Multitasking, education, and unemployment as determinants of work-related mental health

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Abstract

This dissertation analyzes the role multitasking, education, and unemployment play for work-related mental health problems using representative cross sectional data on the German working population from 2006 and 2012.

The first analysis of multitasking as a determinant is exploratory and hence, descriptive. Multitasking – the number of different tasks at work – is associated with mild to severe work-related mental health problems (emotional strain, emotional exhaustion, burnout). Absenteeism and presenteeism due to work-related mental health problems also increase with multitasking which represents a loss in gross value added. A back of the envelope calculation suggests that the increase in multitasking from 2006 and 2012 corresponds to an increase in this loss of roughly € 1.1 billion.

The causal effect of multitasking is analyzed using the introduction of new production and information technology as an instrument. Technological change favors the development of task complementarities which in turn make multitasking more profitable: efficiency gains in performing one task can be carried over to other tasks. Production technology adoption is related more strongly to rising manual multitasking and information technology adoption to cognitive multitasking. There is evidence for a causal effect of multitasking on emotional strain, emotional exhaustion, and burnout.

Regarding the relationship between work-related mental health and education, low compared to medium education is associated with less emotional strain. Job demands and resources are lower but there is no difference in perceived stress from missing resources. Higher education is associated with more emotional strain and emotional exhaustion. Demands and resources are higher and job demands are perceived as more stressful. Compensation for this could arise from higher wages and less atypical work times.

To analyze the role aggregate unemployment trends play for work-related mental health, occupation-federal state specific unemployment data are matched to the 2012 survey. Rising unemployment is associated with higher work-related mental health problems among employed individuals. Occupation specific unemployment drives this relationship, while the spatial dimension (region) is less important. The relationship hinges on individual past unemployment experience as rising unemployment is not associated with mental health problems for individuals without any own unemployment experience. The duration of past unemployment does not seem to play a role.

Keywords: work-related mental health, multitasking, non-monetary returns to education

Zusammenfassung

Diese Disseration beschäftigt sich mit Multitasking, Bildung und Arbeitslosigkeit als mögliche Determinanten arbeitsbezogener psychischer Probleme. Die Analysen basieren auf repräsentativen Querschnittsdaten der deutschen Erwerbsbevölkerung aus den Jahren 2006 und 2012.

Die erste Multitasking-Analyse ist explorativer Natur und daher deskriptiv. Multitasking – die Anzahl an verschiedenen Arbeitsaufgaben ("tasks") – geht mit einer höheren Prävelenz milder bis schwerer psychischer Probleme (emotionale Belastung, emotionale Erschöpfung, Burnout) einher. Durch diese Probleme bedingter Absentismus und Präsentismus steigen ebenfalls. Für einen Anstieg des Multitaskings, wie er von 2006 bis 2012 in etwa stattfand, beläuft sich der durch Absentismus und Präsentismus zusätzlich verursachte Bruttowertschöpfungsverlust auf ca. 1,1 Milliarden Euro.

Der kausale Effekt von Multitasking auf arbeitsbezogene psychische Probleme wird mit der Einführung von neuen Produktions- und Informationstechnologien als Instrument untersucht. Technologischer Wandel begünstigt die Enstehung von Komplementaritäten, die wiederum die Effizienz von Multitasking erhöhen: Effizienzgewinne in der Ausführung einer Arbeitsaufgabe lassen sich auf andere übertragen. Die Einführung neuer Produktionstechnologie ist eher mit einem Anstieg manueller Aufgaben verbunden, die Einführung neuer Informationstechnologie vor allem mit kognitiven Aufgaben. Es findet sich ein kausaler Effekt von Multitasking auf emotionale Belastung, emotionale Erschöpfung und Burnout.

Was den Zusammenhang zwischen Bildungsgrad und arbeitsbezogenen psychischen Problemen betrifft, so fällt emotionale Belastung bei geringer Gebildeten niedriger aus als bei Erwerbstätigen mit mittlerem Bildungsniveau. Geringer Gebildete haben weniger Arbeitsanforderungen und -ressourcen, fühlen sich durch fehlende Ressourcen aber nicht gestresster. Bei Höhergebildeten treten sowohl emotionale Belastung als auch Erschöpfung häufiger auf. Sie sehen sich höheren Anforderungen und Ressourcen gegenüber und fühlen sich durch hohe Anforderungen eher gestresst. Dies könnte durch höhere Gehälter und weniger untypische Arbeitszeiten kompensiert werden.

Um den Zusammenhang von aggregierten Trends in der Arbeitslosigkeit auf arbeitsbezogene psychische Probleme zu analysieren, werden der 2012er-Befragung berufs- und bundeslandspezifische Arbeitslosendaten zugespielt. Dabei zeigt sich, dass berufsspezifische Arbeitslosigkeit mit arbeitsbezogenen psychischen Problemen von Erwerbstätigen einhergeht. Berufsspezifische, nicht regionale Arbeitslosigkeit ist dafür verantwortlich. Der Zusammenhang lässt sich nur für Erwerbstätige beobachten, die in der Vergangenheit arbeitslos waren. Die Dauer scheint jedoch keine Rolle zu spielen.

Schlagworte: arbeitsbezogene psychische Probleme, Multitasking, nicht monetäre Bildungserträge

Contents

CHAPTER 1

Introduction

1 Introduction

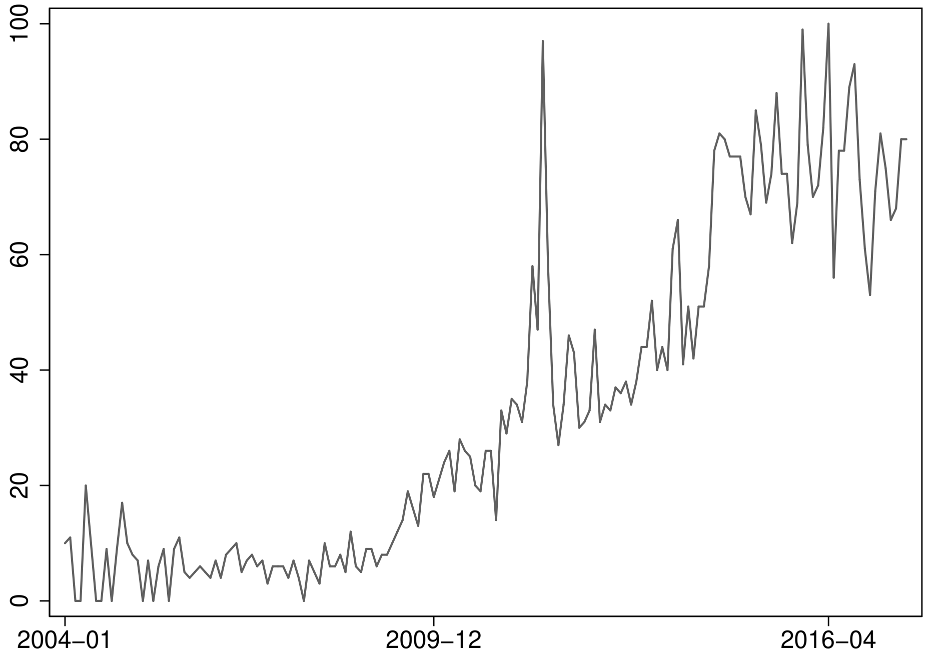
Well-being at work is crucial for a productive, effective, and competitive work force. Yet, the mental health of 27.9% or 55.6 million workers in the EU labor force is at risk due to time pressure, harassment or violence at work (Venema et al., 2009). Understanding the sources and determinants of mental health problems becomes increasingly important as they entail consequences for all economic actors. Individuals experience reduced quality of life, loss of social esteem, job loss or even work incapacity. Firms are affected by reduced efficiency of mentally unhealthy employees, loss of qualified personnel, and loss of reputation. The state faces increased health care, work incapacity, and early retirement expenditures.

In Germany, the number of sickness leaves due to mental health problems and their length rose by around 50% since 2005. Compared to physical diseases, sickness leaves are often longer for mental diseases (Badura et al., 2012). Mental health issues cause 41% of early retirement. On average, affected people are only 48 years old and leave the labor market 19 years before the legal retirement age of 67 (Lohmann-Haislah, 2012). This is especially problematic in the current labor market situation where demographic change decreases the size of the working population and increases the number of pensioners. The balance between both groups is fundamental for the functioning of the pension system. Demographic change and in particular the imminent retirement of the baby boomer generation impact the skill and experience profiles available in the labor market. If mental health problems continue to be a driver for early retirement, demographic change and scarcity of skilled labor could have even larger impacts.

Work-related mental health problems are thus a concern to the whole society. This is also expressed in a rising public interest in the topic. While public interest is hard to measure, the Internet collects unmeasurable amounts of data and conveniently provides access to this information. The Internet is also the most important means of searching for information today. A variety of search engines are available but Google continues to be among the most used engines. Figure 1.1 shows the trend history for the web search of *Burnout Symptome* (burnout symptoms in German).[1] Search interest was quite low for the first five years. Interest began to increase slowly at the end of 2009 and reached a first peak of 97 in September 2011. For more than two years, searches decreased to indexes of 30 to 50 before passing 80 in mid-2014, and reaching 100 in April 2016. Since that, interest mostly remained between 60 and 90.

[1] Google trends offers a web page to review search trends by geographic area, time, category (e.g. cars and vehicles, education, books and literature) and search site (web, images, news, shopping, youtube). Figure 1.1 is based on data web searches for Germany, all available data on a monthly basis and all categories. Trend history data are available since 2004. The trends are built on a random draw of all Google search requests since January 2004 until June 2017. They include only popular search items and eliminate repeated search requests from the same person within a short time frame. Trends are indexes for the search volume in a certain month. The month with the highest search volume is assigned the index 100 (April 2016), the other months' volumes are set in relation to that. The data are accessible at https://trends.google.com/trends/explore?date=all&geo=DE&q=Burnout%20Symptome, last accessed on July 04, 2017.

Figure 1.1: Monthly Google searches for burnout symptoms from January, 2004 to June, 2017



Index numbers, highest search interest = 100. Data source: Google trends for "Burnout Symptome" in Germany.

Despite the rising public interest, measurement, definition, and understanding of work-related mental health problems are still challenging. This requires more research on the causes of work-related mental health problems. Most of this research is done in (work) psychology, organization, and medicine, and is often limited to very specific and small study populations. Several job, some individual, and few organizational factors have been identified as relevant for the development of work-related mental health problems. Less attention has been paid to the role of job design, technological change, education, and aggregate unemployment – common topics in economics. Looking at work-related mental health problems from an economist's perspective adds to a better understanding of exactly where, when, and for whom these problems develop. It does not necessarily answer why and through precisely which mechanism they arise but gives suggestions as to where, when, and to whom prevention could be targeted.

This dissertation analyzes multitasking, education, and unemployment as potential determinants for work-related mental health problems. The empirical foundation is representative cross-sectional data on the German working population from 2006 and 2012. The theoretical framework is the Job Demands and Resources model (Demerouti et al., 2001, Peterson et al., 2008). In this model, work-related mental health problems arise from an imbalance between factors that stress the employee (job demands) and that can buffer against stress (job resources). Work-related mental health problems are defined as mental health problems which arise only in the context of work. They are ranked according to their severity into (ascending order): emotional strain, emotional exhaustion, and burnout. Additional outcomes – except for chapter four – are staying away from work due to work-related mental health problems (absenteeism) or coming to work despite being sick with work-related mental health problems (presenteeism).

Chapter two investigates whether multitasking is related to work-related mental health problems. Multitasking, understood as the number of different tasks an employee performs at work, is replacing specialization as the main job design due to task complementarities arising from technological change and higher levels of education (Lindbeck and Snower, 2000, Boucekkine and Crifo, 2008). Little is known about the impacts on employee well-being at work. On the one hand, Hackman and Oldham (1976) and Herzberg (1966 and 1976) link variety to higher intrinsic motivation and lower absenteeism. On the other hand, stress is higher when simultaneously carrying out different tasks (Freude and Weißbecker-Klaus, 2012). The prevalence of work-related mental health problems indeed increases with multitasking. For one additional task, emotional strain increases by 0.04 standard deviations. Burnout and emotional exhaustion increase by 0.02 standard deviations. Absenteeism and presenteeism due to work-related mental health problems rise by about one percentage point. The findings are driven by tasks that require interaction with other human beings. Simultaneously performing different tasks (common language multitasking) does not play a significant role. The estimates appear small at first sight but multitasking increased by nearly one task from 2006 to 2012. Estimating the increase in the loss in gross value added due to the rise in absenteeism and presenteeism yields roughly € 1.1 billion. Chapter two remains descriptive in that it controls for other relevant factors (job demands, job resources, individual and job characteristics) but does not solve the potential endogeneity of multitasking due to e.g. selection.

This is done in chapter three which analyzes the causal effect of multitasking on work-related mental health problems using the introduction of new production and information technology as an instrument. The instrument is motivated by the fact that technological change favors the development of task complementarities (Lindbeck and Snower, 2000, Boucekkine and Crifo, 2008). Task complementarities mean that efficiency gains in performing one task can be carried over to other tasks. To exploit these, job design changes from jobs with few different or a single task (specialization) to jobs with many different tasks (multitasking). The empirical analysis shows that production technology adoption has larger associations with manual multitasking and informational technology adoption with cognitive multitasking. Instrumental variable estimation suggests a causal effect of multitasking on emotional strain, emotional exhaustion, and burnout. The loss in gross value added from absenteeism and presenteeism due to the increase in multitasking from 2006 to 2012 corresponds to around € 2.6 billion.

Chapter four analyzes the relationship between work-related mental health and education on a descriptive level. The existing literature documents better physical health for higher educated people due to better health literacy (Lleras-Muney, 2005, Culter and Lleras-Muney, 2010, Kemptner et al., 2011). A similar relationship for mental health has not been found (Kamhöfer et al., 2015, Dahmann and Schnitzlein, 2017). The case might be different for explicitly work-related mental health problems where education is the entry ticket into certain jobs with a different working environment. Indeed, the prevalence of work-related mental health problems increases with education. Higher compared to medium education is associated with more emotional strain and emotional exhaustion, while low education is associated with less emotional strain. Work environment and stress perceptions could play a role in this, too. Low educated employees are exposed to fewer demands but also have fewer resources. At the same time, they do not perceive a lack of resources as more stressful than medium educated. This is different for higher educated employees. They have significantly higher demands and resources but also perceive high job demands as more stressful. Potential compensation occurs in monetary (wage) and non-monetary terms (less atypical work times) but does not comprise job satisfaction or job security.

In chapter five, occupation- and region-specific unemployment data is matched to the 2012 survey to analyze the relationship between aggregate unemployment trends and work-related mental health among employed individuals. In focusing on clearly work-related mental health, the analysis contributes to the literature on the effects of unemployment itself (Clark and Oswald, 1994, Weich and Lewis, 1998, Murphy and Athanasou, 1999, Paul and Moser, 2009, Schmitz, 2011, Marcus, 2013), job insecurity (Green, 2011, Reichert and Tauchmann, 2011, Jiang and Probst, 2017), and aggregate unemployment on individual well-being (Di Tella et al., 2003). Clark et al. (2010) identify worse outside options as one channel through which aggregate unemployment affects employees. If an employee is exposed to adverse working conditions, leaving current employment could protect mental health. Rising unemployment worsens outside options. The probability of finding new employment is smaller in an environment of rising unemployment. This might deter the employee in her current job where continued exposure to adverse working conditions decreases work-related mental health. Rising unemployment is significantly associated with a higher risk for work-related mental health problems among employed individuals. Occupation specific unemployment drives this relationship, while the spatial dimension of unemployment (region) is less important. The relationship hinges on individual past unemployment experience as rising unemployment is not associated with mental health problems for individuals without any own unemployment experience. The duration of past unemployment does not play a role.

To conclude, job design, technological change, education, and aggregate unemployment play a role for mental well-being at work. The results suggest to target prevention and intervention, first, at employees performing many different tasks at work, especially if these tasks require interaction with other human beings, second, at employees exposed to technological change that alters job design from specialization to multitasking, third, at higher educated employees who have different working environments with more job demands and an increased stress perception, and fourth, at employees facing worse outside options through rising occupation specific unemployment and having had prior unemployment experience.

Chapter 2

The task composition and work-related mental health – a descriptive study

2 The task composition and work-related mental health – a descriptive study

2.1 Introduction

Technology changes the way work is done (e.g. Spitz-Oener, 2008, Autor and Dorn, 2009). By substituting some parts of the work process and complementing others technological change affects job design. According to the task literature, a certain task is substituted when it is sufficiently well understood to be written in computer language (Autor et al., 2003). Tasks which are too complex or too unforeseeable cannot (yet) be programed and are complemented by technology. Jobs consist of a bundle of tasks, usually both substitutable and non-substitutable tasks. The substitution process demands a re-bundling of tasks to new jobs (Autor et al., 2002). New jobs can focus on few tasks (specialization) or demand a high number of different tasks (multitasking). In the organization of the firm literature, a firm decides between specialization and multitasking depending on whether there are gains from specialization or gains from task complementarities. While specialization was the job design of the twentieth century, multitasking becomes increasingly important (Oldham and Hackman, 2010). This organizational change reflects a move from exploiting gains from specialization to exploiting gains from task complementarities. Task complementarities arise from advances in production and information technology as well as from rising levels of education (Lindbeck and Snower, 2000, Boucekkine and Crifo, 2008). In Germany, empirical evidence shows that there is more multitasking today than in the past (Spitz-Oener, 2006, Antonczyk et al., 2009, Pikos and Thomsen, 2016).

Evidence on what this increase in multitasking does to human beings is still sparse. According to Herzberg (1966 and 1976), enriched jobs that demand skill variety lead to higher intrinsic motivation. The common language "multitasking" (carrying out tasks simultaneously) is much better analyzed. Simultaneity is associated with higher levels of stress (e.g. Freude and Weißbecker-Klaus, 2012). Similarly, multitasking could result in stress, especially in a rapidly changing environment that demands continuous updating of skills. In the framework of the Job Demands and Resources model, burnout arises from an imbalance between job demands and job resources (Demerouti et al., 2001). Job demands are factors which stress the employee, while job resources are factors which can buffer the detrimental influence of job demands. High job demands do not lead to burnout if the individual has many job resources. Work-related mental health suffers when demands weigh heavier than resources. In this model, multitasking could act as a job demand.

To the best of my knowledge, there is no research on a possible link between organizational change and work-related mental health outcomes yet. This paper aims at filling this gap by using two cross sections on the German working population to analyze the relationship between work-related mental health and multitasking. Work-related mental health problems are (ranked by severity): emotional strain, emotional exhaustion, and burnout. I find that rising multitasking is associated with increased emotional strain, emotional exhaustion, and burnout. Absenteeism and presenteeism due to work-related mental health problems also increase at both the extensive and the intensive margin. This suggests that multitasking acts as a job demand. The relationship is driven by tasks that require interactions with other human beings and is strongest where work depends on the often missing cooperation of clients (nursing, protecting, training). Physical tasks such as “manufacturing” and “repairing” are associated with lower work-related mental health problems. Whether tasks are carried out simultaneously is not relevant. The association between work-related mental health and multitasking is significant but point estimates are small (0.02 standard deviations). Nevertheless, a back of the envelope calculation shows that for an increase in multitasking as it occurred from 2006 to 2012, an additional 108,000 individuals suffer from burnout and € 1.1 billion gross value added are lost.

The remainder of this paper is structured as follows: section 2.2 gives an overview over the relevant literature. Section 2.3 is dedicated to data, descriptive statistics, and methodology. Results are presented in section 2.4. Section 2.5 analyzes compensation for multitasking and section 2.6 discusses the main results. The last section concludes.

2.2 Related literature

2.2.1 Multitasking as a job design

One of the core decisions in job design is the job’s task composition, i.e. which tasks have to be performed by the job holder. There are two extremes, specialization and multitasking, which aim at maximizing productivity with different strategies. Specialization dates back to Adam Smith’s description of pin production and became known in the early twentieth century as Taylorism. Work processes are broken down into very small and simple units, e.g. for the pin production example: drawing out the wire, straightening it, cutting it. Each worker performs a limited amount of these small units, at the extreme only one. By repeating the same task over and over again, the worker becomes an expert in his task which he carries out in the most efficient manner (“intratask” learning). This is the gain from specialization. In multitasking, a worker performs more than one task. He does not acquire expert knowledge in all his tasks but he makes use of task complementarities: he carries over knowledge gained in performing one task to another task which he can then perform more efficiently. The gain from multitasking arises from these task complementarities (“intertask” learning). See Oldham and Hackman (2010) for a more detailed overview.

With the turn of the century, the literature put a greater emphasis on modeling the transition from specialization to multitasking which was observed in many industries. In their static framework, Lindbeck and Snower (2000) identify four driving forces for this transition. First, technological task complementarities arise from advances in production technology. Machines are more versatile and re-programmable which allows adaptation to changing production processes. Workers need to know not only how to operate a machine but also how to adapt it. Second, informational task complementarities arise from advances in information technologies which permit easier access to information. This shortens for example feedback cycles between employees and customers which favors faster adaption to customer needs. A higher exchange of information also increases employee contact with different tasks within a firm. Informational task complementarities enhance decentralization of decision making, team work, and job rotation which in turn imply a broader scope of tasks for the employee. Third, increases in human capital make workers more versatile. Levels of education are rising in all OECD countries. Lindbeck and Snower (2000) argue that this has led to improvements not only of particular skills ("capital deepening") but also of the ability to acquire a variety of different skills ("capital widening"). More versatile workers can perform more tasks, e.g operating and programming a machine or selling and redesigning products. Fourth, workers developed a preference for more versatile work. Specialized jobs are very narrow and often highly standardized. Variety and challenges are missing which might result in reduced engagement and job satisfaction. Herzberg (1966, 1976) analyzes the dangers of simplified jobs and suggests enriched jobs to increase intrinsic motivation. As workers have the ability to do multitasking, they also developed a taste for it.

Boucekkine and Crifo (2008) model the transition from specialization to multitasking in a dynamic framework and condense the four driving forces to two: technological change results in both technological and informational task complementarities, and rising human capital increases both the ability to multitask and the taste for multitasking. This transition is also framed as part of skill-biased organizational change (SBOC). Caroli and Van Reenen (2001) define organizational change as decentralization of authority, fewer management layers, and increased multitasking. With French and British establishment data, they show the link between SBOC and education in a declining demand for less skilled labor and in a larger impact of SBOC in higher skilled workplaces.

SBOC is closely linked to skill-biased technological change (SBTC). According to the SBTC literature, technological change does not affect heterogeneous population groups homogeneously. Highly educated workers often find their skills and tasks complemented by technological change, while low educated workers are increasingly substituted by technology. Recently, the focus has shifted from the level of education to tasks. The task literature argues that not sociodemographic characteristics but job content should be the dimension for analyzing the consequences of technological change for different groups.

This literature commonly classifies tasks into three to five categories according to their degree of routine work and cognitive ability requirements. The main argument is that it is easier to substitute both routine manual and routine cognitive tasks by technology. Non-routine manual and non-routine cognitive tasks, on the other hand, are complemented by technology. The understanding of the consequences of SBTC concentrates on labor market measures such as employment and wages (e.g. Autor et al., 2003, Spitz-Oener, 2006, Goos and Manning, 2007, Autor et al., 2008, Dustmann et al., 2009, Autor and Handel, 2013). Technological change brought routinization and digitization to the workplace. This in turn affected job design but the link between both literatures is rather weak. Spitz-Oener (2008) and Autor and Dorn (2013) document that work contents and work environment changed substantially due to technological change. Spitz-Oener (2006), Antonczyk et al. (2009) and Pikos and Thomsen (2016) show that work became more “complex”, i.e. that individuals perform more tasks. All three studies are based on cross-sectional surveys from the German working population (Qualification and Career surveys) but concentrate on the time before 2000 (except Pikos and Thomsen, 2016). The link between SBTC and SBOC is illustrated in the case study in Autor et al. (2002) where technological change automated programmable routine tasks. The remaining tasks were bundled into both specialized and enriched jobs depending on management goals to exploit gains from specialization or task interdependencies. For Gibbs et al. (2010), the decision for specialization or multitasking depends on whether ex ante optimization is feasible and close to perfect (specialization) or not (multitasking). This relates back to the task complementarities in Lindbeck and Snower (2000) which allows for feedback cycles between tasks.

2.2.2 Analyzing work-related health outcomes

In the scientific literature, burnout is the most extensively investigated work-related mental health problem. There are many studies, predominantly in work psychology, that analyze the determinants of burnout in small samples focusing on one specific occupation in one location. Since burnout was first documented in nurses and physicians, hospitals are a common unit of analysis. Only few studies consider larger populations, e.g. Zimmermann et al. (2012) study teachers in and around the German city of Freiburg. Research on teachers’ burnout dates back to the end of the 1980s (Schwab et al., 1986). Studies generally measure bad mental health with validated scales such as the Maslach Burnout Inventory (MBI, Maslach and Jackson, 1981 and 1984), or the General Health Questionniare (GHQ). Very few studies use secondary data across different occupations. Hasselhorn and Nübling (2004) for example consider the the whole German working population (Qualification and Career Survey 1999). They rank occupations according to their mental health risk and identify a common factor for bad mental health: professions in which the outcome of work depends on the cooperation of others who often lack cooperation, for example doctors/nurses and patients, teachers and students.

Burnout consists of three components: emotional exhaustion, cynicism, and personal inefficacy (e.g. (Maslach and Jackson, 1981 and 1984, Jackson and Schuler, 1982). Exhaustion arises when an employee cannot cope with demands and stress at her job anymore. Employees often perceive a high workload, lack of support, or time pressure as transitory in the beginning. In trying to keep up with their work, they become more and more exhausted. They react to the overwhelmingly impossible situation by adopting withdrawal behavior, both physically by staying away from work and mentally by showing a cynical attitude towards the organization, themselves, and/or their clients. Exhaustion and this self-protection behavior lower productivity, efficacy, and quality of work.[1] Being less and less able to live up to their personal standards and work goals can result in an even higher effort to keep up and more withdrawal behavior when failing to do so. Burnout is often a vicious cycle from which exit is hard (Schaufeli and Enzmann, 1998).

Theoretical frameworks for the determinants of burnout are built on an imbalance between demands/effort and resources/reward (Lohmann-Haislah, 2012). In the Job Demands and Resources model (JD-R), burnout arises from an imbalance between job demands and job resources (Demerouti et al., 2001, Peterson et al., 2008). Job demands and resources are found on different levels: situational (working conditions), organizational (hierarchy), and individual (personality). Situational and organizational job demands are for example workload, work pressure, conflicts at work, and interruptions, role ambiguity, role conflict, and obstacles at work (Hasselhorn and Nübling, 2004, Leiter and Maslach, 2009, Gusy et al., 2010, McHuge et al. 2011, Basińska and Wilczek-Rużyczka, 2013, Bakker and Costa, 2014, Llorens-Gumbau and Salanova-Soria, 2014, Lundqvist et al., 2014). Job resources are controlling and influencing own working process, autonomy, and freedom regarding work tasks (Jackson and Schuler, 1982, Basińska and Wilczek-Rużyczka, 2013, Lundqvist et al., 2014). Help and support from colleagues and supervisors also buffers against adverse mental health (Hombrados-Mendieta and Cosano-Rivas, 2013). Individual factors are for example gender, age, and personality (Langelaan et al., 2006, Bakker and Costa, 2014, Innanen et al., 2014) but also leisure activities (e.g. meeting friends) and work-life conflicts (Schaufeli et al., 2009, Nübling and Hasselhorn, 2010, Bakker and Costa, 2014, Lin et al., 2014).

The literature has long focused on ill-health such as burnout. A stream of positive psychology emerged when researchers began to look at desirable health outcomes. The positive counterpart of burnout is engagement (Schaufeli et al., 2002, Zhang et al., 2007, Maslach et al., 2001 and 2012). Engagement is a recent construct and not yet part of large scale surveys. These often include job satisfaction as a measure of well-being at work. While psychology and sociology use job and life satisfaction for a long time,

[1] Initially and especially among young professionals, professional efficacy can increase with exhaustion and cynicism (Singh et al., 2012).

it has a harder stand in economics due to its subjectivity. Clark and Oswald (1996) and Lévy-Garboua and Montmarquette (2004) show that subjective assessment is consistent over time and correlated with observable events and actions (e.g. poor mental health, length of life, coronary heart disease, labor turnover, absenteeism, counter- and non-productive work). Clark et al. (1998) use job satisfaction to analyze quit behavior, Winkelmann and Winkelmann (1998) measure losses in life satisfaction due to unemployment.

2.2.3 Multitasking and work-related mental health outcomes

The relationship between multitasking and work-related mental health is not a priori clear. In the Job Characteristics Model (JCM) of work motivation, Hackman and Oldham (1976) consider skill variety as one of five job dimensions that foster high intrinsic motivation, performance, satisfaction, and low absenteeism. They understand skill variety as the variety of different activities on the job, which corresponds to the denomination multitasking. Similarly, multitasking could be associated with lower work-related mental health problems and higher engagement.

On the other hand, the individual experiences pressure to do more tasks in less time in an environment where time and resources are scarce. The term “multitasking" means something different in common language and work psychology: simultaneously performing more than one task or constantly switching between two or more tasks. This “simultaneity” is an extreme example of multitasking. On a neurophysiological level, the human brain is not made for simultaneously processing activities that require attention (Freude and Weißbecker-Klaus, 2012). When two of these activities are performed simultaneously, the brain processes their information sequentially and both activities affect each other. It is not surprising that multitasking is detrimental to both efficiency and quality, especially when the same quality and efficiency exigencies exist for both activities (e.g. Hembrooke and Gay, 2003, Adler and Benbunan-Fich, 2012, Jeong and Hwang, 2012). Even though this is inefficient, people still perform tasks simultaneously because they perceive ignoring or postponing new incoming information as more stressful (Lehle et al., 2009). There is also evidence that an increase in work tasks (which corresponds to multitasking) is associated with bad health. Härenstam et al. (2003) identify eight clusters according to individual conditions in paid work and in the private sphere. [2] Members of one group experienced increases in work tasks, responsibilities and demands in the previous year. Their physical and psychological workload was high. This group showed high psychological distress (measured by the 12-item General Health Questionnaire), musculoskeletal symptoms, and a bad general health status. This suggests that multitasking could act as a job demand in the JD-R framework.

[2] The conditions comprise supporting and straining psychosocial factors, ergonomic-physical factors, occupational hygiene factors, employment conditions, balance work/private sphere, work location in time and place, and changed conditions.

The composition of the multitasking measure could matter for the direction and strenght of the relationship, e.g. manual vs. cognitive or routine vs. non-routine tasks. Multitasking in interactive tasks could be associated with worse work-related mental health. Hasselhorn and Nübling (2004) identify occupations in which the risk of poor mental health is higher. These are teaching and social professions where the employee has to cooperate with people whose cooperation is necessary for reaching the work target but who often do not cooperate (e.g. students, patients, children). Multitasking in routine tasks could generate variety in otherwise repetitive jobs. This might reduce work-related mental health problems.

2.3 Data and methods

2.3.1 Data

The data come from the 2006 and 2012 working population surveys operated by the Research Data Centre of the German Federal Institute for Vocational Training (*Bundesinstitut für Berufsbildung*, BIBB) and the Federal Institute for Occupational Safety and Health (*Bundesanstalt für Arbeitsschutz und Arbeitsmedizin*, BAuA). The first working population survey was conducted in 1979 by the Institute for Employment Research (*Institut für Arbeitsmarkt- und Berufsforschung*, IAB) to close gaps in the topics covered in official statistics. The focus is on qualification and working conditions. Cross-sectional surveys have since been conducted roughly every sixth year. A health section on frequent complaints during and after work was first included in 1999. In that year, however, the type of mental health problems was rather general (e.g. depression). The determinants of general mental health problems are even more complex than the determinants of work-related mental health problems including e.g. genetic predisposition, death of a relative, breakups and family conflicts. Since there is no information on any of these factors, the analysis is limited to clearly work-related mental health problems. The 2006 and 2012 surveys on the Working Population on Qualification and Working Conditions (QaC) sample the working population older than 15 years working at least ten hours a week. Individuals interrupting their activity for a maximum of three months (e.g. parental leave) are included, while people in voluntary work and initial training are excluded. 20,000 individuals were interviewed in each year in computer-assisted telephone interviews (Rohrbach-Schmidt, 2009, Rohrbach-Schmidt and Hall, 2013).

In the health section, participants are asked to say which health complaints they had during work or on working days in the last 12 months. This is followed by a list of around 20 complaints. One of them is burnout in 2006 and emotional exhaustion in 2012. The health section also contains information on whether individuals consulted a physician due to their health problems and on sickness behavior. Assuming that consultation is a signal for severity, both variables equal 0 if there is no exhaustion/burnout, 1 if there is exhaustion/burnout but no consultation took place, and 2 if consultation took place. Among the detailed questions on working conditions, individuals are asked how often they felt emotional strain in their job. Since wording and meaning are very similar to emotional exhaustion, this variable is considered as an outcome, too. Answer categories are "often", "sometimes", "rarely", and "never" (coded from 3 to 0). The three outcomes differ in terms of severity. Burnout is without doubt the most severe work-related mental health problem. Its component emotional exhaustion is mild but could be the beginning of a burnout. Emotional strain is not part of burnout conceptually but might be the pre-stage to emotional exhaustion. To get an overall work-related mental health measure, I construct a combined measure indicating the presence of burnout/exhaustion and/or emotional strain ranging from 0 to 5. All four variables are standardized.

When being sick, two reactions are possible: taking sick leave (absenteeism) or coming to work despite being sick and better having stayed home (presenteeism). Combining this information with the prevalence of exhaustion/burnout allows to assess absenteeism and presenteeism due to work-related mental health problems. Absenteeism and presenteeism are behaviors or reactions to mental health problems and thus occur later in the process. Arguably, presenteeism indicates lower severity because the individual is still able to be present at the workplace. Absenteeism would indicate a more severe problem but could also be a form of shirking.[3] Both variables are binaries.

The positive counterpart of work-related mental health problems is job satisfaction. There is information on general job satisfaction, satisfaction with income, career opportunities, working hours, working climate, supervisor, tasks, application of skills, further training, equipment, and physical working conditions. Satisfaction ranges from "very satisfied" (3) to "not satisfied" (0) and is standardized.

Detailed information on tasks carried out during work and their intensity is also available. "I will now give you a number of specific activities. Please tell me how often these activities occur in your work, whether they occur often, sometimes or never." Multitasking is measured as the number of the following tasks an individual often performs on her job.[4]

1. manufacturing, producing goods and commodities
2. measuring, testing, quality control
3. monitoring, control of machines, plans, technical processes

[3]On the one hand, work-related mental health problems are stigmatized which results in under-reporting. On the other hand, German employees need physician certificates for absenteeism and shirking is easier the harder it is to be detected as such. While it is easy to diagnose a broken leg, mental illnesses are more difficult to assess. Usually, the physician asks a set of questions which are then answered subjectively by the employee. In this sense, "objective" health data from insurance companies is not much more objective than self-reported survey data. Nevertheless, due to the stigma which was still considerably larger in 2006 and 2012, such over-reporting should be the exception rather than the rule. Many mental health problems are diagnosed as physical illnesses due to stigma or because they are discovered only when they affected physical health, too (e.g. neck pain or lumbago).

[4]There are two more tasks in the list, "working with computers" and "using the Internet or editing e-mails (2012 only)", which are excluded from the multitasking measure. Both tasks are likely performed jointly with another task (e.g. online marketing, customer service mails).

