The Economic Burden of Burnout

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Abstract

We study occupational stress, from its initial symptoms to permanent productivity loss, using Swedish administrative data. Stress symptoms emerge and steadily intensify over a year, culminating in a tipping point of burnout. High-stress occupations do not see higher burnout rates among stress-tolerant workers, but disproportionately affect those with low stress tolerance. Burnout results in substantial and permanent earnings losses, with similar magnitude across genders, despite women being three times more susceptible. Burnout's toll spills over, reducing spousal earnings and children's human capital (school grades and college enrollment), especially in lower-educated families, thereby stalling intergenerational mobility. Through sick leaves, earnings losses, and spillovers, burnout reduces national labor income by 3.6%. Combining our cost estimates with a prediction model of burnout—enhanced by a brief, high-frequency occupational stress survey—can optimize the scope and targeting of preventive programs and reduce the economic burden of burnout.

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Introduction

Stress is a salient feature of today's jobs. Recent workforce surveys reveal an alarming prevalence of occupational stress. 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 38 percent in Sweden, the focus of our study (Gallup, 2023).[1]

Psychological experiments and neurobiological evidence suggest that while mild and transient stress enhances productivity, intense and prolonged stress impairs job performance, as described by the Yerkes-Dodson law in psychology (Yerkes and Dodson, 1908; Broadhurst, 1957) or the hormesis dose-response model in biomedicine (Calabrese and Baldwin, 2002; Calabrese, 2008). In particular, half a century of research in psychology and medicine has established that prolonged high levels of occupational stress can culminate in a tipping point, defined as *burnout* (Freudenberger, 1974; Maslach, 1976; Maslach and Leiter, 2022). Burnout symptoms include physical fatigue, cognitive impairments (such as difficulties with concentration and memory), and emotional and behavioral problems (such as inability to multitask or work under pressure) (Van Dam, 2021). Evidence suggests that these symptoms may persist for years despite treatment, underscoring the lasting impact of burnout and primacy of prevention as a more effective remedy (Glise et al., 2020; Gavelin et al., 2022).

In response to the rising prevalence of occupational 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 (WHO) officially recognized burnout as a syndrome caused by chronic work stress in the revised International Classification of Diseases (WHO, 2019). As of May 2024, 132 countries are at various stages of implementing the new classification (WHO, 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.[2] A second and more challenging task is to understand and quantify the micro-level toll burnout exacts on individuals and their families—an area that remains largely unexplored. Closing these gaps is the central aim of this study.

We quantify burnout's prevalence, identify its risk factors, and assess its consequences for the entire Swedish labor force. We then explore how our findings can be used to prevent burnout. We define burnout as a clinical diagnosis of a stress-related illness followed by an extended sick leave. Sweden's early adoption of clinical burnout diagnosis presents a rare opportunity to trace the long-term effects of stress across the population.

We begin by empirically tracing the accumulation of occupational stress and its progression toward

[1]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.4a). Global occupational 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).

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

burnout. Self-reported stress symptoms—such as insomnia and intrusive work-related thoughts—strongly predict future burnout, while showing no meaningful link to other job-related ailments like back or shoulder pain. Burnout risk escalates nonlinearly with each additional symptom, implying that stress effects accumulate rather than act in isolation.[3] Longitudinal tracking reveals that stress symptoms begin to escalate a year before diagnosis and intensify steadily, peaking just before a clinical burnout diagnosis.

Jobs vary in stress requirements, and people differ in stress tolerance. We examine this heterogeneity and their interaction by combining two distinct datasets: occupational stress-tolerance requirements from O*NET and individual stress-tolerance scores. These individual scores are assessed by psychologists at age 18 during the military draft. They have the advantage of being measured before labor market entry, but are only available for men. The burnout rate is systematically higher in high-stress occupations. Within these high-stress occupations, workers with low stress tolerance exhibit a significantly higher burnout rate than their more stress-tolerant peers. In contrast, this gap is significantly diminished in low-stress jobs. Reflecting this complementarity, we find that stress-intolerant individuals sort into low-stress occupations. However, the degree of sorting is quantitatively modest and insufficient to fully equalize burnout risk.

Beyond stress tolerance, gender stands out as a potent risk factor for burnout. Women are three times more likely to be diagnosed with burnout than men, 1.85 percent annually compared to 0.54 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, indicating that the toll of occupational stress falls heaviest on the most vulnerable.

We next turn to studying the economic consequences of burnout. We apply a one-to-one matched differences-in-differences estimator that is similar to the estimator applied by the literature on job displacement effects (e.g. Schmieder et al., 2023). It compares a burned-out individual before, during, and after burnout with an observationally similar peer who never burns out.[4] Our choice to use designs similar to the job displacement literature is based on a fundamental similarity between the two phenomena: both burnout and layoff are pivotal work-related tipping events, with potentially significant consequences for workers.

We bolster this design in three ways. First, to address concerns about the effect of skill demand on stress and earnings, we compare similar workers within the same industry.[5] Second, to address potential selection on unobserved time-invariant factors, we compare a burned-out individual to a similar individual who experiences burnout a few years later, leveraging quasi-random timing of burnout within a small window of time (Hilger, 2016). Third, to isolate the effect of work stress from concurrent personal life events—such as divorce—that may both increase stress and affect labor market outcomes, we use an instrumental variable strategy, similar to the grouped-data approach of Angrist (1991). In the matched sample, we instrument the effect of burnout on differential post-burnout outcomes by time-varying industry-level burnout risk. The resulting estimates are quantitatively similar across all designs, suggesting that the detected burnout effect in our main design is primarily driven by work stress.

Burnout causes a large and enduring negative effect on labor income—effects comparable in magnitude

[3] One rare empirical example of such non-linearity is documented in Paserman (2023) among professional tennis players.

[4] An increasing number of studies use similar matched differences-in-differences as their main empirical design (e.g. Jäger et al., 2025; Adams-Prassl et al., 2024).

[5] The displacement literature has yet to reach a consensus on whether within-industry or between-industry comparisons are more appropriate; see, for example, (e.g. Schmieder et al., 2023; Lachowska et al., 2020; Halla et al., 2020).

and persistence to the displacement effects from layoffs (Davis and Von Wachter, 2011). At onset, annual earnings fall by nearly 15 percent, driven mostly by sick leave (median 55 days). Yet the damage to productivity is long-lasting: seven years later, earnings remain 12 percent lower. A decomposition reveals that long-run earnings losses are driven by transitions to part-time positions and labor market exit, 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's impact extends beyond the individual, disrupting both their spouse's career and children's human capital. Female spouses experience an immediate and persistent income drop of 4.4 percent—about 30 percent of the direct effect. For male spouses, the corresponding decline is just 1.1 percent, or one-fourth as large. Hence, women not only face a three-times higher risk of burning out and suffering long-term career setbacks, but their careers are also more vulnerable when their partners burn out. In addition, burnout leaves a demographic imprint: fertility falls permanently for women who burn out, whereas for men, the reduction is transitory.

The consequences of burnout do not end with the first generation—they cascade into the next. Parental burnout during a child's schooling years significantly reduces academic performance and college enrollment, compared to a control group whose parents experience burnout only after high-stakes exams or after the typical age of college decision-making. Specifically, parental burnout lowers grades by 5.3 percent and college enrollment by 2.5 percentage points, or 8 percent. IV estimates are of the same magnitude. Importantly, the effect is weaker among children of college-educated parents, suggesting burnout amplifies inequality and hampers intergenerational mobility.[6]

The macroeconomic implications of our findings are substantial. The high incidence of burnout and its pronounced gender gap indicates 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 effects through sick leave, permanent career setbacks for affected individuals, and spillovers to their families. We estimate that in 2019, burnout led to a 2.3 percent reduction in aggregate labor income. This estimate understates the true cost, as our data on diagnosed burnout begins only in 2006. Therefore, in the spirit of life-expectancy calculations, we project that this loss would rise to 3.6 percent in a steady state if 2019 conditions persist. 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 significant burden of burnout calls for policy interventions. Preventing burnout is more effective than treating it after onset, as with other mental health conditions (Tetrick and Winslow, 2015; Aust et al., 2023). While the design of preventive programs remains an active research frontier (Bouskill et al., 2022), effective implementation hinges on identifying and targeting high-risk individuals and understanding the economic costs of burnout to calibrate program scope (Demerouti et al., 2021).

As the final part of our analysis, 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 high accuracy comes close to benchmarks for mortality

[6] In Sweden, there are no college tuition fees and students receive stipends and subsidized loans, suggesting that our results are unlikely to be driven by income effects.

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 occupational stress measures alongside basic demographic information reduces the optimal program size by half while boosting net gains by a factor of 2.5. Importantly, a handful of self-reported stress measures rivals the full breadth of Swedish administrative data in predictive power.[7] 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.

Finally, we explore the external validity of our findings. Observed burnout cases arise from the interplay between underlying occupational 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 blend worker health with the availability of disability benefits (Autor and Duggan, 2003). Sweden pairs a generous welfare state—with paid sick leave and formal medical recognition of burnout—with occupational stress levels below the global average. Two countervailing forces complicate cross-country comparisons. On one hand, higher baseline stress elsewhere suggests greater potential social costs; for instance, occupational stress appears 30 percent lower in Sweden relative to the U.S. On the other hand, Sweden's expansive welfare provisions magnify the observed cost burden. To gauge the strength of this mechanism, we exploit a kink in the sick leave benefit schedule. Our estimates indicate that eliminating benefit payments for burnout would cut incidence by two-thirds. Yet lower incidence need not imply lower social costs, as forcing burned-out workers to stay on the job may sap productivity and exacerbate health deterioration. All told, the social burden of occupational stress in the U.S. appears comparable in magnitude to that in Sweden.

Related Literature 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.[8] 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 the symptoms of burnout (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 the effects reported for general sick leave—both physical and mental—in the study by Kolsrud et al. (2020).

Finally, our findings provide individual-level evidence linking economic conditions and mental health. This relates to prior work that has documented how unemployment (Paul and Moser, 2009), firm reorganization (Dahl, 2011) and corporate mergers (Bach et al., 2023) affect employee mental health. The

[7]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.

[8]The latter relates to other experimental work where job seekers demonstrate a large willingness to pay for a variety of amenities, such as flexibility in hours and work autonomy (Mas and Pallais, 2017; Maestas et al., 2023). 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).

positive association we document between career advancement and subsequent burnout may help explain the counter-cyclical pattern of health outcomes documented for the U.S. (Ruhm, 2000; Notowidigdo et al., 2024).[9]

The paper unfolds as follows. Section 1 describes clinical burnout, its symptoms and diagnoses, and describes how we measure it in administrative data. Section 2 identifies the symptoms of burnout 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 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

1.1 Definition and Measurement

Burnout The term *burnout* originates in American social- and work psychology.[10] It was first used in the early 1970s by Herbert Freudenberger, a practicing American psychologist, who used the term to describe the gradual emotional depletion, loss of motivation, and reduced commitment among clinic volunteers in New York (Freudenberger, 1974). Since then, the concept and its diagnosis have been developed within the field of psychology.

The conceptualization of burnout on the basis of the 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. The COR theory describes how people are motivated to obtain, retain, and protect their resources and emphasizes how stress has a central environmental, social, and cultural basis in terms of the demands on people. According to the theory, stress at work occurs when individuals fail to maintain their resources. Therefore, stress is not a single event but rather an unfolding process leading to burnout when resources are depleted (Shirom, 2003).[11]

There exist several established measures of burnout. The Shirom-Melamed Burnout Questionnaire (SMBQ) (Melamed et al., 1992) is based on the 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 for burnout is the Maslach Burnout Inventory (MBI) (Maslach and Jackson, 1981).[12] In spite of some

[9]More broadly, there is a growing body of research exploring how treating mental health conditions affects economic outcomes in developing countries (Lund et al., 2022).

[10]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).

[11]Other definitions of burnout are conceptually similar. The Dictionary of Psychology defines burnout as "physical, emotional, or mental exhaustion accompanied by decreased motivation, lowered performance, and negative attitudes toward oneself and others. It results from performing at a high level until stress and tension, especially from extreme and prolonged physical or mental exertion or an overburdening workload, take their toll." (American Psychological Association, n.d.). The World Health Organization (WHO) defines burnout as a "syndrome conceptualized as resulting from chronic workplace stress that has not been successfully managed," and consists of feelings of energy depletion or exhaustion, increased mental distance from one's job or feelings of negativism or cynicism related to one's job, and reduced professional efficacy (WHO, 2019).

[12]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).

dissimilarities, all measures of burnout emphasize the role of exhaustion as a key component of the construct (Schaufeli and Enzmann, 1998).

Diagnosis of Clinical Burnout 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 being seen merely as a psychological concept to a formally diagnosed medical condition. This evolution was influenced by the social security systems in countries like Sweden and the Netherlands, which cover sick leave payments for both physical and mental health issues. In these nations, obtaining a medical diagnosis is essential for receiving insurance benefits. In the European Union, nine countries—Denmark, Estonia, France, Hungary, Latvia, Netherlands, Portugal, Slovakia, and Sweden—recognize burnout as an occupational illness (Lastovkova et al., 2018). Diagnosing burnout is thus crucial for ensuring access to healthcare services and compensation for sick leave.

The definition of clinical burnout is usually based on the criteria of work-related neurasthenia in the International Classification of Diseases (ICD-10) of the World Health Organization. It comprises the following features (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 of the following additional symptoms: insomnia, cognitive deficits, pain, palpitations, gastroenteric problems, sound and light sensitivity. These complaints and symptoms (iii) must be present nearly every day for at least two weeks; (iv) are due to psychosocial stressors that have been present for at least six months before diagnosis; and (v) lead to clinically significant distress or impairment (Grossi et al., 2015; Van Dam, 2021).

In many countries, there is, however, not a clear consensus among clinicians on which classification in the ICD-10 matches clinical burnout (Grossi et al., 2015). Therefore, to clarify the diagnostic criteria, the Swedish National Board of Health and Welfare (Socialstyrelsen) introduced "exhaustion disorder" (*utmattningssyndrom*) into the Swedish version of the 10th revision of the International Classification of Diseases (ICD-10-SE) in 2005.[13] In other countries, special guidelines for clinicians have been introduced. For example, the Royal Dutch Medical Association issued guidelines for assessing and treating stress-related disorders in occupational and primary health care in 2000 (Van Der Klink and Van Dijk, 2003)

Clinical Condition Exhaustion syndrome is a characteristic reaction to prolonged stress—usually psychosocial, occasionally physical stress—without the possibility of adequate recovery (Åsberg et al., 2010). Exhaustion syndrome 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 try to reduce the burden. If they do not succeed, the next stage, the acute phase, may occur. The acute phase is characterized by very 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 (e.g., acute difficulty in recollection, sudden memory impairment, temporary aphasia-like inability to find the right word in normal conversation). The recovery phase is characterized with a gradual return of symptoms but with marked sensitivity to stress and a tendency to relapse. A full-blown exhaustion syndrome is a severe and long-lasting condition that results in a total or partial loss of work capacity for a long time. The majority of patients appear to retain increased stress sensitivity after referral, which influences their work capacity.

[13] This was preceded by a significant upsurge in sick leave rates due to stress-related illnesses, starting in the 1990s and was particularly prominent among women (Persson et al., 2006; Försäkringskassan, 2020).

Burnout Symptoms 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 impacts the immune system, cardiovascular system, digestive system, endocrine system, and reproductive system. Chronic stress can, therefore, cause a variety of physical symptoms in burnout patients, such as headaches, intestinal problems, muscle tension or pain, chest pain, fatigue, change in sex drive, stomach upset, and vulnerability to diseases.

Cognitive problems: Chronic stress affects cognitive performance. Studies have shown that cognitive functions such as attention, concentration, and working memory are impaired in clinical burnout (Deligkaris et al., 2014). The cognitive impairments observed in burnout patients seem to especially affect the more complex, higher cognitive processes, such as executive functioning, rather than the more simple cognitive processes (Deligkaris et al., 2014). Specific symptoms include difficulties thinking clearly and learning new things at work, being forgetful and absent-minded, indecisiveness, poor memory, attention and concentration deficits, and trouble staying focused at work (Linden et al., 2005; The National Board of Health and Welfare, 2003). Since executive control is crucial for performance on tasks that require 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 capability to control emotions (Raio et al., 2013). Chronic stress, therefore, leads to emotional instability, manifested by intense emotional reactions. Specific symptoms include feeling frustrated and angry at work, irritability, anxiety and panic, overreacting, and feeling unable to control one's emotions at work. Due to the cognitive impairments and increased emotional lability, burnout patients will have more conflicts with other people. Other behavioral problems may relate to the consumption of food, alcohol, and medication.

1.2 Medical Diagnosis and Sick Leave in Sweden

Medical Diagnosis The diagnostic criteria of The Swedish National Board of Health and Welfare for exhaustion disorder (clinical burnout) is described in detail in The National Board of Health and Welfare (2003). We summarize the criteria in Online Appendix A. In short, the criteria consist of physical and psychological symptoms of fatigue for at least two weeks and that the symptoms have developed as a result of one or more identifiable stressors that have been present for at least six months. Individuals must have at least four symptoms every day for two weeks: (Memory impairment, Reduced ability to cope with time pressure, Emotional irritability, Sleep disturbance, Physical weakness, and Physical symptoms). These symptoms cause clinically significant suffering or impairment at work, socially, or in other important respects. If workers also satisfy the criteria for other illnesses, such as depression or anxiety disorder, exhaustion disorder is listed only as a secondary diagnosis.

Sick Leave A mandatory, government-financed national sickness insurance system was introduced in Sweden in 1955 (Henrekson and Persson, 2004; Adlercreutz and Nyström, 2021). At the onset of the sickness spell, the employers are required to finance leave from work due to sickness for the first two weeks (Adlercreutz and Nyström, 2021). After that, workers are covered by the Social Insurance Agency. The replacement rate is 80 percent during the first year, after which it declines to 75 percent of insurable earnings. However, many collective agreements stipulated a top-up of around 10 percent. Sick leave payments are taxable. After 90 (180) days, the Social Insurance Agency re-assesses individuals' eligibility based on their ability to return to work at their previous employer (any employer). As a general rule, sick pay is terminated after 365 days, but exceptions may apply (Adlercreutz and Nyström, 2021). Individuals who are permanently unable to work are eligible for disability insurance, which is typically granted only after an extended period of sick leave (Wikström, 2024). 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).

1.3 Data and Descriptive Statistics

Data on Sick Leave and Diagnosis Our data on sick leave absence from work and medical certificates come from the Social Insurance Agency. Their sick leave register includes all individuals registered for sick leave at the Agency, with information on the start and end date of all sick spells and 3-digit ICD-10 codes of their diagnosis. We measure burnout as sick leave resulting from an illness diagnosed with a 3-digit ICD-10 code of F43 (Reaction to severe stress and adjustment disorders).[14] This measure is available consistently from 2006 to 2020. The F43 code includes stress disorders (such as clinical burnout), adjustment disorders, and post-traumatic stress disorder. Differentiating between these disorders is challenging in practice, as doctors were not required to specify the exact disorder prior to 2010 and often hesitated to do so afterward (Försäkringskassan, 2020). However, there has been improvement in recent years. In 2019, adjustment disorder accounted for 6.5 percent and post-traumatic stress disorder for 2 percent of the diagnoses.

Other Data Sources We match the sick leave register with seven other administrative data sets: (i) RAMS contains 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 spell register from the Public Employment Service provides us with an exact duration of unemployment spells; (iv) the Wage Survey (*Lönestrukturstatistiken*) provides information on occupations and hours; (v) FEK provides information on firms' balance sheets; (vi) military enlistment data from the Military Archives contains assessments of cognitive and non-cognitive ability (vii) the Swedish Work Environment Survey (AMU) provides information on workplace conditions and worker's occupational health. We describe the Wage Survey, enlistment data, and the Swedish Work Environment Survey in further detail below.

Information on workers' occupations is drawn from the Wage Survey, which is a large-scale administrative survey of firms. The advantage of this source is that information is sampled directly from firms. The drawback, however, is that coverage is not complete. More precisely, we observe occupations of 58 percent of the workforce each year, with large firms and the public sector being over-represented.[15]

We measure individuals' skills, including their stress tolerance, using tests administered at military enlistment. The results of these tests are available from the Swedish Military Archives for the years 1969 to 2010. During our sample period, almost all men went through a draft 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).

[14] In addition to code F43, the ICD-10 also defines code Z73, which is captures "Problems related to life-management difficulty", including burnout (Z73.0). This diagnosis denotes occupational exhaustion as a non-disease factor rather than a psychiatric disorder. Z73 is used to flag overwork or poor work–life balance but does not by itself constitute a mental health diagnosis and does therefore not serve as a basis for sick-leave certificate or entitlement to paid sick leave. By contrast, an F43 code reflects a clinically recognized stress-related psychiatric disorder, qualifies for a medical certificate, paid sick leave, and triggers access to formal treatment pathways (e.g.psychotherapy, pharmacotherapy, occupational rehabilitation). Treatment for Z73 typically involves workplace adjustments, coaching or counseling to improve coping strategies, whereas F43 disorders require structured mental-health interventions.

