# The Economic Burden of Burnout

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**Abstract**

We study the economic consequences of stress-related occupational illnesses (burnout) using Swedish administrative data. Using a mover design, we find that high-burnout firms and stressful occupations universally raise burnout risk yet disproportionately impact low-stress-tolerance workers. Workers who burn out endure permanent earnings losses regardless of gender—while women are three times more susceptible. Repercussions of burnout extend to the worker's family, reducing spousal income and children's educational achievements. Through sick leaves, earnings scars, and spillovers, burnout reduced the national labor income by 2.3% in 2019. We demonstrate how estimated costs, combined with a prediction model incorporating workers' self-reported stress, 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 2 studies the role of jobs. Section 3 focuses on workers and quantifies the individual and aggregate loss of burnout. Section 4 uses administrative data and a work environment survey to predict burnout and evaluates the optimal design of prevention programs. Section 5 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 Jobs and Burnout

Workplace stress is, by definition, the primary cause of burnout. Therefore, this section studies how moving between firms and occupations with different levels of stress and burnout risk affects workers' own risk of burnout, estimating the degree of burnout risk pass-through.

## 2.1 Jobs Where Workers Burn Out

We begin by demonstrating that burnout rates exhibit significant variation across jobs. Figures 1a and 1b plot the distribution of burnout rates at both the industry and occupation levels for 2014-2018. To mitigate the impact of noise on the industry-level burnout rates, we employ an empirical Bayes shrinkage approach, utilizing Beta-Binomial distributions (Kleinman, 1973).[17]

The mean annual burnout rate is 1.2 percent across industries and 1.6 percent across

[17] Appendix Figure A.3 shows the sample averages for industries and occupations and the estimated posterior means.

occupations.[18] The standard deviation in burnout rates is more pronounced across occupations (0.8 percentage points) than across industries (0.5 percentage points), underscoring greater variability in the former. To further explore this heterogeneity in relation to work-related stress, Figure 1c presents a binned scatter plot that compares occupation-level burnout rates with the stress tolerance requirements for occupations as delineated by O*NET data. This visualization illustrates a robust correlation between the level of work-related stress and the incidence of burnout.

## 2.2 Workplace Determinants of Burnout

**Firm Switches** To examine the influence of firms on worker burnout, we utilize the firm moving design described in Card et al. (2013). This event-study methodology compares the burnout rates among new hires before and after joining firms with different burnout risks measured by burnout rates among other employees. If firms influence worker burnout, we expect workers who join firms where burnout rates are high to have a higher likelihood of burnout after their transition compared to those who join firms with low burnout risk.

For each worker, we classify firms based on the average burnout risk among other workers. In order to reduce the influence of sample variance on estimated firm-level heterogeneity, we restrict the sample to firms with at least 50 worker-year observations. We then rank firms by their average burnout risk within a firm-size decile. Following Card et al. (2013), we focus on movers with at least two years of tenure at the origin and destination firm. We then assign each mover to a cell based on the quartiles of burnout rates at the origin and destination firms. To aid visual clarity, we focus on movers from firms in the bottom and top quartiles.

Figure 2a, studies the evolution of burnout rates among movers around the firm-switching event. Regardless of the destination, movers initially employed at low-burnout firms exhibit low burnout rates. However, their likelihood of burnout changes as they move to the new firms. For those moving to similarly low-risk firms, the likelihood of burnout is still low in the new job. In contrast, those who move into more risky firms are more likely to experience burnout. The most dramatic increase is seen for those who move into the most risky firms, for whom the burnout likelihood almost quadruples.

Focusing instead on workers leaving firms with high burnout rates, the figure shows the reverse but symmetric pattern. Individuals moving from risky firms to firms with less burnout risk are less likely to experience burnout subsequent to moving. Such symmetric patterns have been documented in the literature on wage differences across firms (Card et al., 2013).[19] Figure 2a presents a novel result showing that the same holds for a non-wage characteristic of jobs. This

[18] Compared to the population average burnout rate of 1.54 percent during this period, smaller industries, and to a lesser extent larger occupations, experience higher rates of burnout. Figure A.2 plots the time series of burnout rates for men and women.

[19] Appendix Figure A.12 shows that the qualitative patterns we document also hold if we classify firms using AKM firm fixed effects.

echoes the finding of Lachowska et al. (2024), who show that the same is true for the take up of unemployment insurance.

An intriguing observation is that the impact of firms on burnout manifests as early as one year following the transition. This finding is consistent with our other evidence suggesting a high-frequency relationship between working conditions and burnout. For example, we document that burnout is closely correlated with work-related stress in the year before (Section 4.1). This immediate firm effect may, however, reflect differences in firm culture, including factors such as tolerance for sick leave or misuse of the social insurance system. One way to evaluate this interpretation is to study individuals who move within a firm between jobs of different stress levels. This is what we do next.

**Occupation Switches** Next, we study the effect of occupations on burnout. We follow the methodology outlined in the firm analysis above. For each occupation-worker pair, we calculate a leave-one-out burnout rate for each individual within a given occupation. Additionally, we narrow the focus to those individuals who have completed at least two years of tenure with their current employer and have subsequently switched occupations and/or jobs.

Figure 2b, studies the relationship between the change in individual workers' burnout rate and the change in the occupation-level burnout risk.[20] First, we focus on movers within a firm, ensuring that firm culture and other related factors are constant. The relationship is approximately linear with a slope of 0.69, in line with the symmetrical and immediate effects of firm moves in panel (a). The pass-through of occupation burnout risk is 69 percent: individuals who switch into an occupation with a 1 percentage point higher burnout risk are 0.69 percentage points more likely to experience burnout themselves. However, we estimate the pass-through to be almost the same (0.70) for those who change both firms and move into occupations with greater burnout risk. The comparison between firm stayers and movers suggests that the result documented in panel (a) not only reflects differences in sick leave take-up but rather the effect of firms on burnout.

Figure 2 suggest that the workplace influences worker's likelihood of burnout. The main candidate factor is the level of stress at work. Indeed, there is a strong correlation between occupation-level burnout rates and the stress tolerance requirement of occupation according to O*NET (Figure 1c). Next, we study whether exposure to work-related stress affects individuals equally.

### 2.3 Mismatch of Individual Stress Tolerance and Job Stress Level

So far, we have observed that entering certain jobs (occupations or firms) raises the risk of burnout. Is the risk uniform across all individuals, or does it depend on the interaction of individual and job characteristics? To study such match effects, we require two key components.

The first component requires assessing the level of stress associated with a job. Our initial

[20] The Swedish occupation classification changed in 2014. For this reason, we split the sample in 2014 and compute occupation-specific (leave-one-out) burnout rates separately for each side of the cutoff. Within each time frame, we pool over the entire period.

approach, similar to the prior section, involves calculating the leave-one-out burnout rate at the firm level. Although this method offers high statistical power, it is susceptible to sorting biases. Our second approach involves assessing the stress tolerance requirement of an occupation sourced from O*NET.[21] This approach carries several caveats, including measurement noise within O*NET data, its focus on assessing stressful occupations within the U.S. context, and discrepancies in the occupational code between Sweden and the U.S. Nonetheless, its advantage lies in its focus on the *nature* of the occupation, rendering it immune to sorting.

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.[22] 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 3 presents the results. The first row indicates that workers with higher stress tolerance tend to, on average, work in more stressful workplaces.[23] This is evidenced by their employment in firms with higher burnout rates and occupations that necessitate higher stress tolerance levels, according to O*NET. Sorting is somewhat stronger across occupations than jobs, suggesting that workers may be more informed about how stressful occupations are compared to knowing the stress level across jobs. 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.[24]

More importantly, the second row indicates that workers with low stress tolerance are more susceptible to burnout, especially when employed in highly stressful jobs.[25] 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.

### 2.4 Career Progress

Having established the connection between jobs and burnout, we now study how burnout relates to career progress. We proxy career with growth in labor income between two consecutive years.

[21] Documented in Figure 1c, 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.

[22] 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.

[23] Figure A.8 shows the entire distribution of firm and occupation types for each level of individual stress tolerance.

[24] 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. The fact that sorting is limited is in line with the result in Figure 2a, showing symmetry in the increase and decrease in the likelihood of burnout among those who move to high and low-risk firms.

[25] Appendix Figure A.7 shows that the negative relationship between stress tolerance and the likelihood of burnout is robust to controlling for other cognitive and non-cognitive skills.

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]

Figure 4c 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.4). 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 individuals with stable earnings tend to have lower rates of burnout. Secondly, those with fluctuating incomes, particularly those experiencing increases in income, exhibit the highest rates of burnout.[29] This result complements those above on the impact of job changes, indicating a connection between career progression, such as promotions, and subsequent burnout.[30] A question remains about how such jobs are compensated and how productive they are. We study this next.

### 2.5 Compensating Wage and Productivity Differentials

When workers have job choices and job amenities are observable, wages must adjust to compensate for differences in amenities (Rosen, 1974). To study whether workers are compensated for the risk of burnout, we follow Brown (1980) and include worker fixed-effect, leveraging panel aspect of our employer-employee data. The inclusion of worker fixed-effects implies that compensating differentials are estimated from firm movers and are not biased by sorting of high-ability workers into high-amenity jobs.

More precisely, we estimate the following model regressing $w_{i,t}$, individual $i$'s log wage in $t$, on $B_{J(i,t)}$, the leave-one-out time-invariant burnout rate of her employer, $J(i,t)$, that is,

$$w_{i,t} = \beta B_{J(i,t)} + \phi_i + \delta_t + \gamma_{o(i,t)} + \psi_{I(i,t)} + \alpha \mathbf{X}_{i,t} + \varepsilon_{it} \quad (1)$$

[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 3, 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).

[29] The same patterns are present among employed men, as shown in Appendix Figure A.5b. As a result of burnout being less frequent among men, the estimates are less precise than for women.

[30] The results 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.6).

controlling for fixed effects for individual, time, 4-digit occupation, and 5-digit industry—$\phi_i, \delta_t, \gamma_{o(i,t)}, \psi_{I(i,t)}$, respectively—, in addition to a set of time-varying individual characteristics, $\mathbf{X}_{it}$, that is, gender- and education-specific third-order polynomials in age similar to Card et al. (2013).

Panel (a) in Table 2 shows that the coefficient of interest, $\beta$, is precisely estimated for various specifications.[31] However, contradicting the standard theory of compensating wage differentials, it suggests a negative wage differential for burnout risk. Controlling for occupation and industry, moving to a firm with one standard deviation higher burnout risk (an increase of 0.5 percentage points) is associated with a 0.23 percent decline in the hourly wage. Using our estimated pass-through rate of 0.70 (Figure 2b), a worker transitioning to a firm with a 0.35 percentage point higher burnout rate likelihood would receive a wage that is 0.23 percent lower.[32]

Firms are likely to differ across numerous non-wage amenities other than stress levels. To account for this, in the sixth column of Table 2, we control for a comprehensive measure of firm utility—PageRank, as proposed by Sorkin (2018). PageRank locates a firm on the job ladder based on revealed preferences (worker flows), analogous to how Google originally ranked web pages. The inclusion of PageRank does not change the estimated coefficient, suggesting that when other factors, such as wages and amenities, are held constant, a worker earns more in jobs with a lower burnout risk.

Our findings contrast with recent experimental evidence suggesting that workers demand higher wages for hypothetical jobs with increased stress levels (Nagler et al., 2023). A possible reconciliation is that job seekers may not be fully informed about the stress levels or general workplace conditions and amenities before joining a firm. An alternative interpretation is the measurement error in PageRank. Another alternative is that stressful jobs may be associated with higher productivity growth and career progression, possibly increasing the likelihood of higher wages in the future. For example, transitioning from being a medical intern to being a resident to being an attending is associated with a reduction in stress while an increase in increase in pay (Stucky et al., 2009). The same is likely true for other "up-or-out" jobs, such as transitioning from being an associate to a partner in a law firm.

Panel (b) of Table 2 extends the analysis by studying firm productivity, measured by value added per worker based on firm balance sheets. Transitioning to a firm with one standard deviation higher burnout rate is associated with a decrease in productivity of -1.98 percent. When comparing the two panels, the consistency in the direction of the correlations—–indicated by the sign of the coefficients—is striking. Further, coefficients of both burnout rate and PageRank are one order of magnitude higher for productivity than wage.[33]

[31] The statistical significance of our results contrasts, in particular, with Brown (1980) who studies compensating differential for stress, and, more generally, estimates from other studies using panel data (Lavetti, 2023).

[32] These results stand in contrast to Duncan and Holmlund (1983), who estimated a positive, albeit statistically insignificant, wage compensation for "hectic" jobs.

[33] One potential reason might be that the outcome in panel (b) is at a firm level while at the individual level in panel (a). However, the one-order-of-magnitude difference between the coefficients of two panels is maintained when we replicate the analysis in both panels at the firm level by reweighting observations by the inverse of firm size (Appendix

## 3 Workers and Burnout

This section first describes a few salient characteristics of workers who burn out and then studies the consequences of burnout both for the individuals and their families.

### 3.1 Who is at Risk of Burning Out?

**Demographic Characteristics** We start with a general description of the demographic characteristics of those who burn out. Figure 4a plots the rate of burnout by gender and family type, partitioned into four groups by marital and parental status.[34] 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.[35]

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.

**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 4b plots the burnout rates of married and cohabiting women against the labor incomes of each of the spouses within the couple.[36] 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.,

Table A.3).

[34]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.

[35]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.19, we find no evidence supporting this hypothesis.

[36]Appendix Figure A.5a presents the corresponding figure for married and cohabiting men.

their own income. This figure uses a two-dimensional moving average and rank-adjusted income (see Section 2).

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.

**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 1).

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.[37] 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 4a. The decomposition implies that gender alone accounts for one-third of the explained variance. All other demographics and work-related factors contribute 42.5 percent. The remaining 24.3 percent can be attributed to the correlation of gender with other observed predictors of burnout, highlighting the importance of the interaction of gender and both family and work characteristics.

## 3.2 The Consequences of Burnout

### 3.2.1 Effect on Individual's Labor Market Outcomes

To evaluate the consequences of burnout for an individual's labor market outcomes, we use two 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,

[37] 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.

both in unobservable characteristics and in their career trajectories. In particular, as documented in Section 3.1, 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). We first describe the procedure underlying the main empirical strategy before describing the fixed-delta method. 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.[38] 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 5a 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 5a, we estimate difference-in-differences, comparing the group of workers who burn out to their matched control group. Our estimation equation is:

$$Y_{i,k} = \phi_{G_i,T_i} + \delta_{G_i,k} + \sum_{k \in \mathcal{K}} \alpha_k T_i + \varepsilon_{i,k} \tag{2}$$

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, $\phi_{G_i,T_i}$, and group-time fixed effects, $\delta_{G_i,k}$. The coefficients of interest are $\alpha_k$, which measure the dynamic treatment effects. Standard errors are clustered at the individual level.

Figure 6a presents the estimated effects of burnout on labor market outcomes based on

[38] 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.

equation (2). 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 4c, 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 women seven years after burnout.[39] 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 4c). The complementary design evaluates the effects compared to a control group that also experiences burnout but $\delta$ years later. To evaluate this design, Figure 5b 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.9 demonstrates the robustness of this pattern, rolling $\delta$ from 2 to 7 years and contrasting them with our baseline estimate from Figure 6a.

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, $\delta$, showing that income life-cycle patterns are the primary source of identification, similar to (Nekoei and Seim, 2023).

[39] The labor income dynamics following burnout cannot be explained purely by increased sick leave take-up. In Appendix Figure A.11, 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).

**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.10). 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, $Y_{i,t}^{p}$, that takes the control value if individual $i$ does not belong to partition $p$,

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

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

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

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 6, 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.[40]

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 2, moving to less stressful occupations does not result in diminished income.

Do burnout workers move to less stressful jobs? To answer this question, Figure 6d 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 2.

**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 6c 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

[40] The results are quantitatively similar across genders as shown in Appendix Figure A.14. Transitions to part-time explain the largest share of the earnings loss among women, whereas exit from the labor force constitutes the main adjustment margin for men.

to the five percent long-term decrease in *consumption* following both physical and mental health shocks estimate in Kolsrud et al. (2020).

### 3.2.2 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).

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 7a 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 3.2.1. 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.

### 3.2.3 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 7b 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.21 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 7c 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.21 reports estimated effects on fertility using the fixed-delta method, exploiting the timing of burnout. This figure shows the same patterns as Figure 7c, further confirming that burnout is associated with less fertility among women and suggesting that childbirth may be a contributing factor to burnout.

#### 3.2.4 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 educational attainment and school performance.

We study the impact of parental burnout on the age of children at the time.[41] 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 college enrollment, which might be gender specific. We thus demean the outcome 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. Our primary measure of the impact of children's education is college enrollment by age 21, i.e., an indicator of whether a child enrolls in college at age 19, 20, or 21. Figure 8 plots the

[41]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.

coefficients from regression (5) of demeaned college enrollment on child's age at parent's burnout. The reference group in the regression is those whose parents had burnout at age 22, implying that our estimates are difference-in-differences comparing the effect on treated children—net of control—before and after schooling age. We estimate a negative effect of parental burnout on college enrollment. On average, children whose parents go into burnout at ages 7 to 21 are 2.5 percentage points less likely to enroll in college than the reference group. This implies an 8.1 percent reduction compared to the average attendance 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.

If the effects we estimate reflect the impact of the event of parents going into burnout, rather than the effect of a potential buildup to that event or systematic differences in the college education of children of those that go into burnout, the estimated effects at ages 22 and above can serve as placebo tests of our design. We estimate no effect of parental burnout on college enrollment among children whose parents go into burnout at ages 22 to 25.

We study the heterogeneity of these effects with respect to the parental background in Appendix Figure A.17. Children's education is more adversely impacted when their parents have lower levels of education. This implies that parental burnout contributes to reducing intergenerational mobility in education. The effect of a mother's burnout on the education 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.[42]

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

To further evaluate the effect of parental burnout on their children's human capital accumulation, we study the effect on performance at school. 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 evaluate the effect of parental burnout on test performance. More specifically, 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

[42] 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.

opportunities as admission to oversubscribed subjects is determined by the student's GPA (see, e.g. Ramstedt, 2005, for further discussion and details).