4. repairing, refurbishing
5. purchasing, producing, selling
6. transporting, storing, shipping
7. advertising, marketing, public relations
8. organizing, planning and preparing work processes (not own)
9. developing, researching, constructing
10. training, instructing, teaching, educating
11. gathering information, investigating, documenting
12. providing advice and information
13. entertaining, accommodating, preparing food
14. nursing, caring, healing
15. protecting, guarding, patrolling, directing traffic
16. cleaning, removing waste, recycling

Tasks are grouped to the five categories from the literature (Autor et al., 2003 for the U.S., Spitz-Oener 2006 and 2008 for Germany): non-routine manual, routine manual, routine cognitive, non-routine interactive and non-routine analytic. Each of the task categories consists of a number of "single tasks" (five non-routine manual, three routine manual, three routine cognitive, three non-routine interactive and two non-routine analytic). These are not single activities but rather a grouping of similar activities under one task according to the survey questionnaires (e.g. repairing and refurbishing as one task).

Table 2.1: Task categories

category	tasks
non-routine manual	repairing, refurbishing entertaining, accommodating, preparing food nursing, caring, healing protecting, guarding, patrolling, directing traffic cleaning, removing waste, recycling
routine manual	manufacturing, producing goods and commodities monitoring, control of machines, plans, technical processes transporting, storing, shipping
routine cognitive	measuring, testing, quality control purchasing, producing, selling gathering information, investigating, documenting
non-routine interactive	advertising, marketing, public relations training, instructing, teaching, educating providing advice and information
non-routine analytic	organizing, planning and preparing work processes (not own) developing, researching, constructing

Task categories according to Spitz-Oener (2006) and Pikos and Thomsen (2016). Data sources: BIBB/BAuA. Own table.

Covariates comprise job demands and resources, sociodemographic and job characteristics. A high workload is measured by the variables reaching the limits of one's capacity and feeling overstrained. Psychological demands are interruptions during work, deadline pressure, and when even small mistakes can entail huge financial losses. Repetition, minimum performance, having to work fast, and following very detailed predetermined steps can also exert pressure. Lacking resources are measured by missing or untimely information. Job resources comprise four variables for scope of decision making: plan/schedule own work, influence own workload, decide when to break, and perform tasks independently. Good collaboration measures interpersonal resources. There are four variables which, depending on individual factors, can act either as a job demand or as a job resource: being a supervisor (more responsibility versus more scope for decision making), getting familiar with tasks, improving methods, and being demanded unknown things (positive challenge or excessive demand). Sociodemographic characteristics are age, gender, having a partner, having children, and level of education. Job variables comprise company size and sector, experience, tenure, atypical work (temporary or limited contract), working overtime, and working at atypical hours (night, shift, standby duty) but also attitudes: successful work-life balance, feeling that own work is important, and working in one's dream job (motivation vs. overcommitment).[5]

[5] Age, hours, and tenure have variance inflation factors (VIF) larger than 10 which hints at multicollinearity. Excluding them from the econometric analysis does not substantially change the coefficient of interest (multitasking). Results reported include these variables.

The analysis is limited to German nationals aged 18 to 65 years who provided information on their tasks and occupation code (around 26,000 individuals). The data is weighted according to census data. Summary statistics are displayed in table A2.1 in the appendix.

Table 2.2: Covariates

job demands and resources	sociodemographics	job characteristics
job demands	gender	hours, squared hours
reach limits of own capacity	having a partner	tenure
interrupted during work	having children	atypical work (short or temporary)
deadline/performance pressure	education	night work
work fast	(base: medium)	shift work
minimum performance	age, age square	work on weekends
overstrained		standby duty
risk of financial loss		feel work is important
no timely information about future		successful work life balance
do not receive all necessary information		
details predetermined		
repetition		
job resources		
plan/schedule own work		
influence own workload		
decide when to break		
perform tasks independently		
good collaboration		
ambiguous factors		
supervisor for somebody		
get familiar with tasks		
improve methods		
demanded unknown things		

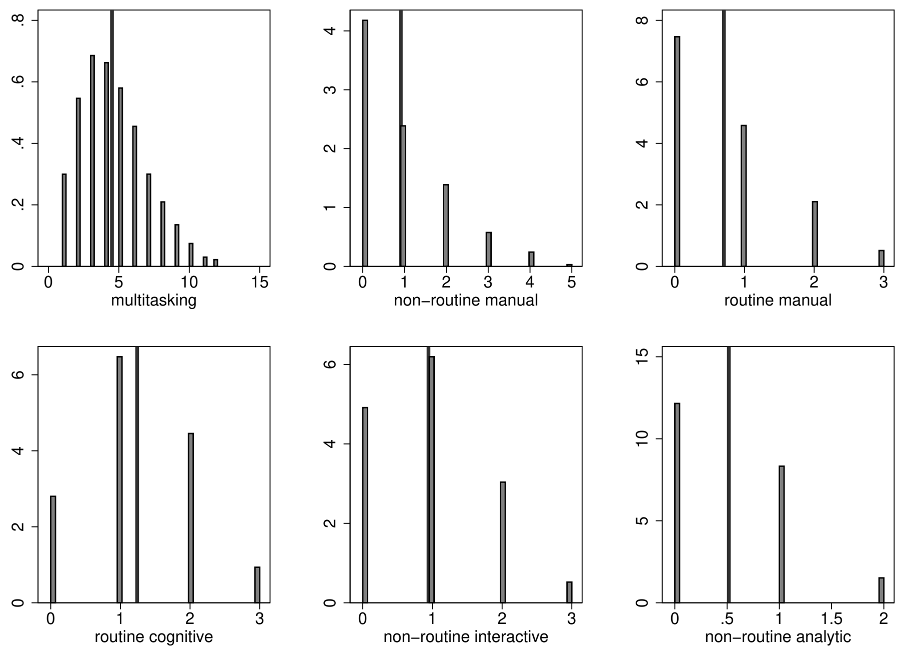
2.3.2 Descriptives

German employees perform 4.4 tasks on average.[6] Multitasking is censored at 12 tasks since numbers of observations in the highest categories are very low. The lowest quartile of the multitasking distribution frequently performs two different activities at work, the highest quartile six. Figure 2.1 depicts a histogram for general multitasking and multitasking within task categories. 45% of the employees perform neither non-routine manual nor routine manual tasks. Around 30% perform one manual task. 21% do not carry out any routine cognitive and 39% no non-routine interactive task. 44% perform one routine cognitive and 40% one routine interactive task. Non-routine analytic tasks are less frequent as 58% does

[6] 4.0 in 2006 and 4.8 in 2012. The difference is significant.

not do any of them. The average employee performs 0.9 non-routine manual, 0.8 routine manual, 1.2 routine cognitive, 0.9 non-routine interactive and 0.5 non-routine analytic tasks.

Figure 2.1: Histograms of multitasking measures



Vertical black lines: mean. Task categories according to table 2.1. Data sources: BIBB/BAuA. Own figure.

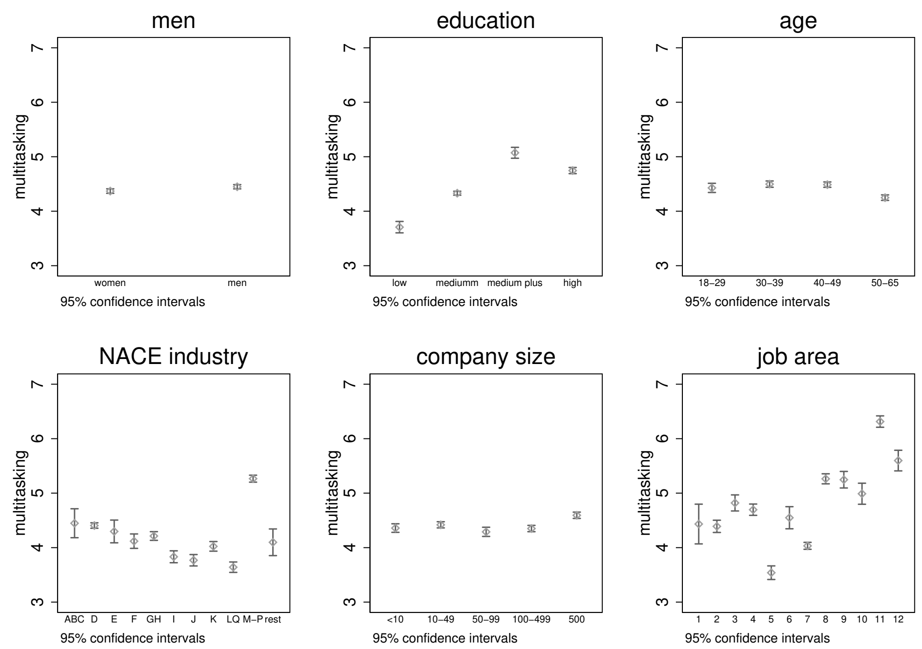
To get a better understanding of general multitasking, figure 2.2 illustrates differences for some sociodemographic and job characteristics. Men perform 4.3 tasks on average, women 4.1.[7] Low educated employees carry out 3.6 tasks on the job, people with medium plus education 4.7 tasks on average. Medium and high educated employees do 4.2 and 4.3 tasks.[8] People aged 50 to 65 perform 4 tasks on average, 18 to 29-year-olds 4.2, and 30 to 49-year olds 4.3. Multitasking is highest in public and private services (5) and lowest in finance and public administration (3.2). Company size matters to some extent for multitasking which is highest (4.3 tasks) in smaller companies with fewer than 50 and in huge companies with more than 500 employees. In companies with between 50 and 500 employees, 4.1 tasks are the average. The bottom right panel displays multitasking by job area in 2012 (not available in 2006). "Health and

[7] Since multitasking is a self-reported measure, overconfidence is a concern. Men could be more likely than women to state that they perform an activity "often". To address this concern, t-tests compare the mean multitasking for men and women in each two digit occupation. Men report significantly higher multitasking than women in 27 occupations. These differences could still reflect different jobs within two digit occupations. Limiting the analysis to men and women who have the most common level of education in their two digit occupation and who work more than 34 hours a week, 8 differences remain significant. In one case, medium educated "goods merchants", women perform more tasks than men.

[8] It makes sense that medium plus educated employees perform more tasks than higher educated employees. Medium plus educated individuals start their working career with an apprenticeship (medium education) and work some years. To climb up the hierarchical ladder, they go through additional training (master craftsmen, technician). Afterwards they continue to work in their job but are now in a higher position. In addition to their regular tasks they need to organize, coordinate, and interact with superiors, clients and subordinates. Higher educated employees in high positions focus more on these leadership tasks and carry out fewer other tasks.

social work" demand more than six different tasks. "Traffic, transport, security" and "office, services" need less than four different tasks.

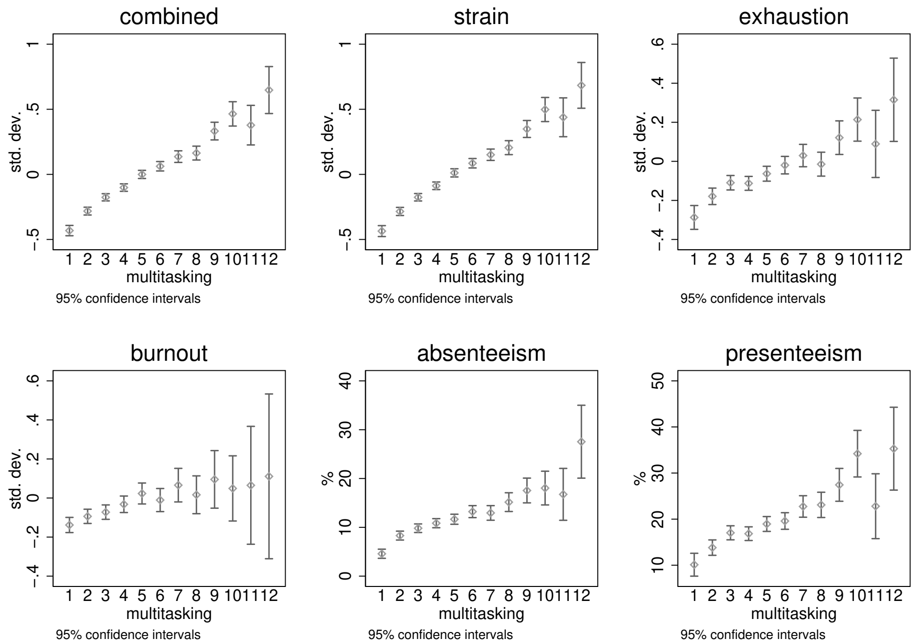
Figure 2.2: Multitasking by individual and company characteristics



NACE industries: A&B: Agriculture & fishery, C&D: Mining & manufacturing, E: Energy & water supply, F: Construction, G&H: Commerce and hotels, I: Transport, J: Finance, K: Real estate etc., L&Q: Public administration, M-P: Public & private services, rest not elsewhere allocated. Legend of job areas: 1. production of raw materials, 2. processing, repairing, 3.operating, maintaining machines, 4. commodity trade, sales, 5. traffic, transport, security, 6. gastronomy, cleaning, 7. office, services, 8. technical, natural sciences, 9. law, management, economics, 10. artists, media, social sciences, 11. health, social, 12. teachers. Data sources: BIBB/BAuA. Own calculations.

Work-related mental health problems increase with multitasking (figure 2.3). People performing less than five tasks have below mean work-related mental health problems. Absenteeism does not exceed 10%. 15% go to work despite being sick. Among people with ten or more different tasks, exhaustion is 0.2 and strain 0.5 standard deviations above the mean. Except for an outlier at 11 different tasks, absenteeism and presenteeism are at 20% and 30%. The increase is rather slow for burnout and overlapping confidence intervals do not suggest that high multitaskers experience more burnout than medium multitaskers. The increase is steepest for emotional strain which ranges from -0.5 to 0.8 standard deviations. Multitasking seems to be associated more strongly with the two mild mental health problems, strain and exhaustion.

Figure 2.3: Work-related mental health outcomes by multitasking



Multitasking measured as the number of tasks at work (1 to 12). Data sources: BIBB/BAuA. Own calculations.

2.3.3 Estimation procedure

The relationship between multitasking and work-related mental health outcomes is estimated with OLS according to equation 2.1.[9] Y_i is a standardized variable (combined measure, emotional strain, emotional exhaustion, and burnout) or a dummy variable (absenteeism and presenteeism) for individual i's health. $multitasking_i$ measures the number of activities with values between 1 and 12, $\mathbf{X}_i$ is a vector of control variables, α is a constant, and u_i the error term. For binary outcomes, equation 2.1 is a linear probability model. As a point of reference, Y_i is regressed on multitasking only. Then, variables capturing job demands, job resources, sociodemographic and job characteristics are added (table 2.2). A survey dummy accounts for macroeconomic differences (e.g. changed public perception of mental health problems). $\hat{\beta}$ gives the association between multitasking and work-related mental health but is not a causal effect. Multitasking can be endogenous for two reasons. First, individuals with bad work-related mental health could select systematically into multitasking (reversed causality). Second, there could be an underlying factor inducing individuals to choose multitasking and making their work-related mental health more vulnerable (selection). Individuals select into multitasking for example through job crafting by switching tasks with a colleague or taking over newly created tasks. To identify a causal effect of multitasking on work-related mental health requires an exogenous variation in multitasking. Such an increase could

[9] The results are similar for binary dependent variables with marginal effects after logit estimation – 0 if no exhaustion/burnout/no frequent strain, 1 if exhaustion/burnout/frequent strain.

in principle come from any of the four driving forces identified by Lindbeck and Snower (2000) but is not the focus of this paper which remains exploratory.

$$Y_i^* = \alpha + \beta multitasking_i + \mathbf{X}_i'\delta + u_i \tag{2.1}$$

2.4 Estimation results

2.4.1 Main results

Higher multitasking is significantly associated with worse work-related mental health. Table 2.3 displays the multitasking coefficients, their standard errors, the constant, number of observations, and adjusted R^2. The upper panel contains the estimates of the base model with multitasking as the only explanatory variable, the lower panel the estimates of the full model with all covariates according to table 2.2. Dependent variables are given in the column headers. Absenteeism and presenteeism are binary, all other outcomes standardized. Base model coefficients roughly decrease by half in the full model with all controls.[10] Multitasking explains between 0.5% and 4.3% of the variation in the outcome. Full models explain 7.5% (burnout) to 28.6% (combined).

An increase in multitasking by one, i.e. performing one additional task at work, is associated with an increase in any work-related mental health problem of 0.041 standard deviations in the full model. The coefficient is the same for strain. Multitasking is associated with an increase in exhaustion and burnout of 0.02 standard deviations. Absenteeism and presenteeism increase by 0.6 and 0.8 percentage points. 11% do not come to work with work-related mental health problems, while 16% go to work despite mental health problems. An additional task translates to increases in both probabilities of 5%. There is thus a significant positive relationship between work-related mental health problems and multitasking. In terms of magnitude, the effects are rather small, especially for more severe conditions.

[10]Model selection criteria such as the AIB and BIC favor the full model with all controls (not reported). Including hourly wage as another proxy for job type does not change the coefficients of interest.

Table 2.3: OLS estimates for work-related mental health outcomes

	combined	strain	exhaustion	burnout	absenteeism	presenteeism
base model						
multitasking	0.085***	0.089***	0.041***	0.033***	0.013***	0.018***
	(0.004)	(0.004)	(0.004)	(0.006)	(0.001)	(0.002)
constant	-0.421***	-0.425***	-0.268***	-0.142***	0.065***	0.100***
	(0.018)	(0.019)	(0.021)	(0.025)	(0.006)	(0.009)
full model						
multitasking	0.041***	0.041***	0.020***	0.021***	0.006***	0.008***
	(0.004)	(0.004)	(0.004)	(0.007)	(0.001)	(0.002)
constant	-0.720***	-0.582***	-0.748***	-0.513**	-0.080*	0.019
	(0.122)	(0.131)	(0.140)	(0.204)	(0.044)	(0.061)
N	20089	20120	13521	6576	20102	13548
R^2 adj. base	0.041	0.043	0.010	0.005	0.008	0.011
R^2 adj. full	0.286	0.252	0.153	0.075	0.120	0.147

Standardized dependent variable given in column header (absenteeism, presenteeism: binary). Combined: emotional exhaustion, burnout and/or emotional strain. Full model contains job demands and resources, sociodemographic and job covariates according to table 2.2. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

The relationship between multitasking and work-related mental health could be driven by certain task categories, e.g. routine versus non-routine or cognitive versus manual. Table 2.4 displays the results for multitasking within task categories in the full model. Of the 16 tasks, five are non-routine manual, three routine manual, three routine cognitive, three non-routine interactive, and two non-routine analytic (see table 2.1). Multitasking measures within task categories range from 0 to the maximum number of tasks within that category and are standardized for comparability.

Non-routine manual multitasking is significantly associated with all work-related mental health problems. An increase in one standard deviation of non-routine manual multitasking is associated with an increase in any work-related mental health problem of 0.102 standard deviations. Strain increases by 0.114 standard deviations and exhaustion by 0.026 standard deviations. The estimate for burnout is 0.039 and significant at the 5% level. Absenteeism increases by 1.1 percentage points and presenteeism by 1.6 percentage points. Routine manual multitasking is associated with lower emotional strain, emotional exhaustion, absenteeism, and presenteeism (the latter significant at the 5% level). The point estimate for burnout is insignificant. A one standard deviation increase in routine manual multitasking is associated with a decrease in any work-related mental health of 0.06 standard deviations. Routine cognitive multitasking is associated with risk increases for burnout (0.05 standard deviations), emotional strain (0.023 standard deviations), and absenteeism (0.6 percentage points, significant at the 5% level). The estimates for exhaustion and presenteeism are insignificant. Non-routine interactive multitasking is highly significant and positive for all outcomes. The point estimates are larger than for non-routine manual multitasking. A one standard deviation increase is associated with an increase in strain of 0.13 standard deviations, exhaustion of 0.06 standard deviations, and burnout of 0.05 standard deviations. The probabilities for absenteeism and presenteeism increase by 1.8 and 2.4 percentage points. Non-routine analytic multitasking is related to higher exhaustion (0.025 standard deviations) and strain (0.016 standard deviations) at the 5% level but not to burnout. Absenteeism increases by 0.5 and presenteeism by 0.8 percentage points (10% level).

Table 2.4: OLS estimates for work-related mental health outcomes, task categories

	combined	strain	exhaustion	burnout	absenteeism	presenteeism
non-routine manual						
multitasking	0.102***	0.114***	0.026***	0.039**	0.011***	0.016***
	(0.008)	(0.008)	(0.010)	(0.015)	(0.003)	(0.004)
constant	-0.629***	-0.493***	-0.681***	-0.477**	-0.065	0.046
	(0.121)	(0.131)	(0.139)	(0.202)	(0.044)	(0.061)
routine manual						
multitasking	-0.062***	-0.059***	-0.039***	-0.022	-0.011***	-0.010**
	(0.008)	(0.009)	(0.010)	(0.015)	(0.003)	(0.004)
constant	-0.643***	-0.503***	-0.689***	-0.476**	-0.069	0.046
	(0.121)	(0.132)	(0.138)	(0.202)	(0.044)	(0.060)
routine cognitive						
multitasking	0.028***	0.023***	0.012	0.051***	0.006**	0.005
	(0.008)	(0.009)	(0.009)	(0.014)	(0.003)	(0.004)
constant	-0.595***	-0.459***	-0.670***	-0.410**	-0.060	0.052
	(0.121)	(0.131)	(0.139)	(0.202)	(0.044)	(0.061)
non-routine interactive						
multitasking	0.126***	0.130***	0.061***	0.050***	0.018***	0.024***
	(0.008)	(0.009)	(0.011)	(0.015)	(0.003)	(0.005)
constant	-0.627***	-0.489***	-0.677***	-0.461**	-0.065	0.049
	(0.120)	(0.131)	(0.139)	(0.202)	(0.044)	(0.060)
non-routine analytic						
multitasking	0.020**	0.016**	0.025**	0.001	0.005*	0.008*
	(0.008)	(0.008)	(0.010)	(0.013)	(0.003)	(0.004)
constant	-0.595***	-0.459***	-0.659***	-0.465**	-0.060	0.055
	(0.122)	(0.132)	(0.139)	(0.202)	(0.044)	(0.060)
N	20089	20120	13521	6576	20102	13548

Standardized dependent variable given in column header (absenteeism, presenteeism: binary). Combined: emotional exhaustion, burnout and/or emotional strain. Models include job demands and resources, sociodemographic and job covariates according to table 2.2. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

The positive relationship between multitasking and work-related mental health is thus driven by non-routine manual and non-routine interactive tasks, while routine manual multitasking is associated with better health. As outlined in subsection 2.2.3, it makes sense that interactive tasks are associated with worse work-related mental health. To analyze whether the grouping into the categories masks any individual task effects, tables 2.5 to 2.9 show the coefficients for single task dummies.

The positive relationship of non-routine manual tasks and mental health is driven by “nursing” and “protecting”, two tasks that require interaction with potentially not cooperating customers (patients and criminals), and by “accommodating” which requires interaction with potentially unsatisfied customers (hotel guests, table 2.5). Point estimates are largest for “nursing”. The increase in any work-related mental health problem is 0.478 standard deviations. The largest coefficient is the one for strain (0.536). Exhaustion and burnout increase about 0.1 standard deviations. “Accommodating” coefficients are second largest except for burnout (insignificant). Strain increases by 0.247 standard deviations, exhaustion by 0.1 standard deviation. Point estimates for “protecting” are 0.164 for strain and below 0.1 for exhaustion and burnout. Absenteeism increases by 4 percentage points for “accommodating” and “nursing”. The “protecting” estimate is half that size. Presenteeism increases about 4 percentage points. The estimates for “repairing” are negative which fits to the finding that (routine) manual tasks are associated with better mental health. The “cleaning” coefficient is positive for burnout and strain but negative, small, and insignificant for exhaustion. “Cleaning” is also insignificant for health behaviors. This is probably because “cleaning” generally requires less interaction.

Table 2.5: OLS estimates for work-related mental health outcomes, non-routine manual tasks

	combined	strain	exhaustion	burnout	absenteeism	presenteeism
repairing						
dummy	-0.118***	-0.118***	-0.054**	-0.029	-0.014*	-0.014
	(0.022)	(0.023)	(0.024)	(0.046)	(0.008)	(0.011)
constant	-0.617***	-0.479***	-0.677***	-0.466**	-0.064	0.049
	(0.121)	(0.131)	(0.139)	(0.203)	(0.044)	(0.060)
accommodating						
dummy	0.232***	0.247***	0.100***	0.036	0.040***	0.037**
	(0.026)	(0.028)	(0.033)	(0.052)	(0.011)	(0.015)
constant	-0.668***	-0.534***	-0.703***	-0.472**	-0.073*	0.040
	(0.121)	(0.131)	(0.138)	(0.203)	(0.044)	(0.060)
nursing						
dummy	0.478***	0.536***	0.130***	0.113***	0.037***	0.047***
	(0.021)	(0.022)	(0.027)	(0.039)	(0.008)	(0.012)
constant	-0.782***	-0.665***	-0.717***	-0.509**	-0.076*	0.035
	(0.121)	(0.130)	(0.139)	(0.204)	(0.044)	(0.060)
protecting						
dummy	0.160***	0.164***	0.075***	0.067*	0.022***	0.041***
	(0.018)	(0.019)	(0.023)	(0.036)	(0.007)	(0.010)
constant	-0.638***	-0.500***	-0.686***	-0.482**	-0.067	0.043
	(0.121)	(0.131)	(0.139)	(0.202)	(0.044)	(0.060)
cleaning						
dummy	0.044**	0.056***	-0.014	0.063*	0.002	0.008
	(0.019)	(0.020)	(0.022)	(0.038)	(0.007)	(0.009)
constant	-0.623***	-0.490***	-0.666***	-0.491**	-0.063	0.047
	(0.122)	(0.132)	(0.140)	(0.204)	(0.044)	(0.061)
N	20089	20120	13521	6576	20102	13548

Standardized dependent variable given in column header (absenteeism, presenteeism: binary). Combined: emotional exhaustion, burnout and/or emotional strain. Models include job demands and resources, sociodemographic and job covariates according to table 2.2. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

“Manufacturing” is clearly driving the negative association between routine manual tasks and work-related mental health problems (table 2.6). Performing manufacturing tasks is associated with a decrease in mental health problem of 0.188 standard deviations. The point estimate is largest for emotional strain. Exhaustion and burnout are 0.087 and 0.109 standard deviations lower. The probabilities to stay home sick or to go to work sick are 2.9 and 3.1 percentage points smaller. “Monitoring” is negative and significant for all outcomes except presenteeism. The point estimates are smaller than for “manufacturing”. “Transporting” is significantly associated with exhaustion only, the coefficient is similar in size to the “monitoring” estimate.

Table 2.6: OLS estimates for work-related mental health outcomes, routine manual tasks

	combined	strain	exhaustion	burnout	absenteeism	presenteeism
manufacturing						
dummy	-0.188***	-0.188***	-0.087***	-0.109***	-0.029***	-0.031***
	(0.021)	(0.023)	(0.024)	(0.036)	(0.008)	(0.010)
constant	-0.619***	-0.482***	-0.675***	-0.458**	-0.064	0.050
	(0.121)	(0.131)	(0.139)	(0.202)	(0.044)	(0.060)
monitoring						
dummy	-0.083***	-0.077***	-0.044**	-0.072**	-0.012*	-0.006
	(0.018)	(0.019)	(0.021)	(0.034)	(0.007)	(0.009)
constant	-0.606***	-0.468***	-0.670***	-0.463**	-0.062	0.051
	(0.122)	(0.132)	(0.139)	(0.202)	(0.044)	(0.060)
transporting						
dummy	-0.016	-0.008	-0.037*	0.047	-0.009	-0.009
	(0.018)	(0.019)	(0.021)	(0.035)	(0.006)	(0.009)
constant	-0.602***	-0.466***	-0.662***	-0.476**	-0.060	0.053
	(0.122)	(0.131)	(0.140)	(0.202)	(0.044)	(0.061)
N	20089	20120	13521	6576	20102	13548

Standardized dependent variable given in column header (absenteeism, presenteeism: binary). Combined: emotional exhaustion, burnout and/or emotional strain. Models include job demands and resources, sociodemographic and job covariates according to table 2.2. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

The positive relationship between routine cognitive tasks and work-related mental health problems comes from the task “documenting” (table 2.7). The size of the estimates is similar to the ones for the non-routine manual task “protecting”. The two other routine cognitive tasks, “measuring” and “purchasing”, have an ambiguous association with mental health. “Measuring” is negatively significant for exhaustion and strain but insignificant for burnout and presenteeism. “Purchasing” is positively associated with exhaustion and negatively with strain. This is probably because the task is composed of somewhat heterogeneous single activities which have different associations with mental health.[11]

[11] “Purchasing” includes purchasing, producing, and selling. Purchasing and selling involve some degree of customer and supplier interaction (which should be related positively to mental health problems), while producing refers more to “manufacturing” (negative association). The largely insignificant estimates for “purchasing” suggest that these two single associations cancel out.

Table 2.7: OLS estimates for work-related mental health outcomes, routine cognitive tasks

	combined	strain	exhaustion	burnout	absenteeism	presenteeism
measuring						
dummy	-0.059***	-0.053***	-0.071***	0.043	-0.009	-0.024***
	(0.015)	(0.016)	(0.019)	(0.027)	(0.006)	(0.008)
constant	-0.599***	-0.463***	-0.657***	-0.467**	-0.061	0.056
	(0.121)	(0.131)	(0.139)	(0.202)	(0.044)	(0.060)
purchasing						
dummy	-0.020	-0.041**	0.041*	-0.003	-0.000	0.022**
	(0.017)	(0.018)	(0.023)	(0.031)	(0.006)	(0.010)
constant	-0.596***	-0.449***	-0.693***	-0.465**	-0.062	0.040
	(0.122)	(0.132)	(0.138)	(0.204)	(0.044)	(0.061)
documenting						
dummy	0.180***	0.173***	0.089***	0.139***	0.032***	0.027***
	(0.016)	(0.017)	(0.019)	(0.028)	(0.006)	(0.008)
constant	-0.648***	-0.509***	-0.697***	-0.459**	-0.070	0.043
	(0.121)	(0.131)	(0.139)	(0.203)	(0.044)	(0.060)
N	20089	20120	13521	6576	20102	13548

Standardized dependent variable given in column header (absenteeism, presenteeism: binary). Combined: emotional exhaustion, burnout and/or emotional strain. Models include job demands and resources, sociodemographic and job covariates according to table 2.2. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

All three non-routine interactive tasks are significantly associated with worse work-related mental health (table 2.8). “Training” point estimates are largest except for presenteeism and burnout. Performing the task “training” is associated with an increase in any work-related mental health problem of 0.222 standard deviations. “Informing” and “advertising” are associated with increases of 0.181 and 0.113 standard deviations. “Training” coefficients are similar to “accommodating” estimates. “Informing” and “advertising” are similar to “protecting”.

Table 2.8: OLS estimates for work-related mental health outcomes, non-routine interactive tasks

	combined	strain	exhaustion	burnout	absenteeism	presenteeism
advertising						
dummy	0.113***	0.102***	0.096***	0.080**	0.019**	0.041***
	(0.022)	(0.023)	(0.031)	(0.040)	(0.008)	(0.014)
constant	-0.626***	-0.486***	-0.692***	-0.466**	-0.066	0.042
	(0.121)	(0.131)	(0.139)	(0.202)	(0.044)	(0.060)
training						
dummy	0.222***	0.225***	0.117***	0.068**	0.036***	0.035***
	(0.019)	(0.020)	(0.025)	(0.033)	(0.007)	(0.011)
constant	-0.636***	-0.498***	-0.685***	-0.480**	-0.067	0.047
	(0.121)	(0.131)	(0.139)	(0.203)	(0.044)	(0.060)
informing						
dummy	0.181***	0.194***	0.065***	0.062**	0.020***	0.033***
	(0.016)	(0.017)	(0.020)	(0.029)	(0.006)	(0.008)
constant	-0.738***	-0.610***	-0.716***	-0.503**	-0.077*	0.029
	(0.121)	(0.132)	(0.139)	(0.203)	(0.044)	(0.060)
N	20089	20120	13521	6576	20102	13548

Standardized dependent variable given in column header (absenteeism, presenteeism: binary). Combined: emotional exhaustion, burnout and/or emotional strain. Models include job demands and resources, sociodemographic and job covariates according to table 2.2. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

The association between non-routine analytic tasks and mental health is rather weak in comparison (table 2.9). “Organizing” is significant for all outcomes but burnout. Emotional strain increases by 0.073 standard deviations, exhaustion by 0.065 standard deviations. “Researching” is insignificant for all outcomes but the combined measure and emotional strain. The point estimates are negative (-0.054 and -0.065). All other coefficients are very small and negative. The different associations reflect that “organizing” (organizing, planning and preparing work processes of others) involves interaction with coworkers or subordinates, while “researching” (developing, researching, constructing) requires less interaction. All in all, there are differences even within task categories regarding the relationship with work-related mental health. These differences seem to arise from different degrees of interaction that the single task requires. The analysis confirms a significant positive association between interactive tasks and work-related mental health problems. The association is stronger where cooperation from clients is necessary but potentially missing (nursing, protecting, training).

Table 2.9: OLS estimates for work-related mental health outcomes, non-routine analytic tasks

	combined	strain	exhaustion	burnout	absenteeism	presenteeism
organizing						
dummy	0.076***	0.073***	0.065***	0.003	0.013**	0.025***
	(0.016)	(0.017)	(0.020)	(0.028)	(0.006)	(0.009)
constant	-0.616***	-0.477***	-0.682***	-0.466**	-0.064	0.047
	(0.121)	(0.132)	(0.139)	(0.202)	(0.044)	(0.060)
researching						
dummy	-0.054**	-0.065***	-0.009	-0.002	-0.001	-0.011
	(0.022)	(0.023)	(0.027)	(0.039)	(0.008)	(0.012)
constant	-0.606***	-0.469***	-0.673***	-0.466**	-0.062	0.051
	(0.121)	(0.131)	(0.139)	(0.202)	(0.044)	(0.060)
N	20089	20120	13521	6576	20102	13548

Standardized dependent variable given in column header (absenteeism, presenteeism: binary). Combined: emotional exhaustion, burnout and/or emotional strain. Models include job demands and resources, sociodemographic and job covariates according to table 2.2. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

2.4.2 Gender difference and intensive margins

A common prejudice is that men are worse multitaskers than women. Even though this relates to the common language multitasking, i.e. simultaneously performing tasks, there might also be a gender difference in the association between work-related mental health and the number of tasks. Table 2.10 displays the results for women and men separately. Point estimates are about three times larger for women than for men. Multitasking is associated with an increase in any work-related mental health problem of 0.062 standard deviations for women and 0.017 standard deviations for men. The difference is the same for strain. Exhaustion increases by 0.029 standard deviations for women and by 0.1 standard deviations for men. The female multitasking coefficient is 0.037 for burnout, the male one is insignificant (0.005). Female absenteeism and presenteeism increase 0.9 percentage points with multitasking (around 5%). Male absenteeism is not affected by rising multitasking but presenteeism increases by 0.7 percentage points (4%). Female work-related mental health is more strongly affected than male health. This makes sense taking into account that women tend to select into tasks that require human interaction, while men are more apt to carry out physical tasks in manufacturing.[12]

[12] Male overconfidence in task reporting could be an issue, see footnote 7. The weaker overall association for men could be partially explained by this if misreporting was higher for higher levels of multitasking only. This seems rather unlikely.