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

The evaluation process consists of standardized tests to assess cognitive skills along 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 the Work Environment Survey (AMU). The AMU is a biannual survey conducted by Statistics Sweden as a supplement to the Labor Force Survey to report on working conditions in the Swedish labor market. The survey is nationally representative of the employed population aged 16—64, stratified at age, gender, and labor market characteristics. It consists of around 157 questions on work arrangements, worker's perceptions of their workplace, as well as health problems related to work. Importantly, the survey serves no function in the administration of sick leave, nor are employers notified of their employees' participation. Therefore, respondents face no repercussions for reporting truthfully. Around 7,000 to 9,000 employees are surveyed in each wave. Our analysis is based on waves 2005 to 2019, yielding a sample of 61,12 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, of over 970 occupations derived from surveys of workers and surveys of "occupation analysts." We use the Stress Tolerance requirement variable, which captures the importance of "accepting criticism and dealing calmly and effectively with high-stress situations" for an occupation.

Descriptive Statistics 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?

The medical definition of burnout is a condition caused by intense and prolonged occupational stress. This section investigates and validates this link empirically by addressing three questions. First, which working conditions and symptoms are most strongly associated with burnout? Second, how do different symptoms interact and exacerbate one another? Third, how long do symptoms accumulate prior to the onset of burnout?

To address the first question, we regress burnout on work conditions as well as physical and stress symptoms reported in the previous year in the Work Environment Survey (AMU). More precisely, we use a multivariate regression of burnout—defined as an indicator of being diagnosed with burnout and taking extended sick leave—on a set of working conditions and symptoms, all measured in the last quarter of the preceding calendar year. As described in Section 1, the AMU survey is unrelated to the administration of sick leave, and employers are not informed of employee participation. Respondents thus face no disincentive to report truthfully. We restrict the analysis to survey questions consistently available across the sample period to maximize sample size (see Appendix C for exact question wording and translations). For each question, we construct a binary indicator equal to one if the response is above the median and zero otherwise. The regression controls for demographic characteristics and year fixed effects. We rank the conditions and symptoms by the strength of their association with burnout in the medical literature, using the assistance of a large language model (see Appendix C for details). Figure 1a shows the results.

The most significant coefficients correspond to the same three occupational stress symptoms that form part of the diagnostic criteria for burnout, as defined by the Swedish National Board of Health and Welfare: inability to detach thoughts from work, inability to sleep due to work, perceiving a job to be mentally stressful (Figure 1a). The same three symptoms are also the most closely related to burnout in the medical literature. The fourth largest coefficient belongs to suffering from headaches, which is the last item that completes the core diagnostic criteria for burnout (see Appendix A for details). In contrast, other work-related health problems—such as muscle pain—exhibit a weaker and statistically insignificant association with burnout.

Having established the link between burnout and specific symptoms of occupational stress, we examine how the interaction of different symptoms contributes to burnout risk. To this end, we focus on the subset of AMU questions that capture the core diagnostic criteria for burnout, which happen to be those most strongly correlated with burnout in Figure 1a.[16] We use these four questions to construct an index of stress. For each symptom, we assign a score of 1 to workers who report experiencing it at the highest intensity (e.g., being unable to sleep due to work every day of the week). We assign a score of -1 to workers who report the lowest symptom intensity (e.g. never unable to sleep due to work). Finally, we assign a score of zero if intensity falls between these two extremes. We then sum the scores across the four symptoms. This yields a stress index ranging from -4 (no symptoms) to 4 (all symptoms at maximum severity); see Appendix D for further details.

Figure 1b plots the relationship between the stress index and burnout incidence in the subsequent year. Workers reporting no stress symptoms exhibit a near-zero probability of burnout in the following year. As the number of reported symptoms increases, the risk of burnout rises—not linearly, but at an accelerating rate. Among workers reporting all four symptoms, the likelihood of burnout in the following year reaches approximately 5 percent. The non-linear association between burnout and stress is reminiscent of the inverted-U dose–response relationship long recognized in psychology (Yerkes and Dodson, 1908) and in biomedicine (Calabrese and Baldwin, 2002). This pattern suggests that stress symptoms accumulate and compound, rather than contributing additively.

The last question about the nature of burnout we address here is whether burnout results from sustained, chronic stress or a rapid accumulation of stress that leads to a tipping point. To investigate this, we examine the time path of stress symptoms that lead to burnout. We adopt a benchmarking approach akin to a difference-in-differences design, matching workers who experience burnout to observationally similar individuals who do not, based on demographic characteristics and pre-burnout labor income deciles (For more details, see Section 4).

Figure 1c plots the evolution of the stress index for individuals with and without subsequent burnout. Among those who experience burnout, symptoms increase sharply in the year leading up to burnout, peaking in the quarter when individuals begin sick leave. Thereafter, stress symptoms decline and return to levels comparable to those observed one year before burnout. As we show later, this decline is partly driven by transitions to less demanding jobs and reductions in work intensity following burnout. The evidence suggests that burnout is best understood as a tipping-point phenomenon, triggered by chronic pressure that builds up over the course of a year.

[16] In Section 5, we provide complementary validation of this reduced question set, showing that this subset of four items outperforms nearly all other four-question combinations in predicting burnout. In addition, Appendix Figure A.4 plots the relationship between burnout and each of these stress symptoms separately.

3 Who is at Risk of Burning Out?

In the previous section, we documented how occupational stress accumulates and leads to burnout. This section examines the risk factors of burnout.

3.1 Job Stress Requirements and Individual Stress Tolerance

Do occupations differ systematically in their stress levels? To what extent do individuals vary in their tolerance for stress? And is there complementarity between job stress and individual stress tolerance—that is, are less stress-tolerant individuals always more prone to burnout, regardless of job type, or does their risk of burnout rise disproportionately when placed in high-stress occupations? Answering these questions requires two additional pieces of data.

The first data is the level of stress associated with a job. We use the stress tolerance requirement of an occupation delineated by O*NET (Peterson et al., 1999). A key advantage of ONET is its emphasis on the *nature* of occupations, capturing the tasks required by each occupation. This is measured independently of the workers occupying these roles and is therefore immune to the sorting of workers into occupations. Nonetheless, the use of ONET information may induce two types of measurement error, which will attenuate the results. First, ONET's occupational stress assessments are based on the U.S. context and might not fully align with actual work conditions in Sweden.[17] Second, discrepancies between occupational classification systems in the two countries may introduce additional measurement error. Both sources of measurement error dampen the observed correlation between burnout rates and occupational stress levels, suggesting that any patterns we observe should be interpreted as lower-bound estimates.

The second data is a measure of individual stress tolerance. We obtain this measure from data collected during the Swedish military draft of all 18-year-old men.[18] Trained psychologists conduct these assessments as part of a comprehensive evaluation encompassing both cognitive and non-cognitive skills. Individual stress tolerance is defined as the "ability to control and channel nervousness, tolerance of stress, and disposition of anxiety" (Mood et al., 2012). It is quantified on a scale of 1 to 5, where a score of 3 denotes a "normally functioning eighteen-year-old male" (Mood et al., 2012).

Figure 2a documents the relationship between job stress and burnout by presenting a binned scatter plot that relates occupation-level burnout rates to occupational stress tolerance requirements. The figure shows a robust correlation between the level of stress and the incidence of burnout in the data. The figure also adds examples of occupations across the spectrum of stress tolerance requirements. Examples of occupations that require high stress tolerance include psychiatric nurses, midwives, and preschool teachers. Occupations that do not require tolerance to stress include construction machine operators and mining workers.

It is remarkable that there are no occupations that are classified as low-stress in ONET but exhibit high rates of burnout in our data for Sweden. This strong relation between jobs stress requirement and individual stress tolerance confirms the connection between *occupational* stress and burnout. If burnout were a result of other factors, such as stress in private life, we would not expect such a clear pattern.

[17] Since our analysis uses an occupation's rank in the distribution of stress tolerance requirements, rather than the absolute rating score, we are not concerned with measurement error stemming from differences in stress levels or their dispersion. The measurement is valid as long as the ordering of occupations in terms of stress tolerance requirements is the same in Sweden as in the U.S.

[18] Only observing men is a serious limitation since burnout is more prevalent among women, as we document below. One possibility would have been to impute the stress tolerance of women using that of their brothers. However, since previous work has documented substantial heterogeneity in stress tolerance across brothers (Almgren, Kramer, and Sigurdsson, 2025), we refrain from such imputation.

If occupations vary in stress levels, do workers with different degrees of tolerance to stress sort into them accordingly? Figure 2b reveals some degree of sorting along this dimension. Workers with higher stress tolerance tend, on average, to work in occupations that necessitate higher stress tolerance levels.[19] The sorting is far from perfect: the most stress-tolerant individuals work in occupations with an average stress-requirement rank of 60 compared to a rank of about 45 for the least stress-tolerant individuals. By contrast, under perfect sorting, we would expect the average rank to be 92.7 among those most stress tolerant and 0.08 for those least tolerant to stress. This gap is expected—occupational choice reflects more than just stress tolerance.

Figure 2c plots the burnout rate of workers by stress level of their occupations and their individual stress tolerance. Workers with low stress tolerance are more susceptible to burnout than their stress-tolerant peers, especially when working in highly stressful occupations.[20] The gap between workers widens with the stress level of the occupation: among those in the top quartile of the most stressful jobs, the burnout rate among the least stress-tolerant individuals is roughly three times higher than that for the most stress-tolerant workers.

The observed complementarity between job stress requirements and individual stress tolerance is most evident at the extremes: low–tolerance individuals in the top quartile of stressful occupations face the highest burnout risk. Surprisingly, for workers in the top quartile of stress tolerance, burnout rates show little correlation with occupational stress levels.[21] The complementarity implies that the observed imperfect sorting does not minimize the aggregate burnout rate, given the marginal distributions of stress and tolerance. This is unsurprising, as occupational choice is shaped by many factors beyond stress tolerance.

3.2 Gender, Family, and Career

Burnout risk varies systematically with the stressfulness of jobs and individual stress tolerance. This fact has been established, due to data limitations, only for men. 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 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 the rate of burnout among men and women, which we further separate by family type, 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 in the year prior.

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

[19] Figure A.10 shows the entire distribution of occupation types for each level of individual stress tolerance.

[20] Appendix Figure A.9 shows that the negative relationship between stress tolerance and the likelihood of burnout is robust to controlling for other cognitive and non-cognitive skills.

[21] Caution is warranted in interpreting levels—particularly the absence of near-zero burnout rates—due to likely measurement error in our occupation-level stress metrics, as previously discussed.

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 are affected by burnout over their lifetime. For the cohort born in 1985, we can observe each individual's sick leave history between ages 25 to 40. By the age of 40, around 14 percent of women and 5 percent of men in this cohort have experienced at least one burnout event, implying 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 they key pattern in Figure 3a, showing the unconditional gender gap in burnout. Comparing columns (1) to (3), approximately 25 percent of the gender difference can be explained by observed characteristics: the coefficient declines from 1.33 to 1.01, implying that the complete set of controls reduces the gap by about one percentage point, based on the gender difference in burnout rates. Comparing columns (4) and (5) for women and columns (6) and (7) for men in Table 2 highlights the significant explanatory power of occupation.[22] 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.[23] 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 are the characteristics that explain burnout? For female workers, being foreign-born or married is associated 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.3. 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 occupation is controlled for, suggesting that 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 is related to the incomes of couples and the relative position

[22]Occupation has a stronger explanatory power than industry and all other characteristics in this table together (see Appendix Table A.2).

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

of women within the household. Figure 3b plots a heat map of burnout rates of married and cohabiting women against the labor incomes of each of the spouses within the couple.[24] 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 burnout rate given that observations are non-uniformly distributed (see Appendix Figure A.6). More precisely, we report the average rate of 38,416 observations in the circular vicinity of each point. The number of observations is based on a power calculation for the binomial distribution and is sufficient to create 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.[25] This approach is equivalent to a non-parametric wage inflation adjustment.[26] The adjustment renders individual labor incomes comparable over time but does not affect nominal income growth rates.[27]

Darker shades of red depict higher burnout rates among women. We overlay a line marking the median couple's total income. The figure shows that 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 the household income is below the median, the average burnout rate for women is as high as 2.19 percent. This result is interesting when compared to the strikingly high rates of burnout among single mothers who are, by definition, the breadwinners in their households. The burnout rate drops to 1.29 percent for primary-earner women in couples with above-median income. Similarly, burnout rates of women are lower in households where women earn less than their husbands, although still higher in households with less than median labor income.

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, women experiencing fluctuating incomes—particularly those whose labor income increases substantially—show the highest burnout rates.[28] Taken together, these findings highlight the importance of women's relative earnings within the household and their career trajectories as determinants of burnout risk.

[24] Appendix Figure A.7a presents the corresponding figure for married and cohabiting men.

[25] 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).

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

[27] 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).

[28] The same patterns are present among employed men, as shown in Appendix Figure A.7b. As a result of burnout being less frequent among men, the estimates are less precise. The results for women and men are almost identical when we restrict the sample to individuals who stay at the same firm in the two years before burnout (Appendix Figure A.8).

4 The Economic Burden of Burnout

This section studies the consequences of burnout for workers and their families and estimates the aggregate income loss due to burnout.

4.1 Effect on Individuals' Labor Market Outcomes

To estimate the impact of burnout on individual labor-market outcomes, we start by comparing workers who experience burnout at a given date with a control group of observationally similar individuals who never experience burnout. Specifically, we implement 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). This design permits us to follow the trajectory of labor-market outcomes for treated individuals before, during, and after burnout, and contrast these dynamics with those of matched controls. A potential concern is that burnout coincides with a negative demand shock for a worker's skills, which could independently drive long-run differences between treated and control groups. To address this, we refine the matching procedure to include industry, ensuring treated and control individuals operate within the same sector.

The key identifying assumption is that, in the absence of burnout, treated and control individuals would have followed parallel outcome trends. We will assess this assumption by testing for parallel trends in the pre-treatment period. A potential threat to identification is that, even after matching on observables, individuals who burn out may differ in unobservable characteristics and exhibit systematically different outcome trajectories than those who do not burn out. In particular, as documented in Section 3, burnout is preceded by career progression, which can lead to an underestimate of earnings losses. Therefore, to mitigate such potential bias in the estimates of the cost of burnout, we complement our primary design with a timing-of-treatment approach. That is, among those who burn out, we compare those who go into burnout 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).

A remaining threat is the presence of contemporaneous shocks that both affect outcomes and influence the timing of burnout. To isolate the effect of occupational stress and associated burnout, we employ an instrumental variables strategy, where individual burnout is instrumented by changes in the industry-level burnout rate. The rationale is that idiosyncratic private-life shocks—such as divorce—average out at the industry level, so shifts in industry burnout rates primarily reflect changes in work-related sector-specific stress. Rather than using industry as the unit of analysis, we follow the spirit of Angrist (1991), who shows that using grouped data is equivalent to an IV strategy using individual data with group averages serving as the instruments.[29]

We first describe the procedure underlying the main empirical strategy, and then describe the fixed-delta method and the instrumental variables approach in turn.

Matched Difference-in-Differences 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 a 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 to treatment

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

within this demographic group, and their employment in the four years prior to treatment. Out of all individuals who have a burnout event, 99.34 percent can be matched with an observationally similar individual that serves as a control. The matched treated group consists of a balanced panel of 150,834 individuals.

We begin by plotting in Figure 4a the raw averages of labor income of the group that goes into burnout at time 0 and the control group that does not. In the years prior, labor incomes of both groups rise gradually, even more so among the treated group. In the year where burnout takes place, incomes of the treated group fall in absolute terms before stabilizing and growing from a lower level. Among those in the control group, however, income continues growing almost at the same rate, with a slight sign of mean reversion.

In order to obtain an estimate of the effect of burnout on labor income, moving beyond the income drop descriptively shown in Figure 4a, we estimate a difference-in-difference regression. It compares the outcomes of workers who burn out to the outcomes of matched control observations. Our estimation equation is:

$$Y_{i,k} = \phi_{G_i,T_i} + \delta_{G_i,k} + \sum_{k=-4}^{7} \alpha_k T_i + \varepsilon_{i,k} \tag{1}$$

where $Y_{i,k}$ is the outcome of interest for individual i at event time k, T_i is the treatment indicator, and G_i is the observation group that individual i belongs to (defined by the characteristics used in matching). The regression includes both group-treatment status fixed effects, ϕ_{G_i,T_i}, and group-time fixed effects, $\delta_{G_i,k}$. The coefficients of interest are α_k, which measure the dynamic treatment effects. Standard errors are clustered at the individual level.

Figure 5a presents the estimated effects of burnout on labor market outcomes based on equation (1). In the years prior to burnout, there is a small but significant upward trend in earnings. This is consistent with the evidence presented in Figure 3c, showing that burnout is associated with income growth in the years prior, reflecting factors such as promotions or firm changes. In the year when individuals go into burnout, there is an immediate drop in income of roughly 10 percent, further dropping to almost 15 percent in the subsequent year before stabilizing. The permanent loss in annual earnings, measured up to seven years later, is 12.1 percent. This earnings loss is, as we document in Appendix Figure A.13, not explained by sick leave as the median duration of burnout sick leave is 55 days. Instead, as we document below, it reflects a permanent decline in employment and productivity.[30] The magnitude of the income drop is similar to, but slightly exceeds, the income drop of about 10 percent subsequent to all health shocks, physical and mental, leading to sick leave, as estimated by (Kolsrud et al., 2020). Burnout therefore appears to inflict a more severe scarring effect than the average health shock. The earnings losses are also comparable to the long-term displacement effects observed after layoffs, which range from 10 to 20 percent depending on macroeconomic conditions (Davis and Von Wachter, 2011).

In Section 3, we documented that women are three times more likely to burn out than men. In Figure 6b, 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. [31] Taken together, these results suggest that while the incidence of burnout varies substantially by gender, the severity of its economic consequences is more uniform.

Results are robust to matching within industry to account for potential negative demand shocks to

[30] In Appendix Figure A.13, we show that days spent on burnout-related sick leave spike in the year of the first incident and quickly subside thereafter. The distribution of sick leave duration is highly skewed to the right, reflected in the large difference between mean duration (161 days) and median duration (55 days).

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

workers' skills. Appendix Table A.4 compares estimates from random matching and industry-specific matching; the coefficients are quantitatively similar, indicating that sectoral shocks do not drive our findings.

Fixed-delta Method 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. To evaluate this design, Figure 4b plots the raw average labor income for the group that goes into burnout at time 0 and a control group that burns out five years later, i.e., $\delta = 5$. Consistent with the results when matching to never-treated controls, both groups exhibit parallel income trends in the pre-burnout period, diverging only as income falls when workers go into burnout. Appendix Figure A.11 demonstrates the robustness of this pattern, rolling δ from 2 to 7 years and contrasting them with our baseline estimate from Figure 5a.

The estimated earnings drop at impact is similar using both designs, reassuring us of the negligible role of unobserved characteristics. Moreover, the estimated long-term effect is similar but slightly larger than using the never-treated control group, estimated at 14.9 percent (Appendix Table A.4). The positive pre-trend in income is similar in both methods, reflecting an acceleration in income in the lead-up to burnout. 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 Nekoei and Seim (2023).

Instrumental Variables To isolate the effect of work stress from concurrent personal life events that may both increase stress and affect labor market outcomes, we augment the matched difference-in-differences strategy by instrumenting the effect of burnout on post-burnout outcomes with the burnout rate in individuals' narrow (5-digit) industry. The assumption is that idiosyncratic life events do not systematically aggregate up at the industry level, implying that changes in the burnout rate in an industry over time reflect changes in the level of work-related stress. For each individual, the annual industry-level burnout rate is calculated among the full sample of workers in the industry, leaving out themselves and their coworkers in their firm. By leaving out all workers in their own firm, we err on the side of caution not to incorporate firm shocks that might affect income and employment directly.

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 $t_i - 1$).[32] We estimate the following first-stage regression:

$$T_i = \beta B_i + \phi_{J_i} + \psi_{G_i} + \epsilon_i, \tag{2}$$

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.[33] 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 the industry-level burnout rates at

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

[33] 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 $\psi_{G_{i,t_i}}$.

the individual level—generated either by time-variation in the industry-level burnout rate or moves of individuals between industries. Industry-origin fixed effects absorb variation in sorting across individuals.

Figure 4c visually demonstrates the first stage through a binned scatter of individual's own burnout rate and the leave-one-out industry-level burnout rate. The figure displays a strong, positive, and linear relationship and the statistical strength of the instrument is reflected in a first-stage F-statistic of 174. We report the instrumental variables estimate of the effect on labor income in Appendix Table A.4. This approach yields an estimated income loss of 13.8 percent, similar in magnitude to our baseline estimates. This suggests that estimated effects are not driven by other private-life events coinciding with burnout.

Mechanisms and Decomposition Do individuals experiencing burnout suffer income reductions due to fewer promotions within their current job, or do they transition to lower-paying positions? Alternatively, are income declines driven by reductions in working hours or 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 proceed to decompose the 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.12). 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 the number of months when workers go into burnout. There is a persistent loss of labor of about one month less work per year on average. 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 gauges the dynamic quantitative importance of each of these channels. 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.[34]

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, for any outcome, $Y_{i,t}$, we denote its matched counterpart in the control group by $Y_{c(i),t}$.

