The Economic Burden of Burnout

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Abstract

We study stress-related occupational illnesses (burnout) using Swedish administrative data. We document that work-stress symptoms emerge and progressively intensify over a year, reaching a tipping point of burnout. Burnout results in similar permanent income loss for both genders, although women are three times more susceptible. The repercussions extend beyond the individual, diminishing spousal earnings and lowering children's human capital—school grades and college enrollment—with stronger impacts on lower-educated families, reducing intergenerational mobility. Through sick leaves, earnings scars, and spillovers, burnout reduced national labor income by 2.3% in 2019. We show how estimated costs, combined with a prediction model incorporating a short work-stress survey, can improve the design of prevention programs.

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Introduction

Recent workforce surveys have revealed alarming levels of work-related stress worldwide. In one survey, 53 percent of American workers and 44 percent globally report being stressed for much of the previous day.[1] In response, the World Health Organization designated burnout as a health condition caused by chronic workplace stress in 2019 (WHO, 2019). Nine European countries, including Sweden, the country we study, had previously established medical diagnosis criteria for burnout (Lastovkova et al., 2018), drawing on decades of research in psychology and medicine (Freudenberger, 1974; Maslach, 1976; Maslach and Leiter, 2022).

Work-related stress can have severe negative health consequences, with symptoms including physical fatigue, cognitive problems (e.g., with concentration and memory), and emotional exhaustion (Shirom, 2003). In addition, it incurs substantial fiscal costs. In Sweden, 1.12 percent of workers were diagnosed with stress-related illness in 2019 and received sick pay equivalent to 0.33 percent of aggregate labor income. This figure is in the same order of magnitude as unemployment insurance claims, which stood at 0.76 percent.

Policymakers are alarmed by the escalating levels of work-related stress and its fiscal implications. Economists have three reasons to be concerned. First, the First Welfare Theorem breaks down in the presence of information asymmetry between employers and employees regarding work-related stress levels or their consequences, implying an insufficient compensating wage differential.[2] Second, private information about burnout risk results in the market under-providing insurance, justifying the provision of public insurance.[3] Third, even in scenarios with perfect information, burnout generates fiscal externalities via health or unemployment insurance systems that can justify a second-best policy intervention (Lipsey and Lancaster, 1956).

This study advances our understanding of the economic consequences of work-related stress by examining risk factors of burnout, studying its economic implications, and documenting the presence of private information about work-related stress. Our primary data source is the universe of sick leave records and associated medical diagnoses from 2006 to 2020. We identify burned-out workers as those who have been diagnosed with a stress-related illness and taken sick leave. Sweden's early adoption of specific burnout diagnosis criteria presents a unique opportunity to analyze long-run labor market outcomes for burned-out workers. By integrating this data with various administrative datasets and a work environment survey, we are able to conduct a comprehensive analysis.

In the first step, we study how jobs contribute to the risk of burnout. We begin by documenting substantial heterogeneity in burnout rates across industries and occupations.[4] To evaluate the

[1] Gallup (2023). For similar evidence, see two surveys by the American Psychological Association, "Stress in America" and "Work in America," (APA, 2023a,b) and the "European Working Conditions Survey" (Eurofound, 2007, 2016). For more, see ILO (2016).

[2] Previously, the compensating wage differential for layoff risk has been extensively researched, e.g., Lalive and Zweimuller (2006) and Del Bono and Weber (2008); see Nekoei (2014) for an overview.

[3] In the case of layoff risk, private information causes the insurance market to unravel (Hendren, 2017).

[4] This echoes prior findings of larger burnout rates in occupations with social interactions (Maslach et al., 2001; Seidler et al., 2014; Maslach and Leiter, 2016), and in the service sector (American Psychological Association, n.d.).

effect of firms on burnout, disentangling the impact of worker sorting, we adopt the methodology of the seminal work by Card et al. (2013) to study workers who switch between firms with different burnout risks as measured by the burnout rate of other workers.[5] Most strikingly, moving from the least risky quartile of firms to a firm in the most risky quartile quadruples the likelihood of burnout.

To evaluate whether the change in the likelihood of burnout subsequent to changing firms reflects differences in sick leave take-up or work stress, we use the mover design to study workers who switch occupations. We find that occupational changes—within or across firms—yield a pass-through of 70 percent: transitioning into an occupation with a one percentage point higher burnout risk increases a worker's likelihood of burnout by 0.7 percentage points. The consistency in pass-through rates for occupation changes, whether within or across firms, emphasizes the significance of the nature of work over the culture in firms. We complement our evidence of the impact of jobs on burnout by using a regression framework with individual and occupation fixed effects. We discover that firms with high burnout rates pay lower wages—contradicting the existence of a compensating wage differential for stress—and exhibit lower value added per worker.

Burnout occurs more commonly among workers in stressful jobs, especially for those with a low tolerance for stress. To document this, we use information on stress tolerance requirements of occupations from O*NET and individuals' stress tolerance assessed at age 18 by psychologists during the Swedish military draft.[6] We first document patterns of systematic but quantitatively limited sorting of stress-tolerant workers into stressful jobs. We then show that in high-stress occupations, low-stress-tolerant workers exhibit a significantly higher likelihood of burnout compared to those with higher stress tolerance. However, this disparity does not appear in low-stress jobs. This mismatch exacerbates the prevalence of burnout.

In the second step, we study the economic consequences of burnout. We use a matched differences-in-differences design where we compare each burned-out individual with an observationally similar peer who did not burn out.[7] Burnout is preceded by steady earnings growth, which is faster than that of the control group. Burning out has a negative, substantial, and persistent effect on labor income, similar to the well-documented displacement effect of layoff (Davis and Von Wachter, 2011). At impact, annual income drops by nearly 15 percent, largely attributed to sick leave days. Seven years later, the income drop stabilizes at 12 percent, with half resulting from labor market exit and the other half from transitions into part-time employment. In addition, workers are more likely to move to jobs with lower burnout risk

[5] In our dataset, we observe both firms and plants (establishments). Unless specified otherwise, our analysis is conducted at the plant level, though we refer to them as "firms" for simplicity in terminology.

[6] Caveats of the first measure are potential measurement errors in O*NET, uncertainty in the occupation crosswalk between Sweden and the U.S., and differences in the nature of occupations between the two countries. A limitation of the second measure is its availability only for men.

[7] We also use a complementary strategy that compares a burned-out individual to a similar individual who burns out few years later, leveraging random timing of burnout in a small window of time (Nekoei and Seim, 2023). This design addresses the concern of underestimating earnings losses as burnouts are preceded by increased career progression. Reassuringly, we find that our estimated income scars from burnout are not sensitive to the choice of strategies.

subsequent to burnout. This, however, contributes positively to workers' income, in line with the lack of wage compensation for burnout risk we documented. While social insurance reduces immediate earnings losses through sick pay and other transfers, disposable income falls by more than 6 percent in the long run. In sum, going into burnout permanently scars workers' labor and disposable incomes, sometimes forcing them to dramatically reduce their working hours or exit the labor market entirely.

Women are disproportionately hurt by work-related stress, being three times more likely to burn out than men (1.85 vs. 0.54 percent).[8] The severity of the income loss is, however, unrelated to gender. The high rates of burnout and the gender difference in those propensities implies that burnout is not confined to a small subset of the population: By the age of 40, one in every seven women has experienced a burnout, and one in every 20 men.

We further document how the repercussions of burnout transcend the individual worker and extend to their families, affecting their spouse's career and their children's human capital. Female spouses experience an immediate and persistent drop in labor income of 4.4 percent. The corresponding drop for male spouses is much smaller (1.1 percent). Hence, women are not solely more likely to burn out, with the associated scars on their careers, but their careers are also more susceptible when spouses burn out. Furthermore, we estimate a permanent reduction in fertility among women who burn out, while for men, the reduction is only transitory.

Parental burnout during children's schooling years reduces their college enrollment by 2.5 percentage points, or 8 percent, compared to a control group whose parents burn out when children have passed college-decision age. Similarly, we estimate a negative effect on grades at national-level exams at age 16. The effect size decreases by parental education, implying that burnout reduces intergenerational mobility. Given the potential two-way interaction between children's education outcomes and parental burnout, we isolate the effect of burnout due to work-related stress. We use the industry-wide burnout rate, excluding coworkers, as an instrumental variable for parental burnout, knowing, as we documented, that the work environment significantly influences burnout. The IV estimates align closely in magnitude with our differences-in-differences estimates.

Aggregating across channels—the direct effect of sick leave and the career consequences for those affected and their families—we estimate a 2.3 percent loss of aggregate labor income due to burnout in 2019. This figure likely underestimates the long-term loss, given that our diagnosed burnout data only extends back to 2006. We project that this loss will escalate to 3.5 percent in a steady state if conditions remain unchanged as of 2019.

In the third and final step, we explore a path toward a remedy. This unfolds in three parts. First, we use a nationally representative work environment survey to document a strong correlation between self-reported subjective work stress and burnout in the subsequent year. Second, using machine learning, we accurately predict higher burnout risk in 81 percent of

[8]For other evidence on the gender difference in the flow rate, see Hallsten et al. (2002); Norlund et al. (2010); Purvanova and Muros (2010); Artz et al. (2022).

comparisons between pairs of individuals, one experiencing burnout and the other not.[9] The additional prediction power of adding self-reported stress levels to workers' basic demographic information is as large as adding the kitchen-sink of Swedish administrative data. To our surprise, self-reported stress contains additional information beyond what is captured by the kitchen-sink of administrative data, suggesting the existence of private information (Hendren, 2017). Furthermore, we document the importance of observing self-reported stress in real-time. Third, we show how integrating our cost estimates and the prediction model can help design the optimal scope and targeting of a preventive program. A naive cost-benefit analysis shows that the optimal size of the program is reduced by half, and its net gain is 2.5 times larger once we use the survey on top of basic information to target those at risk.

Literature Review Our paper contributes to various strands of literature. First, we analyze the economic consequences of workplace stress and burnout. This complements the prior medical literature on these issues, which has primarily focused on the symptoms of burnout (Van Dam, 2021) and the health consequences of stress (O'Connor et al., 2021). Our analysis contributes 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 all types of sick leave (encompassing both physical and mental health issues that impair work capacity) in the study by Kolsrud et al. (2020).

Our results also provide individual-level evidence for a link between economic conditions and mental health. This relates to prior work that has documented the connection between unemployment (Paul and Moser, 2009), firm reorganization (Dahl, 2011) and mergers (Bach et al., 2023) with employee mental health. The positive correlation between increased career progression and burnout we document might be a contributing factor to the counter-cyclicality of health outcomes documented for the U.S. (Ruhm, 2000; Notowidigdo et al., 2024).[10]

Second, extensive literature has studied the role of firms in the labor market, focusing mainly on their influence on pay (Abowd et al., 1999; Card et al., 2013; Song et al., 2019). We contribute to the growing literature on job heterogeneity in non-wage characteristics (Hall and Mueller, 2018; Sorkin, 2018) by documenting differences in exposure to work stress and health risks across jobs. Concurrent research has documented how firms play a role in their workers' utilization of health care services (Ahammer et al., 2024) and unemployment insurance (Lachowska et al., 2024). Moreover, we highlight a specific channel through which imperfect sorting of individuals' personality traits and job requirements leads to adverse labor market outcomes, contributing to the literature on the cost of skill mismatch (Fredriksson et al., 2018; Lise and Postel-Vinay, 2020).

Third, we contribute to a nascent literature within economics studying stress: Postel-Vinay and

[9] Our AUC is 0.813 compared with 0.867 for mortality and 0.864 for health costs predictions (Einav et al., 2018; Handel et al., 2023).

[10] 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).

Jolivet (2024) studying the interplay of work-related stress, health, and job dynamics, and Nagler et al. (2023) eliciting willingness to pay for stressful jobs.[11] Relatedly, Blackburn et al. (2023) study burnout among health professionals and find that it increases turnover and lowers productivity and patient satisfaction. Lastly, our findings of firm heterogeneity in mental health risks hold implications for the optimal design of sick leave. Absent compensating differentials and limited co-financing of sick pay, employers potentially oversupply stressful jobs. One potential solution could be the experience-rating of sick pay, akin to proposals made for disability insurance (Autor, 2011; Burkhauser and Daly, 2012).

The paper unfolds as follows. Section 1 describes the burnout definition and its measurement in our data. Section **??** studies the role of jobs. Section 4 focuses on workers and quantifies the individual and aggregate loss of burnout. Section 5 uses administrative data and a work environment survey to predict burnout and evaluates the optimal design of prevention programs. Section 7 concludes. We relegate additional background material and auxiliary analyses to an appendix.

1 Definition, Measurement, and Data

1.1 Definition and Measurement

Burnout The term *burnout* originates in American social- and work psychology.[12] 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 has 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).[13]

[11] 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).

[12] 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).

[13] 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

There exist several validated 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).[14] In spite of some 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, in order to solve diagnostic controversies, 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.[15] 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

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).

[14]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).

[15]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).

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 psycho-social, 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.

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

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). 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.[16]

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). 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

[16]Firms in the private sector are chosen using stratified sampling from 530 strata: 83 industries $\times$ 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).

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 A.1 presents descriptive statistics of the estimation sample for our event-study difference-in-differences estimates as well as three relevant comparison groups: i) the overall workforce between ages 25 to 60 over the entire 2002-2020 period, ii) the subset of workers taking stress-related sick leave, iii) the subset of workers taking stress-related sick leave between 2009 and 2013. The table demonstrates that workers experiencing burnout differ from other workers in several ways. They are disproportionally female and exhibit higher college graduation rates than the average worker while having slightly lower earnings. Workers experiencing burnout have also taken more leave days for all diagnosis categories in the last five years.

Building on existing studies, including our prior research, we define employment as earning a labor income above a certain threshold. But unlike those studies that use a uniform minimum income threshold for all individuals, whether it be a predetermined arbitrary amount (Cederlöf et al., 2021) or one derived from social security regulations (Nekoei and Seim, 2023), we consider a worker employed if her income surpasses the minimum income observed among full-time workers with the same gender, native status, age, and education level, as recorded in the Wage Survey.

2 What is Burnout?

By definition, burnout is an illness caused by work-related stress. In this section, we empirically illustrate this relationship using data from the Work Environment Survey (AMU).

Figure 1a reports estimates from a *multivariate* regression of a burnout indicator on a range of work-environment factors and work-related health problems, all measured during the preceding year. The regression controls for demographic characteristics and year fixed effects.[17] For each survey question, we construct a binary indicator based on whether responses are above or below the median. The figure shows that stress at or related to work, as well as stress-related symptoms, strongly correlates with burnout. In contrast, other work-related health problems exhibit a weaker or no significant association. The factor most strongly linked to burnout is difficulty with sleeping due to thoughts about work. Appendix Figure A.3 provides further detail on these correlations by examining individual questions. The likelihood of burnout is steadily rising in how frequently

[17] We restrict the analysis to questions consistently available in the survey throughout our sample period to maximize sample size.

workers experience sleep problems in a given week due to thoughts about work. Approximately 40 percent of workers report their job as somewhat or very stressful. Workers perceiving their jobs as very stressful are almost five times more likely to go on sick leave due to burnout in the subsequent year compared to those reporting no work-related stress.

To further examine the relationship of burnout to work-related stress, we construct an index of stress symptoms. We identify in AMU questions that closest connect to aspects of the diagnosis criteria for burnout by the Swedish National Board of Health and Welfare (Appendix A). We identify four questions which we use to construct the index, which ranges from -4 for those who do not show any stress symptoms to 4 for those who show all symptoms; see Appendix D for details. Figure 1b shows the relationship between this index and burnout in the subsequent year. Workers reporting no stress symptoms have approximately zero probability of experiencing burnout in the following year. This probability rises steadily with the number of stress symptoms; among workers reporting all symptoms, the likelihood of burnout is approximately 5 percent.

Is burnout driven primarily by chronic stress or by rapid increases in stress? Distinguishing these patterns is essential for understanding the determinants of burnout and identifying effective preventive measures. To examine this, we analyze the evolution of stress symptoms surrounding burnout episodes. We adopt a benchmarking approach similar to a difference-in-difference framework, matching workers who experience burnout to observationally similar workers who do not, based on demographic characteristics and pre-burnout labor income deciles. Figure 1c plots the trajectories of stress symptoms for both groups. Two years prior to burnout, future burnout cases already exhibit slightly elevated stress symptoms compared to the matched control group. However, in the year leading up to burnout, stress symptoms sharply increase, reaching their peak in the quarter when workers initiate burnout-related sick leave. After workers go on sick leave, stress symptoms decline to levels observed one year prior. As we will later document, this decline partly reflects transitions into different jobs and reduced work intensity following burnout episodes.

3 Who is at Risk of Burning Out?

3.1 Mismatch of Job Stress Level and Individual Stress Tolerance

In the previous section, we documented a strong link between burnout and work-related stress. However, the questions that remain are whether jobs differ systematically in their stress levels and, especially, whether being exposed to stress at work affects everyone the same or if burnout depends on individual's tolerance to stress. Answering these questions requires two key components.

The first component requires assessing the level of stress associated with a job. For this, we use the stress tolerance requirement of an occupation delineated by O*NET (Peterson et al., 1999). This approach carries two potential sources of measurement error. First, measurement noise may arise within the ONET data itself, as the data primarily reflects occupational stress assessments based

on the U.S. context. Second, discrepancies between occupational classification systems in Sweden and the U.S. may introduce additional measurement error. Nevertheless, a key advantage of this approach is its emphasis on the *nature* of occupations, capturing the inherent tasks required by each occupation rather than characteristics of the workers occupying these roles and is therefore immune to sorting of workers into occupations.

The second component necessitates 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 and occupational stress tolerance requirements. This visualization illustrates a robust correlation between the level of work-related stress and the incidence of burnout. The figure also adds examples of occupations across the spectrum of stress tolerance requirements. Examples of occupations requiring high-stress tolerance are psychiatric nurses, midwives, and preschool teachers, while occupations not requiring tolerance to stress include construction machine operators and mining workers. Notably, the north-west corner of the figure is empty, displaying that there are no low-stress occupations with high rates of burnout.

If occupations vary in stress levels, do workers with different degrees of tolerance to stress sort into them accordingly? Figure 2b shows a limited 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] However, sorting is quantitatively limited compared to what might be required to minimize burnout: 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.[20]

Figure 2c presents the burnout rate of workers by stressfulness of their occupations and their own stress tolerance. Importantly, workers with low stress tolerance are more susceptible to burnout than those with more tolerance to stress, especially when employed in highly stressful jobs.[21] When working in the most stressful positions, the burnout rate for the least stress-tolerant individuals is threefold higher than that for the most stress-tolerant workers.

[18] We find substantial heterogeneity in stress tolerance across brothers. Therefore, we refrain from imputing the risk tolerance for women based on that of their brothers.

[19] Figure A.9 shows the entire distribution of occupation types for each level of individual stress tolerance.

[20] Under perfect sorting, we would expect the average rank to be 90 among those most stress tolerant and 10 for those least tolerant to stress.

[21] Appendix Figure A.8 shows that the negative relationship between stress tolerance and the likelihood of burnout is robust to controlling for other cognitive and non-cognitive skills.