Table 2.10: OLS estimates for work-related mental health outcomes by gender

	combined	strain	exhaustion	burnout	absenteeism	presenteeism
women						
multitasking	0.062***	0.062***	0.029***	0.037***	0.009***	0.009***
	(0.005)	(0.005)	(0.006)	(0.010)	(0.002)	(0.003)
constant	-0.603***	-0.341*	-0.869***	-0.688***	-0.110*	0.052
	(0.169)	(0.181)	(0.222)	(0.266)	(0.067)	(0.092)
men						
multitasking	0.017***	0.017***	0.010*	0.005	0.003	0.007***
	(0.005)	(0.006)	(0.006)	(0.009)	(0.002)	(0.003)
constant	-0.967***	-0.982***	-0.634***	-0.367	-0.037	0.009
	(0.182)	(0.197)	(0.194)	(0.305)	(0.064)	(0.087)
N women	10654	10668	7094	3563	10661	7106
N men	9435	9452	6427	3013	9441	6442

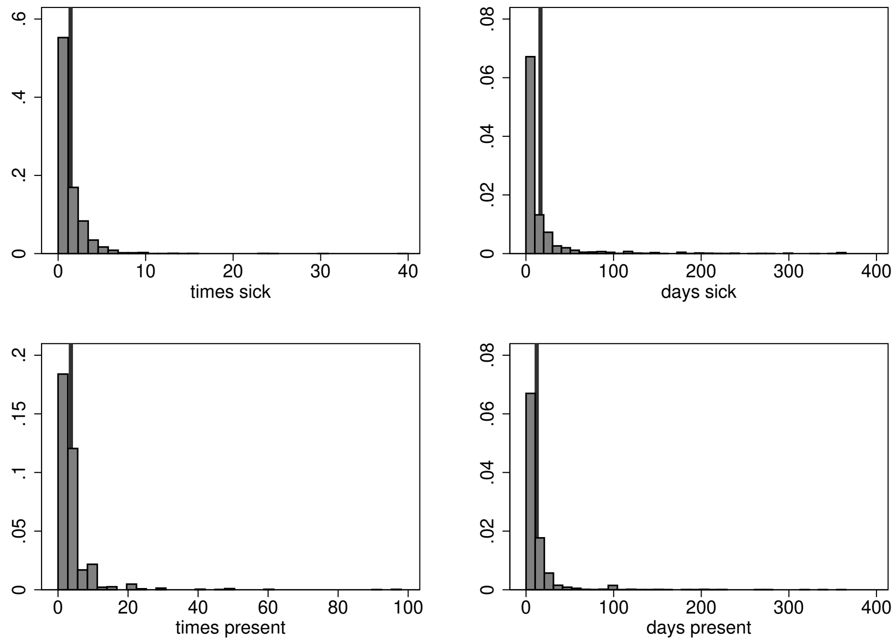
Standardized dependent variable given in column header (absenteeism, presenteeism: binary). Combined: emotional exhaustion, burnout and/or emotional strain. Full model contains job demands and resources, sociodemographic, and job covariates according to table 2.2. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

Multitasking is associated with increased absenteeism and presenteeism at the extensive margin, i.e. whether or not employees are on sick leave or come to work sick. The intensive margin is recorded as the number of times (2012 only) and the number of days this occurred. Figure 2.4 shows the histograms for the intensive margins of absenteeism (upper panel) and presenteeism (lower panel). In 2012, employees were on sick leave with emotional exhaustion 1.4 times on average. They were on sick leave with burnout in 2006 on 20 days and with emotional exhaustion on 15 days in 2012. Employees went to work despite being exhausted 3.6 times and on 12 days in 2012.

The distribution of the count data suggests a Poisson distribution but as it is often the case with sick day data, the variation is large. This is why sick days models are often negative binomial regression models: the count variable follows a Poisson distribution but variation can be larger (called "overdispersion"). Indeed, conditional variances exceed conditional means (i.e. in each multitasking category, see table 2.11).[13] Table 2.12 displays the multitasking coefficients of negative binomial regressions for the four count variables. A one task increase in multitasking is associated with a decrease in the difference in the logs of the expected number of sick leaves (0.023, significant at the 5% level). Similarly, multitasking is associated with increases in the difference in the logs of expected number of presenteeism times and days (0.045 and 0.030, significant at the 5% level). The estimate for the number of sick days is not significant. In the full model with all covariates, the estimate for times sick is not significant any more. Multitasking

[13]This is confirmed when running Poisson and binomial negative regressions in Stata. After *poisson*, the goodness-of-fit chi-squared test is highly statistically significant, suggesting that a Poisson model is not the best choice. The likelihood-ratio chi-square test in the *nbreg* command (binomial negative regression) tests that the dispersion parameter is zero. In this case, a Poisson would be sufficient. The test is rejected at the 1% level for all models and outcomes.

Figure 2.4: Histogram of times and days of absenteeism and presenteeism



Vertical lines: mean. Times sick: times on sick leave (2012), days sick: days on sick leave (2006 and 2012), times present: times sick but went to work (2012), days present: days sick but went to work (2012). Data sources: BIBB/BAuA. Own figure.

is associated with an increase in sickness days and times and days of presenteeism. Interpreting the exponentiated point estimates, an increase in multitasking of one task is associated with an increase in sickness days of a factor of 1.026 (2.6%). Times present increase by 2% and presenteeism days by 4.2%.

Table 2.11: Overdispersion

	times sick			days sick			times present			days present		
multitasking	mean	var	n	mean	var	n	mean	var	n	mean	var	n
1	1.6	3.4	89	25.3	2529.5	150	4.5	54.4	83	15.3	619.6	84
2	1.8	6.2	321	22.1	2560.7	429	2.9	12.2	301	10.9	365.1	292
3	1.4	2.4	567	16.0	1232.1	713	3.1	23.9	534	10.7	385.5	538
4	1.4	4.7	615	14.4	924.8	782	3.5	39.1	588	11.8	453.6	591
5	1.4	3.8	654	13.9	1113.6	790	3.1	17.0	618	10.7	427.6	610
6	1.3	2.0	541	17.0	1649.5	627	3.8	48.2	509	11.9	611.7	502
7	1.3	4.0	369	15.5	1663.3	442	4.5	86.4	339	15.4	905.3	345
8	1.3	2.2	266	14.0	844.4	309	4.1	37.1	241	12.3	313.4	249
9	1.4	2.4	218	16.8	1945.3	250	4.8	52.6	199	12.4	298.3	195
10	1.2	1.5	143	22.2	2450.9	159	4.7	39.6	132	17.1	1246.2	127
11	1.3	1.9	48	16.3	1595.1	53	3.9	24.8	46	17.7	1054.8	46
12	1.5	2.8	50	32.8	4137.8	53	4.8	49.8	45	15.6	1039.9	40
Total	1.4	3.4	3881	16.6	1514.5	4757	3.7	37.8	3635	12.2	526.2	3619

Var: variance, n: number of observations. Sick: sick leave, present: went to work despite being sick. Sickness: burnout (2006), emotional exhaustion (2012). Data sources: BIBB/BAuA. Own calculations.

Table 2.12: Negative binomial regression estimates for absenteeism and presenteeism frequency and amount

	times sick	days sick	times present	days present
base model				
multitasking	-0.023***	-0.004	0.045***	0.030***
	(0.008)	(0.013)	(0.009)	(0.011)
full model				
multitasking	-0.005	0.026*	0.020*	0.041***
	(0.010)	(0.015)	(0.010)	(0.013)
N	3614	4171	3402	3392

Sick: sick leave, present: went to work despite being sick. Sickness: burnout (2006), emotional exhaustion (2012). Full model contains job demands and resources, sociodemographic and job covariates according to table 2.2. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

2.4.3 Robustness

This subsection analyzes the robustness of the above findings to alternative measurements of the outcomes and alternative multitasking measures. Table 2.13 considers alternative measures of work-related mental health. The outcomes emotional strain, emotional exhaustion, burnout, absenteeism, and presenteeism were chosen based on availability in the data. To check whether they represent a common underlying factor "work-related mental health problems", factor analyses determined a common factor for all outcomes measured in 2012 (exhaustion, strain, absenteeism, presenteeism) and 2006 (burnout, strain, absenteeism) with an iterated principal factor. One factor had an eigenvalue larger than 1. The common factors were predicted after rotation. The regression results for these common factors are displayed in columns one and two. Multitasking is highly significant for both common factors in the full model.

The third and fourth column display the results for binary measures of emotional exhaustion and burnout indicating the presence of either health problem but not distinguishing by physician consultation. An additional task is associated with an increase in burnout of 0.6 percentage points. Since 7% of the weighted sample suffer from burnout, the relative increase is 8%. The associated increase for emotional exhaustion is 1 percentage point. At a mean prevalence of 24%, this corresponds to 4%. With the binary definition, the relative increase is larger for burnout.

Hackman and Oldham (1976) suggest that skill variety is related to lower absenteeism. This was not confirmed for absenteeism due to work-related mental health problems. Columns five and six regress overall absenteeism and presenteeism on multitasking and covariates to check whether their prediction holds for general measures. The point estimate for absenteeism is negative but small and insignificant (-0.003). The multitasking coefficient for presenteeism is positive (0.002) but insignificant, too. While there is no association as suggested by Hackman and Oldham (1976), this robustness check confirms that the previous finding of increased absenteeism and presenteeism is determined by the cause (work-related mental health problems) and is not a general finding.

Table 2.13: OLS estimates for alternative work-related mental health outcomes

	common 2012	common 2006	burnout	exhaustion	absenteeism	presenteeism
multitasking	0.022***	0.021***	0.006***	0.010***	-0.003	0.002
	(0.004)	(0.007)	(0.002)	(0.002)	(0.002)	(0.002)
constant	-0.636***	-0.506**	-0.058	-0.032	0.368***	0.622***
	(0.145)	(0.202)	(0.056)	(0.066)	(0.077)	(0.088)
N	13521	6573	6577	13525	20094	13518

Dependent variable given in column header. Common 2012: common factor from factor analysis with emotional exhaustion, emotional strain, absenteeism and presenteeism. Common 2006: burnout, emotional strain, absenteeism. Burnout/exhaustion: binary. Absenteeism/presenteeism: general, not only due to work-related mental health problems. Models include job demands and resources, sociodemographic, and job covariates according to table 2.2. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

The role multitasking plays for work-related mental health could depend on the context, e.g. on the general multitasking distribution or on the occupation-specific multitasking distribution.[14] Adding one

[14]The concept of comparisons to the context dates back to Festinger (1954)'s theory of social comparison processes. His second hypothesis states that people evaluate opinions and abilities in comparing themselves to others if no objective standard is available.

more task might be less relevant in practice as people compare their own situation to that of others. Individual multitasking might have a different effect if it is high (above the average) or extremely high (larger than the mean plus one standard deviation) compared to the general level of multitasking or compared to the occupation-specific level. 39% of the individuals have above mean multitasking and 43% perform more tasks than the average in their occupation in 2006 or 2012. 16% are extreme multitaskers both in general and within their occupation. Another way to account for the context is to consider occupational instead of individual multitasking. In the task literature, it is common practice to work with occupational tasks because individual task information is seldom available. The QaC is one of the few exceptions. While it makes sense to let tasks vary within a job, measurement error on the individual level might be larger. Occupation-specific multitasking averages 4.2 tasks with a standard deviation of 0.86. The level of aggregation is two-digit occupation codes according to the 1992 version of the German classification of occupations ("Klassifikation der Berufe"). The sample contains 89 different occupations.

Table 2.14 shows the estimates for alternative multitasking measures. The first two panels consider above average and extreme multitasking in general. The average of multitasking is 4.2, the standard deviation is 2.3. Performing 5 tasks or more compared to less than 5 is associated with an increase in the risk for any work-related mental health problem of 0.138 standard deviations. The increase in strain is 0.135 standard deviations and larger than for burnout (0.095 standard deviations) and exhaustion (0.069 standard deviations). The probability to miss work due to sickness is 1.8 percentage points higher and the probability to go to work sick 2.5 percentage points. Extreme multitasking of 7 or more tasks is associated with higher exhaustion, strain, absenteeism, and presenteeism. Point estimates are similar to the ones obtained with the above average measure for complaints and larger for health behaviors (27. and 4.0 percentage points).

Mean occupation multitasking ranges from 2 (stoneware and brick makers) to 7.7 tasks (beverage and tobacco makers). Performing more tasks than one's occupation average is significantly associated with all outcomes but health behaviors. The increase is largest for burnout (0.1 standard deviations). Strain and exhaustion increase by 0.051 and 0.032 standard deviations (the latter at the 10% level). Extreme occupation multitasking is significantly related to the combined measure, absenteeism, and presenteeism at the 5% level. The coefficients for health behaviors are larger than for the above mean measure. The remaining point estimates are positive but insignificant. All in all, above mean multitasking is associated with worse work-related mental health. Extreme multitasking is more detrimental to health behaviors.

The last two panels in table 2.14 compare individual to occupational multitasking. Both measures are standardized. Occupational multitasking is significantly related to all outcomes but burnout. The point estimates are comparable to the ones with individual multitasking for exhaustion and absenteeism. The estimate for strain is larger with the occupational measure, the one for presenteeism with the individual measure. Overall, individual multitasking seems to be more relevant for more severe work-related mental health.

Table 2.14: OLS estimates for work-related mental health outcomes, alternative multitasking

	combined	strain	exhaustion	burnout	absenteeism	presenteeism
above average						
multitasking	0.138***	0.135***	0.069***	0.095***	0.018***	0.025***
	(0.016)	(0.017)	(0.019)	(0.030)	(0.006)	(0.008)
constant	-0.618***	-0.479***	-0.692***	-0.459**	-0.064	0.044
	(0.121)	(0.131)	(0.139)	(0.203)	(0.044)	(0.060)
extreme						
multitasking	0.129***	0.134***	0.069**	0.026	0.027***	0.040***
	(0.022)	(0.023)	(0.028)	(0.042)	(0.008)	(0.012)
constant	-0.609***	-0.470***	-0.676***	-0.463**	-0.063	0.049
	(0.122)	(0.132)	(0.139)	(0.202)	(0.044)	(0.061)
above average occupation						
multitasking	0.062***	0.051***	0.032*	0.100***	0.008	0.012
	(0.016)	(0.016)	(0.019)	(0.029)	(0.006)	(0.008)
constant	-0.610***	-0.471***	-0.677***	-0.466**	-0.063	0.049
	(0.121)	(0.131)	(0.139)	(0.203)	(0.044)	(0.060)
extreme occupation						
multitasking	0.043**	0.031	0.041	0.047	0.019**	0.024**
	(0.021)	(0.022)	(0.027)	(0.040)	(0.008)	(0.012)
constant	-0.605***	-0.467***	-0.673***	-0.459**	-0.062	0.051
	(0.121)	(0.131)	(0.139)	(0.202)	(0.044)	(0.060)
individual						
multitasking, std.	0.095***	0.095***	0.046***	0.048***	0.015***	0.020***
	(0.008)	(0.009)	(0.010)	(0.015)	(0.003)	(0.004)
constant	-0.555***	-0.416***	-0.651***	-0.427**	-0.054	0.060
	(0.121)	(0.131)	(0.139)	(0.202)	(0.044)	(0.061)
occupational						
multitasking	0.117***	0.131***	0.048***	0.000	0.014***	0.016***
	(0.008)	(0.008)	(0.011)	(0.013)	(0.003)	(0.004)
constant	-0.671***	-0.540***	-0.708***	-0.466**	-0.070	0.038
	(0.121)	(0.131)	(0.138)	(0.202)	(0.044)	(0.060)
N	20089	20120	13521	6576	20102	13548

Standardized dependent variable given in column header (absenteeism, presenteeism: binary). Combined: emotional exhaustion, burnout and/or emotional strain. Above average (occupation) multitasking: binary for multitasking that is larger than average (occupation) multitasking, extreme multitsaking (occupation): binary for multitasking that is larger than average (occupation) multitasking plus one standard deviation, individual/occupational multitasking: standardized. Models include job demands and resources, sociodemographic and job covariates according to table 2.2. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

Multitasking is defined differently in organizational job design than in the public usage of the term where multitasking means performing different tasks at the same time or switching between short sequences of different tasks. A measure for this simultaneity is how often people need to keep an eye on different work processes or sequences at the same time. 60% report doing so often, a quarter sometimes. 10% rarely do different things at the same time and 6% never do. Estimation results for the standardized measure of simultaneity in the base and the full model are reported in table 2.15. The simultaneity measure explains a similar percentage of variation in the outcomes as the multitasking measure. Simultaneity is significantly associated with all outcomes in a model without any covariates (upper panel). Coefficients decrease to half or one eighth in the full model with all controls and turn insignificant except for the combined measure and strain. A one standard deviation increase in simultaneity is associated with an increase in strain of 0.03 standard deviations. This is three times smaller than with the standardized multitasking measure from table 2.14. The simultaneity of tasks appears to be much less important than the number of tasks.

Table 2.15: OLS estimates for work-related mental health outcomes, simultaneity

	combined	strain	exhaustion	burnout	absenteeism	presenteeism
base model						
simultaneity	0.198***	0.204***	0.097***	0.047***	0.020***	0.041***
	(0.008)	(0.009)	(0.009)	(0.016)	(0.003)	(0.004)
constant	-0.029***	-0.015*	-0.066***	-0.013	0.126***	0.189***
	(0.008)	(0.009)	(0.010)	(0.013)	(0.003)	(0.004)
full model						
simultaneity	0.026***	0.030***	0.013	-0.024	0.003	0.006
	(0.009)	(0.009)	(0.010)	(0.017)	(0.003)	(0.004)
constant	-0.597***	-0.459***	-0.668***	-0.479**	-0.061	0.052
	(0.121)	(0.131)	(0.139)	(0.201)	(0.044)	(0.060)
N	20087	20118	13520	6575	20100	13547
R^2 adj. base	0.040	0.042	0.012	0.002	0.004	0.012
R^2 adj. full	0.279	0.246	0.151	0.073	0.119	0.146

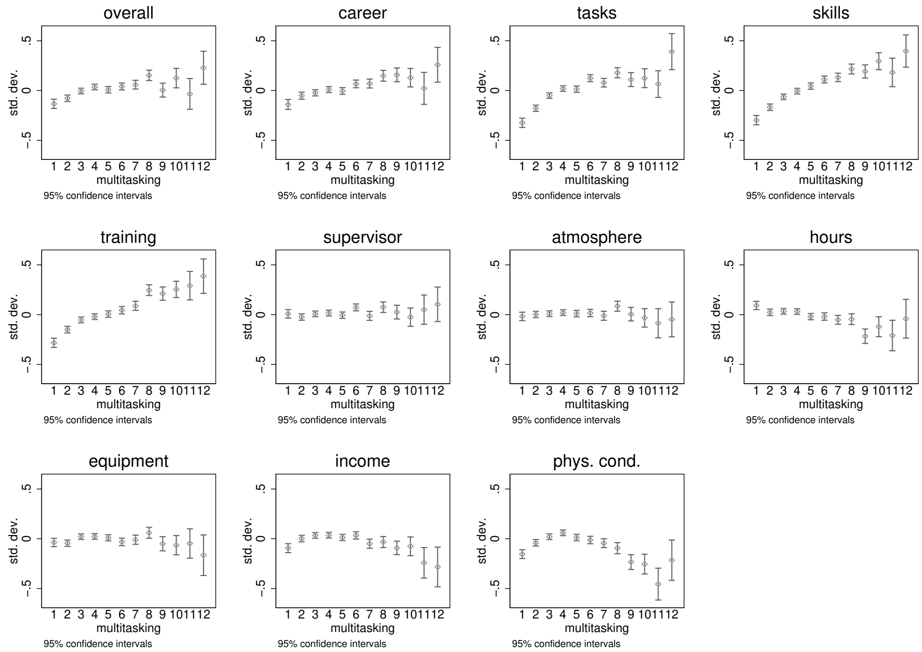
Standardized dependent variable given in column header (absenteeism, presenteeism: binary). Combined: emotional exhaustion, burnout and/or emotional strain. Models include job demands and resources, sociodemographic, and job covariates according to table 2.2. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

2.5 Compensation

This section analyzes whether there are positive effects of multitasking in the work context that could offer compensation for the detrimental link to work-related mental health problems. In the Job Chracteristics Model, Hackman and Oldham (1976) associate skill variety with intrinsic motivation and job satisfaction. The term "skill variety" designates the variety of different activities on the job, which corresponds to multitasking. The model suggests a positive association between multitasking and job satisfaction. The relationship between standardized job satisfaction and multitasking is depicted in figure 2.5.

Overall job satisfaction and career satisfaction are slightly higher for higher multitasking. The pattern is steeper for satisfaction with tasks, application of skills, and further training. Multitasking does not seem to be related to satisfaction with supervisor and working atmosphere. Satisfaction with hours, working equipment, and income decrease slowly over multitasking, while the decrease is more pronounced for satisfaction with physical working conditions for high multitasking.

Figure 2.5: Job satisfaction by multitasking



Standardized job satisfaction. Phsc. cond.: physical working conditions. Data sources: BIBB/BAuA. Own figure.

Table 2.16 displays the multitasking coefficients in the full model with all covariates. An additional task is associated with an increase in overall job satisfaction of 0.019 standard deviations. The point estimate is small but positive and significant for career satisfaction. Coefficients are larger for satisfaction with application of skill, further training and tasks (around 0.02 to 0.03). Contrary to the bivariate descriptive evidence, multitasking is somewhat relevant for satisfaction with supervisor and working atmosphere (0.01 at the 5% and the 10% level). The results for satisfaction with income and physical working conditions confirm the descriptive picture: multitasking is related to lower satisfaction (-0.02 standard deviations). In general, the multitasking estimates are smaller than the ones for the combined mental health measure and emotional strain suggesting that even though there might be compensatory effects, these are probably smaller.

Table 2.16: OLS estimates for job satisfaction

	overall	career	tasks	skills	training	supervisor	atmosphere	hours	equipment	income	phys. cond.
multitasking	0.019***	0.010**	0.023***	0.029***	0.029***	0.010**	0.006*	0.002	-0.001	-0.021***	-0.016***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
constant	0.517***	0.714***	-0.136	-0.317**	0.543***	0.373***	1.008***	0.288**	0.266*	0.055	0.456***
	(0.144)	(0.160)	(0.142)	(0.156)	(0.147)	(0.140)	(0.128)	(0.140)	(0.144)	(0.160)	(0.139)
N	20121	18342	20121	20105	19829	19952	20104	20103	19995	20106	20054
Adj. R^2	0.196	0.127	0.136	0.143	0.155	0.174	0.250	0.208	0.095	0.107	0.198

Standardized dependent variable given in column header. Phys. cond.: Satisfaction with physical working conditions. Full model contains job demands and resources, sociodemographic, and job covariates according to table 2.2. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

In addition to non-monetary compensation, multitasking could be associated with higher wages. Indeed, Pikos and Thomsen (2016) find a positive association between the number of task categories (one to five) an individual carries out and the hourly wage. The relationship was strongest in the 1980s where a one standard deviation increase was associated with an increase in hourly wages by 8%. This reduced to half the size after 2000. At the same time, multitasking became much more common. The relationship between multitasking and wages is also weaker for higher educated employees. Both findings suggest that multitasking pays off less when it is more common. Hence, if there is monetary compensation, it is becoming less and less important.

2.6 Discussion

Rising multitasking is significantly and robustly associated with worse mental health at work, absenteeism, and presenteeism. The magnitude of these associations is small at first sight: for an additional task, burnout and exhaustion increase by about 0.02 standard deviations, absenteeism and presenteeism by 0.6 and 0.8 percentage points. A one task increase in multitasking corresponds nearly to the increase in the average number of tasks from 2006 (4) to 2012 (4.8). Assuming that the increase in multitasking is equally distributed across time and continues in the future, the estimated associated increases of one task would occur within seven to eight years.

To calculate the cost of rising multitasking regarding work-related mental health, one needs to estimate the average cost of work-related mental health problems. This is problematic because data is scarce. Among the three outcomes – emotional strain, emotional exhaustion, and burnout – there is only data on burnout and even that is rare. The main reason is that burnout is not coded in a single category in the International Statistical Classification of Diseases and Related Health Problems which is used by physicians to classify diseases. In the 10th revision, German Modification (ICD-10-GM), it is coded in category Z73 among "other problems to cope with life".[15] Burnout costs arise to individuals (reduced quality of life, loss of self esteem, reduced work capacity), companies (value added, expertise, loss of reputation), and society (health care expenditures, early retirement, work incapacity). Due to lacking data, the following will be a back of the envelope calculation of the loss in gross value added.

To put a value on absenteeism and presenteeism, it is necessary to estimate the number of cases, the average number of days, and the average value loss per day. The German Federal Institute for Occupational Safety and Health (*Bundesanstalt für Arbeitsschutz und Arbeitsmedizin*, BAuA) calculates an average of € 59,000 of gross value added per employee in 2009. There were around 253 working days in

[15] These comprise for example accentuation of personality traits, limited activities due to handicap, lack of relaxation or leisure, social role conflict, stress, and insufficient social competences (not classified elsewhere).

2009.[16] Thus, gross value added per day and employee was around € 233,20. In the QaC, people reporting burnout in 2006 missed 20 working days on average.[17] This implies a total loss in gross value added per burnout of € 4,664. Around 10.9% stayed home with burnout. The total German working population subject to social security contribution (not including self-employed and public sector employment) was 27 million in 2009. This gives 2.9 million absenteeism cases.[18] Hence, the total loss in gross value added would be around € 13.7 billion. Holding the working population constant,[19] an increase in absenteeism by 0.6 percentage points corresponds to about 3.1 million employees on sick leave, an increase of 162,000. Sickness days increase by 2.6% to 20.5 days. This slightly increases absenteeism costs per burnout case to € 4,781. The total cost of absenteeism rises by € 1.1 billion to around € 14.8 billion in total.

Costs from presenteeism are harder to calculate because data are even sparser. In the QaC, presenteeism is recorded in 2012 only. As emotional exhaustion is a component of burnout and thus mild, the following can be seen as a lower bound estimate for the presenteeism cost of burnout. On average, employees went to work despite feeling emotionally exhausted on 12 days. The costs from presenteeism come for example from lower work quality, higher rate of mistakes, and higher risk for accidents (Volber, 2014). Assuming that lower work quality and higher rate of mistakes entail a loss of about 20%, gross value added per day would be reduced by € 46.64 to € 185.56.[20] This is a loss of € 559.68 for 12 days. 18.6% of the employees went to work despite being emotionally exhausted. This corresponds to 5 million employees who would lose about € 2.8 billion. Holding the working population constant, an increase in presenteeism by 0.8 percentage points corresponds to 5.2 million sick employees at work, an increase of around 200,000. Presenteeism days increase by 4.1% to 12.5 days. The total loss of presenteeism rises by € 241 million to € 3.1 billion in total. In sum, the additional cost from increased multitasking for seven to eight years corresponds to a loss in gross value added of about € 1.3 billion. For the time period 2006 to 2012, € 900 million are lost due to absenteeism and € 200 million due to presenteeism (80%). The total loss hence amounts to € 1,1 billion.

[16] The number of working days differs by federal state (between 252 and 254). This is mainly due to different religious holidays for catholic and protestants, the two major religions in Germany. Northern federal states are predominantly protestant, southern federal states predominantly catholic.

[17] According to the WHO, individuals with burnout miss 30.4 working days on average. In Germany, data availability depends on health insurance companies. There are private and public health insurances and their estimates differ. In the largest public health insurance (*Allgemeine Ortskrankenkassen*, AOK), there are 5.1 sickness cases due to category Z73 and 101,6 sick leave days for 1,000 insurants (Springer, 2017). This corresponds to around 20 days/case. A medium sized private health insurance (*Betriebskrankenkassen*, BKK) records 40 days of sickness leave for "mental disorders" (Henrich, 2015). The AOK-estimate includes mild conditions than burnout (e.g. deficient social skills, social role conflict) and is probably downward biased. The BKK-estimate is likely upward biased as recovery from their included mental health disorders (e.g. schizophrenia) can take more time. This suggests that the true number of sick leave days due to burnout is somewhere in the middle. I use the 20 days from the QaC.

[18] This is downward biased as individuals suffering from burnout who left the working population are not included.

[19] In fact, the German working population increased to nearly 29 million people in 2013.

[20] There is an estimate that mental health presenteeism would equal a loss of 1.5 hours on an 8 hour working day which corresponds to a similar percentage (Marquart, 2011).

The above calculation does not include health care expenditures for burnout treatment because no estimates are available. All I can say here is that the number of burnouts increases by 0.02 standard deviations (or 0.5 percentage points at a standard deviation of 0.25)[21]. 6.8% report burnout in the data. This corresponds to 1.8 million people. A 0.5 percentage points increase translates into about 135,000 (from 2006 to 2012:108,000) additional employees with burnout for whom health care costs (also including co-morbidity)[22] , reduced employability costs, early retirement costs, and work incapacity costs have to be added.

2.7 Conclusion

Rising multitasking is significantly and robustly associated with higher emotional strain, emotional exhaustion, and burnout. Absenteeism and presenteeism increase at the extensive and the intensive margin. Multitasking thus acts as a job demand in the Job Demands and Resources model. Simultaneity (common language "multitasking") is only associated with the least severe work-related mental health outcome (strain). Neuroscience suggests that the human brain is not made for doing different things simultaneously and that stress can arise from simultaneity. The results presented here confirm that while this is true to some degree, simultaneity is not significantly associated with more medium to severe mental health conditions (emotional exhaustion, burnout) nor health behavior once controlling for job demands and resources, sociodemographic and job characteristics.

The relationship between multitasking and work-related mental health is driven by tasks that require interactions with other human beings and is strongest where work depends on the often missing cooperation of "clients" (nursing, protecting, training). This confirms the findings of Hasselhorn and Nübling (2004) who identify cooperation with people whose cooperation is often missing as the common denominator of occupations in which the risk for poor mental health is high. Physical tasks (manufacturing and repairing) are associated with lower work-related mental health problems. This can be related to Cato who praised farming over trading and money-landing in his "De agri cultura" (even though he focused on the prestige of occupations and not mental health outcomes, Froesch, 2009).

In line with the Hackman and Oldham's Job Characteristics Model (JCM) of work motivation (Hackman and Oldham, 1976), multitasking is associated with higher job satisfaction. It plays a positive albeit smaller role for overall job satisfaction, satisfaction with career, tasks, training application of skills, and

[21]This is close to the estimate with the binary burnout variable of 0.6 percentage points

[22]Co-morbidity means that other health problems arise together with burnout, e.g. respiratory diseases because of a stressed immune system or heart problems due to stress. Early retirement costs are relevant because in Germany, 41% of early retirement is caused by mental health issues (Lohmann-Haislah, 2012). The absenteeism and presenteeism costs calculations include co-morbidity if burnout and emotional exhaustion are reported because absenteeism and presenteeism reports do not distinguish between sickness types. As long as participants stated burnout or exhaustion, their co-morbidity – if it translated into absenteeism or presenteeism – is included.

supervisor. The JCM suggests that skill variety is associated with lower absenteeism and turnover but absenteeism due to work-related mental health problems increases with multitasking. Multitasking is insignificant for general absenteeism and presenteeism suggesting that the reason for this discrepancy could lie in a different understanding of "absenteeism". In the JCM, absenteeism carries the connotation of voluntary absenteeism or shirking, while the present measure relates to actual sick leaves for which physician certificates are required usually in Germany. Mental health problems were still stigmatized much more in 2006 and 2012 and the main part of shirking should be justified with other health complaints.

The results suggest a trade-off between mental health and job satisfaction as the former decreases with multitasking, while the latter increases. Overall job satisfaction, satisfaction with career opportunities, tasks, application of skills, training, supervisor, and working atmosphere rise with multitasking but point estimates are about half as large as for health problems. Satisfaction with working hours and equipment are unaffected, satisfaction with income and physical working conditions decrease with multitasking. Hence, non-monetary compensation is rather small. Similarly, monetary compensation exists but decreases over time. The trade-off between satisfaction/wage and work-related mental health requires a thorough rethinking of job design and mental health problems prevention strategies. Particular attention should be paid to employees in jobs with a high number of interactive tasks, especially when customers' cooperation is important but difficult to obtain.

This paper shows that job design is related to mental health at work. A word of caution is necessary, as the associations analyzed are not causal. This is left for future work. Nevertheless, a back of the envelope calculation suggests that an increase in multitasking as it occurred from 2006 to 2012 (roughly) is associated with 108,000 additional employees suffering from burnout. Increased absenteeism and presenteeism leads to an estimated loss in gross value added of € 1.3 billion. Direct health care expenditures for burnout treatment, indirect costs for co-morbidity, early retirement, and the reduction in quality of life should be added to complete this picture but data is scarce. Further research also in other fields needs to lay the ground for assessing the individual, economic, and societal costs of multitasking regarding work-related mental health problems.

CHAPTER 3

The causal effect of multitasking on work-related mental health – the more you do, the worse you feel

3 The causal effect of multitasking on work-related mental health – the more you do, the worse you feel

3.1 Introduction

When IBM's supercomputer Deep Blue won against chess grandmaster Garry Kasparov in 1997, humans still conserved the advantage of adaptation: Deep Blue was a master in chess but would not have been able to play a simple game such as noughts and crosses without being re-programmed (Hassabis, 2017). In March 2016, Google DeepMind's AlphaGo bet the world's best player Lee Sedol at go, a complex Chinese board game. Contrary to Deep Blue, AlphaGo is a learning algorithm that could train, learn from mistakes and develop new strategies. As artificial intelligence becomes reality, people ask themselves what it will do to mankind. Understanding how it will change human beings' life is closely related to philosophical questions about the place of the human being in the universe, the role of human beings in society, and their identity (e.g. articles in The Guardian, MinnPost, Wirtschafswoche, Zeit online).

Before attempting to answer these questions, it is necessary to understand what present technology, i.e. current production and information technology as used throughout developed countries, does to human beings. We know for example that technological change has heterogeneous effects on the demand for skilled and unskilled labor. According to the skill-biased technological change literature, unskilled jobs are substituted by technology and skilled jobs are complemented. A recent strand of literature proposes that work tasks are the relevant unit for the substitution. Routine tasks can be expressed in computer language and are therefore substitutable. Non-routine tasks cannot be written in "if-then" language and are complemented by technology. Technological change decreases the demand for routine tasks and increases the demand for non-routine tasks (Autor et al., 2003, Spitz-Oener, 2006, Goos and Manning, 2007, Autor et al., 2008, Dustmann et al., 2009, Autor and Handel, 2013). Technological change is also related to organizational change: it alters the way work is done (e.g. Spitz-Oener, 2008, Autor and Dorn, 2009). In particular, people perform more tasks at work (Spitz-Oener, 2006, Antonczyk et al., 2009, Pikos and Thomsen, 2016). In the job design literature, the number of different tasks carried out at work is called multitasking and is the opposite of specialization. As chapter two shows, multitasking is related to worse work-related mental health (emotional strain, emotional exhaustion, burnout) but the analysis remains exploratory. Bias may arise from reversed causality or self-selection into multitasking.

The present paper aims at investigating whether this relationship is causal by using technological change as an instrument for multitasking. Technological change facilitates the development of task complementarities (Lindbeck and Snower, 2000). Efficiency gains in performing one task can be carried over to another task. Multitasking is an appropriate job design to exploit these complementarities. Work content and processes change when new production or information technology is adopted. Assuming that technology adoption is decided upon by the firm and is hence exogenous to the employee, technology adoption generates exogenous variance in multitasking. This allows to analyze the causal effect of multitasking on work-related mental health. The data come from two cross-sectional surveys covering the German working population in 2006 and 2012.

Production technology adoption and information technology adoption are significantly associated with higher multitasking. There are differences across manual and cognitive tasks. In general, production technology adoption has larger associations with manual multitasking and information technology adoption with cognitive multitasking. There is evidence for a causal effect of multitasking on work-related mental health using both instruments. With the production technology instrument, general multitasking increases mild to medium severe work-related mental health problems by around 0.2 standard deviations. This is driven by non-routine manual and routine cognitive multitasking. With the information technology instrument, effects are larger (around 0.2 to 0.4 standard deviations) and also significant for burnout. Cognitive tasks are driving this finding. The increase in multitasking from 2006 to 2012 led to a loss in gross value added through absenteeism and presenteeism of € 2.7 million.