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,

$$Y^p_{i,t} \equiv Y_{i,t} \mathbb{1} \left(\pi_{i,t} = p \right) + Y_{c(i),t} \mathbb{1} \left(\pi_{i,t} \neq p \right) \tag{3}$$

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

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

The last equation implies that the average treatment effect can be decomposed in the same way, and that

[34] 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.

we can calculate the contribution of the partitions:

$$\sum_{p \in P} \frac{\mathbb{E}(Y_{i,t}^p - Y_{c(i),t}^p)}{\mathbb{E}(Y_{i,t} - Y_{c(i),t})} = 1 \tag{5}$$

where each fraction is measuring 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 attributable to burned-out workers ceasing work or transitioning to part-time employment. Conversely, the intensive margin arises from the reduced income of those who return to full-time work following a burnout episode, further dissected 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 5, panel (b), presents the outcomes of our dynamic decomposition. The predominant portion of the lasting income loss post-burnout is attributable to the extensive margin, with workers either exiting the workforce without returning or, more significantly, shifting to part-time roles. A minor fraction of the income loss can be ascribed to stalled career advancement, solely attributable to stagnant incomes among workers who remain with their pre-burnout employer.[35]

Interestingly, transitioning to a different firm after experiencing burnout mitigates the income loss. This finding suggest a lack of compensating wage differentials for burnout risk. Assuming burnout originates from high workplace stress and firms compensate employees for such conditions, then leaving a stressful job should entail a loss of a firm-specific wage premium. The absence of such a pattern suggests that, in practice, workers do not receive compensating differentials for stressful work. As a result, moving to less stressful occupations does not entail a reduction in earnings.

Do workers move to less stressful jobs after experiencing burnout? To answer this question, Figure 5d focuses on firm switchers and studies the evolution of their industry-level burnout rates. Following a burnout episode, workers tend to exit high-risk industries in favor of those with lower burnout risk. Two years after burnout, individuals exiting their pre-burnout employer move to industries with 0.027pp lower burnout rates, a reduction equal to 4.5 percent of the standard deviation across firm movers in the control group. This finding indicates that workers are aware of burnout risk differences at the industry level—at least after having experienced burnout. In addition, moving to lower-risk jobs (Panel (d)) but earning more (Panel (b)) suggests the negative compensation wage differential.

Disposable Income Our measurement of burnout is directly linked to the receipt of social insurance claims. Therefore, it is natural to ask to what extent public insurance buffers the earnings loss following burnout. In addition to paid sick leave, Sweden maintains a generous social insurance system through disability insurance and progressive taxation. Figure 5c shows the dynamic response of income when sick pay, and all remaining taxes and transfers (including pensions) are added to labor income. In the short run, sick pay compensates burned-out workers for a large share of their lost earnings. Since the typical sick leave spell associated with burnout lasts for less than two months, and eligibility is capped at one year, the income

[35] The results are quantitatively similar across genders as shown in Appendix Figure A.14. 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.

buffer from sick pay fades out quickly. In the long run, an increase in other public transfers compensates 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. [36]

4.2 Effect on Spouse's Labor Market Outcomes

We now turn to the effect of burnout on 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.[37]

To perform our event study for spousal earnings, we focus on workers who were married or cohabiting in the year prior to burnout and follow their spouse over time. We follow the spouses regardless of whether they separate in subsequent periods, and study separation as an outcome by itself. 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, with the sole exception that this time, matching is done at spouse-level so that the treatment and control spouses are born in the same year. Our estimation sample includes 57,441 spouses married to workers experiencing burnout.

Figure 6a depicts the dynamic effects of burnout on 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—consistent with caregiving norms that disproportionately burden women—is corroborated by U.S. survey data showing that only female spouses report reducing labor supply in response to a worker's health shock Anand et al. (2022). Appendix Table A.5 presents IV estimates of these spillover effects. The estimates imply a somewhat stronger negative spillover effects than the difference-in-differences estimates. Taken together, these findings imply that intra-family spillovers constitute a meaningful component of the aggregate cost of burnout.

4.3 Fertility and Separations

Burnout may undermine workers' well-being not only by affecting their labor market outcomes but also by disrupting their private lives. Moreover, changes in family circumstances—such as childbirth—or major life events—such as separation from a spouse—can heighten overall stress levels and compound the burden of occupational stress.

Figure 6c presents the effects of burnout on separations from spouses (including both cohabitation and marriage). The outcome variable is an indicator for having the same spouse as in $t = -4$. The figure shows that individuals who experience burnout are generally more likely than the control group to separate from their spouses—as indicated by the pre-trend—but this gap does not widen in the period leading up to

[36] 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).

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

the burnout event. In the year of burnout, there is a 4 percentage point jump in relationship separations, corresponding to about 50 percent increase in the annual separation rate.[38] However, seven years after burnout, the share of couples who have separated is close to what would have been predicted by a linear extrapolation of the pre-trend, suggesting that burnout accelerates, but does not amplify, relationship separations. To evaluate whether the burnout event is only associated with more separations in the short run, Appendix Figure A.19 reports estimated effects on separations using the fixed-delta method. The figure confirms that separations do not precede burnout but that following burnout, there is a sharp increase in separations.

Figure 6d presents the effects on fertility. Burnout leads to a permanent reduction in fertility among women. Seven years after going into burnout, women have about 0.02 fewer children (1.3 percent) than those who do not.[39] Men, in contrast, have fewer children in the short run but more in the long run. The figure also shows that women's burnout is preceded by increased rate of childbirth the year before, while there is no such pattern for men. To evaluate whether these effects reflect differential trends between treated and never-treated, Appendix Figure A.19 reports estimated effects on fertility using the fixed-delta method, exploiting the timing of burnout. This figure shows the same patterns as Figure 6d, further confirming that burnout is associated with less fertility among women and suggesting that childbirth may be a contributing factor to burnout.

4.4 Effect on Children's Human Capital

Parental burnout may affect children through a range of channels, including reduced parental time, attention, and emotional support. To assess these potential effects, we examine the impact of parental burnout on children's human capital accumulation, as measured by school performance and educational attainment. As we will show to be an important aspect of our empirical design, we conduct the analysis separately by the child's age at the time of parental burnout.[40]

Our empirical strategy is to match children whose parent experiences burnout to a comparable control group of children whose parents never experience burnout. We match children to control observations based on their birth cohort, gender, and sibling order. The only role of the control group is to identify deviations in the treated group from potential cohort trends in educational outcomes, which might be gender-specific. We thus demean the outcomes with the control-group mean so that child i's outcome is $\hat{y}_i = y_i - \bar{y}_i^c$, where $\bar{y}_i^c$ is the mean of control-group assigned to individual i. We then run the following regression

$$\hat{y}_i = \sum_k \beta_k \mathbb{I}(a_i = k) + X_i + \varepsilon_i \tag{6}$$

where $\mathbb{I}(a_i = k)$ is an indicator for the parent of child i burn out when the child is at age k. The regression includes controls, X_i, which contain 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 estimate the impact of parental burnout on their children's human capital, focusing on both school

[38] Appendix Table A.5 presents the corresponding IV estimate, which are similar in magnitude.

[39] Appendix Table A.5 presents the corresponding IV estimate, which is negative but not statistically different from zero. This estimate pools men and women for statistical power. Estimated separately for men and women, the IV estimates qualitatively align with the difference-in-differences estimates, indicating negative effect for women, -22.6% (SE 13.8), and positive for men, 13.1% (SE 14.9).

[40] We measure age at parental burnout as the age of first potential burnout of either mother or father. Overall, the correlation in spousal burnout is low. Our results are similar when restricting to burnout of mothers, as they constitute the largest share of burnout events.

performance and educational attainment. School performance is measured using results from high-stakes national exams taken at the end of compulsory schooling. All Swedish students complete these exams during the spring term of 9th grade, the year they turn 16. We define an indicator for achieving a GPA of 240 or higher, which corresponds to an average grade of C (15) across 16 subjects—roughly the median GPA. These exams are high-stakes, as GPA determines eligibility for oversubscribed secondary programs and ultimately affects college admission (see, e.g., Ramstedt, 2005, for further discussion and details). Educational attainment is captured by college enrollment by age 21—an indicator for whether a student enters college at age 19, 20, or 21.

Figure 7a plots the coefficients from regression (6) of demeaned grade-9 test scores on child's age at parent's burnout. The reference group in the regression is those whose parents burned out when the children were of age 17, implying that our estimates are difference-in-differences comparing the effect on treated children—net of control—before and after the exam year.

Figure 7a shows a negative effect of parental burnout on school performance. On average, children whose parents went into burnout when they were between the ages of 10 and 16 are 1.9 percentage points less likely to score an average grade of C or higher than the control group. This implies a 5.3 percent reduction compared to the average grade of the control group. The estimates are slightly smaller in absolute value for children who were younger at the time of parental burnout and further from taking the grade-9 exams, although not statistically different.

If the effects we estimate reflect the impact of the event of parents going into burnout, rather than systematic differences in the school performance of children whose parents experience burnout compared to children whose parents do not, the estimated effects at ages 17 and above—post exam—can serve as placebo tests of our design. We find no effect of parental burnout on school grades among children whose parents go into burnout at ages 17 to 25.

Figure 7c presents the estimated effect on college enrollment. The reference group in the regression is children who were 17 years old when their parents went into burnout. We estimate a 2.5 percentage point reduction in college enrollment, or 8.1 percent reduction compared to the average enrollment of the control group. The estimates are, as perhaps expected, somewhat smaller for children already at college age when their parents have burnout. However, the effects are statistically indistinguishable for ages 7-17, although point estimates are slightly larger for those at younger ages when impacted. Among children whose parents burn out at later ages, 22 to 25, there is no statistically significant difference in school performance.

We study the heterogeneity of these effects with respect to the parental background in Figures 7b and 7d. Children's school performance and educational attainment are more adversely impacted when their parents have lower levels of education. This implies that parental burnout contributes to reducing intergenerational mobility in education. In Appendix Figure A.17, we investigate whether effects are heterogeneous by the gender of children or the parent who burns out. The effect of a mother's burnout on the college enrollment of her children is slightly larger than when the father burns out, and the effect on boys and girls is about the same.[41]

We study college enrollment by age 21 for two reasons. First, many Swedish students complete their college education in longer than standard time, making enrollment rather than degree completion a preferable outcome. Second, and related to the former, extending the outcome definition to later ages

[41] The fact that there is not a statistically significant difference in the effects of the burnout of mothers and fathers is surprising given the traditionally greater role of mothers in child rearing. However, while the mechanisms likely differ, this is consistent with earlier work documenting that paternal job loss has a large effect on the education of children, in some cases larger than that of maternal job loss (Hilger, 2016; Bingley et al., 2023). Further in line with this interpretation, as we document above, women are also substantially affected by the burnout of their husbands.

implies that we can study fewer birth cohorts with our empirical design. As a robustness check, we estimate (6) with college enrollment by age 24 as the outcome. As shown in Appendix Figure A.15 the results are comparable to our main definition of college education, and imply an 8.1 percent reduction in college enrollment by age 24.

The event of parental burnout can happen simultaneously as other events in the life of the parent, child, or the family more generally. To isolate the effect occupational stress and burnout on children, we proceed in the same way as we did in Section 4.1 when studying the effect of burnout on labor income and instrument parental burnout by the burnout rate in their industry. We then run a 2SLS version of equation (6), where we instrument the indicators for parental burnout at a child's given age by the industry burnout rate in the year before, controlling for industry fixed effects. The instrumental-variable estimates are reported in Figures 7a and 7c. In both cases, IV estimates are similar in magnitude to the difference-in-difference estimate, implying that parental burnout leads to a 5.3 percentage point reduction in school grades and 8.7 percent reduction in college enrollment, relative to the control group mean.

4.5 Aggregate Labor Income Loss due to Burnout

What are the aggregate implications of burnout for the economy? We are now equipped to provide a quantitative answer to this question by calculating the total loss of labor income due to burnout in 2019 through four channels: i) days on sick leave, ii) scarring effects, and spillovers on other family members through effects on iii) spousal earnings and iv) children's education outcomes.[42]

The following formula lays out these four channels:

$$\text{Share of Aggregate Income Lost} = \frac{\sum_i \sigma_i \hat{y}_i + \alpha^o \frac{y_i^o}{1-\alpha^o} + \alpha^s \frac{y_i^s}{1-\alpha^s} + \alpha^c \frac{y_i^c}{1-\alpha^c}}{\sum_i \hat{y}_i + \frac{y_i^o}{1-\alpha} + \frac{y_i^s}{1-\alpha^s} + \frac{y_i^c}{1-\alpha^c}} \tag{7}$$

where y_i^o, y_i^s and y_i^c denote, respectively, the income of individual i who burned out in the past, whose spouse burned out in the past, and whose parent burned out in the past (all within the scope of our data, i.e., post-2005). The terms α^o, α^s, and α^c represent the proportional income losses experienced through these three forms of exposure to burnout, which we parametrize using the difference-in-difference estimates in Figures 5a, 6a, and 7c. In the last case, we convert the college-enrollment effect to an income effect using estimates of returns to college in Sweden from Sinn (2024). 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.[43]

Figure 8 documents our measured total loss of income in 2019 due to burnout. Lost working days in 2019 led to a loss of 0.5 percent in potential labor income. Scarring effects from past burnout accumulate to 1.6 percent of potential income, thereby accounting for the lion's share of the cost of burnout. Intra-family spillovers on spouses and children add around 0.3 percent, resulting in a total of 2.3 percent. This back-of-the-envelope calculation demonstrates that while the overall cost of burnout might be high, more than three-quarters of the total loss is driven by long-run scarring effects and spillovers.[44]

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

[43] 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.

[44] Hassard et al. (2018) conduct a systematic review of estimates of the cost of occupational stress. Although their methodology differs from ours, their conclusions regarding the relative magnitude of cost components are broadly consistent. They find that productivity-related losses account for 70 to 90 percent of total costs, with healthcare and medical expenses comprising the remaining 10 to 30 percent.

What would the aggregate loss be if the burnout rate observed in 2019 were to persist indefinitely? Our loss calculation for 2019 underestimates the contribution of long-run effects, as our data on burnout diagnoses only extends back to 2006. This truncation implies that we do not observe prime-age earnings for some individuals who were affected either directly by burnout or indirectly as family members. For example, most children of parents who burn out during our sample period have not yet entered the labor market or are at an early stage of their careers, which mechanically limits the calculation of the aggregate earnings loss.

To overcome this shortcoming, we calculate the loss in a hypothetical steady state. Specifically, we assume that the burnout rate in Sweden stays constant at its 2019 level, implying that we can compute survival rates as a function of age similar to what is frequently done in studies of life expectancy.[45]

Figure 8 shows that in steady-state, the estimated aggregate loss amounts to 3.63 percent of labor income. While the permanent loss of individuals' income increases from 1.6 to 2.6 percent, the largest proportional change occurs in the spillover effect on children, which increases from 0.07 to 0.26 percent.

The following stylized calculation illustrates the intuition behind the magnitudes in our results. A two percentage point drop in college enrollment, multiplied by a 38% college return, yields an expected permanent income loss of 0.6%. 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 0.18%.

To put the magnitude of the aggregate cost into perspective, we divide it by the prevalence of burnout in the population. This calculation implies that each case of burnout is associated with a loss equivalent to three years of average income (3.63/1.12), or three and a half years of income for the affected individual, given their lower-than-average earnings ($3.63/1.12 \times 325/303$). The scale of this economic burden underscores the need for policy intervention—a topic we turn to next.

5 Predicting and Preventing Burnout

Preventing burnout is more effective than treating it after onset, as with other mental health conditions (Tetrick and Winslow, 2015; Aust et al., 2023). While preventive programs can be effective, they are also costly, requiring the planner to determine their optimal scope and targeting. Two key ingredients are essential for this optimization. The first is a comprehensive estimate of the cost of burnout, which we provided in Section 4. The second is the ability to identify individuals at risk accurately.

In this section, we first show how at-risk individuals can be identified. We discuss how subjective stress assessments, collected through worker surveys, can improve the prediction of burnout, and how the Work Environment Survey used in Section 2 fulfills this role in our empirical analysis. We then demonstrate how combining our cost estimates with the burnout prediction model can inform the optimal design of preventive programs. In particular, we quantify the gains from using self-reported stress symptoms to target potential interventions.

[45] 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.

5.1 Predicting Burnout using Administrative and Survey Data

This section assesses the predictive value of both administrative and survey data for identifying workers at elevated risk of burnout.

As shown in Section 3, individuals' observable characteristics are highly correlated with the risk of burnout. The patterns suggest that burnout risk can be partially predicted using occupational histories and demographic information. However, even within occupations with high exposure to stress, burnout remains relatively uncommon, underscoring the limitations of conventional administrative data. In fact, a comparison of Figures 1b and 2a suggests that self-reported stress symptoms may be a more reliable predictor of burnout than occupational category. We now systematically conduct a horse race between these predictors.

To leverage the high-dimensional data provided by administrative records and workplace surveys, we employ an Extreme Gradient Boosting algorithm (Chen and Guestrin, 2016), a sequential ensemble method that iteratively constructs a series of decision trees and can flexibly incorporate interactions of independent variables used for prediction. This is a state-of-the-art method and has been widely used in economics, (e.g. Einav et al., 2018; Zeltzer et al., 2023). Appendix E provides details on the prediction procedure.

We predict burnout in the *next* calendar year, using six models trained on different samples and information sets. The two samples that we consider are the AMU survey sample and the entire Swedish population. For the AMU sample, we form four information sets: (i) basic demographics; (ii) basic demographics plus survey responses; (iii) a comprehensive collection of administrative data available to us ("kitchen sink" approach); and (iv) the administrative data augmented with survey responses. Basic demographic information includes gender, citizenship, age, and detailed education, comprising 348 categories. These categories cover specific qualifications (e.g., trained cardiologist) and fields of study (e.g., biology). We consider this to be the set of information available on a standard resume. Administrative data encompasses more detailed information such as marital status, duration since marriage or divorce, children's ages, spouse's income rank, occupation, earnings, employment, and sick leave over the past five years, firm-specific information like industry and turnover, and for men: cognitive and non-cognitive skills assessed during military enlistment. With few exceptions, basic demographics and administrative data are available for the entire Swedish population.

Table 3 presents the results. We measure classifier performance with the area under the curve (AUC). AUC is the area under the Receiver Operating Characteristic (ROC) curve, that is, the true positive rate against the false positive rate.

Focusing on the AMU sample, the simplest model—using only basic demographic variables—yields an AUC of 0.664. Incorporating survey responses into the set of predictors enhances model performance, raising the AUC to 0.724. In contrast, substituting survey responses with the full "kitchen sink" of administrative records, the AUC stands at a lower 0.703. The comparison reveals that predictions based on basic demographics and survey responses are more accurate than those using the full suite of administrative data.[46]

Targeted surveys that capture workers' own assessments of their work experience offer substantial information for predicting burnout that is not captured by administrative data. This likely helps explain why such assessments are already widespread in practice: 44 percent of European establishments with

[46] Appendix Figure A.22 evaluates the statistical confidence of the AUC for each set of predictors using the AMU survey sample. Using 1,000 random sample partitions, it plots the median AUC and a confidence interval reflected by the AUC at the 2.5th and 97.5th quantiles. The figures show that the AUCs reported in Table 3 are close to the median across these 1,000 random sample partitions.

a workforce exceeding twenty employees have surveyed their staff about work-related stress in the past three years (Howard et al., 2022).[47] However, these surveys are rarely followed by preventive interventions, despite evidence of the effectiveness of such programs (West et al., 2014; Linzer et al., 2015).

Consistent with their widespread use, self-reported stress assessments exhibit substantial independent predictive power. Figure 9b visualizes this result: the Cumulative Gains Chart exhibits a markedly larger outward shift when using information from survey data, compared to a model trained solely on administrative data. Notably, the highest prediction accuracy—an AUC of 0.742—is attained when combining survey and administrative data, further underlining the added value of subjective assessments alongside rich occupational and medical data.

Given the costs associated with large-scale survey initiatives, we use our prediction technology to explore two aspects that can inform the cost-efficient design of survey-based prevention schemes. First, we assess how frequent a survey would need to be to provide useful information for burnout prediction. Secondly, we investigate whether the survey can be reduced to a core set of questions while maintaining its predictive performance.

To assess the impact of survey frequency, we extend our prediction window to two years in the third column of Table 3. While self-reported stress helps predict burnout for the subsequent year, its contribution to predicting burnout two years ahead is limited compared to using administrative data alone. This pattern aligns with earlier evidence from Figure 1c, which shows that burnout is typically preceded by a sharp rise in stress levels during the year immediately preceding the event. These findings underscore a key trade-off: surveys capture acute, short-term signals, whereas administrative records—particularly those reflecting slow-moving characteristics like occupation—are better suited for predicting long-term risk.

To investigate the role of survey length, we focus on four predictors used in our stress index in Section 2. Their choice was informed by the medical literature (see Section 2). As a first step, we compare the performance of a classifier trained on these survey responses with that of classifiers trained on alternative sets of survey questions of the same length.[48] Appendix Figure A.21a shows that the stress index outperforms 94.4 percent of all other four-question combinations. This result provides an alternative, data-driven justification for our stress index.

Notably, Appendix Figure A.21a shows that the four-question stress index achieves an AUC of 0.711 relative to a baseline of 0.655 for only basic demographics. In comparison, a model trained on the full survey information yields a slightly higher AUC of 0.725. These results imply that the four-item index captures 80 percent of the predictive gains provided by the full survey. This share slightly increases to 85.4 percent when we perform the comparison with a richer set of administrative data. Taken together, these results imply that a parsimonious survey, focused on a small set of early-warning symptoms, provides substantial incremental value in identifying individuals at high risk of burnout.