3.2 The Role of Gender, Family, and Career

We examine the demographic characteristics of those who burn out. Figure 3a plots the rate of burnout by gender and family type, partitioned into four groups by marital and parental status.[22] 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. While there is virtually no difference across the other three groups of men, among women after the single mothers, singles without children have the next-highest rate of burnout, then married with children, and finally, married without children have the lowest rate. Strikingly, among the group of women with the lowest risk of burnout—married without a child—burnout is still twice as likely than among single fathers, the group of men at the highest risk.[23]

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, implying that burnout is not confined to a small subset of the population.

Gender The evidence presented above underscores significant heterogeneity in burnout risk by gender. A potential explanation for this disparity is that women and men differ systematically along dimensions of their careers that expose them to greater burnout risk, such as in which industries and occupations they work, with examples of female-dominated professions such as nursing and teaching carrying a relatively high burnout risk (see Figure 2a).

To explore the role of gender, we conduct a variance decomposition analysis. We regress the indicator for burnout on four sets of predictors. First, a matrix of demographics encompassing family type (four categories), education level (three categories), and year (15 years), a dummy for being born in Sweden, the number of children and a dummy for the presence of a child below the age of eight. Secondly, dummies for earnings (five groups) and fixed-effects for 5-digit industry and 4-digit occupation codes.[24] This regression is performed in the years 2014 to 2018 and yields an R^2 value of 0.75 percent. The results are reported in Figure 3a. The decomposition implies

[22] Appendix Table A.1 summarizes the burnout rate in the Swedish population by other demographic dimensions. This table reports, e.g., that among women, higher rates of burnout are found among those with education beyond compulsory schooling, those in their late 30s and early 40s, with more and young children, and those with lower incomes, conditional on year, industry, and occupation fixed effects.

[23] An extensive literature has studied whether sickness insurance affects work absence behavior (e.g. Henrekson and Persson, 2004; Johansson and Palme, 2005). To investigate whether burnout-related sick leave is affected by the replacement level, we study whether there is a kink in the uptake of burnout-related sick leave for individuals around the kink in the replacement rate. As documented in Appendix Figure A.21 and discussed in more detail in Section 6,we find a small decline in sick leave above the kink.

[24] This regression model is the same as reported in Appendix Table A.1, columns (3) and (6), estimated for the pooled sample of men and women.

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.

Couples To shed further light on the gender disparity in burnout risk, we study how it relates to the incomes of couples and the relative position of women within the household. Figure 3b plots the burnout rates of married and cohabiting women against the labor incomes of each of the spouses within the couple.[25] 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. This figure uses a two-dimensional moving average and rank-adjusted income (see Section **??**).

Darker shades of red depict higher burnout rates among women. We overlay a line marking the median couple's total income. The figure documents that burnout rates are particularly high among women in below-median earning households but when they earn more than their spouses, depicted 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 below-median-earning households.

3.3 Career Progress

Having established the connection between burnout and women's relative earnings position within the household, we now study how burnout relates to career progress. We proxy career with 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 $t-1$. We perform a rank adjustment to 2020 Swedish krona (SEK) to render labor income 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.[26] This approach is equivalent to a non-parametric wage inflation adjustment.[27] This adjustment renders individual labor incomes comparable over time but does not affect nominal income growth rates.[28]

[25] Appendix Figure A.6a presents the corresponding figure for married and cohabiting men.

[26] 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).

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

[28] In order to maintain consistency compared to 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).

Figure 3c plots the burnout rate of women against their earnings growth. We use a two-dimensional moving average of burnout rate given that observations are non-uniformly distributed (Appendix Figure A.5). More precisely, we report the average rate of approximately 38,416 observations in the circular vicinity of each point. This number of observations is based on a power calculation for the binomial distribution and suffices to create the statistical significance of differences of size 10^{-4}. This can be viewed as a simple version of a variable kernel estimator.

Two key patterns emerge. Firstly, the light-colored diagonal reveals that women with stable earnings tend to have the lowest rates of burnout among full-time employed women. Secondly, those with fluctuating incomes, particularly those experiencing increases in income, exhibit the highest rates of burnout.[29]

Together, the results above highlight how the relative earnings position of women within their household and their career progress relate to their burnout rate.

4 The Consequences of Burnout

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

4.1 Effect on Individual's Labor Market Outcomes

To evaluate the consequences of burnout for an individual's labor market outcomes, we use three research designs. In the first design, we compare those who experience burnout at a certain time to a control group of individuals who never experience burnout but are observationally similar to those who do in dimensions correlated with their labor market trajectories. This is our main empirical strategy. However, those who burn out may be systematically different from those who do not, both in unobservable characteristics and in their career trajectories. In particular, as documented in Section 3, burnout is preceded by career progression, which can lead to an underestimate of earnings losses. Therefore, we complement our first design with a design exploiting the timing of burnout. That is, among those who burn out, we compare those who go into burnout in year t to similar individuals who instead burn out in year $t + \delta$. We refer to this method as the *fixed-delta* method (Fadlon and Nielsen, 2019; Nekoei and Seim, 2023). These two designs study the event of going into burnout. This could be a result of work-related stress but it could also stem from stress in the private life. To isolate the effect of stress related to work, we apply an instrumental variables approach where we instrument the burnout rate of individuals with a change in the burnout rate among workers in her industry. We first describe the procedure underlying the main empirical strategy before describing in turn the fixed-delta method and the

[29] The same patterns are present among employed men, as shown in Appendix Figure A.6b. As a result of burnout being less frequent among men, the estimates are less precise than for women. The results for women and men are almost identical when we restrict the sample to individuals that stay at the same firm in the two years prior to burnout (Appendix Figure A.7).

instrumental variables approach. The estimation sample is a balanced panel of individuals whom we have observed for twelve years.

We chose the control group from individuals who never experienced burnout and satisfied the sample selection criteria listed above. We match burned-out individuals to controls based on the year of birth, education, gender, income percentile in the year prior to treatment computed within this demographic group, and their employment history for four years prior to treatment. We perform exact matching, meaning that the control has to be identical to the treated individual along all dimensions we consider.

We match one-to-one without replacement, so each treated individual is matched to exactly one control individual.[30] 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 start 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 they burn out and the year after, 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 slight evidence 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 difference-in-differences, comparing the group of workers who burn out to their matched control group. Our estimation equation is:

$$Y_{i,k} = \phi_{G_i,T_i} + \delta_{G_i,k} + \sum_{k \in \mathcal{K}} \alpha_k T_i + \varepsilon_{i,k} \tag{1}$$

where $Y_{i,k}$ is the outcome of interest for individual i at event time k where $k \in \mathcal{K} = \{k_0, k_0 + 1, ..., k_1 - 1, k_1\}$, 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). Results are shown separately for men and women. In the years prior to burnout, there is a small but significant upward trend in earnings for both genders. 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 longer hours or promotions. 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 and stabilizing at 13 percent for men and 12 percent for

[30] It is possible that individuals appear in multiple control groups if, for example, they are matched to a treated individual at age 40 and at age 45. In our final matched sample, 4,526 individuals appear in two control groups, 100 appear in three, and one in four control groups.

women seven years after burnout.[31] 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 as leave estimated by (Kolsrud et al., 2020). This suggests that the scarring effect of burnout is larger than the average health shock leading to sick leave.

One potential explanation for the observed permanent income loss is that those who burn out miss out on promotional opportunities. However, to account for the abrupt and persistent income loss, this explanation necessitates that those who experience burnout forego a promotion in the same year when the burnout event occurs. While this scenario is plausible, it likely explains only a small fraction of the total income loss. Additionally, the income of the affected group shows a notable absolute decline, indicative of a diminished capacity to work, which logically could lead to job departure. This aspect will be explored further in our subsequent analysis.

Fixed-delta Method We complement our analysis with a second 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. $\delta = 5$. The figure shows that the same as for the matched difference-in-differences design, the two groups follow the same trend in income prior to burnout, deviating only as income falls when workers go into burnout. Appendix Figure A.10 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. 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 delta method in contrast to the stagnant effect in the diff-in-diff method. 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 Estimates Burnout is an illness resulting from stress. This can stem from work, as documented in Sections C and 3, but it may also stem from factors in the personal life that are unrelated to work, such as going through a divorce. In order to isolate the effect of burnout resulting from work-related factors, we instrument burnout with the burnout rate in individuals' 5-digit industry, 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

[31] The labor income dynamics following burnout cannot be explained purely by increased sick leave take-up. In Appendix Figure A.12, we show that days spent on burnout-related sick leave spike 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 (164 days) and median duration (58 days).

err on the side of caution not to incorporate firm shocks that might affect income and employment directly. The underlying idea behind this research design is that idiosyncratic life events do not systematically aggregate up at the industry level, implying that changes in the burnout rate in an industry reflect changes in the level of work-related stress.

Let $\mathcal{J}$ denote the set of industries, and let $J(i,t) \in \mathcal{J}$ denote the industry where worker i worked at time t. As in the event-study, let G_i index the matched group of individual i one period prior to the event. Formally, we estimate the following first-stage regression:

$$T_i = \omega r_{J(i,t),t} + \phi_{J(i,t-1)} + \phi_{G_i} + \epsilon_i \tag{2}$$

where T_i is the treatment status of individual i, $r_{J(i,t),t}$ is the industry-level leave-one-out burnout rate of industry J at time t, and $\phi_{J(i,t-1)}$ and ϕ_{G_i} are industry-origin and matched-group fixed effects. The coefficient ω 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 are changes in the industry-level burnout rates at the individual level, which are brought about either through 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 relationship and the statistical strength of the instrument is reflected in a first-stage F-statistic of 106.

We report the instrumental-variables estimate of the effect on labor income in Figure 5a, together with the matched difference-in-differences and fixed-δ estimates. Using this method, we estimate an income loss of 11.6 percent. Although this value is of a similar magnitude to our estimates obtained through other strategies, it is slightly smaller, suggesting that burnout due to private-life events may lead to even larger income losses than those induced by work-related stress.

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, does the income decrease stem from reduced working hours or ceasing employment altogether? And does the answer evolve over time?

To address these queries, conventional analysis of intensive versus extensive margins is insufficient. Thus, in our subsequent analysis, we aim to decompose the average income loss post-burnout into its various components. But first, we start with a simple descriptive exercise studying changes in months worked, full-time employment, and turnover following a burnout (Appendix Figure A.11). There is a slight pre-trend in labor income, 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. To illustrate this, we denote the partition by its indexing function: if individual i belongs to partition p at time t, then $\pi_{i,t} = p$, for a $p \in P$. Moreover, for any outcome, $Y_{i,t}$, we denote its counterpart in the control group by $Y_{c(i),t}$.

To estimate the contribution of partition p, we use as outcome, $Y^p_{i,t}$, that takes the control value if individual i does not belong to partition p,

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

Varying p, these will decompose the average treatment effect, as the difference between the outcome of treated and controlled individuals can be written as the sum of the contribution of each respective partition as

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

The strength of this decomposition lies in its dynamic nature; the categorization 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.[32]

[32]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

Interestingly, transitioning to a different firm after experiencing burnout mitigates the income loss. This finding echoes our prior results and contradicts the existence of compensating wage differentials. Assuming burnout originates from high workplace stress and firms compensate employees for such adversities, a shift to another employer would typically result in the loss of a firm-specific wage premium. Without the presence of compensating differentials, as detailed in Section **??**, moving to less stressful occupations does not result in diminished income.

Do burnout workers move to less stressful jobs? To answer this question, Figure 5d focuses on firm switchers and studies the evolution of their industry-level burnout rates. Subsequent to burnout, workers leave industries with a higher risk of burnout for those where the risk is lower. 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)) echoes the negative compensation wage differential we documented in Section **??**.

Disposable Income Our measurement of health condition 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 burn-out workers for a large share of their lost earnings. Since the average sick leave spell associated with burnout lasts for less than three months, and eligibility is capped at one year, the income 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. 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 estimate in Kolsrud et al. (2020).

4.2 Effect on Spouse's Labor Market Outcomes

We now turn to the effect of burnout on spousal labor market outcomes among married workers. The motivation for analyzing intra-household spillovers is twofold. First, spousal labor supply can act as a private insurance mechanism to earnings shocks, which has implications for the optimal design of public insurance (Cullen and Gruber, 2000; Autor et al., 2019). At the same time, burnout, like other disabilities, can be severe enough to require caregiving by family members, who in turn reduce labor supply (Løken et al., 2017).

adjustment margin for men.

To perform our event study for spousal earnings, we focus on workers who were married/cohabiting in the year prior to burnout and follow their spouse over time regardless of whether they separate in subsequent periods. We require that spouses satisfy the same sample restrictions we impose for workers in our baseline analysis. We perform the same matching procedure as in the baseline analysis, with the sole exception that this time, the treatment and control spouses are born in the same year. Our estimation sample includes 57,441 spouses married to workers experiencing burnout.

Figure 6b shows the estimated dynamic effects of burnout on spousal earnings. While male earnings decline prior to their wife's burnout and remain stable afterward, earnings of female spouses exhibit an immediate and persistent drop, mirroring the average effect for burned-out workers' own earnings documented in Section 4.1. The asymmetry in earnings responses is consistent with gender differences in caregiving norms. Using U.S. survey data Anand et al. (2022) document that following workers' health shocks, only female spouses report reducing labor supply due to caregiving. Seven years after burnout, female spouses earn 4.4 percent less than observationally similar women in the control group. Intra-family spillovers are, therefore, an important component of the aggregate cost of burnout.

4.3 Fertility and Separations

Burnout may affect worker's well-being not only through its impact on their labor market outcomes but also through impacts on their private life. Moreover, changes in family circumstances, such as childbirth, or life events, such as separation from spouse, may contribute to increasing stress load and lead to burnout. 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 the population that burns out is, in general, more likely than the control group to separate from their spouses—suggested by the pre-trend—but this disparity is not more significant the closer to the burnout event. In the year of burnout, there is a 4 percentage point jump in separations, corresponding to about 50 percent increase in the annual separation rate. 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, implying that burnout accelerates separations. To evaluate whether the burnout event is only associated with more separations in the short run, Appendix Figure A.18 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 is associated with 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. Men, on the other hand, have fewer children in the short run but more in the long run. The figure also shows that women's burnout is preceded by childbirth the year before, while there is no such pattern for men. To evaluate whether these effects reflect inherent but unobserved characteristics of the population that experiences

burnout, Appendix Figure A.18 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

We evaluate the impact of parental burnout on their children. Having a parent who goes into burnout may impact children in various ways, e.g., through reduced time and support that parents can provide their children. We, therefore, investigate how burnout affects the human capital accumulation of children, measured by school performance and educational attainment.

We study the impact of parental burnout on the age of children at the time.[33] 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 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 allocated to individual i. We then run the following regression

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

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 measure the effect of parental burnout on their children's human capital both in terms of school performance and educational attainment. We measure the former with performance on high-stakes exams. At the end of compulsory school, all Swedish children complete national-level exams. These take place during the Spring term in 9th grade, the year when children turn 16. We define an indicator for having a GPA of 240 or above, corresponding to an average subject grade of C (15) across a total of 16 subjects. This corresponds to roughly the median GPA. These are high-stakes exams as they determine college enrollment opportunities as admission to oversubscribed subjects is determined by the student's GPA (see, e.g. Ramstedt, 2005, for further discussion and details). We measure educational attainment with college enrollment by age 21, i.e., an indicator of whether a child enrolls in college at age 19, 20, or 21.

Figure 7a plots the coefficients from regression (5) 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

[33] 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.

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. We estimate a negative effect of parental burnout on school performance. On average, children whose parents go into burnout when they were at ages 10 to 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 estimate 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 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 age 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 statistical 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 is 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.16 we investigate if effects are heterogeneous by gender of children or the parent that burns out. The effect of a mother's burnout on the college enrollment of her children is slightly larger, yet not statistically, than when the father burns out, but the education of boys and girls is similarly negatively affected.[34]

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 implies that we can study fewer birth cohorts with our empirical design. However, in order to evaluate the robustness of our results, we study enrollment by age 24. We plot our estimates of regression (5) in Appendix Figure A.15. The results are comparable to our

[34]The fact that there is not a statistically significant difference in the effects of the burnout of mothers and fathers is surprising. 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.

main definition, implying an 8.1 percent reduction in college enrollment by age 24.

Parental burnout can result from several interacting factors, both related to their work and family life. In extreme cases, children's school problems may lead to parental burnout. In this admittedly extreme case, the estimated effect of parental burnout on the educational attainment of children suffers from reverse causality. To isolate the effect on children stemming from parent's high-stress workplace, 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 (5), 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 effect. As before, this strategy exploits time variation in the burnout rate in parents' industry or parental moves between industries with different burnout rates. The instrumental-variables estimates are reported in Figures 7a and 7c. In both cases, the magnitude of the IV estimates are similar to DiD estimate, implying that parental burnout leads to a 5.3 percentage point reduction in school grades and 8.7 percent reduction in college enrollment, measured compared to average outcomes of the control group.

4.5 Aggregate Labor Income Loss due to Burnout

What are the aggregate implications of burnout for the economy? To quantify this, we measure the total loss of income due to burnout in 2019 through four channels: i) lost days at work, ii) scarring effects and spillovers on other family members through effects on iii) spousal earnings and iv) children's education outcomes.[35]

The following formula lays out these four channels:

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

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 are the proportional income loss due to burnout of own, spouse, or parent, which we will borrow from Figures 5a, 6b, and 7c. In the last case, we convert the college-enrolment effect to an income effect using estimates of returns to college 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.[36]

Figure 8 documents our measured total loss of income in 2019 due to burnout. In total, we measure a 2.3 percent loss in potential aggregate labor income. Lost working days in 2019 led

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

[36] In the last case, we refrain from using 2019 income data, acknowledging its distortion by the scaring 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.

to a loss of 0.5 percent in potential labor income. Scarring effects from past burnout accumulate to 1.5 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.

What would the aggregate loss be if the burnout rate observed in 2019 were to persist indefinitely? Our estimated loss in 2019 underestimates future losses as our data on burnout diagnoses only extends back to 2006. 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, implying that, mechanically, the calculated earnings loss will be small.

To overcome this shortcoming, in Figure 8, we perform a calculation of the loss in a steady state. That is, we assume that the state of burnout in Sweden stays constant at its 2019 level and perform a calculation similar to what is frequently done in studies of life expectancy.[37] The steady-state estimated aggregate loss is 3.5 percent of labor income.[38] While the permanent loss of individuals' income increases from 1.5 to 2.6 percent, the largest proportional change is in the spillover effect on children, increasing from 0.07 to 0.26 percent.

5 Predicting and Preventing Burnout

Preventing burnout proves to be more effective than addressing it post-occurrence, akin to other mental health issues (Tetrick and Winslow, 2015; Aust et al., 2023). While the development of preventive programs is a dynamic area of research (Bouskill et al., 2022), implementing such programs in practice necessitates identifying individuals most at risk for its effective targeting and knowledge of burnout cost to optimize its scope (Demerouti et al., 2021).

This section demonstrates how our prior findings and burnout prediction can guide the optimal scope and targeting of preventive programs. In particular, we document the significant additional prediction power of self-reported stress.