The remainder of this paper is structured as follows: section 3.2 gives an overview over the relevant literature. Section 3.3 is dedicated to data, section 3.4 explains the methodology. Results are presented in sections 3.5 and 3.6 and discussed in section 3.7. The last section concludes.

3.2 Related literature

Multitasking as a job design is the opposite to specialization. Specialized workplaces are narrow and demand only one task at the extreme. Focusing on one task exploits intratask learning: over time, repetition increases efficiency in performing the task. The concept roots in Adam Smith's pin factory example and was used widely in the twentieth century (Taylorism). Multitasking means carrying out different tasks and exploits intertask learning: knowledge acquired at performing task a is used to more efficiently perform task b (Oldham and Hackman, 2010). Multitasking is one consequence of the reorganization of work which was documented in case studies first and from the 1990s onwards in representative studies for Japan ("Toyota model"), the U.S., and Europe. The reorganization implies delegation, team work, job rotation, and multitasking (e.g. Aoki, 1988, Osterman, 1994). This organizational change is skill-biased because delegation, job rotation, and multitasking increase the demand for higher skilled labor. Therefore, skill-biased organizational change benefits higher skilled workers at the expense of lower skilled workers. Multitasking began to become popular with the turn of the century. See Lindbeck and Snower (2001) for an overview of the reorganization of work literature.

SBOC is related to skill-biased technological change (SBTC). Technological change has different impacts on employees along the skill distribution. It complements the skills and tasks performed by highly skilled people but substitutes lower skilled jobs. The computerization of the workplace for example replaced many simple production line jobs but complemented data analysts' work. Taking a closer look at this substitution process reveals that "skill" might not be the relevant factor. Beginning with Autor et al. (2003), a smaller unit has become the focus of attention: tasks. Not the skill level of the worker matters for the substitution process but the nature of the work performed. In principle, anything that follows a rule-based logic can be substituted. This is generally the case when work processes are sufficiently well understood to be expressed in computer language ("if-then" language). Computerization thus substitutes routine tasks ("repetitive" tasks) and complements non-routine tasks ("complex" tasks). The task literature largely focuses on employment and wage developments of single task categories (routine versus non-routine, sometimes distinguished further into manual and cognitive; e.g. Autor et al., 2003, Spitz-Oener, 2006, Goos and Manning, 2007, Autor et al., 2008, Dustmann et al., 2009, Autor and Handel, 2013) but has paid little attention to the inseparability of different tasks (exceptions are Spitz-Oener, 2006, Antonczyk et al., 2009, Pikos and Thomsen, 2016). This is problematic because jobs usually consist of more than a single task. Demand changes from routine to non-routine tasks do hence not necessarily substitute whole jobs.[1] When technological change substitutes certain tasks and complements others, jobs are partially substituted and complemented and need to be redesigned. The case study in Autor et al. (2002) illustrates managerial discretion in re-bundling non-substitutable tasks into either simpler (specialization) or more complex jobs (multitasking). When there are intertask complementarities, multitasking is an attractive design.

Lindbeck and Snower (2000) and Boucekkine and Crifo (2008) model the transition to multitasking with technological change (technological and informational task complementarities) and rising levels of education (ability to multitask and taste for multitasking) as the driving forces. According to Lindbeck and Snower (2000), technological change results in two task complementarities: technological and informational. The first arises from advances in production technology that make machines more versatile and re-programmable (adaptable). This in turn increases the task scope of the worker who needs not only to operate the machine but also to adopt it. The second task complementarity comes from advances in information technology that make access to information easier and cheaper. Interactions with clients become faster and communication increases. This favors decentralization of decision making, team work, and job rotation – all of which increase multitasking. Rising levels of education make workers more able but also more willing to do multitasking. Education does not only improve particular skills ("capital deepening") but also the ability to acquire different skills ("capital widening"). Hence, workers have

[1] Not taking this into account may be one reason for the controversy raised by Frey and Osborne (2013) who find that 47% of the U.S. employment is at risk of computerization.

the ability to multitask. Finally, more educated workers have a preference for multitasking (e.g. more variety, challenges).

Hackman and Oldham (1976) give a motivation for multitasking from the firm's perspective: they link skill variety to intrinsic motivation. In their Job Characteristics Model (JCM), skill variety is one of five factors that are related to high intrinsic motivation, job satisfaction, low absenteeism, and performance. Analyzing simplified jobs, Herzberg (1966, 1976) arrives at a similar conclusion: enriched jobs can increase intrinsic motivation. Looking at multitasking from this side, employee engagement is the main goal. Engagement is a construct from work psychology that emerged as a positive counterpart to burnout (Schaufeli et al., 2002, Zhang et al., 2007, Maslach et al., 2001 and 2012).

Burnout is a mental health problem that arises in the context of work (Maslach and Jackson, 1981 and 1984). It consists of tree components: emotional exhaustion, cynicism, and reduced professional efficacy. A common framework to analyze burnout is the Job Demands and Resources Model (JD-R) where adverse health outcomes develop from an imbalance between demands and resources (Demerouti et al., 2001, Peterson et al., 2008). At work, an individual experiences strain from job demands, e.g. from a high workload or a narrow time frame. Up to a certain point, she can deal with this strain by using her job resources, e.g. receiving support from colleagues. When job demands increase, accumulate over time and when resources are depleted, fulfilling work requirements becomes more and more difficult and energy-demanding. Psychological strain, for example in patients' care, from supervisors or colleagues, plays an important role in the development of emotional exhaustion. The individual tries to cope with her exhaustion by distancing herself and adopting a cynical attitude towards work and its requirements but also towards customers, herself, and the company. As exhaustion and cynicism increase, the individual is less and less able to fulfill her work requirements. This reinforces exhaustion and cynicism: perceiving the loss in efficacy entails a higher effort to keep up (exhaustion) and more cynicism when failing to do so.

Coming from Herzberg (1966, 1976) and Hackman and Oldham (1976), multitasking is associated with engagement and lower burnout. Yet, chapter two documents that multitasking is related to increased work-related mental health problems such as emotional strain, emotional exhaustion, and burnout. The driver of this association appear to be interactive tasks, i.e. tasks that require interaction with other human beings. This is in line with Hasselhorn and Nübling (2004) who find that mental health is lower in occupations depending on cooperation with people whose cooperation is often missing (e.g. physicians/nurses and patients, teachers and students). The aim of the present paper is to investigate whether this association is causal.

3.3 Data

Burnout diagnosis is not straightforward. In medicine, burnout is classified in category Z73 as one of several "problems regarding difficulties in coping with life" in the International Classification of Diseases (ICD). Health insurance data is hence not very helpful. Most studies in (work) psychology use validated scales such as the Maslach Burnout Inventory or the Oldenburg Burnout Inventory. These scales are usually administered to narrow study populations, and do not form part of large scale surveys. Surveys often include self-reported mental health but seldom work-related mental health. An exception are the Qualification and Career Surveys 2006 and 2012. They were designed in 1979 to cover topics missing in official statistics (professional career developments, qualification, and working conditions) and are since run every sixth year. Work-related mental health was first included in 2006. The Research Data Centre of the German Federal Institute for Vocational Training (*Bundesinstitut für Berufsbildung*, BIBB) and the Federal Institute for Occupational Safety and Health (*Bundesanstalt für Arbeitsschutz und Arbeitsmedizin*, BAuA) sample 20,000 individuals in both 2006 and 2012. Each cross sections is representative of the German working population (Rohrbach-Schmidt, 2009, Rohrbach-Schmidt and Hall, 2013).[2]

In the surveys' health section, participants state whether they frequently experienced "burnout" (2006) and "emotional exhaustion" (2012) during or immediately after work in the last 12 months. They also provide information on whether they consulted a physician due to this. Taking physician consultation as an indicator for a more severe health problem, the corresponding outcomes equal 0 if the health problem does not exist, 1 if burnout/exhaustion is reported but no physician was consulted, and 2 if a physician was consulted. A third outcome is taken from a section on working conditions where information on the degree of emotional strain at work is provided (often, sometimes, rarely, never; coded from 3 to 0). Emotional strain has a similar but mild wording than emotional exhaustion. A fourth outcome is a combination of strain and burnout/exhaustion ranging from 0 to 5. All outcomes are standardized for the analysis. When work-related mental health problems exist, individuals can react in two ways: take sick leave (absenteeism) or go to work despite being sick (presenteeism). Binary information on both is available in the data (1: yes, 0: no).

The multitasking measure is constructed as the number of different tasks participants often perform at work. The following list of complaints is read out to them and they state whether they carry out a task often, sometimes or never.[3]

[2]"Working" is defined as doing paid work at least ten hours a week. Participants need to be older than 15, may currently interrupt their work for a maximum of three months but may not do voluntary work or be in their initial training.

[3]The list contains two more tasks, "working with computers" and "using the Internet or editing e-mails (2012 only)", which are generally carried out jointly with another tasks.

1. manufacturing, producing goods and commodities
2. measuring, testing, quality control
3. monitoring, control of machines, plans, technical processes
4. repairing, refurbishing
5. purchasing, producing, selling
6. transporting, storing, shipping
7. advertising, marketing, public relations
8. organizing, planning and preparing work processes (not own)
9. developing, researching, constructing
10. training, instructing, teaching, educating
11. gathering information, investigating, documenting
12. providing advice and information
13. entertaining, accommodating, preparing food
14. nursing, caring, healing
15. protecting, guarding, patrolling, directing traffic
16. cleaning, removing waste, recycling

The task literature commonly groups single tasks into three to five categories according to their routine/non-routine nature and their manual/cognitive skill requirements (e.g. Autor et al., 2003 for the U.S., Spitz-Oener, 2006 and 2008 for Germany). I use the five task category operationalization: non-routine manual, routine manual, routine cognitive, non-routine interactive and non-routine analytic. Table 3.1 shows the categorization.

Table 3.1: Task categories

category	tasks
non-routine manual	repairing, refurbishing entertaining, accommodating, preparing food nursing, caring, healing protecting, guarding, patrolling, directing traffic cleaning, removing waste, recycling
routine manual	manufacturing, producing goods and commodities monitoring, control of machines, plans, technical processes transporting, storing, shipping
routine cognitive	measuring, testing, quality control purchasing, producing, selling gathering information, investigating, documenting
non-routine interactive	advertising, marketing, public relations training, instructing, teaching, educating providing advice and information
non-routine analytic	organizing, planning and preparing work processes (not own) developing, researching, constructing

Task categories according to Spitz-Oener (2006) and Pikos and Thomsen (2016). Data sources: BIBB/BAuA. Own table as in chapter two.

The surveys contain basic sociodemographic and company information. The analysis is limited to 18 to 65-year-old German nationals who are neither self-employed nor employed in the public sector. Helping family members and individuals who do not provide their tasks or occupation code are excluded. This leaves around 26,000 observations.

3.4 Estimation procedure

The relationship between multitasking and work-related health outcomes can be formalized as in equation 3.1, where Y_i is a standardized variable (combined, emotional strain, emotional exhaustion, burnout) for individual i's health. $multitasking_i$ measures the number of different tasks (1 to 12) or different tasks within categories (as in table 3.1). $\mathbf{X}_i$ is a vector of control variables, α is a constant, and u_i the error term. $\mathbf{X}_i$ includes only variables which should be unaffected by technological change (survey dummy, basic individual and company characteristics, see table A3.1).[4] For the binary outcomes absenteeism and presenteeism, equation 3.1 is a linear probability model.

$$Y_i = \alpha + \beta multitasking_i + \mathbf{X}_i'\delta + u_i \tag{3.1}$$

Estimating equation 3.1 with OLS gives the association between multitasking and work-related mental health, $\hat{\beta}$. $\hat{\beta}$ is biased if there is reversed causality, e.g. employees with worse mental health doing more tasks, or selecting into multitasking, e.g. through job crafting. To identify a causal effect, exogenous variation in multitasking is needed. In principle, any of the four factors identified by Lindbeck and Snower (2000) can generate this variation. Measures for advances in production and information technology are available in the data.

In a section labeled "Changes in the last two years", participants state whether new manufacturing/process technologies, new machines/equipment, or new computer programs were introduced in their immediate working environment. The first two items provide a measure for changes in production technology, the last item for changes in information technology. The usage of both instruments relies on two data related assumptions. First, to eliminate the endogeneity arising from selection, it is necessary to assume that the firm and not the individual worker decides on technology.[5] In this case, the decision whether or not to adopt new technology is exogenous to the worker except for selection into more or less technology driven companies (which NACE sectors could inform about to some degree). Second, it is necessary to assume that the time frame between the measurement of instrument and outcomes is sufficient for a) firms to alter job design (transition from specialization to multitasking) and b) individuals to develop and observe work-related mental health problems (in response to multitasking). Individuals report work-related mental health problems for the last 12 months before the interview and technological change in the company for the last 24 months. The distance between measurement of health and technology can be very small and the ordering could be reversed. But even if mental health is measured before tech-

[4]One could be concerned that there is bias from unobserved variables, e.g. from working hours or tenure. Including these variables and their squares into the estimation, decreases the coefficients of interest somewhat but not substantially (see table A3.2 in the appendix). Another concern are employees who change their job in response to technology adoption. If an individual has a strong preference against new technology that her company introduces, she might change to another company that does not adopt new technology. Individuals usually restrict their search, e.g. to a geographic area, and identifying such a company takes time and resources. Most people find it easier not to change employment (preference for status quo, cognitive bias or behavioral inertia). Even if some people do change – assuming they change because their work-related mental health is more vulnerable and would suffer if they stayed – this should downward bias the results. Job demands and resources are not included as regressors. There is an extensive literature mostly from work psychology showing which demands and resources are related to burnout. The theoretical framework is the Job Demands and Resources model of Demerouti et al. (2001) and Peterson et al. (2008). Job demands are factors that put strain on the employee such as a high workload or deadline pressure. Job resources are for example leeway of decision making regarding workload, schedule, or breaks and good collaboration with colleagues. When job demands outweigh job resources, burnout can arise. Demands and resources play a central part for work-related mental health but are excluded from the vector of control variables because they might be affected by technological change, too.

[5]Some workers may still have some leeway of deciding whether or not to adopt a particular technology in their specific job.

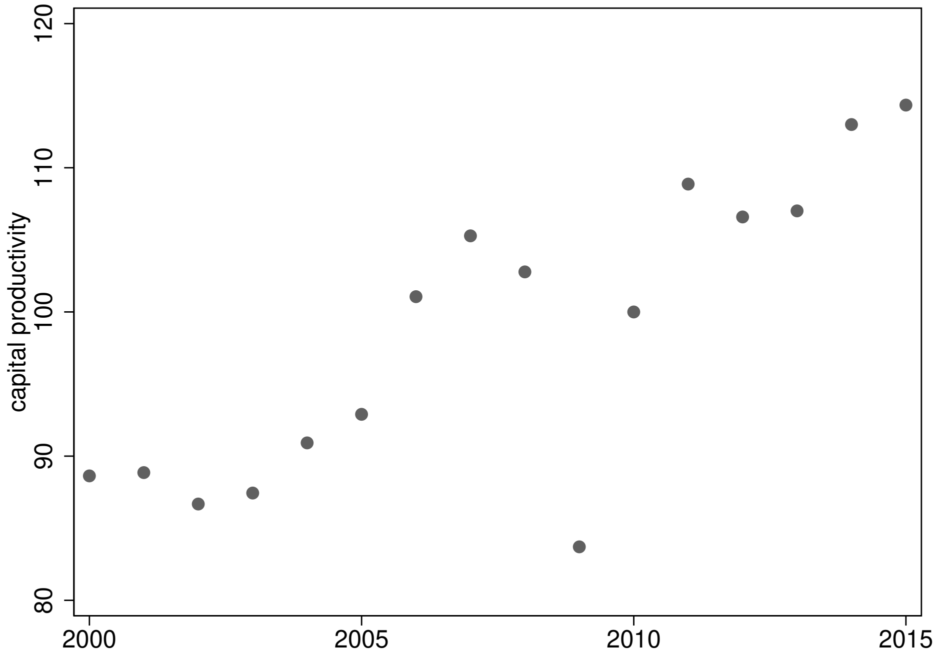
nological change, organizational change and job re-design usually occur before the actual introduction of technology. More information on the decision taking and timing of technology adoption would be helpful but is not available in the data.

Two assumptions are necessary for instrumental variables: relevance and exclusion restriction. Why should technology adoption be relevant for multitasking? The theoretical support for this comes from Lindbeck and Snower (2000) and Boucekkine and Crifo (2008) who identify technological change as a driver of the transition from specialization to multitasking. New technology demands more multitasking as production technology is more versatile and as information technology makes access to and exchange of information easier (see section 3.2). This results in technological and informational task complementarities which can be exploited with multitasking. Of course, technology adoption is only a convincing instrument if it really changes job design. In principle, new technology could simply replace depreciated capital without introducing any changes to the firm. If, on the other hand, new technology substantially changes the way work is done, this should affect productivity. Figure 3.1 depicts capital productivity over time in manufacturing as an index with 2010 as base year. For the participants of the 2005/06 survey, the technology adoption question refers to changes since 2003/04. Participants of the 2011/12 survey were asked about changes since 2009/10. Capital productivity increased in both time periods. There is hence reason to regard technological changes during that time as having an impact on firms and their job design. This is confirmed empirically in section 3.5. Technology adoption is significantly associated with multitasking in the first stages.

The exclusion restriction stipulates that technology adoption has no direct effect, i.e. influences work-related mental health only through multitasking. There are certainly people who feel stressed by new technologies but this is in general not due to the technology itself but the change accompanying the introduction of new technology. Individuals need to learn how to use the new technology, how to react to problems, and they might need to change established work routines. This broadens their task scope (multitasking). The stress they might feel from this change does not have its origin in the technology itself but in the resulting increase in multitasking.

Table 3.2 shows the percentage of the German working population experiencing the introduction of production (PT) and information technologies (IT) in their immediate working environment. 55% report new PT and 48% the adoption of new IT. Technological change was higher in 2006 than in 2012. The difference is around 4 percentage points for PT and 7 percentage points for IT. Production technology adoption differs across company size and sector (figure 3.2). It is most common in the manufacturing sector (70%) and lowest in the service sectors (commerce, hotels, finance, real estate, administration). More than 60% of the employees in companies with 100 and more employees report new production

Figure 3.1: Capital productivity in manufacturing



Index numbers, 2010=100. Data source: Volkswirtschaftliche Gesamtrechnungen – Inlandsprodukt-berechnung – Detaillierte Jahresergebnisse. Destatis 2016. Own figure.

technology. 45% of the women face new PT in their immediate working environment. This share is 20 percentage points higher among men. Middle aged workers (30 to 49) are slightly more often exposed to new PT. Adoption increases slightly over the level of education to 60% for medium plus educated employees but only 40% of higher educated employees experience new PT.

Information technology adoption is highest in the finance sector and lowest in construction, agriculture, fishery, and mining (figure 3.3). Adoption increases with company size and is largest in huge companies with 500 and more employees (60%). The gender difference is smaller than for PT adoption: every second man faces new IT, the share for women is around 44%. Adoption is 50% for all age groups except the youngest. Less than 40% of the employees under 30 report new IT. Medium plus and higher educated employees are more often exposed to new IT (60%).

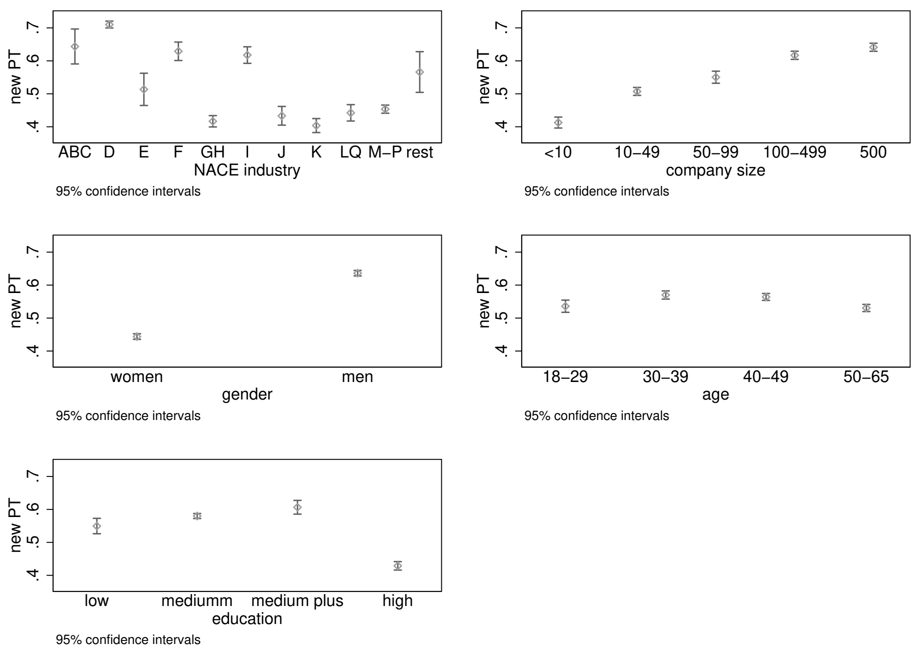
Both figures suggest that technological change is not random across the working population but differs across industries, company size, age, gender, and education. Instrumenting multitasking with PT/IT adoption in the full sample might still deliver somewhat biased estimates if there is selection into certain sectors or companies. Focusing on subsamples in which adoption should be (more) random reduces the sample to one industry, one company size, and one level of education only. Numbers of observations decrease rapidly which is problematic as IV is a data hungry method. To have sufficient power, I use the full sample first and control for company and individual characteristics (section 3.5). Then, I focus on the smaller subsamples (section 3.6).

Table 3.2: Production and information technology adoption in %

	all	2006	2012
PT	55.2	57.3	53.5
IT	47.6	51.8	44.3

Production technology (PT): introduction of new manufacturing/process technologies or new machines/equipment in the immediate working environment. Information technology (IT): introduction of new computer programs (excluding updates) in the immediate working environment. Data sources: BIBB/BAuA.

Figure 3.2: Production technology adoption by company and individual characteristics



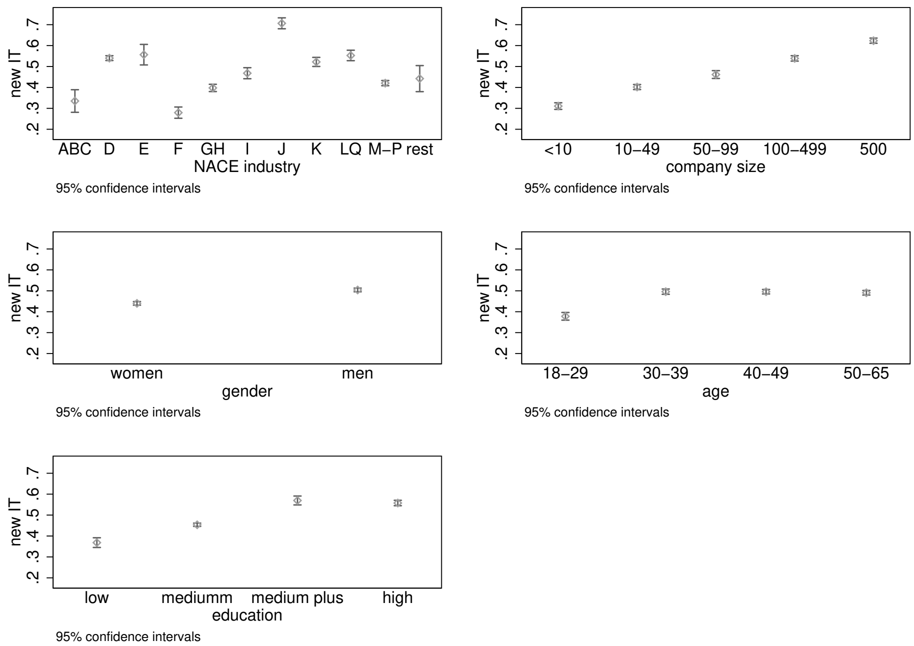
NACE industries: ABC: Agriculture, fishery, mining, D: Manufacturing, E: Energy & water supply, F: Construction, G&H: Commerce and hotels, I: Transport, J: Finance, K: Real estate etc., L&Q: Public administration, M-P: Public & private services, rest not elsewhere allocated. Data sources: BIBB/BAuA. Own figure.

3.5 Full sample results

3.5.1 Descriptives and general multitasking

Figures 3.4 and 3.5 show multitasking by PT and IT adoption. Employees who experienced production technology adoptions perform 0.3 standard deviations more tasks than those who did not. This is due to large differences in non-routine manual tasks (0.25 standard deviations) and routine manual tasks (0.6 standard deviations). They perform more routine cognitive and non-routine analytic tasks, too, but the

Figure 3.3: Information technology adoption by company and individual characteristics

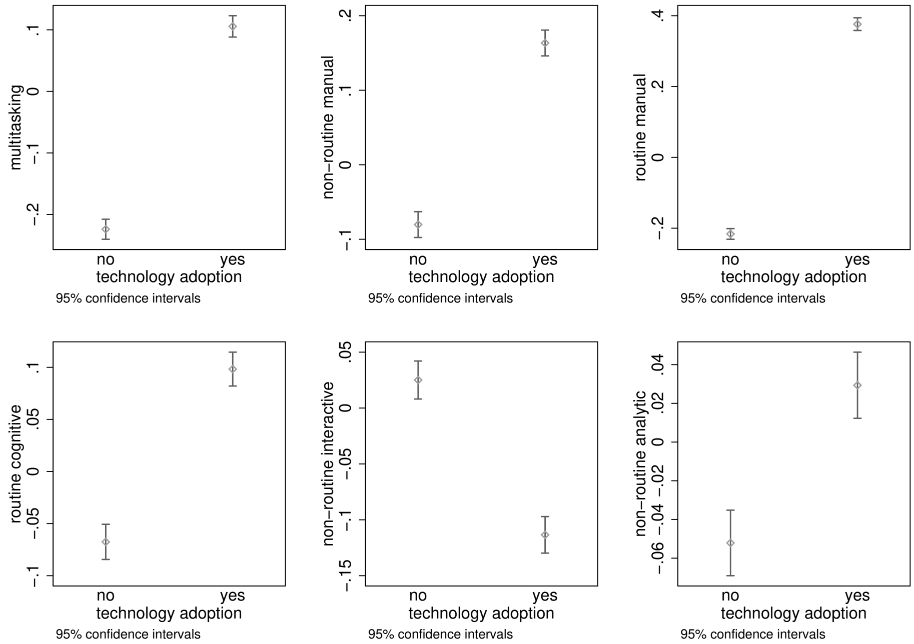


NACE industries: ABC: Agriculture, fishery, mining, D: Manufacturing, E: Energy & water supply, F: Construction, G&H: Commerce and hotels, I: Transport, J: Finance, K: Real estate etc., L&Q: Public administration, M-P: Public & private services, rest not elsewhere allocated. Data sources: BIBB/BAuA. Own figure.

differences are smaller (0.15 and 0.08 standard deviations). PT adoption is related to fewer non-routine interactive tasks (about 0.15 standard deviations). General multitasking is 0.25 standard deviations higher among employees facing IT adoption but this is driven by differences in cognitive tasks (figure 3.5). Employees with IT adoptions report about 0.28 standard deviations higher multitasking in routine cognitive tasks. The difference in non-routine analytic tasks is 0.22 standard deviations and around 0.18 standard deviations in non-routine interactive tasks. Non-routine manual tasks are lower (0.18 standard deviations). There is no significant difference by IT adoption for routine manual multitasking.

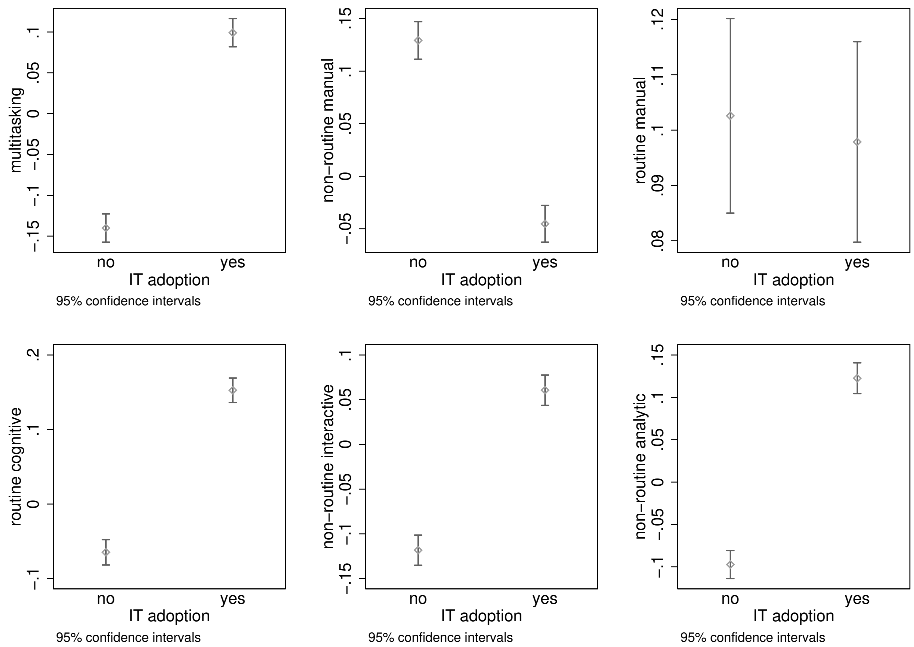
Table 3.3 displays OLS results in the first panel and IV results with both instruments in the second and third panel. First stage coefficients and their t-statistics can be found at the bottom of the table. A rule of thumb is that the first stage is weak when the F-statistics of the excluded instrument is below ten (squared t-statistic in the single instrument case). Controls for company sector (base: manufacturing) and size (base: 10-49 employees), gender, age (continuous), and level of education (base: medium) are included in all models. In OLS, multitasking is significantly associated with work-related mental health problems. The coefficients are larger for milder conditions (emotional strain) than for burnout. Turning to the first stages, the adoption of new technology is associated with an increase in multitasking of around 0.3 standard deviations. The coefficient's t-statistic ranges from 16 (only one year available) to 23. New

Figure 3.4: Multitasking by production technology adoption



Data sources: BIBB/BAuA. Own figure.

Figure 3.5: Multitasking by information technology adoption



Data sources: BIBB/BAuA. Own figure.

IT is associated with an increase in multitasking of around 0.26 standard deviations. The t-statistic is between 9 and 16. Both instruments are hence relevant for multitasking.

Using PT introduction as an instrument gives larger multitasking coefficients in the second stage than in OLS. Standard errors increase by a factor of 5 to 6. The estimate for burnout is insignificant and not that much larger than in OLS. The multitasking coefficient for exhaustion increases by a factor of 2.5 compared to OLS. Multitasking increases strain by 0.26 standard deviations and exhaustion by 0.21 standard deviations. Absenteeism and presenteeism due to burnout/exhaustion increase by 5 and 9 percentage points. Given the average prevalence of 11% and 19%, the relative increase is around 45% in both cases.

With IT adoption as an instrument, all second stages are highly significant. Coefficients are larger than in OLS and also larger than with the PT instrument. The point estimate for burnout (0.253) is larger than the one for exhaustion (0.181). Multitasking increases strain by 0.43 standard deviations, absenteeism by 6 percentage points, and presenteeism by 9 percentage points. All in all, multitasking worsens work-related mental health significantly. The impact is more severe if the increase in multitasking occurs due to IT adoptions (significant point estimate for burnout, larger estimate for strain). The following subsection analyzes whether certain task categories are driving these results.

Table 3.3: Multitasking estimates for work-related mental health outcomes

	combined	strain	exhaustion	burnout	absenteeism	presenteeism
OLS						
multitasking	0.171***	0.177***	0.082***	0.059***	0.019***	0.039***
	(0.008)	(0.008)	(0.010)	(0.011)	(0.002)	(0.004)
constant	-0.399***	-0.407***	-0.232***	-0.141***	0.036***	0.190***
	(0.038)	(0.039)	(0.048)	(0.049)	(0.012)	(0.021)
IV PT						
multitasking	0.275***	0.261***	0.213***	0.089	0.050***	0.087***
	(0.043)	(0.044)	(0.058)	(0.056)	(0.014)	(0.024)
constant	-0.400***	-0.407***	-0.227***	-0.142***	0.035***	0.192***
	(0.038)	(0.040)	(0.049)	(0.049)	(0.012)	(0.021)
IV IT						
multitasking	0.435***	0.430***	0.181**	0.253**	0.064***	0.091***
	(0.064)	(0.066)	(0.075)	(0.102)	(0.021)	(0.032)
constant	-0.408***	-0.416***	-0.247***	-0.136***	0.034***	0.186***
	(0.040)	(0.041)	(0.049)	(0.050)	(0.012)	(0.021)
N	23755	23797	13281	10490	23777	13313
			first stage IV PT			
new PT	0.357	0.357	0.346	0.369	0.357	0.347
t-statistic	23.25	23.28	16.58	16.42	23.25	16.62
			first stage IV IT			
new IT	0.245	0.246	0.270	0.211	0.245	0.271
t-statistic	15.85	15.91	12.86	9.21	15.87	12.92

Standardized dependent variable given in column header (absenteeism, presenteeism: binary). Combined: emotional exhaustion, burnout and/or emotional strain. Models include controls for age, gender, industry and company size. IV PT: production technology adoption as instrument. IV IT: information technology adoption as instrument. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

3.5.2 Multitasking within task categories

Multitasking in non-routine manual tasks is significantly associated with worse work-related mental health in OLS (table 3.4). Coefficients are rather small and below one standard deviation even for emotional strain. New PT is significantly associated with an increase in multitasking of 0.26 standard deviations. The t-statistic is between 12 and 18. In the corresponding second stage, multitasking significantly increases strain by 0.35 standard deviations and exhaustion by 0.275 standard deviations. The point estimate for burnout is insignificant. Absenteeism and presenteeism increase by 7 and 11 percentage points which is somewhat larger than the effects for multitasking in general. As figure 3.5 suggests, new IT is associated with a reduction in non-routine manual multitasking but this reduction is small (0.04 standard deviations). The coefficient is significant but the t-statistic is below 3. Since the first stage is weak, no second stage is reported.

Table 3.4: Non-routine manual multitasking estimates for work-related mental health outcomes

	combined	strain	exhaustion	burnout	absenteeism	presenteeism
OLS						
non-routine manual	0.105***	0.110***	0.051***	0.033***	0.013***	0.029***
	(0.008)	(0.008)	(0.010)	(0.011)	(0.003)	(0.005)
constant	-0.411***	-0.419***	-0.243***	-0.143***	0.034***	0.184***
	(0.038)	(0.040)	(0.048)	(0.049)	(0.012)	(0.021)
IV PT						
non-routine manual	0.371***	0.350***	0.275***	0.127	0.068***	0.112***
	(0.060)	(0.061)	(0.076)	(0.080)	(0.019)	(0.032)
constant	-0.443***	-0.448***	-0.279***	-0.152***	0.028**	0.171***
	(0.041)	(0.042)	(0.051)	(0.049)	(0.013)	(0.022)
N	23755	23797	13281	10490	23777	13313
			first stage IV PT			
new PT	0.265	0.266	0.268	0.260	0.264	0.269
t-statistic	17.80	17.84	13.49	11.57	17.75	13.56
			first stage IV IT			
new IT	-0.043	-0.043	-0.041	-0.047	-0.044	-0.041
t-statistic	-2.87	-2.85	-2.04	-2.09	-2.87	-2.00

Standardized dependent variable given in column header (absenteeism, presenteeism: binary). Combined: emotional exhaustion, burnout and/or emotional strain. Models include controls for age, gender, industry and company size. IV PT: production technology adoption as instrument. IV IT: information technology adoption as instrument. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

Table 3.5 reports the results for routine manual multitasking. In OLS, routine manual multitasking is not significantly associated with any outcome. Point estimates are negative for strain and exhaustion. New PT is associated with a 0.4 standard deviations increase in multitasking. The t-statistic ranges from 17 to 26. In the second stage, routine manual multitasking increases strain and exhaustion by 0.232 and 0.179 standard deviations. Absenteeism and presenteeism increase by 4.5 and 7.3 percentage points. Effect sizes are smaller than for non-routine manual multitasking. The IT instrument fails the relevance assumption (first stages in the bottom panel). As illustrated in figure 3.5, routine manual multitasking is not significantly affected by the adoption of new IT. First stages are insignificant.