Lastly, we explore to what extent prediction accuracy hinges on the sample under study. Unlike the survey responses, administrative records are available for the entire population. For the entire population, using basic demographics yields an AUC of 0.727, while the AUC increases to 0.81 when we use the full administrative data set for prediction.[49] This indicates that if we randomly choose one individual

[47] Among these, Nordic countries demonstrated the highest engagement rates, with Sweden leading at an eighty-four percent survey participation rate among establishments.

[48] Given the computational burden of evaluating all potential combinations of four questions and the fact that some questions might only be asked in a few survey waves, we pre-select a set of twenty-five viable questions that generate the best prediction when added to baseline observables individually. 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.

[49] Figure 9b also shows that the Cumulative Gains Charts for the population are shifted out when adding the kitchen-sink, and the

with burnout and another without, we have an 81 percent chance of correctly identifying the individual with a higher risk of burnout. The effectiveness of this algorithm in predicting burnout, especially when benchmarked against previous research, is noteworthy. For instance, Einav et al. (2018) achieved an AUC of 0.87 in predicting mortality, highlighting the robust performance of our model in the context of burnout prediction.

To disentangle differences in sample composition from potential returns to scale in predictive performance, we train our model on the full population sample and evaluate it on the AMU survey sample (Mueller and Spinnewijn, 2024). Appendix Figure A.20b displays Cumulative Gains Charts for various combinations of training samples and predictor sets. Comparing models trained on the full population to those trained on the AMU sample, we observe improved predictive accuracy—reflected in an outward shift of the gains curves—particularly when the model leverages the full set of administrative variables. In this setting, the AUC rises from 0.712 to 0.760. These findings indicate that when models are estimated on a rich set of predictors, expanding the training sample yields substantial improvements in performance, suggesting meaningful returns to scale.

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 prevention program. We then evaluate the additional value of incorporating a stress survey.

5.2.1 Cost-Benefit Analysis: Theoretical Framework

We start by theoretically examining the economic costs and benefits of a preventive program.[50] The program consists of two stages. The first is screening (triage), which identifies individuals at high risk. Triage costs p. It has a true positive rate α, and a false positive rate β. The second stage is treatment, applied to those detected, costing P per individual, and achieving a success rate θ. The success rate captures both the extensive margin—preventing burnout—and the intensive margin—reducing symptoms. The treatment cost should be weighed against the cost of burnout, denoted by C, which includes immediate and persistent income losses as well as spillover effects. The net benefit of treating an individual with a 100 percent risk of burnout is therefore given by $\theta C - P$.

To fix ideas, assume the entire population is enrolled in the prevention program. The per-capita gain from the program is given by:

$$(\theta C - P) \times \underbrace{\alpha b}_{\text{True positives}} - P \times \underbrace{\beta(1-b)}_{\text{False positives}} - p \tag{8}$$

where b is the true burnout rate in the population. If this expression is positive, then the program should be applied indiscriminately to the entire population or a random subset of individuals. If this expression is negative, which we assume, targeting is required for the program to be cost effective.

In practice, however, the planner (an employer or a government agency) observes some information that allows for risk stratification and selective referral of high-risk individuals to the program. Consider a scenario where the planner relies on a basic set of observable characteristics—gender, citizenship, age, and

plot is much smoother when using the population than the AMU sample.

[50]Our cost-benefit calculation does not constitute a full welfare analysis, as it omits utility costs associated with work, burnout, program participation, and exposure to risk.

education—to predict each worker's risk of burnout. We denote the rate of true burnout cases identified by the prediction model as $\pi(x)$ and the false positive rate as $\eta(x)$. The empirical counterpart to $\pi(x)$ in our context is illustrated by the Cumulative Gains Chart in Figure 9a. Individuals sent to the program are either true positives—correctly identified as high-risk—or false positives—mistakenly flagged by the prediction model. Formally:

$$x = b \times \underbrace{\pi\left(x\right)}_{\text{True positive rate}} + (1-b) \times \underbrace{\eta\left(x\right)}_{\text{False positive rate}} \tag{9}$$

The benefit of the program arises from those at risk who passed the triage—true positives. In contrast, false positives incur a net cost equal to the treatment cost P, without generating any corresponding benefit. The planner balances these benefits and costs when choosing the optimal share of the workforce eligible for the program, denoted by x, and seeks to maximize the per-capita net gain from the program:

$$W\left(x\right) = \left(\theta C - P\right) \times \underbrace{\alpha b \pi\left(x\right)}_{\text{True positives}} - P \times \underbrace{\beta(1-b)\eta\left(x\right)}_{\text{False positives}} - px \tag{10}$$

The optimal size of the program, denoted by x^*, is determined by equating the marginal benefit of expanding coverage to its marginal cost. The first-order condition for this optimization problem is:

$$\frac{\partial \pi\left(x^*\right)}{\partial x} = \frac{1}{b} \times \frac{p + \beta P}{\alpha\left(\theta C - P\right) + \beta P} \tag{11}$$

which follows from differentiating the per-capita net gain $W(x)$, and applying the identity (9) to eliminate the derivative of the false positive rate.

At optimum, the marginal true positive rate must exceeds one. This follows from the fact that the right-hand side of equation (11) exceeds one, because the program is not cost-effective when applied to the entire population, i.e., the expression (8) is negative. Consequently, the planner must concentrate the intervention on high-risk individuals, such that the marginal group added contains more than one true case of burnout per person treated.

The net impact of the program at the optimum is

$$W\left(x^*\right) = b[\alpha\left(\theta C - P\right) + \beta P] \times I(\pi) \tag{12}$$

where $I(\pi) = \pi\left(x^*\right) - x^* \frac{\partial \pi(x^*)}{\partial x}$ is the intercept of the cumulative gains curve at x^*. Geometrically, this is the value at which the tangent line—whose slope equals the marginal true positive rate—intersects the vertical axis, i.e., the line, given the detection rate, where the marginal benefit of screening another worker is equal to its cost. Equation (12) implies that the proportional change in the net gain of an improvement in the prediction model is equal to the proportional gain in the size of the intercept.

Now, consider augmenting the basic demographic information with data from a stress survey. Since the survey captures additional information beyond what is observable in demographics alone, the predictive model based on both sources yields a uniformly higher detection rate: $\pi_s(x) \geqslant \pi(x)$ for all x. The per-capita gain under the improved model becomes:

$$W_s\left(x\right) = \left(\theta C - P\right) \times \alpha b \pi_s\left(x\right) - P \times \beta(x - b\pi_s(x)) - px - \sigma \tag{13}$$

where σ is the per-capita cost of the survey. The optimal size of the program is determined by equalizing marginal cost and benefit, analogous to equation (11). The resulting net gain at the optimum is given by:

$$W_s\left(x_s^*\right) = b[\alpha\left(\theta C - P\right) + \beta P] \times I(\pi_s) - \sigma \tag{14}$$

Improved prediction reduces the required scope of the program, since it raises the marginal return—i.e., the likelihood of detecting true burnout by evaluating one additional person—for any given level of coverage. 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.

5.2.2 Cost-Benefit Analysis: Numerical Calculations

This section links the theoretical results on gains from optimal targeting, presented earlier, to our empirical predictions and the estimates of prevalence and cost. To calibrate the model, we assume that the type II error rate in the triage is 20 percent, corresponding to $\alpha = 0.8$, and a 10 percent type I error rate, $\beta = 0.1$. The cost of burnout is calibrated using our estimated aggregate loss of 3.63 percent, shown in Figure 8, and an average burnout prevalence of 1.12 percent in the population. This yields $C = 3.63/1.12 = 3.24$ and $b = 1.12\%$. We consider a preventive intervention with a success rate θ of 25 percent—broadly consistent with current evidence on program effectiveness—and a cost equivalent to one month of the average worker's income.[51] Finally, we assume a cost of triage of six hours.

The optimal size of the program can now be calculated using the equation (11). The optimal slope is equal to $\frac{\partial \pi(x^*)}{\partial x} = 1.5$. 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 9a).

Given this estimate, the total per-capita gain from optimal coverage of the program is $W\left(x^*\right) = 0.74\% \times 8.5\% = 0.063\%$. To gauge the magnitude, the same preventive program applied to a random sample of the same size would generate 0.12% loss.[52] Thus, incorporating even a simple prediction model based on basic observables converts a loss into a gain of similar magnitude—highlighting the value of targeted prevention.

Adding survey information to the prediction increases its performance, which shifts out the Cumulative Gains Chart (Figure 9a). Detection based on the survey, in addition to the basic demographics, reduces the optimal size of the triage group almost by half, from 31 percent to 18 percent of the population. The intuition for this reduction is that private information unrelated to demographics is highly informative about who is on the brink of burning out. The tangent to the new curve has an intercept of 18.2 percent.

The net gain of implementing the survey depends on its cost. We assume that the survey takes ten minutes to complete, in line with our finding presented earlier that most of its prediction power can be harnessed through a set of four questions (Appendix Figure A.21a). The total per-capita gain from the

[51] This assumption is supported by recent randomized controlled trials and quasi-experimental studies. For example, a recent meta-study of the effects of burnout reduction programs among nurses, found that interventions reduced emotional exhaustion—a result of chronic stress—with a standardized mean difference (SMD) of -0.75 and alleviate burnout (SMD: -0.7) (Lee and Cha, 2023). Using standard approximations that convert SMDs into changes in probability, these effect sizes correspond to reductions in burnout symptoms of about 20 percentage points, or a 40 percent improvement relative to a 50 percent baseline. Rousson and Guseva Canu (2023) shows that organizational and combined organizational and individual interventions reduce exhaustion with SMDs of 0.30 and 0.54, respectively, implying success rates of approximately 15–30 percent.. Hassan and Mohamed (2023) find that an 8-week mindfulness intervention halved emotional exhaustion scores among ICU nurses compared to controls. For further evidence from meta-analyses on program effectiveness, see, e.g., Zhang et al. (2020); Salvado et al. (2021).

[52] Using expression (8), $-0.0039125 * 31\% = -.12\%$

program with optimal coverage is: $W_s(x_s^*) = .13\%$. Therefore, the program's welfare gain is more than twice as large when complemented by a survey.

Until now, our examination of the costs and benefits of a preventative program has focused solely on labor productivity. We conclude by discussing how obtaining a more comprehensive measure of the cost of burnout—which includes the disutility associated with experiencing burnout—might affect our results.

As a hypothetical scenario, suppose we possess a measure of workers' willingness to pay to avoid burnout, and that this exceeds the estimated cost based on earnings losses. In this case, the benefit of the preventative program would be higher, the slope of the optimal policy flatter, and the scope of the optimal program broader. Consequently, the welfare gain from the program, as captured by equation (12), would be amplified through two channels: a higher benefit from prevention and an expanded optimal scope of the program. The same logic applies when prediction includes the survey (equation (14)). 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 of the larger welfare gain from prevention. In sum, as our baseline cost estimates underestimate the willingness to pay to avoid burnout, our estimated program gain represents a lower bound, while the incremental gain from the survey is uncertain.

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, occupational stress—via burnout—contributes to a substantial loss in aggregate labor productivity in Sweden.

To assess the external validity of our findings, it is crucial to recognize that burnout arises from the interaction between occupational 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.[53] 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 occupational stress in Sweden is well below the global average (Gallup, 2023). For example, stress levels in the U.S. are about 50 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, in contrast to the United States, where no paid sick leave program exists. 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 be one where similar individuals were exposed to the same degree of occupational stress, but with one residing in a country with paid sick leave and one 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

[53] 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).

with respect to daily benefit levels.[54] 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.23 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.[55] However, this does not imply that the total cost of burnout would decline proportionally. The extent to which inducing burned-out workers to continue working would increase overall labor income depends on the productivity of affected individuals when employed. Moreover, reduced eligibility for sick leave benefits could also lead to a deterioration in health outcomes, creating additional societal costs (Gelber et al., 2023; Black et al., 2024).

Although our findings suggest that the total cost of burnout might be lower in a hypothetical scenario where Sweden abolished paid sick leave, this does not imply that the total cost of burnout is lower in the U.S. or other countries without paid sick leave. As noted above, stress levels in the U.S. are substantially higher than in Sweden. Thus, while Sweden's system increases reported burnout rates by providing insurance, the true prevalence of burnout and associated economic costs may be even higher in the U.S. Quantifying the cost of occupational stress and burnout in the U.S. remains an important avenue for future research.

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 shifts, worker stress has been rising.[56] In our setting, a stark manifestation of this growing occupational 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.[57]

In this paper, we provide a comprehensive analysis of occupational stress, particularly the economics of

[54] 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.

[55] 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.

[56] 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).

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

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, when incentive compatible, such surveys can serve as effective tools for identifying individuals at risk and targeting preventive interventions.

We emphasize that our effort to understand this multifaceted issue is an invitation for 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, 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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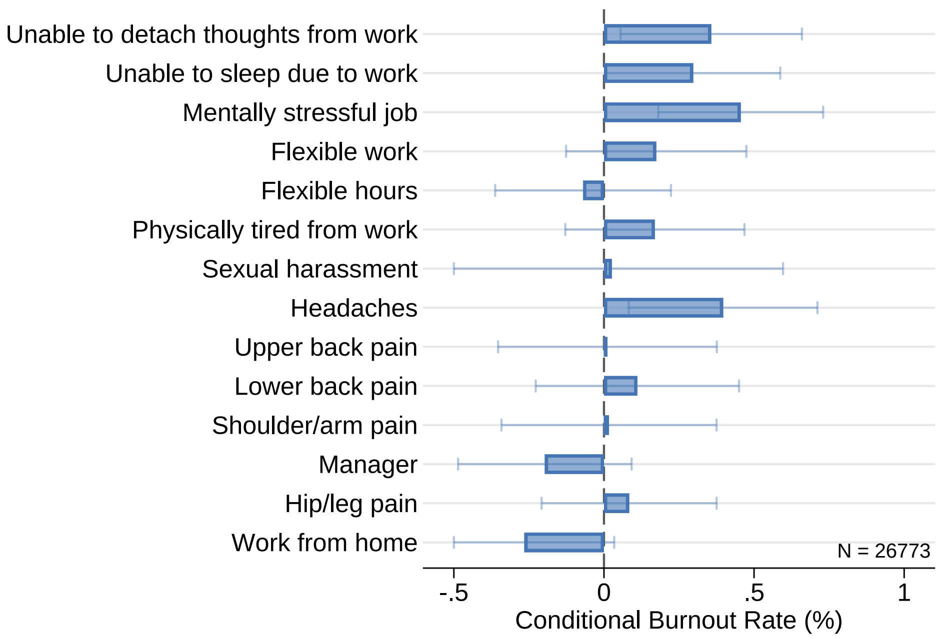
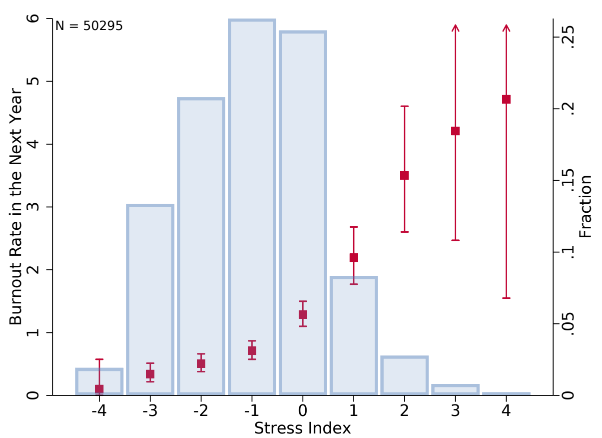
Figure 1: What is Burnout?

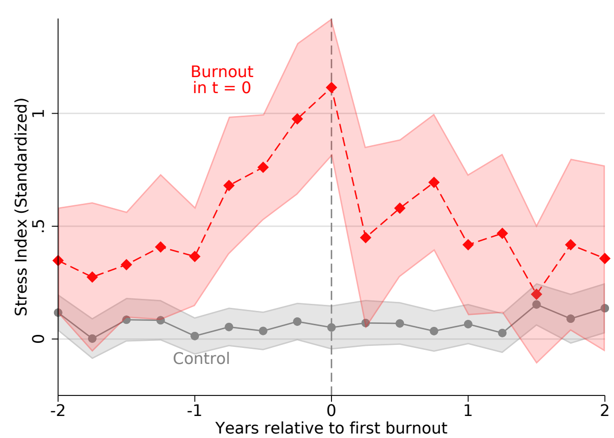
(a) Work Conditions and Burnout (multivariate regression)



(b) Stress Symptoms and Burnout Next Year



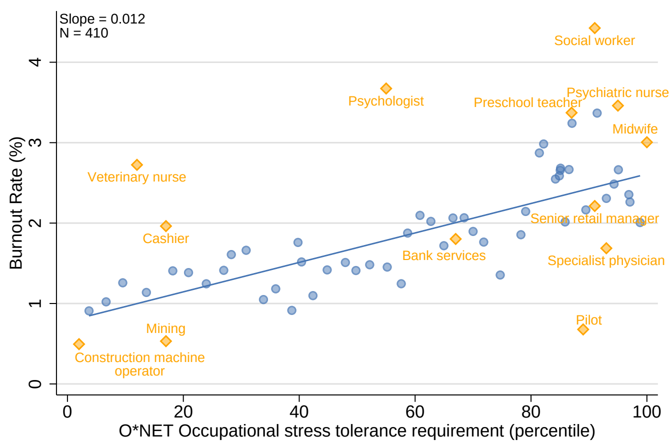
(c) Evolution of Stress Symptoms around Burnout



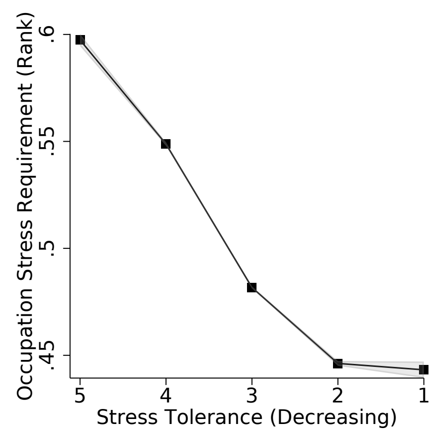
Notes: The figure documents the relationship between burnout and work conditions measured with the Work Environment survey (AMU). **Panel (a)** plots the coefficients from a regression of a burnout indicator on self-reported work condition in the previous calendar year, controlling for gender × education × age × family type fixed effects and year fixed effects. Work conditions are ordered by their relative association with burnout according to medical literature using an LLM (See Appendix C). For each work condition, we define 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. The stress index is constructed using self-reported conditions in panel a, which are 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. **Panel (c)** shows the evolution of the stress index around the time of burnout in cross-sectional data. As in a standard matched difference-in-difference design, we match workers with burnout to observationally similar workers based on demographic characteristics and the pre-burnout decile of labor income. The outcome is the z-score of the stress index with 95 percent confidence intervals.

Figure 2: Who is Affected by Burnout? Job Stress and Individual Stress Tolerance

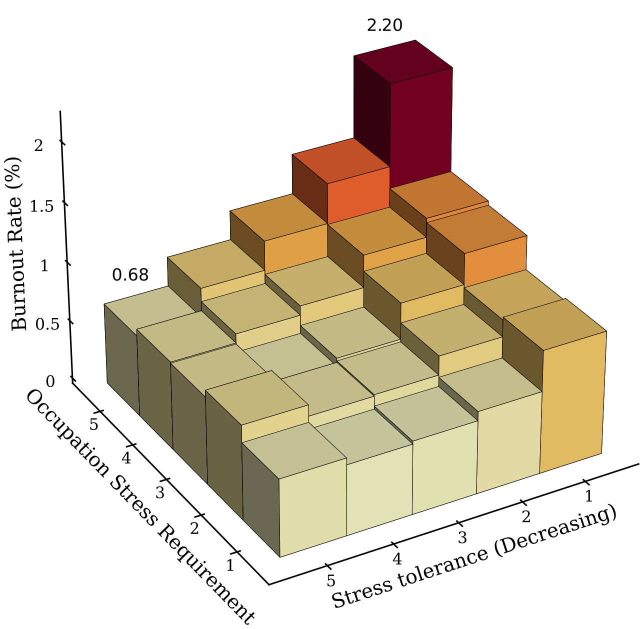
(a) Occupational Stress Tolerance Requirements



(b) Occupational Sorting



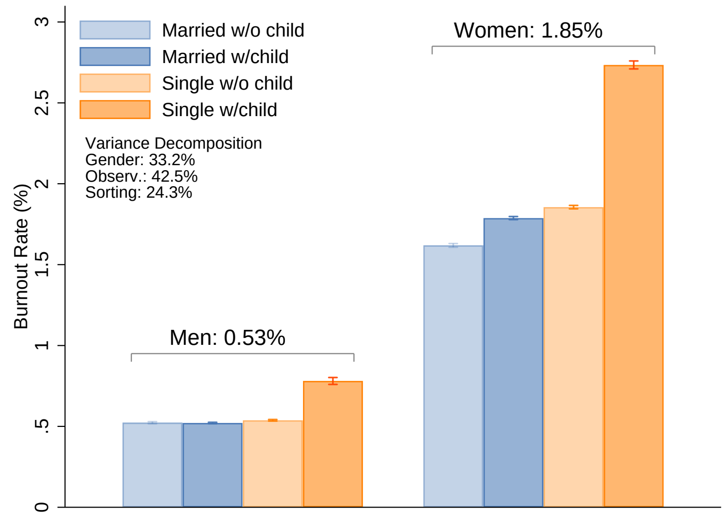
(c) Interaction Between Occupational Stress Tolerance Requirements and Workers' Stress Tolerance



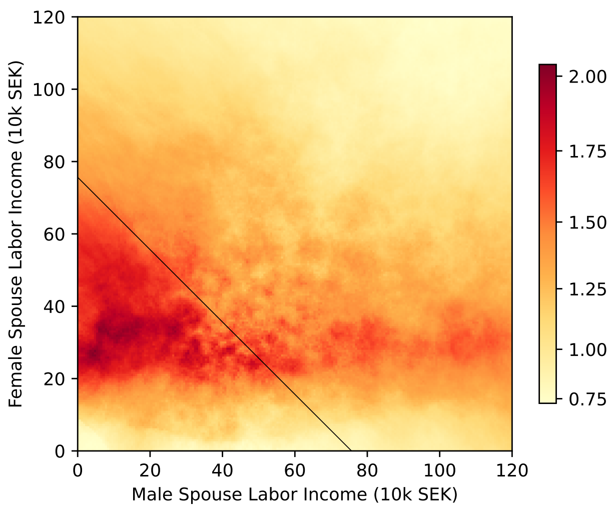
Notes: **Panel (a)** plots in solid blue dots the binned scatter plot of occupation-level burnout rate against occupational stress-tolerance requirement from O*NET. Orange diamonds are a selected subset of occupations. **Panel (b)** displays the sorting of workers with different stress tolerance across jobs with varying stress levels. **Panel (c)** plots individual burnout rates by the interaction of their stress tolerance and the stress tolerance requirement in their occupation. The occupational stress tolerance requirement is defined as the degree to which "Job requires accepting criticism and dealing calmly and effectively with high-stress situations." The individual stress tolerance is assessed at the age of 18 by psychologists in association with the Swedish military conscription. Panel (a) includes the both men and women whole panels (b) and (c) include only men due to data availability on individual stress tolerance.