5.1 Self-reported Stress and Future Burnout

As we showed in Section **??**, the burnout rate varies substantially by individuals' observable characteristics. This variation can be leveraged to classify individuals' burnout risk based on occupational histories and demographic factors. However, even within the most stressful occupations, burnout is still a relatively rare event.

[37] We would like to emphasize that this calculation should be viewed as a thought experiment, rather than a statement implying that burnout is a permanent condition. Historical instances of mental conditions, such as neurasthenia and industrial fatigue, may actually suggest the contrary, highlighting the adaptive capabilities of humans (Johannisson, 2006; Schaufeli, 2017).

[38] Unavoidably, we must adopt an assumption regarding the data generating process for the burnout time series. We opt for a simple form, assuming a Markov process. We further assume transition probabilities are independent of age, validated by data for prime-age workers.

Targeted surveys regarding workers' own work experience can provide useful additional information to predict burnout. Furthermore, businesses or public entities might benefit from gathering real-time data on employee well-being. In fact, it is common for firms to survey employee satisfaction: 44 percent of European establishments with a workforce exceeding twenty employees have surveyed their staff about work-related stress in the past three years (Howard et al., 2022).[39] However, these surveys are rarely followed up by preventive programs, despite evidence of their success (West et al., 2014; Linzer et al., 2015).

Given this context, we evaluate the power of small-scale surveys in detecting those at risk of burnout. We exploit the Swedish Work Environment Survey, AMU (See Section 1 for a detailed description). While not explicitly targeted at burnout prevention, the survey contains information on several early warning signs of burnout. We assume that AMU is incentive-compatible, as it does not play an administrative role and does not relate directly to sick leave management. This assumption becomes less straightforward when discussing the utilization of survey results to tailor interventions for an identified preventive problem (Section 5.3). The exploration of how program design and survey methodologies interact is reserved for future research.

5.2 Predicting Burnout using Administrative and Survey Data

This section assesses the effectiveness of both administrative and survey data in identifying workers at high risk of burnout. While we have shown in C that survey responses are associated with burnout after controlling for basic observables consistent with the medical literature, we now turn to a more complete quantitative assessment of their predictive power. 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 F provides details on the prediction procedure.

We predict burnout in the *next* calendar year, using six models: either for the sample surveyed in the AMU or across the Swedish population, using one of the three information sets: basic demographics, basic demographics plus survey responses, and a comprehensive collection of administrative data available to us ("kitchen sink" approach). Basic demographic information consists of gender, citizenship, age, and detailed education, i.e., 348 categories, including specific qualifications (e.g., trained cardiologist) and fields of study (e.g., biologist). We consider this to be the set of information available on a standard CV. 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

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

assessed during military enlistment.

Table 3 presents the results. We evaluate 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 demographics yields an AUC of 0.664. Incorporating survey responses into the predictors enhances model performance by approximately 10 percent, raising the AUC to 0.724. If instead we incorporate "kitchen sink" of administrative records, the AUC stands lower at 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.[40] This highlights the substantial predictive capacity of the survey data. Figure A.19b demonstrates this pattern, showing how the Cumulative Gains Chart shifts out more using information from survey data than the kitchen-sink. This effectiveness is further demonstrated when survey data is combined with all available administrative records, significantly enhancing prediction accuracy and resulting in a combined AUC of 0.742.

These results underscore the value of targeted surveys for burnout prediction. Since large-scale surveys are costly, we use our prediction technology to explore two aspects that can inform the cost-efficient design of survey-based prevention schemes. First, we ask how frequent a survey would need to be to provide useful information for burnout prediction. Secondly, we ask whether the survey can be reduced to a core set of predictors while maintaining its predictive performance.

To evaluate the impact of survey frequency, we extend our prediction window to two years ahead in the third column of Table 3. While self-reported stress aids in predicting burnout for the subsequent year, its contribution to predicting burnout two years ahead is limited compared to administrative data alone. This finding is consistent with our earlier result in Figure 1c showing that burnout is preceded by year-long spikes in stress levels.

To assess the role of survey length, we focus on four predictors used in our stress index. Their choice was informed by the medical literature (see Section C). To start, we compare the performance of a classifier trained on these survey responses against the performance of classifiers trained on alternative sets of survey questions of the same length. [41] Appendix Figure A.20a shows that the four questions of stress index outperforms 94.4% of all other permutations. This result provides an alternative, data-driven justification for our stress index.

More importantly, Appendix Figure A.20a shows that a prediction using only core predictors in addition to basic demographic characteristics generates 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. This suggests that by reducing the survey to four core

[40] 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.

[41] 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.

questions, we can capture 80% of the performance gains provided by the survey. This share slightly increases to 85.4% when we perform the comparison with a richer set of administrative data additional predictors. These results imply that a parsimonious survey capturing a small set of early symptoms yields substantial, additional predictive power to detect those at 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.[42] This indicates that if we randomly choose one individual 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. Since the comparison of the survey and population sample integrates both sample differences and potential returns to scale, we try to isolate the latter by training the model on the entire population and testing it on the survey sample.

5.3 Optimal Scope of a Preventive Program

Our objective in this section is to demonstrate how one can apply the prediction model together with our cost estimates to design the optimal scope of a given prevention program and place a value on additional information obtained through a targeted survey.

5.3.1 Cost-Benefit Analysis: Theory

We start by theoretically examining the economic costs and benefits of a preventive program. If we assume that agents are risk-neutral and neglect disutility from burnout and utility from participation in the program, our calculation is equivalent to a welfare calculation.

The program has two stages. The first stage is screening (triage), which detects those at high risk. Triage costs p, has a true positive rate of α, and a false positive rate of β. The second stage is the treatment of those detected that costs P and has a success rate θ. The success rate captures both the extensive margin—burnout prevention—and the intensive margin—symptom reduction. The cost of treatment should be compared to the cost of burnout, denoted by C. The latter encompasses the immediate and lasting income loss and spillover effects. The net benefit of treating an individual at 100 percent risk of burnout is $\theta C - P$.

The benefit of the program stems from those at risk who passed the triage (true positives),

$$\Gamma = \alpha b \left(\theta C - P\right) \tag{7}$$

[42] Figure A.19b also shows that the Cumulative Gains Charts for the population are shifted out when adding the kitchen-sink, and the plot is much smoother when using the population than the AMU sample.

The false positives create a net cost of

$$\Lambda = \beta(1-b)\left(-P\right) \tag{8}$$

Consider the case where the planner uses a basic set of information about each worker—gender, citizenship, age, and education—to predict their risk of burnout. We denote the rate of true burnouts detected in this prediction by $\pi(x)$. This is the Cumulative Gains Chart, depicted in Figure A.19a.

The planner chooses the share of the workforce eligible for the program, denoted by x, to maximize the per-capita gain from the program, that is:

$$W\left(x\right) = \Gamma \times \underbrace{\pi\left(x\right)}_{\text{Share detected}} + \Lambda \times \eta(x) - \underbrace{p}_{\text{Triage cost}} \times \underbrace{x}_{\text{Pop. share covered}} \tag{9}$$

The optimal size of the program is defined by equalizing the marginal cost and benefit for the marginal worker:

$$\underbrace{\Gamma\frac{\partial\pi\left(x^*\right)}{\partial x} + \Lambda\frac{\partial\eta\left(x^*\right)}{\partial x}}_{\text{Marginal benefit}} = \underbrace{p}_{\text{Marginal cost}} \tag{10}$$

The net impact of the program at optimum is

$$W\left(x^*\right) = \Gamma\left[\pi\left(x^*\right) - \frac{\partial\pi\left(x^*\right)}{\partial x}x^*\right] + \Lambda\left[\eta\left(x^*\right) - \frac{\partial\eta\left(x^*\right)}{\partial x}x^*\right] \tag{11}$$

Equation (13) 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 adding survey information to the basic demographic information. The detection rate from the new prediction using both survey and demographic information exceeds the initial prediction, $\pi_s(x) \geqslant \pi(x)$ for all x. The gain, as a function of the share of the population treated, is now:

$$W_s\left(x\right) = \Gamma\pi_s\left(x\right) + \Lambda\eta_s(x) - px - \sigma \tag{12}$$

where σ is the per-capita cost of the survey. The optimal size of the program is determined by equalizing marginal cost and benefit similar to equation (10). This implies that using the survey decreases the optimal size of the program, as a better prediction model leads to a marginal return—likelihood of detecting burnout by evaluating one additional person—at each level of coverage.

Carrying out a survey will yield a positive net gain if the survey cost is small relative to the gain from an improved detection rate and the cost reduction due to the resulting decrease in the optimal program size.

Specialization To facilitate graphical analysis of the optimization problem, we now consider the special case in which the triage successfully identifies all individuals without the condition, that is, the false positive rate $\eta(x)$ is zero for all $x \in [0,1]$. Under this assumption, the welfare gain in optimum satisfies

$$W(x^*) = \Gamma\left[\pi(x^*) - \frac{\partial \pi(x^*)}{\partial x} x^*\right] = \Gamma I(\pi) \tag{13}$$

where $I(\pi)$ is the intercept of the optimal tangent line, i.e., the line, given the detection rate, where the marginal benefit of screening another worker is equal to its cost.

Similar to equation (13), the net gain of a survey is equal to the proportional gain in the size of the intercept net of the cost of the survey.

$$W_s(x_s^*) = \Gamma I(\pi_s) - \sigma \tag{14}$$

5.3.2 Cost-Benefit Calculations

To calibrate our model, we assume a conservative values of 20 percent for type II errors of the triage, corresponding to $\alpha = 0.8$. The cost of burnout can be calibrated using our aggregate cost of 3.51 percent reported in Figure 8 and the average burnout rate of 1.12 percent in the population. We consider a preventive treatment with a success rate θ of 10 percent, which is likely to be conservative according to existing evidence on program effectiveness, and a cost equivalent to one month of the average worker's income.[43] Using equations (7) and (8), we first calculate the benefit of the program net of costs as .2 percent measured in terms of average annual labor income, or, equivalently, 4.05 hours (see Appendix F for details).

Next, we use equation (10) and assume a cost of triage of 6.5 hours, which leads at an optimal slope of $\frac{\partial \pi(x^*)}{\partial x} = 1.6$. When the prediction is only based on basic demographics, this optimal slope implies that the optimal size of the triage group is 26 percent of the population and the intercept of the tangent to the curve is 3.19 percent (Figure A.19a). Given this estimate, the total per-capita gain from optimal coverage of the program is:

$$W(x^*) = \Gamma I(\pi) = 4.05 \times 3.19\% = 13\% \tag{15}$$

of an hour. Relative to the burnout cost, bC, the net gain from the program is 0.18 percent, and relative to the burnout cost of those admitted to the program, it is 0.86 percent (see Appendix F for details).

Adding survey information to the prediction increases its performance, which shifts out the Cumulative Gains Chart (Figure A.19a). Detection based on the survey, in addition to the basic demographics, reduces the optimal size of the triage group by half, from 26 percent to 13

[43] A recent meta-study of the effects of burnout reduction programs among nurses, including both randomized controlled trials and quasi-experimental studies, 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). For further meta-analysis on program effectiveness, see, e.g., Zhang et al. (2020); Salvado et al. (2021).

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 11.76 percent. That is, the rate of detection of true cases increases by fourfold.

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 that most of its prediction power can be harnessed using a selected set of questions. The total per-capita gain from the program with optimal coverage is:

$$W_s\left(x_s^*\right) = \Gamma(\pi_s) - \sigma = 4.05 \times 11.76\% - \frac{1}{6} = 31\% \tag{16}$$

of an hour. Therefore, the program's welfare gain is twice and a half larger when complemented by a survey.

Until this point, 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 of experiencing burnout—might influence our results. As a hypothetical scenario, suppose we possess a measure of workers' willingness to pay to avoid burnout, which exceeds the estimated cost based on earnings losses. This leads to a higher benefit of the preventative program, Γ, reduces the slope of the optimal policy, and broadens the scope of the optimal program. Consequently, the welfare gain from the program, as derived from our model (equation (15)), would be amplified through two channels: an increased benefit from prevention and an expanded optimal scope of the program. The same logic applies when prediction includes the survey (equation (16)). However, the relative gain from including the survey may be larger or smaller than we have estimated above. This depends on two factors. 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 summary, as our cost estimates underestimate the willingness to pay to avoid burnout, our estimated program gain is a lower bound, but the size of the added gain from the survey is uncertain.

6 Discussion

We have documented that workers exposed to stress at work are at risk of burnout. Those who burn out experience a permanent loss in labor income. The adverse effects of burnout extend to their families, affecting their spouse's labor supply and offspring's human capital. In the aggregate, burnout and spillover effects of work-related stress lead to a substantial loss in labor income in Sweden.

The prevalence and effect of burnout arise from two primary determinants: occupational stress and the generosity of the welfare state. At a given level of stress, the propensity to reduce working

hours or take leave hinges on the social safety net's generosity. Hence, assessing external validity necessitates attention to both dimensions.

In international comparison, workforce surveys suggest that work-related stress in Sweden is well below the global average (Gallup, 2023). For example, stress levels in the U.S. are about 50% higher than in Sweden. Sweden maintains a generous welfare state with paid sick leave, similar to Germany and other European countries with strong welfare systems, much more generous than U.S. Moreover, Sweden is one of 9 countries that established medical diagnosis criteria for burnout and one of 5 who have integrated it 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 work-related stress, but one in a country with paid sick leave and one without. In the absence of such a comparison, we study the effect of varying the replacement rate, estimating the sensitivity of burnout-related sick leave take-up with respect to daily benefit levels. 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 due to burnout at the kink. For workers earning below this threshold, sick pay is a fixed proportion of income, whereas, above the kink, it becomes a fixed amount.

Appendix Figure A.21 illustrates the benefit schedule—the daily sick leave benefit level a function of income—and the burnout rate around the kink. Our regression kink design estimates suggest that a 1 SEK increase in daily sick pay benefits reduces 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 annual burnout rate—or more precisely, 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. However, this does not imply that the total cost of burnout would be similarly reduced. The extent to which inducing burnt-out workers to continue working would result in an increase in overall labor income depends on the productivity of affected individuals when employed. 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 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. Stress levels in the U.S. are higher than in Sweden, as noted earlier. Thus, while Sweden's system increases reported burnout rates by providing insurance, the true prevalence and severity of burnout in the U.S. may be even greater—potentially leading to higher economic costs.

7 Conclusion

The labor market has undergone a structural change in recent decades. First, jobs have changed. While hours at work have declined on average, more and more jobs require workers to be "always on". Additionally, while jobs have become less physically straining, they have become more mentally demanding. Second, more and more households consist of dual-earners, implying a career-family tradeoff for both spouses. Perhaps as a consequence of these factors, stress among workers appears to be on the rise.[44] A salient aspect of this is that a sizable share of the population—about 1 percent per year—is severely affected by chronic work-related stress and goes into burnout.

In this paper, we have engaged in a comprehensive analysis of the economics of burnout, leveraging an extensive source of Swedish administrative data on firms and workers linked to medical diagnoses of sick-leaves. We emphasize three main conclusions we draw from our results. First, the importance of firms in influencing a non-pay dimension of work. Previously, extensive and growing literature has studied the role of firms in the labor market, focusing mainly on their influence on pay (Abowd et al., 1999; Card et al., 2013; Song et al., 2019). We find workers who move into firms where burnout rates are high—and, more generally, into jobs with higher stress levels—are more likely to burn out. Moreover, we find no evidence of a positive compensating wage differential at firms where the risk of burnout is high, nor that those firms are more productive, rather the opposite. Second, we find that burnout has severe and lasting effects on workers' careers. Moreover, it affects the careers of their spouses and the human capital of their children. Third, we show how the likelihood of burnout can be accurately predicted, especially when worker characteristics are complemented by subjective stress levels measured in a survey. We argue that, if incentive compatible, surveys may be effectively used in identifying those at risk of burnout and assigning them to preventive treatment. Finally, we would like to emphasize that our attempt to understand this multifaceted issue should be viewed as an invitation for further research on the economic aspects of work-related stress and burnout.

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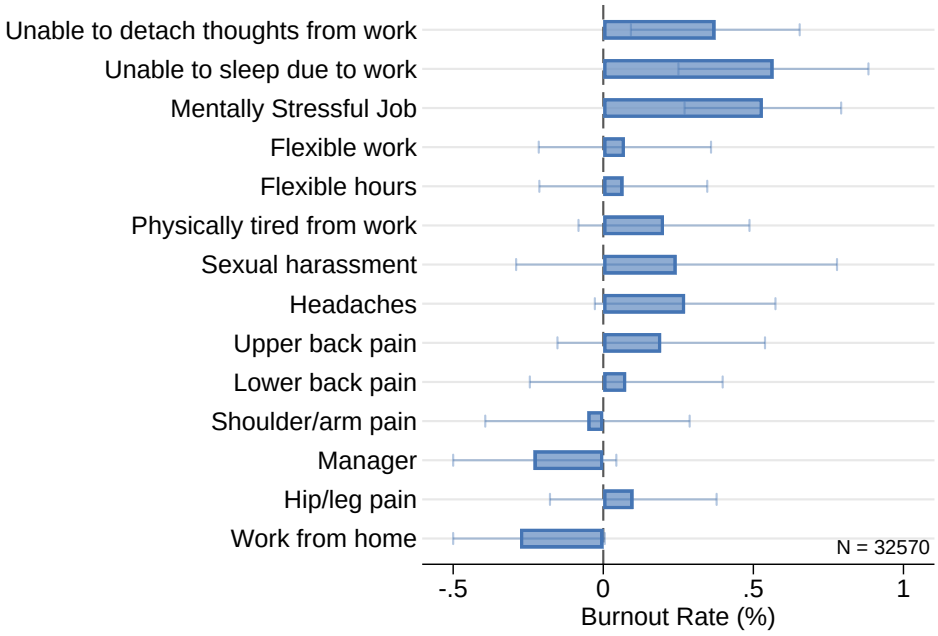
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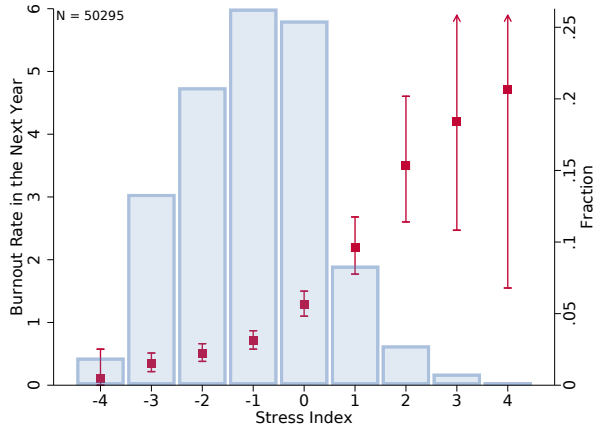
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Figure 1: What is Burnout?