Table 3.5: Routine manual multitasking estimates for work-related mental health outcomes

	combined	strain	exhaustion	burnout	absenteeism	presenteeism
OLS						
routine manual	-0.007	-0.007	-0.009	0.013	0.000	0.005
	(0.008)	(0.009)	(0.010)	(0.010)	(0.003)	(0.004)
constant	-0.395***	-0.403***	-0.231***	-0.146***	0.036***	0.186***
	(0.038)	(0.040)	(0.049)	(0.049)	(0.012)	(0.021)
IV PT						
routine manual	0.245***	0.232***	0.179***	0.085	0.045***	0.073***
	(0.040)	(0.040)	(0.049)	(0.054)	(0.013)	(0.021)
constant	-0.511***	-0.513***	-0.317***	-0.181***	0.015	0.155***
	(0.044)	(0.045)	(0.054)	(0.055)	(0.014)	(0.023)
N	23755	23797	13281	10490	23777	13313
			first stage IV PT			
new PT	0.401	0.401	0.411	0.387	0.400	0.412
t-statistic	26.40	26.43	19.95	17.36	26.39	19.98
			first stage IV IT			
new IT	0.018	0.018	0.024	0.011	0.018	0.024
t-statistic	1.12	1.13	1.12	0.46	1.13	1.13

Standardized dependent variable given in column header (absenteeism, presenteeism: binary). Combined: emotional exhaustion, burnout and/or emotional strain. Models include controls for age, gender, industry and company size. IV PT: production technology adoption as instrument. IV IT: information technology adoption as instrument. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

Routine cognitive multitasking is associated with increases in burnout and exhaustion of about 0.05 standard deviations (table 3.6). The OLS coefficient for strain is larger (0.113). Absenteeism and presenteeism are 1 to 2 percentage points higher. New technology is associated with increases in routine cognitive multitasking of 0.2 standard deviations. t-statistics are smaller than for the earlier models (9 to 13). In the second stage, multitasking increases exhaustion and strain by 0.464 and 0373 standard deviations but is insignificant for burnout. Absenteeism increases by 9 and presenteeism by 15 percentage points (i.e. both double). New IT is significantly associated with 0.2 standard deviations increases in routine cognitive multitasking. All second stages are significant. Strain increases by 0.5 standard deviations, burnout and exhaustion increase by around 0.2 standard deviations. The coefficient for exhaustion is smaller than with the PT instrument. The same is true for the point estimates for absenteeism and presenteeism (8 and 12 percentage points). All in all, routine cognitive multitasking coefficients are larger than general multitasking coefficients suggesting a stronger relationship.

Table 3.6: Routine cognitive multitasking estimates for work-related mental health outcomes

	combined	strain	exhaustion	burnout	absenteeism	presenteeism
OLS						
routine cognitive	0.111***	0.113***	0.045***	0.055***	0.012***	0.021***
	(0.008)	(0.008)	(0.010)	(0.011)	(0.002)	(0.004)
constant	-0.403***	-0.411***	-0.237***	-0.141***	0.035***	0.188***
	(0.038)	(0.040)	(0.048)	(0.049)	(0.012)	(0.021)
IV PT						
routine cognitive	0.489***	0.464***	0.373***	0.164	0.089***	0.152***
	(0.082)	(0.083)	(0.106)	(0.105)	(0.026)	(0.045)
constant	-0.419***	-0.426***	-0.251***	-0.143***	0.032**	0.182***
	(0.041)	(0.042)	(0.051)	(0.049)	(0.013)	(0.022)
IV IT						
routine cognitive	0.526***	0.519***	0.242**	0.269**	0.077***	0.122***
	(0.082)	(0.083)	(0.101)	(0.108)	(0.025)	(0.044)
constant	-0.430***	-0.440***	-0.263***	-0.139***	0.031**	0.177***
	(0.042)	(0.043)	(0.050)	(0.050)	(0.013)	(0.022)
N	23755	23797	13281	10490	23777	13313
			first stage IV PT			
new PT	0.201	0.201	0.198	0.201	0.201	0.198
t-statistic	12.90	12.92	9.34	8.80	12.93	9.35
			first stage IV IT			
new IT	0.203	0.204	0.202	0.198	0.203	0.203
t-statistic	13.09	13.17	9.61	8.66	13.10	9.67

Standardized dependent variable given in column header (absenteeism, presenteeism: binary). Combined: emotional exhaustion, burnout and/or emotional strain. Models include controls for age, gender, industry and company size. IV PT: production technology adoption as instrument. IV IT: information technology adoption as instrument. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

The association between multitasking and work-related mental health is strongest for multitasking in non-routine interactive tasks (table 3.7). OLS coefficients are larger than for all other multitasking measures (except the routine cognitive coefficient for burnout). Despite the descriptive suggestion that PT adoption is relevant for non-routine interactive multitasking, this is not true controlling for company and individual characteristics: first stages with new PT as an instrument are insignificant (third panel). Coefficients are negative and small (0.02 standard deviations) and t-statistics are below 2. New IT is significantly associated with increases in non-routine interactive multitasking of nearly 0.2 standard deviations. t-statistics are between 9 and 13. All second stages are highly significant and comparable in size to the estimates for routine cognitive. Non-routine interactive multitasking increases strain by nearly 0.6 standard deviations and burnout and exhaustion by about 0.3 standard deviations. Absenteeism increases by 9 percentage points and presenteeism by 15 percentage points.

Table 3.7: Non-routine interactive multitasking estimates for work-related mental health outcomes

	combined	strain	exhaustion	burnout	absenteeism	presenteeism
OLS						
non-routine interactive	0.175***	0.184***	0.081***	0.045***	0.017***	0.036***
	(0.008)	(0.008)	(0.011)	(0.011)	(0.003)	(0.005)
constant	-0.367***	-0.373***	-0.217***	-0.133***	0.039***	0.196***
	(0.038)	(0.039)	(0.048)	(0.049)	(0.012)	(0.021)
IV IT						
non-routine interactive	0.587***	0.582***	0.289**	0.270**	0.086***	0.146***
	(0.090)	(0.091)	(0.120)	(0.109)	(0.028)	(0.052)
constant	-0.295***	-0.304***	-0.187***	-0.087*	0.051***	0.216***
	(0.044)	(0.046)	(0.057)	(0.053)	(0.014)	(0.025)
N	23755	23797	13281	10490	23777	13313
			first stage IV PT			
new PT	0.025	0.025	0.031	0.018	0.025	0.031
t-statistic	1.70	1.70	1.55	0.83	1.72	1.55
			first stage IV IT			
new IT	0.182	0.182	0.169	0.197	0.182	0.170
t-statistic	12.52	12.54	8.63	9.15	12.52	8.66

Standardized dependent variable given in column header (absenteeism, presenteeism: binary). Combined: emotional exhaustion, burnout and/or emotional strain. Models include controls for age, gender, industry and company size. IV PT: production technology adoption as instrument. IV IT: information technology adoption as instrument. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

Non-routine analytic multitasking is associated with worse work-related mental health in OLS but the association is weaker than for routine cognitive and non-routine interactive (table 3.8). First stage coefficients with the PT instrument are significant and around 0.1 standard deviations. The corresponding t-statistics are rather low (5 to 8). Second stages deliver comparably large coefficients that are highly significant for all outcomes except for burnout. The point estimate for strain and exhaustion is 0.74 standard deviations. Absenteeism increases by 14 percentage points and presenteeism by 30 percentage points. These estimates are – likely due to the rather low first stage coefficients – comparatively large and should be interpreted with care. New IT is associated with about 0.18 standard deviations increases in non-routine analytic multitasking (t-statistics range from 8 to 12). Multitasking is highly significant in all second stages. Point estimates are comparable to routine cognitive and non-routine interactive multitasking results.

Table 3.8: Non-routine analytic multitasking estimates for work-related mental health outcomes

	combined	strain	exhaustion	burnout	absenteeism	presenteeism
OLS						
non-routine analytic	0.093***	0.098***	0.041***	0.024**	0.007***	0.016***
	(0.008)	(0.008)	(0.010)	(0.010)	(0.002)	(0.004)
constant	-0.390***	-0.398***	-0.231***	-0.138***	0.036***	0.190***
	(0.038)	(0.040)	(0.048)	(0.049)	(0.012)	(0.021)
IV PT						
non-routine analytic	0.787***	0.743***	0.740***	0.211	0.144***	0.300***
	(0.148)	(0.147)	(0.247)	(0.136)	(0.043)	(0.103)
constant	-0.333***	-0.346***	-0.166**	-0.124**	0.048***	0.217***
	(0.048)	(0.048)	(0.066)	(0.051)	(0.014)	(0.028)
IV IT						
non-routine analytic	0.601***	0.593***	0.281**	0.293**	0.088***	0.141***
	(0.096)	(0.098)	(0.118)	(0.120)	(0.029)	(0.052)
constant	-0.365***	-0.375***	-0.230***	-0.114**	0.041***	0.194***
	(0.043)	(0.045)	(0.051)	(0.051)	(0.013)	(0.023)
N	23755	23797	13281	10490	23777	13313
			first stage IV PT			
new PT	0.125	0.125	0.100	0.156	0.125	0.100
t-statistic	8.30	8.33	4.80	7.19	8.32	4.84
			first stage IV IT			
new IT	0.177	0.179	0.174	0.182	0.178	0.175
t-statistic	11.65	11.73	8.30	8.24	11.67	8.37

Standardized dependent variable given in column header (absenteeism, presenteeism: binary). Combined: emotional exhaustion, burnout and/or emotional strain. Models include controls for age, gender, industry and company size. IV PT: production technology adoption as instrument. IV IT: information technology adoption as instrument. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

When instrumenting multitasking with production technology advances, multitasking is not significant for burnout, the most severe work-related mental health problem. With IT adoption as an instrument, multitasking is always significant also for burnout. OLS associations are generally smaller than IV estimates. For routine manual multitasking, OLS suggests an insignificant or negative relationship, while IV estimates with PT adoption are positive. Comparing the two instruments, technological task complementarities are more relevant for manual multitasking and informational task complementarities for cognitive multitasking. Second stage multitasking coefficients with the PT instrument are larger for non-routine manual than for routine manual multitasking suggesting a stronger relationship. Cognitive multitasking second stage coefficients with the IT instrument are similar and clearly drive the coefficient size for the general multitasking measure. Regarding the PT instrument, even though it matters more for manual multitasking, routine cognitive multitasking seems to be the main driver of the general measure's results regarding work-related mental health.

3.6 Subsample results

3.6.1 Subsample definitions

Figures 3.2 and 3.3 suggest that PT and IT adoption is not random across company and individual characteristics. Hence, selection into industries, companies, or education could mean selection into "treatment" (technology adoption) and this might drive the findings of the previous section. To find subsamples in which the adoption of PT/IT should be random and where estimation is still feasible, I narrow down the sample first by industry, second by company size, and third by education. First, I choose the largest industries (manufacturing with 7,300 and services with 6,200 observations). There will thus be four groups: one for each instrument in each sector. Most employees work in companies with 10 to 49 employees (6,500) but companies with 100 to 499 and 500 and more employees are also common (about 5,900 observations for each group). As shown in appendix figure A3.1, PT adoption increases with size and is most likely in companies with 100 and more employees in both manufacturing and service companies. New IT is more likely in manufacturing companies with 500 and more employees which is also the size group with most observations. For services, IT adoption does not differ significantly between companies with 100 to 499 and companies with 500 and more employees. Looking at differences across levels of education, PT adoption is lower for higher educated employees in both the manufacturing and the service sample, IT adoption is lower for low educated employees in service companies (A3.2). The final samples in which PT/IT adoption should be random given employees choices for industry, company size, and education, are hence:

1. PT 1: 3,700 low to medium plus educated in manufacturing companies with 100 and more employees (controls: gender, age, level of education, size)
2. PT 2: 1,600 low to medium plus educated employees in service companies with 100 and more employees (controls: gender, age, level of education, size)
3. IT 1: 2,500 employees in manufacturing companies with 500 and more employees (controls: gender, age, level of education)
4. IT 2: 2,300 medium to higher educated employees in service companies with 100 and more employees (controls: gender, age, level of education, size)

3.6.2 Subsample results

To detect multitasking differences by PT/IT adoption, the relationship between the instrument and multitasking is depicted for all multitasking measures in the four samples in appendix figures A3.3 to A3.6.

The difference by the instrument for general multitasking is always significant. For low to medium plus educated employees in manufacturing companies (PT 1) and in service companies (PT 2) with technology adoption in their immediate working environment, all multitasking is higher than for those without adoption (figures A3.3 and A3.4, except except non-routine interactive in PT 1). Employees reporting IT adoption in huge manufacturing companies have higher cognitive multitasking. Manual multitasking does not seem to differ (figure A3.5). For medium to higher educated employees in services, routine manual, routine cognitive, and non-routine interactive multitasking is higher when IT adoption took place (figure A3.6). The confidence intervals for non-routine manual and non-routine analytic multitasking overlap.

Nevertheless, I check all first stages in each sample. New PT is insignificant or a weak instrument for routine cognitive, non-routine interactive, and non-routine analytic multitasking in the PT 1 sample (table A3.3). t-statistics do rarely exceed 3. Hence, I report OLS and second stages for general multitasking, non-routine manual, and routine manual. For low to medium plus educated employees in service companies with 100 and more employees (PT 2), the instrument is insignificant for non-routine interactive and analytic multitasking (table A3.4). First stages in the IT 1 sample are insignificant or come with low t-statistics for all outcomes except general multitasking (table A3.5). For medium to higher educated employees in service companies with 100 and more employees (IT 2), only the first stage for general multitasking is significant and not too weak (table A3.6). t-statistics are between 4 and 5 except for the burnout model (2.6). OLS and second stages will thus be run for the following multitasking measures in each subsample:

1. PT 1: multitasking, non-routine manual, routine manual
2. PT 2: multitasking, non-routine manual, routine manual, routine cognitive
3. IT 1: multitasking
4. IT 2: multitasking

The OLS and second stage results for low to medium plus educated employees in manufacturing companies with 100 and more employees are displayed in table A3.7. There are 3,700 observations for outcomes observed in both years and 1,600 for burnout in 2006. OLS estimates with general multitasking are significant for the combined measure and strain only (0.098 and 0.133). The introduction of new PT is associated with increases in multitasking of 0.32 to 0.4 standard deviations. t-statistics are between 5 and 8. Second stage coefficients are more than 3 times larger than in OLS except for burnout, standard errors increase by 5 times or more. Multitasking increases strain by 0.349 standard deviations and exhaustion by 0.408 standard deviations at the 5% level. All other point estimates are insignificant. Non-routine manual multitasking is insignificant for all outcomes in OLS. In the first stage, new PT is associated with a 0.25 to 0.28 standard deviations increase in non-routine manual multitasking. t-statistics are between 4 and 7. Non-routine manual multitasking increases strain by 0.427 standard deviations and exhaustion by 0.402 standard deviations. These estimates are similar to the ones obtained with the general measure. OLS coefficients with routine manual are negative for the combined measure and strain (around -0.04). New PT is associated with an increase in routine manual multitasking of 0.43 to 0.48 standard deviations. t-statistics are between 6 and 9. In the second stage, multitasking coefficients become positive as in the full sample (except for burnout). Routine manual multitasking increases any work-related mental health problem by 0.273 standard deviations. IV estimates are significant at the 5% level for strain (0.257) and exhaustion (0.264). Compared to the full sample, the insignificance of any multitasking measure for burnout is confirmed in this sample (point estimates are virtually zero and much smaller than in the full sample). Coefficients for the combined measure, strain, and exhaustion are larger, while estimates for absenteeism and presenteeism are of similar size but insignificant because standard errors are up to ten times larger. This loss in estimation power comes from the reduced number of observations.

Table A3.8 shows the results for low to medium plus educated employees in service companies with 100 and more employees. Numbers of observations vary from 600 to 1,600. OLS estimates are significant for general multitasking (except burnout). New PT is associated with increases in general multitasking of about 0.6 standard deviations (t-statistics between 6 and 9). All second stages are insignificant. Point estimates for the combined measure, strain, and exhaustion are smaller than in OLS while standard errors are about 3 times larger. The coefficients for burnout (large) and absenteeism (small) turn negative. For presenteeism, the coefficient is comparable to OLS. Non-routine manual multitasking is significantly and positively related to all outcomes in OLS. First stages are similar to the general multitasking first stage (coefficients around 0.5, t-statistics between 5 and 7). Second stages are insignificant because coefficients decrease to one half or one third of the OLS size, while standard errors increase by a factor of five to six. The estimates for burnout and absenteeism are negative, the presenteeism estimate is somewhat larger than in OLS but insignificant. In OLS, routine manual multitasking is significantly associated with strain only (10% level). First stage coefficients are around 0.6 with somewhat larger t-statistics (7 to 12). All second stages are insignificant. Coefficients and standard errors change similarly to the other two multitasking measure models. Routine cognitive multitasking is significantly associated with the combined measure and strain (0.193 and 0.217) but no other outcome. New PT is associated to multitasking increases of 0.3 standard deviations. t-statistics range from 4 (burnout model) to 6. All second stages are insignificant. Compared to the full sample, no significant OLS associations are left for the routine manual and routine cognitive multitasking measure. Sample size is quite small and might not be representative of the full sample anymore. All second stage estimates are much smaller and not significant. Point estimates are negative for burnout and absenteeism.

The results for employees in manufacturing companies with 500 and more employees are displayed in table A3.9. There are between 1,100 and 2,500 observations. Multitasking is significantly associated with increases in the combined measure and emotional strain of 0.1 standard deviations. The increases in exhaustion (0.034 standard deviations) and burnout (0.037 standard deviations) are smaller and insignificant. Estimates for absenteeism and presenteeism are insignificant. The introduction of new IT is associated with an increase in multitasking of between 0.26 to 0.27 standard deviations (table A3.5). t-statistics range from 4 to 6. In the second stage, multitasking significantly increases burnout by 0.593 standard deviations but is insignificant for exhaustion and strain. The rather high coefficient should be interpreted with care due to the potentially weak first stage (F-statistic just above 10). Absenteeism increases by 16 percentage points. The burnout and absenteeism coefficients are highly significant and about twice as large as in the full sample.

Multitasking is significantly associated with worse health for medium to higher educated employees in service companies with 100 and more employees (table A3.10). There are between 800 and 2,200 observations. Strain increases by 0.259 standard deviations and exhaustion by 0.107 standard deviations. Health behaviors increase by 2.1 percentage points (absenteeism) and 5 percentage points (presenteeism). Multitasking is insignificant for burnout. The first stage coefficient is between 0.23 and 0.31 (table A3.6). t-statistics are 4 to 5 but only 2.6 in the burnout model (weak). Second stages are insignificant. Point estimates are comparable to OLS for the combined measure and strain but standard errors up to eight times larger. Coefficients for exhaustion, absenteeism, and presenteeism change sign, while the one for burnout increases by a factor of seven.

Analyzing the relationship between multitasking and work-related mental health in subsamples in which the instrument, production or information technology adoption, should be random given industry, company size, and education choice is challenging due to reduced sample size. The small samples do not always seem to be representative of the full sample, for example OLS is largely insignificant in the second and third subsamples. Small sample size is a problem in particular with the IT adoption instrument. Some first stages are still significant but with rather low t-statistics. With the production technology adoption instrument, there is some evidence for a causal effect of multitasking on emotional strain and exhaustion in the manufacturing sample.

3.7 Discussion

This paper shows evidence for a causal effect of multitasking on work-related mental health. The subsample analyses are stricter in avoiding selection into technology adoption given employees' choices on industry, company size, and level of education but this comes at the cost of reduced estimation power. OLS results in the subsamples do not seem to be overly representative of the full sample. This restricts the technical possibility to find second stage coefficients that are comparable to the full sample. While there is no strong support of a causal effect in the subsamples, there is evidence for a causal effect in the full sample controlling for individual and company characteristics.

Using production technology as an instrument, general multitasking increases mild to medium severe work-related mental health problems in both the full sample and the subsamples. This seems to be driven by non-routine manual (full and subsamples) and routine cognitive multitasking (full sample). The conservative size of the causal effect is around 0.2 standard deviations (full sample). Since one standard deviation is 2.32 tasks, this corresponds to 8.6 percentage points for an increase of one task. At a mean prevalence of 24% for exhaustion, this is a relative increase of 36%. Multitasking increased from an average 4.0 tasks in 2006 to 4.8 in 2012. During this time period, exhaustion rose by 29%. Holding the German working population constant at 27 million, an additional 2.3 million suffer from emotional exhaustion.[6] The conservative causal effects identified in the full sample with PT are 5 and 8.7 percentage points for absenteeism and presenteeism. These percentage points correspond to a one standard deviation increase in multitasking. The standard deviation is 2.32 tasks, hence the causal effects for one task are 2.2 and 3.75 percentage points. From 2006 to 2012, absenteeism increased by 1.7 percentage points and presenteeism by 3 percentage points.

Instrumenting multitasking with information technology introduction, effects are larger and also significant for the severe condition burnout in the full sample. Routine cognitive, non-routine interactive, and non-routine analytic tasks are equally contributing to this finding. The subsample first stages are insignificant or rather weak and second stage coefficients are not significantly different from zero. In the full sample, the conservative causal effect is 0.4 standard deviations for strain and about 0.2 standard deviations for exhaustion and burnout (again, one standard deviation is 2.32 tasks, hence 0.2 standard deviations corresponds to 8.6 percentage points). An average of 6.8% of the German working population report burnout. The relative effect for a one task increase in multitasking is 126%. As multitasking increased by 0.8 tasks from from 2006 to 2012, burnout doubled.

[6] 27 million is the total German working population subject to social security contribution (not including self-employed and public sector employment) from 2009. This figure increased to nearly 29 million people in 2013.

When significant, IV estimates are larger than OLS in most of the cases. As discussed in the returns to education literature (e.g. Card, 1999 and 2001, Ichino and Weber, 1999), one reason is that IV does not yield an average treatment effect (ATE) for multitasking but a local average treatment effect (LATE) for compliers. Compliers are the group of people that increases their multitasking due to the introduction of new production or information technology. Compliers would not perform more tasks if technology did not change. The average estimate in OLS includes not only compliers but also always-takers and never-takers. Always-takers always perform more tasks independently of whether or not their company introduces new production or information technology. Never-takers carry out fewer tasks and never increase their multitasking. Both groups are unaffected by technology adoption. The OLS estimates are lower because they include, first, never-takers who do not increase their tasks and hence, whose work-related mental health does not decrease, and second, always-takers who do not react as strongly to higher multitasking as compliers, i.e. their work-related mental health does not decrease that much.

According to the back of the envelope calculation at the end of chapter two, the multitasking increase from 2006 to 2012 translates into a loss in gross value added due to absenteeism and presenteeism of € 1.1 billion. This was based on OLS estimates which yielded increases in absenteeism and presenteeism of 0.6 and 0.8 percentage points. The causal effects are 2.2 and 3.75 percentage points. Based on the calculation from chapter two, one absenteeism case of 20 days costs € 4,664 and one presenteeism case of 12 days loses € 559.68. From 2006 to 2012, absenteeism increases from 10.9% by 1.68 percentage points (80% of 2.2) to 12.6%, presenteeism rises from 18.6% by 3 percentage points (80% of 3.75) to 21.6%. The additional loss from absenteeism amounts to € 2,2 billion, the additional loss from presenteeism to € 453 million. Taken together, a 0.8 task increase in multitasking as it took place from 2006 to 2012 costs about € 2.7 billion in terms of gross value added. This is more than double the amount from the descriptive analysis and its calculation (€ 1.1 billion) and does not take into account that absenteeism and presenteeism days probably increased as well. As in chapter two, individual (treatment, loss of quality of life) and welfare costs (health care, early retirement, work incapacity) should be added to complete the picture.

3.8 Conclusion

In analyzing the causal effect of multitasking on work-related mental health this paper also provides insight in the relationship between technological change and employee well-being. Multitasking decreases work-related mental health, hence it can make employees sick. Since technological change is associated with increases in multitasking, technological change can contribute to decreased mental well-being at work. Regarding the nature of technological change, production technology change is more relevant for manual multitasking, and information technology change for cognitive multitasking. This is not surprising but confirms that some types of technological change are more important for some employees than for others. What can be derived from this analysis is not that technological change is bad per se but rather that it can have adverse effects on employees' work-related mental health. The challenge is to better prepare people for the changes new technology brings to their work places and thereby reduce health problems. This is important not only from an individual perspective (loss of quality of life) but also from the firm's and from the society's point of view: firms lose through absenteeism and presenteeism (loss in productivity, efficiency, quality), society through public health expenditures, incapacity, and early retirement. Reducing adverse effects is hence a common interest. It is impossible to make any prediction what the effect of future technological changes will be but if they – as today's technological change – increase multitasking, improvements in work-related mental health can only come from reductions in other job demands or from better coping with multitasking.

Apart from these general conclusions, the paper also contributes to the task literature by showing that technological change does not necessarily substitute some task categories (routine) and complements others (non-routine) for the individual employee. Instead, technological change is associated with performing more different tasks independently of their routine or non-routine nature. This calls for paying more attention to the inseparability of tasks on the individual level and to the role job design plays in re-bundling tasks to jobs after technological change.

The study is subject to three limitations. First, it is not possible to accurately measure the time distance between technological change and work-related mental health problems as the exact timing of technological change is not recorded in the data. Taking into account that organizational change often occurs even before technological change, this should not be overly problematic to identification in general. Not finding any significant effect for the most severe work-related mental health problem, burnout, with the production technology instrument might be a hint that there was not enough time between technological change and mental health measurement. Of the three outcomes considered, burnout takes most time to develop. The first step into burnout is often emotional exhaustion, a component of burnout, for which the estimates are significant. Thus, there might not have been sufficient time after the change for the development of burnout. Another reason could lie in the second limitation: the analysis is subject to survival bias. Individuals whose work-related mental health is so deteriorated that they have to give up employment are not included in the study population. Burnout is the most severe outcome. If individuals suffering from burnout leave employment to a larger extent where production technology adoption occurred (compared to information technology adoption), the survival bias could contribute to the insignificant result with this instrument. In any case, the survival bias should bias the estimates downwards. Third, being concerned that selection of certain individuals into certain companies might drive the results, the analysis is repeated in subsamples where the adoption of technology should be close to random given employees' choices regarding industry, company size, and level of education. These subsamples become quite small and do not always seem to be representative of the full sample. Many first stages are insignificant or weak. As IV is a data hungry method, standard errors increase and most second stages are insignificant.

Nevertheless, the full sample results provide evidence for a causal relationship between rising multitasking and worse work-related mental health. Multitasking reduction could be an approach to improve mental health at work but this might entail unwanted negative consequences on for instance job satisfaction which increases with multitasking (chapter two). The lesson to be drawn from this paper is a more general one: there is a relationship between technological change and work-related mental health. Future work could shed further light on this by analyzing whether there are possible mediators to this relationship, e.g. whether job environment (demands and resources) plays a role.

Chapter 4

Education and work-related mental health – higher educated employees are worse off

4 Education and work-related mental health – higher educated employees are worse off

4.1 Introduction

Education is one of the most important factors of getting into better paying jobs. Apart from the monetary returns to education (e.g. Card, 2001, Heckman et al., 2016), there are non-monetary returns, for higher occupational prestige and less unemployment (overview in Oreopoulos and Salvanes, 2013). Benefits from education are not limited to work. There is a growing literature on health returns to education. More educated people have lower mortality, smoke less, and abuse less of alcohol (Lleras-Muney, 2005, Culter and Lleras-Muney, 2010, Kempter et al., 2011, Heckman et al., 2016). The reason for this is improved health literacy: educated people understand health relevant information and the consequences of bad health behavior better. No such protective effect of education has been documented for mental health suggesting that health literacy does not play any role (Kamhöfer et al., 2015, Dahmann and Schnitzlein, 2017).

Departing from the work and organizational psychology literature, education could be related to work-related mental health through another channel: the working environment. The working environment is important for work-related mental health as unfavorable working conditions are considered as determinants of burnout (e.g. Maslach et al., 2001). According to Demerouti et al. (2001), working conditions can be divided into factors that stress the individual (job demands) and factors that buffer adverse influences (job resources). An employee facing deadline pressure, a high workload, and frequent interruptions has high job demands. This does not automatically lead to detrimental health consequences if she can use help from colleagues and has leeway of decision making e.g. regarding the timing of different tasks, her breaks, and working hours. When demands increase or resources decrease, the resulting imbalance favors the development of work-related mental health problems. In this model, education opens access to different jobs which come with different working environment. Higher educated employees for example have more leeway of decision making (job resource) but also bear more responsibility (job demand).

This paper investigates whether there is a relationship between mental well-being at work and the level of education. The analysis is exploratory and is based on cross-sectional data from the 2006 and 2012 Qualification and Career surveys covering the German working population. Work-related mental health problems are measured in three degrees of severity (ascending): emotional strain, emotional exhaustion, and burnout. Health problems increase with level of education. Low compared to medium education is associated with lower emotional strain but not with more severe outcomes. Higher education is significantly associated with higher strain and exhaustion. The results hold when controlling for job demands, job resources, individual and job characteristics. Education is significantly related to job demands and job resources: demands and resources are lower for low educated employees and higher for higher educated employees. While low educated employees do not perceive their missing resources as stressful, higher educated employees do not only face higher job demands but also higher perceived stress from these demands. These findings suggest that there is education does not play a protective role regarding work-related mental health. On the contrary, education is detrimental for well-being at work and job satisfaction. As a means of compensation, higher education is associated with better work life balance and less atypical working times.

The remainder of this paper is structured as follows: section 4.2 introduces the related literature. Section 4.3 is dedicated to the data and section 4.4 to the empirical results. Section 4.5 discusses sources of bias, section 4.6 examines potential channels and compensation. The last section concludes.

4.2 Related literature

Studies analyzing health returns to education usually focus on mortality, physical health, or risky health behavior. Lleras-Muney (2005) shows that in the U.S., education decreases the mortality rate. According to Cutler and Lleras-Muney (2010), education increases prevention and decreases smoking and alcohol abuse in Great Britain and the U.S. They suggest cognitive ability as a channel through which education impacts health. Cognitive ability determines how information is processed and understood by individuals. Better economic resources, such as income and health insurance, and social integration can also result in better health. In Germany, Kemptner et al. (2011) document that education protects against long-term illness and work disability. The health effects Clark and Royer (2013) estimate in Great Britain are rather small.

Evidence on mental health is sparser. Kamhöfer et al. (2015) use information on parental income and instrument education by eligibility to an education subsidy ("BaFöG"). For individuals taking up university education between 1958 and 1990, they do not find any effect on mental health measured in a summary score. Dahmann and Schnitzlein (2017) instrument education with a compulsory schooling reform and distance to college for men born between 1933 and 1952. They document a positive association between years of schooling and general mental health in OLS but do not find a causal effect with IV. It is not implausible that education does not affect mental health to similar degree as it affects physical health. Better health literacy reduces bad health behavior (e.g. smoking) but does not seem to provide advantages to more educated individuals regarding their mental health.

The present paper focuses on clearly work-related mental health outcomes. The mechanism through which education can have an impact on mental health is therefore different. Education grants access to different jobs which come with different working environments. Working environments in turn matter for the development of work-related mental health problems. A common analytical framework for the job environment regarding burnout is the Job Demands and Resources model (JD-R, Demerouti et al., 2001, Peterson et al., 2008). In this model, the job environment is divided into two categories: job demands and job resources. Job demands are factors which put strain on the individual, e.g. deadline pressure or a high workload. Job resources are factors which favor an individual's engagement at work, e.g. leeway of decision making or good collaboration with colleagues. Resources can buffer the negative influence of demands to some extent. In this model, burnout arises from an imbalance between job demands and job resources: when job demands weigh more heavily than job resources, mental health at work deteriorates. The deterioration is a long process which is often imperceptible in the beginning. Burnout consists of the three components emotional exhaustion, cynicism, and personal inefficacy which develop over time and reinforce one another (Maslach and Jackson, 1981 and 1984, Jackson and Schuler, 1982). Individuals perceive the burden of job demands but believe that this will be a transitory state and that they can handle it. Good collaboration for example can help to overcome a stressful working situation when facing a deadline. As the situation persists, resources are depleted, e.g. because colleagues also suffer from deadline pressure or because work pressure increases. Individuals feel exhausted and try to cope by adopting a cynical attitude towards their work or by withdrawing from work. As this aggravates over time, the individual becomes less productive and experiences personal inefficacy. In response to this, she may increase her effort thereby becoming more exhausted. Burnout is a long-term illness that does neither develop quickly nor disappear quickly (Schaufeli and Enzmann, 1998).

The following table provides an overview of the determinants of burnout (table 4.1). Determinants are categorized into job demands, job resources, individual factors, and job factors. Important job demands are a high workload, role conflict, and pressure. Demands are not necessarily located at the job level but are also present at the organizational level (bad leadership) or the macroeconomic level (austerity). The main job resources are leeway of decision making (control, autonomy, influence, freedom) and social support. Among the individual factors associated with burnout are sociodemographic characteristics such as gender (women are affected more often) and age (burnout occurs more often at the beginning or close to the end of the career) but also personality and values. Conflicts in private life are important contributors to burnout, while recovery activities (e.g. yoga and mediation) can buffer adverse influences. Job factors such as working hours (longer hours favor exhaustion) and employment type (higher job insecurity in limited contracts) are also relevant.

Table 4.1: Determinants of burnout – literature overview

job demands	
role ambiguity/stress/conflict	Jackson and Schuler (1982), Schwab et al. (1986), McHugh et al. (2011), Basińska and Wilczek-Rużyczka (2013), Bakker and Costa (2014)
high workload	Leiter et al. (2009), Bakker and Costa (2014)
work/time/performance pressure	Gusy et al. (2010), Basińska and Wilczek-Rużyczka (2013), Bakker and Costa (2014)
conflicts at work	Lundqvist et al. (2013)
interruptions	Hasselhorn and Nübling (2004)
lack of decision making/social support	Schwab et al. (1986)
obstacles	Llorens-Gumbau and Salanova-Soria (2014)
bad leadership	Nübling et al. (2013), Ray et al. (2013)
financial austerity/shortages	Rachiotis et al. (2014)
job resources	
control	Jackson and Schuler (1982), Lundqvist et al. (2013)
autonomy	Basińska and Wilczek-Rużyczka (2013), Lundqvist et al. (2013)
influence	Lundqvist et al. (2013)
freedom	Lundqvist et al. (2013)
social support (colleagues)	Basińska and Wilczek-Rużyczka (2013), Hombrados-Mendieta and Cosano-Rivas (2013), Lundqvist et al. (2013)
feedback	Basińska and Wilczek-Rużyczka (2013), Lundqvist et al. (2013)
satisfaction/task identity	Tsigilis (2006), Basińska and Wilczek-Rużyczka (2013)
rewards	Jackson and Schuler (1982)
individual factors	
age, gender	Maslach et al. (2001)
overestimation	Sandmark and Renstig (2010)
private & work life conflicts	Lundqvist et al. (2013)
family conflicts	Sandmark and Renstig (2010), Singh et al. (2912), Piko (2006)
personality factors	Langelaan et al. (2006), Bakker and Costa (2014), Innanen et al. (2014), Laschinger and Fida (2014)
values	Leiter et al. (2009)
recovery activities	Singh et al. (2012), Bakker and Costa (2014), Lin et al. (2014)
job factors	
salary	Basińska and Wilczek-Rużyczka (2013)
career opportunitires	Basińska and Wilczek-Rużyczka (2013)
job security	Basińska and Wilczek-Rużyczka (2013)
hours	Montero-Marín et al. (2013 and 2014)
high expectations	Jackson and Schuler (1982)
atypical employment	Mantocci et al. (2014)

Note: Selected list of papers, not exhaustive.