Appendix Figure A.16 presents the estimated effect on school grades. The reference group is children who were 17 when their parents went into burnout. We estimate a 5.3 percent reduction in school performance among children whose parents go into burnout when they were at ages 10 to 16. Among children whose parents go into burnout at later ages, there is no statistical difference in school performance.

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 instrument parental burnout by the burnout risk of their job. As we will document, burnout is strongly related to jobs–both where individuals work and what they do. To capture that, we first measure the parental burnout risk as the average burnout rate across all other firms in their industry. By leaving out their own firm, we err on the side of caution not to incorporate firm shocks that might affect parents in other ways, such as their employment and earnings. To first establish the power of this instrument, Appendix Figure A.18 reports the correlation between the leave-one-out industry burnout rate and worker's likelihood of burnout. The figure displays a linear relationship: working in an industry with a 1 percentage point higher burnout rate is associated with a 0.87 percentage point higher likelihood of burnout, when conditioning on an industry fixed effect.[43] We then run a 2SLS version of equation (5), where we instrument the indicators for parental burnout at a given age by the industry burnout rate in the year before, controlling for industry fixed effect. The IV-DiD estimate is slightly larger than the (OLS) DiD estimate, implying that parental burnout reduces college enrollment by 2.7 percentage points or 8.7 percent. We apply the same methodology to estimate the effect on school grades, estimating effects of a similar magnitude as before.

### 3.3 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.[44]

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,

[43] Controlling for both industry and time fixed effects, the correlation is 0.62.

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

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 $\alpha^o$, $\alpha^s$, and $\alpha^c$ are the proportional income loss due to burnout of own, spouse, or parent, which we will borrow from Figures 6a, 7a, and 8. 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 $\sigma_i$ denotes the proportion of the year they were on sick leave due to burnout.[45]

Figure 9 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 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 9, 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.[46] The steady-state estimated aggregate loss is 3.5 percent of labor income.[47] 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.

## 4 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

[45] 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.

[46] 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).

[47] 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.

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.

### 4.1 Self-reported Stress and Future Burnout

As we showed in Section 3.1, the burnout rate varies substantially by individuals' observable characteristics. This variation can be leveraged to identify individuals at high risk. Furthermore, businesses or public entities might benefit from gathering real-time data on employee well-being. In fact, it's 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).[48] 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 surveys in detecting those at risk of burnout. We exploit the Swedish Work Environment Survey (AMU).[49] 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 4.3). The exploration of how program design and survey methodologies interact is reserved for future research.

Survey responses confirm the prevalence of workplace stress in the Swedish labor market and its tight relationship with burnout. In Figure 10a, we report the frequency distribution of responses to the question: *Do you find your work mentally stressful or calm and pleasant?* Around 40 percent of workers find their work to be somewhat or very stressful. Workers who perceive their jobs as very stressful are almost five times as likely to go on sick leave due to burnout in the following year compared to workers who report no work-related stress. Figure 10b documents a similar correlation between burnout and the worker's inability to relax after work. These results validate that our measure of burnout—medical diagnosis as the base of sick leave from work—is closely connected to work-related stress. In Figure 10c, we report coefficients from a *multivariate* regression on a range of questions from the AMU on the work environment and health problems related to work.[50] This figure shows that stress at work and in connection with work, as well as related factors such as lack of sleep, are closely correlated with burnout, while other work-related health problems are not.

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

[49]See Section 1 for a detailed description of AMU.

[50]For this regression, we limit the set of questions to those available in the survey during our sample period in order to maintain as large a sample as possible.

## 4.2 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. We predict burnout in the Swedish population using 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 D 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 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 0.635. Incorporating survey responses into the predictors enhances model performance by approximately 10 percent, raising the AUC to 0.690. If instead we incorporate "kitchen sink" of administrative records, the AUC stands lower at 0.677. The comparison reveals that predictions based on basic demographics and survey responses are more accurate than those using the full suite of administrative data.[51] This highlights the substantial predictive capacity of the survey data. Figure 11b 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 0.712.

For the 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.[52] This indicates that if we randomly choose one individual with burnout and another without, we have an 81 percent

[51] 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.

[52] Figure 11b 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.

chance of correctly identifying the individual with a higher risk of burnout. The effectiveness of this algorithm in predicting burnout, especially when benchmarked against previous research, is noteworthy. For instance, Einav et al. (2018) achieved an AUC of 0.87 in predicting mortality, highlighting the robust performance of our model in the context of burnout prediction.

To 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.

### 4.3 Optimal Scope of a Preventive Program

Our objective in this section is to demonstrate how one can apply our cost estimates and prediction model to design the optimal scope of a given prevention program.

#### 4.3.1 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 $\alpha$, and a false positive rate of $\beta$. The second stage is the treatment of those detected that costs $P$ and has a success rate $\theta$. 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),

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

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 11a.

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:

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

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

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

The net impact of the program at optimum is

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

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. Equation (11) 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:

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

where $\sigma$ is the per-capita cost of the survey. The optimal size of the program is determined by equalizing marginal cost and benefit $\frac{\partial \pi_s(x^*)}{\partial x} = p/(\Gamma + \Lambda)$ 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.

Similar to equation (11), 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.

$$W_s(x_s^*) = (\Gamma + \Lambda) I(\pi_s) - \sigma \tag{13}$$

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.

#### 4.3.2 Cost-Benefit Calculations

To calibrate our model, we take conservative values of 5 percent and 20 percent for type I and II errors of the triage, corresponding to $\alpha = 0.8$ and $\beta = .05$. The cost of burnout can be calibrated using our aggregate cost of 3.51 percent reported in Figure 9 and the average burnout rate of 1.12 percent in the population. We consider a preventive treatment with a success rate $\theta$ 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.[53] 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 D 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 11a). Given this estimate, the total per-capita gain from optimal coverage of the program is:

$$W\left(x^*\right) = \left(\Gamma + \Lambda\right) I(\pi) = 4.05 \times 3.19\% = 13\% \tag{14}$$

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 D for details).

Adding survey information to the prediction increases its performance, which shifts out the Cumulative Gains Chart (Figure 11a). 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 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.

With this estimate, and assuming that the survey takes ten minutes to complete, the total per-capita gain from the program with optimal coverage is:

$$W_s\left(x_s^*\right) = \left(\Gamma + \Lambda\right) I(\pi_s) - \sigma = 4.05 \times 11.76\% - \frac{1}{6} = 31\% \tag{15}$$

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, $\Gamma$, reduces the slope of

[53] 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).

the optimal policy, and broadens the scope of the optimal program. Consequently, the welfare gain from the program, as derived from our model (equation (14)), 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 (15)). 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.

# 5 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.[54] 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

[54] Appendix Figure A.1 reports the share of workers reporting to experience stress during a lot of the day before, according to Gallup's State of the *Global Workplace* survey since 2008 (Gallup, 2023).

research on the economic aspects of work-related stress and burnout.

## References


ABOWD, J. M., F. KRAMARZ, AND D. N. MARGOLIS (1999): "High wage workers and high wage firms," *Econometrica*, 67, 251–333.

ADLERCREUTZ, A. AND B. NYSTRÖM (2021): *Labour law in Sweden*, Kluwer Law International BV.

AHAMMER, A., A. PACKHAM, AND J. SMITH (2024): "Firms and Worker Health," Working paper, National Bureau of Economic Research.

AMERICAN PSYCHOLOGICAL ASSOCIATION (n.d.): "APA Dictionary of Psychology," https://dictionary.apa.org/burnout, retrieved April 8, 2024.

ANAND, P., L. DAGUE, AND K. L. WAGNER (2022): "The role of paid family leave in labor supply responses to a spouse's disability or health shock," *Journal of Health Economics*, 83, 102621.

APA (2023a): "Stress in America," Retrieved April 8, 2024.

——— (2023b): "Work in America Survey: Workplaces as engines of psychological health and well-being," Retrieved April 8, 2024.

ARTZ, B., I. KAYA, AND O. KAYA (2022): "Gender role perspectives and job burnout," *Review of Economics of the Household*, 20, 447–470.

ÅSBERG, M., T. GRAPE, I. KRAKAU, Å. NYGREN, M. RODHE, A. WAHLBERG, AND P. WÄHRBORG (2010): "Stress som orsak till psykisk ohälsa," *Läkartidningen*, 107, 1307–10.

AUST, B., J. L. MØLLER, M. NORDENTOFT, K. B. FRYDENDALL, E. BENGTSEN, A. B. JENSEN, A. H. GARDE, M. KOMPIER, N. SEMMER, R. RUGULIES, ET AL. (2023): "How effective are organizational-level interventions in improving the psychosocial work environment, health, and retention of workers? A systematic overview of systematic reviews," *Scandinavian Journal of Work, Environment & Health*, 49, 315.

AUTOR, D., A. KOSTØL, M. MOGSTAD, AND B. SETZLER (2019): "Disability benefits, consumption insurance, and household labor supply," *American Economic Review*, 109, 2613–2654.

AUTOR, D. H. (2011): "The unsustainable rise of the disability rolls in the United States: Causes, consequences, and policy options," *Working Paper, National Bureau of Economic Research*.

BACH, L., R. BAGHAI, M. BOS, AND R. SILVA (2023): "How Do Mergers Affect the Mental Health of Employees?" *Swedish House of Finance Research Paper*.

BAKKER, A. B., H. VAN EMMERIK, AND P. VAN RIET (2008): "How job demands, resources, and burnout predict objective performance: A constructive replication," *Anxiety, Stress, & Coping*, 21, 309–324.

BARTEL, A. AND P. TAUBMAN (1986): "Some economic and demographic consequences of mental illness," *Journal of Labor Economics*, 4, 243–256.

BIASI, B., M. S. DAHL, AND P. MOSER (2021): "Career effects of mental health," Working paper, National Bureau of Economic Research.

BINGLEY, P., L. CAPPELLARI, AND M. OVIDI (2023): "When It Hurts the Most: Timing of Parental Job Loss and a Child's Education," IZA Discussion Paper No. 16367.

BLACKBURN, B., T. CHAN, E. CHEROT, R. B. FREEMAN, X. HU, E. MATT, AND C. A. RHODES (2023): "Beyond burnout: from measuring to forecasting," Working paper, National Bureau of Economic Research.

BOUSKILL, K. E., M. S. DANZ, L. S. MEREDITH, C. CHEN, J. CHANG, S. M. BAXI, D. HUYNH, H. AL IBRAHIM, A. MOTALA, J. LARKIN, ET AL. (2022): *Burnout: Definition, Prevalence, Risk Factors, Prevention, and Interventions Literature Reviews*, RAND.

BROWN, C. (1980): "Equalizing differences in the labor market," *The Quarterly Journal of Economics*, 94, 113–134.

BURKHAUSER, R. V. AND M. C. DALY (2012): "Social Security Disability Insurance: time for fundamental change," *Journal of Policy Analysis and Management*, 454–461.

CARD, D., J. HEINING, AND P. KLINE (2013): "Workplace heterogeneity and the rise of West German wage inequality," *The Quarterly Journal of Economics*, 128, 967–1015.

CEDERLÖF, J., P. FREDRIKSSON, A. NEKOEI, AND D. SEIM (2021): "Mandatory advance notice of layoff: Evidence and efficiency considerations," Discussion Paper No. DP16387, CEPR.

CHEN, T. AND C. GUESTRIN (2016): "Xgboost: A scalable tree boosting system," in *Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining*, 785–794.

CULLEN, J. B. AND J. GRUBER (2000): "Does unemployment insurance crowd out spousal labor supply?" *Journal of Labor Economics*, 18, 546–572.

DAHL, M. S. (2011): "Organizational change and employee stress," *Management science*, 57, 240–256.

DAVIS, S. J. AND T. VON WACHTER (2011): "Recessions and the Costs of Job Loss," *Brookings Papers on Economic Activity*, 42, 1–72.

DEL BONO, E. AND A. WEBER (2008): "Do wages compensate for anticipated working time restrictions? Evidence from seasonal employment in Austria," *Journal of Labor Economics*, 26, 181–221.

DELIGKARIS, P., E. PANAGOPOULOU, A. J. MONTGOMERY, AND E. MASOURA (2014): "Job burnout and cognitive functioning: A systematic review," *Work & stress*, 28, 107–123.

DEMEROUTI, E. AND A. B. BAKKER (2008): "The Oldenburg Burnout Inventory: A good alternative to measure burnout and engagement," *Handbook of stress and burnout in health care*, 65.

DEMEROUTI, E., A. B. BAKKER, M. C. PEETERS, AND K. BREEVAART (2021): "New directions in burnout research," *European Journal of Work and Organizational Psychology*, 30, 686–691.

DUNCAN, G. J. AND B. HOLMLUND (1983): "Was Adam Smith right after all? Another test of the theory of compensating wage differentials," *Journal of Labor Economics*, 1, 366–379.

EINAV, L., A. FINKELSTEIN, S. MULLAINATHAN, AND Z. OBERMEYER (2018): "Predictive modeling of US health care spending in late life," *Science*, 360, 1462–1465.

EUROFOUND (2007): *Fourth European survey on working conditions 2005*, Luxembourg: Publications Office of the European Union.

——— (2016): *Sixth European survey on working conditions 2015*, Luxembourg: Publications Office of the European Union.

FADLON, I. AND T. H. NIELSEN (2019): "Family health behaviors," *American Economic Review*, 109, 3162–3191.

——— (2021): "Family labor supply responses to severe health shocks: Evidence from Danish administrative records," *American Economic Journal: Applied Economics*, 13, 1–30.

FOLKE, O. AND J. RICKNE (2022): "Sexual harassment and gender inequality in the labor market," *The Quarterly Journal of Economics*, 137, 2163–2212.

FÖRSÄKRINGSKASSAN, S. (2020): "Sjukfrånvaro i psykiatriska diagnoser—En registerstudie av Sveriges arbetande befolkning i åldern 20–69 år," *Sickness absence in psychiatric diagnoses. A register study of Sweden's working population aged 20–69*.

FREDRIKSSON, P., L. HENSVIK, AND O. N. SKANS (2018): "Mismatch of talent: Evidence on match quality, entry wages, and job mobility," *American Economic Review*, 108, 3303–3338.

FREUDENBERGER, H. J. (1974): "Staff burn-out," *Journal of social issues*, 30, 159–165.

GALLUP (2023): "State of the global workplace," Retrieved April 8, 2024.

GROSSI, G., A. PERSKI, W. OSIKA, AND I. SAVIC (2015): "Stress-related exhaustion disorder–clinical manifestation of burnout? A review of assessment methods, sleep impairments, cognitive disturbances, and neuro-biological and physiological changes in clinical burnout," *Scandinavian journal of psychology*, 56, 626–636.

HALL, R. E. AND A. I. MUELLER (2018): "Wage dispersion and search behavior: The importance of nonwage job values," *Journal of Political Economy*, 126, 1594–1637.

HALLSTEN, L., K. BELLAAGH, AND K. GUSTAFSSON (2002): "Utbränning i Sverige–en Populationsstudie [Burnout in Sweden–a population study]. 2002," *National Institute for Working Life: Stockholm*.

HANDEL, B., J. KOLSTAD, T. MINTEN, AND J. SPINNEWIJN (2023): "The socio-economic distribution of choice quality: Evidence from health insurance in the netherlands," *American Economic Review: Insights*.

HENDREN, N. (2017): "Knowledge of future job loss and implications for unemployment insurance," *American Economic Review*, 107, 1778–1823.

HENREKSON, M. AND M. PERSSON (2004): "The effects on sick leave of changes in the sickness insurance system," *Journal of Labor Economics*, 22, 87–113.

HILGER, N. G. (2016): "Parental job loss and children's long-term outcomes: Evidence from 7 million fathers' layoffs," *American Economic Journal: Applied Economics*, 8, 247–283.

HOBFOLL, S. E. (1989): "Conservation of resources: a new attempt at conceptualizing stress." *American psychologist*, 44, 513.

HOBFOLL, S. E., A. SHIROM, ET AL. (2000): "Conservation of resources theory: Applications to stress and management in the workplace," *Handbook of organization behavior*, 2, 57–81.

HOWARD, A., R. ANTCZAK, AND K. ALBERTSEN (2022): *Third European Survey of Enterprises on New and Emerging Risks (ESENER 2019): Overview Report: how European Workplaces Manage Safety and Health*, Publications Office of the European Union.

ILO (2016): "Workplace Stress: A collective challenge," Retrieved April 8, 2024.

JOHANNISSON, K. (2006): "Modern fatigue: A historical perspective," *Stress in health and disease*, 1–19.

JOHANSSON, P. AND M. PALME (2005): "Moral hazard and sickness insurance," *Journal of Public economics*, 89, 1879–1890.

KLEINMAN, J. C. (1973): "Proportions with extraneous variance: single and independent samples," *Journal of the American Statistical Association*, 68, 46–54.

KOLSRUD, J., C. LANDAIS, AND J. SPINNEWIJN (2020): "The value of registry data for consumption analysis: An application to health shocks," *Journal of Public Economics*, 189, 104088.

KRISTENSEN, T. S., M. BORRITZ, E. VILLADSEN, AND K. B. CHRISTENSEN (2005): "The Copenhagen Burnout Inventory: A new tool for the assessment of burnout," *Work & Stress*, 19, 192–207.

LACHOWSKA, M., I. SORKIN, AND S. A. WOODBURY (2024): "Employers and Unemployment Insurance Take-Up," Working paper, National Bureau of Economic Research.

LALIVE, R. AND J. ZWEIMULLER (2006): "Compensating Wage Differentials for Employment Risks: Evidence from Linked Firm-Worker Data," Working paper, University of Lausanne.

LASTOVKOVA, A., M. CARDER, H. M. RASMUSSEN, L. SJOBERG, G. J. DE GROENE, R. SAUNI, J. VEVODA, S. VEVODOVA, G. LASFARGUES, M. SVARTENGREN, ET AL. (2018): "Burnout syndrome as an occupational disease in the European Union: an exploratory study," *Industrial health*, 56, 160–165.