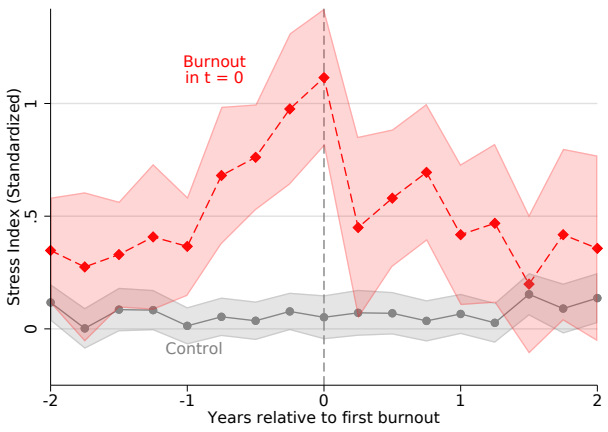
(a) Work Conditions and Burnout (multivariate regression)



(b) Stress Symptoms and Burnout Next Year



(c) Evolution of Stress Symptoms around Burnout

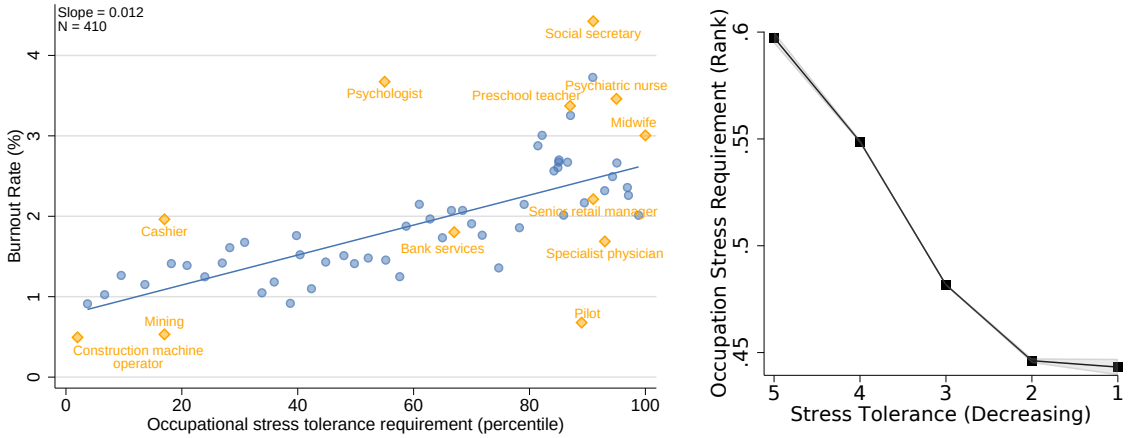


Notes: The figure documents the relationship between burnout and work conditions measured with the Work Environment survey (AMU). **Panel (a)** plots the coefficients from a regression of a burnout indicator on self-reported work condition in the previous calendar year, controlling for gender × education × 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 Section XXX). 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 disengage 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.

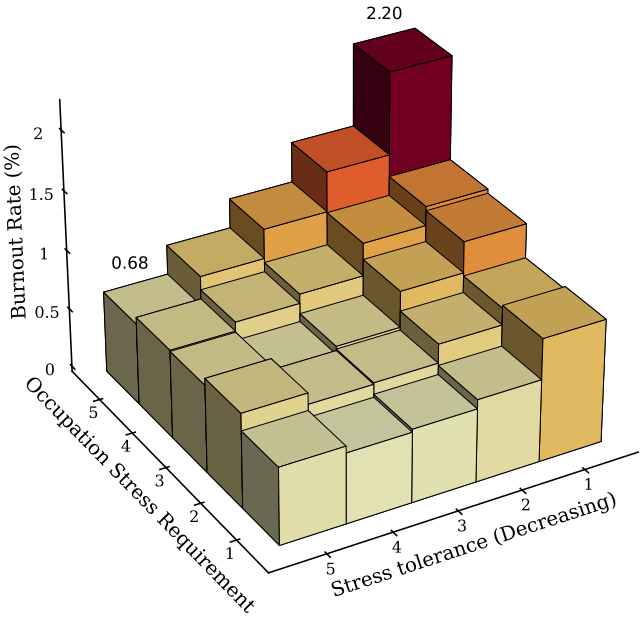
Figure 2: Who is Affected by Burnout? Job Stress and Individual Stress Tolerance

(a) Occupational Stress Tolerance Requirements

(b) Occupational Sorting



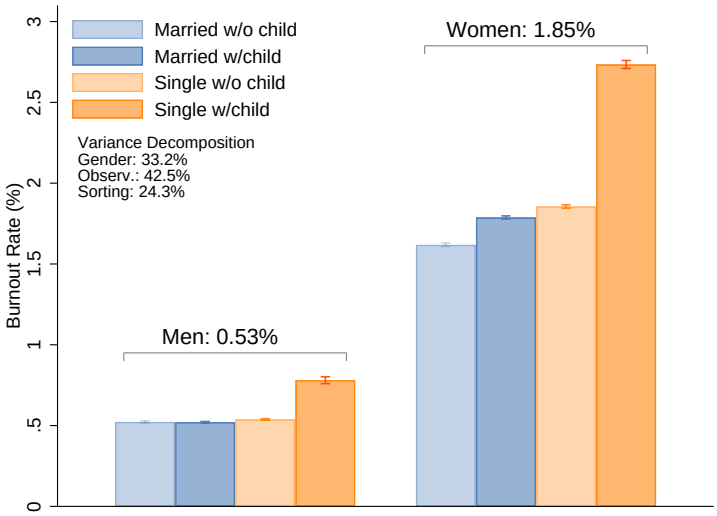
(c) Interaction Between Occupational Stress Tolerance Requirements and Workers' Stress Tolerance



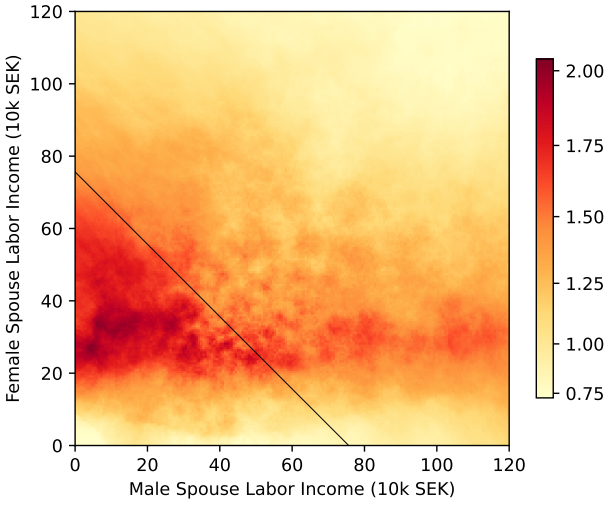
Notes: **Panel (a)** plots in solid blue dots the binned scatter plot of occupation-level burnout rate against occupational stress-tolerance requirement. Orange diamonds are a selected subset of occupations. **Panel (b)** displays the sorting of workers with varying levels of stress tolerance across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

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

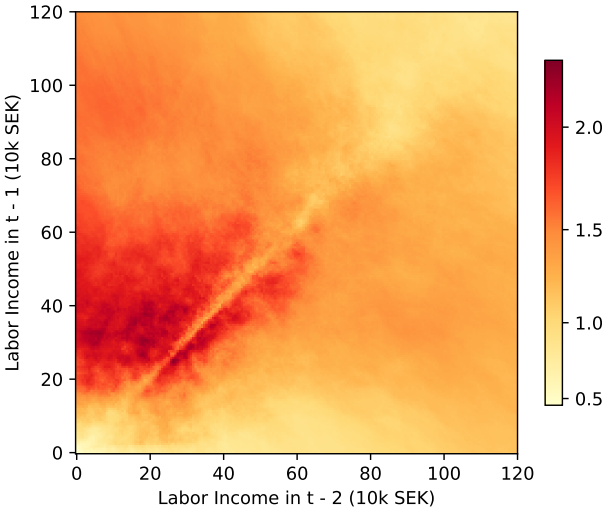
(a) Burnout Rate by Gender & Family Type



(b) Women: Burnout Rate against Couple Incomes



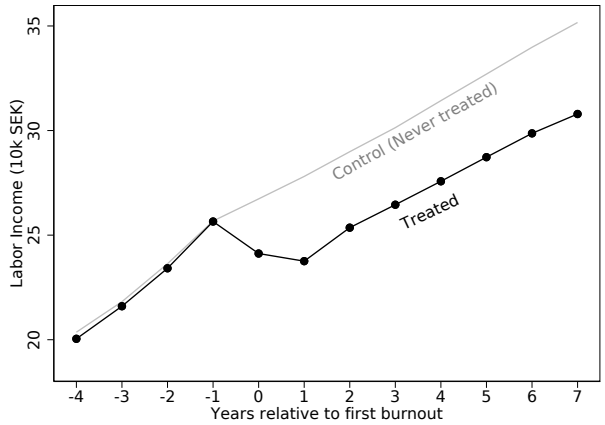
(c) Women: Burnout Rate against Income Growth



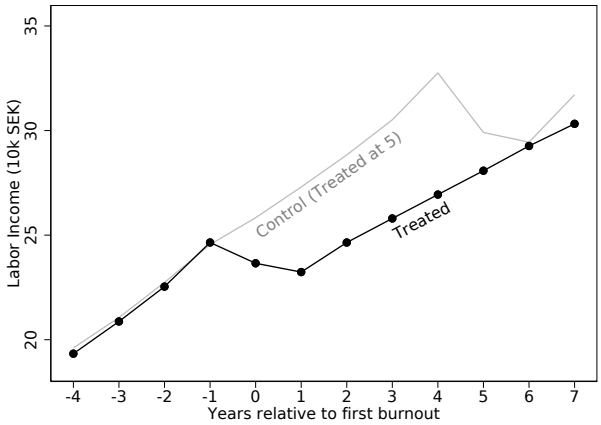
Notes: **Panel (a)** displays the annual burnout rate by marital and parental types by gender, with an average of 1.12% for the entire employed population (20.0 million women and 24.9 million men). The respective shares in the four groups are 24%, 37%, 31%, and 8% for women, and 19%, 41%, 37%, and 3% 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.5 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

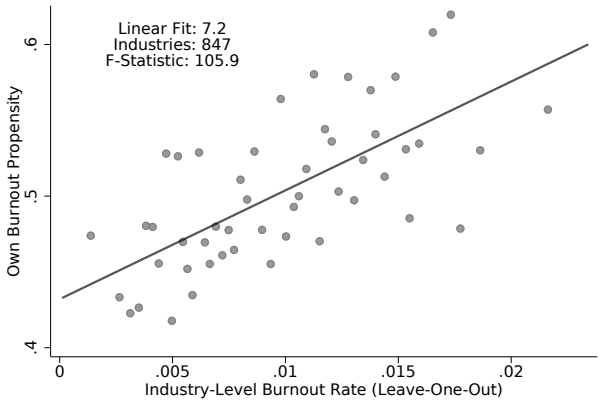
(a) Matched Difference-in-Differences



(b) Fixed-δ Method



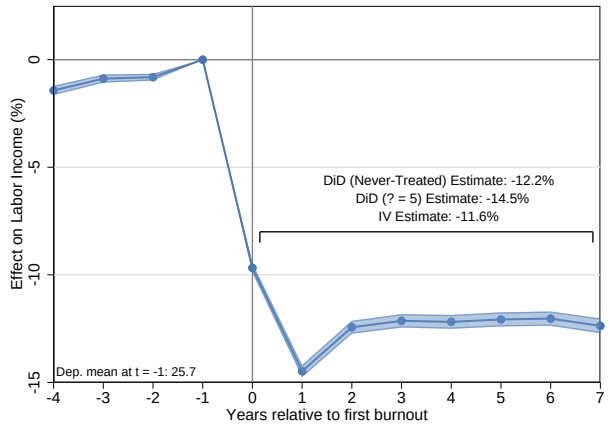
(c) IV First-Stage



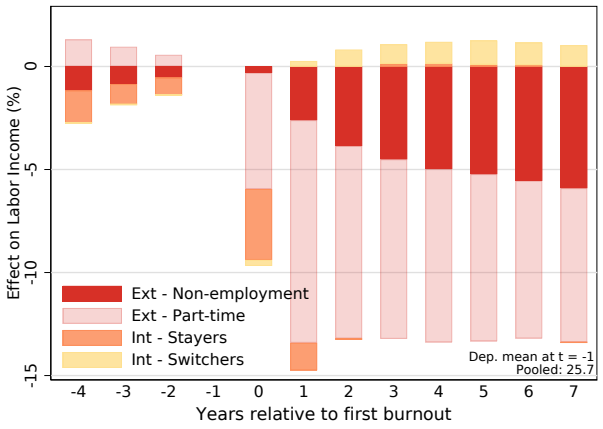
Notes: This figure showcases our three empirical designs. The estimation sample is a balanced panel of treated individuals with their first burnout between 2006 and 2013, aged 29 to 53 (so that all outcomes considered are from prime age, 25-60). **Panel (a)** shows the raw average labor income for the 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

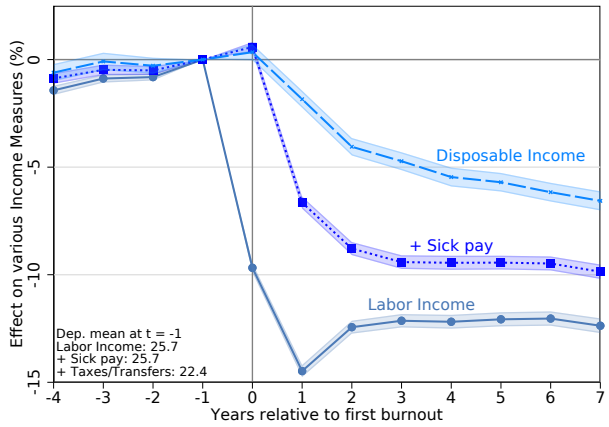
(a) Scaring Effect on Labor Income



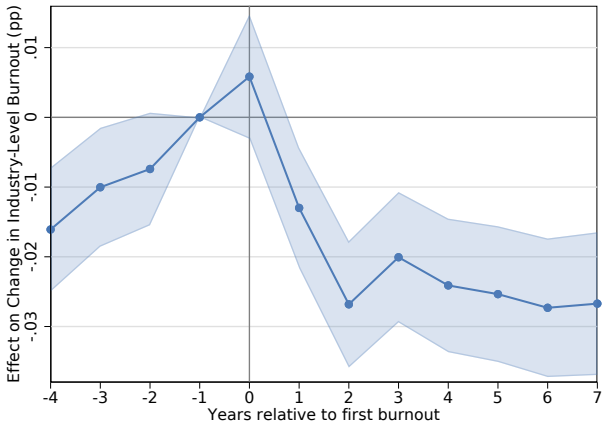
(b) Dynamic Decomposition of Labor Income Effect



(c) Social Insurance



(d) Avoiding Future Stress

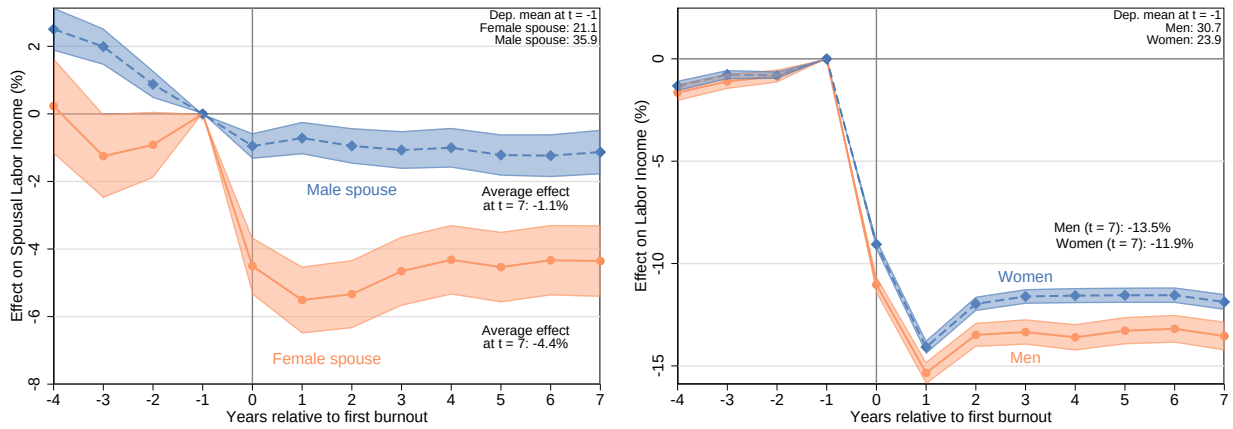


Notes: **Panel (a)** shows the proportional effect of burnout on labor income. Pre-treatment average incomes in 10k SEK and proportional effects are reported in the upper right corner. It is based on the dynamic matched difference-in-difference model, plotting the coefficients on event-time fixed effect 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

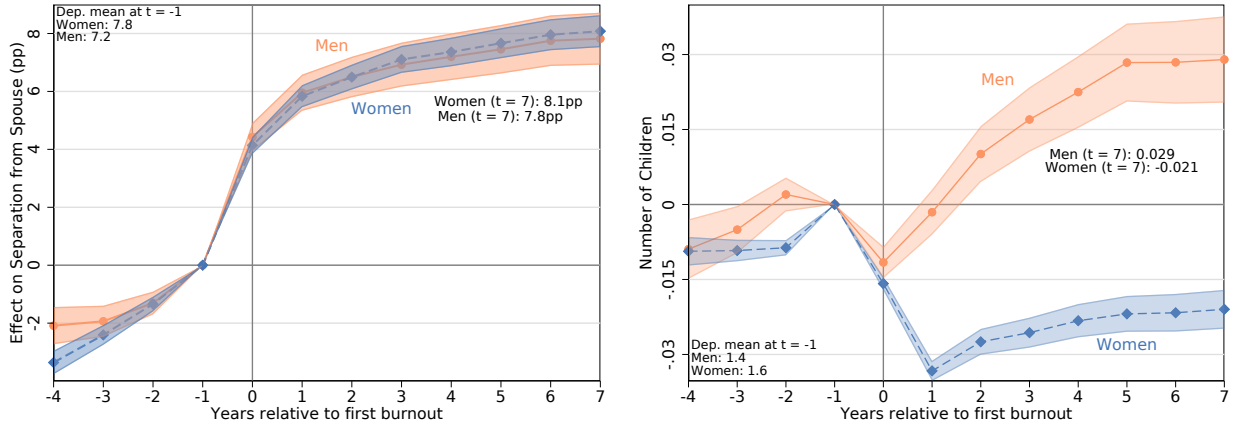
(a) Spousal Labor Income

(b) Own Labor Income



(c) Separation

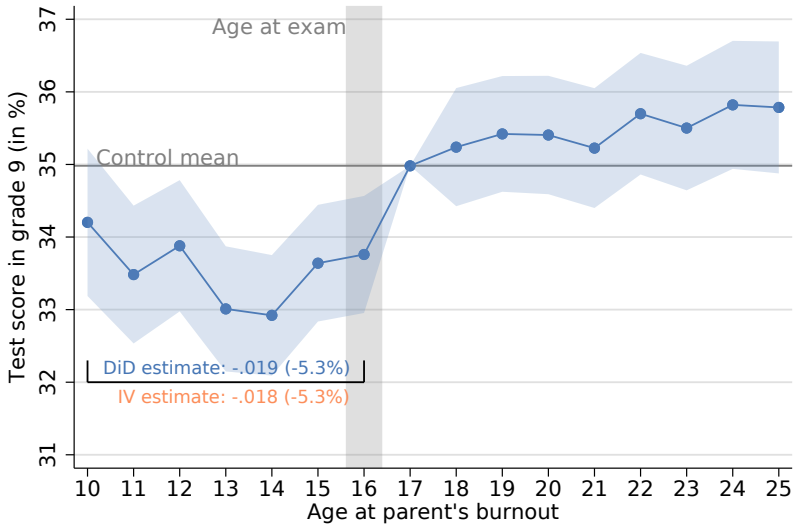
(d) Fertility



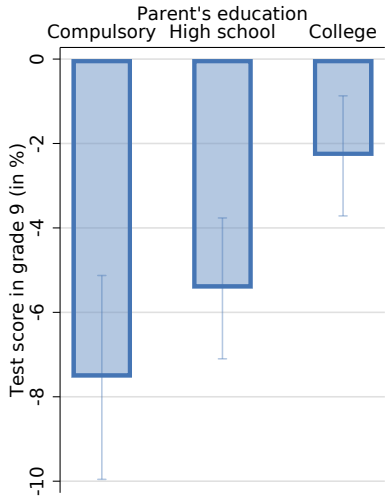
Notes: **Panel (a)** plots the proportional effect of burnout on the labor income of 57,441 spouses (married/cohabiting partners in the year prior to burnout), irrespective of the current marital status. It plots the coefficients on event-time fixed effect interacted with an indicator for burnout and 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