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

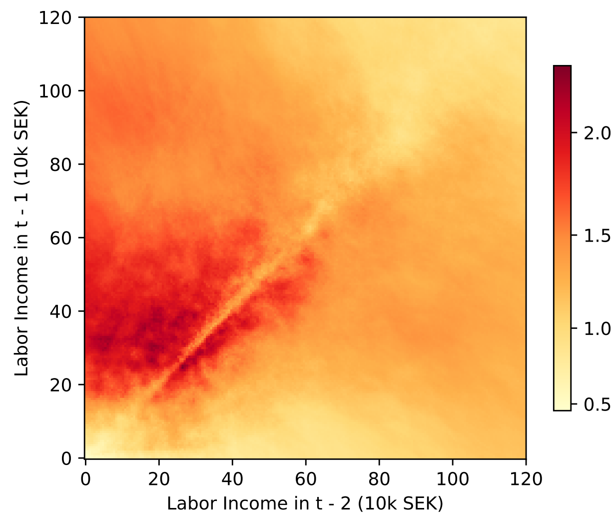
(a) Burnout Rate by Gender & Family Type



(b) Women: Burnout Rate by Couple Incomes



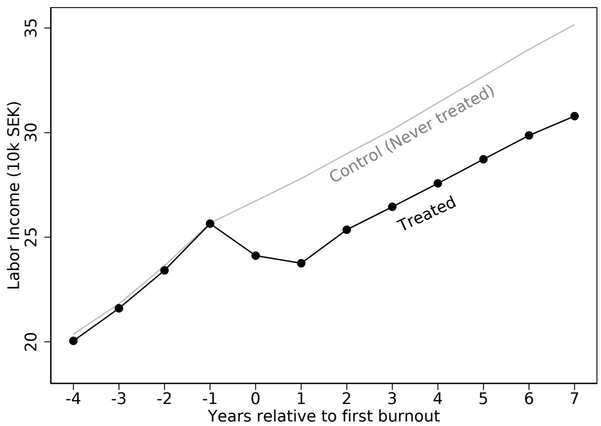
(c) Women: Burnout Rate by Income Growth



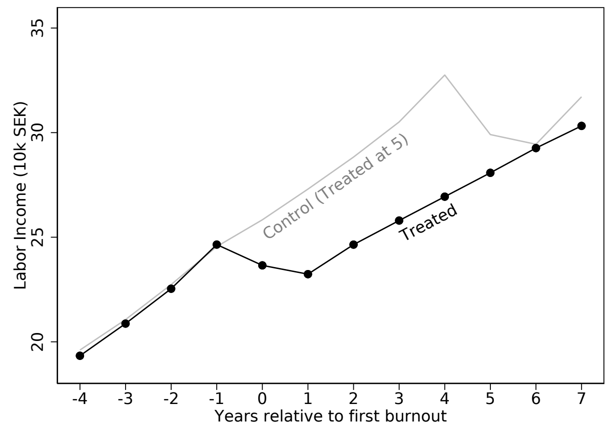
Notes: **Panel (a)** displays the annual burnout rate by marital and parental status and by gender, with an average of 1.12% for the entire employed population (20.0 million women and 24.9 million men). The respective shares in the four groups are 24%, 37%, 31%, and 8% for women, and 19%, 41%, 37%, and 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. Aside from gender and family type, the explanatory variables include native status, education, age, number of children and their age, labor income, 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 P97 of men and 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.6 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: Three Empirical Designs

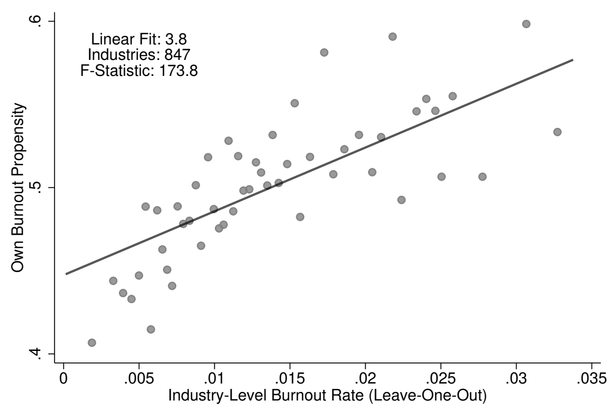
(a) Matched Difference-in-Differences



(b) Fixed-δ Method



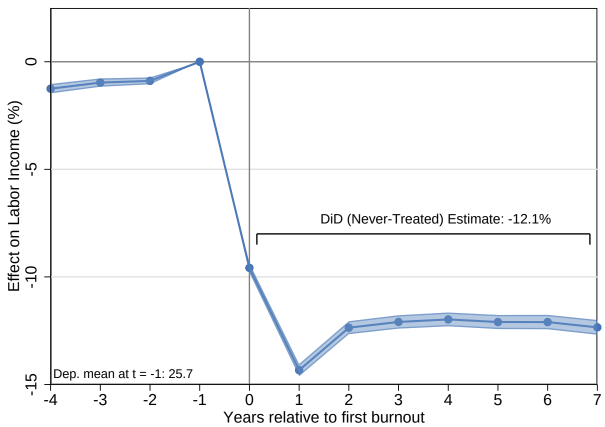
(c) IV First-Stage



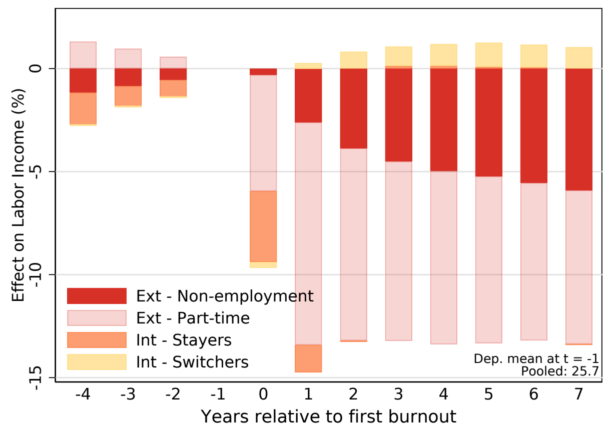
Notes: This figure showcases our three empirical designs. The estimation sample is a balanced panel of treated individuals with their first burnout between 2006 and 2013, aged 29 to 53 (so that all outcomes considered are from prime age, 25-60). **Panel (a)** shows the raw average labor income for the treatment (burned out) and control (never burned out) groups. 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 burnout and their employment history up to that year. This leads to a sample of 150,834 matched cases. **Panel (b)** shows the raw average labor income for the treatment (burned out) and control (burned out five years later) groups. We match treated and controlled individuals one-to-one on the same variables, with the sole exception being income where we use deciles instead of the percentile to increase the number of treated individuals for whom a control can be assigned. This leads to a sample of 99,861 matched cases. Labor income is nominal and expressed in terms of 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). **Panel (c)** plots the first stage in our IV regressions: a binned scatter plot of individuals' own burnout rate against the burnout rate among other workers in their industry. The sample of workers is the same matched sample as in panel (a) where, by construction, half of the workers burn out—the treated group—and the other half—the matched control group—does not. The industry-level burnout rates are calculated among the full sample of workers, leaving out the respective worker and their firm.

Figure 5: Burnout Effect on Income and Employment

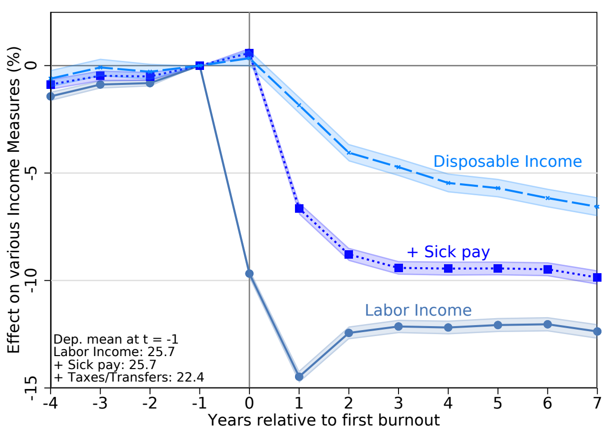
(a) Scarring Effect on Labor Income



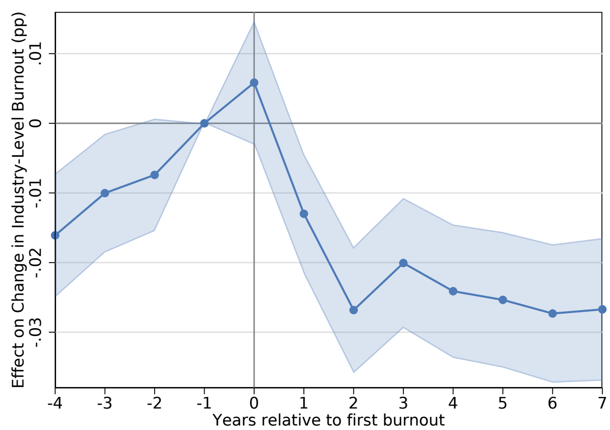
(b) Dynamic Decomposition of Labor Income Effect



(c) Social Insurance

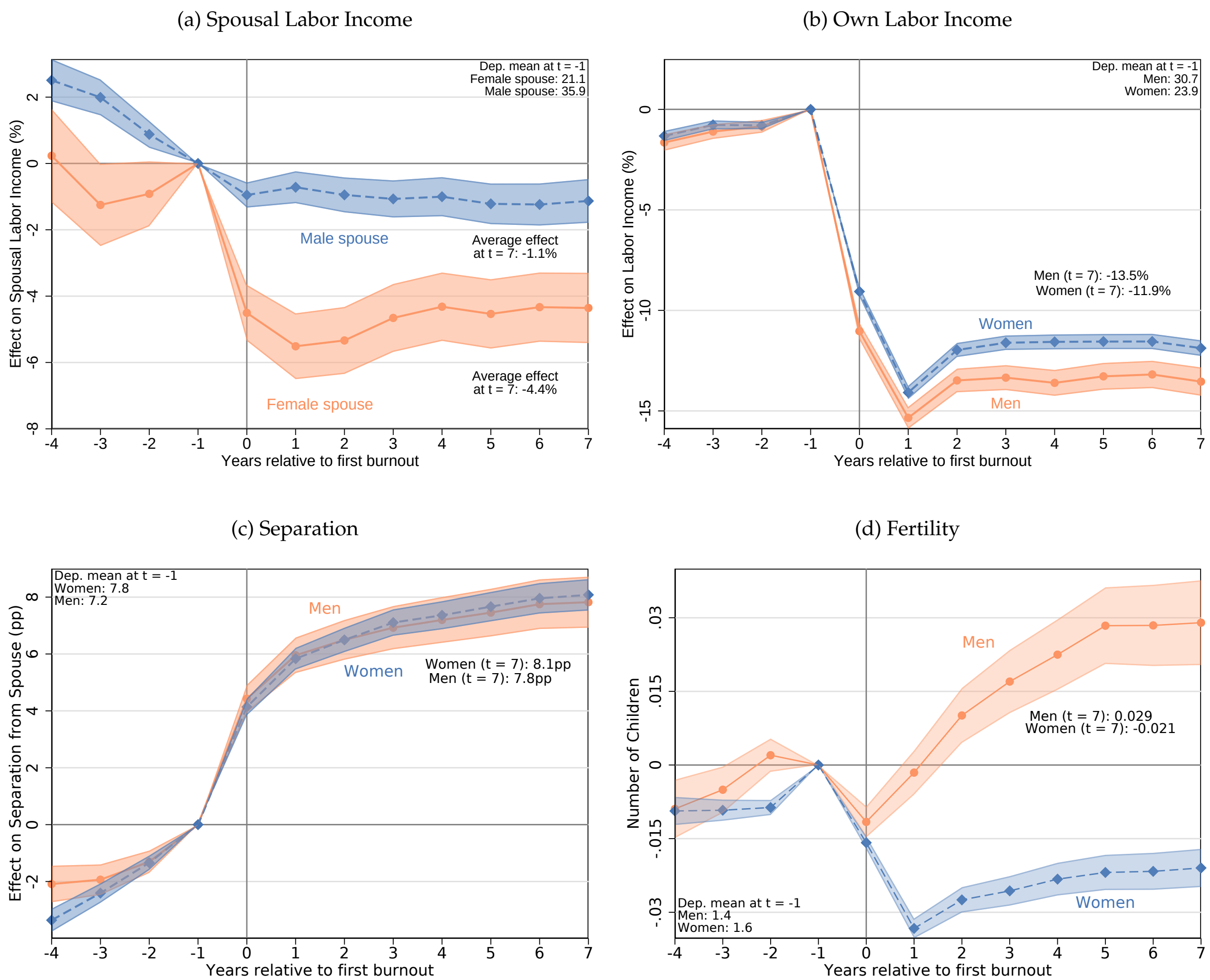


(d) Avoiding Future Stress



Notes: **Panel (a)** shows the proportional effect of burnout on labor income. Pre-treatment average incomes in 10k SEK and proportional effects are reported in the bottom left corner. It is based on the dynamic matched difference-in-difference model, plotting the coefficients on event-time fixed effect interacted with an indicator for burnout in equation (1). The shaded area is the 95 percent confidence interval based on individual-level-clustered standard errors. **Panel (b)** plots the dynamic decomposition of labor income loss according to equation (3) 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 the effect of burnout on labor income similar to Panel (a), labor income plus sick pay, and net income after all taxes and transfers. **Panel (d)** focuses on firm switchers and reports the burnout effect on the difference in burnout rates between their current industry and their industry in the year prior to burnout. Given the small number of firm switchers, we perform one-to-many matching to aid with the precision of the estimated treatment effects. All figures are based on a pooled sample of men and women except Panel (a).

Figure 6: Burnout Effect on Spousal Labor Income, Separation, and Fertility

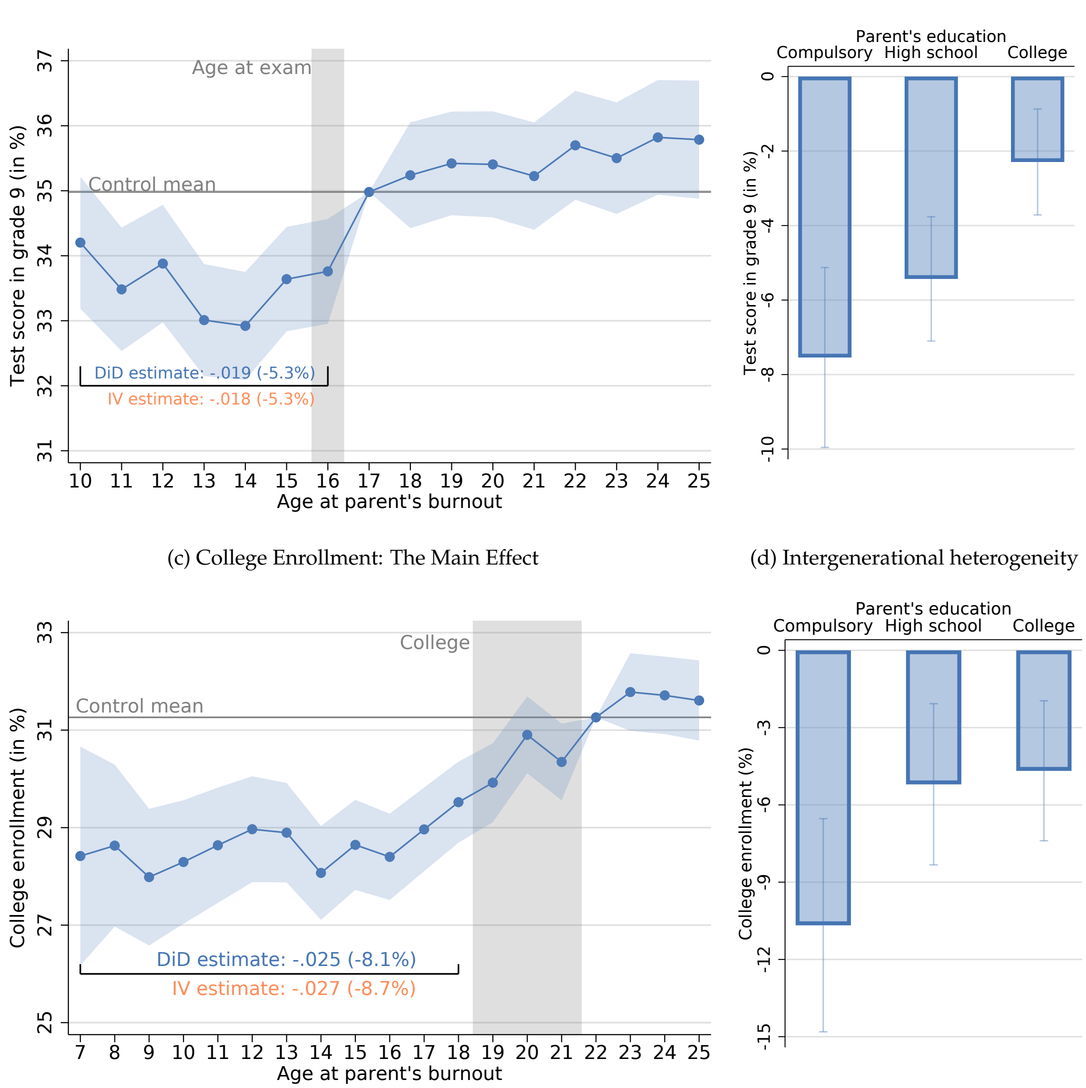


Notes: **Panel (a)** plots the proportional effect of burnout on the labor income of 57,441 spouses (married/cohabiting partners in the year prior to burnout), irrespective of the current marital status. It plots the coefficients on event-time fixed effect interacted with an indicator for burnout and 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 proportional effect of burnout on individuals' own labor income by gender. **Panel (c)** uses the same regression model to investigate the evolution of marital status. Separation is not being married to/cohabiting with the pre-burnout ($t = -4$) spouse. **Panel (d)** plots 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 7: Effects of Parental Burnout on Children's Human Capital

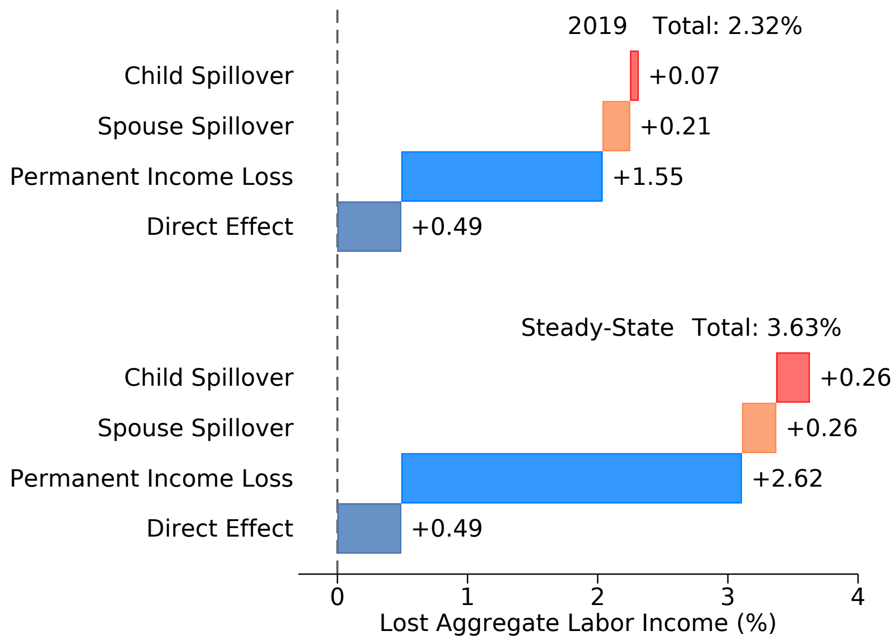
(a) School Grades: The Main Effect (b) Intergenerational heterogeneity

