-0.590	-0.569	-0.530
	(0.005)	(0.005)	(0.008)	(0.011)	(0.011)	(0.014)
Age						
31 - 35	0.122	0.107	0.139	0.382	0.355	0.402
	(0.006)	(0.006)	(0.010)	(0.013)	(0.013)	(0.018)
36 - 40	0.166	0.138	0.207	0.535	0.494	0.567
	(0.006)	(0.006)	(0.010)	(0.014)	(0.014)	(0.018)
41 - 45	0.175	0.136	0.214	0.480	0.419	0.517
	(0.006)	(0.006)	(0.010)	(0.014)	(0.014)	(0.018)
46 - 50	0.164	0.116	0.201	0.376	0.293	0.408
	(0.006)	(0.007)	(0.011)	(0.014)	(0.014)	(0.019)
51 - 55	0.101	0.044	0.128	0.265	0.158	0.292
	(0.007)	(0.007)	(0.011)	(0.015)	(0.015)	(0.020)
56 - 62	0.073	0.009	0.091	0.177	0.054	0.191
	(0.007)	(0.008)	(0.012)	(0.016)	(0.016)	(0.021)
Labor Income						
P25 - P50	-0.071	-0.057	-0.139	-0.173	-0.166	-0.388
	(0.005)	(0.005)	(0.008)	(0.008)	(0.008)	(0.011)
P50 - P75	-0.158	-0.121	-0.270	-0.453	-0.412	-0.823
	(0.005)	(0.005)	(0.009)	(0.009)	(0.010)	(0.014)
P75 - P90	-0.218	-0.170	-0.381	-0.765	-0.677	-1.155
	(0.005)	(0.006)	(0.011)	(0.012)	(0.013)	(0.019)
P90+	-0.325	-0.264	-0.527	-1.192	-1.041	-1.537
	(0.006)	(0.007)	(0.013)	(0.015)	(0.016)	(0.026)
Number of Children						
1	0.122	0.127	0.144	0.368	0.332	0.270
	(0.006)	(0.006)	(0.009)	(0.013)	(0.013)	(0.017)
2	0.105	0.113	0.119	0.417	0.371	0.300
	(0.005)	(0.005)	(0.008)	(0.012)	(0.012)	(0.015)
3 +	0.169	0.171	0.173	0.650	0.569	0.501
	(0.006)	(0.006)	(0.010)	(0.013)	(0.013)	(0.017)
Young Child	0.031	0.027	-0.003	0.083	0.102	0.067
	(0.005)	(0.005)	(0.008)	(0.010)	(0.010)	(0.014)
Year Fixed-Effects	✓	✓	✓	✓	✓	✓
Industry Fixed-Effects		✓	✓		✓	✓
Occupation Fixed-Effects			✓			✓
Mean	0.544	0.544	0.622	1.882	1.882	2.000
N (Millions)	23.6	23.6	10.4	19.1	19.1	12.2
R2	0.0743	0.1345	0.2006	0.3039	0.3720	0.4433

Notes: The table reports the results of different linear probability models for burnout, separately by gender. Due to a break in the occupation classification code in 2014, we estimate separate occupation fixed-effects prior to and after 2014. Standard errors are reported in brackets.

Table A.4: Sample Selection and Matching Results

	Men	Women	Total
a) Sample selection			
First cases 2002 - 2020	161,741	441,105	602,846
First cases 2006 - 2013	53,285	148,429	201,714
Ages 29 - 53	40,422	112,796	153,218
Alive 7 years after treatment	39,823	112,046	151,869
Education information complete	39,768	111,984	151,752
b) Matching			
Never-treated	39,527	111,373	150,900
Fixed-delta ($\delta = 2$)	19,749	63,187	82,936
Fixed-delta ($\delta = 3$)	22,039	70,007	92,046
Fixed-delta ($\delta = 4$)	23,855	73,598	97,453
Fixed-delta ($\delta = 5$)	24,873	74,988	99,861
Fixed-delta ($\delta = 6$)	26,474	76,811	103,285
Fixed-delta ($\delta = 7$)	26,126	75,282	101,408

Notes: The table reports the impact of various selection criteria, as well as the matching procedure, on the sample used for the matched difference-in-difference model described in Section 4.