LAVETTI, K. (2023): "Compensating wage differentials in labor markets: Empirical challenges and applications," *Journal of Economic Perspectives*, 37, 189–212.

LEE, M. AND C. CHA (2023): "Interventions to reduce burnout among clinical nurses: systematic review and meta-analysis," *Scientific Reports*, 13, 10971.

LINDEN, D. V. D., G. P. KEIJSERS, P. ELING, AND R. V. SCHAIJK (2005): "Work stress and attentional difficulties: An initial study on burnout and cognitive failures," *Work & Stress*, 19, 23–36.

LINZER, M., S. POPLAU, E. GROSSMAN, A. VARKEY, S. YALE, E. WILLIAMS, L. HICKS, R. L. BROWN, J. WALLOCK, D. KOHNHORST, ET AL. (2015): "A cluster randomized trial of interventions to improve work conditions and clinician burnout in primary care: results from the Healthy Work Place (HWP) study," *Journal of general internal medicine*, 30, 1105–1111.

LIPSEY, R. G. AND K. LANCASTER (1956): "The general theory of second best," *The Review of Economic Studies*, 24, 11–32.

LISE, J. AND F. POSTEL-VINAY (2020): "Multidimensional skills, sorting, and human capital accumulation," *American Economic Review*, 110, 2328–2376.

LØKEN, K. V., S. LUNDBERG, AND J. RIISE (2017): "Lifting the burden: Formal care of the elderly and labor supply of adult children," *Journal of Human Resources*, 52, 247–271.

LUND, C., K. ORKIN, M. WITTE, T. DAVIES, J. WALKER, J. HAUSHOFER, S. MURRAY, J. BASS, L. MURRAY, AND V. PATEL (2022): "Treating Mental Health Conditions Improves Labor Market and Other Economic Outcomes in Low and Middle-Income Countries," *University of Oxford, Working Paper*.

LUNDGREN-NILSSON, Å., I. H. JONSDOTTIR, J. PALLANT, AND G. AHLBORG (2012): "Internal construct validity of the Shirom-Melamed burnout questionnaire (SMBQ)," *BMC public health*, 12, 1–8.

MAESTAS, N., K. J. MULLEN, D. POWELL, T. VON WACHTER, AND J. B. WENGER (2023): "The value of working conditions in the United States and implications for the structure of wages," *American Economic Review*, 113, 2007–2047.

MAS, A. AND A. PALLAIS (2017): "Valuing alternative work arrangements," *American Economic Review*, 107, 3722–3759.

MASLACH, C. (1976): "Burned-out," *Human behavior*, 5, 16–22.

MASLACH, C. AND S. E. JACKSON (1981): "MBI: Maslach burnout inventory," *Palo Alto, CA*, 1, 49–78.

MASLACH, C. AND M. P. LEITER (2016): "Understanding the burnout experience: recent research and its implications for psychiatry," *World psychiatry*, 15, 103–111.

——— (2022): *The Burnout Challenge: Managing People's Relationships with Their Jobs*, Harvard University Press.

MASLACH, C. AND W. B. SCHAUFELI (2018): "Historical and conceptual development of burnout," in *Professional burnout*, CRC Press, 1–16.

MASLACH, C., W. B. SCHAUFELI, AND M. P. LEITER (2001): "Job burnout," *Annual review of psychology*, 52, 397–422.

MCCLELLAN, M. B. (1998): "Health events, health insurance, and labor supply: Evidence from the health and retirement survey," in *Frontiers in the Economics of Aging*, University of Chicago Press, 301–350.

MEDIATION OFFICE (2022): "Kvalitetsdeklaration - Lönestrukturstatistik, hela ekonomin [Quality Declaration - Structure of Earnings Survey, Entire Economy]," .

MELAMED, S., T. KUSHNIR, AND A. SHIROM (1992): "Burnout and risk factors for cardiovascular diseases," *Behavioral medicine*, 18, 53–60.

MOOD, C., J. O. JONSSON, AND E. BIHAGEN (2012): "Socioeconomic persistence across generations: cognitive and noncognitive processes," .

NAGLER, M., J. RINCKE, AND E. WINKLER (2023): "High-Pressure, High-Paying Jobs?" *Review of Economics and Statistics*, 1–45.

NEKOEI, A. (2014): "Essays on Unemployment and Labor Supply," Ph.D. thesis.

NEKOEI, A. AND D. SEIM (2023): "How do inheritances shape wealth inequality? Theory and evidence from Sweden," *The Review of Economic Studies*, 90, 463–498.

NORLUND, S., C. REUTERWALL, J. HÖÖG, B. LINDAHL, U. JANLERT, AND L. S. BIRGANDER (2010): "Burnout, working conditions and gender-results from the northern Sweden MONICA Study," *BMC public health*, 10, 1–9.

NOTOWIDIGDO, M., A. FINKELSTEIN, F. SCHILBACH, AND J. ZHANG (2024): "Lives vs. Livelihoods: The Impact of the Great Recession on Mortality and Welfare," *University of Chicago, Becker Friedman Institute for Economics Working Paper*.

O'CONNOR, D. B., J. F. THAYER, AND K. VEDHARA (2021): "Stress and health: A review of psychobiological processes," *Annual review of psychology*, 72, 663–688.

PAUL, K. I. AND K. MOSER (2009): "Unemployment impairs mental health: Meta-analyses," *Journal of Vocational behavior*, 74, 264–282.

PERSSON, G., M. DANIELSSON, M. ROSÉN, K. ALEXANDERSON, O. LUNDBERG, B. LUNDGREN, M. STENBECK, AND S. WALL (2006): "Health in Sweden: the national public health report 2005," *Scandinavian Journal of Public Health*, 34, 3–10.

PETERSON, N. G., M. D. MUMFORD, W. C. BORMAN, P. R. JEANNERET, AND E. A. FLEISHMAN, eds. (1999): *An occupational information system for the 21st century: The development of O*NET*, American Psychological Association.

PINES, A. AND E. ARONSON (1988): *Career burnout: Causes and cures.*, Free press.

POSTEL-VINAY, F. AND G. JOLIVET (2024): "A Structural Analysis of Mental Health and Labor Market Trajectories," *The Review of Economic Studies*.

PURVANOVA, R. K. AND J. P. MUROS (2010): "Gender differences in burnout: A meta-analysis," *Journal of vocational behavior*, 77, 168–185.

RAIO, C. M., T. A. OREDERU, L. PALAZZOLO, A. A. SHURICK, AND E. A. PHELPS (2013): "Cognitive emotion regulation fails the stress test," *Proceedings of the National Academy of Sciences*, 110, 15139–15144.

RAMSTEDT, K. (2005): "National assessment and grading in the Swedish school system," *Stockholm: The Swedish National Agency for Education*.

ROSEN, S. (1974): "Hedonic prices and implicit markets: product differentiation in pure competition," *Journal of political economy*, 82, 34–55.

RUHM, C. J. (2000): "Parental leave and child health," *Journal of health economics*, 19, 931–960.

SALVADO, M., D. L. MARQUES, I. M. PIRES, AND N. M. SILVA (2021): "Mindfulness-based interventions to reduce burnout in primary healthcare professionals: A systematic review and meta-analysis," in *Healthcare*, MDPI, vol. 9, 1342.

SCHAUFELI, W. AND D. ENZMANN (1998): *The burnout companion to study and practice: A critical analysis*, CRC press.

SCHAUFELI, W. B. (2017): "Burnout: A short socio-cultural history," *Burnout, fatigue, exhaustion: An interdisciplinary* *perspective on a modern affliction*, 105–127.

SEIDLER, A., M. THINSCHMIDT, S. DECKERT, F. THEN, J. HEGEWALD, K. NIEUWENHUIJSEN, AND S. G. RIEDEL-HELLER (2014): "The role of psychosocial working conditions on burnout and its core component emotional exhaustion–a systematic review," *Journal of occupational medicine and toxicology*, 9, 1–13.

SHIROM, A. (2003): "Job-related burnout: A review." *Handbook of occupational health psychology.*, 245–264.

SINN, F. (2024): "Does who we work with matter? The Effect of Coworkers on Income," Working Paper, Stockholm University.

SONG, J., D. J. PRICE, F. GUVENEN, N. BLOOM, AND T. VON WACHTER (2019): "Firming up inequality," *The Quarterly Journal of Economics*, 134, 1–50.

SORKIN, I. (2018): "Ranking firms using revealed preference," *The Quarterly Journal of Economics*, 133, 1331–1393.

SPASOVA, S., D. BOUGET, AND B. VANHERCKE (2016): "Sick pay and sickness benefit schemes in the European Union," *Background report for the Social Protection Committee's In-Depth Review on sickness benefits*.

STUCKY, E. R., T. R. DRESSELHAUS, A. DOLLARHIDE, M. SHIVELY, G. MAYNARD, S. JAIN, T. WOLFSON, M. B. WEINGER, AND T. RUTLEDGE (2009): "Intern to attending: assessing stress among physicians," *Academic medicine*, 84, 251–257.

TARIS, T. W. (2006): "Is there a relationship between burnout and objective performance? A critical review of 16 studies," *Work & Stress*, 20, 316–334.

TETRICK, L. E. AND C. J. WINSLOW (2015): "Workplace stress management interventions and health promotion," *Annu. Rev. Organ. Psychol. Organ. Behav.*, 2, 583–603.

THE NATIONAL BOARD OF HEALTH AND WELFARE (2003): *Utmattningssyndrom–Stressrelaterad psykisk ohälsa [Exhaustion Disorder. Stress-related mental illness]*, Bokförlaget Bjurner och Bruno AB.

VAN DAM, A. (2021): "A clinical perspective on burnout: diagnosis, classification, and treatment of clinical burnout," *European Journal of Work and Organizational Psychology*, 30, 732–741.

VAN DER KLINK, J. J. AND F. J. VAN DIJK (2003): "Dutch practice guidelines for managing adjustment disorders in occupational and primary health care," *Scandinavian journal of work, environment & health*, 478–487.

WEST, C. P., L. N. DYRBYE, J. T. RABATIN, T. G. CALL, J. H. DAVIDSON, A. MULTARI, S. A. ROMANSKI, J. M. H. HELLYER, J. A. SLOAN, AND T. D. SHANAFELT (2014): "Intervention to promote physician well-being, job satisfaction, and professionalism: a randomized clinical trial," *JAMA internal medicine*, 174, 527–533.

WHO (2019): "Burn-out an "occupational phenomenon": International Classification of Diseases," Retrieved April 8, 2024.

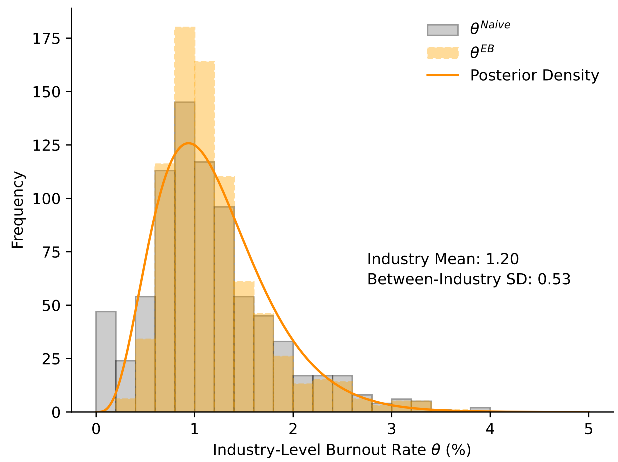
WIKSTRÖM, J. (2024): "The Long-Run Effects of Stricter Eligibility Criteria in Short-Term Disability Insurance," Manuscript in preparation.

ZELTZER, D., L. EINAV, A. FINKELSTEIN, T. SHIR, S. M. STEMMER, AND R. D. BALICER (2023): "Why is end-of-life spending so high? Evidence from cancer patients," *Review of Economics and Statistics*, 105, 511–527.

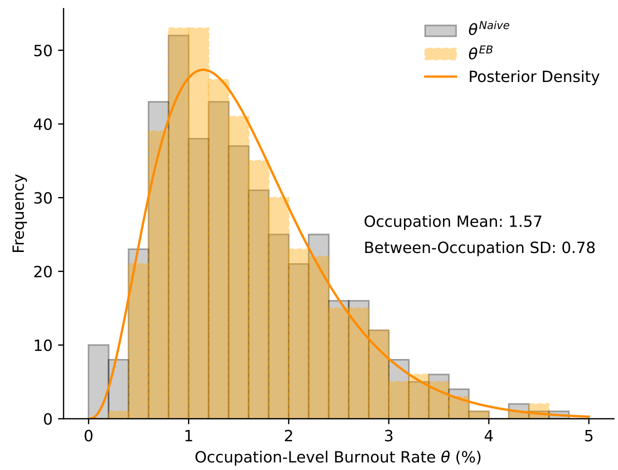
ZHANG, X.-J., Y. SONG, T. JIANG, N. DING, AND T.-Y. SHI (2020): "Interventions to reduce burnout of physicians and nurses: An overview of systematic reviews and meta-analyses," *Medicine*, 99, e20992.

Figure 1: Heterogeneity in Burnout Rates Across Jobs

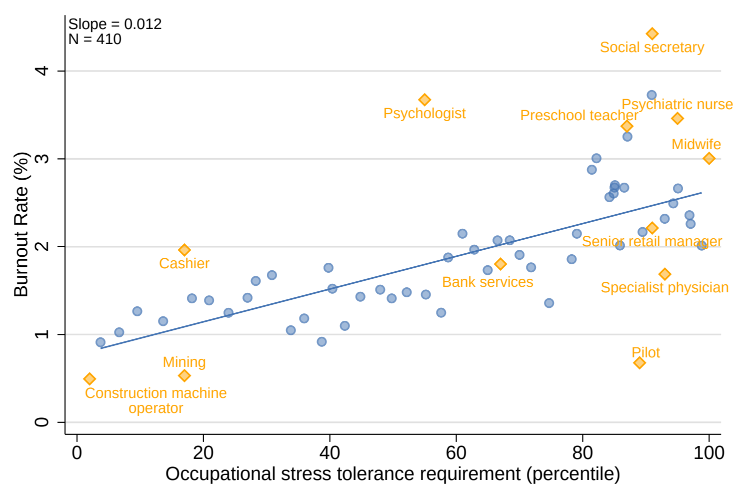
(a) Industries




(b) Occupations



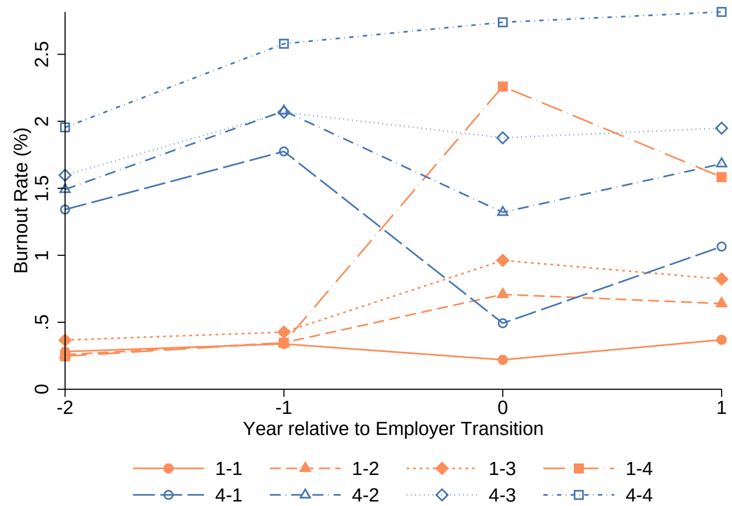

(c) Stress Tolerance Requirements and Burnout Rates



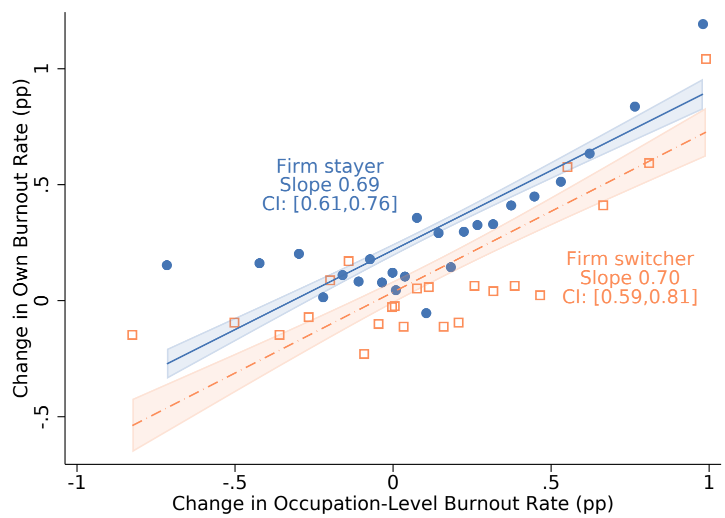

*Notes:* **Panels (a) and (b)** show the distribution of annual burnout rate across occupations and industries, respectively, and the empirical Bayesian (EB) adjusted distributions using Beta-Bernoulli distributions with an empirical prior. **Panel (a)** uses 806 industries from 15.1 million full-time workers between 2014 and 2018. The industries at the two tails are "Care in special forms of accommodation for adults with substance abuse problems," with an EB burnout rate of 3.86 percent, and "Growing of cereals (except rice), leguminous crops and oil seeds" with a 0.22 percent EB burnout rate. **Panel (b)** shows the histogram of burnout rate across 429 occupations from 8.41 million full-time workers between 2014 and 2018. The occupations at the two tails are "Deacon" with an EB burnout rate of 4.51 percent and "Operator of Agricultural or Silvicultural Machinery" with a 0.26 percent EB burnout rate. To enhance visual representation, we drop one industry and two occupations with naive burnout rates above 5 percent. **Panel (c)** plots in solid blue dots the binned scatter plot of occupation-level burnout rate against stress-tolerance requirement according to O*NET. In orange diamonds, the figure plots a selected sub-set of occupations.