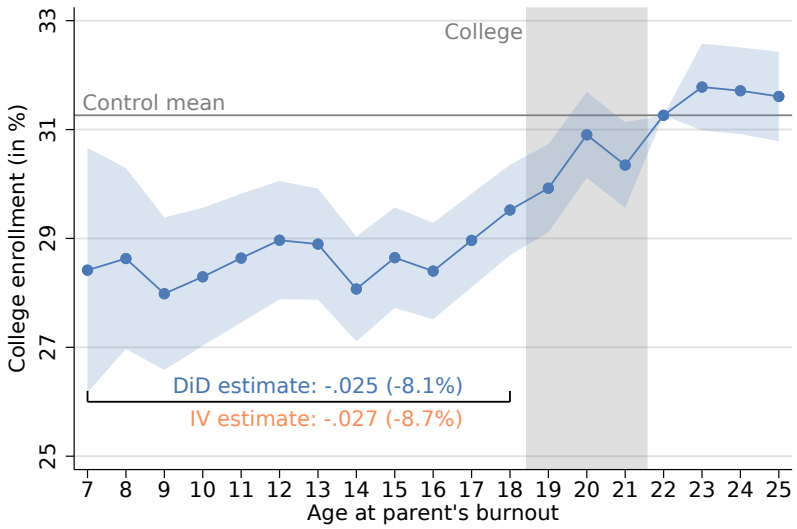
(a) School Grades: The Main Effect



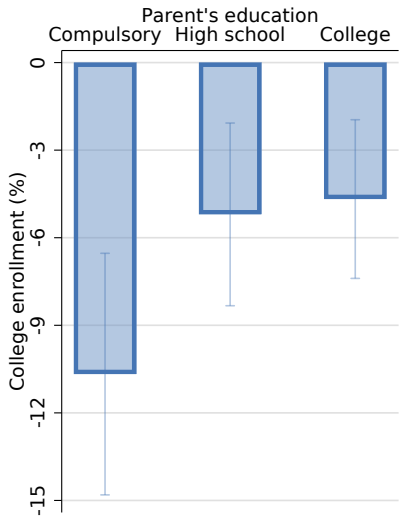
(b) Intergenerational heterogeneity



(c) College Enrollment: The Main Effect

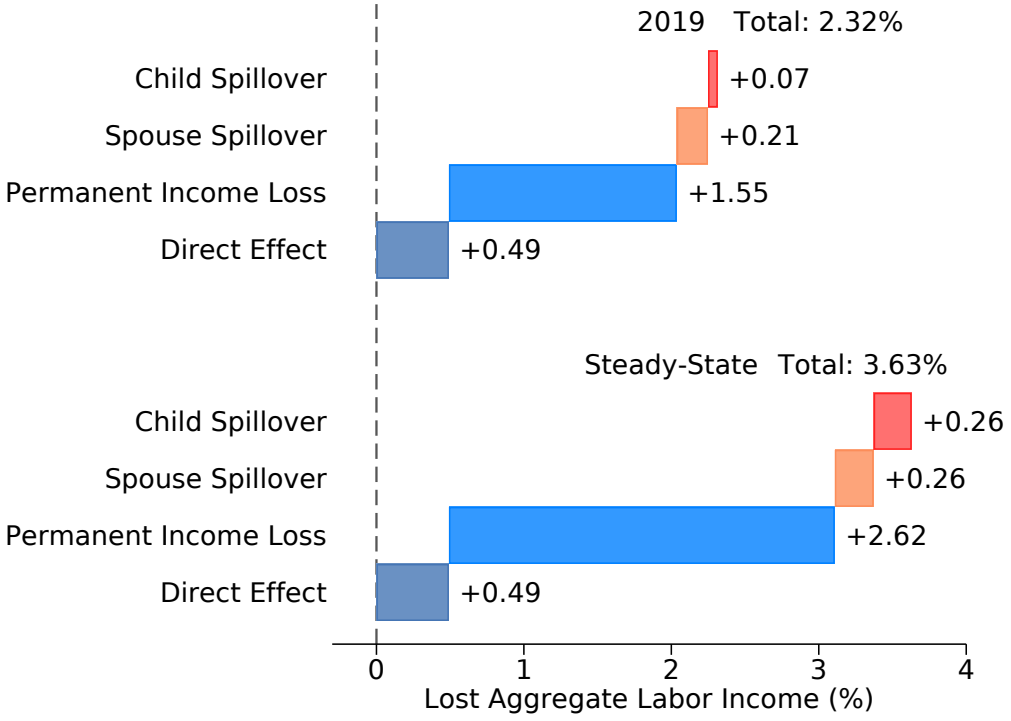


(d) Intergenerational heterogeneity



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)**, receptively. 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 (5) 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 (5) 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.

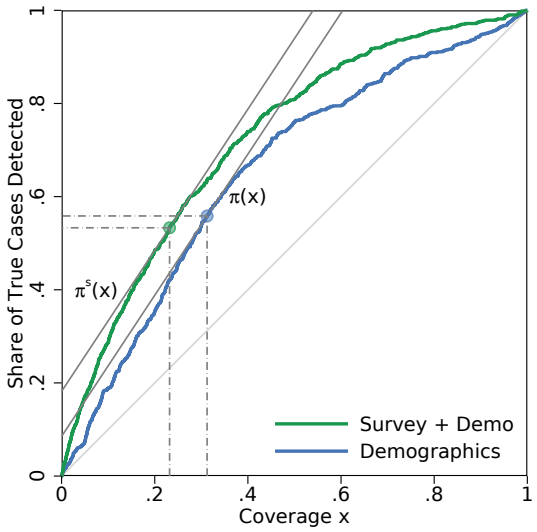
Figure 8: Aggregate Loss in Income Due to Burnout



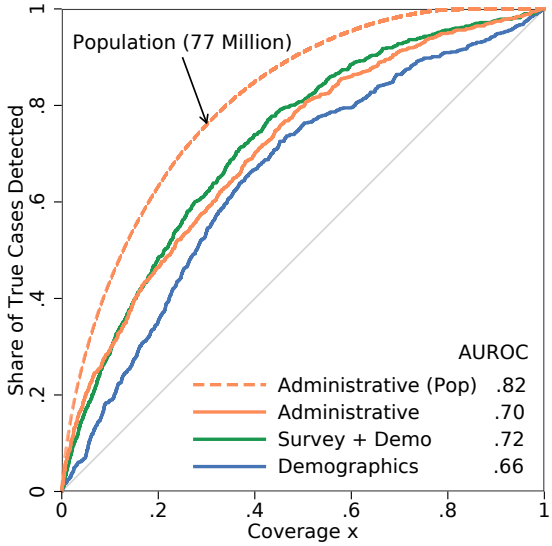
Notes: The figure presents our estimates of the loss of aggregate labor income due to burnout. The upper panel presents estimates for the year 2019, whereas the lower panel presents steady-state estimates assuming that the 2019 conditions are permanent. The aggregate loss is calculated using equation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

Figure 9: Predicting Burnout

(a) Surveys vs. Basic Demographic



(b) Survey vs. Admin data



Notes: The figure shows the Cumulative Gains Chart for prediction models of burnout in the 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

	Employed	Burn-out	Burn-out 2006-2013	Matched sample
	a) Individual-level characteristics			
Female	0.44	0.75	0.75	0.74
Age	43.62	42.92	43.39	41.2
Native	0.87	0.86	0.86	0.85
Married	0.61	0.52	0.53	0.56
Education				
Compulsory	0.34	0.29	0.33	0.31
Upper secondary	0.37	0.38	0.36	0.37
College	0.28	0.32	0.31	0.32
Labor Income (1,000 SEK) in t - 1	362.04	278.75	253.01	256.59
Not Employed in t - 1 (%)	0.0	24.5	25.72	24.93
Unemployment days in t - 1	4.19	13.62	15.83	15.45
	b) Sick leave information			
Days in t - 1				
All	5.69	25.47	24.98	16.47
Stress-related	1.01	10.07	8.3	0.0
Other mental	0.92	5.94	6.06	5.94
Non-mental	3.62	9.08	10.12	9.77
Missing	0.13	0.75	0.8	0.76
	c) Firm-level information			
Establishment size	682	728	780	776
Industry shares (%)				
Agricultural	1.0	0.4	0.4	0.4
Mining	0.2	0.1	0.1	0.1
Manufacturing	15.7	7.8	8.5	9.3
Utilities	1.3	0.9	0.8	0.8
Construction	7.0	2.7	2.5	2.7
Retail	11.3	9.2	9.1	9.7
Transport	5.1	3.4	3.8	3.8
Financial services	2.5	2.0	2.0	2.1
Non-financial services	13.6	13.0	13.2	13.8
Public administration	6.5	7.4	6.9	6.6
Education	10.2	16.7	16.6	15.9
Health	15.6	26.3	26.3	24.8
Entertainment	1.5	1.5	1.6	1.6
Other	6.3	4.8	4.2	4.7
Missing	2.3	3.9	4.0	3.8
Number of individuals	5,397,425	604,259	220,715	150,834

Notes: The table reports summary statistics for different sub samples used in the analysis. Samples are constructed from the entire Swedish population who are alive and between ages 25 to 60 from 2006 until 2020.

Table 2: Burnout: Compensating Wage and Productivity Differentials

	(1)	(2)	(3)	(4)	(5)	(6)
Panel (a): Wages (Log)						
Firm Burnout Rate	-0.89	-0.65	-0.23	-0.15		-0.15
	(0.09)	(0.07)	(0.05)	(0.05)		(0.05)
Firm PageRank					0.20	0.21
					(0.04)	(0.04)
R2	0.935	0.940	0.941	0.941	0.941	0.941
Number of Worker-Years (Mil)	13.4	13.4	13.3	13.3	13.3	13.3
Number of Plants	15,939	15,939	15,939	15,939	15,936	15,936
Number of Firms	7,737	7,737	7,734	7,734	7,732	7,732
Panel (b): Value Added Per Employee (Log)						
Firm Burnout Rate	-6.83	-6.10	-1.98	-1.98		-3.17
	(1.57)	(1.41)	(1.00)	(1.00)		(1.02)
Firm PageRank					1.92	2.04
					(0.50)	(0.52)
R2	0.804	0.808	0.843	0.843	0.843	0.843
Number of Worker-Years (Mil)	6.6	6.6	6.6	6.6	6.6	6.6
Number of Plants	8,611	8,611	8,610	8,610	8,609	8,609
Number of Firms	6,487	6,487	6,483	6,483	6,483	6,483
Demographics	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓
Individual FEs	✓	✓	✓	✓	✓	✓
Occupation FEs		✓	✓	✓	✓	✓
Industry FEs			✓	✓	✓	✓
Public Sector FE				✓	✓	✓

Notes: The table investigates the relation between firm burnout rate and wage (compensating wage differential for burnout) in **Panel (a)** and productivity in **Panel (b)**. The regressions are at the individual level, weighted by the inverse of firm size. Robust standard errors, clustered at the firm level, are in parentheses. Firm Burnout Rate is the leave-one-out time-invariant average burnout rate. Firm PageRank is the firm's rank in the job ladder based on revealed preferences (worker flows) (Sorkin, 2018). Both firm's burnout rate and RageRank are standardized by their standard deviation in the firm distribution. The estimation sample is the Swedish working population, excluding self-employed, who are alive and aged 25 to 60. The sample period is 2006-2020. We restrict the sample to workers for whom at least one thousand observations can be used to compute the leave-one-out firm-level burnout rate. Demographics are gender- and education-specific third-order polynomials in age similar to Card et al. (2013). To ensure precision of Firm Burnout variable, we restrict the sample of firms to those with 500 worker observations over the period 2006-2020. Moreover, we ensure that all models are estimated on the same sample, dropping, for example, individuals whose firm does not report value-added but for which burnout rates can be computed. The estimated coefficients are similar when we estimate each specification on the largest common sample (Appendix Table **??**).

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 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.

Online Appendix of:

The Economic Burden of Burnout

Arash Nekoei, Jósef Sigurdsson, and Dominik Wehr
March 20, 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.2 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. The treatment group contains 151,752 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 Section **??**. 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 17,709,818 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 39,120,155 individual-year observations.

PageRank Estimation We start with a full sample of workers employed between 2005 and 2020. We drop spells at firms with one employee. We then construct monthly earnings using total earnings over the year and the reported start and end dates of the employment spell within a given year. We keep observations with monthly earnings exceeding 10,000 SEK to focus on workers with strong labor force attachment and reduce the influence of employer transitions due to hours constraints. For each worker we define their primary employer has the employer with the highest total earnings in a given year, and restrict the sample to primary employers.

In order for observed employer-to-employer flows to represent unconstrained choices of the worker, we eliminate transitions possibly reflecting re-employment after layoffs from the sample. We focus on transitions occurring in two consecutive years and require that workers report no days in unemployment in either year. Moreover, we keep only transitions for workers who spent

at least two years at the origin firm as their primary employer. Counting the number of transitions for each origin-firm edge between 2006 and 2020 yields the adjacency matrix underlying the PageRank algorithm.

Compensating Wage Differential and Productivity The sample used to estimate compensating wage differentials for burnout risk is constructed as follows. Starting with our main sample of prime-aged workers during the period 2006 to 2020, we drop individuals who according to tax exhibit some form of self-employment. Within this sample, we estimate leave-one-out burnout rates for each establishment. We then restrict the sample to plants with more than 1,000 individual-year observations over the entire fifteen-year period we consider. We drop all individuals who have already experienced their first burnout (including the year of the first incident), to avoid capturing scarring effects in our wage regression. We winsorize leave-one-out rates (at the individual level) at the upper 1% of the distribution. Finally, we restrict the sample to individuals with full-time employment to reduce variation in hours across workers.

Variable Construction A few remarks on variable construction are in order. In order to control for occupation, we create dummies for each occupational code under SSYK96 or SSYK2012. We code workers as private sector if they are recorded as private white-collar, or private blue-collar workers.

Using the firm identifiers in the matched employer-employee data, we link workers to their firm balance sheets from FEK and obtain value-added and the number of employees. Again, we drop individuals at a firm with only one employee to avoid including those self-employed. We merge this data set with the PageRank estimates described above and take the logarithm of the PageRank value. We winsorize the upper 5% of the PageRank distribution (across establishments), and subsequently normalize by dividing by the standard deviation of the winsorized log-PageRank distribution. We proceed in a similar way for log value-added, with the difference being that i) moments are computed at the firm-level distribution since balance sheets are only available at the firm-level, ii) we winsorize the top 1% of the distribution, iii) we abstain from normalization. We also normalize the burnout rate using its standard deviation across establishments (ignoring some within-establishment variation).

C Questions in the Work EnvironmentSurvey

In Section 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 (model XXX) 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 Sexual Harassment and Burnout

As documented in Section **??**, burnout is substantially more prevalent among women than men. It was, therefore, particularly unfortunate that our investigation on the impact of work-related stress and an individual's tolerance to stress was limited to male workers. In light of this, we also investigate another stressor: sexual harassment in the workplace. To this end, we use data from the nationally representative Swedish Work Environment Survey, with two questions about sexual harassment from colleagues or managers (for more details see, e.g., Folke and Rickne, 2022).

We first investigate burnout by workers' own experience of sexual harassment. Appendix Figure A.13, panel (a), reports almost twice as high burnout rates among women who have experienced sexual harassment in the last 12 months. This also holds true when conditioning on age, education, and occupation. For comparison, panel (b) reports the same for men, showing that men who experience sexual harassment are also more likely to burn out. We then study burnout by exposure to sexual harassment, measured by the prevalence of sexual harassment of women in the occupation. We report in panel (c) the burnout rate of men and women by this occupation-level exposure to sexual harassment. The figure reports higher burnout rates, both among women and men, in occupations with a high prevalence of sexual harassment.

F Prediction and Prevention

F.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% 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% of the sample.

F.2 Basic Demographic and Administrative Data

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

Sick leave records yield the count data for sick leave spells in each past year (up to five years)

for the following diagnosis categories: physical and unrelated to pregnancy, physical related to pregnancy, single-episode depression, recurring depression, anxiety, stress-related mental health diagnoses, other mental health diagnoses, missing diagnosis. For each category, we include the total number of spells in the last five years as a predictor.

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

F.2.1 Details of Cost-Benefit Calculations

We calculate the benefit of the program net of costs as

$$\begin{aligned}\Gamma + \Lambda &= \alpha \times b \times (\theta C - P) - \beta \times (1-b) \times P \\ &= 80\% \times 1.12\% \times \left(10\% \frac{3.51\%}{1.12\%} - \frac{1}{24}\right) - 1\% \times (1 - 1.12\%) \times \frac{1}{24} = .2\%\end{aligned}$$

when measured in terms of average annual labor income, or, equivalently, 4.05 hours (see main text for details on numerical values). Next, using equation (10), we calculate $\frac{\partial \pi(x^*)}{\partial x} = 1.6$ using a cost of triage of 6.5 hours.