Table A.5: Estimates of Burnout Effect on Income

	DiD (1)	Fixed-Delta (2)	DiD (Industry) (3)	IV (4)
Effect	-12.36	-14.85	-12.47	-13.79
	(0.002)	(0.002)	(0.002)	(4.955)
F-Statistic				173.8
N	3621600	2396664	2328312	648261

Notes: The table shows the estimated treatment effect of burnout on labor income estimated with four different empirical strategies. Column (1) uses matched difference-in-differences (DiD) where the control group are individuals who never burn out. Column (2) matched DiD where the control group are individuals who burn out five years later. Column (3) uses matched DiD where the control group are individuals within the same industry who never burn out. Column (4) uses the matched sample of individuals who burn out and a control group are individuals who never burn out, and instruments the effect of burnout on post-burnout outcomes by the leave-on-out industry-level burnout rate, conditioning on industry fixed effect. All estimates are based on labor income two years post burnout. Estimates are reported in percent terms relative to the pre-treatment average income among the control group in columns (1)-(3) and among the untreated compliers in column (4) (Abadie, 2002). Standard errors are reported in parentheses.

Table A.6: Instrumental Variable Estimates of Burnout Effects

	Spousal Earnings	Fertility	Divorce
Effect	-21.2	-10.8	95.7
	(8.6)	(10.3)	(46.5)
F-Statistic	47.4	44.5	173.8
N	249250	92339	648261

Notes: The table shows the estimated treatment effects of burnout on spousal labor income, fertility, and divorce implied by the instrumental variable estimator described in Section 4. Estimates are reported in percent terms relative to the average outcome among the untreated compliers (Abadie, 2002). Estimated effects on fertility are restricted to individuals who do not have a child a year before burnout. Standard errors are reported in parentheses.

Table A.7: Effects of Parental Burnout on Children's Outcomes

	College Enrollment		Grade 9 Test Score	
	DD	IV	DD	IV
	(1)	(2)	(3)	(4)
Effect	-2.526	-2.768	-1.861	-1.851
	(0.329)	(0.436)	(0.203)	(0.385)
F-Statistic		109,708		209,130
N	297,668	270,206	352,890	323,710

Notes: The table reports estimates of the effect of parental burnout on children's college enrollment by age 21 and the probability of earning at least 240 points on the grade 9 test. Columns (1) and (3) report the headline difference-in-differences estimates shown in Figures 8a and 8c. Columns (2) and (4) report instrumental-variable estimates. Effects and standard errors are expressed in percentage points. Standard errors clustered at the parent level are reported in parentheses. The Kleibergen–Paap rk Wald F-statistic is reported as the weak-identification diagnostic.

Table A.8: Burnout Prediction

Outcome: Burnout in	t + 1	t + 1	t + 2
CV	0.636	0.727	0.628
CV + AMU	0.688		0.653
Admin Data	0.683	0.814	0.674
Admin Data + AMU	0.718		0.671
Sample	AMU	Population	AMU
Sample Size	61,121	77,138,798	53,710

Notes: The table reports the area under curve (AUC) of predicting an indicator of burnout in the next calendar year (columns (1) and (2)), and two years ahead in column (3). The set of variables used for training is kept fixed in each row. *CV* contain gender, native, age, and education. *Admin Data* stands for a larger set of variables from kitchen-sink of administrative data (For the list of variables, see Section 5). The second and fourth rows add information from the AMU (Work Environment Survey). The sample in columns 1 and 3 is AMU for every second year between 2005 and 2019, whereas column 2 is based on the entire Swedish prime-age population for 2005 to 2019. The results are obtained by setting the learning rate of the random forest algorithm to $\eta = 0.01$, whereas model predictions with a learning rate of $\eta = 0.1$ underlie the results in Table 3.

Table A.9: Variables used for burnout prediction

Demographics & ability	**Own medical history**	**Family / private life**	**Career / workplace**
Gender, age, native	Burnout (t, $t-1 \ldots t-5$)	Divorce tenure	Earnings rank
Municipality	Physical health	Spousal earnings rank	Earnings growth ($t \ldots t-5$)
Education level	non-pregnancy	Number of children	Employment
Field of study	pregnancy	Age of 1st–6th child	Total employment
Education (detailed)	Depression (singular)	Child diagnosis (t)	Hours worked
Social maturity	Depression (recurring)	Child sick days	Firm size
Intensity	Anxiety	Child MH sick days	Tenure
Psychological energy	Other mental health	Child disability	Separation
Stress tolerance	Sick leave w/o diagnosis	Child years on disability	EE-/NE-move
Inductive skills	Sick leave days	Child first disability	Turnover, Turnover change
Verbal comprehension		Spouse diagnosis (t)	Unemployment
Spatial ability		Spouse sick days	Long-term unemployment
Technical understanding		Spouse MH sick days	Unemployment duration
Physical ability		Spouse disability	Industry, industry change
Psychological health		Spouse years on disability	SSYK 4-digit (2012, 1996)
		Spouse first disability	Firm/industry cum. incidence

Notes: The table reports the set of variables used for the prediction of burnout in Table 3.