Figure 2: Workplace Determinants of Burnout: Mover Design

(a) Firm Switchers

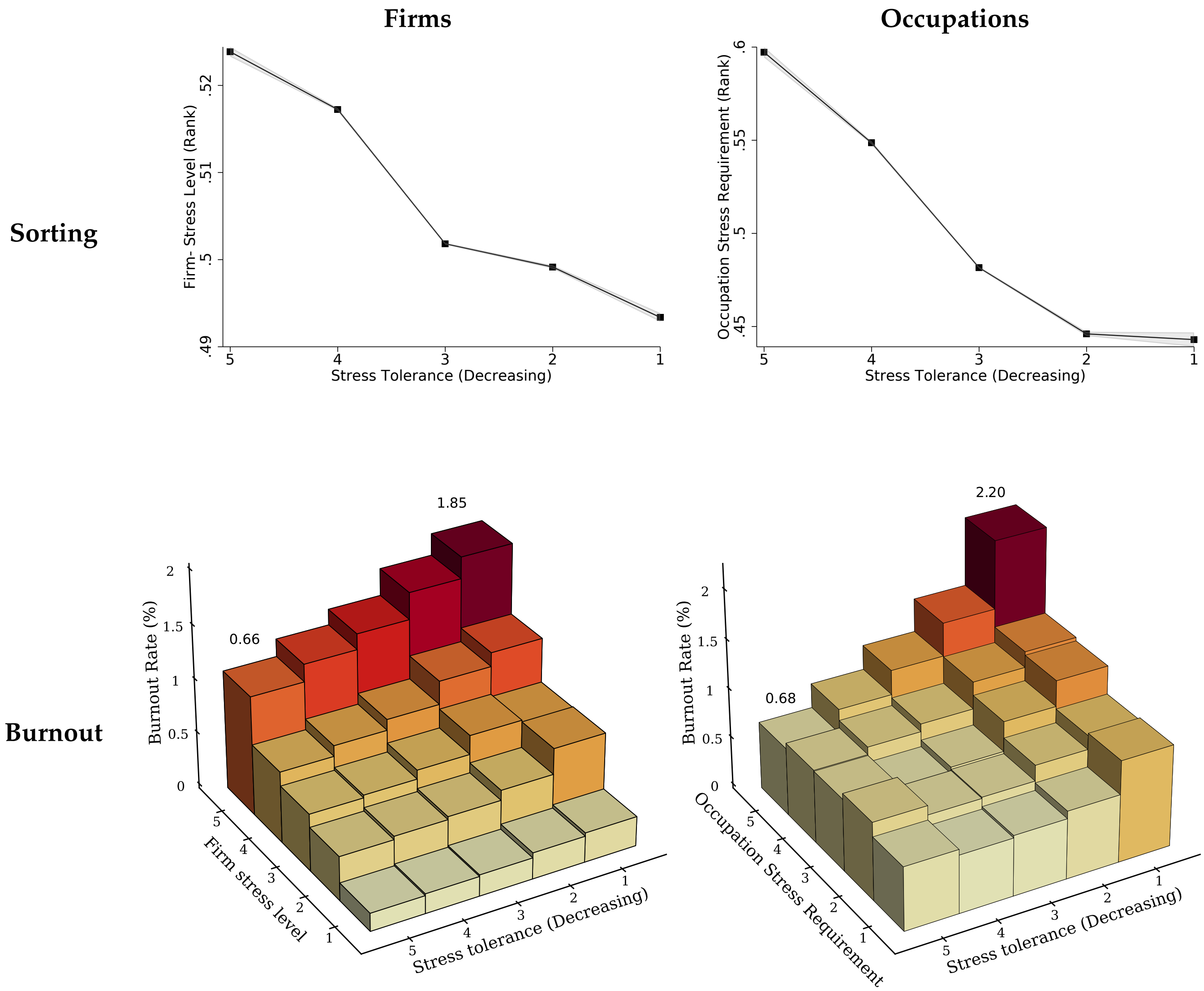



(b) Occupation Switchers




*Notes:* **Panel (a)** focuses on workers switching firms. Firms are grouped into quartiles based on the mean burnout rate among coworkers within the same-size firms. The sample is composed of 183,888 firm switchers with at least two years of tenure in their preceding and new jobs, following (Card et al., 2013). **Panel (b)** focuses on workers switching occupations within or between firms. It plots a binned scatter of changes in their burnout rate against changes in the leave-one-out average burnout rate of their 4-digit occupations. The linear fit and 95 percent confidence intervals obtained from robust standard errors are reported. The sample is composed of 1,599,325 occupation switchers with at least two years of tenure at their preceding firm.

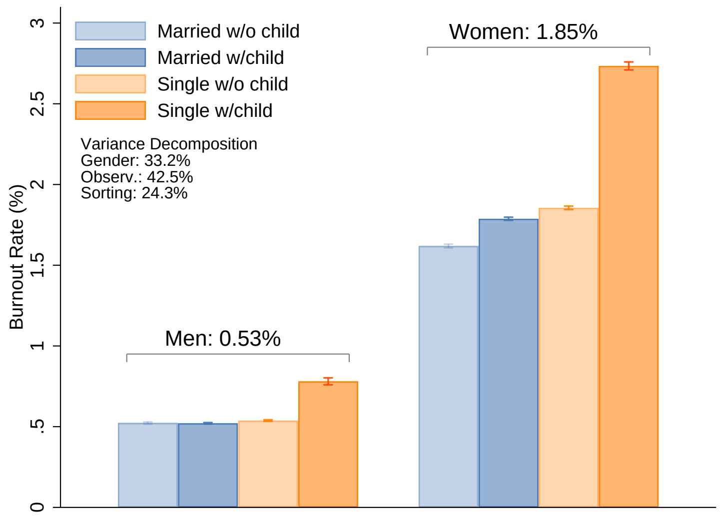
Figure 3: Sorting & Mismatch: Stressful Jobs vs. Stress Tolerant Workers



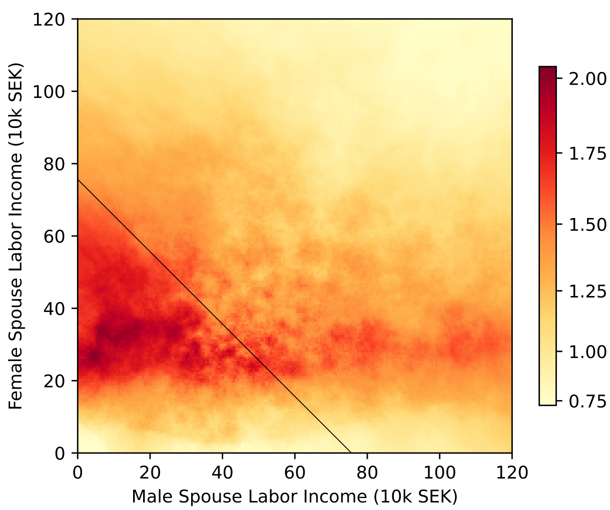

*Notes:* The figure displays the sorting of workers with varying levels of stress tolerance across jobs with varying stress levels (row 1) and their corresponding burnout rates (row 2). Jobs are firms in column 1 and occupations in column 2. Stress tolerance is assessed by psychologists around age 18 before military service. The firm stress level is the quintile of the firm-level burnout rate. 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." We use a crosswalk between the U.S. and Swedish occupation codes and translate this measure into a quintile rank of occupations. This figure is based entirely on male workers due to the availability of the stress tolerance measure.

Figure 4: Burnout: Gender, Family, & Career

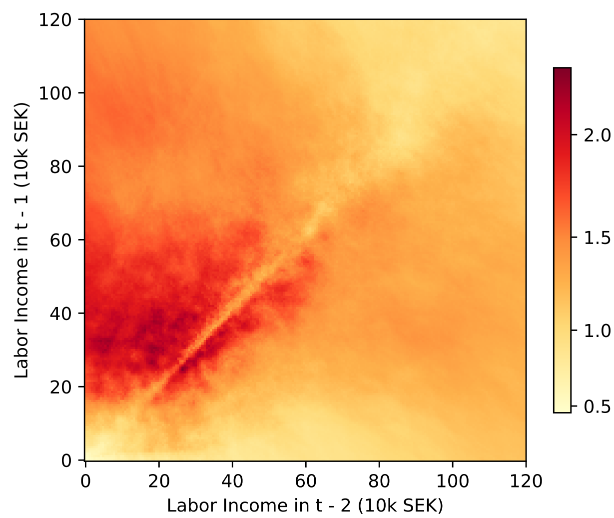
(a) Burnout Rate by Gender & Family Type




(b) Women: Burnout Rate against Couple Incomes




(c) Women: Burnout Rate against Income Growth

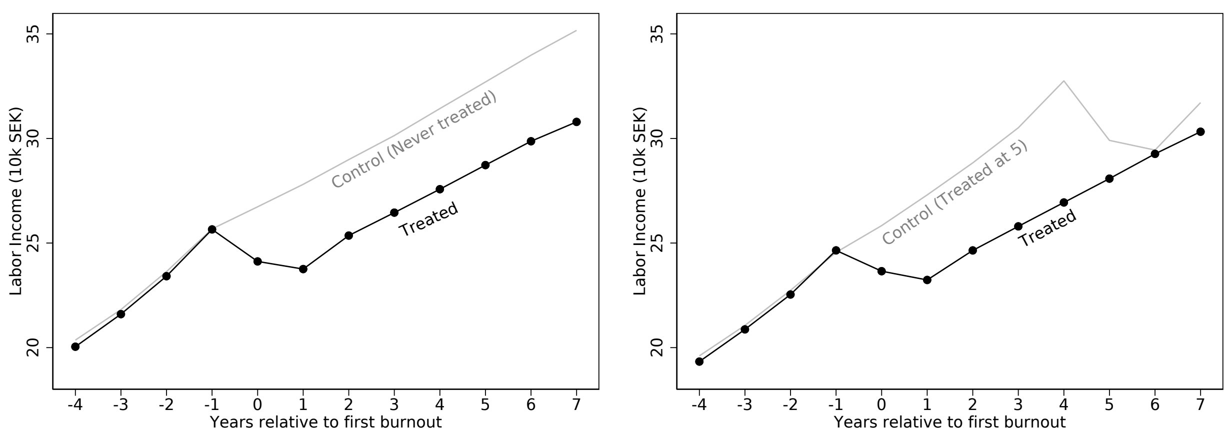



*Notes:* **Panel (a)** displays the annual burnout rate by marital and parental types by gender, with an average of 1.12% for the entire employed population (20.0 million women and 24.9 million men). The respective shares in the four groups are 24%, 37%, 31%, and 8% for women, and 19%, 41%, 37%, and 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 3); (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.4 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 5: Empirical Designs

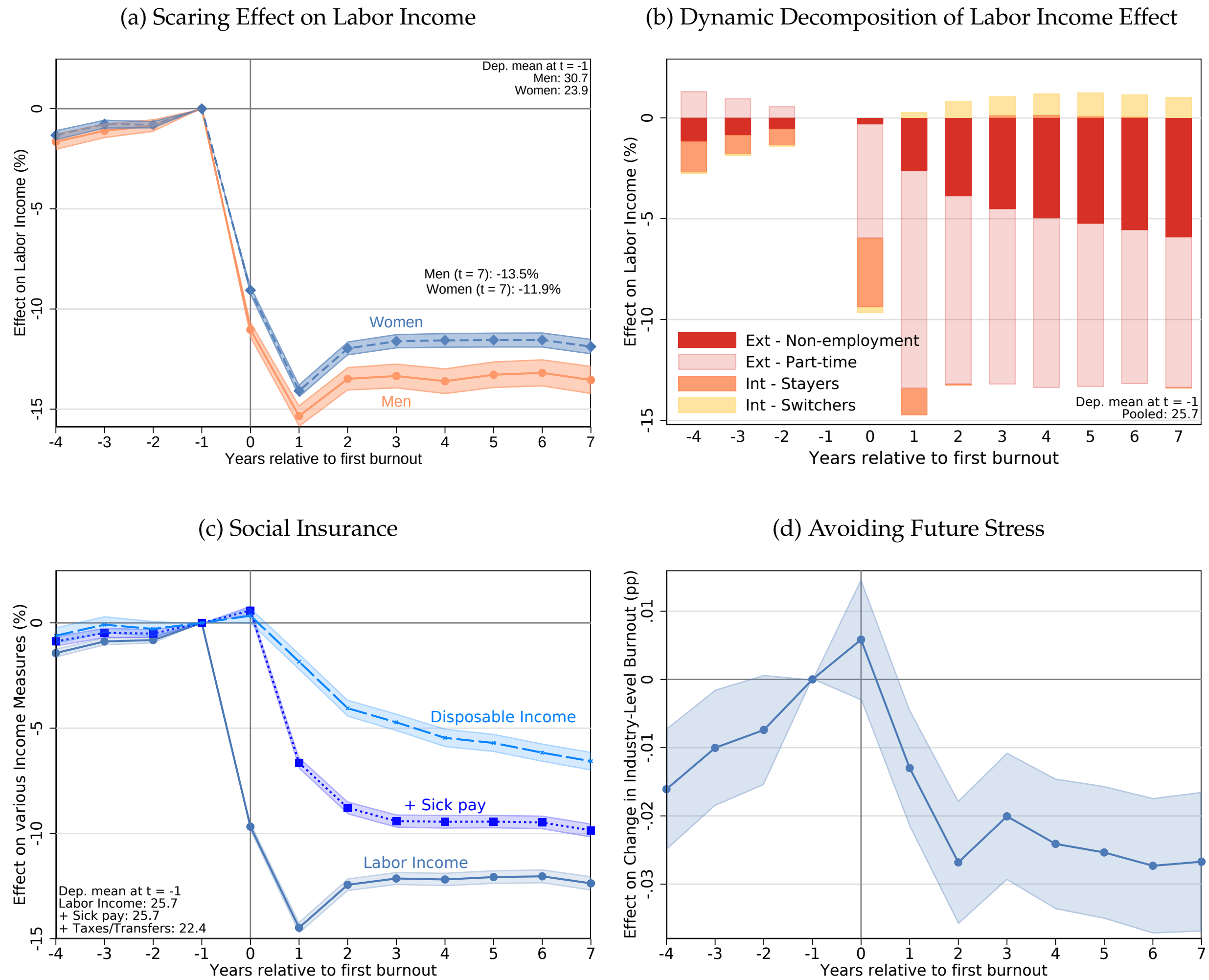
(a) Matched Difference-in-Differences

(b) Fixed-$\delta$ Method




*Notes:* This figure showcases our two 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).

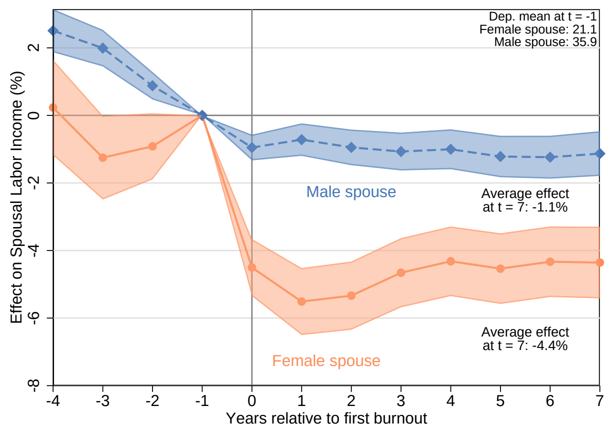
Figure 6: Burnout Effect on Own Labor Outcomes



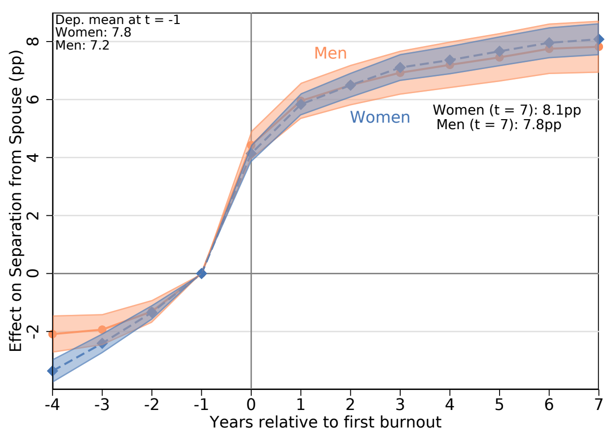

*Notes:* **Panel (a)** shows the proportional effect of burnout on labor income. Pre-treatment average incomes in 10k SEK and proportional effects are reported in the upper right corner. It is based on the dynamic matched difference-in-difference model, plotting the coefficients on event-time fixed effect interacted with an indicator for burnout in equation (2). 95 percent confidence interval based on individual-level-clustered standard error. **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 secured 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 7: Burnout Effect on Spousal Labor Income, Separation, and Fertility