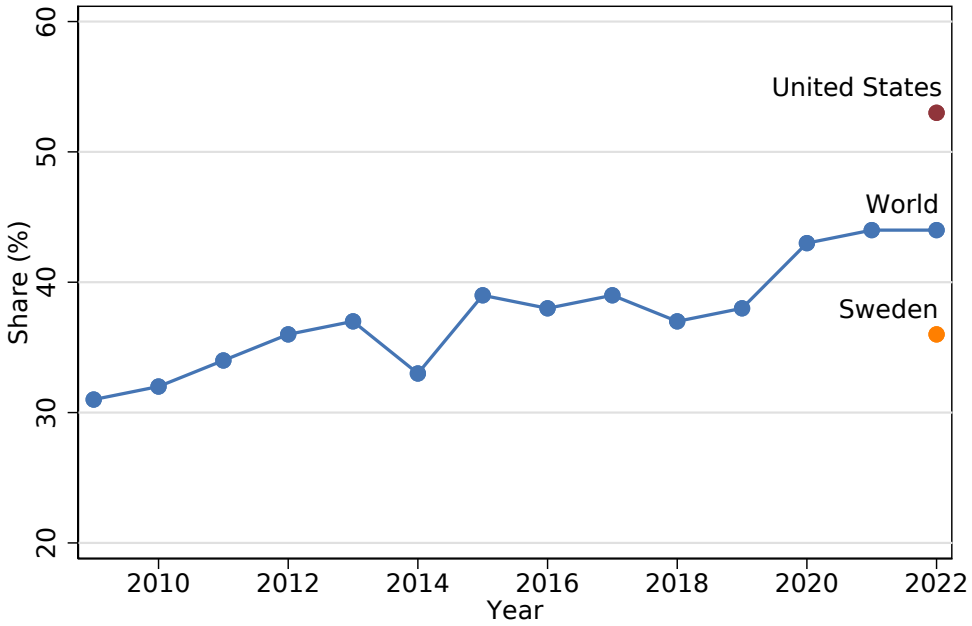
With this estimate, the total gain from optimal coverage of the program is:

$$W(x^*) = (\Gamma + \Lambda) I(\pi) = 4.05 \times 3.19\% = 13\%$$

of an hour. In terms of burnout cost, bC, the net gain is $.2 \times 3.19\%/3.51 = 0.18$ percent, and in terms of burnout cost of those selected, is $(.2 \times 3.19\%)/(3.51 \times .26 \times .8) = 0.86$ percent.

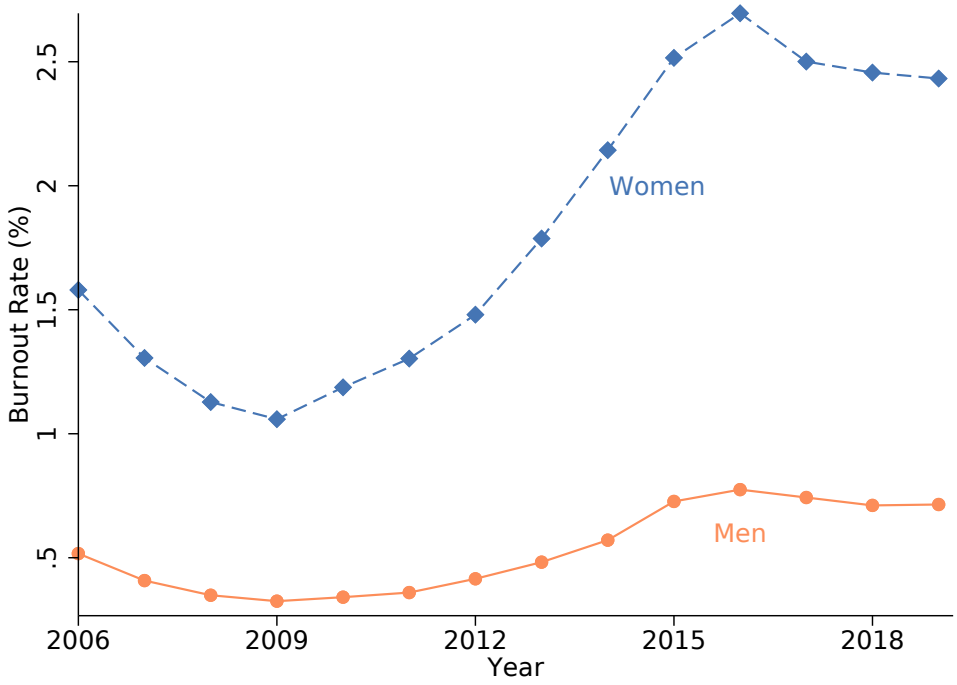
G Supplementary Figures

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



Did you experience stress during A LOT OF THE DAY yesterday? (Yes = 1)
Source: Gallup, State of the Global Workplace

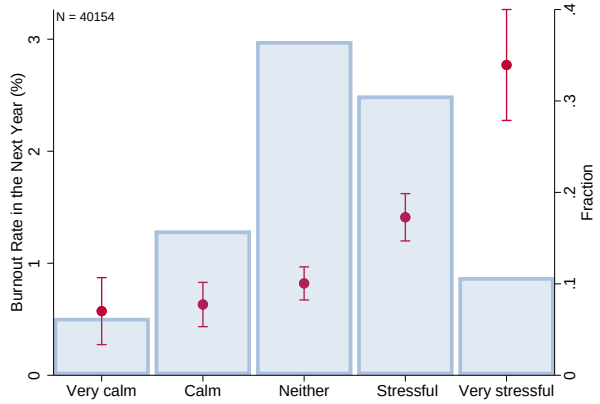
Figure A.2: Evolution of Burnout Rates over Time



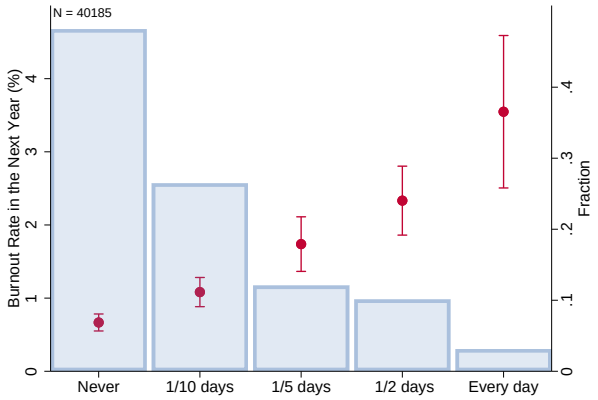
Notes: The figure plots the burnout rate, defined as the share of the population experiencing at least one burnout sick-leave spell in a given year among those full-time employed in the previous year between 2006 and 2019, the years where we have data on sick-leave spells and diagnoses for the full year.

Figure A.3: Components of Stress Index

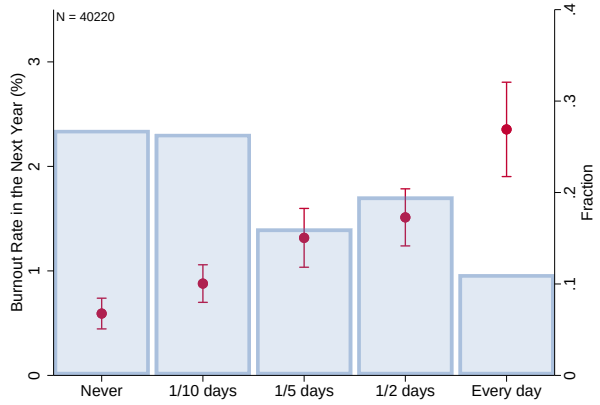
(a) Do you find your work mentally stressful or calm?



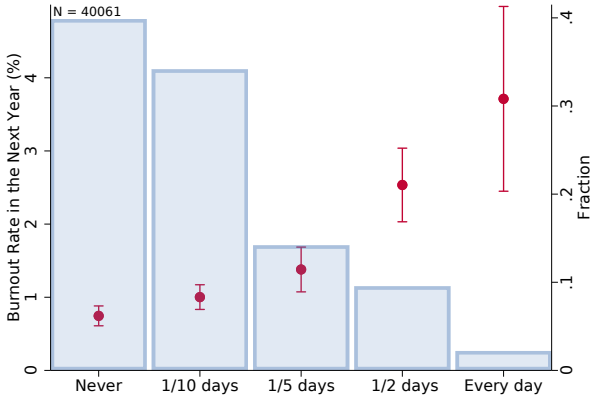
(b) Are you Unable to sleep due to thoughts about work?



(c) Unable to detach thoughts

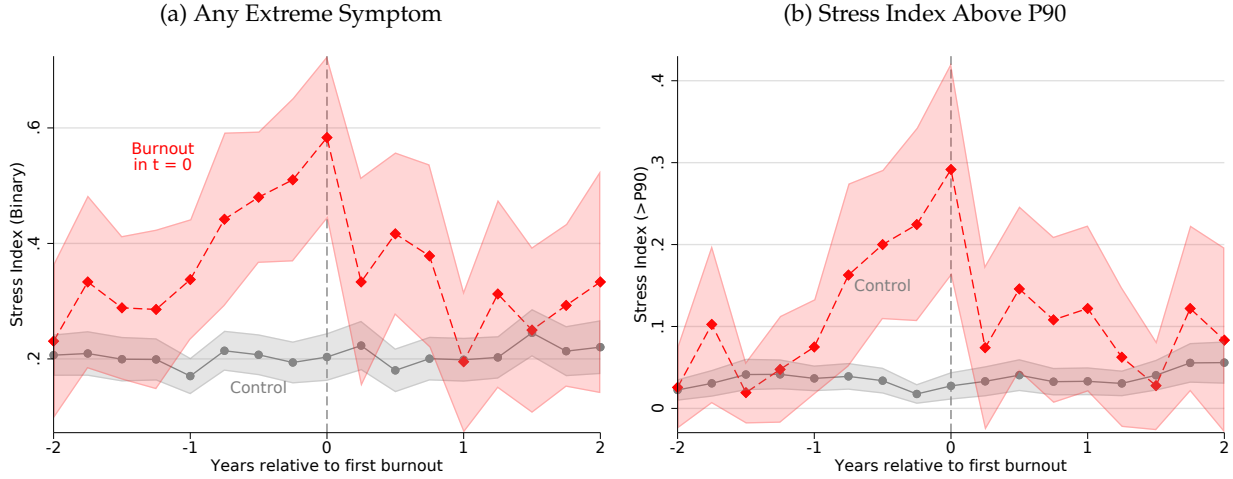


(d) Did you experience headaches during the previous three months?



Notes: The figure ...

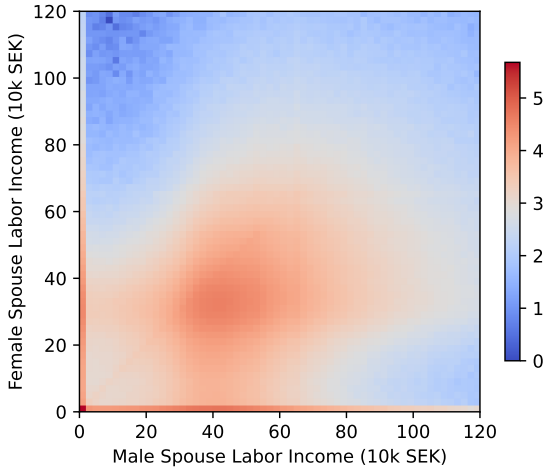
Figure A.4: Evolution of Alternative Stress Indices Around Burnout



Notes: The figure shows the evolution of alternative measures for work-related stress around burnout. In **Panel a)** the outcome is an indicator assuming value one if a respondent gives the highest response to one the four questions about symptoms of burnout used in the construction of the stress index described in Figure 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.

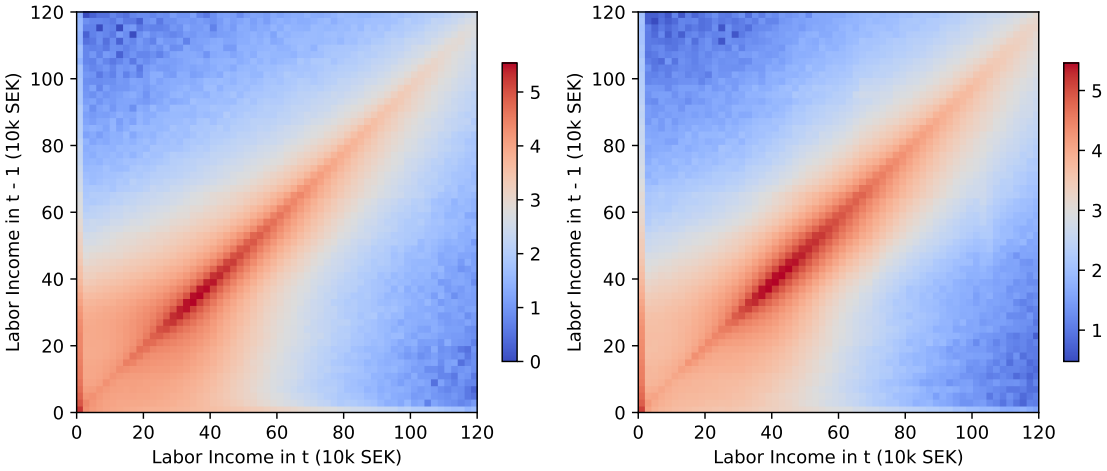
Figure A.5: Distribution of Labor Income Histories

(a) Joint distribution of spousal labor incomes



(b) Income history (Women)

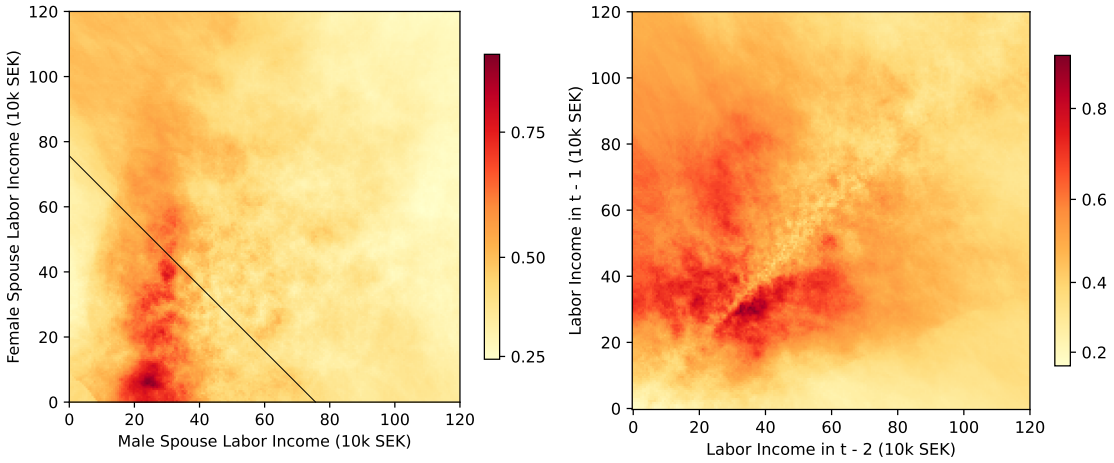
(c) Income history (Men)



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.6: Burnout Rate of Men: Couple Incomes & Career

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

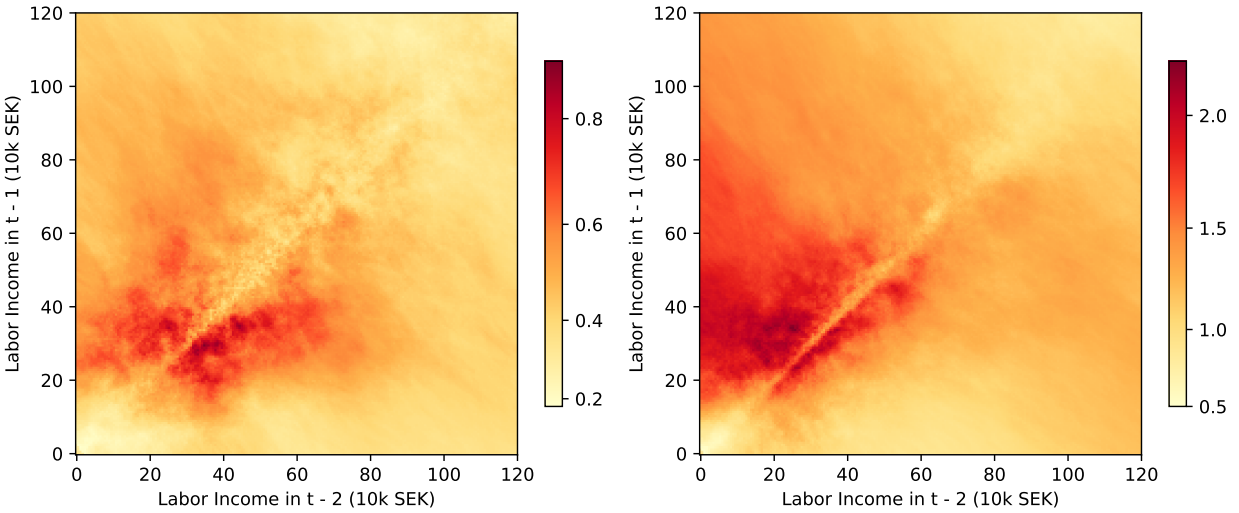


Notes: **Panel (a)** shows burnout rates over the joint distribution of spousal labor incomes for 11,008,512 couple-year observations in each subfigure. The two lines are 45-degree lines and a line marking the median couple's total income of 756k SEK. Annual labor income is winsorized at 1,200k (corresponding to P97 of men and P99 of women) and rank-adjusted to 2020 SEK when the exchange rate was 9,20 to USD and 10,49 to Euro. Two-dimensional moving averages are used so that the burnout rate represents the average rate for approximately 40000 individuals in the circular vicinity of each point. **Panel (b)** reports burnout rates in $t+1$ across individuals' labor income histories. The x-axis reports labor income in $t-1$. The y-axis reports labor income in t. We perform a rank-adjustment to 2020 levels for labor income in $t-1$ and compute income in t using rank-adjusted labor income in the previous year and nominal income growth at the individual level. The sample consists of individuals aged 25 to 55 between the years 2005 and 2019 without prior burnout sick leave. We drop observations within a two-year window of childbirth. See notes in Figure A.5 for a more detailed description of the sample construction.