(c) College Enrollment: The Main Effect (d) Intergenerational heterogeneity



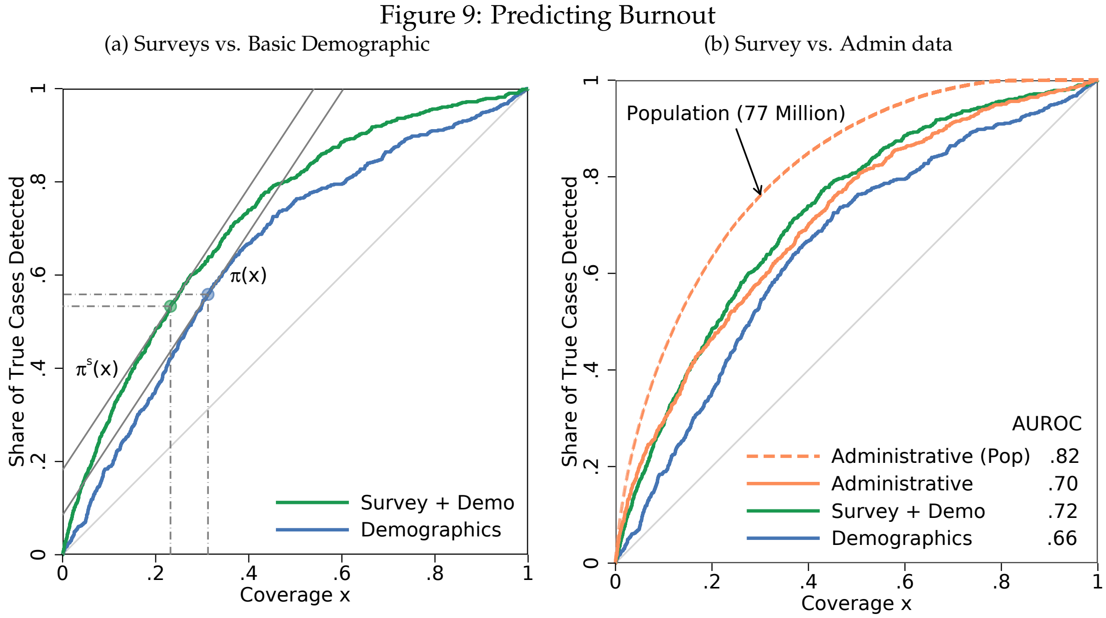
Notes: The figure plots the effect of parental burnout on children's performance (GPA) in national-level tests at the end of 9th grade around age 16 (**Panel (a)**), and on college enrollment measured at ages 19, 20, or 21 (**Panel (c)**). Heterogeneous effects on test scores and college enrollment by parental education are reported in **Panels (b)** and **(d)**, respectively . To separate treatment effect from cohort-specific trends, we demean the outcome using 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 (6) that controls for the parent's birth cohort and gender and the child's birth cohort, gender, and sibling order. The coefficient estimates measure the outcomes of children by age at the time of first parental burnout relative to those whose parents burn out when children are at age 17 (22), i.e., difference-in-differences, scaled by adding the mean outcome of the control group. The shaded area reflects 95 percent confidence intervals based on robust standard errors clustered at the parent level. "DiD estimate" reports the average effect for ages 10-16 (7-18). "IV estimate" reports an effect for ages 7-18 estimated by instrumenting parental burnout in equation (6) by the burnout rate among workers in their industry, leaving out the parent herself and her firm. The regression conditions on an industry fixed effect, exploiting variation in workplace stress within industries over time. The first-stage F-statistic in panel (a) is 3289 and 1123 in (b). In panels (b) and (d), we control for parent's birth cohort as well as child's birth cohort, gender, and sibling order. Parent's education is the education of the parent that burns out. The sample in panels (a) and (b) consists of 352,891 children whose parents experienced burnout in our sample period (2005-2019) and have turned 16 by the end of our sample period, implying that the youngest age in the sample is ten. Similarly, the sample of panels (c) and (d) consists of 297,668 children of burned out parents who have turned 21 by the end of our sample period, implying that the youngest age in the sample is seven.

Figure 8: Aggregate Loss in Income Due to Burnout



Notes: The figure presents our estimates of the loss of aggregate labor income due to burnout. The upper panel presents estimates for the year 2019, whereas the lower panel presents steady-state estimates assuming that the 2019 conditions are permanent. The aggregate loss is calculated using equation (7) 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 5a, iii) spillover effects on spousal earnings, reported in Figure 6a, and iv) spillovers on children's college enrollment, reported in Figure 7c.

Figure 9: Predicting Burnout



Notes: The figure shows the Cumulative Gains Chart for prediction models of burnout in the next 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, giving the optimal size of the program for each prediction. **Panel (b)** tests the prediction gain once the model includes all administrative data available to us. The sample consists of 61,121 individual-year observations in the AMU survey sample, with the exception of the dotted yellow line, where the sample extends to all 77,138,798 observations in the admin data. It assesses the advantage of a large number of observations. Administrative data (yellow lines) include information on family history (including spousal earnings); work history and occupational environment (including past earnings, sectoral mobility, unemployment experiences), medical history (sick leave spells by various diagnoses types), and physical, cognitive, and non-cognitive abilities.

Table 1: Descriptive Statistics

	Population 2006-2020	Burnout 2006-2020	Burnout 2006-2013	Matched sample
	(1)	(2)	(3)	(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				
$\mathbb{E}[Y \mid Y > 0]$	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 averages of key descriptive statistics across samples. Column (1) includes averages for the entire Swedish population who are between the ages of 25 and 60 in the period from 2006 to 2020. Column (2) restricts the sample to 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-difference design, which is a subset of column (3) restricted to individuals' first burnout incidents. Section 4 describes the construction of the estimation sample. Appendix Table A.3 shows impact of different sample restrictions on the size of the estimation sample. 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. We define natives as individuals born in Sweden. Married refers to both legally married couples as well as cohabitating couples with children. More granular information on the industry composition of the sample is reported in Appendix Table A.1.

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	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, estimates are weighted by the sampling weights. Because the occupational-classification system changed in 2014, we allow occupation fixed effects to differ before and after that year. The R^2 is expressed in percentage points. Standard errors are shown in parentheses.

Table 3: Burnout Prediction

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

Notes: The table reports AUC of predicting an indicator of burnout in the next calendar year (columns (1) and (2)), and two years ahead in column (3). AUC (Area under the Receiver Operating Characteristic Curve) is a common performance metric used in machine learning to evaluate binary classification models. The set of variables used for training is kept fixed in each row. *Basic Demographics* 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 over the same period.

Online Appendix of:

The Economic Burden of Burnout

Arash Nekoei, Jósef Sigurdsson, and Dominik Wehr
June 29, 2025

A Diagnosis Criteria for Clinical Burnout

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

A. Physical and psychological symptoms of fatigue for at least two weeks. The symptoms have developed as a result of one or more identifiable stressors that have been 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 direct physiological effects of any substance (e.g. drug of abuse, medication) or any somatic disease/injury (e.g. hypothyroidism, diabetes, infectious disease).

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

B Sample Selection

Event-Study Estimation Sample This section describes the construction of our estimation sample used in Section 4. Appendix Table A.3 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 EnvironmentSurvey

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 Prediction and Prevention

E.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.

E.2 Basic Demographic and Administrative Data

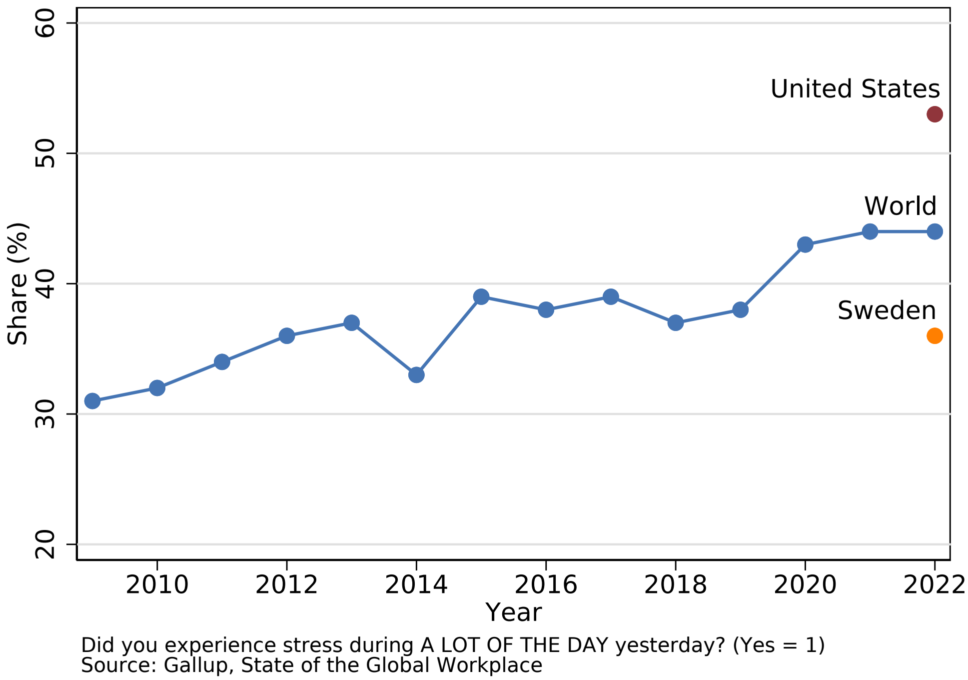
Basic Demographic data contain the following set of predictors: gender, age, citizenship status, education level (3 categories), education field (348 categories), municipality of the employer. For men, we also scores from the military enlistment tests on: inductive reasoning, verbal comprehension, spatial 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 interindustry 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.

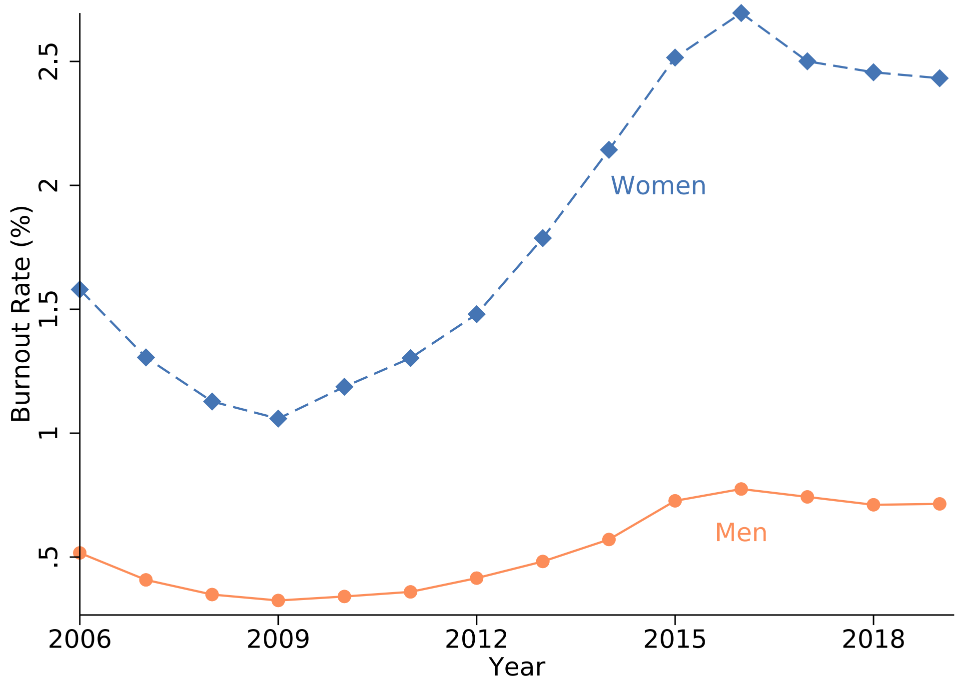
F Supplementary Figures

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.

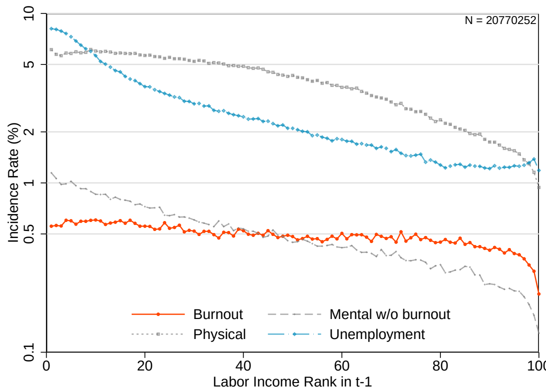
Figure A.2: Evolution of Burnout Rates over Time



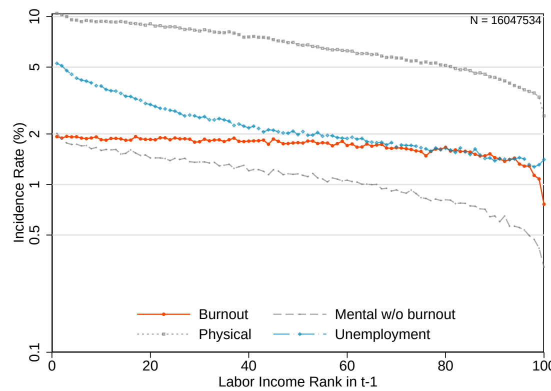
Notes: The figure plots the burnout rate, defined as the share of the population experiencing at least one burnout sick-leave spell in a given year among those full-time employed in the previous year between 2006 and 2019, the years where we have data on sick-leave spells and diagnoses for the full year.

Figure A.3: Incidence Across Income Distribution

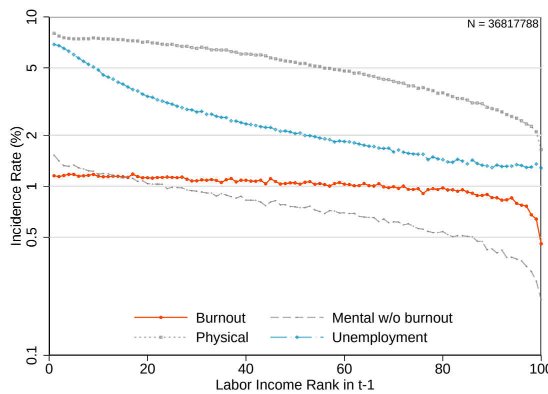
(a) Men



(b) Women

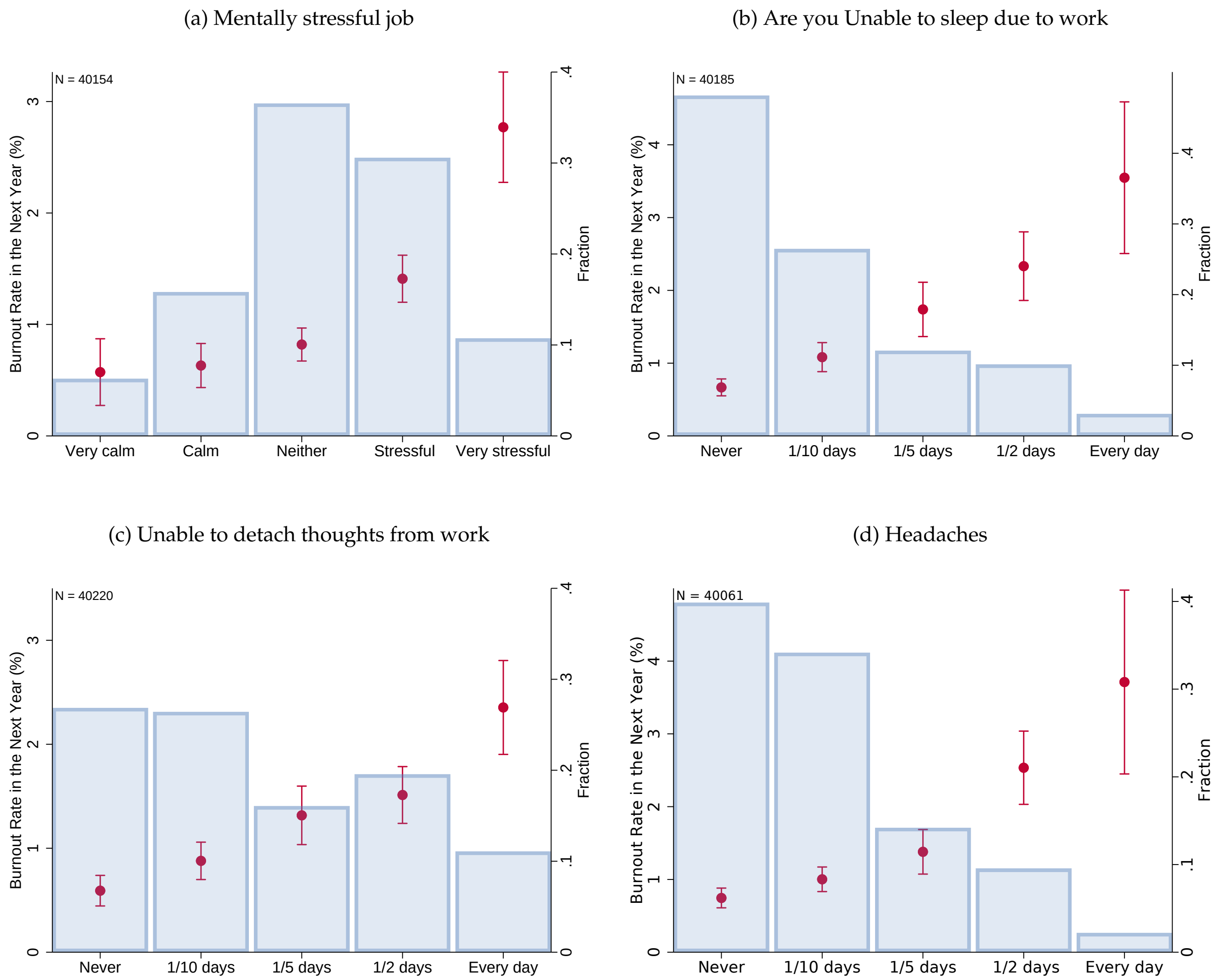


(c) Pooled



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 without 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.

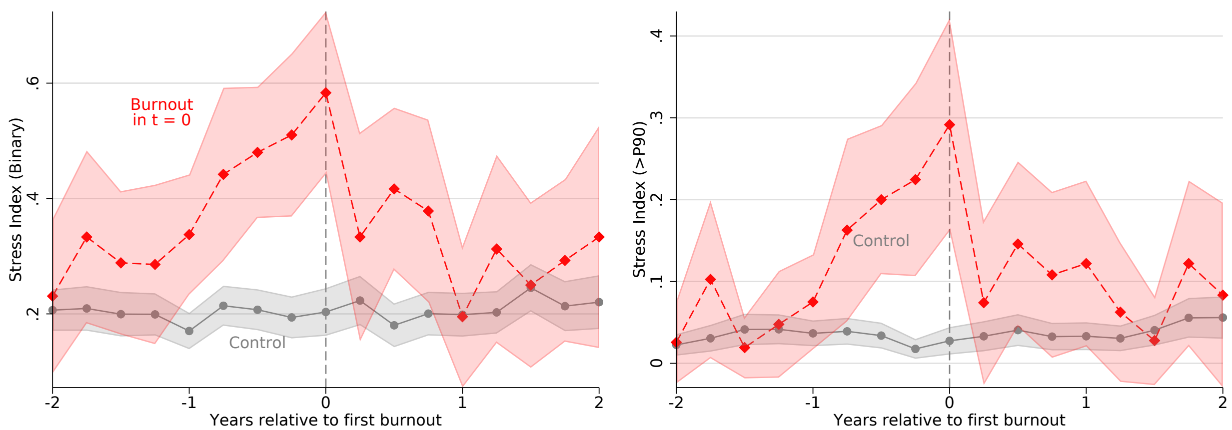
Figure A.4: Components of Stress Index



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.5: Evolution of Alternative Stress Indices Around Burnout

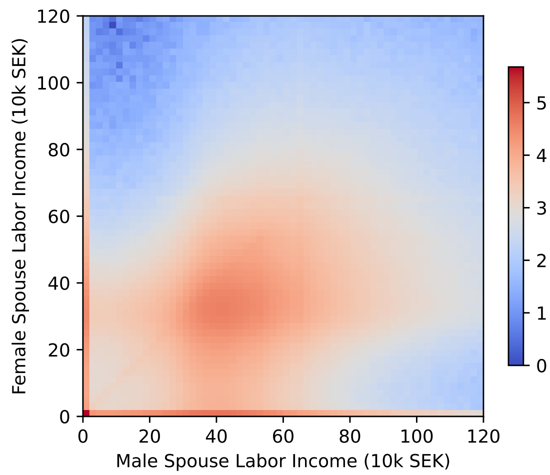
(a) Any Extreme Symptom (b) Stress Index Above P90



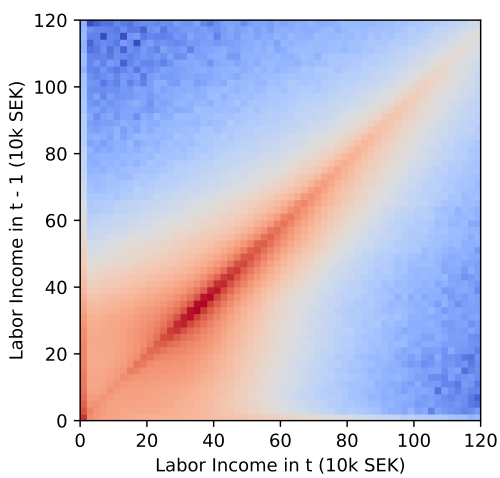
Notes: The figure shows the evolution of alternative measures for work-related stress around burnout. In **Panel a)** the outcome is an indicator assuming value one if a respondent gives the highest response to one the four questions about symptoms of burnout used in the construction of the stress index described in Figure 1. In **Panel b)**, the outcome is a binary indicator returning value one if the stress index, constructed in Figure 1, exceeds the 90th percentile of its cross-sectional distribution for a given respondent.