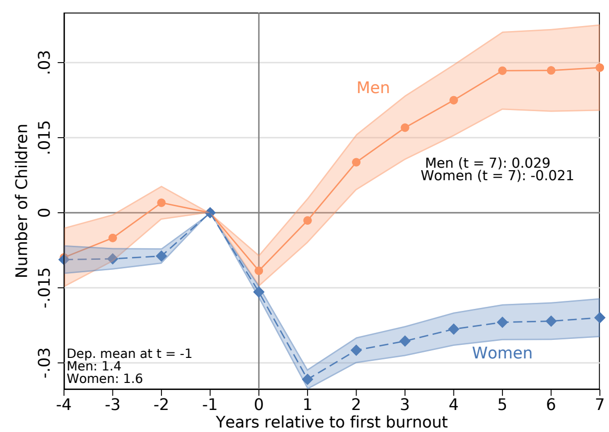
(a) Spousal Labor Income




(b) Separation

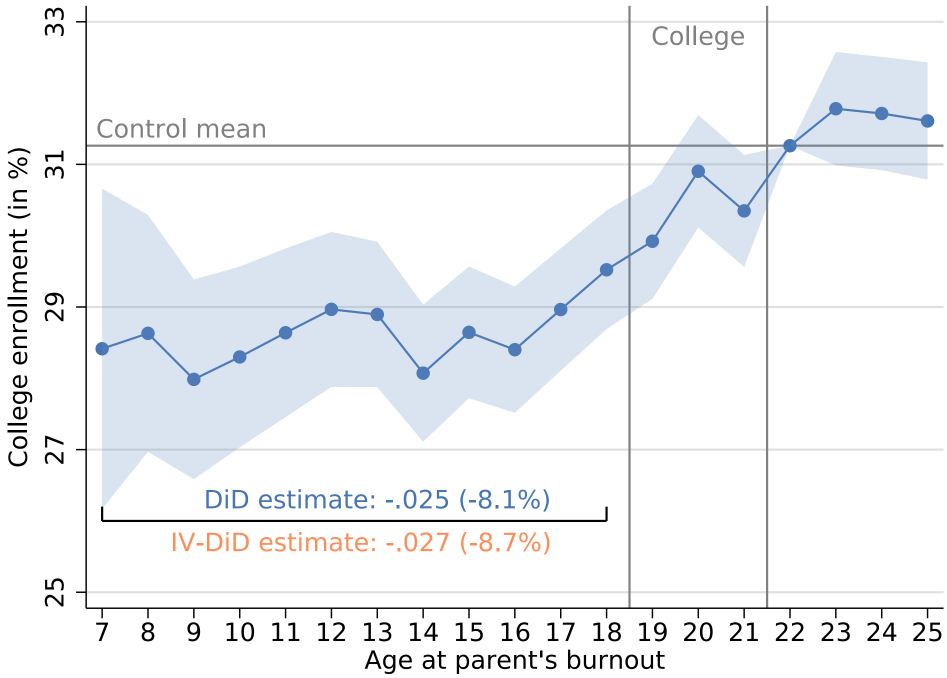



(c) Number of Children



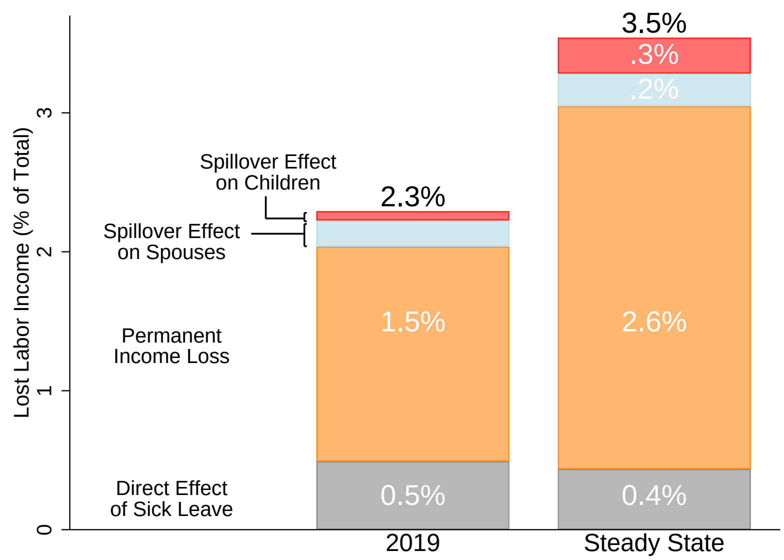

*Notes:* **Panel (a)** plots the proportional effect of burnout on the labor income of 57,441 spouses (married/cohabiting partners in the year prior to burnout), irrespective of the current marital status. It plots the coefficients on event-time fixed effect interacted with an indicator for burnout and their 95 percent confidence interval based on individual-level-clustered standard error from the dynamic matched difference-in-difference model in equation (2). **Panel (b)** 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 (c)** plots the effect of burnout on fertility, measured as the number of children. The sample underlying the results in Panel (c) is the baseline matched sample without additional restrictions regarding marital status/presence of a spouse.

Figure 8: Effects of Parental Burnout on Children's College Enrollment




*Notes:* The figure plots the effect of parental burnout on children's college enrollment measured at ages 19, 20, or 21. 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 college enrollment of children by age at the time of first parental burnout relative to those whose parents burn out when children are at age 22, 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 7-18. "IV-DiD estimate" reports an effect for ages 7-18 estimated by instrumenting parental burnout by the burnout rate in their industry. More precisely, we instrument the indicators for parental burnout in equation (5) by the average burnout rate across all firms in their industry except where they work. The regression conditions on an industry fixed effect and exploits variation in workplace stress within industries over time. The first-stage F-statistic is 1123. The sample consists of 297,668 children whose parents experienced burnout in our sample period (2005-2019) and have turned 21 by the end of our sample period, implying that the youngest age in the sample is seven.

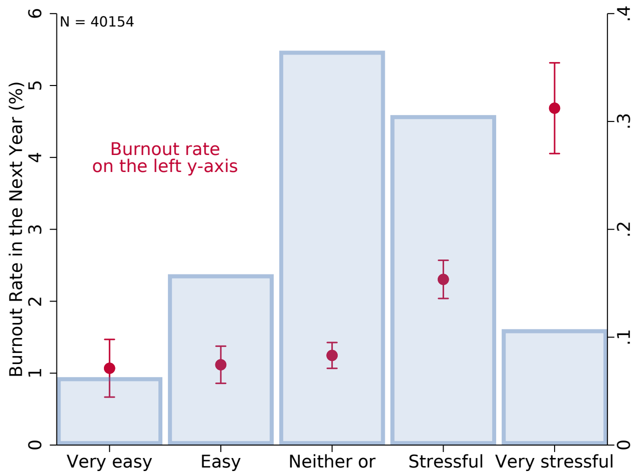
Figure 9: Aggregate Loss in Income Due to Burnout



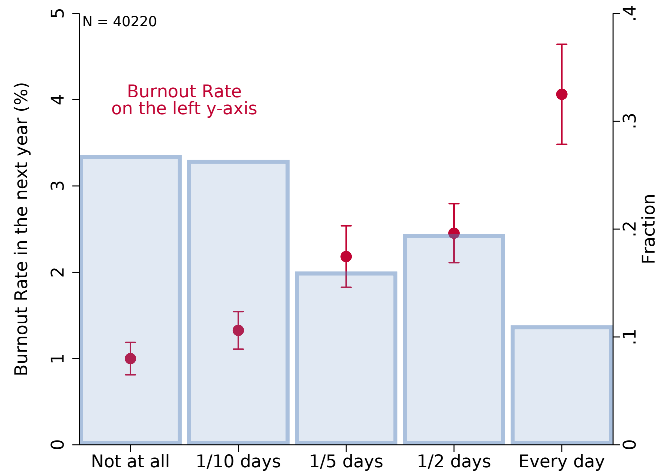

*Notes:* The figure shows our estimates of the loss of aggregate labor income due to burnout. The left bar presents estimates for the year 2019, whereas the right bar presents steady-state estimates assuming that the 2019 conditions are permanent. The aggregate loss has four components: i) lost days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

Figure 10: Self-reported Work condition & Burnout Rate in the Subsequent Year

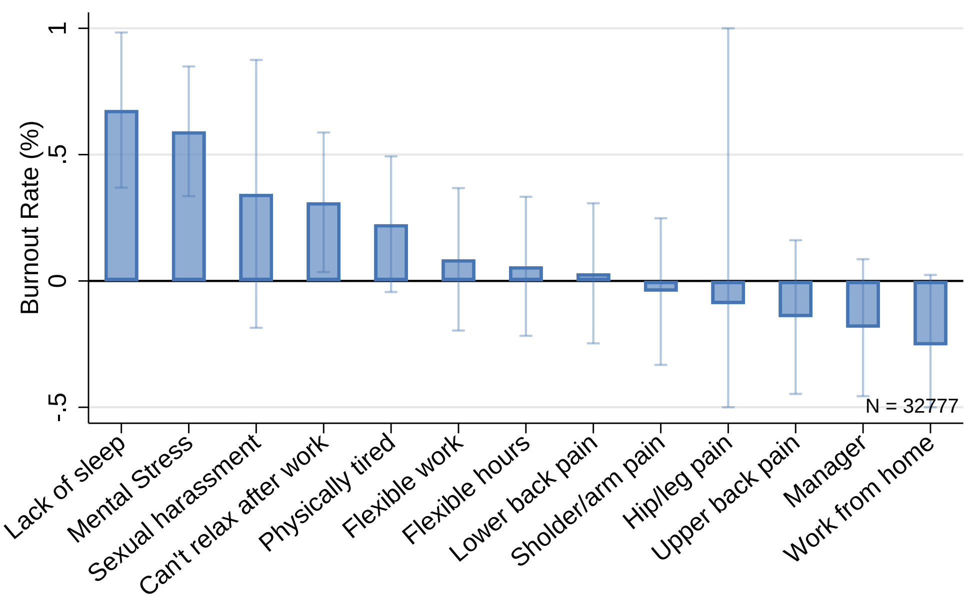
(a) Survey Question: Is your work mentally stressful?




(b) Survey Question: Can not relax thoughts from work?

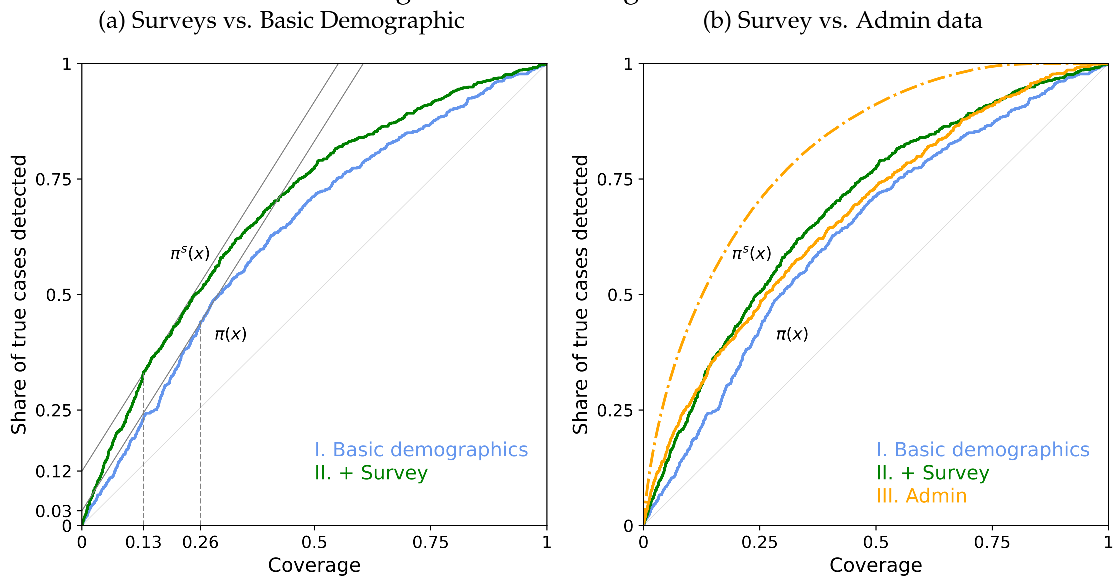



(c) Multivariate regression: Work conditions




*Notes:* This figure documents the relationship between the self-reported work condition in the "Work Environment Survey"(AMU) and the burnout rate of the same worker in the year after the survey. **Panel (a)** focuses on how mentally stressful workers judge their job, and **Panel (b)** how frequently workers are unable to relax their thoughts after work. The distribution of responses is reported on the second (right) y-axis. **Panel (c)** responses are converted to a binary indicator of the above median. This regression controls for gender × education × age × family type fixed effects and year fixed effects.

Figure 11: Predicting Burnout




*Notes:* The figure shows the Cumulative Gains Chart for prediction models of burnout in the next calendar year using Extreme Gradient Boosting. It depicts the share of positives discovered at a given level of coverage. **Panel (a)** compares the prediction power of adding questions about work conditions from the Work Environment Survey (AMU) to basic demographics (gender, age, native status, and detailed educational qualification). **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 AMU, with the exception of the dotted yellow line in panel (b), where the sample extends to all 77,138,798 observations in 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 A.2).

Table 3: Burnout Prediction

| *Outcome: Burnout in* | t + 1 | t + 1 | t + 2 |
|---|---|---|---|
| Basic Demographics | 0.635 | 0.727 | 0.630 |
| Basic Demographics + AMU | 0.690 | | 0.652 |
| Admin Data | 0.677 | 0.813 | 0.665 |
| Admin Data + AMU | 0.712 | | 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 4). 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
October 30, 2024

## 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 3. Appendix Table A.4 reports the sample size after each sample selection step. To build our treated sample, we start with 201,714 burnout cases, with their first burnout incident occurring from 2006 to 2013. We chose this time frame since 2006 is the first year where our data has complete information on diagnoses, and 2013 since we follow individuals for seven years after their burnout, and our last year of data is for 2020. We focus on the first incidence so that prior burnouts do not influence pre-trends. We restrict the sample to individuals between the ages 29 to 53 for whom we can observe labor market trajectories during prime age (25-60). This results in a sample of 153,218 first burnout cases. We drop 1,349 individuals who die within seven years after treatment. We then dropped 117 observations with missing education information. 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 3.1. 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 Sexual Harassment and Burnout

As documented in Section 3.1, 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.

# D Prediction and Prevention

## D.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.

## D.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.

### D.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.

# E Supplementary Figures

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

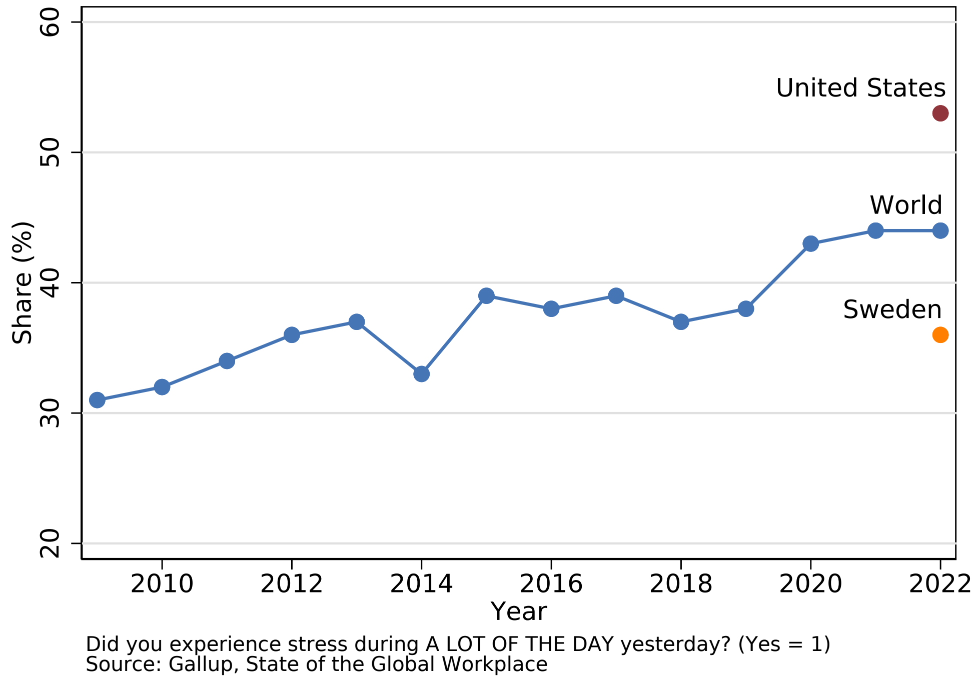
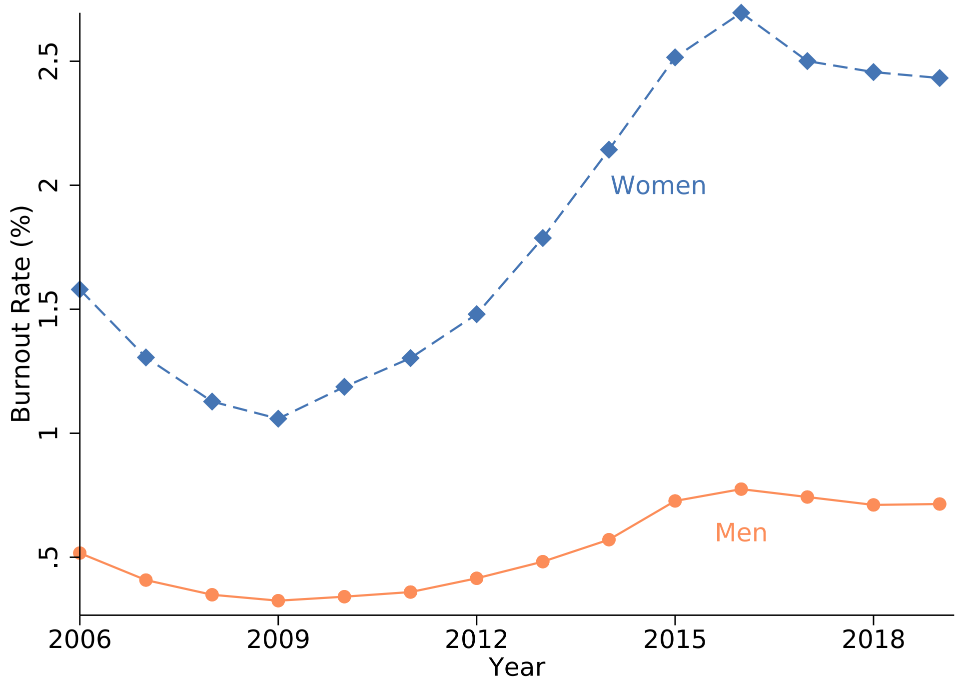