Figure A.7: Burnout and Labor Income Histories (Stayers)

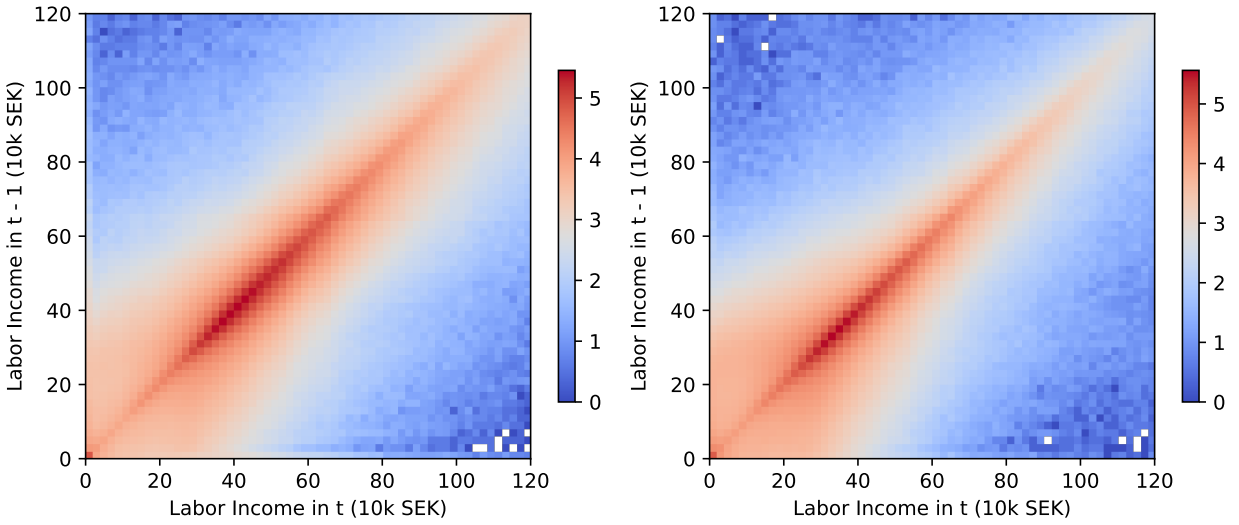
(a) Men: Burnout Rate among Stayers

(b) Women: Burnout Rate among Stayers



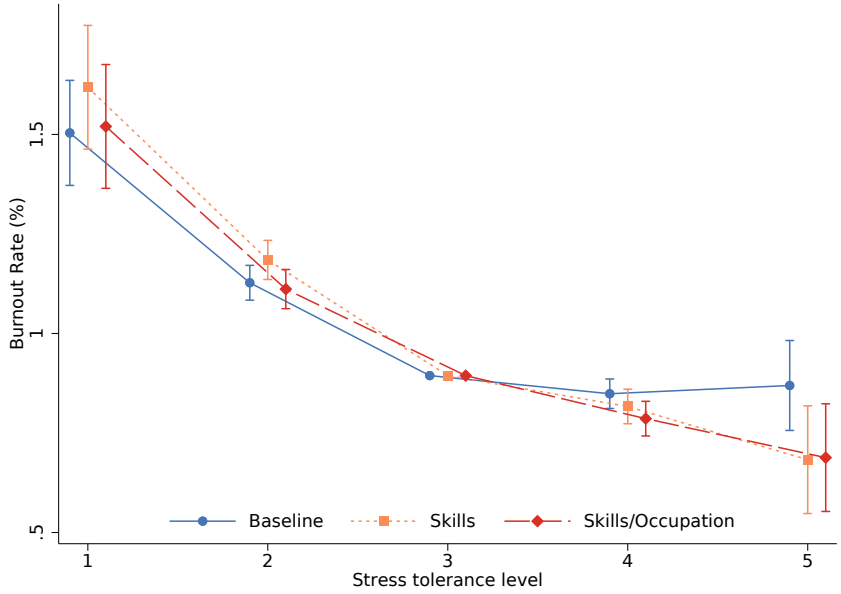
(c) Men: Histogram of Income Histories

(d) Women: Histogram of Income Histories



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

Figure A.8: Individual's stress tolerance and burnout

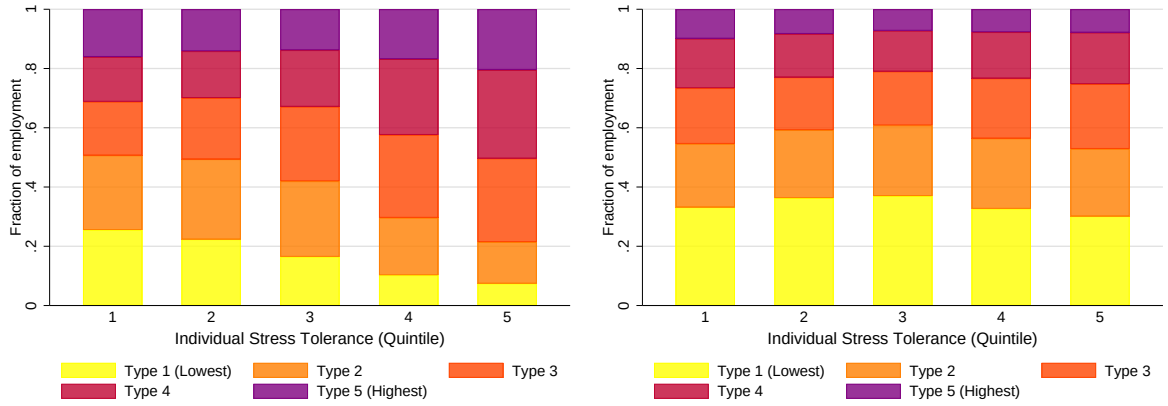


Notes: The figure plots the average individual burnout rates by individual stress tolerance, measured in association with the military draft. Blue circles are averages estimated using a regression where the median group is the reference category. Orange squares are estimates from a similar regression 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.9: Sorting

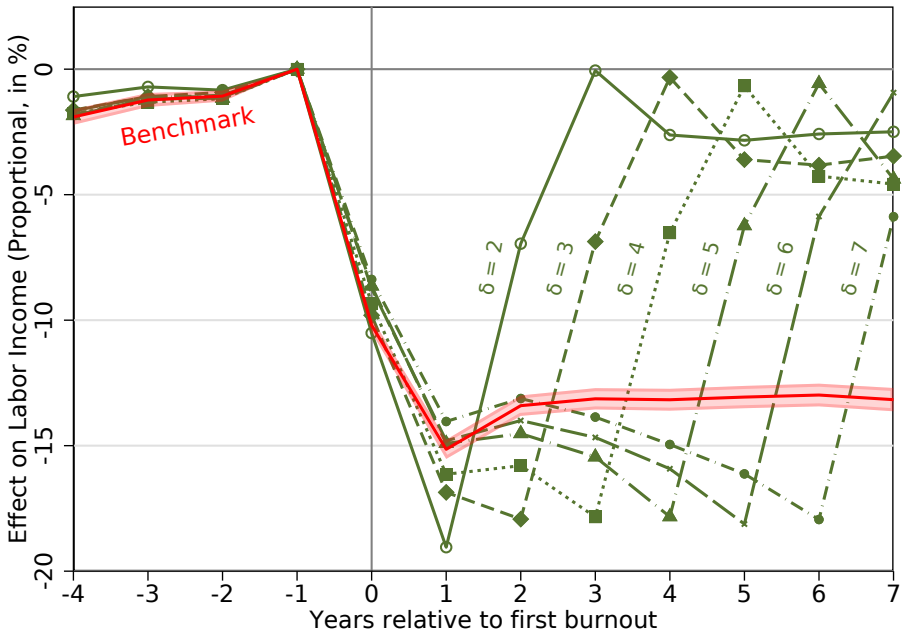
(a) Sorting into Occupations

(b) Sorting into Firms



Notes: This figure shows the distribution of employment across firm/occupation stress levels conditional on workers stress tolerance in Sweden from 2005 to 2019. The sample space is the same as in the second row of Figure **??** for both firms and occupation. The stress tolerance measures used are only available for men.

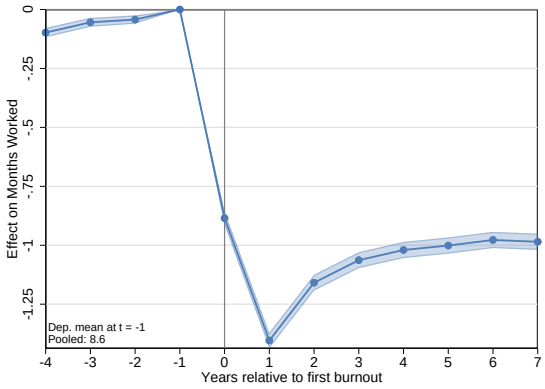
Figure A.10: Effect of Burnout on Labor Income: Baseline vs. Fixed-Delta Method



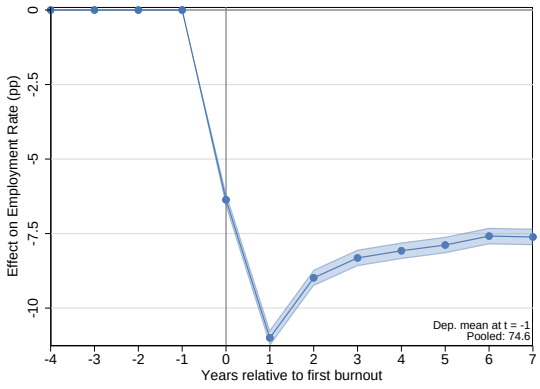
Notes: The figure shows the proportional effect of burnout on labor income as estimated with different matched control groups. The red line labeled *Benchmark* depicts the estimated effects when never-treated individuals are used as a control (Figure 5a). The control group in the remaining lines are 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.11: Burnout Effect on Labor Income: Extensive vs. Intensive Margins

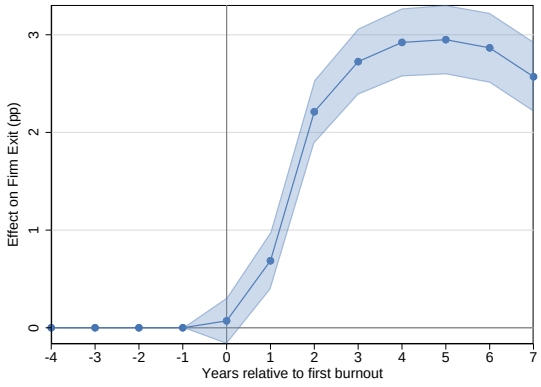
(a) Months worked



(b) Employment Rate

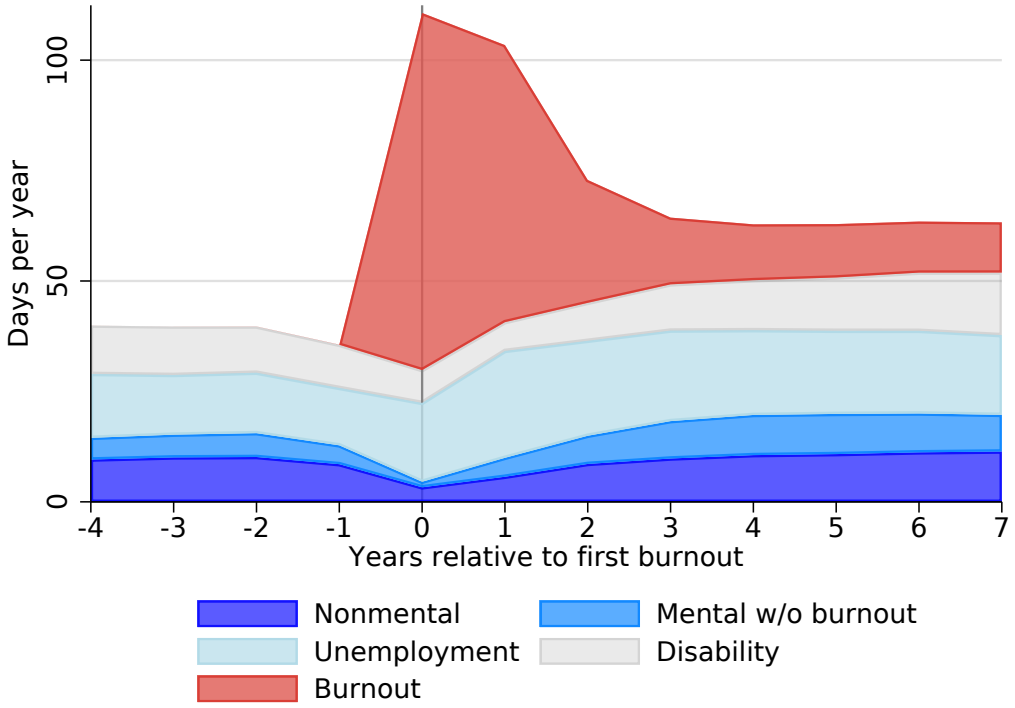


(c) Firm Switching



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.

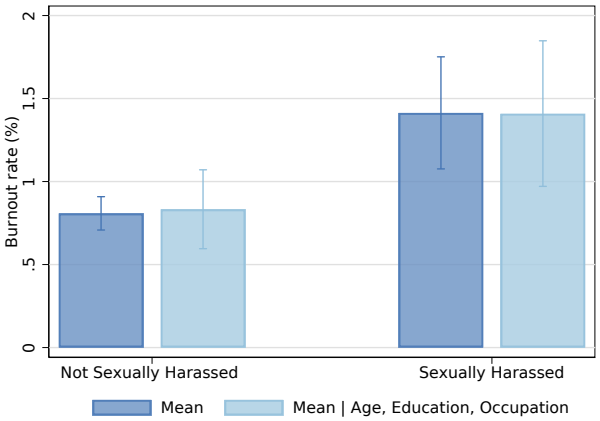
Figure A.12: The Effect of Burnout on Days Worked



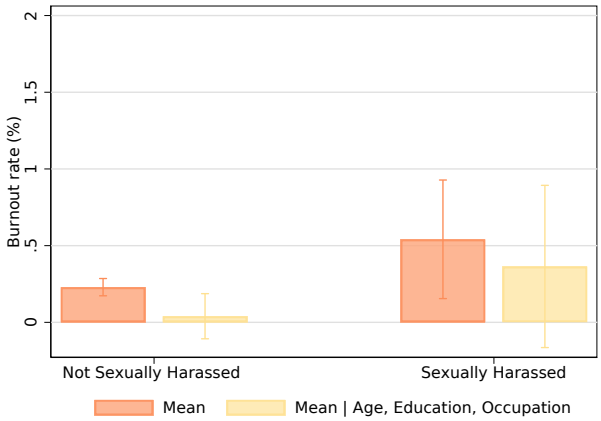
Notes: This figure presents estimation results of the dynamic difference-in-difference model for days on sick leave by diagnosis category, as well as days in unemployment and on disability.

Figure A.13: Burnout By Experience of or Exposure to Sexual Harassment

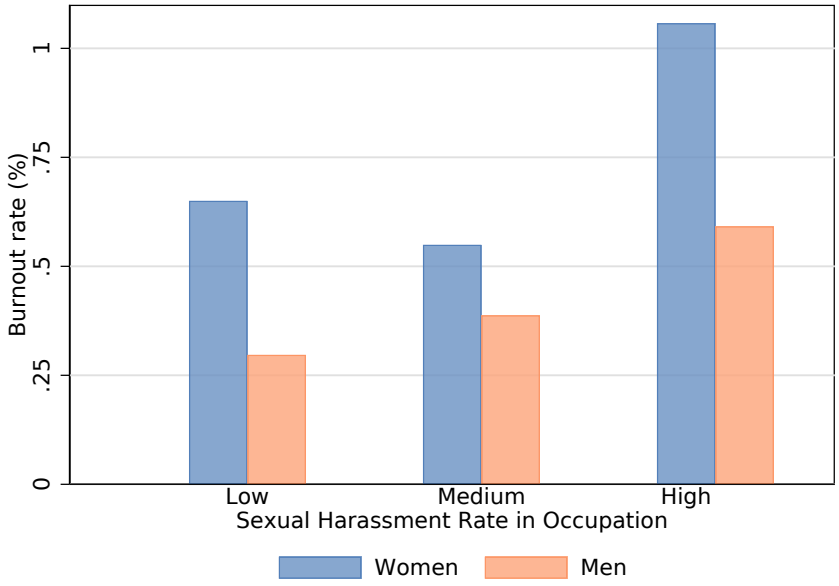
(a) Women: Sexual Harassment in Workplace



(b) Men: Sexual Harassment in Workplace



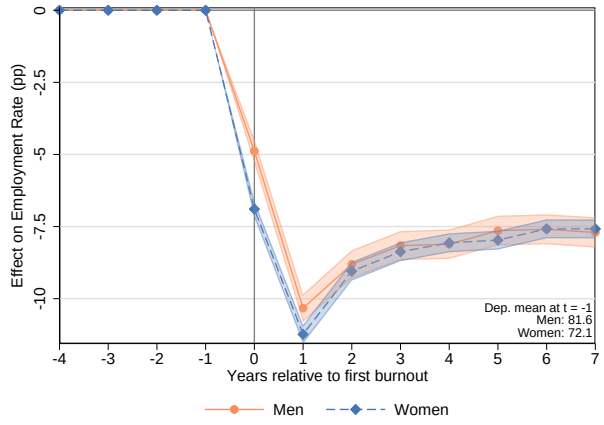
(c) Occupations: Prevalence of Sexual Harassment



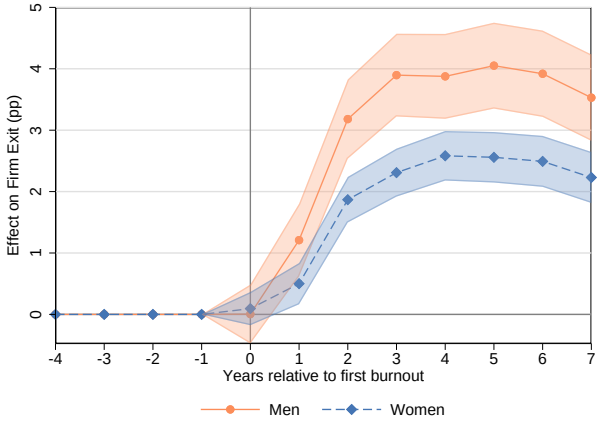
Notes: This figure reports the share of workers with burnout by exposure to sexual harassment. **Panel (a)** measures the burnout rate among women depending on whether they report having experienced sexual harassment at work in the last 12 months, either by supervisors or colleagues. The share of women in the sample who have been harassed is 5.1%. Dark blue bars show the raw means, whereas light blue bars show means controlling for age, education, and 3-digit occupation fixed effects. **Panel (b)** reports the same for men. **Panel (c)** plots the burnout rate among men and women by the prevalence of sexual harassment in their occupation. Occupations are split in terciles.