There are two ways to measure burnout. Most studies in the fields of work psychology and organization research use a validated measure. Participants have to answer a set of questions or rate a set of statements on Likert scales which relate to an unmentioned underlying factor (e.g. emotional exhaustion). The individual items are then combined to give an overall rating of mental health. Examples are the Maslach Burnout Inventory (MBI), the Oldenburg Burnout Intenvory (OLBI) or the Burnout Clinical Subtype Questionnaire (BCSQ-36). The disadvantage of this measure is that it is time and cost intensive. Not surprisingly, nearly all burnout studies focus on a small professional group of people. The second way to measure burnout are self-reported measures. In this case, participants are asked directly for the information required, e.g. whether they feel emotionally exhausted. Self reports in general are subject to social desirability effects (e.g. Montero-Marín et al. 2014) but have also been found to be similar to objective measurements.[1] Self-reported measures can easily be incorporated in large scale surveys.

Work psychology and organization research has long focused on ill-health. This changed with the emergence of positive psychology. The focus of positive psychology is on desirable health states instead of ill-health. Along with this trend, engagement is considered as the positive counterpart of burnout (Maslach et al., 2001 and 2012, Schaufeli et al., 2002, Zhang et al., 2007). Validated measures for engagement are applied to small samples (similar to burnout). An alternative positive outcome variable which is often found in large scale surveys is self-reported life or job satisfaction. Research on job satisfaction or happiness has long been common in psychology and sociology. In economics, satisfaction experienced a rise in interest as an alternative measure of utility which complements monetary measures (such as wage). Empirical evidence that there is more to utility derived from labor than just payment comes e.g. from unemployment studies (Winkelmann and Winkelmann, 1998). There is a large literature on satisfaction showing that subjective assessments of satisfaction are correlated to observable events and actions (e.g. poor mental health, length of life, coronary heart disease, labor turnover, absenteeism, counter- and non-productive work), and that assessments are consistent over time (Clark et al., 1996 and Lévy-Garboua et al., 2004). Empirically, job satisfaction has proven to be a good indicator for quit behavior (Clark et al., 1998).

4.3 Data and descriptives

The data come from the 2006 and 2012 surveys on the German working population (Qualification and Career Survey, QaC). The surveys are run every six years and represent a cross section of the working population older than 15 years working at least ten hours a week.[2] The surveys include questions on health complaints during or on working days. Participants select complaints they experienced frequently during the last 12 months from a list which includes burnout (2006) and emotional exhaustion (2012).[3] They also state whether they consulted a physician due to the specific problem. Assuming that consultation indicates severity, the variable takes the value 0 for no burnout/exhaustion, 1 for burnout/exhaustion

[1] Härenstam et al. (2003) gathered data on individual (employee) and organizational level (managers) through observations, interviews, and questionnaires and conclude that self-reported work conditions are similar to objectively measured work conditions.

[2] Operators are the Research Data Centre of the German Federal Institute for Vocational Training (*Bundesinstitut für Berufsbildung*, BIBB) and the Federal Institute for Occupational Safety and Health (*Bundesanstalt für Arbeitsschutz und Arbeitsmedizin*, BAuA). Work is defined as a paid activity/occupation or an activity related to income. Individuals who interrupted their activity for a maximum of three months (e.g. parental leave) are included. Voluntary work and people employed as part of their initial training are excluded (Rohrbach-Schmidt, 2009 and Rohrbach-Schmidt and Hall, 2013).

[3] The surveys date back to 1979 but health first entered in 1999. Work-related mental health was not explicitly present in the health section before 2006.

but no consultation, and 2 for burnout/exhaustion and consultation. The third depended variable comes from a section on job characteristics. Individuals provide information on the degree to which they feel emotional strain at work (often, sometimes, rarely, never; coded from 3 to 0). Since the wording is very similar to emotional exhaustion, this variable is considered as a an additional work-related mental health outcome.[4] Exhaustion is more severe than emotional strain. In the literature, exhaustion is a (sometimes even considered to be *the*) component of burnout. Ranked by severity (ascending), the outcomes are: emotional strain, emotional exhaustion, and burnout. The fourth dependent variable is a constructed combined measure that sums each individual's burnout/exhaustion and strain scores and ranges from 0 to 5. Job satisfaction is considered as a positive counterpart of these health complaints. Participants state their degree of satisfaction with the job in general and several facets: income, career opportunities, hours, working atmosphere, supervisor, tasks, application of skills, further training, equipment, and physical working conditions. Answer categories are "very dissatisfied", "dissatisfied", "satisfied", and "very satisfied" (0 to 3). All dependent variables are standardized for the analysis.

The surveys were designed to close thematic gaps in the official statistics and ask very detailed questions on qualification and career. There is information on which secondary and tertiary education participants obtained.[5] The common education measure in Germany is the degree obtained: no professional training (low education), apprenticeship (medium), tertiary education (higher). There is a fourth category, "medium plus", consisting of individuals who first completed an apprenticeship, worked for some years, and later went through additional job specific training that prepares them to climb up the hierarchy ladder (technician, craftsmaster; *Techniker, Meister* in German). Years of education are not recorded in Germany but can be constructed based on school degree and educational training according to the SOEP group (2014). Using the information given in the QaC, years of schooling are calculated according to table 4.2.

[4]Work-related mental health measures are self-reported. The results could at least partially be driven by higher educated employees being more likely to answer "yes" when the list of health problems is read out to them. This is a considerable shortcoming which is, however, unavoidable. Even "objective" health data, e.g. health insurance data based on physicians' diagnoses, suffer from this limitation. Diagnosing a physical health problem such as a broken leg is very easy compared to diagnosing mental health problems where physicians ask their patient a set of questions and base their diagnosis on the patient's answers which are subject to the same self-reporting bias. A problem regarding the validity of work-related mental health measurement is potential over-reporting that uses work-related mental health problems as a reason for sickness leaves, work incapacity, or early retirement. Because work-related mental health problems are more difficult to diagnose, mis-reporting is also more difficult to detect. As extensive tools for diagnosis have reduced mis-reporting in physical health problems, mis-reporting might now move to mental health problems. While this might be true for single cases, work-related mental health problems are still highly stigmatized on average. Affected individuals are often diagnosed with physical health problems instead (e.g. back pain). Stigmatization decreases over time but was still very high in 2006 and 2012.

[5]The German school system sorts children at the age of ten into three different tracks. The low track (*Hauptschule*) finishes after the obligatory nine years. Traditionally, students can do unskilled work and access few apprenticeship programs. The medium track (*Realschule*) is completed after ten years and allows access to apprenticeship programs which combine theory in occupation specific schools and practice in companies. The high track (*Gymnasium*) takes twelve to thirteen years depending on federal state and grants access to the tertiary education system.

Table 4.2: Constructed years of education

school education	years	professional training[a]	years
no degree	7	no professional training	0
low school degree (*Hauptschule*)	9	apprenticeship	2
intermediary degree (*Realschule*)	10	additional job specific training	3
professional college degree (*Fachabitur*)	12	university degree	5
high school degree (*Abitur*)	13		

[a] Refers to highest training completed in the QaC and is broader than in the SOEP. The SOEP data distinguish between apprenticeships (1.5 years) and technical schools (2 years) and between higher technical college (3 years) and university degree (5 years). I impute 3 years for additional job specific training which is composed of the 2 years from the apprenticeship and 1 year for the additional training.

The data contain several questions on requirements at work and their frequency (often, sometimes, rarely, never). These can be divided into job demands and job resources as displayed in table 4.3. Job demands are physical and mental factors straining the individual at the work place, while job resources are strain containing factors such as leeway of decision making.

Table 4.3: Job demands and resources in the BIBB/BAuA Qualification and Career Survey

Job demands	Job resources
reach limits of own capacity	plan/schedule own work
interrupted during work	influence own workload
deadline/performance pressure	decide when to break
work fast	good collaboration
minimum performance	feel as part of community
overstrained	get help from colleagues
risk of financial loss	get help from supervisor
no timely information about future	perform tasks independently
do not receive all necessary information	
details predetermined	
repetition	

Four variables can act as either demands or resources depending on individual preferences (e.g. shaped by personality): to be a supervisor, to think through tasks before starting to work, to improve methods, and to be demanded unknown things. While some individuals may perceive these factors as challenging and motivating, others may feel additional stress due to responsibility. Job demands and resources are standardized. There is also information on whether individuals feel stressed by high demands or missing resources (binary).

The analysis is limited to German employees aged 18 to 65. Another 3,000 individuals who did not provide information on their education (school degree and further education) are excluded.[6] 30,800 individuals remain. The data is weighted according to census data. The mean age is 42 years. 54% are men. The majority acquired medium education (62.4%). 6.6% supplemented their medium with additional education (medium plus). 22.4% completed tertiary education and 8.6% have low education. For an overview of all variables including their mean, standard deviation, minimum, and maximum, see table A4.1.

Work-related mental health problems increase with level of education (figure 4.1). The difference in the prevalence of any work-related mental health problem ("combiend") between low and higher educated employees amounts to 0.6 standard deviations. The linear relationship is clearest for the least severe condition emotional strain. For emotional exhaustion, the pattern looks similar but the difference between low and higher educated employees is reduced to 0.2 standard deviations. Differences in prevalence between low and medium educated employees, between medium and medium plus, and between medium plus and higher educated employees are not statistically different as the 95% confidence intervals overlap. Nevertheless, exhaustion is higher for medium plus than for low educated employees and higher for higher educated employees than for medium educated employees. The share of burnout does not seem to differ for low, medium, and medium plus educated employees. Higher educated employees are significantly more exposed to the severest condition. The difference is around 0.2 standard deviations. Thus, while mild and medium severe work-related mental health problems clearly increase with education, only higher education versus not higher education seems to be relevant for the severest problem.

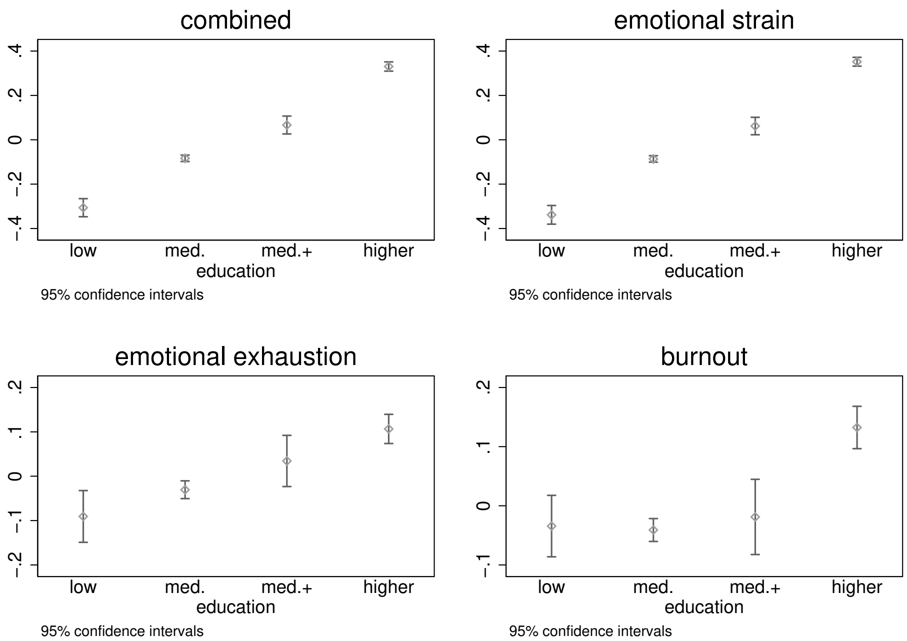
4.4 Estimation

4.4.1 Estimation procedure

The relationship between work-related health outcomes Y_i and education $Educ_i$ of an individual i is formalized in equation 4.1 where $Educ_i$ is a vector of dummy variables for low education (no professional raining), medium plus education (apprenticeship and additional professional training), and higher education (tertiary education). Medium education (apprenticeship) is the reference category. Two specifications are estimated. In the sparse one, $\mathbf{X}_i$ only contains controls unaffected by educational choice (age, gender, survey dummy). Gender is relevant since work-related mental health problems tend to be more prevalent among women (e.g. Sandmark and Renstig, 2010). Age accounts for individual time effects such as different attitudes regarding mental illness or differences in potential exposure to the work

[6]Excluded individuals are more often women, are younger, slightly less educated and satisfied with their job, work somewhat longer hours, and have longer tenure and experience. Contract types (limited versus unlimited) are not statistically different.

Figure 4.1: Standardized work-related mental health outcomes by level of education



Emotional exhaustion and burnout range from 0 (no) to 1 (yes, no physician consultation) and 2 (yes, and physician consultation). Emotional strain ranges from 1 (never) to 4 (often). Combined is a measure indicating the presence of exhaustion/burnout and/or strain (0 to 6). Data sources: BIBB/BAuA. Own calculations. See text for details.

environment. A survey dummy captures macroeconomic time effects such as a higher public perception of burnout and other work-related mental health problems in 2012. The full model adds job demands, job resources, individual and job characteristics as in table **??**. u_i is the error term, α a constant.

$$Y_i = \alpha + Educ_i'\beta + \mathbf{X}_i\gamma + u_i \tag{4.1}$$

The coefficients of interest, $\hat{\beta}$, are associations and not a causal effect of education on work-related mental health. Education itself is a choice and potentially endogenous. An underlying variable could drive both education and health outcomes, e.g. a character trait encouraging an individual to acquire higher education but also making her work-related mental health more vulnerable. A discussion on threats to causality and counter-strategies is provided in section 4.5.

4.4.2 Estimation results

Table 4.4 displays the education coefficients and the constant of sparse (1) and full models (2) for all four outcomes. Numbers of observations are between 20,000 (both years) and 7,500 (2006) due to missing information on covariates.[7]

Low compared to medium education is associated with a decrease in any work-related mental health problem of 0.215 standard deviations. The coefficient decreases to 0.091 in the full model but is still highly significant. Medium plus and higher education are associated with increases in work-related mental health problems. The coefficient for higher education is larger than for medium plus education (0.295 standard deviations and 0.195 standard deviations in the sparse model). Both coefficients roughly halve in the full model but remain highly significant. The sparse model explains 4% of the variation in the outcomes, the full model 28%. The results are very similar for emotional strain. Point estimates are slightly larger for low and higher education. Low education is associated with a decrease in strain of 0.109 standard deviations in the full model. Medium plus and higher education are associated with increases of 0.092 and 0.148 standard deviations. The full model explains 25% of the variation. Low education is not significantly associated with medium and severe work-related mental health problems: the coefficients for exhaustion and burnout are insignificant. This is not due to slightly increased standard errors but rather because point estimates are five to eight times smaller. Medium plus education is associated with higher exhaustion at the 10% level (full model: 0.071 standard deviations) but not with higher burnout. Point estimates are more than half the size for exhaustion compared to strain, while the estimates for burnout are close to zero. Higher education is significantly associated with an increase in emotional exhaustion of 0.085 standard deviations (full model, 5% level) but only significant in the sparse model for burnout (0.068 standard deviations, 5% level). Full models explain 15% of the variation in exhaustion and 8% of the variation in burnout.

[7] Of the 30,800 individuals, 20,100 provide information on outcomes, all job demands and resources, individual and job characteristics. Individuals providing all information are more likely to be women, are older and less likely to have limited contracts, work longer hours, have somewhat lower tenure but higher experience, and are slightly more satisfied with their job. Education does not differ significantly.

Table 4.4: OLS estimates for work-related mental health outcomes

	combined		strain		exhaustion		burnout	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
low education	-0.215***	-0.091***	-0.242***	-0.109***	-0.047	-0.012	-0.028	-0.000
	(0.036)	(0.032)	(0.037)	(0.034)	(0.041)	(0.040)	(0.052)	(0.049)
medium plus	0.195***	0.101***	0.195***	0.092***	0.104**	0.071*	0.016	0.015
	(0.031)	(0.027)	(0.030)	(0.027)	(0.041)	(0.039)	(0.050)	(0.048)
higher education	0.295***	0.152***	0.302***	0.148***	0.136***	0.085**	0.068**	0.056
	(0.019)	(0.021)	(0.019)	(0.021)	(0.027)	(0.033)	(0.030)	(0.035)
constant	-0.217***	-0.334***	-0.105***	-0.240***	-0.137***	-0.227***	-0.060	0.038
	(0.036)	(0.066)	(0.037)	(0.067)	(0.045)	(0.087)	(0.046)	(0.107)
N	20096	20096	20120	20120	12532	12532	7570	7570
Adj. R^2	0.042	0.284	0.046	0.254	0.018	0.153	0.001	0.083

Standardized dependent variable given in column header. Combined: emotional exhaustion, burnout and/or emotional strain. Model specifications: (1) sparse model (age, gender, survey dummy), (2) full model (job demands and resources, sociodemographic and job covariates) according to table A4.2. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

To relate the findings to the literature, the following repeats the analysis with years of education instead of level of education (table 4.5) and alternative health outcomes (table 4.6). An internationally comparable measure of education are years of education. Years of education range from 7 to 18, the mean is 13.1 and the standard deviation 2.8 years. Years of education are significantly related to all work-related mental health outcomes (table 4.5). An additional year of education is associated with an increase in any work-related mental health problem of 0.033 standard deviations. This coefficient appears to be driven by the least severe condition. The point estimate is half the size for exhaustion (0.017) and one third for burnout (0.011). The size of the education coefficients make sense compared to the results from table 4.4. Medium educated employees should complete three additional years of education compared to low educated employees on average. The low educated employees coefficient for strain is -0.109. The corresponding years of education coefficient is 0.033 implying that a three-year difference would equal 0.099. Similarly, the higher educated employees coefficient is 0.148 which is in between the four- to five-year difference range of 0.132 to 0.165 (tertiary education takes four to five years on average).

Table 4.5: OLS estimates for work-related mental health outcomes, years of education

	combined		strain		exhaustion		burnout	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
years of educ.	0.056***	0.033***	0.058***	0.033***	0.025***	0.017***	0.013***	0.011**
	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
constant	-0.985***	-0.715***	-0.893***	-0.621***	-0.472***	-0.414***	-0.240***	-0.083
	(0.056)	(0.067)	(0.057)	(0.070)	(0.069)	(0.093)	(0.076)	(0.108)
N	20096	20096	20120	20120	12532	12532	7570	7570
Adj. R^2	0.044	0.285	0.048	0.255	0.019	0.154	0.002	0.084

Standardized dependent variable given in column header. Combined: emotional exhaustion, burnout and/or emotional strain. Model specifications: (1) sparse model (age, gender, survey dummy), (2) full model (job demands and resources, sociodemographic and job covariates) according to table A4.2. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

Table 4.6 displays estimates for alternative outcomes which are not necessarily work-related in the same strict sense although the framing is still "during work or on working days".[8] Alternative outcomes are complaints that can have their origin in mental health problems (night-time sleeping disorders, general tiredness, nervousness, and the blues) but also general health and physical health. All outcomes are binary. The exception are two summary indexes, one for mental and one for physical health, which are standardized. The mental health summary measure consists of the four mental conditions sleeping disorders, tiredness, nervousness, and blues as suggested by Lohmann (2012). Similarly, physical health problems is a summary measure for the presence of shoulder, neck or back pain and problems with extremities, hips or knees.

Low education is significantly related to three of five general mental health problems (higher depression, sleeping disorders, and tiredness), and the summary mental health measure. The magnitude of this association is between 3.5 and 5.2 percentage points. Low education is not associated with nervousness, blues, and the physical health measure but with worse general health (3.6 percentage points). Medium plus and higher education are significant for physical health problems (-5.7 and -7.3 percentage points respectively). Higher education is also associated with an increase in sleeping disorders of 3.1 percentage points. The insignificance of higher education for general mental health is in line with the existing literature that often uses summary measures. As illustrated here, this might hide significant effects for components (sleeping disorders). The significant and positive medium plus and higher education coefficients for physical health are also in line with the literature.

[8] As outlined in section 4.2, burnout and emotional exhaustion arise in the context of work only, i.e. cannot occur in a work-free context. All other health problems can develop independently from the work context.

Table 4.6: OLS estimates for alternative health outcomes

	depri	sleeping	tired	nervous	blues	mental	physical	bad health
low education	0.035**	0.032**	0.052***	-0.011	0.001	0.046**	-0.025	0.036***
	(0.017)	(0.016)	(0.019)	(0.015)	(0.015)	(0.018)	(0.016)	(0.013)
medium plus	0.007	0.002	-0.003	-0.008	-0.009	0.017	-0.057***	-0.004
	(0.009)	(0.013)	(0.015)	(0.014)	(0.012)	(0.015)	(0.015)	(0.009)
higher education	0.009	0.031***	0.015	0.016	-0.008	0.010	-0.073***	-0.003
	(0.006)	(0.010)	(0.011)	(0.010)	(0.009)	(0.011)	(0.012)	(0.007)
constant	0.014	0.046	0.435***	0.293***	0.182***	0.454***	0.612***	-0.004
	(0.021)	(0.030)	(0.035)	(0.031)	(0.029)	(0.035)	(0.035)	(0.023)
N	7574	20106	20111	20110	20114	20126	20126	20114
Adj. R^2	0.076	0.143	0.149	0.146	0.142	0.162	0.126	0.113
Mean	0.036	0.226	0.438	0.270	0.208	0.546	0.709	0.125

Binary dependent variable given in column header. Sleeping: night-time sleeping disorder, tired: general tiredness, nervous: nervousness/irritability, mental: mental health problem (sleeping disorder, tiredness, nervousness, blues), phys.: physical health problem (shoulder, neck, back, extremities, hips, knees). Full model controlling for job demands and resources, sociodemographic and job covariates according to table A4.2. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Mean: weighted mean among medium educated. Data sources: BIBB/BAuA. Own calculations.

4.5 Bias discussion

The previous section showed that low compared to medium education is associated with decreased mild work-related mental health problems. Medium plus and in particular higher education are related to mild and medium severe problems. Controlling for job demands and resources, individual and job characteristics reduces point estimates. This suggests that there is considerable bias in the sparse model estimations. The bias is reduced in the full model but might still exist if relevant covariates are unobserved. It is very likely that not all relevant job demands and resources are included in the model. Individual job demands and resources are determinant for the development of work-related mental health problems but demands and resources should be more similar within an occupation than across occupations. Appendix table A4.3 includes two-digit occupation dummies in both the sparse model (1) and the full model (2). This is not the preferred specification as variance inflation factors larger than 10 indicate multicollinearity problems. Low, medium plus, and higher education are still significantly associated with the combined measure and mild work-related mental health problems but not with exhaustion and burnout. The signs remain the same as in table 4.4 but coefficients are smaller for low and higher education and slightly larger for medium plus. Medium plus education is associated with higher exhaustion in the sparse model at the 10% level but the coefficient becomes insignificant in the full model. Higher education is not significant for emotional exhaustion and burnout.

An econometrically less problematic attempt to further reduce potential bias is to include one-digit occupation or industry dummies. Multicollinearity is not an issue in these models but they are less convincing from a theoretical point of view: due to the higher level of aggregation, jobs in one-digit occupations or industries are less similar to each other than jobs in two-digit occupations. The results for both specifications can be found in appendix tables A4.4 and A4.5. With one-digit occupation dummies, higher education coefficients are smaller and not significant in the full exhaustion model nor in any burnout model (A4.4). Point estimates are smaller for low education and slightly larger for medium plus education but equally significant as in table 4.4. With industry dummies, education coefficients are smaller than in table 4.4 and twice significant at a lower level (higher education coefficient in full exhaustion and sparse burnout model, A4.5). Overall, these robustness checks suggest that there might be some omitted variable bias but education remains significant for mild and medium severe (and partially for severe) work-related mental health problems.

There are two other sources of bias: reversed causality and selection into education. Reversed causality would drive the findings if work-related mental health problems existed before the completion of professional education. Despite lifelong learning and training, the majority still completes professional education before beginning to work.[9] This is not true for medium plus educated employees. A reduced number of medium educated people choses to upgrade their education after some years on the job to acquire a higher professional status (such as technician for example). Reversed causality could explain the positive association between emotional strain/exhaustion and medium plus education: medium educated employees who select into medium plus education could be emotionally strained or more fragile in work-related mental health already before they choose to acquire more education. Similarly, selection into education could explain the positive association if there is for example an underlying characteristic that is driving individuals simultaneously to take up higher education and to be more vulnerable in mental health. Individuals who worry more about the future might select into higher education as a means to get better jobs which protect against low wages and unemployment. These individuals might also be more concerned by challenges from their working environment (job demands, missing resources) which could drive them into work-related mental health problems. The positive association between work-related mental health problems and education would then arise from the underlying factor (which in this sense can also be considered an omitted variable).

There are several approaches to solve the endogeneity problem in the German context (e.g. Gross et al., 2017). Literature examples are not exhaustive and focus on mental health where available. Kamhöfer et al. (2015) use college availability based on geographical proximity (number of universities and num-

[9] Some people complete apprenticeships after school and work in their jobs for some time until they – rarely more than five years later – acquire tertiary education. Common reasons are missing economic resource restraints after school and hope for better career opportunities.

ber of student places) and student loan eligibility based on parental income as instruments for higher education in their estimation of non-monetary returns to education. Dahmann and Schnitzlein (2017) instrument education with proximity to university and the prolongation of compulsory schooling after WWII. What follows is a brief discussion of these strategies. Student loans, education expansion, and geographical proximity are instruments for higher education, while the prolongation of compulsory schooling affects the lower end of the ability distribution. Based on the descriptive findings and the results from OLS, variation towards the upper end of the ability distribution seems to matter more for work-related mental health.[10]

Regarding student subsidies, there should be a discontinuous jump in the enrollment into tertiary education (among eligible students) around the time of the introduction in 1971. I do not observe enrollment, nor parental income but educational attainment and parental occupation. The jump in attainment should occur four to five years after the introduction. Eligible students must have the highest school leaving degree ("Abitur"). Parental background is not strictly necessary as the jump should also be visible in the full population. There is no jump in the data. A reason for this might be that the educational expansion occurring at the same time increased the share of people acquiring the highest school leaving degree and that a lower fraction of these continued into tertiary education.

One could take advantage of this parallel occurring expansion by exploiting increasing university capacities in and around the 1980s. New universities were build and existing ones took in more students. An increased offer of tertiary education attracts more people into enrollment. First, if there is a university close to the student's parental home, enrollment is more likely as accommodation costs are low. There more universities there are, the higher the probability of one of them being close enough to enroll. Secondly, entry barriers are lower if more spots are to be filled up. The issue here is that in the 1980s, people were less mobile than they are today. What mattered to an individual's decision to enroll were likely not overall but local conditions. In order to appropriately take this into account, disaggregated information on residence at completion of secondary education is necessary. There are two types of residence information in the data: residence at time of survey (both years) and residence at completion of highest school degree (2006 only). Both are measured at the at the federal state level which is too broad a geographical unit to convincingly employ the distance instrument.[11]

[10] After WWII, the West German federal states successively extended compulsory schooling from eight to nine years. This generates variance in the years of schooling at the lower end of the ability distribution which would relate to the results using years of education as the explanatory variable. While this regression is useful for inter-country comparisons, it is questionable whether years of education translate into different jobs. For jobs, the degree of education, not the length intself, is determinant. The instrument is therefore unlikely to induce treated people to end up in different jobs.

[11] One could obtain more disaggregated information on residence at survey but this instrument is not too convincing due to mobility after school. While it is true that some studies use state of current residence as a proxy and mobility in Germany is lower than e.g. in the U.S., higher educated employees are more mobile than the average of the population.

In the returns to schooling literature, Ichino and Winter-Ebmer (1999) use parental background as an instrument. The authors compare father-in-war and father's education as instruments for education. Considering ability and liquidity as the two determinant factors for schooling, they argue that able but liquidity constrained individuals ("smart poor") are affected by the first instrument and less able but not liquidity constrained individuals ("stupid rich") by the second instrument. Their analysis suggests that the first instrument is an upper bound estimate for the returns to schooling and the second one a lower bound estimate. Parental occupation, job position, and supervisor status is recorded in the 2012 data. Following Ichino and Winter-Ebmer (1999), smart and rich people are always-takers, i.e. they acquire higher education independently of whether their parents completed tertiary education. Stupid and poor people never choose tertiary education (never-takers). The compliers are stupid and rich people who acquire tertiary education only if their parents did. Parents commonly want their children to have a higher (or at least similar) standard of living and hence, level of education. Higher educated parents induce their children to higher education and they are able to afford it. Empirically, higher parental education is significantly related to higher education of the child (see the "first stage" column in table 4.7). With parental higher education, the probability for higher education of the child is 28 percentage points larger.

The problem here is not the relevance assumption but the exclusion restriction. Parental education must not have any influence on children's work-related mental health except through education. One concern is that children of highly educated parents might be exposed to parental work-related mental health problems. Mean age is 42, hence birth years are around 1970. Assume for simplicity that parents are 25 years old at the child's birth (i.e. born around 1945) and work from 16 to 60. Then, their work life lasts from 1961 to 2005. Life and work followed a much slower pace during most of the parents' work life, and mental health problems were less an issue than today. But even if parents experienced work-related mental health problems, the bias is rather downward than upward. Parental health problems could have three effects on children's outcomes: avoidance, better coping strategies, and increased awareness. First, to not repeat parents' mistakes, children might chose different career paths. They might end up in less stressful jobs and experience fewer work-related mental health problems which would lead to a downward bias of the estimate. Second, if children learn coping strategies from parents, e.g. to seek professional help in stressful situations, this should also result in a downward bias. A third effect could be increased awareness of work-related mental health problems. On the one hand, different reporting behavior could overstate the true prevalence of work-related mental health problems. On the other hand, more knowledge about mental health problems, which are still stigmatized and less well-known than physical health problems, might reduce reporting errors (e.g. distinguish between sometimes feeling exhausted and suffering from burnout). A last concern threatening the exclusion restriction comes from underlying character traits in parents which – through nature or nurture – are passed onto children and induce both generations to acquire more education and be more vulnerable in work-related mental health. While there is substantial literature on genetics in mental health problems like depression (e.g. Sullivan et al., 2000, Kendler at el., 2010, Lohoff, 2010), much less is known about work-related mental health problems. Personality measures such as BIG5 might help to address this concern, if they succeed in capturing this specific trait, but are not available in the data.

Being aware of the problems with the instrument, table 4.7 displays instrumental variable results with parental higher education as an instrument for individual higher education. The first three columns contain the OLS estimates. Higher education compared to lower, medium or medium plus education is associated with increases in strain of 0.397 standard deviations and in exhaustion of 0.127 standard deviations. The first stage is highly significant with a t statistic of 25 (corresponding to an F-statistic of excluded instruments of 225 in the case of a single instrument). Parental higher education is associated with an increase in children's higher education of 28 percentage points. Second stage estimates are larger than OLS. The coefficient for strain increases by 47% (0.583), the estimate for exhaustion by 37% (0.174, significant at the 5% level).

Even without the problematic exclusion restriction, Card (1999) suggests that univariate OLS with own education and IV estimates with parental education yields more biased estimates than a bivariate OLS with own and parental education as regressors. Table 4.7 displays the OLS education coefficients with (2) and without (1) a control for parental occupational prestige. The results in (1) are different from the ones in table 4.4 because only people who provided information on their parental background are included. Parental occupational prestige is not significant. Coefficients for low and medium plus education are unchanged. The higher education estimate for exhaustion is somewhat larger when controlling for parental occupational prestige. While no claim on causality can be made, there is at least evidence that the findings from the previous subsection are robust to the inclusion of parental background. Due to the lack of a fully convincing instrument, the following analyses stay at the descriptive OLS level.

Table 4.7: Estimates for work-related mental health problems

	OLS			first	second stages		
	combined	strain	exhaustion	stage	combined	strain	exhaustion
higher education	0.383***	0.397***	0.127***		0.554***	0.583***	0.174**
	(0.023)	(0.022)	(0.023)		(0.091)	(0.087)	(0.083)
gender	-0.257***	-0.208***	-0.190***	-0.001	-0.256***	-0.207***	-0.190***
	(0.021)	(0.020)	(0.020)	(0.008)	(0.021)	(0.020)	(0.020)
age	0.008***	0.006***	0.006***	0.002***	0.008***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
par. higher educ.				0.283***			
				(0.012)			
constant	-0.203***	-0.248***	-0.184***	0.079***	-0.231***	-0.279***	-0.192***
	(0.046)	(0.045)	(0.040)	(0.017)	(0.048)	(0.047)	(0.043)
N	14311	14342	14322	14355	14311	14342	14322

Parental education available in 2012 only. Standardized dependent variable given in column header. Combined is a measure for the presence of exhaustion and/or strain. First stage dependent variable: higher education (binary). Par. higher educ.: parental higher education (binary for SIOPS prestige classification larger than 50). Number of observations: 14355. First stage t-statistic (par. higher educ.): 25. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

Table 4.8: OLS estimates for work-related mental health outcomes with parental occupational prestige

	combined		strain		exhaustion	
	(1)	(2)	(1)	(2)	(1)	(2)
lower education	-0.081*	-0.081*	-0.097**	-0.097**	-0.003	-0.003
	(0.043)	(0.043)	(0.045)	(0.045)	(0.043)	(0.043)
medium plus	0.083**	0.083**	0.067*	0.066*	0.060	0.062
	(0.035)	(0.035)	(0.035)	(0.035)	(0.040)	(0.040)
higher education	0.141***	0.143***	0.127***	0.125***	0.081**	0.088**
	(0.031)	(0.032)	(0.030)	(0.030)	(0.035)	(0.036)
par. occ. prestige		-0.000		0.000		-0.001
		(0.001)		(0.001)		(0.001)
constant	-0.257***	-0.248***	-0.287***	-0.302***	-0.232**	-0.185*
	(0.090)	(0.096)	(0.089)	(0.094)	(0.092)	(0.100)
N	11213	11213	11225	11225	11216	11216

Parental education available in 2012 only. Standardized dependent variable given in column header. Combined: emotional exhaustion, burnout and/or emotional strain. Model specifications: (1) sparse model (age, gender, survey dummy), (2) full model (job demands and resources, sociodemographic and job covariates) according to table A4.2. Par. occ. prestige: parental occupational prestige (SIOPS, continuous). Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

4.6 Potential channels and compensation

4.6.1 Potential channels

The inclusion of job demands and resources in the full decreased the education coefficients. If – as hypothesized – education itself is the entry ticket into certain jobs, this should not only be visible in health outcomes but also in job environments from which work-related mental health problems can arise. This subsection regresses job demands, job resources, and ambiguous factors on education dummies and the controls from the sparse model providing descriptive evidence on the relationship [12] . As discussed in the previous section, causal claims cannot be made.

Low education is associated with lower job demands, medium plus, and higher education are associated with higher demands (table 4.9). Numbers of observations are larger than for work-related mental health outcomes because there are less missing values. Dependent variables are standardized except for overstrain (binary) and hours (ordinal). Compared to medium education, low education is associated with decreases in deadline pressure (0.437 standard deviations), simultaneity (0.384 standard deviations), and interruptions (0.357 standard deviations). The number of different tasks performed ("multitasking") is 0.28 standard deviations lower. The coefficients for missing information, being at one's capacity limit ("limit"), potentially large financial losses for even small mistakes ("loss"), and working fast are between 0.1 and 0.2 standard deviations. Low educated employees work 4.8 hours less. Being demanded too much ("over") increases by 3 percentage points. Since this concerns 20% of the medium educated employees, the relative increase is 17%. Low education is associated with an increase in repetition of 0.061 standard deviations but is not significantly related to predetermined tasks and minimum performance.