Figure A.6: Distribution of Labor Income Histories

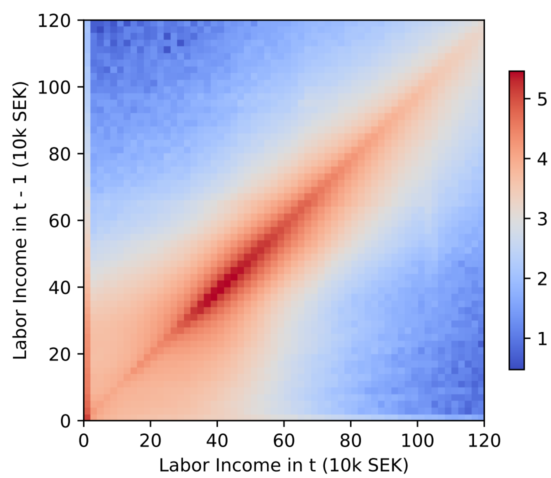
(a) Joint distribution of spousal labor incomes



(b) Income history (Women)

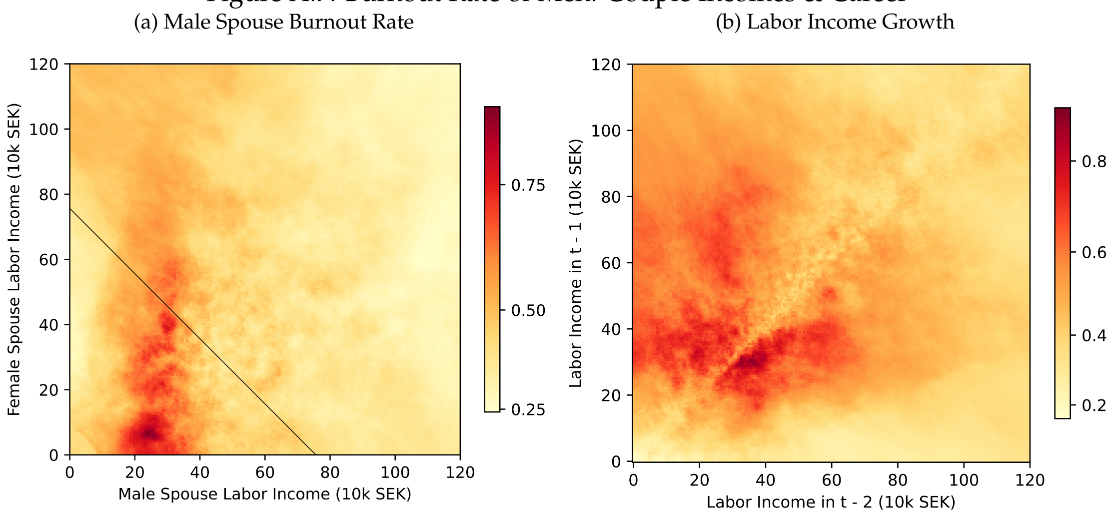


(c) Income history (Men)



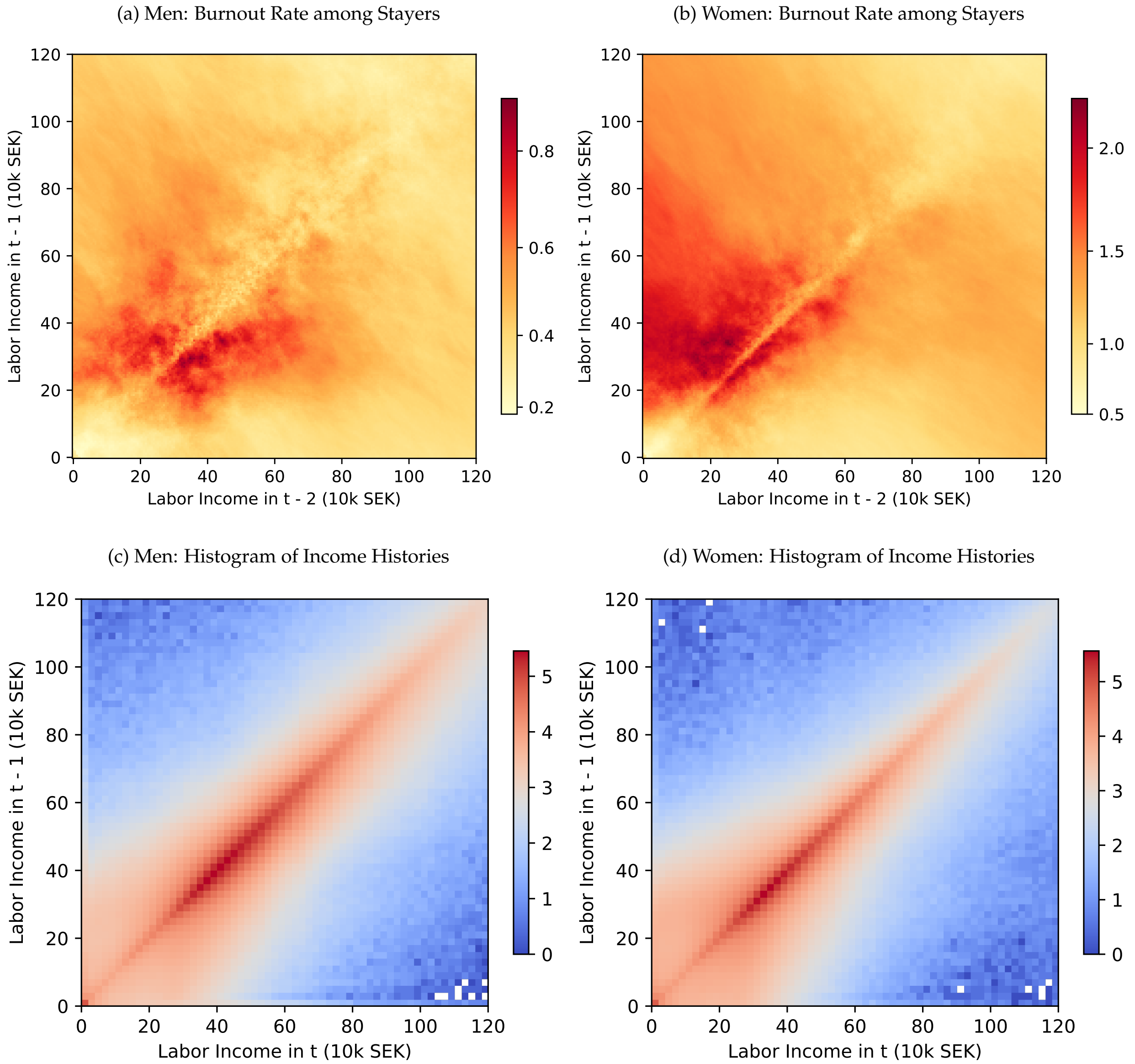
Notes: The figure shows the frequency distribution of labor income histories and joint income allocations. We discretize the state space using a grid with 2k SEK increments. The construction of the sample is described in Appendix Section B.

Figure A.7: Burnout Rate of Men: Couple Incomes & Career



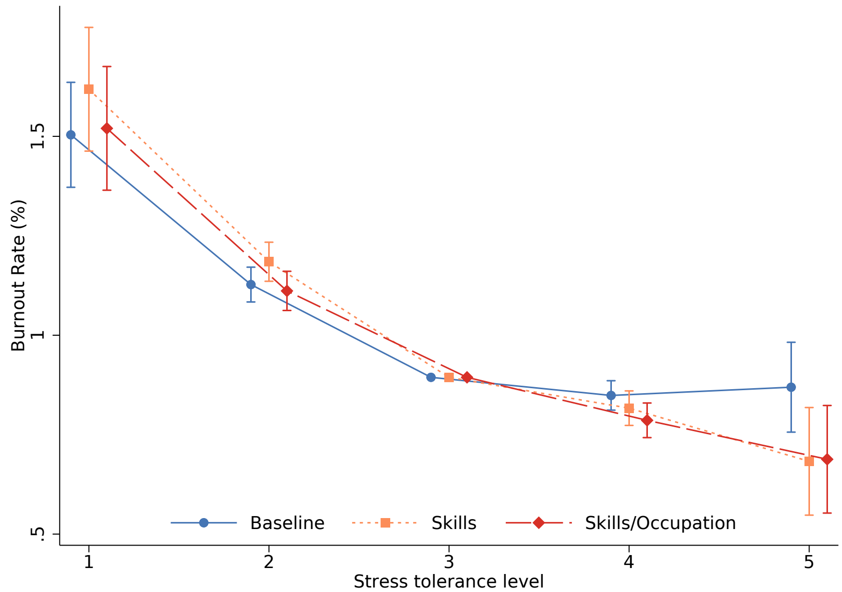
Notes: **Panel (a)** shows burnout rates over the joint distribution of spousal labor incomes for 11,008,512 couple-year observations in each subfigure. The two lines are 45-degree lines and a line marking the median couple's total income of 756k SEK. Annual labor income is winsorized at 1,200k (corresponding 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.6 for a more detailed description of the sample construction.

Figure A.8: Burnout and Labor Income Histories (Stayers)



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.

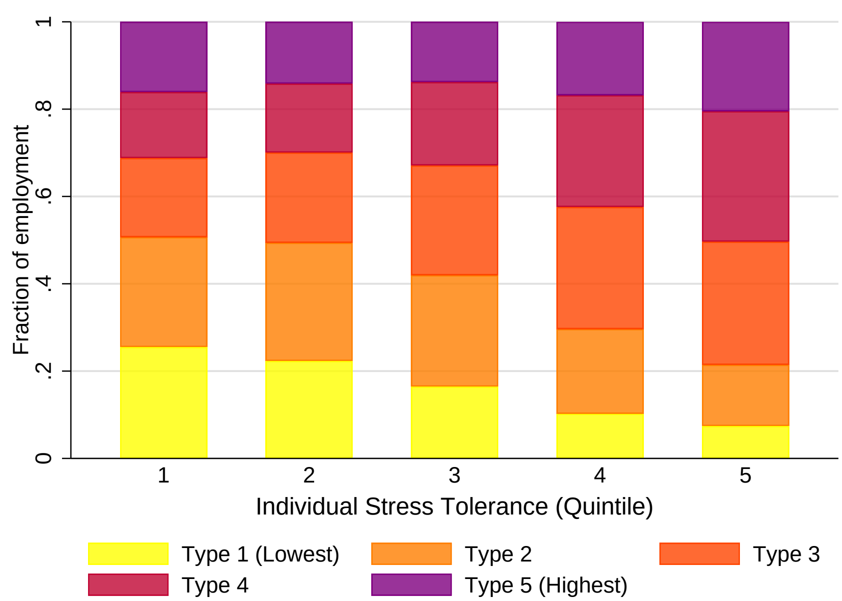
Figure A.9: Individual's stress tolerance and burnout



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.

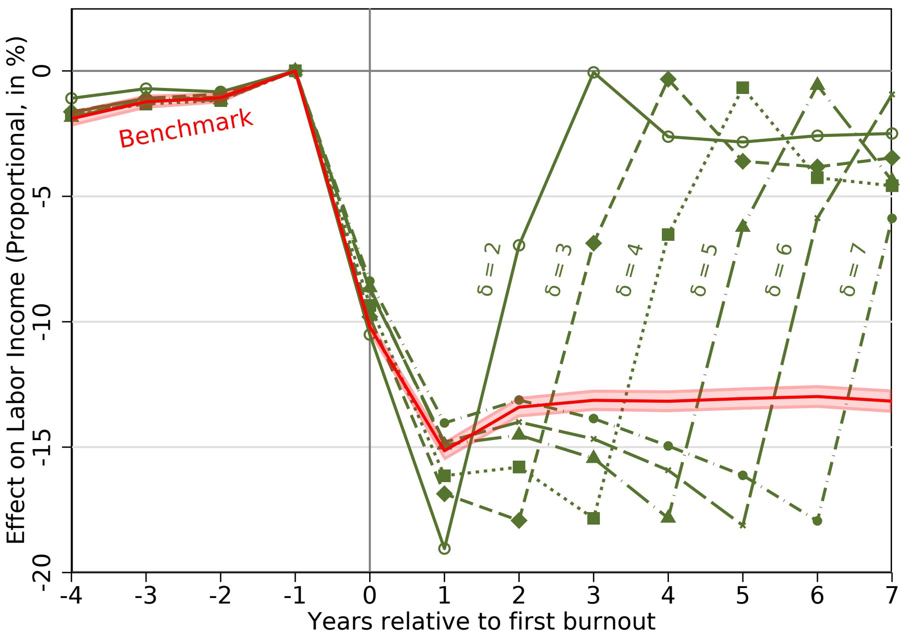
Figure A.10: Sorting

(a) 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.11: Effect of Burnout on Labor Income: Baseline vs. Fixed-Delta Method



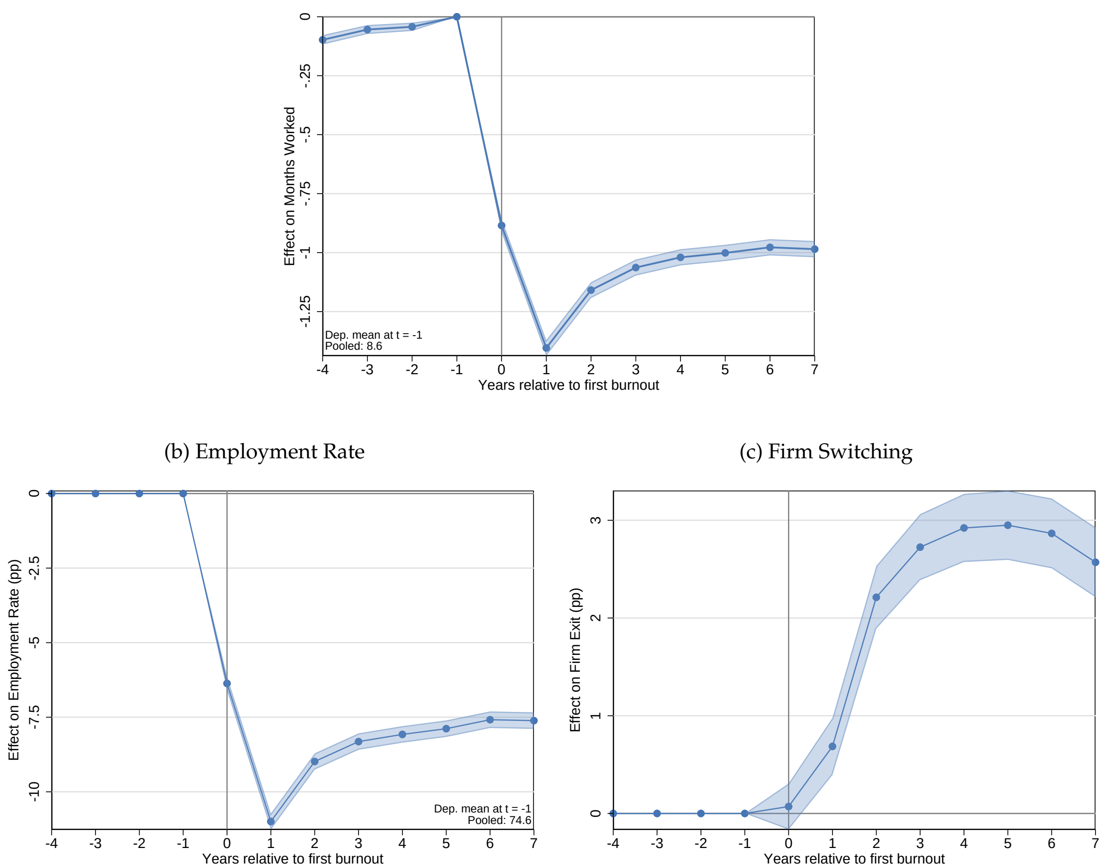
Notes: The figure shows the proportional effect of burnout on labor income as estimated with different matched control groups. The red line labeled *Benchmark* depicts the estimated effects when never-treated individuals are used as a control (Figure 5a). The control group in the remaining lines are 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.12: Burnout Effect on Labor Income: Extensive vs. Intensive Margins

(a) Months worked

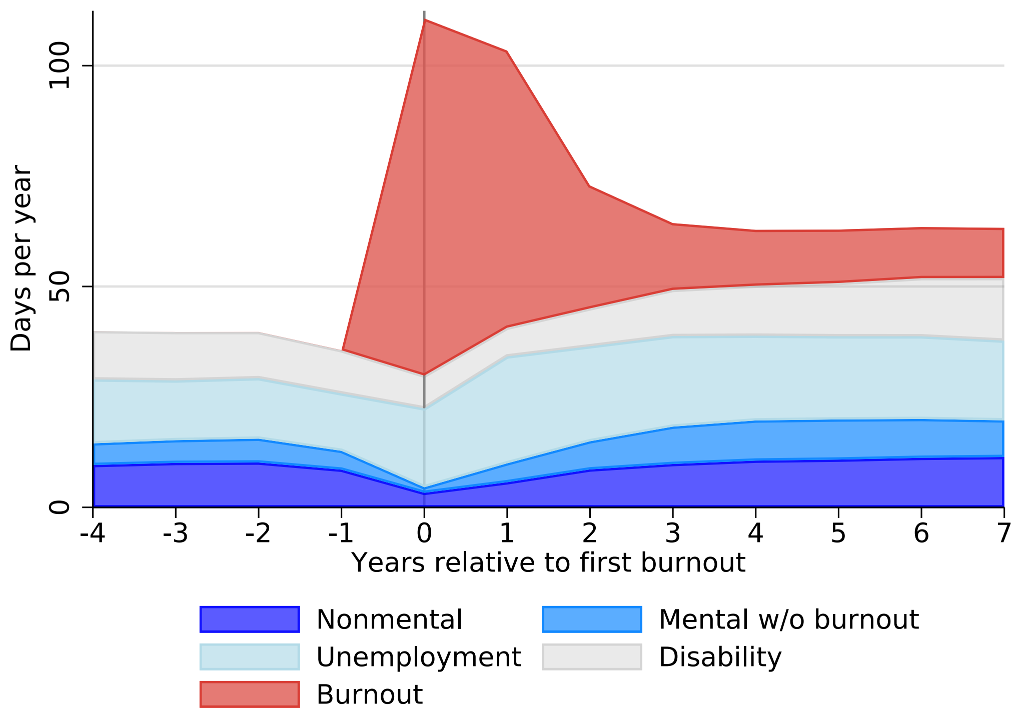
(b) Employment Rate

(c) Firm Switching



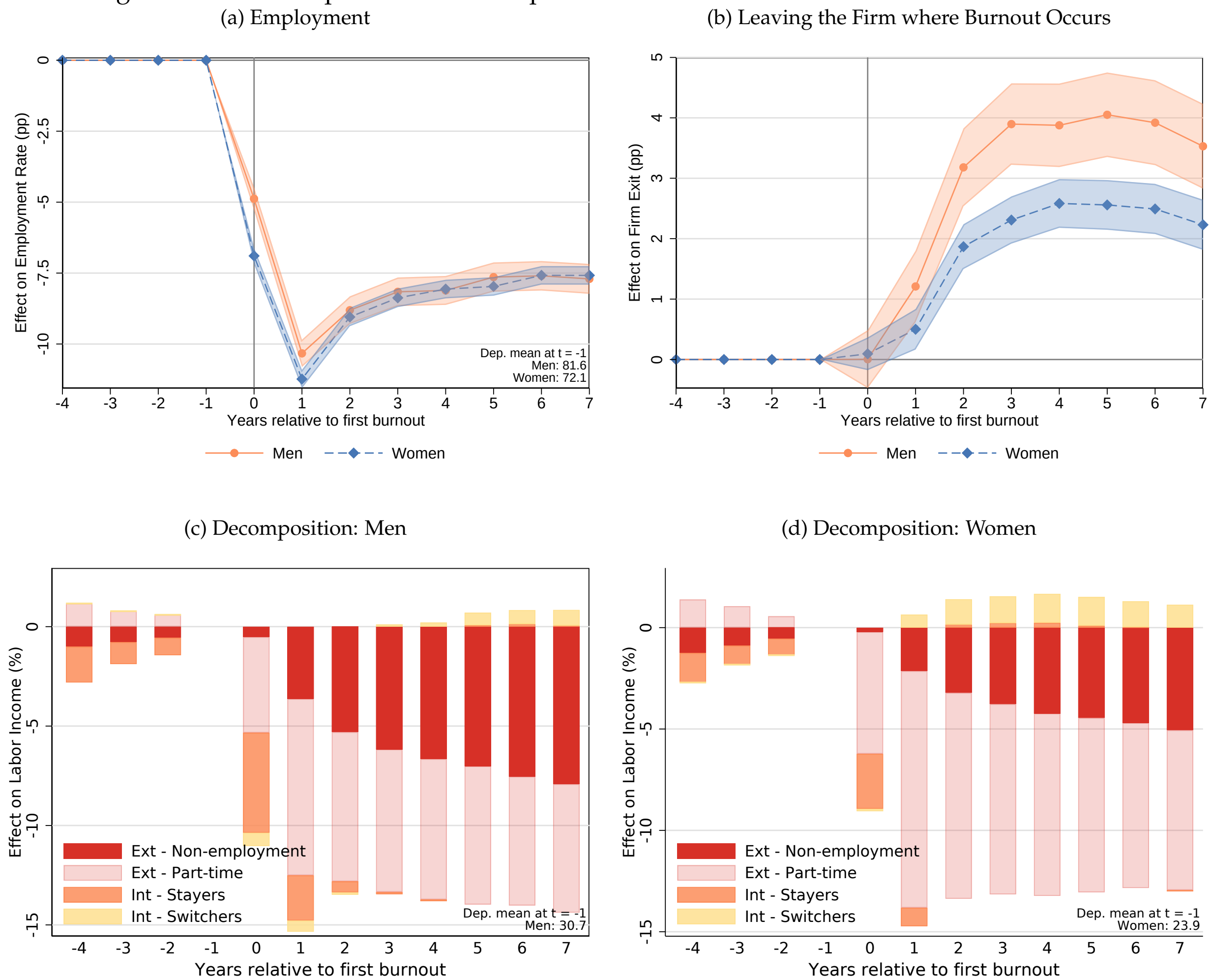
Notes: **Panels (a-c)** plot the coefficients on event-time fixed effect interacted with an indicator for burnout, and their standard error, from the dynamic difference-in-difference model in equation (1) for various labor market outcomes. **Panel (a)** reports the coefficients when the model is estimated 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.13: The Effect of Burnout on Days Worked