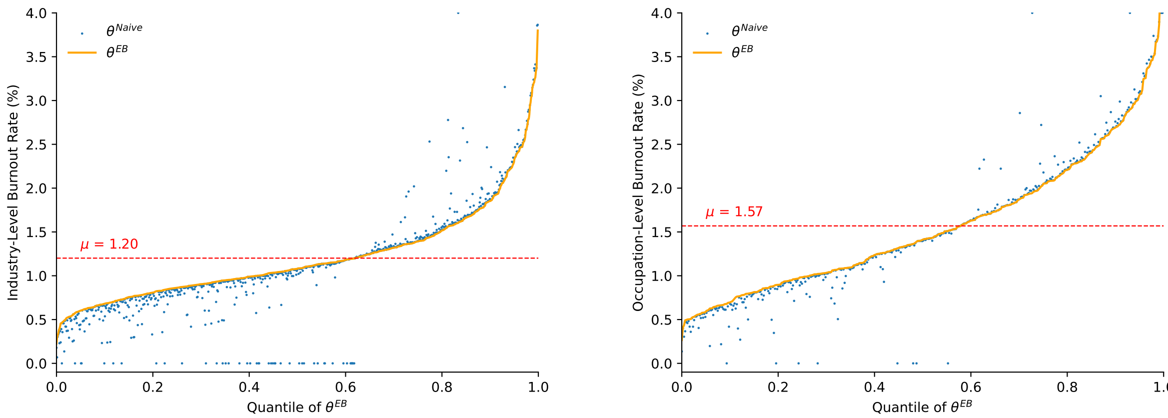
Figure A.2: Evolution of Burnout Rates over Time




*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: Estimation of Industry- and Occupation-Level Heterogeneity

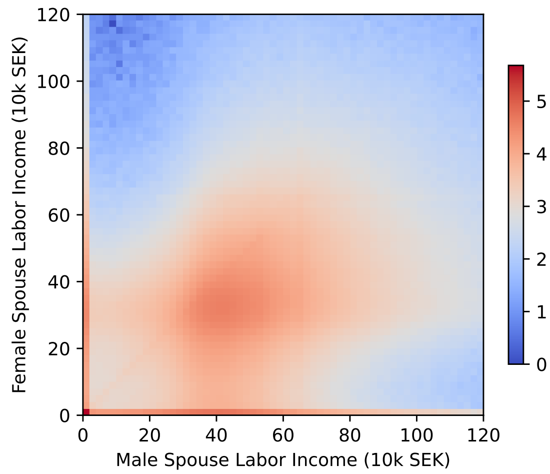
(a) Industries (b) Occupations



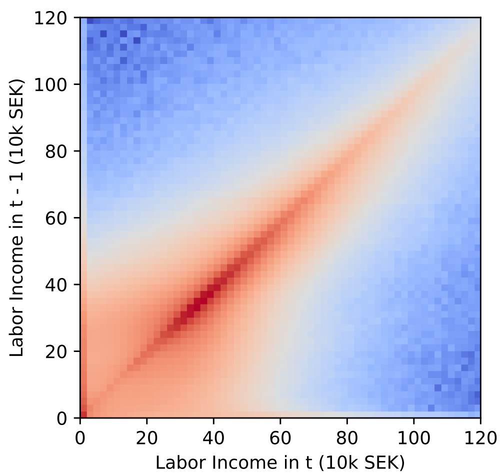

*Notes:* The figure illustrates our estimation of industry (**Panel (a)**) and occupation-level (**Panel (b)**) burnout rates. The underlying sample consists of all workers with information on industry or occupation between 2014 and 2018. In each panel, a dot represents the burnout rate estimated using the sample average for a given industry or occupation. The orange line represents the posterior expected value for the burnout rate obtained by estimating a Beta-Binomial distribution with empirical priors. Observations are ordered by their quantile in the distribution of posterior expected values.

Figure A.4: Distribution of Labor Income Histories

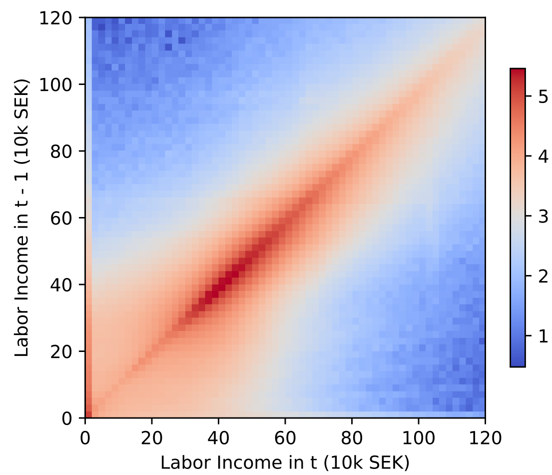
(a) Joint distribution of spousal labor incomes




(b) Income history (Women)

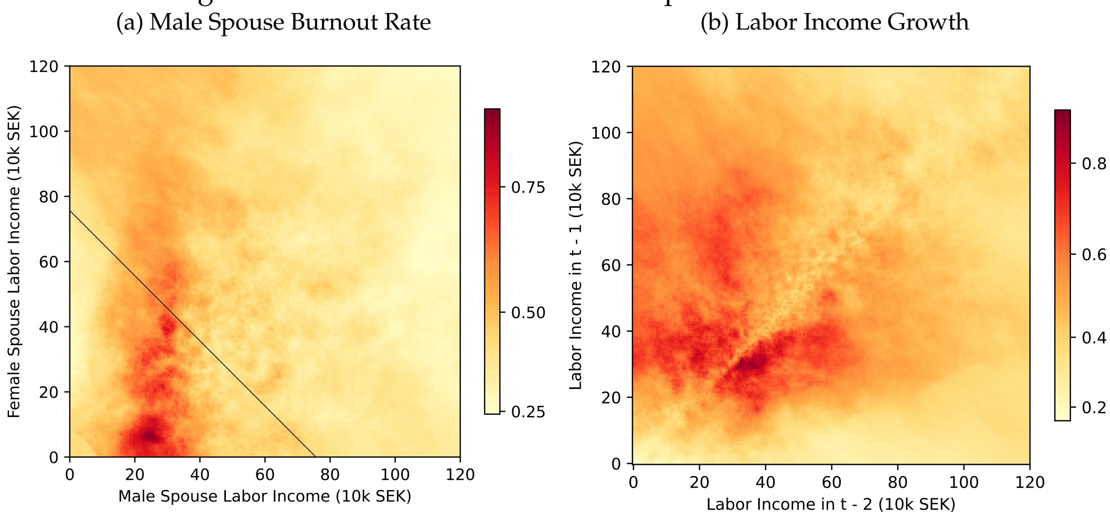



(c) Income history (Men)




*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.5: Burnout Rate of Men: Couple Incomes & Career




*Notes*: **Panel (a)** shows burnout rates over the joint distribution of spousal labor incomes for 11,008,512 couple-year observations in each subfigure. The two lines are 45-degree lines and a line marking the median couple's total income of 756k SEK. Annual labor income is winsorized at 1,200k (corresponding to P97 of men and P99 of women) and rank-adjusted to 2020 SEK when the exchange rate was 9,20 to USD and 10,49 to Euro. Two-dimensional moving averages are used so that the burnout rate represents the average rate for approximately 40000 individuals in the circular vicinity of each point. **Panel (b)** reports burnout rates in $t+1$ across individuals' labor income histories. The x-axis reports labor income in $t-1$. The y-axis reports labor income in t. We perform a rank-adjustment to 2020 levels for labor income in $t-1$ and compute income in $t$ using rank-adjusted labor income in the previous year and nominal income growth at the individual level. The sample consists of individuals aged 25 to 55 between the years 2005 and 2019 without prior burnout sick leave. We drop observations within a two-year window of childbirth. See notes in Figure A.4 for a more detailed description of the sample construction.

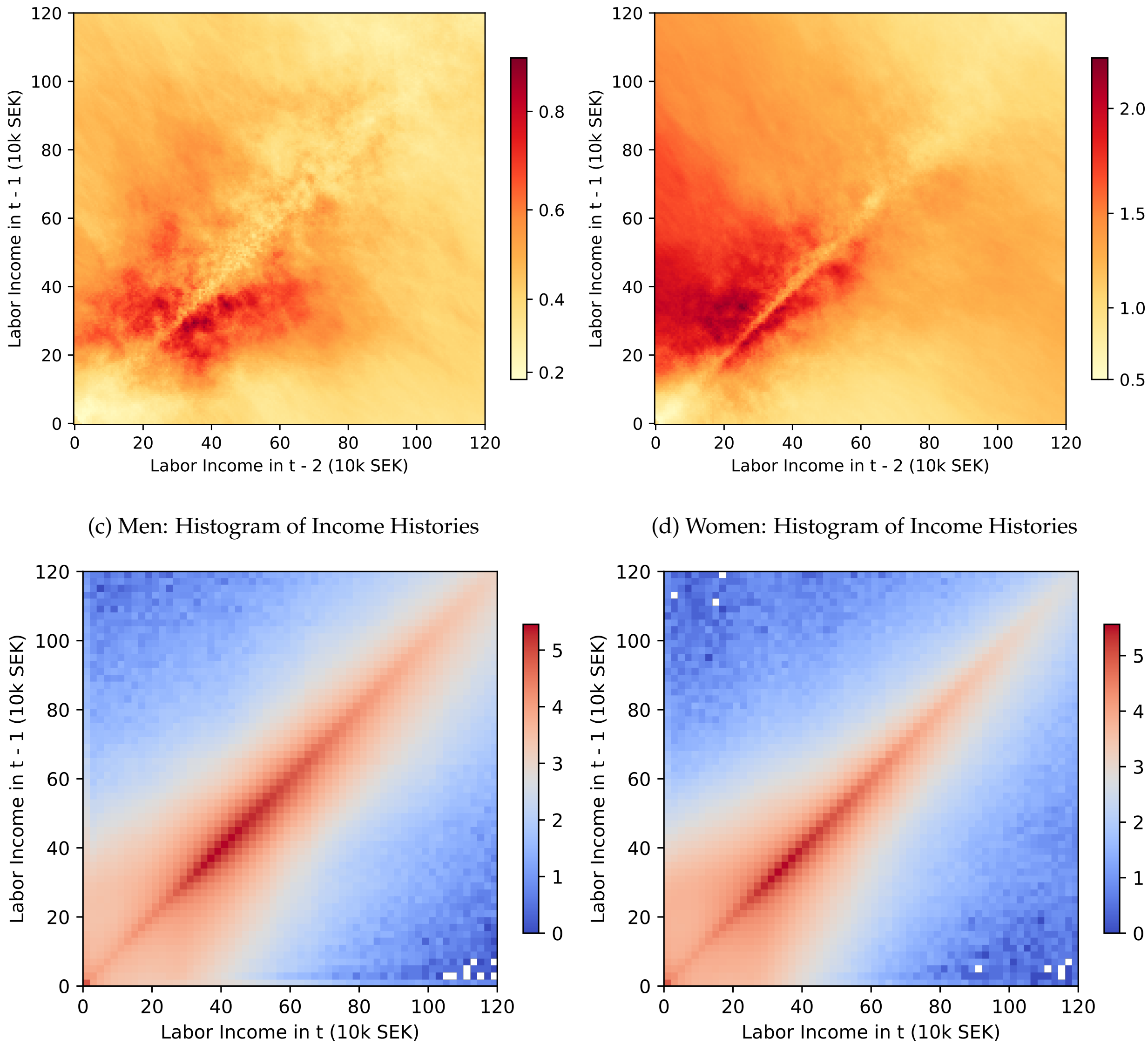
Figure A.6: Burnout and Labor Income Histories (Stayers)

(a) Men: Burnout Rate among Stayers

(b) Women: Burnout Rate among Stayers

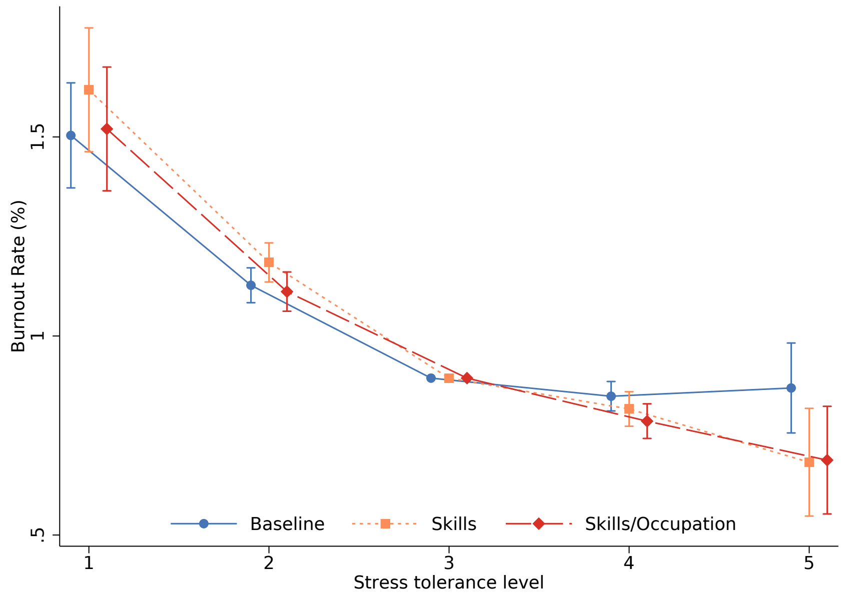
(c) Men: Histogram of Income Histories

(d) Women: Histogram of Income Histories



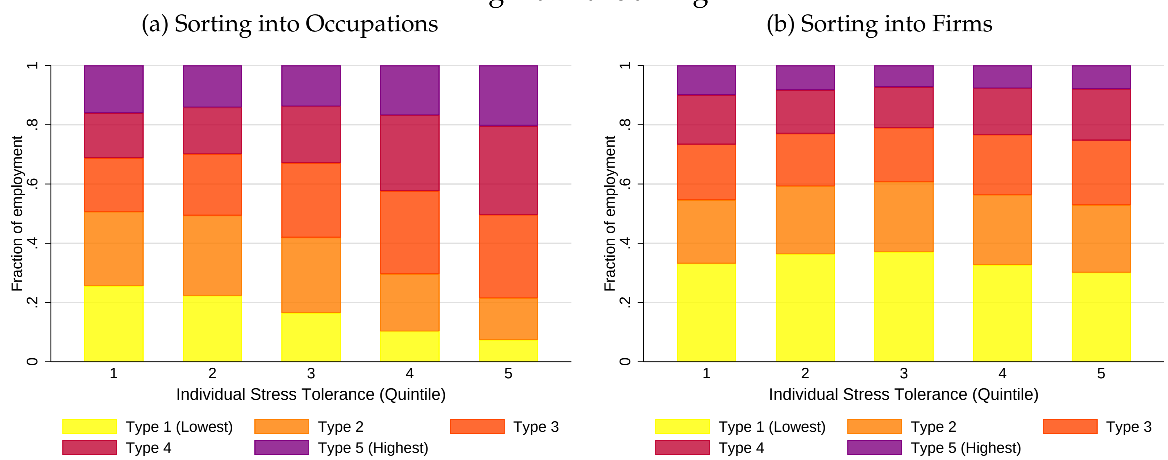

*Notes:* **Panels (a) and (b)** reports burnout rates by gender among workers staying at the same employer in the past two years against their labor income histories during the same period. The construction of the sample is described in Appendix Section B. Details on the estimation procedure are provided in Section 3. **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.7: Individual's stress tolerance and burnout



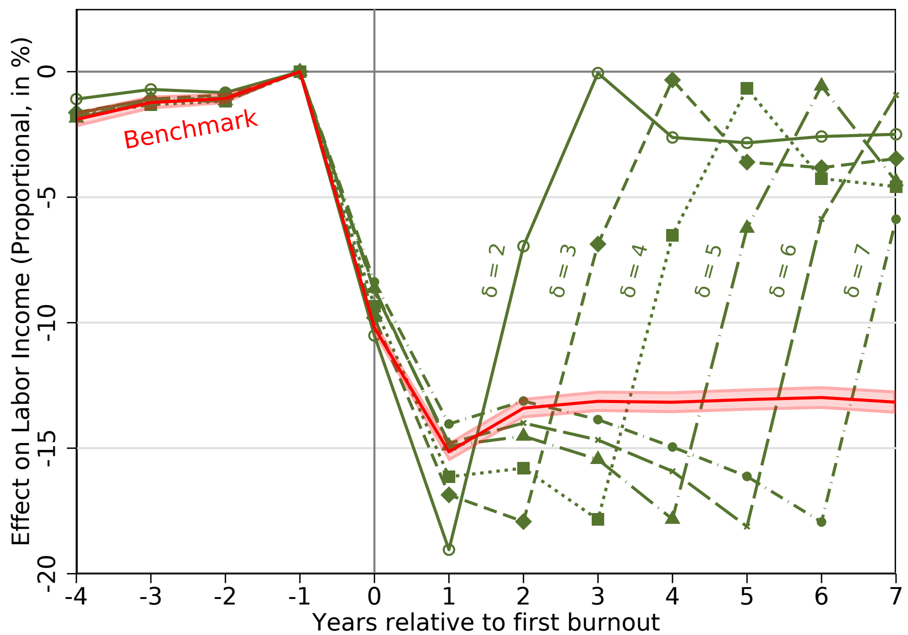

*Notes*: The figure plots the average individual burnout rates by individual stress tolerance, measured in association with the military draft. Blue circles are averages estimated using a regression where the median group is the reference category. Orange squares are estimates from a similar regression 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.8: Sorting




*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 3 for both firms and occupation. The stress tolerance measures used are only available for men.