Medium plus education is associated with increased simultaneity (0.324), multitasking (0.296), interruptions (0.269), large financial losses for small mistakes (0.231), and deadline pressure (0.209). Coefficients are around 0.1 standard deviations for capacity limit and missing information. Weekly hours increase by 1.6 hours, predetermined tasks decrease by 0.203 standard deviations, and repetition decreases by 0.295 standard deviations. Medium plus education is not significant for being demanded too much, working fast, and minimum performance.

Higher education is associated with increases in simultaneity (0.417), deadline pressure (0.251), and multitasking (0.194). The estimates for capacity limits, interruptions, and missing information are smaller.

[12] Results are similar including sociodemographic and job characteristics (not reported). I report the sparse specification, since the theoretical framework for job demands and resources does not necessarily correspond to the one for work-related mental health outcomes regarding sociodemographic and job factors. For example, it is rather unlikely that having a partner, children and atypical working times are related to job demands. Controlling for working in one's dream job could make sense if this made employees more blind regarding demands and more generous in perceiving resources.

Working hours increase by 3.6 hours, being demanded too much by 26% (or 5.5 percentage points). Repetition and predetermined tasks decrease by 0.776 and 0.493 standard deviations. Large financial losses for small mistakes and minimum performance are also lower. These results make sense as low scope (predetermined tasks) and repetition decrease over educational level while psychological demands associated with jobs of higher hierarchical levels (accessible only with more education) increase with educational attainment. Differences across education are more pronounced for simultaneity, deadline pressure, multitasking, interruptions, and repetition.

Education is associated similarly with job resources and ambiguous factors (table 4.10). Resources are lower for low educated employees compared to medium educated employees and higher for medium plus and higher educated employees. Low education is related to lower scheduling freedom (0.352), community feeling (0.301), and collaboration (0.207). Influence over workload and breaks are 0.1 standard deviations lower, support from coworkers 0.196 standard deviations, and supervisor support 0.092 standard deviations lower. The estimate for task independence is small (0.058). Medium plus education is associated with higher influence over work schedule (0.403), workload (0.235), and breaks (0.207). There is no difference between medium plus and medium educated employees regarding collaboration and colleague support but medium plus feel somewhat more as part of a community (0.096) and get more supervisor support (0.058). They are 0.113 standard deviations more independent in their tasks. Higher education is significantly associated with increased influence – ranging from 0.461 standard deviations for scheduling to 0.181 for task independence – and somewhat higher social support (0.058 to 0.095 standard deviations).

Ambiguous factors are lower for low educated employees. Point estimates are larger for getting familiar with tasks (“familiar”, 0.429) and improving methods (“improve”, 0.347) than for being demanded unknown things (“unknown”, 0.141). The probability to be a supervisor is 8 percentage points lower (28%). The increase in ambiguous factors is larger for higher than for medium plus educated employees except for supervisor status where the increase is 52% for medium plus and 31% for higher educated employees (15 and 9 percentage points respectively). Higher compared to medium education is associated with increases of getting familiar and improving of around 0.5 standard deviations.

It is not clear whether ambiguous factors enter the Job Demands and Resources model on the demand or resource side. Given that low education is associated with lower strain and given that medium plus and higher education are associated with higher strain and exhaustion, one would expect an imbalance between demands and resources. The JD-R predicts higher resources than demands for decreasing work-related mental health problems (low education) and higher demands than resources for increasing problems (medium plus and higher education). Demands and resources are lower for low educated employees and higher for medium plus and higher educated employees. This could be one reason for why low education is significant only for strain and for why medium plus education is not significant for burnout. An imbalance could still arise due to the weighting of individual demands and resources in the JD-R. Another possibility is a different perception of stress from demands and missing resources. Perceived stress is binary and only recorded for individuals who report to suffer from job demands frequently or to lack job resources (answer “never”). Thus, the following analysis applies to pre-selected groups exposed to high job demands and low job resources and is not necessarily representative of the whole population.[13]

Table 4.11 displays the results for perceived stress from high job demands. Low education is associated with lower perceived stress from simultaneity, interruptions, and missing information about the future (2.9 to 4.6 percentage points). In relative terms, the change is largest for simultaneity (12%). All other point estimates are insignificant and mostly very small. Medium plus education is related to increased stress from deadline pressure, interruptions, and missing information. Repetition is perceived as less stressful. Relative effect sizes are roughly between 5 and 15%. The association of higher education and perceived stress from job demands is stronger in terms of size but also significance: a single point estimate (“loss”) is insignificant. Higher educated employees perceive both psychological demands and imposed limits (predetermined tasks, repetition) as more stressful. The largest relative increase is the one for perceived stress from simultaneity (31%). Considering that job demands increase for medium plus and higher educated employees and that also perceived stress from job demands increases, the positive association with work-related mental health problems makes sense. Point estimates for job demands and perceived stress are usually larger for higher than for medium plus educated employees which could translate into larger coefficients of higher education for mild to medium severe outcomes.

To shed light on whether the lower resources of low educated employees could affect them differently, table 4.12 shows the results for perceived stress from missing resources and ambiguous factors. Low education is significantly associated with lower perceived stress from a missing influence over workloads and breaks suggesting that a lack of these resources does not weigh as much for low as for medium educated employees. Perceived stress from lacking coworker support is larger. It is not possible to determine which effect weighs more for the JD-R but lower demands and resources and largely unchanged stress perception could explain the insignificant association of low education with medium to severe work-related mental health problems. Perceived stress from lacking resources is higher for medium plus and especially higher educated employees. This is interesting in itself but does not directly contribute to shedding light on possible mechanisms. The last two columns of table 4.12 are more relevant to this: perceived stress from getting familiar with tasks and being demanded unknown tasks is higher for higher educated employees. Both ambiguous factors also rise by 0.5 to 0.3 standard deviations compared to

[13]Stress perception is not available for overstrain, multitasking, hours, task independence, improvising, and supervisor.

medium education, suggesting that they could act as job demands and contribute to the development of work-related mental health problems.

To conclude this subsection, education is significantly related to job demands, job resources, and ambiguous factors. Demands and resources are lower for low educated employees and higher for medium plus and higher educated employees. Different stress perceptions play a role for the association of education with work-related mental health: job resources are lower for low compared to medium educated employees but there is no change in perception of missing resources, while job demands are higher for medium plus and higher educated employees and perceived stress from job demands is also higher.

Table 4.9: OLS estimates for job demands

	deadline	limit	simult.	inter.	over	multi	no info	hours	det.	rep.	loss	no info II	fast	min
low	-0.437***	-0.159***	-0.384***	-0.357***	-0.029***	-0.280***	-0.185***	-4.809***	-0.003	0.061**	-0.186***	-0.161***	-0.123***	0.022
	(0.034)	(0.031)	(0.035)	(0.032)	(0.011)	(0.028)	(0.031)	(0.374)	(0.030)	(0.026)	(0.028)	(0.030)	(0.032)	(0.029)
med plus	0.209***	0.109***	0.324***	0.269***	0.012	0.296***	0.102***	1.588***	-0.203***	-0.295***	0.231***	0.098***	0.021	0.005
	(0.024)	(0.026)	(0.024)	(0.025)	(0.012)	(0.028)	(0.027)	(0.229)	(0.027)	(0.027)	(0.027)	(0.026)	(0.027)	(0.027)
higher	0.251***	0.113***	0.417***	0.162***	0.055***	0.194***	0.056***	3.562***	-0.493***	-0.776***	-0.077***	0.070***	-0.030**	-0.020
	(0.014)	(0.015)	(0.014)	(0.016)	(0.007)	(0.015)	(0.015)	(0.164)	(0.015)	(0.016)	(0.015)	(0.016)	(0.015)	(0.016)
constant	-0.079**	-0.152***	0.026	0.178***	0.183***	-0.083***	-0.020	33.800***	0.202***	0.168***	0.217***	0.010	0.359***	0.260***
	(0.032)	(0.030)	(0.031)	(0.031)	(0.012)	(0.030)	(0.031)	(0.318)	(0.030)	(0.028)	(0.030)	(0.031)	(0.030)	(0.030)
N	30781	30766	30772	30773	28125	29724	30676	30758	30741	30758	30670	30743	30720	30713
Adj. R^2	0.040	0.010	0.051	0.022	0.006	0.044	0.007	0.218	0.048	0.117	0.082	0.014	0.009	0.014

Binary dependent variable given in column header. Deadline: deadline/performance pressure, limit: reach limits of own capacity, simult.: do different things simultaneously, inter.: interruptions during work, over: overstrained, unable to cope/asked too much, multi: multitasking/number of different tasks, no info: no timely information about the future, hours: weekly working hours (between 10 and 120), det.: work details are predetermined, rep.: work steps have to be repeated into small details, loss: even small mistakes can lead to large financial losses, no info II: not receiving all information necessary for correct work, fast: work fast, min.: minimum performance. Controls: age, gender, survey dummy as in sparse model in table A4.2. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

Table 4.10: OLS estimates for job resources and ambiguous factors

	job resources								ambiguous factors			
	schedule	workload	break	coll.	comm.	support I	support II	indep.	familiar	improve	unknown	supervisor
low educ.	-0.352***	-0.115***	-0.120***	-0.207***	-0.301***	-0.186***	-0.092***	-0.058***	-0.429***	-0.347***	-0.141***	-0.081***
	(0.035)	(0.028)	(0.031)	(0.037)	(0.038)	(0.036)	(0.032)	(0.016)	(0.033)	(0.031)	(0.029)	(0.011)
medium plus	0.403***	0.235***	0.207***	0.039	0.096***	-0.014	0.058**	0.113***	0.312***	0.288***	0.117***	0.153***
	(0.022)	(0.027)	(0.025)	(0.026)	(0.025)	(0.027)	(0.027)	(0.013)	(0.024)	(0.026)	(0.026)	(0.014)
higher educ.	0.461***	0.256***	0.198***	0.068***	0.095***	0.058***	0.077***	0.181***	0.534***	0.497***	0.302***	0.090***
	(0.013)	(0.015)	(0.015)	(0.015)	(0.014)	(0.015)	(0.016)	(0.007)	(0.014)	(0.015)	(0.016)	(0.008)
constant	-0.183***	-0.286***	-0.153***	0.031	0.093***	0.220***	0.113***	0.522***	0.026	0.039	0.133***	0.152***
	(0.031)	(0.030)	(0.030)	(0.030)	(0.030)	(0.029)	(0.031)	(0.016)	(0.030)	(0.030)	(0.030)	(0.013)
N	30760	30670	30707	30562	30709	30613	30453	25374	30773	30765	30753	30756
Adj. R^2	0.062	0.022	0.015	0.005	0.012	0.010	0.003	0.042	0.087	0.064	0.027	0.040

Binary dependent variable given in column header. Job resources: schedule: plan/ schedule own work, workload: influence own workload, break: plan and schedule own breaks, coll.: good collaboration, comm.: feel as a part of a community at work, support I: receive help and support from colleagues, support II: receiving help and support from supervisor, indep.: perform tasks independently (binary). Ambiguous factors: familiar: think through/ get familiar with tasks, improve: improve methods/ try new things, unknown: demanded unknown things, supervisor: be a supervisor (binary). Controls: age, gender, survey dummy as in sparse model in table A4.2. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

Table 4.11: OLS estimates for perceived stress from job demands

	deadline	limit	simult.	inter.	no info	det.	rep.	loss	no info II	fast	min
low	-0.006	0.002	-0.029**	-0.035*	-0.046*	0.001	0.010	0.012	-0.019	0.009	-0.035
	(0.018)	(0.023)	(0.015)	(0.019)	(0.026)	(0.019)	(0.012)	(0.029)	(0.027)	(0.018)	(0.021)
med plus	0.033**	-0.013	-0.003	0.044***	0.082***	0.029	-0.021*	-0.037	0.122***	0.005	0.044*
	(0.016)	(0.023)	(0.013)	(0.017)	(0.023)	(0.022)	(0.012)	(0.023)	(0.022)	(0.018)	(0.023)
higher	0.099***	0.067***	0.077***	0.096***	0.099***	0.121***	0.027***	0.025	0.073***	0.036***	0.047***
	(0.009)	(0.012)	(0.008)	(0.010)	(0.013)	(0.015)	(0.009)	(0.016)	(0.014)	(0.010)	(0.013)
constant	0.370***	0.500***	0.111***	0.399***	0.642***	0.081***	0.114***	0.368***	0.747***	0.244***	0.259***
	(0.018)	(0.025)	(0.014)	(0.019)	(0.027)	(0.021)	(0.013)	(0.029)	(0.029)	(0.019)	(0.023)
N	21584	10842	22759	19908	9592	10799	17791	7860	7318	17743	12006
Adj. R^2	0.035	0.037	0.018	0.016	0.014	0.025	0.006	0.015	0.016	0.015	0.017
Mean	0.539	0.614	0.236	0.497	0.612	0.258	0.139	0.437	0.701	0.384	0.404

Standardized dependent variable given in column header (over: binary, hours: ordinal). Perceived stress due to... deadline: deadline/performance pressure, limit: reach limits of own capacity, simult.: do different things simultaneously, inter.: interruptions during work, no info: no timely information about the future, hours: weekly working hours (between 10 and 120), det.: work details are predetermined, rep.: work steps have to be repeated into small details, loss: even small mistakes can lead to large financial losses, no info II: not receiving all information necessary for correct work, fast: work fast, min.: minimum performance. Controls: age, gender, survey dummy as in sparse model in table A4.2. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Mean: weighted mean among medium educated. Data sources: BIBB/BAuA. Own calculations.

Table 4.12: OLS estimates for perceived stress from missing job resources and from ambiguous factors

	job resources							ambiguous factors	
	schedule	workload	break	coll.	comm.	support I	support II	familiar	unknown
low educ.	0.013	-0.044***	-0.029*	0.022	-0.029	0.120**	0.014	-0.007	0.038
	(0.024)	(0.016)	(0.016)	(0.084)	(0.039)	(0.054)	(0.037)	(0.012)	(0.030)
medium plus	0.020	0.064***	0.042*	0.064	0.249***	0.207**	0.120***	-0.012	0.012
	(0.046)	(0.022)	(0.025)	(0.132)	(0.073)	(0.082)	(0.044)	(0.011)	(0.028)
higher educ.	0.107***	0.151***	0.124***	0.203***	0.149***	0.017	0.062**	0.019***	0.075***
	(0.035)	(0.013)	(0.015)	(0.071)	(0.037)	(0.044)	(0.025)	(0.007)	(0.014)
constant	0.155***	0.189***	0.237***	0.752***	0.324***	0.506***	0.498***	0.016	0.218***
	(0.030)	(0.020)	(0.022)	(0.119)	(0.054)	(0.076)	(0.043)	(0.012)	(0.029)
N	2766	9927	6772	468	1531	1247	3550	18953	7502
Adj. R^2	0.006	0.022	0.023	0.038	0.027	0.024	0.013	0.016	0.019
Mean	0.128	0.182	0.149	0.502	0.253	0.329	0.389	0.131	0.338

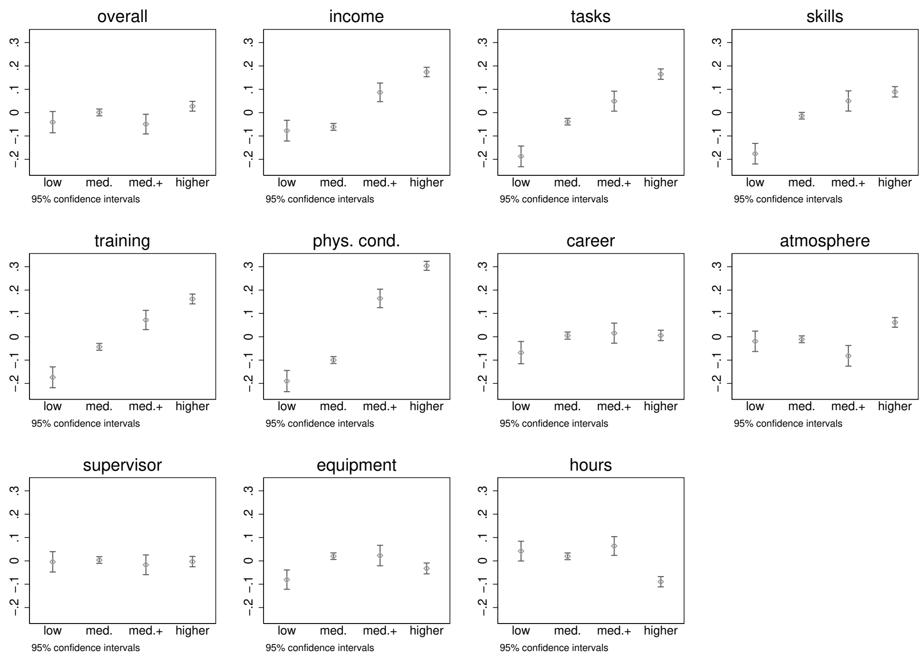
Binary dependent variable given in column header. Perceived stress due to lack of resources: schedule: plan/ schedule own work, workload: influence own workload, break: plan and schedule own breaks, coll.: good collaboration, comm.: feel as a part of a community at work, support I: receive help and support from colleagues, support II: receiving help and support from supervisor. Perceived stress due to ambiguous factors: familiar: think through/ get familiar with tasks, unknown: demanded unknown things. Controls: age, gender, survey dummy as in sparse model in table A4.2. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Mean: weighted mean among medium educated. Data sources: BIBB/BAuA. Own calculations.

4.6.2 Potential compensation

This subsection analyzes whether there is monetary or non-monetary compensation for the adverse work-related mental health effects of higher education. A higher exposure to unfavorable working conditions and thus a higher risk for work-related mental health problems could be compensated by other facets of the job, e.g. wage, job satisfaction, job security, and compatibility with private life. Satisfaction with income, tasks, application of skills, training, and physical working conditions increases over education (figure 4.2). There are no differences for overall and supervisor satisfaction. Higher educated people are more satisfied with working atmosphere but less with working hours. Lower educated employees are less satisfied with career opportunities and working equipment.

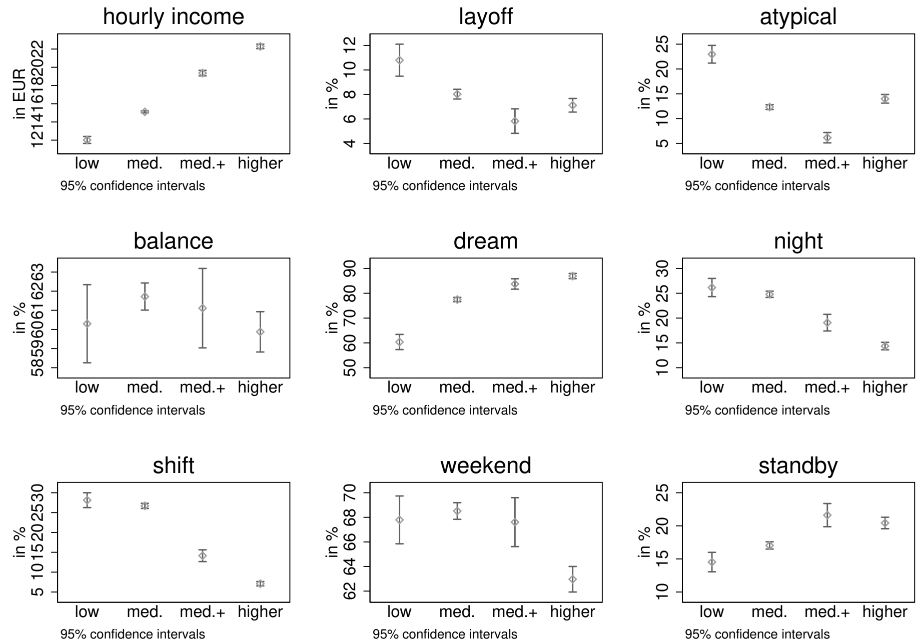
Figure 4.14 depicts potential compensation by level of education. Hourly income and working in one's dream job increase with education. Job insecurity measured as the subjective risk to be laid off soon ("layoff") and limited contracts ("atypical": short-term or temporary contract) decrease from low to medium plus education but are on a comparable level for higher and medium educated employees. There is no difference across education in work life balance success. Night and shift work decrease over education, while standby duty increases. Weekend work is equally common among low, medium, and medium plus educated employees but lower for higher educated employees.

Figure 4.2: Standardized job satisfaction by level of education



Satisfaction measured between 1 (very dissatisfied) and 4 (very satisfied), standardized. Data sources: BIBB/BAuA. Own figure.

Figure 4.3: (Non-)Monetary compensation by level of education



Wage: hourly wage, balance: successful work-life balance, dream (2012): working in one's dream job, important: feel work is important, layoff: risk of being laid off soon, atypical: short-term or temporary contract, night/shift/weekend/standby: regularly occurring. Data sources: BIBB/BAuA. Own figure.

The full model OLS results for job satisfaction are reported in table 4.13. Low compared to medium education is associated with an increase in overall job satisfaction of 0.083 standard deviations (5% level). The estimates for satisfaction with career and atmosphere are of comparable size and significance. Low educated employees are more satisfied with their income (0.146 standard deviations). The remaining point estimates are small and insignificant. Medium plus education is associated with higher satisfaction with physical working conditions (0.168 standard deviations) and with lower overall (0.112) and career satisfaction (0.084). Satisfaction with application of skills (0.088) and working atmosphere (0.048, 10% level) are also lower. Higher education is related to lower overall, skill, career, and working hours satisfaction (all around 0.1 standard deviations). The coefficients for satisfaction with supervisor (0.07) and income (0.05, 10% level) are smaller but significant. Satisfaction with physical working conditions is 0.168 standard deviations higher. The results mirror the findings for work-related mental health: low education is associated with better outcomes, medium plus and higher education with worse outcomes. The exception is satisfaction with physical working conditions which is higher among medium plus and higher educated employees compared to medium educated employees. This confirms the finding that physical health problems are less common, and suggests that there is at least some compensation.

Table 4.14 displays the results for other non-monetary and monetary compensation. All regressions control for age, gender, weekly hours, and experience, include a survey dummy and dummies for partner, children, supervisor status, and task independence. Compared to medium education, low education is associated with about 22% lower hourly wages. The wages for medium plus educated employees are 19% higher and the wages for higher educated employees are 32% higher. This suggest monetary compensation and is in line with an extensive literature on (causal) monetary returns to education. Low education is associated with lower work-life balance success ("balance", 7.5 percentage points), lower probability to work in their dream job (14.4 percentage points), and to consider your work to be important (0.198 standard deviations). Subjective (thinking to be laid off soon) and objective job insecurity (atypical contract) are higher among low educated employees. Work times are more atypical (regular night, shift, weekend, and standby work). Medium plus and higher educated employees have a higher success of work-life balance and higher a probability to be in their dream job. The coefficient for "balance" is larger for medium educated employees; the increase in "dream" is larger for higher educated employees. Medium plus education is associated with an increase in feeling that work is important (0.072 standard deviations). Subjective and objective job insecurity are higher for higher educated employees compared to medium educated employees (1.4 and 2.7 percentage points which corresponds to 18% and 23%). Medium plus educated employees are less often in atypical contracts (3.7 percentage points or 31%). Regarding atypical working times, both medium and higher education are associated with less night (about 32%), shift (up to 58%), and weekend work (around 10%). Higher education is related to an increase in standby duties of 1.5 percentage points (9%).

All in all, there is monetary and some non-monetary compensation for the increase of work-related mental health problems with education. Non-monetary compensation comes from better work life balance, less atypical working times but not from lower perceived job insecurity or higher job satisfaction. With increasing education, workplaces become more psychologically demanding, while physical conditions improve. There is suggestive evidence that this could translate into worse work-related mental health, lower job satisfaction but better physical health.

Table 4.13: OLS estimates for job satisfaction

	overall	income	tasks	skills	training	phys. cond.	career	atmosphere	supervisor	equipment	hours
lower education	0.083**	0.146***	0.039	0.007	0.014	0.011	0.070*	0.080**	0.051	0.004	-0.037
	(0.038)	(0.039)	(0.039)	(0.038)	(0.039)	(0.040)	(0.040)	(0.034)	(0.033)	(0.035)	(0.037)
medium plus	-0.112***	0.021	-0.041	-0.088***	-0.013	0.158***	-0.084***	-0.048*	-0.039	-0.018	-0.007
	(0.028)	(0.030)	(0.031)	(0.030)	(0.029)	(0.028)	(0.030)	(0.028)	(0.027)	(0.032)	(0.028)
higher education	-0.107***	-0.050*	-0.020	-0.096***	-0.018	0.168***	-0.106***	-0.024	-0.070***	-0.037	-0.095***
	(0.021)	(0.027)	(0.023)	(0.022)	(0.024)	(0.022)	(0.023)	(0.021)	(0.021)	(0.024)	(0.022)
constant	0.062	-0.121	-0.088	-0.063	0.013	0.077	0.055	0.288***	0.098	0.007	0.639***
	(0.072)	(0.081)	(0.073)	(0.074)	(0.074)	(0.070)	(0.075)	(0.069)	(0.068)	(0.073)	(0.071)
N	20120	20102	20120	20110	19861	20052	18441	20110	20031	20014	20111
Adj. R^2	0.212	0.147	0.136	0.143	0.157	0.204	0.140	0.270	0.278	0.103	0.202

Standardized dependent variable given in column header. Phys. cond.: physical working conditions. Full model controlling for job demands and resources, sociodemographic and job covariates according to table A4.2. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

Table 4.14: OLS estimates for (non-)monetary compensation

	wage	balance	dream	important	layoff	atypical	night	shift	weekend	standby
lower education	-0.220***	-0.075***	-0.144***	-0.197***	0.022**	0.083***	0.068***	0.029*	0.064***	0.022*
	(0.017)	(0.016)	(0.021)	(0.041)	(0.010)	(0.015)	(0.015)	(0.016)	(0.015)	(0.012)
medium plus	0.190***	0.027*	0.041***	0.072***	-0.011	-0.037***	-0.079***	-0.112***	-0.065***	0.016
	(0.011)	(0.014)	(0.015)	(0.025)	(0.006)	(0.008)	(0.012)	(0.010)	(0.013)	(0.013)
higher education	0.318***	0.019**	0.076***	-0.004	0.014**	0.027***	-0.099***	-0.152***	-0.072***	0.015*
	(0.009)	(0.010)	(0.010)	(0.019)	(0.006)	(0.007)	(0.008)	(0.007)	(0.010)	(0.008)
constant	1.969***	1.068***	0.622***	-0.457***	0.157***	0.397***	0.141***	0.342***	0.479***	0.047**
	(0.031)	(0.029)	(0.035)	(0.065)	(0.018)	(0.024)	(0.025)	(0.026)	(0.029)	(0.023)
N	24956	24884	14795	24892	24684	23492	24920	24944	24953	24926
Adj. R^2	0.275	0.062	0.042	0.035	0.018	0.074	0.039	0.049	0.060	0.037
Mean		0.617	0.775	-0.007	0.080	0.123	0.248	0.267	0.685	0.170

Binary dependent variable given in column header (wage: natural logarithm, important: standardized). Wage: hourly wage, balance: successful work-life balance, dream (2012): working in one's dream job, important: feel work is important (std.), layoff: risk of being laid off soon, atypical: short-term or temporary contract, night/shift/weekend/standby: regularly occurring. Model specification: sparse model (age, gender, survey dummy) plus dummies for partner, child, supervisor, independently performing tasks, plus weekly hours and experience. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

4.7 Conclusion

Education is associated with worse work-related mental health problems. Low compared to medium education is associated with lower emotional strain. Higher education is associated with higher strain, exhaustion, and burnout but also with higher wages and better physical health. The latter findings are in line with the literature, the ones regarding metal health are not. Instead of a protective effect, the opposite is the case: education but seems to be detrimental to work-related mental health. While no claim on causality can be made, this result stands in contrast to the economic literature so far, e.g. Kamhöfer et al. (2015) and Dahmann and Schnitzlein (2017). Both studies do not find a causal relationship between education and general mental health. The reason for this difference seems to come from a different measurement of mental health. Theoretically, education could impact both general mental health and work-related mental health but the mechanisms differ. Studies considering general mental health depart from the mechanism which is relevant for physical health and health behavior: health literacy. In essence, education improves the understanding of sources for health problems, their prevention, and consequences. This is true for physical health and behavior (e.g. smoking) but not for mental health.

The present study measures mental health differently by focusing exclusively on mental health problems arising at work. Departing from the burnout literature and the Job Demands and Resources model, it suggests a different mechanism through which education impacts mental health: the work environment composed of straining factors (job demands) and strain reducing factors (job resources). In this setting, education determines which jobs can be accessed. The job in turn comes with a certain environment. The findings presented here suggest that education is associated with higher job demands, higher job resources, and a different stress perception. High job demands are perceived as more stressful by higher compared to medium educated employees, while low educated employees do not perceive missing resources as more stressful than medium educated employees. Stress perception is relevant for the individual imbalance feeling: in the Job Demands and Resources model, an imbalance between job demands and resources can lead to work-related mental health problems.

This paper also contributes to the economic literature on mental health by documenting that mental health summary measures constructed from single items might – despite their theoretical and statistical justification – not always be the optimal unit of measurement. Significant relationships with some factors might pass unnoticed in combination with other factors' insignificant relationships. Education is insignificant for a mental health summary score consisting of night-time sleeping disorders, general tiredness, nervousness, and blues (all arising during or immediately after work) but is significant for one single factor (sleeping disorders).

Despite its contributions, the analysis suffers from two limitations. First, no claims on causality can be made. Despite robustness and bias checks, the results could be driven by the endogeneity of education as long as there is no exogenous variation in educational attainment. Endogeneity could e.g. come from underlying and unobserved character traits that are correlated with educational choice and vulnerability in work-related mental health. The analyses are nevertheless useful because they provide insight on the working environment in which people, given their educational choice, end up. This is relevant for better understanding work-related mental health problems. Second, the focus on work-related mental health problems subjects the analysis to a survival bias. The data is representative of the German working population but excludes individuals who left the working population due to severe and persistent work-related mental health problems. Assuming that low and higher educated employees are equally likely to leave the working population when suffering from mental health problems, this should not bias the results.

In terms of policy recommendations, the findings suggest the job environment as a starting point to reduce work-related mental health problems. As these problems arise from an imbalance between job demands and job resources, reducing job demands and increasing job resources should be a promising but also difficult approach. Most demands and resources arise at a higher organizational level, e.g. hierarchy in a company. They can thus not be tackled on an individual level. Controversially, most burnout interventions focus on the individual. These interventions might still have some effect if they change individual stress perception. Nevertheless, the results presented here emphasize the need to consider environmental job factors in order to reduce work-related mental health problems. Prevention strategies, e.g. coping with high job demands, should specifically address higher educated employees who face more job demands and eel stressed by this.

Chapter 5

Rising unemployment and work-related mental health – worse outside options can make employees sick

5 Rising unemployment and work-related mental health – worse outside options can make employees sick

5.1 Introduction

Economic downturns impact all three players: individuals, firms, and the state. Individuals are most commonly affected by unemployment or worse employment prospects. Apart from economic consequences, there is an extensive literature showing that the unemployed are less well off in terms of life satisfaction and mental health (Clark and Oswald, 1994, Weich and Lewis, 1998, Murphy and Athanasou, 1999, Paul and Moser, 2009, Schmitz, 2011, Marcus, 2013). Job loss is not necessary to experience these well-being losses. Job insecurity is enough to make people worse off (Green, 2011, Reichert and Tauchmann, 2011, Jiang and Probst, 2017). The threat of job loss does not even need to be close. Aggregate unemployment also reduces happiness among employed people (Di Tella et al., 2003). There are several mechanisms explaining the latter finding: first, aggregate unemployment could increase individually perceived job insecurity, second, individuals who remain employed while others are laid off could feel guilty, and third, individuals could stay in stressful jobs they would otherwise have quit (Clark et al., 2010).

This paper analyzes the third mechanism more closely by focusing on work-related mental health problems. Work-related mental health problems arise in the context of work only. A common framework to model work-related mental health is the Job Demands-Resources model (JD-R, Demerouti et al. 2001), where an imbalance between job demands and job resources leads to detrimental health outcomes. In this framework, rising unemployment deters employees in imbalanced jobs which they might leave if it was not for worse outside options due to rising unemployment. Upon realizing the imbalance between job demands and resources, the rational employee assesses her outside options before leaving her current job to find a more balanced one. If unemployment is high, her probability of finding new employment is lower. This deters the employee in her job where continued exposure to the imbalance can result in work-related mental health problems. The second contribution of this paper lies in the measurement level of unemployment. Most of the literature uses regional unemployment information. I extend this to the occupation level as this is the unit where individuals assess their outside options. A consultant for example would be unconcerned by rising unemployment for plumbers and vice versa.

Health problems and a rich set of job demands and resources, sociodemographic and job characteristics come from a survey which is representative of the German working population. Unemployment data are matched on occupation and federal state level. The key findings are, first, rising occupation- and federal state-specific unemployment is significantly associated with higher work-related mental health problems among employed individuals. The relationship is stronger for mild problems. Second, occupation specific unemployment drives this relationship while the spatial dimension of unemployment (region) is less important. Third, the relationship hinges on individual past unemployment experience: rising unemployment is not associated with mental health problems for individuals without any own unemployment experience. The duration of the past unemployment spell does not play a role.

The remainder of this paper is structured as follows: Section 5.2 introduces the framework for analyzing work-related mental health outcomes and reviews literature on unemployment and mental health. Data, descriptives, and estimation method are presented in section 5.3. Section 5.4 shows the estimation results and section 5.5 identifies potential mechanisms. The last section concludes.

5.2 Related literature

5.2.1 Analyzing work-related health outcomes

Among possible work-related health outcomes, burnout received high scholarly attention. This is due to extensive media and public attention but also because it is intrinsically work-related. Burnout is a mental health problem composed of the three components emotional exhaustion, cynicism, and professional inefficacy which all arise in the work context. For an overview over the literature on the impact of employment and working conditions on mental health see Barnay (2014).

A common framework for analyzing burnout is the Job Demands-Resources model (JD-R, Demerouti et al., 2001, Peterson et al., 2008). In this model, burnout arises from an imbalance between job demands and job resources. High job demands such as a high workload or a narrow time frame put strain on the individual. If this strain persists for a long time, more and more energy is depleted which may lead to exhaustion and physical health problems because it affects the immune system which is then less strong against diseases. Job resources, on the other hand, act as a mediator between job demands and the individual. Resources can reduce the consequences of job demands directly (help from colleagues) or indirectly (motivation and engagement due to working climate). When resources are depleted, job demands unfold their unbuffered damaging consequences. The individual tries to cope with her exhaustion and the overwhelmingly impossible situation by adopting withdrawal behavior. Disengagement from work, a detached attitude towards customers or cynicism towards the organization, oneself, and the system are common self-protection mechanisms. Altogether, both exhaustion and cynicism lead to less professional efficacy. The higher the workload and the more cynical the individual, the less she is able to fulfill her work tasks in a concentrated and efficient manner. Perceiving a loss in own efficiency can result in higher effort and even more exhaustion or higher cynicism. The JD-R has been criticized because it does not include factors outside from work (family problems as non-job-related demands, or yoga and mediation as buffers, Singh et al., 2012). Other models exist but they focus on work factors, too. In comparing four common models (strain and stress model, job demand-control model, transactional stress model, effort-reward-imbalance-model), Lohmann-Haislah (2012) underlines that the imbalance between demands and resources is the common theme across all models. She points out that an individual's subjective (aside from an objective) assessment of the situation is determinant for the reaction (stress or no stress).

This paper uses the framework of the JD-R but differs from most of the above mentioned studies in that it uses secondary survey data. Nearly all burnout studies collect their own data and measure burnout with a validated measure (e.g. Maslach Burnout Inventory, Oldenburg Burnout Inventory or the Burnout Clinical Subtype questionnaire). The study population is usually very narrow (specific occupation or geographic area). Exceptions are Hasselhorn and Nübling (2004) and Lohmann-Haislah (2012) who use a representative sample from the whole German working population in 1999 and 2012, respectively. These data are also used here since they include a broad range of job characteristics and self-rated health (see section 5.3).