Figure A.14: Decomposition of the Impact of Burnout on Labor Income: Men vs. Women

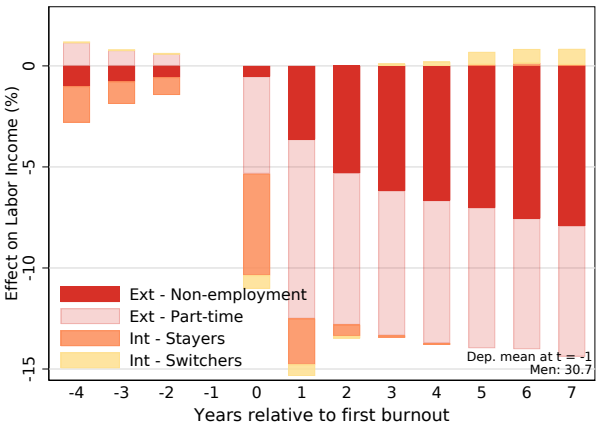
(a) Employment



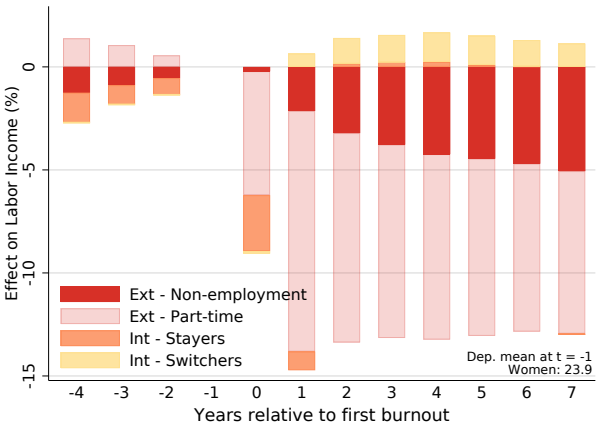
(b) Leaving the Firm where Burnout Occurs



(c) Decomposition: Men

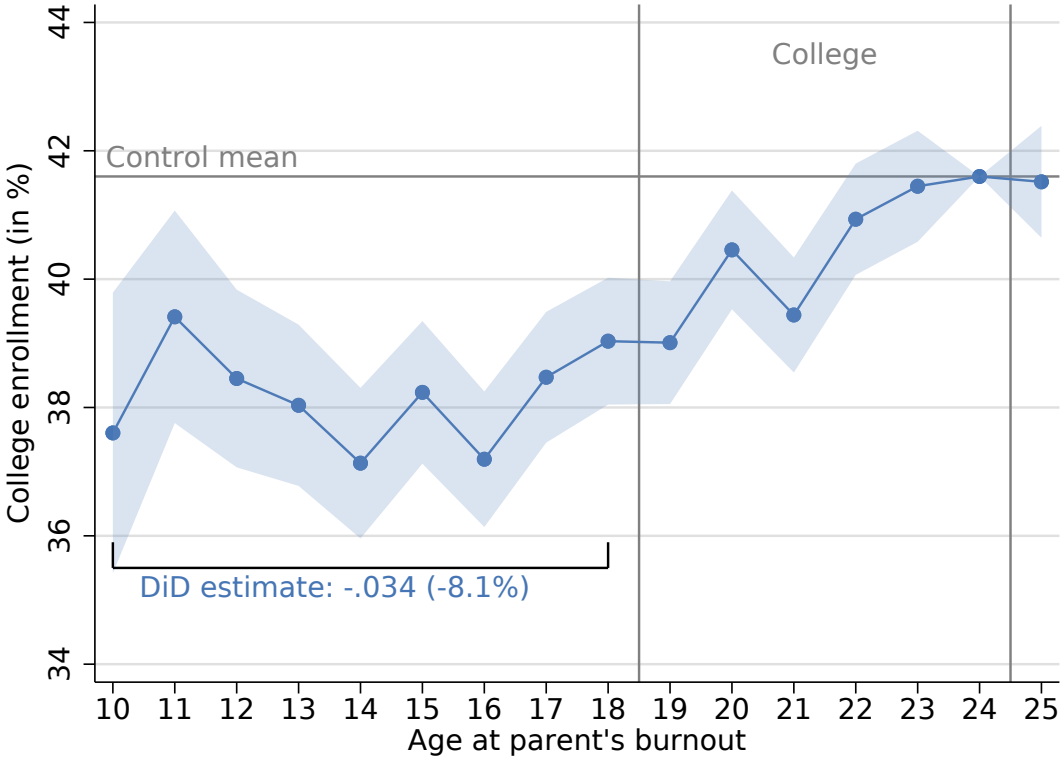


(d) Decomposition: Women



Notes: This figure shows margins of labor market adjustment to burnout and their contribution to earnings dynamics separate by gender. The decomposition follows equations (4) and (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.

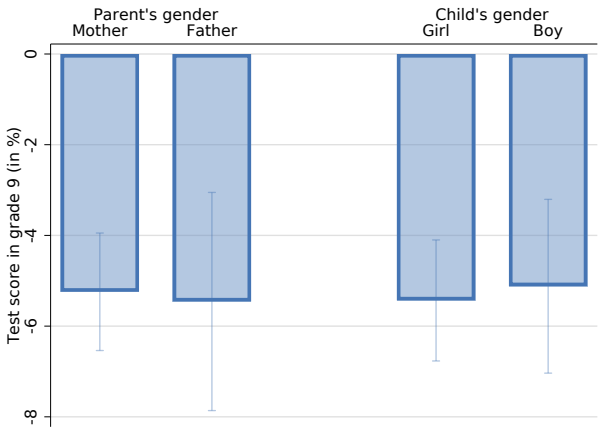
Figure A.15: Effect of Parental Burnout on Child's College Enrollment



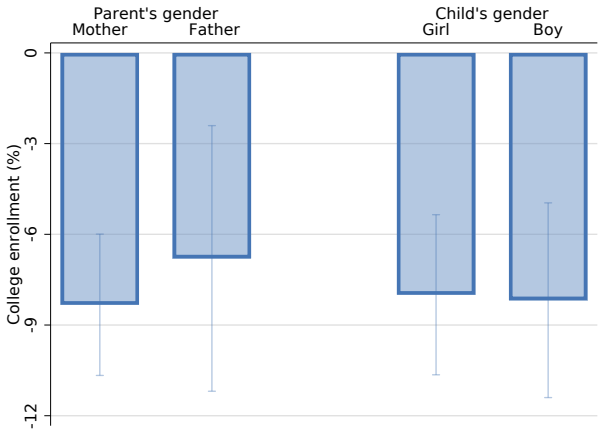
Notes: The figure plots the effect of parental burnout on children's college enrollment measured at some age 19 to 24. To identify deviations in the treated group from potential cohort-specific trends in college enrollment, we demean the outcome with the mean outcome of a control group with the same 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 (5) that includes controls for the parent's birth cohort and gender and the child's birth cohort, gender, and sibling order. The coefficient estimates measure college enrollment of children by their age at the time of first parental burnout relative to those whose parents burn out at age 24, i.e., difference-in-differences, scaled by adding the mean college enrollment of the control group. The shaded area reflects 95% confidence intervals based on robust standard errors clustered at the parent level. "DiD estimate" reports the average effect for ages 10-18.

Figure A.16: Heterogeneity of Effects of Parental Burnout on Child's Human Capital

(a) School Grades

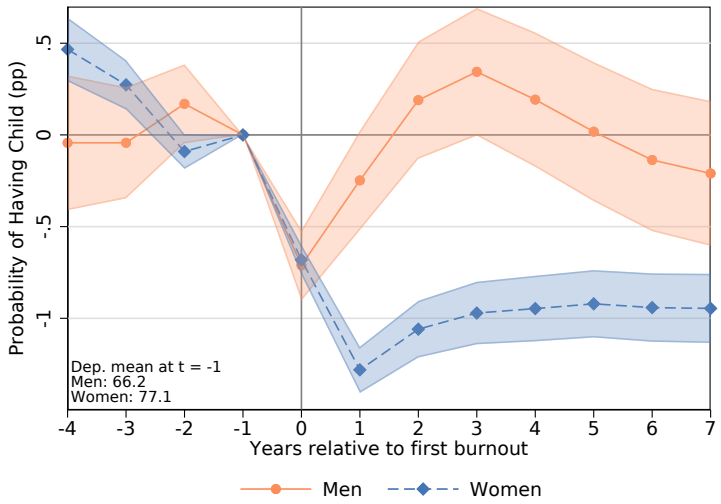


(b) College Enrollment



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 (5). In panel (b), the bars measure the average college enrollment of children whose parents burn out at age 7-18 compared to those whose parents burn out when children are at age 22, estimate with regression (5). In both panels, the coefficient estimates are scaled by dividing by the average outcome for the control group. In the regression, we include controls for the parent's birth cohort and the child's birth cohort, gender, and sibling order. The whiskers are 95 percent confidence intervals where standard errors are clustered at the parent level.

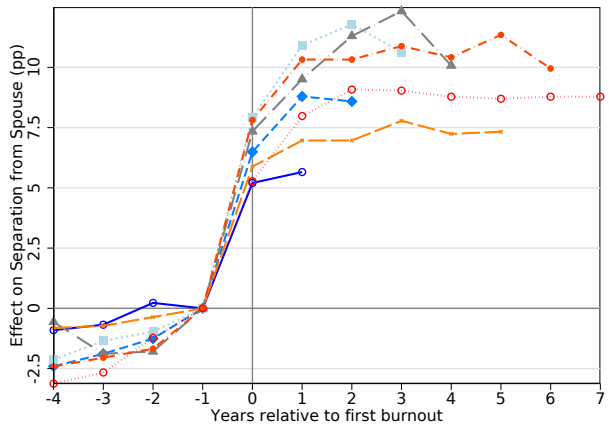
Figure A.17: Burnout Effect on the Probability of Ever Having a Child



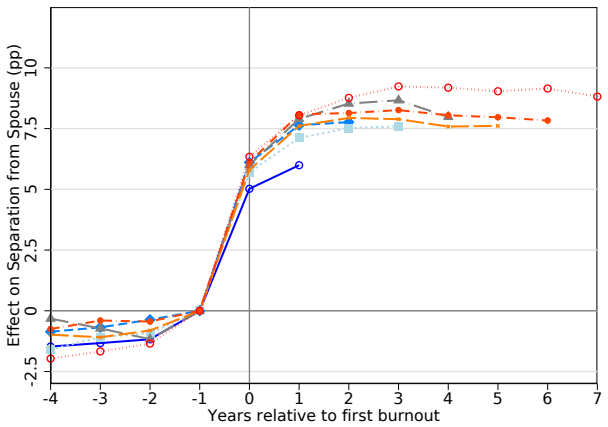
Notes: The figure plots the effect of burnout on the probability of ever having a child based on matched difference-in-differences, as described by equation (1). It plots the coefficients on event-time fixed effect interacted with an indicator for burnout and their individual-level-clustered standard 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.18: The Effect of Burnout on Separation from Spouse and Fertility

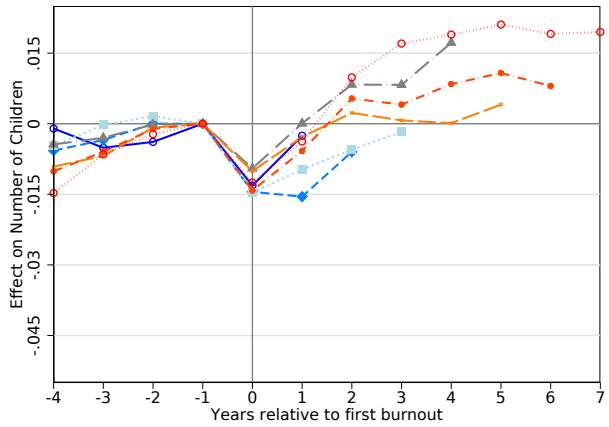
(a) Separations: Men



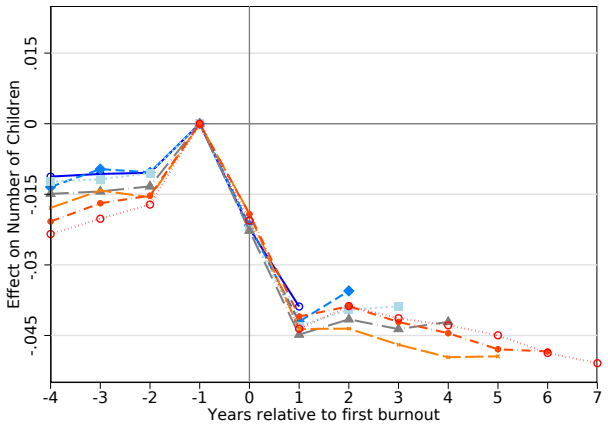
(b) Separations: Women



(c) Number of Children: Men



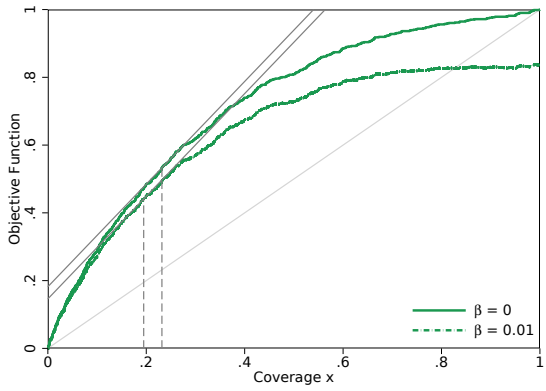
(d) Number of Children: Women



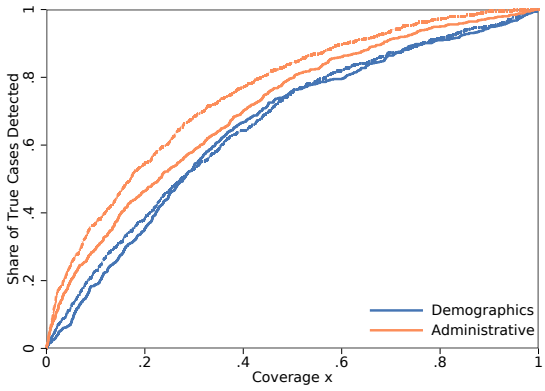
Notes: The figure shows the effect of burnout on separations from spouse **Panels (a) and (b)** and number of children **Panels (c) and (d)**, by gender. Separation is not being married to/cohabiting with the pre-burnout ($t = -4$) spouse. The lines show the estimated coefficients when not-yet-treated 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.19: Predicting Burnout

(a) Surveys vs. Basic Demographic



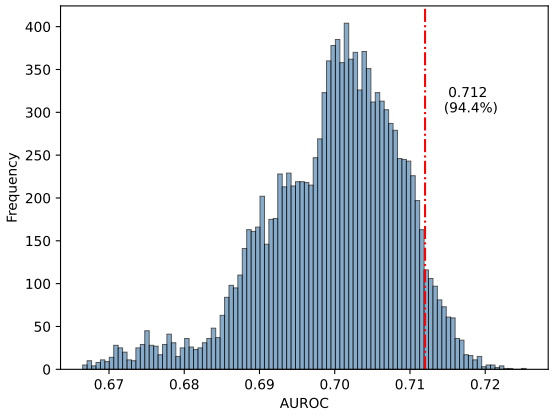
(b) Survey vs. Admin data



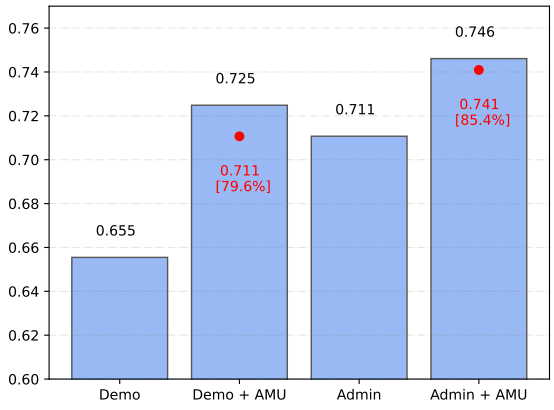
Notes: The figure shows the additional results for burnout prediction. **Panel a)** shows the the welfare gain of the preventive program outlined in () excluding screening costs under different assumptions for the effectiveness of the triage. Formally, the functions are defined as $\pi(x) + \Gamma^{-1}\Lambda f(x)$ 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.20: Prediction Performance of Stress Index Components

(a) Permutations

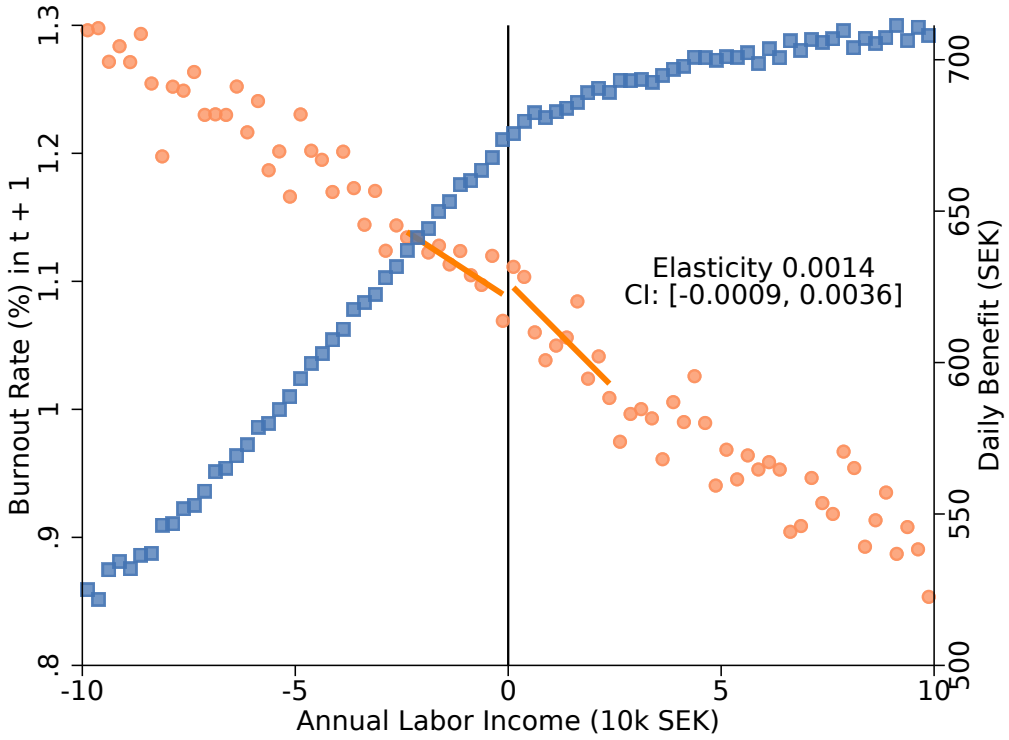


(b) Comparison with Complete Questionnaire



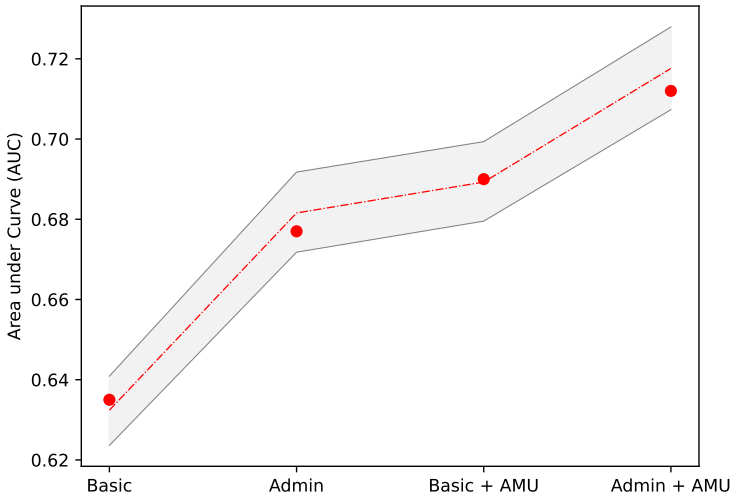
Notes: The figure demonstrates the predictive performance of the four burnout symptoms included in the stress index: lack of sleep, inability to relax, mental stress and headaches. **Panel a)** shows the distribution of the area-under-curve performance metric among alternative combinations of four AMU 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.21: Effect of Benefits on Burnout-Related Sickleave Take-Up



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

Figure A.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.

Table A.1: 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.2: 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	39,522	111,312	150,834
Fixed-delta ($\delta = 2$)	13,685	49,308	62,993
Fixed-delta ($\delta = 3$)	14,717	52,857	67,574
Fixed-delta ($\delta = 4$)	15,573	56,148	71,721
Fixed-delta ($\delta = 5$)	16,351	57,742	74,093
Fixed-delta ($\delta = 6$)	16,977	59,143	76,120
Fixed-delta ($\delta = 7$)	16,988	58,209	75,197

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.3: Instrumental Variable Results

	Own Earnings		Spousal Earnings	
	DiD	IV	DiD	IV
Point Estimate	-13.4	-10.8	-2.9	-5.1
	(0.1)	(5.1)	(0.3)	(15.9)
First-Stage F-Statistic		106.0		26.1
N	3620016	274978	1122840	87110

Notes: The table shows the estimated treatment effects of burnout on own labor income and spousal income implied by the difference-in-difference and instrumental variable estimators described in Section 4. Standard errors are reported in parentheses. Errors are clustered at the individual level for the difference-in-difference estimators.

Table A.4: 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.