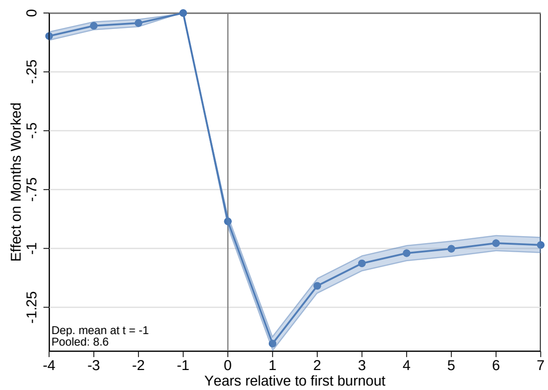
Figure A.9: Effect of Burnout on Labor Income: Baseline vs. Fixed-Delta Method



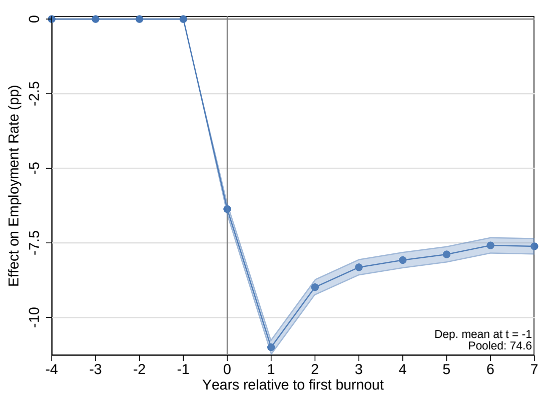

*Notes*: The figure shows the proportional effect of burnout on labor income as estimated with different matched control groups. The red line labeled *Benchmark* depicts the estimated effects when never-treated individuals are used as a control (Figure 6a). The control group in the remaining lines are individuals who burn out $\delta$ 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.10: Burnout Effect on Labor Income: Extensive vs. Intensive Margins

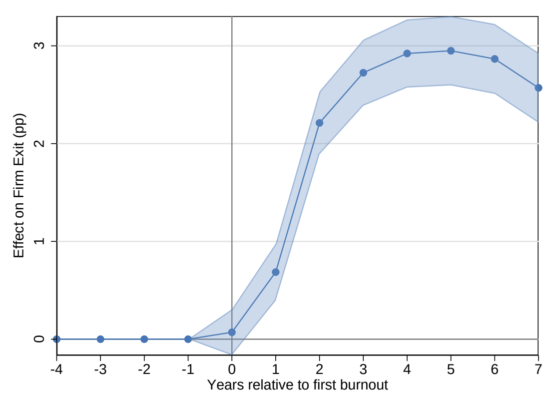
(a) Months worked




(b) Employment Rate

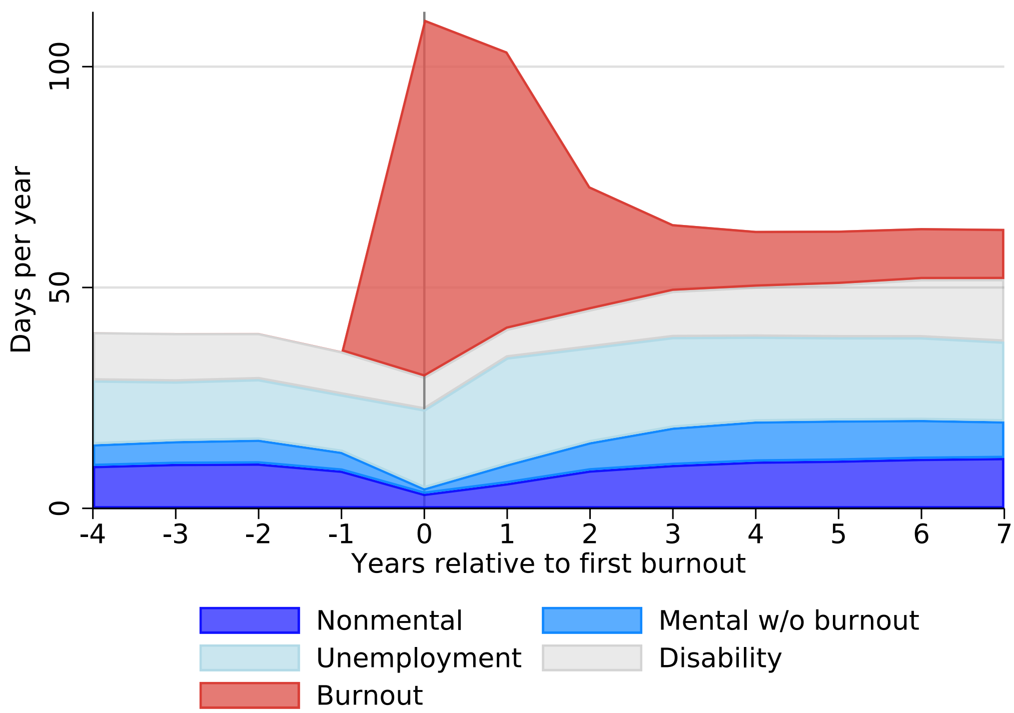



(c) Firm Switching



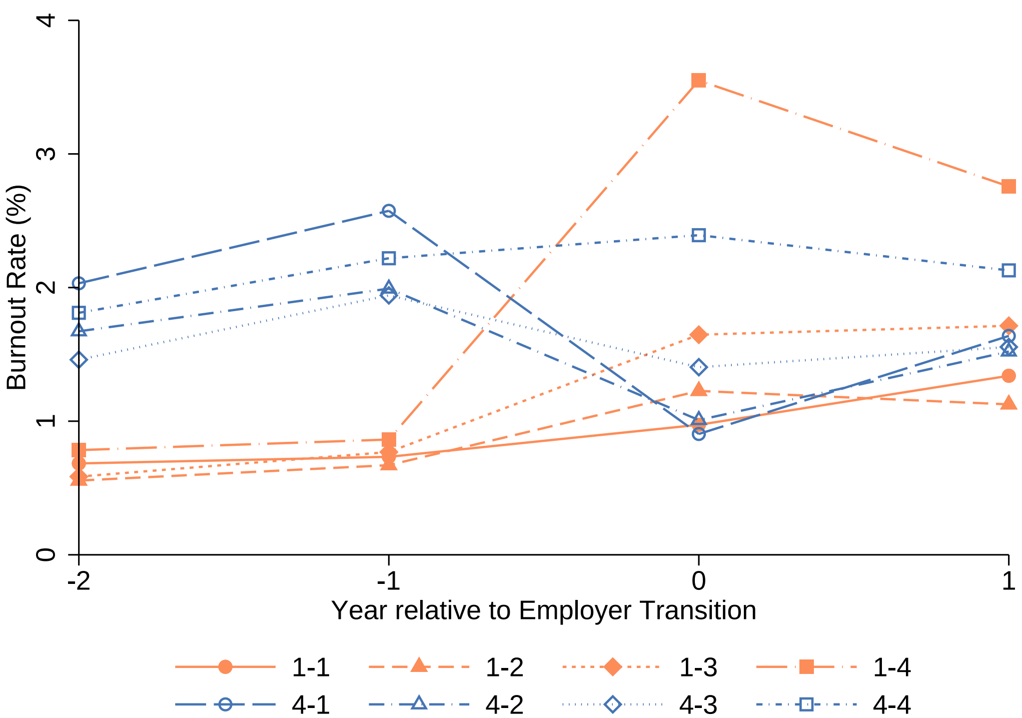

*Notes:* **Panels (a-c)** plot the coefficients on event-time fixed effect interacted with an indicator for burnout, and their standard error, from the dynamic difference-in-difference model in equation (2) for various labor market outcomes. **Panel (a)** reports the coefficients when the model is estimated 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.11: 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.

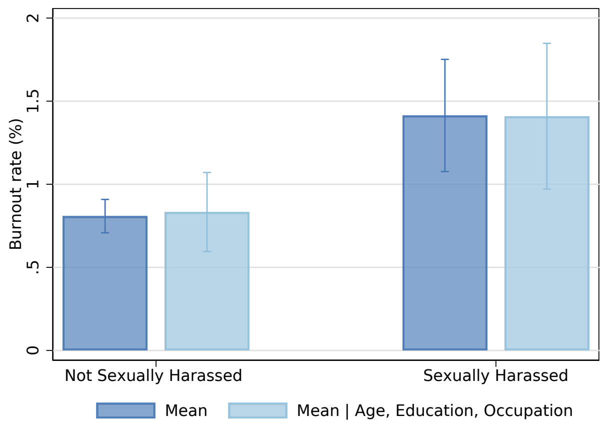
Figure A.12: Movers: AKM



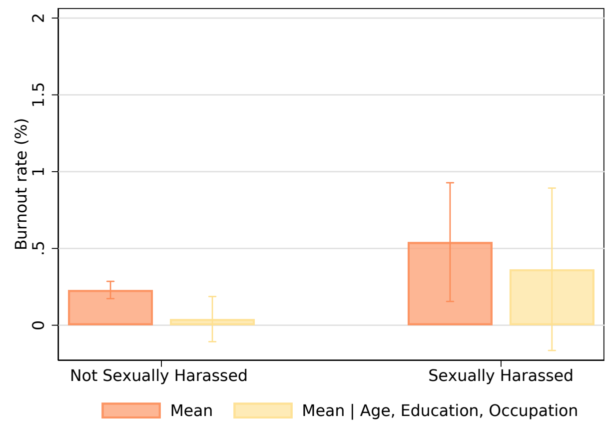

*Notes:* The figure shows the results of the firm-mover event-study described in Section 2. Firms are grouped into quartiles based on the the firm fixed-effects of a linear probability model of burnout with individual and firm-fixed effects, controlling for worker's gender, education, and birth cohort. The sample is composed of switchers with at least two years of tenure in their preceding and new jobs.

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

(a) Women: Sexual Harassment in Workplace



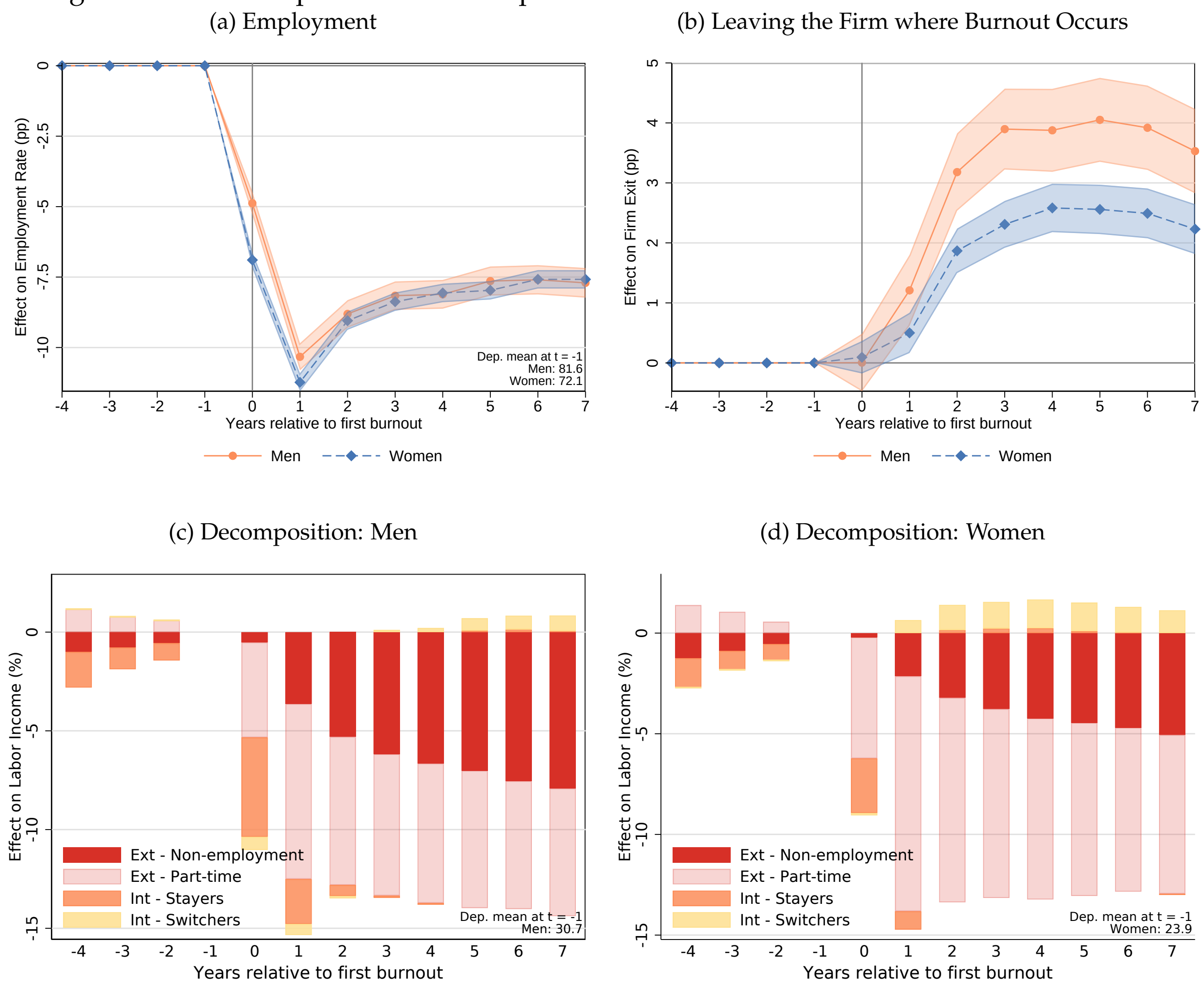

(b) Men: Sexual Harassment in Workplace




(c) Occupations: Prevalence of Sexual Harassment

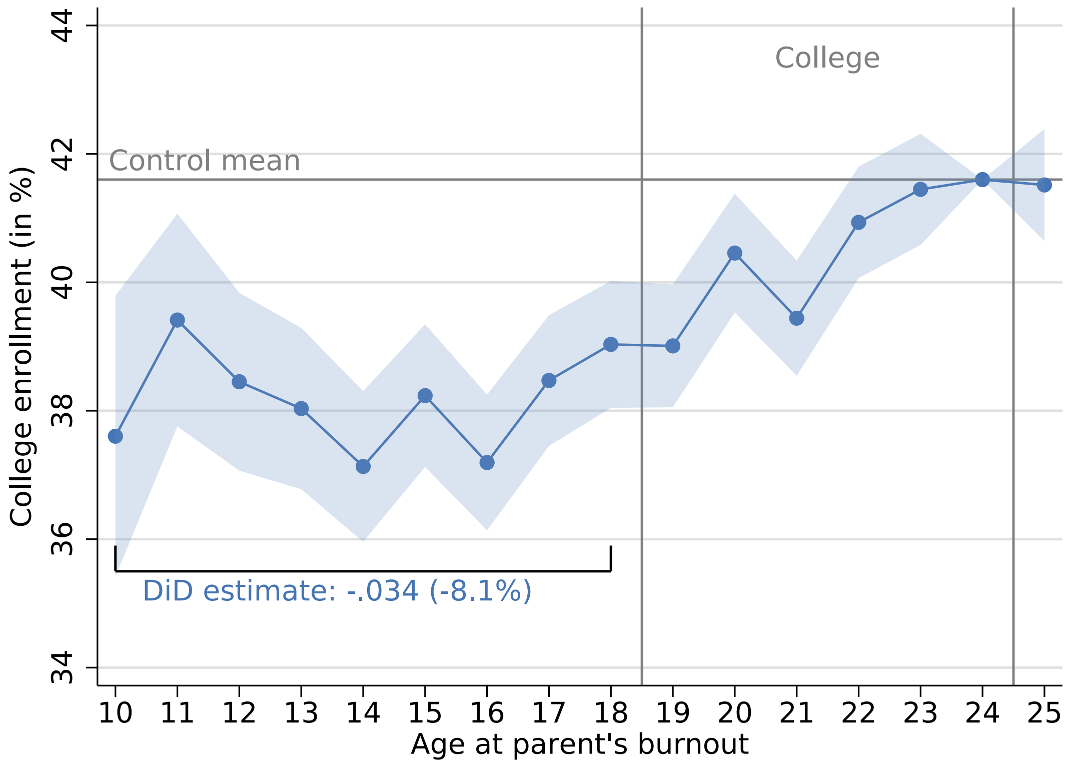

*Notes:* This figure reports the share of workers with burnout by exposure to sexual harassment. **Panel (a)** measures the burnout rate among women depending on whether they report having experienced sexual harassment at work in the last 12 months, either by supervisors or colleagues. The share of women 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



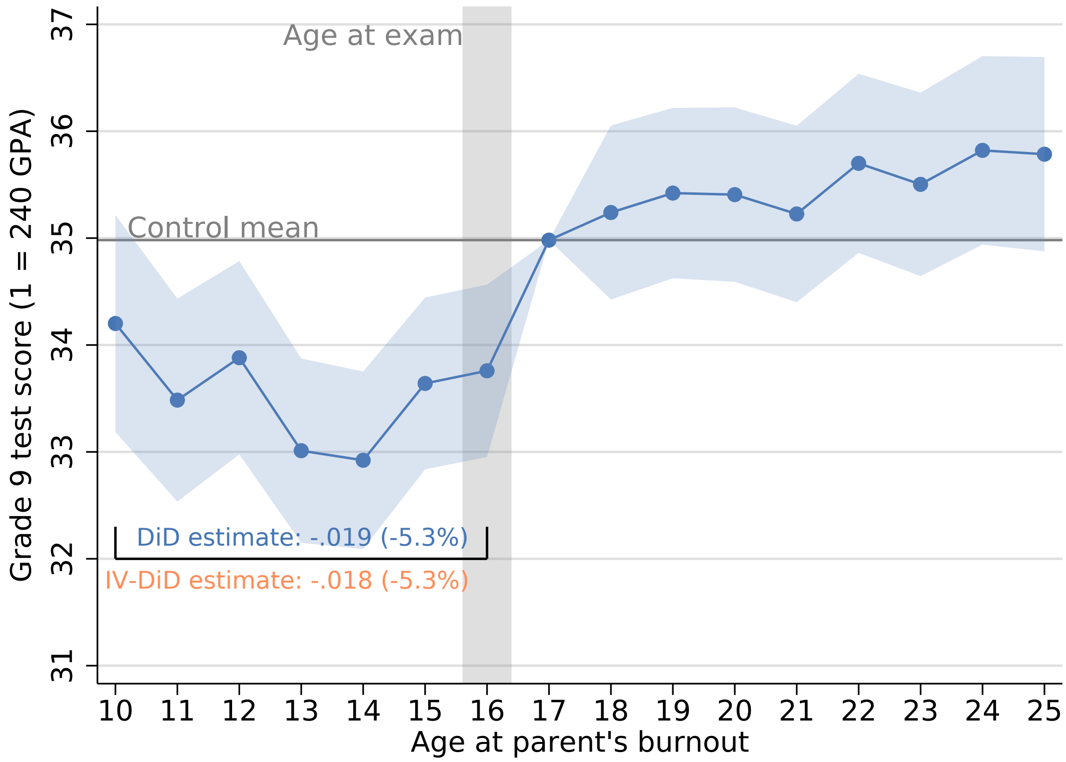

*Notes:* This figure shows margins of labor market adjustment to burnout and their contribution to earnings dynamics separate by gender. The decomposition follows equations (4) and (3). Treated individuals and controls are matched based on year-of-birth, gender, education and the earnings percentile 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