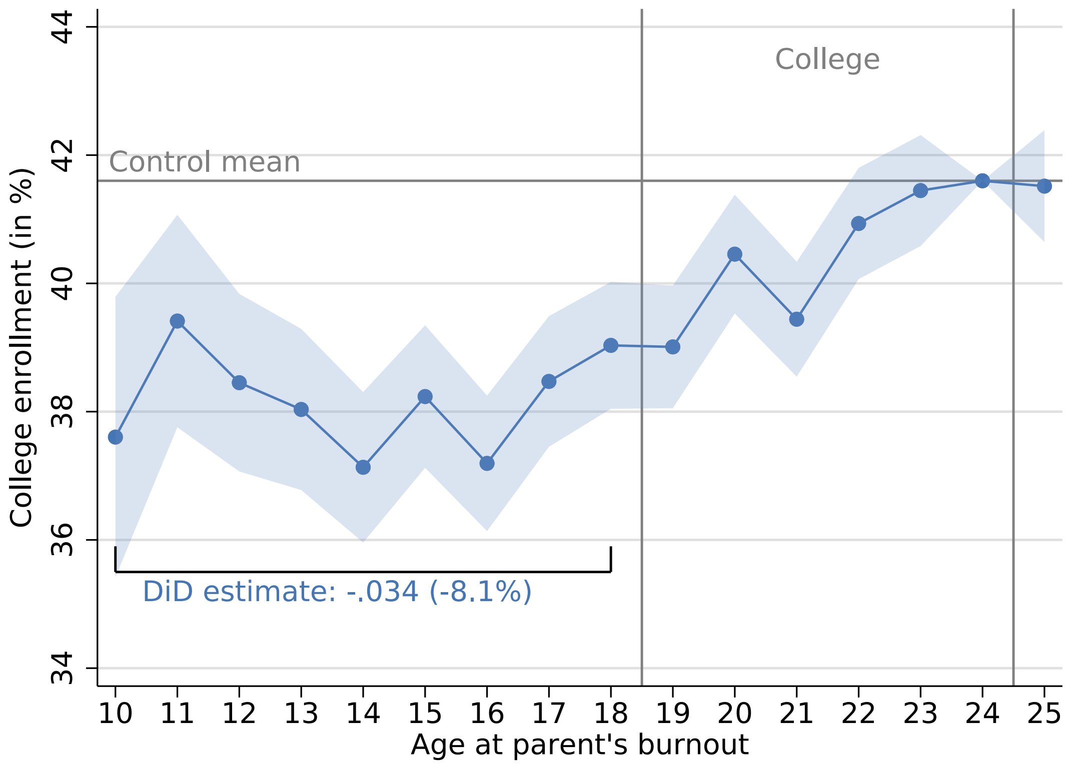
Notes: This figure presents estimation results of the dynamic difference-in-difference model for days on sick leave by diagnosis category, as well as days in unemployment and on disability.

Figure A.14: 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 (5) and (3). 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.

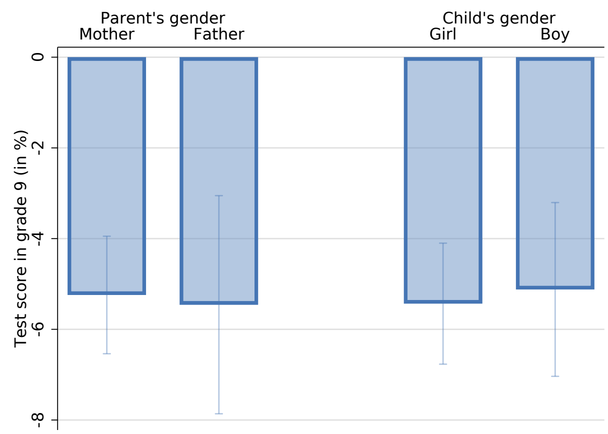
Figure A.15: Effect of Parental Burnout on Child's College Enrollment



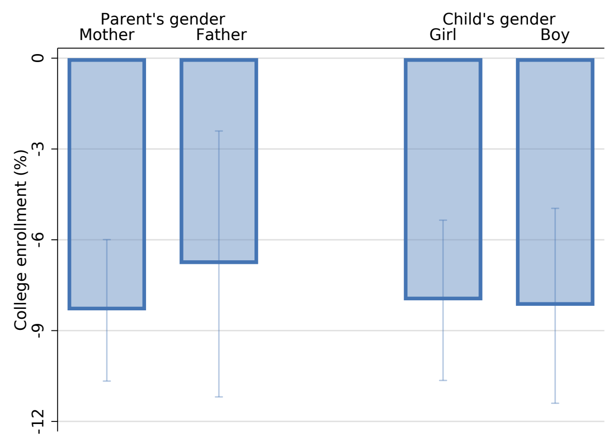
Notes: The figure plots the effect of parental burnout on children's college enrollment measured at some age 19 to 24. To identify deviations in the treated group from potential cohort-specific trends in college enrollment, we demean the outcome with the mean outcome of a control group with the same 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 (6) 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.16: Heterogeneity of Effects of Parental Burnout on Child's Human Capital

(a) School Grades



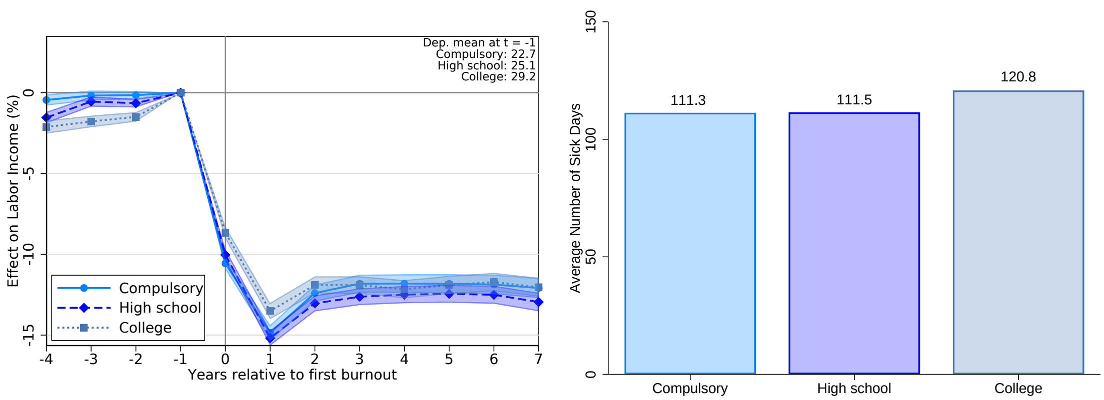
(b) College Enrollment



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 (6). 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 (6). 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.

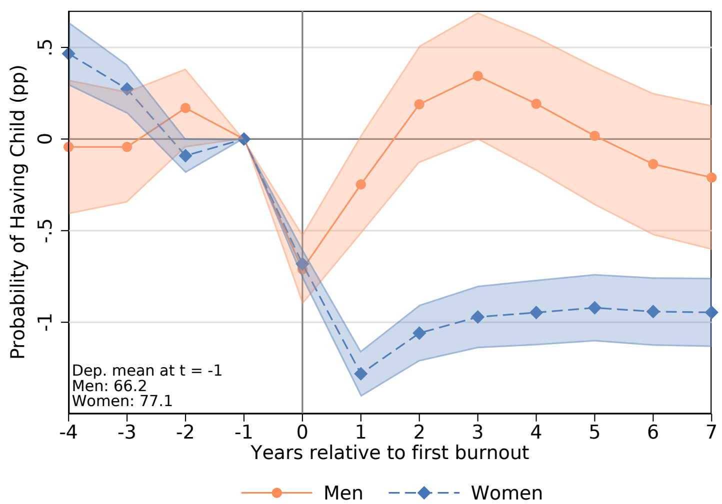
Figure A.17: Heterogeneity of Burnout Effects by Education

(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.18: 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 effect interacted with an indicator for burnout and their individual-level-clustered standard error from the dynamic matched difference-in-difference model in equation (1). The estimation sample is a balanced panel of 150,834 treated individuals with their first burnout between 2006 and 2013, aged 29 to 53. The control group consists of individuals who never experience 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.

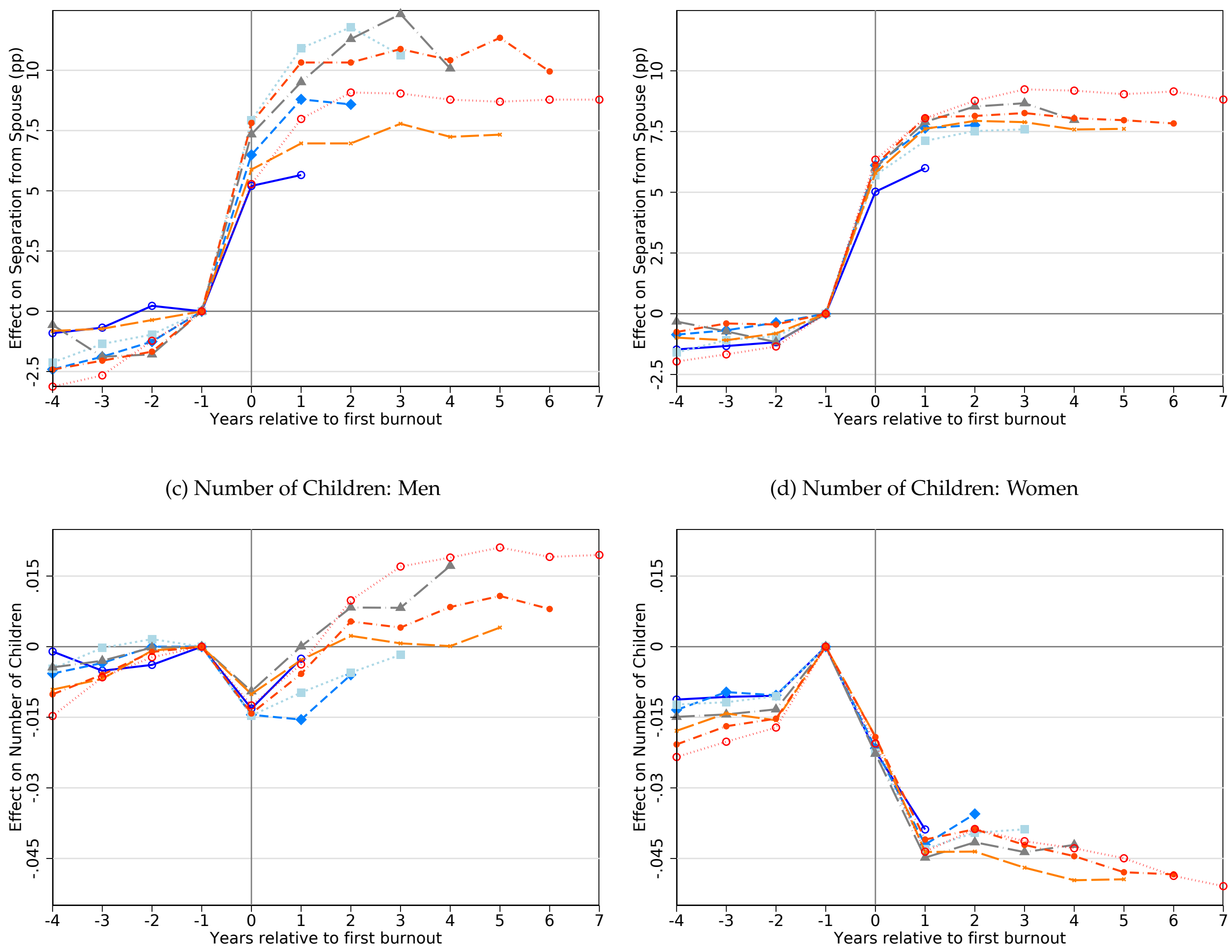
Figure A.19: The Effect of Burnout on Separation from Spouse and Fertility

(a) Separations: Men

(b) Separations: Women

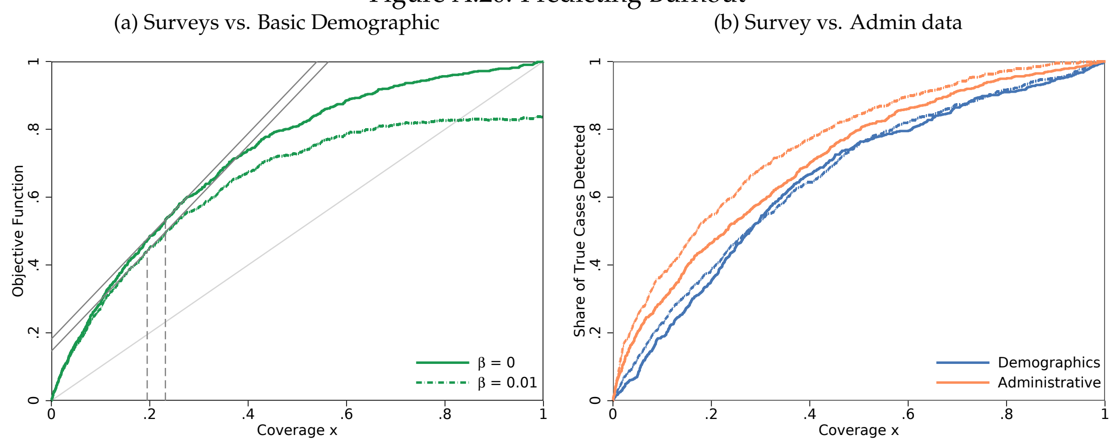
(c) Number of Children: Men

(d) Number of Children: Women



Notes: The figure shows the effect of burnout on separations from spouse **Panels (a) and (b)** and number of children **Panels (c) and (d)**, by gender. Separation is not being married to/cohabiting with the pre-burnout ($t = -4$) spouse. The lines show the estimated coefficients when not-yet-treated individuals who experience a burnout event δ periods ahead of the control group. The figure separately plots estimates for δ between 2 and 7. We plot coefficient estimates up until the period when the control group becomes treated (burns out), that is $t < \delta$. In addition, we provide an estimate using those treated eight to ten years ahead as a control. We match treated and control individuals on birth year, gender, education, and earnings percentile within their demographic cell. 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.

Figure A.20: Predicting Burnout

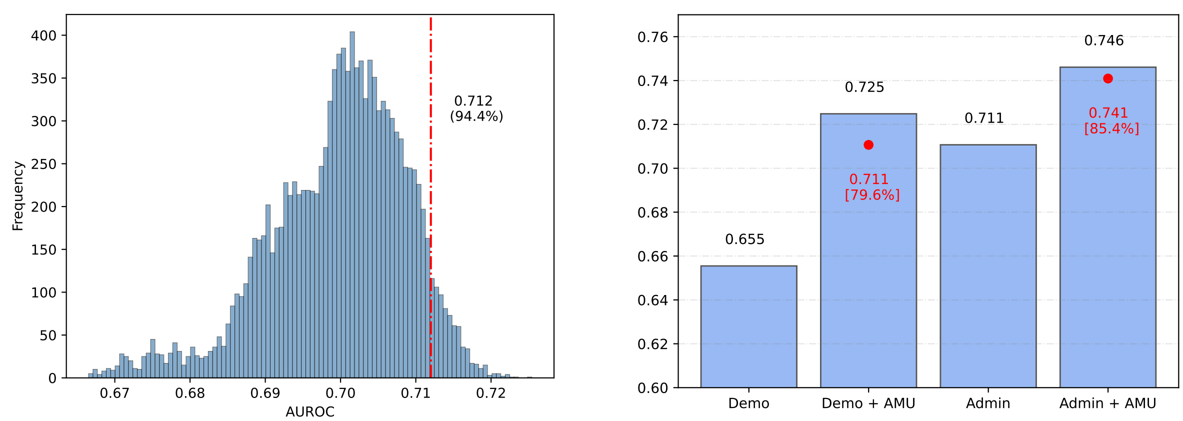


Notes: The figure shows the additional results for burnout prediction. **Panel a)** shows the the welfare gain of the preventive program outlined in () excluding screening costs under different assumptions for the effectiveness of the triage. Formally, the functions are defined as $\pi(x) + \Gamma^{-1}\Lambda f(x)$ where $\pi(x)$ is the true positive rate, $f(x)$ is the false positive and Γ and Λ are the expected returns on a true (false) positive being administered treatment. 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.21: Prediction Performance of Stress Index Components

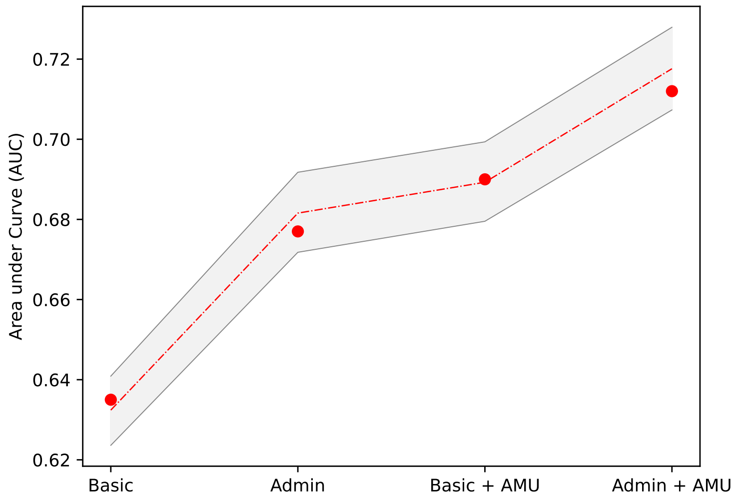
(a) Permutations

(b) Comparison with Complete Questionnaire



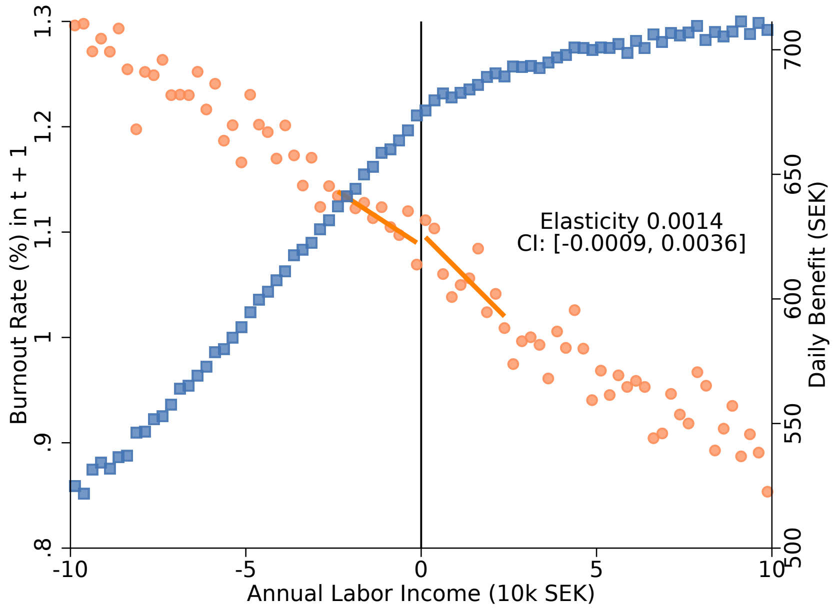
Notes: The figure demonstrates the predictive performance of the four burnout symptoms included in the stress index: lack of sleep, inability to relax, mental stress and headaches. **Panel a)** shows the distribution of the area-under-curve performance metric among alternative combinations of four AMU 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. 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.22: 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.23: 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.

Table A.1: 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.3 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.2: 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.3: 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.4: 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.5: 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.6: Burnout Prediction

Outcome: Burnout in	t + 1	t + 1	t + 2
Basic Demographics	0.636	0.727	0.628
Basic Demographics + 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. *Basic Demographics* 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 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.