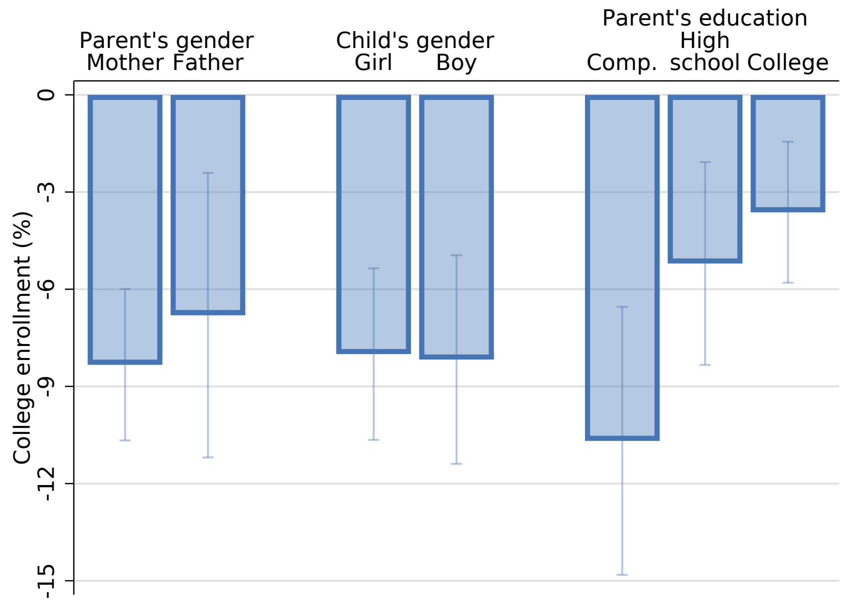

*Notes:* The figure plots the effect of parental burnout on children's college enrollment measured at some age 19 to 24. To identify deviations in the treated group from potential cohort-specific trends in college enrollment, we demean the outcome with the mean outcome of a control group with the same 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: Effect of Parental Burnout on School Grades




*Notes:* The figure plots the effect of parental burnout on performance in national-level tests at the end of 9th grade (age 16). More precisely, the outcome variable is an indicator for receiving a GPA of 240 or higher, corresponding to an average grade of C across all subjects. 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 grades of children by their age at the time of first parental burnout relative to those whose parents burn out at age 17 after the test is completed, i.e., difference-in-differences, scaled by adding the mean 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 10-16. "IV-DiD estimate" reports an effect for ages 10-16 estimated by instrumenting parental burnout by the burnout rate in their industry. More precisely, we instrument the indicators for parental burnout in equation (5) by the average burnout rate across all firms in their industry except the one where they work. The regression conditions on an industry fixed effect and exploits variation in workplace stress within industries over time. The first-stage F-statistic is 3289. The sample consists of 323,701 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.

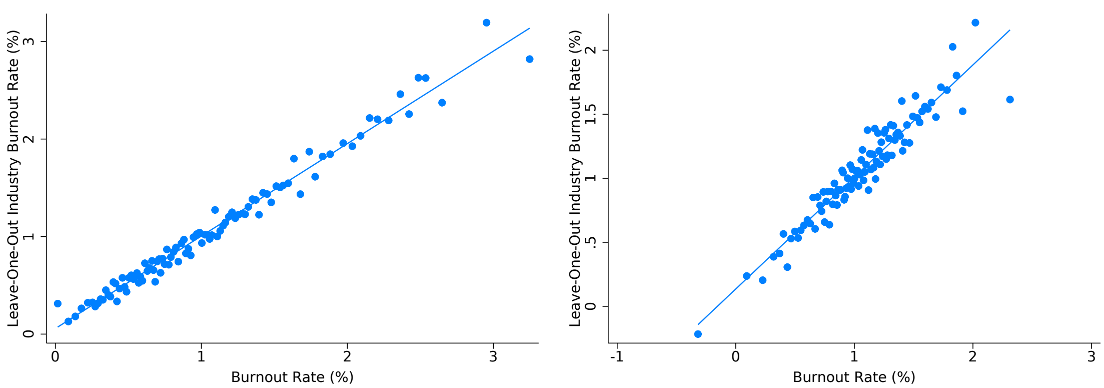
Figure A.17: Heterogeneity of Effects of Parental Burnout on Child's College Enrollment




*Notes:* The figure plots the effect of parental burnout on child's college enrollment at ages 19, 20, or 21 by demographic background. 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. 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). The coefficient estimates are scaled by dividing by the average college enrollment rate in a control group. In the regression, we include controls for the parent's birth cohort and the child's birth cohort, gender, and sibling order. Parent's education is the education of the parent that burns out. The whiskers are 95 percent confidence intervals where Standard errors are clustered at the parent level.

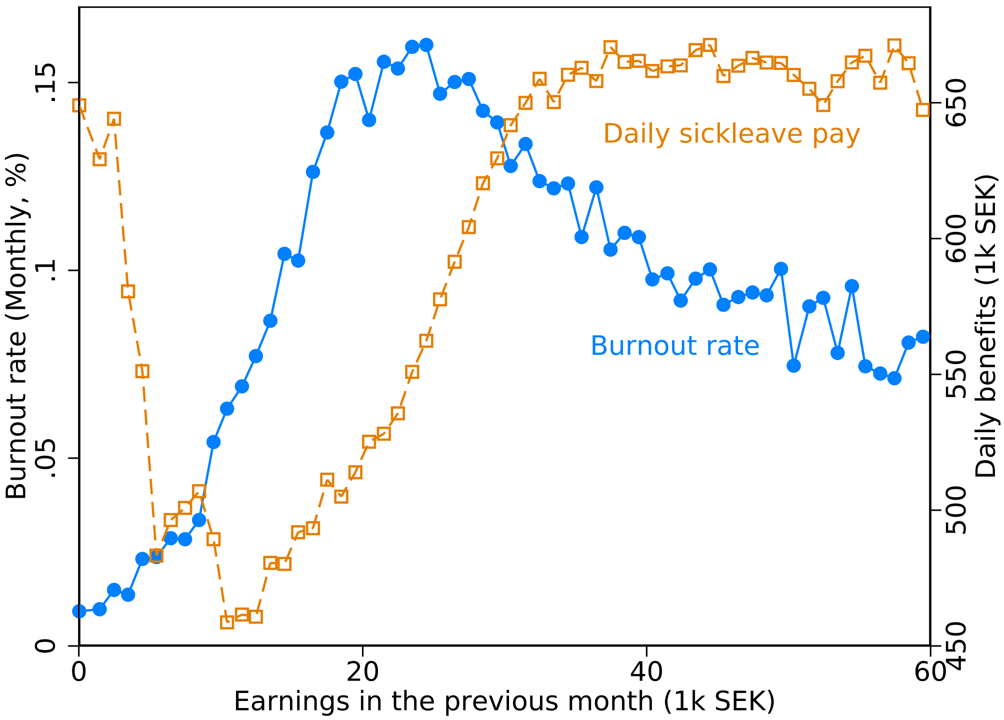
Figure A.18: Leave-One-Out Industry Burnout Rate and Own Burnout Rate

(a) Across industries (b) Within industries



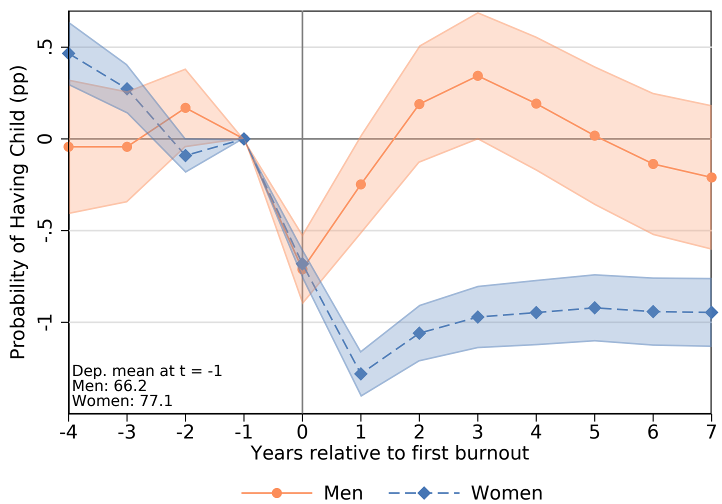

*Notes:* The figure plots the relationship between worker's likelihood of burnout and the average burnout rate across all firms in their industry except the one where they work. **Panel (a)** reports the raw correlation, i.e. incorporating both variation in burnout rates across industries and within industries. **Panel (b)** reports the correlation conditioning on industry fixed effect, i.e. restricting to variation within industries.

Figure A.19: Earnings and sick leave payments



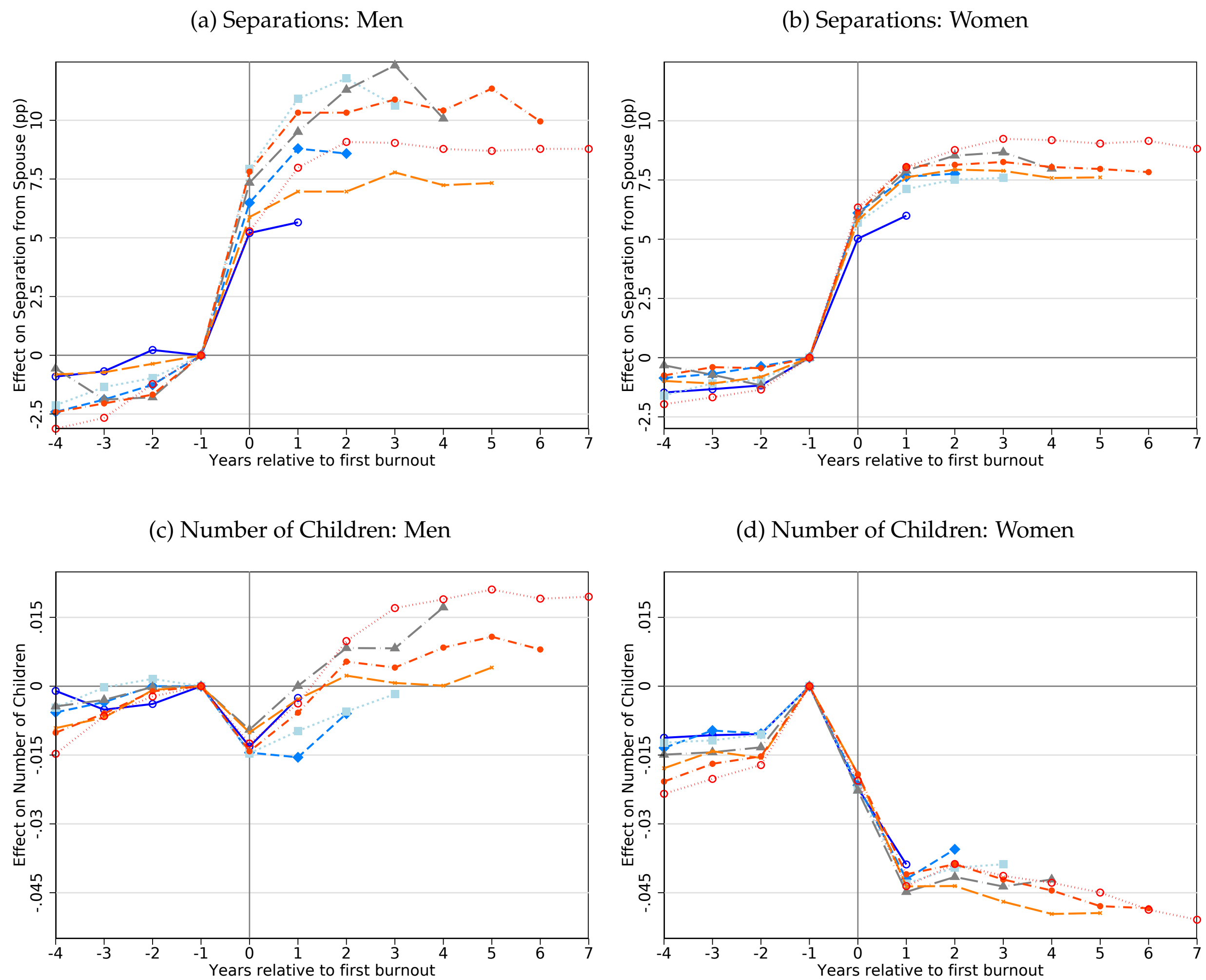

*Notes:* The figure shows the probability taking up burnout-related sick leave in $t$ against earnings (in 1k SEK) in $t-1$ in 2019. Monthly earnings data for the entire population only become available in Sweden in 2019. The figure also shows average daily benefits for any type of sick leave conditional on monthly earnings prior to the spell.

Figure A.20: Burnout Effect on the Probability of Ever Having a Child



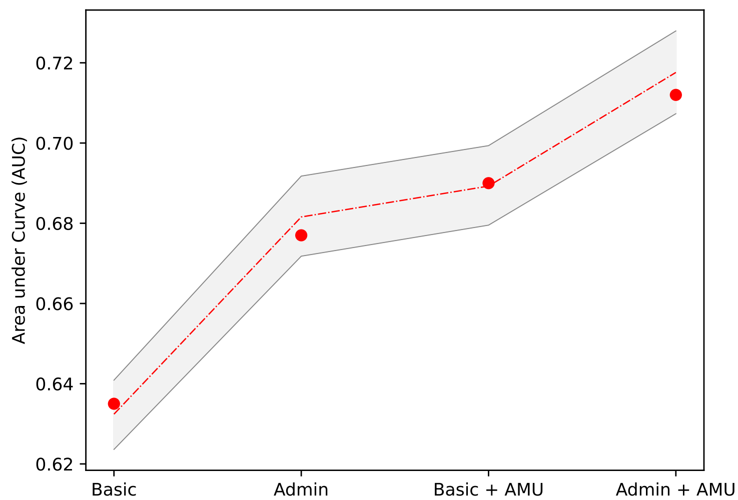

*Notes:* The figure plots the effect of burnout on the probability of ever having a child based on matched difference-in-differences, as described by equation (2). It plots the coefficients on event-time fixed effect interacted with an indicator for burnout and their individual-level-clustered standard error from the dynamic matched difference-in-difference model in equation (2). 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.21: The Effect of Burnout on Separation from Spouse and Fertility




*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 $\delta$ periods ahead of the control group. The figure separately plots estimates for $\delta$ 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.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: Compensating Differentials — Common Sample

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| *Panel (a): Wages (Log)* | | | | | | |
| Firm Burnout Rate | -0.78 | -0.63 | -0.15 | -0.15 | | -0.24 |
| | (0.18) | (0.16) | (0.12) | (0.12) | | (0.11) |
| Firm PageRank | | | | | 0.14 | 0.15 |
| | | | | | (0.06) | (0.06) |
| R2 | 0.931 | 0.934 | 0.935 | 0.935 | 0.935 | 0.935 |
| *Panel (b): Value Added Per Employee (Log)* | | | | | | |
| Firm Burnout Rate | -6.80 | -6.08 | -2.01 | -2.01 | | -3.19 |
| | (1.57) | (1.41) | (1.00) | (1.00) | | (1.03) |
| Firm PageRank | | | | | 1.92 | 2.04 |
| | | | | | (0.50) | (0.52) |
| R2 | 0.805 | 0.809 | 0.843 | 0.843 | 0.844 | 0.844 |
| Number of Worker-Years (Mil) | 6.5 | 6.5 | 6.5 | 6.5 | 6.5 | 6.5 |
| Number of Plants | 8,606 | 8,606 | 8,606 | 8,606 | 8,606 | 8,606 |
| Number of Firms | 6,479 | 6,479 | 6,479 | 6,479 | 6,479 | 6,479 |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Individual FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Demographics | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Occupation FE | | ✓ | ✓ | ✓ | ✓ | ✓ |
| Industry FE | | | ✓ | ✓ | ✓ | ✓ |
| Public 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)**. For a precise description of the variables, see Section 2 and the notes accompanying Table 2. Relative to the results in Table 2, we restrict the sample to be the same across all specifications.

Table A.3: Compensating Differentials — Weighted by Firm Size

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| *Panel (a): Wages (Log)* | | | | | | |
| Firm Burnout Rate | -0.50 | -0.35 | -0.10 | -0.05 | | -0.06 |
| | (0.06) | (0.05) | (0.04) | (0.03) | | (0.03) |
| Firm PageRank | | | | | 0.38 | 0.38 |
| | | | | | (0.03) | (0.03) |
| R2 | 0.949 | 0.953 | 0.953 | 0.953 | 0.953 | 0.953 |
| 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 | -4.77 | -4.41 | -2.78 | -2.78 | | -3.43 |
| | (1.13) | (0.93) | (0.56) | (0.56) | | (0.56) |
| Firm PageRank | | | | | 2.69 | 2.89 |
| | | | | | (0.44) | (0.45) |
| R2 | 0.855 | 0.857 | 0.875 | 0.875 | 0.875 | 0.875 |
| 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 |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Individual FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Demographics | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Occupation FE | | ✓ | ✓ | ✓ | ✓ | ✓ |
| Industry FE | | | ✓ | ✓ | ✓ | ✓ |
| Public 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)**. For a precise description of the variables, see Section 2 and the notes accompanying Table 2. In contrast to Table 2, we weight the regressions by firm size.

Table A.4: Sample Selection and Matching Results

| | Men | Women | Total |
|---|---|---|---|
| **a) Sample selection** | | | |
| First cases 2002 - 2020 | 161,741 | 441,105 | 602,846 |
| First cases 2006 - 2013 | 53,285 | 148,429 | 201,714 |
| Ages 29 - 53 | 40,422 | 112,796 | 153,218 |
| Alive 7 years after treatment | 39,823 | 112,046 | 151,869 |
| Education information complete | 39,768 | 111,984 | 151,752 |
| **b) Matching** | | | |
| Never-treated | 39,522 | 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 3.

Table A.5: 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 4). 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.