The analysis of individual health has long focused on ill-health but recently, positive psychology gained importance. It focuses on desirable health states instead of ill-health. Along with this trend, engagement emerged as the positive counterpart of burnout (Maslach et al., 2001 and 2012, Schaufeli et al., 2002, Zhang et al., 2007). Engagement is usually measured with validated scales, too, but has not entered any large scale surveys yet. An alternative is job satisfaction. Life and job satisfaction are a common outcomes in work psychology and receives rising interest in economics despite its subjectiveness because it is correlated with observable events such as length of life, labor turnover, and unemployment (Clark and Oswald, 1996, Clark et al., 1998, Winkelmann and Winkelmann, 1998, Lévy-Garboua and Montmarquette, 2004).

5.2.2 Unemployment and mental health

Three strands of literature are relevant to this paper: first, the literature on own unemployment and mental health, second, the literature on job insecurity, i.e. the fear of unemployment, and mental health, and third, the literature on aggregate unemployment and mental health.

Most studies analyzing the relationship between unemployment and mental health focus on own unemployment and general mental health or well-being. Clark and Oswald (1994) and Gerlach and Stephan (1996) find that unemployed report lower mental well-being. Weich and Lewis (1998) document that unemployment increases the duration of common mental disorders. According to Winkelmann and Winkelmann (1998), the non-monetary loss (satisfaction) for unemployed is larger than the income loss. Murphy and Athanasou (1999) review 16 longitudinal studies and conclude that unemployment has reliable (negative) effects on mental health. Other studies find increased stress hormones, a deterioration of health behavior and subjectively rated (mental) health, and an increased mortality rate (e.g. Skärlund et al. 2012 and Maier et al. 2006, Åhs and Westerling 2006, Khlat et al. 2004). The most important limitation of this literature is the potential endogeneity due to reversed causality and mental-health related selection effects during job loss and job search. Based on 237 cross-sectional and 87 longitudinal studies, Paul and Moser (2009) judge selection effects to be weak. They calculate that 34% among the unemployed but only 16% among the employed suffer from psychological problems. Marcus (2013) uses plant closures as an exogenous entry into unemployment and analyzes the mental health outcomes of spouses in Germany. He finds that unemployment decreases the mental health of spouses almost as much as the mental health of the directly affected individual. Unemployment leaves lasting impacts on individuals. Clark et al. (2001) analyze the relationship between unemployment and life satisfaction over time with German panel data. Satisfaction is lower for people who are unemployed. Individuals with prior unemployment experiences are also less satisfied ("scars of unemployment"). They benefit, however, from habituation: current unemployment affects their well-being to a lesser extend. A similar scarring effect is possible regarding rising occupation and region specific unemployment.

Closely related to the unemployment literature is the literature on job insecurity. It shows that the threat of unemployment is enough to have a repercussion on health (see Ferrie, 2001 for an overview). Basińska and Wilczek-Rużyczka (2013) for example link job insecurity as a missing resource to burnout. The magnitude of this effect depends on employability. Green (2011) shows that for Australian employees, an increase in the subjective probability of finding new employment soon is associated with a decrease of the detrimental effect of job insecurity on life satisfaction and mental health by about 50%. According to Jiang and Probst (2017), income inequality on country or state level plays a role for the relationship between job insecurity and burnout in the U.S. There are few studies addressing causality. Reichert and Tauchmann (2011) exploit company staff reductions as an exogenous source of job insecurity and show that an increase in fear of unemployment decreases the mental health status of employees. This effect is stronger for employees with low initial mental health. Caroli and Godard (2016) use European data and instrument job insecurity by country level employment protection and industry level of bindingness of employment protection. They find negative effects of job insecurity on few health outcomes (headaches/eyestrain and skin problems).

Finally, there is evidence on a link between macroeconomic indicators such as aggregate unemployment and life satisfaction. Using European and American data, Di Tella et al. (2003) show that macroeconomic conditions, in particular recessions, have an influence on happiness (life satisfaction). They measure recessions with GDP loss and estimate that both unemployed and employed Europeans and

U.S. Americans would have to be paid $200 to be compensated for their loss in well-being. Clark et al. (2010) confirm that aggregate unemployment reduces well-being even for the employed but differentiate by job prospect: how employed and unemployed people's life satisfaction changes depends on their job prospect. There are at least three reasons why employed people are affected by others' unemployment. First, rising unemployment can be perceived as an increase in job insecurity. When many people lose their jobs, economic prospects are bad and one might lose the own job in the future. Second, while employed people keep their employment, others become unemployed. This can make them feel guilty. Third, rising unemployment means that outside options are worse. Employees who are unsatisfied with their current job might want to leave for a better job but worse outside options discourage them from doing so. They stay in their job and dissatisfaction increases.

The present paper focuses on the third channel and differs from these literatures because it focuses on clearly work-related mental health. This decreases the number of confounding factors. Mental health problems in general, such as depression, can have many sources, which are not necessarily related to work (conflicts or death in the family or among friends, genetic predisposition). Even though these factors can certainly influence the formation of work-related mental health problems, their influence should be smaller. Focusing on work-related mental health problems gives a different framework for the analysis. In the JD-R, work-related mental health problems arise from an imbalance between job demands and resources. When there is an imbalance, an employee could react by trying to improve the situation (decrease demands and/or increase resources) or leave the job. Upon leaving the job, she might end up in unemployment at least for some time. The probability of unemployment is higher, the higher aggregate unemployment is. Anticipating unemployment might induce her to stay in her current job: she avoids unemployment but continues her exposure to an imbalanced environment. Over time, this can lead to work-related mental health problems as explained in the previous subsection. The second contribution of this paper is to use occupation specific unemployment measures. What happens in one's occupation is more important than what happens on the regional level.[1]

5.3 Data and Methods

5.3.1 Data

The data stem from the 2012 BIBB/BAuA-Survey on the Working Population on Qualification and Working Conditions (QaC) which is a representative cross section of the German working population. The survey is operated by the Research Data Centre of the German Federal Institute for Vocational Train-

[1]This is true especially assuming that people can move. Even though mobility is lower than in the U.S., in particular younger Germans are becoming more mobile.

ing (*Bundesinstitut für Berufsbildung*, BIBB) and the Federal Institute for Occupational Safety and Health (*Bundesanstalt für Arbeitsschutz und Arbeitsmedizin*, BAuA). It samples the working population older than 15 years working at least ten hours a week.[2] About 20,000 participants are interviewed with computer-assisted telephone interviews (Rohrbach-Schmidt and Hall, 2013). The survey covers a broad range of sociodemographic variables, job and company characteristics including job demands and resources.

A health section includes a list of 24 health complaints during work or on working days in the last 12 months: "Please tell me whether you have had the following health complaints during work or on working days in the last 12 months. We are interested in the frequently occurring ailments." One of these complaints is emotional exhaustion, a component of burnout. In addition to mere prevalence, it is possible to assess the severity of emotional exhaustion because participants stated whether they consulted a physician: "I will read out your health complaints once again. For each of them, please tell me whether you have been treated by a physician or therapist for this condition in the last 12 months." Taking physician consultation as an indicator of a more severe health complaint, the outcome takes the value 0 if there is no exhaustion, 1 if there is exhaustion but no consultation, and 2 if a physician is consulted. The second dependent variable is emotional strain. Emotional strain is included in a section on job characteristics but very similar in wording to emotional exhaustion. Individuals answered the question "How often does it happen that your work puts you in situations that are emotionally straining?" with "never" to "frequently" (0 to 3). A constructed third dependent variable is a combined measure indicating the presence of emotional exhaustion and/or emotional strain (0 to 5).

Information on consequences of bad health are also covered: "Did you stay home sick or have you called in sick in the last 12 months?" allows assessing absenteeism from work. Another reaction to sickness can be to go to work sick as framed in "In the last 12 months, did you ever go to work although you should better have called in sick due to your state of health?" This question assesses presenteeism. Combining the prevalence of work-related mental health problems with information on absenteeism and presenteeism allows to shed light on the consequences and coping behaviors arising from bad mental health. Both variables are binaries.

Since satisfaction as an outcome dominates the literature on unemployment and mental health, it is considered as an outcome, too. Life satisfaction is not covered in the survey. There is a question on general job satisfaction and some facets that are very closely related to overall job satisfaction (hours and tasks). Satisfaction is rated on a four point scale from very dissatisfied to very satisfied (0 to 3).

[2] "Work" means carrying out a paid activity/occupation or an activity related to income including people who interrupted their activity for a maximum of three months (e.g. parental leave) but excluding voluntary work and people employed as part of their initial training.

All dependent variables except absenteeism and presenteeism are standardized. Information on prior unemployment experience is available from: "Have you ever been unemployed during the course of your professional life?" (yes/no) and "For how long have you been unemployed in total, given in approximate full years?".

Unemployment data are obtained from the Institute for Employment Research (*Institut für Arbeitsmarkt- und Berufsforschung*, IAB: *Berufe im Spiegel der Statistik*).[3] The number of unemployed people is available from 1999 to 2011.[4] Occupations are 2-digit occupations according to the German Classification of Occupations (*Klassifizierung der Berufe*, KldB). The highest degree of disaggregation are occupations on federal state level. The unemployment data are merged to the QaC on 2-digit occupation codes and federal states. Due to missing unemployment information on federal state level and comparability between KldB versions in the QaC and the IAB data, there are 609 occupation-federal state combinations after matching. The final sample consists of 14,873 observations and comprises German employees between 18 and 65 years.[5]

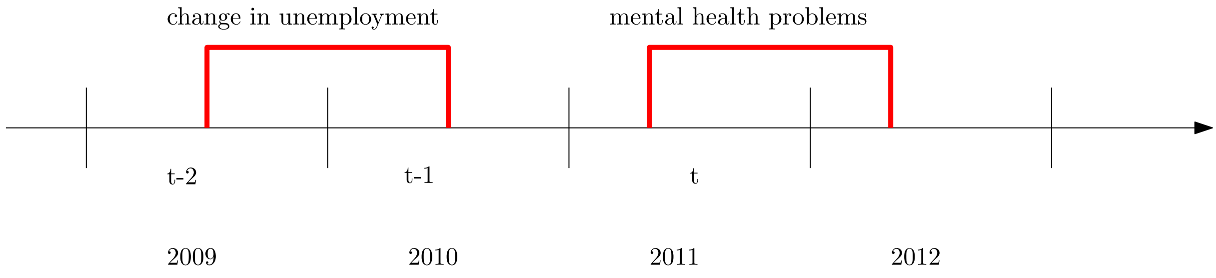
In analyzing the relationship between work-related mental health problems and rising unemployment, timing is crucial for two reasons. First, duration plays an important role for work-related mental health problems. They do not arise from a single or short stressful situation but when exposure is longer (this is especially true for burnout, see Schaufeli and Enzmann, 1998). Second, individuals need time to observe changes in unemployment, especially when these changes are so small that they are unnoticed in the beginning. The interviews for the surveys were conducted around the turn of the year 2011/12 and the health questions explicitly refer to the last 12 months. To allow enough time for unemployment changes to be noticed and mental health problems to develop, the analysis considers unemployment changes from 2009 to 2010 (figure 5.1).

[3] Available at: http://bisds.infosys.iab.de/, last accessed on August 15, 2017.

[4] Reporting month is June each year. Numbers include both German and foreign registered unemployed. In general, the federal employment agency cooperates with municipalities to take care of the unemployed. From 2005 onwards, municipalities could opt for becoming the only responsible by establishing certified local employment agencies (*Jobcenter* in German). Unemployed attended in these agencies are not included in the IAB data which relies on data from the federal employment agency. 69 municipalities, thereof 63 counties and 6 urban municipalities (*Landkreis* and *kreisfreie Stadt*), made use of this so-called option model (*Optionsmodell*). Most municipalities are in located Brandenburg, Hessen, and Niedersachsen, see also section 5.4.2. The experimental phase for the option model ran from 2005 to 2010. In 2011, the limited time frame of the option model was abolished. In 2012, another 41 municipalities assumed responsibility for their unemployed. The latter enlargement does not affect the data at hand which end in 2011. Unemployment rates are not available on a federal state level. The IAB reasons this choice with potential biases if a large fraction of people commutes to another federal state for work. I address this in subsections 5.4.2 and 5.5.1.

[5] Unemployment data on federal state level are available for 42 out of 83 occupations which results in a loss of 25% of the observations in the QaC. The QaC uses the 1992 version of the KldB. The unemployment data relies on this classification, too, but there are differences in three occupations' wording: Number 25 is labeled metal and plant engineering occupations (*Metall und Anlagenbauberufe*) and 27 mechanical engineering and maintenance occupations (*Maschinenbau und Wartungsberufe*) in the QaC but blacksmiths (*Schmiede*) and locksmiths (*Schlosser*) in the unemployment data. The latter denominations designate subgroups of the larger KldB groups. The unemployment data groups meat and fish processors together (*Fleisch und Fischverarbeiter*) under number 40, whereas the QaC puts butchers (*Fleischer*) and fish processors (*Fischverarbeiter*) in the rest group 43. Due to these inconsistencies, all three occupations are excluded. This results in a loss of another 264 observations.

Figure 5.1: Lag between measurement of work-related mental health problems and unemployment



There are two possibilities to measure unemployment changes: absolute and relative. The change in the number of unemployed from one year to another (level change) does not take into account the size of the occupation in the federal state. For example, an increase of 100 people is different for a baseline of 100 or 1,000 unemployed. Similarly, the level of unemployment (100) is not informative about the relative importance either (this is tested in subsection 5.4.2). To account for the relative importance of the change, unemployment changes in occupation o in federal state f, $\Delta Unem_{o,f}$, are calculated according to equation 5.1.

$$\Delta Unem_{of} = \frac{(Unem_{of,t-1} - Unem_{of,t-2})}{Unem_{of,t-2}} \tag{5.1}$$

The covariates are grouped into job demands and resources, sociodemographic and job characteristics according to table 5.1. The main job demands are work itself, pressure, obstacles, and a lack of resources. An excessive workload is measured by reaching the limits of one's capacity. Work is also demanding when interruptions are frequent, when too many different tasks have to be carried out (multitasking), and when different tasks have to be performed simultaneously. Work pressure is accounted for by deadline pressure, working fast, having to reach a minimum performance, and facing too high demands on skills or capacity ("overstrained"). Psychological pressure arises when even small mistakes can entail large financial losses. Obstacles at work are not receiving timely information about the future or not receiving all information that is necessary for efficient work. The scope of influencing one's own work is low when even tiny details in the work process are predetermined or when tasks are repetitive.

There are two important job resources: one is the scope of decision making, the other cooperation. A high scope of decision making means that individuals can plan and schedule their own work, influence their own workload, perform their tasks independently, and decide when to break. Good cooperation is an item itself. Some variables can act as either a job demand or a job resource depending on an individual's personality (ambiguous factors). If both types of personality are in the data, the effects of enhancing and deteriorating mental health might cancel out. These variables can best be described as "challenges".

One is related to hierarchy, three to work tasks. Being a supervisor may on the one hand give higher responsibility (job demand) but on the other also bring more scope to make decisions (job resource). Daily challenges at work arise when the individual has get familiar with her tasks before actually starting to work, when she has to improve methods, and when she is demanded unknown things. This can put additional pressure on the individual (job demand) or motivate her (job resource).

Table 5.1: Covariates

job demands and resources	sociodemographics	job characteristics
job demands	gender	hours, squared hours
reach limits of own capacity	having a partner	tenure
interrupted during work	having children	atypical work (short or temporary)
deadline/performance pressure	education	night work
work fast	(base: medium)	shift work
minimum performance	age, age square	work on weekends
overstrained		standby duty
risk of financial loss		feel work is important
no timely information about future		successful work life balance
do not receive all necessary information		
details predetermined		
repetition		
job resources		
plan/schedule own work		
influence own workload		
decide when to break		
perform tasks independently		
good collaboration		
ambiguous factors		
supervisor for somebody		
get familiar with tasks		
improve methods		
demanded unknown things		

Own figure as in chapter two.

Sociodemographic information comprises gender, age, having a partner (whether married or not) and children. Education is measured as the professional training received and divided into low, medium, medium plus, and higher education.[6] Information on individual characteristics that allow to control for personality are not available. The only variables capturing individuals' attitudes are job-related. Job characteristics comprise job-related variables which do not belong into the typical JD-R but are associ-

[6]Low education means that no professional training took place. Medium education comprises professional training in companies and/or in school (apprenticeship). Individuals with university degrees (or related such as universities of applied sciences) acquired higher education. In Germany, some individuals complement their professional training with further professional training to reach a higher professional position as a master or technician (*Aufstiegsfortbildung zum Meister, Techniker* in German). People with this complement usually continue to work in their field but obtain higher positions with more responsibility than those who went through professional training alone. In that sense, they are in between people with common professional training and people with university education. Here, they are captured in a separate category labeled "medium plus".

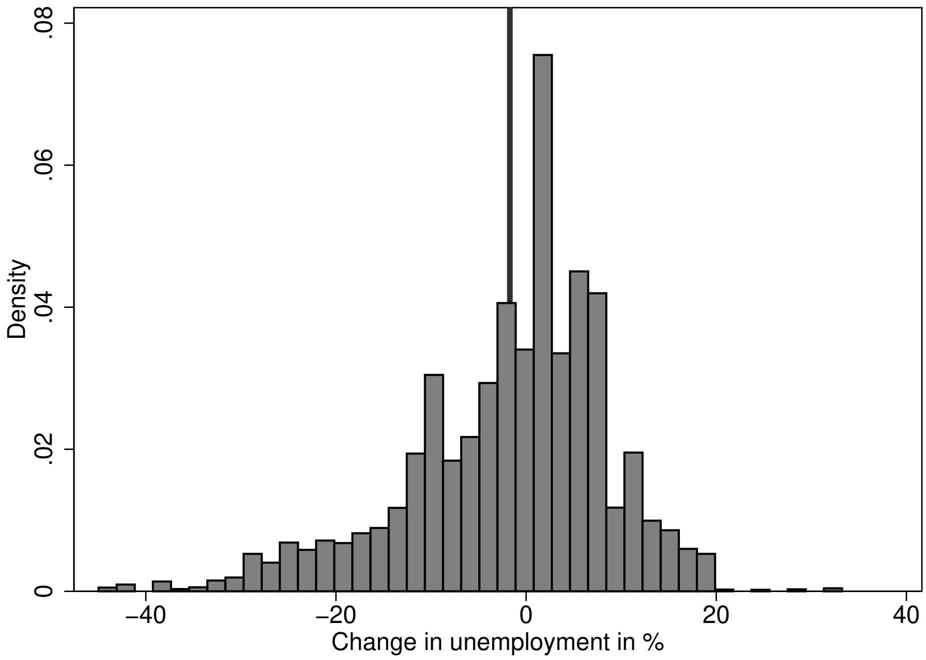
ated with burnout (see subsection 5.2.1). Among them are weekly working hours since excessive hours are related to exhaustion. Employees with limited contracts or in temporary employment have less job security and may be more vulnerable than those with unlimited contracts. Irregular working hours can put additional strain on employees by e.g. disturbing their circadian rhythm (biological rhythm) or restraining social life outside work. This is measured by dummy variables for regular night work, shift work, work on weekends, and standby duty. Three variables account for attitudes towards work: a successful work life balance, working in one's dream job, and feeling that own work is important.

5.3.2 Descriptives

An overview of relevant variables with their mean, standard deviation, minimum, and maximum can be found in table A5.1 in the appendix. Figure 5.2 displays a histogram of relative unemployment changes. Unemployment increased in 169 occupation–federal state combinations (28%). 52% of the individuals faced increasing unemployment, around 25% experienced sharp increases in unemployment of more than 10% (37 occupation-federal state cells). Teachers in eight out of sixteen federal states are exposed to this. Unemployment is high for entrepreneurs, organizers, accountants in six states, and for technicians and guards/servants in four. The occupations with high increases in one or two states are metal-cutters, engineers, technical specialists, goods merchants, bank and insurance specialists, other service merchants, accountants/data processing specialists, social workers, other humanities and natural sciences occupations, and guest attending occupations. 7% of the sample experienced sharp declines in unemployment of more than 20%. For around 40%, changes were below +/-5%. To facilitate the overview, changes in unemployment are grouped into nine categories, five in which occupation specific unemployment on the federal state level decreased or remained constant and four in which unemployment increased.

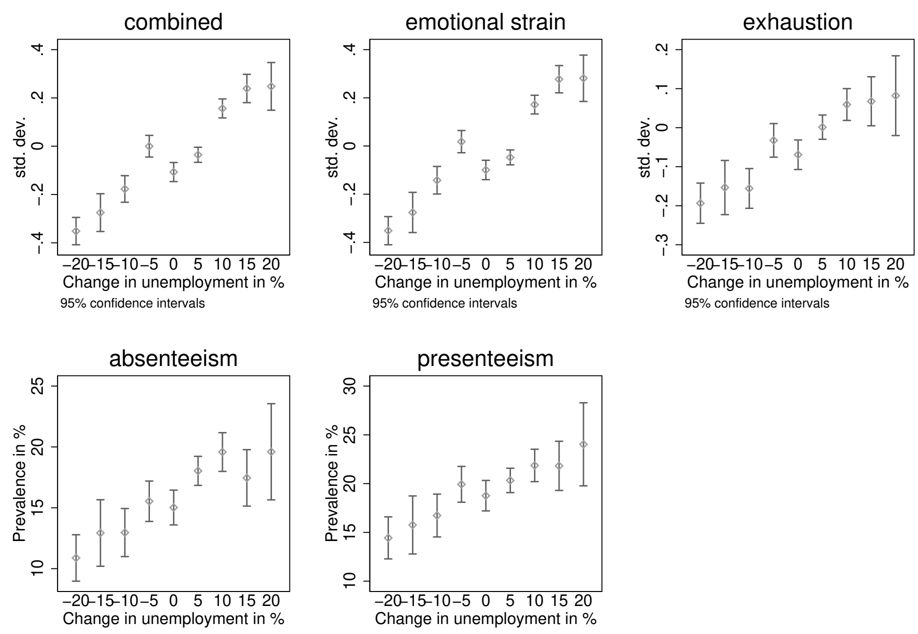
The prevalence of work-related mental health problems increases with unemployment (figure 5.3). Emotional strain, exhaustion, absenteeism, and presenteeism are lowest among individuals whose occupation and federal state specific unemployment decreased markedly (by 10% to 20%). Prevalence increases with unemployment but is comparatively high in the group facing 5% decreases in unemployment. The higher the increases in unemployment, the higher the mean prevalence of mental health problems. Larger confidence intervals suggest that the differences for the groups with unemployment increases of 10% to 20% are not significant. The difference across unemployment is largest for emotional strain as the range comprises 0.7 standard deviations. The range for exhaustion is 0.3 standard deviations. Absenteeism and presenteeism vary in an order of 10 and 8 percentage points.

Figure 5.2: Histogram of unemployment changes



The x-axis shows one period lagged changes in occupation specific unemployment on federal state level. Mean: -1.7% change. Data sources: BIBB/BAuA, IAB. Own figure.

Figure 5.3: Work-related mental health outcomes by changes in unemployment



The x-axis shows one period lagged changes in occupation specific unemployment on federal state level. 95% confidence intervals. Data sources: BIBB/BAuA, IAB. Own figure.

5.3.3 Estimation procedure

The relationship between unemployment changes and work-related health outcomes is formalized in equation 5.2. Individual work-related health outcomes Y_i are regressed on occupation o and federal state f specific changes in unemployment $\Delta Unem_{of}$ and a vector of individual control variables $\mathbf{X}_i$. α is a constant, u_i is the error term.

$$Y_i = \alpha + \beta \Delta Unem_{of} + \mathbf{X}_i' \delta + u_i \tag{5.2}$$

Equation 5.2 is estimated with OLS. For binary outcomes, it is a linear probability model.[7] Standard errors are clustered on the occupation-federal state level to account for potential interdependence of error terms.[8] As a point of reference, I regress health complaints on the change in unemployment before adding variables capturing job demands, job resources, sociodemographic and job characteristics as in table 5.1.[9]

$\hat{\beta}$ does not identify a causal effect of unemployment changes on work-related mental health. The individual i cannot influence $\Delta Unem_{of}$ but it has influence on occupation o and federal state f as she choses a certain occupation in a certain federal state. Individuals with more vulnerable work-related mental health (e.g. due to a different stress perception or fewer coping strategies) could select into occupations in federal states with rising unemployment. This could drive the relationship suggested by figure 5.3. More healthy individuals might leave to occupations or federal states with better conditions, while less healthy individuals might be left behind ("stuck" in unfavorable occupation-federal state cells).[10] A second reason for a biased estimate of β could be omitted variables, namely employability which Green (2011) identified as being central to the relationship of mental health and job insecurity. There is hence no claim on causality.

[7] Marginal effects after logit estimation are comparable.

[8] Moulton (1990) shows that OLS standard errors are downward biased when the data has a grouped structure. Downward biased standard errors in turn inflate test statistics. Data structure is usually grouped when merging micro data (individual survey data) and macro data (occupation-federal state unemployment information). The results are similar when estimating non-clustered robust standard errors.

[9] Variance inflation factors are larger than 10 for age, hours, and tenure. Excluding these variables does not affect the coefficient of interest substantially. The results reported include them.

[10] One could in principle account for one part of this selection and use the variation in the other part for identification, for example by limiting the analysis to one occupation. This would free the estimates from selection into occupation which is arguably the more relevant choice. Variation in unemployment changes would then occur on the federal state level which is much less than in the full sample (16 different values compared to around 600). Another problem with this approach is that samples become rather small as numbers of observations within occupations rarely exceed 600.

5.4 Results

5.4.1 Main results

Rising unemployment is significantly associated with work-related mental health problems (table 5.2). The table reports unemployment coefficients and the constant from the base model (no covariates) and the full model (all covariates from table 5.1). The unemployment coefficients refer to increases in the relative change in unemployment of 10 percentage points. For example, if there are 100 unemployed in occupation o in federal state f in 2009 and 120 in 2010, the relative increase is 20%. An increase of 10 percentage points is an increase by 30%, i.e. to 130 instead of 120 unemployed.[11] Sample sizes differ across the dependent variables due to missing information on the outcome. In general, raw coefficients for unemployment changes in the base model are roughly 1.5 times larger than coefficients in the full model with all covariates. All unemployment coefficients are significant at the 1% level. The full models perform better in terms of the model selection criteria AIC and BIC (not reported) and explain a larger share of the variation in the outcome (R^2).

A 10 percentage point increase in the relative change in unemployment is associated with an increase in any work-related mental health problem by 0.075 standard deviations in the full model. The estimate is similar for strain (0.072), the one for emotional exhaustion is smaller (0.046). Absenteeism and presenteeism increase by 1.6 percentage points. This corresponds to relative increases of 13% and 8% respectively, as absenteeism averages 16% and presenteeism 19%.

Unemployment is not associated with lower job satisfaction (table 5.3). In the base model without any covariates, an increase in the relative change in unemployment change of 10 percentage points is associated with an increase in overall satisfaction of 0.05 standard deviations. The point estimate is insignificant in the full model with all covariates. Base model estimates are smaller for satisfaction with hours (0.03 standard deviations) and larger for satisfaction with tasks (0.09 standard deviations). The unemployment coefficient is insignificant in the full model for both outcomes.

[11] The interpretation would be simpler with the level of unemployed or the level change in unemployment. This is addressed in subsection 5.4.2.

Table 5.2: OLS estimates for work-related mental health outcomes

	combined	strain	exhaustion	absenteeism	presenteeism
base model					
unemployment	0.121***	0.122***	0.066***	0.023***	0.019***
	(0.017)	(0.018)	(0.011)	(0.004)	(0.005)
constant	-0.016	-0.012	-0.016	0.175***	0.200***
	(0.030)	(0.031)	(0.017)	(0.007)	(0.007)
full model					
unemployment	0.075***	0.072***	0.046***	0.017***	0.016***
	(0.013)	(0.014)	(0.010)	(0.004)	(0.004)
constant	-0.698***	-0.579***	-0.592***	0.102	0.081
	(0.172)	(0.184)	(0.166)	(0.070)	(0.072)
N	11307	11325	11311	11308	11304
R^2 adj. base	0.021	0.021	0.006	0.005	0.003
R^2 adj. full	0.302	0.265	0.159	0.122	0.157

Standardized dependent variable given in column header (absenteeism and presenteeism: binaries). Combined: emotional exhaustion and/or emotional strain. Full model contains job demands and resources, sociodemographic and job covariates according to table 5.1. Standard errors clustered on federal state and occupation in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA, IAB. Own calculations.

Table 5.3: OLS estimates for job satisfaction

	overall	hours	tasks
base model			
unemployment	0.054***	0.030**	0.069***
	(0.012)	(0.013)	(0.012)
constant	0.005	0.046***	-0.010
	(0.013)	(0.016)	(0.015)
full model			
unemployment	0.009	-0.004	0.007
	(0.011)	(0.010)	(0.010)
constant	-0.001	0.039	-0.697***
	(0.202)	(0.210)	(0.182)
N	11324	11318	11324
R^2 adj. base	0.004	0.001	0.007
R^2 adj. full	0.245	0.212	0.185

Standardized dependent variable given in column header. Full model contains job demands and resources, sociodemographic and job covariates according to table 5.1. Standard errors clustered on federal state and occupation in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA, IAB. Own calculations.

The positive relationship between work-related mental health problems and rising unemployment could be driven by certain individual or job characteristics. For example, it could differ by job security and exposure time to the job environment. Employees with limited or temporary contracts ("atypical") could be affected differently by rising unemployment because their job security is lower. Full-time employees are exposed during longer hours to adverse working conditions. Table 5.4 displays the results by contract type and working hours. Unemployment is significant for health independently of job security. The point estimates are somewhat larger in the atypical sample for exhaustion and absenteeism. The estimate for presenteeism is of similar size but insignificant due to larger standard errors in the smaller sample. Another difference could arise from working hours. Working full-time is defined as working 35 hours or more. All coefficients are insignificant in the part-time sample (panel four). Part-time workers are exposed fewer hours to adverse working conditions from which their mental health could suffer. A second explanation could be that part-time workers are a pre-selected sample, e.g. working mothers often work part-time. A job loss would be less threatening for them if their husband is employed.[12]

To check whether this safety net is determinant, table 5.5 displays the results for employees with and without a partner. Even though the unemployment coefficients are significant for people with a partner, the point estimates are about one third the size of the estimates for people without a partner. A safety net seems to make employees less vulnerable to worse macroeconomic conditions. The last two panels analyze whether men and women react differently to rising unemployment. The association between emotional strain and unemployment is stronger for men than for women (third and fourth panel). The associated increase is 0.083 standard deviations for men. The coefficient is smaller (0.039) and insignificant for women. For exhaustion and absenteeism, unemployment estimates are larger for women. The association of work-related mental health problems and rising unemployment is hence driven by full-time employees. It is stronger where job insecurity is higher and where there are fewer safety nets. For the rest of the paper, I continue to use the full sample. The results are robust to using full-time employees only.

[12] Gender roles are changing in Germany, especially in the younger generation, but the traditional breadwinner model is still widely diffused.

Table 5.4: OLS estimates for work-related mental health outcomes in subsamples

	combined	strain	exhaustion	absenteeism	presenteeism
no atypical					
unemployment	0.075***	0.074***	0.044***	0.016***	0.016***
	(0.013)	(0.014)	(0.010)	(0.004)	(0.004)
constant	-0.556***	-0.509***	-0.393**	0.156**	0.166**
	(0.184)	(0.197)	(0.170)	(0.076)	(0.079)
atypical					
unemployment	0.067**	0.058*	0.053*	0.024**	0.015
	(0.033)	(0.033)	(0.032)	(0.012)	(0.013)
constant	-1.119**	-0.641	-1.414***	-0.120	-0.233
	(0.443)	(0.473)	(0.436)	(0.165)	(0.153)
full-time					
unemployment	0.082***	0.078***	0.052***	0.019***	0.017***
	(0.013)	(0.014)	(0.011)	(0.004)	(0.005)
constant	-0.404	-0.340	-0.343	0.327**	0.094
	(0.322)	(0.363)	(0.291)	(0.128)	(0.129)
part-time					
unemployment	0.013	0.012	0.008	0.012	0.007
	(0.031)	(0.033)	(0.025)	(0.010)	(0.011)
constant	-0.671**	-0.745**	-0.246	0.125	0.289**
	(0.316)	(0.330)	(0.340)	(0.140)	(0.141)
N no atypical	10086	10103	10090	10088	10084
N atypical	1221	1222	1221	1220	1220
N full-time	8488	8504	8490	8490	8490
N part-time	2819	2821	2821	2820	2820

Standardized dependent variable given in column header (absenteeism and presenteeism: binaries). Combined: emotional exhaustion and/or emotional strain. Full models controlling for job demands and resources, sociodemographic and job covariates according to table 5.1 except objective controls model. Atypical: limited or temporary contract, full-time: 35 weekly hours or more, part-time: less than 35 hours. Standard errors clustered on federal state and occupation in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA, IAB. Own calculations.

Table 5.5: OLS estimates for work-related mental health outcomes in subsamples II

	combined	strain	exhaustion	absenteeism	presenteeism
no partner					
unemployment	0.104***	0.099***	0.065***	0.022***	0.024***
	(0.018)	(0.019)	(0.016)	(0.006)	(0.007)
constant	-0.729***	-0.670***	-0.509**	0.103	0.065
	(0.213)	(0.224)	(0.211)	(0.090)	(0.094)
partner					
unemployment	0.053***	0.053***	0.031**	0.013***	0.010*
	(0.014)	(0.016)	(0.013)	(0.005)	(0.005)
constant	-0.401	-0.299	-0.410	0.222*	0.269**
	(0.275)	(0.300)	(0.303)	(0.122)	(0.124)
women					
unemployment	0.054**	0.039	0.056***	0.026***	0.012*
	(0.024)	(0.026)	(0.018)	(0.008)	(0.007)
constant	-0.476**	-0.383*	-0.423	0.159	0.198*
	(0.215)	(0.225)	(0.265)	(0.110)	(0.105)
men					
unemployment	0.080***	0.083***	0.038***	0.013***	0.016***
	(0.013)	(0.014)	(0.012)	(0.005)	(0.005)
constant	-0.974***	-0.917***	-0.643***	0.100	0.028
	(0.253)	(0.267)	(0.228)	(0.100)	(0.108)
N no partner	5388	5398	5390	5391	5386
N partner	5919	5927	5921	5917	5918
N women	6170	6178	6171	6171	6171
N men	5137	5147	5140	5137	5137

Standardized dependent variable given in column header (absenteeism and presenteeism: binaries). Combined: emotional exhaustion and/or emotional strain. Full models controlling for job demands and resources, sociodemographic and job covariates according to table 5.1 except objective controls model. Standard errors clustered on federal state and occupation in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA, IAB. Own calculations.

5.4.2 Robustness

This subsection analyses the robustness of the results regarding measurement and lag choices of unemployment changes, measurement of work-related mental health, and measurement error in federal states. Measuring unemployment as the relative change from one year to another makes the unit interpretation of the regression output difficult. Here, a one unit change is an increase in the relative change in unemployment by 10 percentage points. Interpretation would be easier using level of unemployment or level changes. Figure A5.1 in the appendix depicts the relationship between work-related mental health and the level of unemployment. There seems to be a negative relationship: a higher number of unemployed is associated with lower health problems. This does not take into account whether the macroeconomic situation is getting better or worse, i.e. whether unemployment decreases or increases. The relationship for the level change is shown in figure A5.2. This figure looks more similar to the relative change figure as mental health problems increase with unemployment. The regression results are displayed in table 5.6. Controlling for job demands and resources, sociodemographic and individual characteristics, neither the level nor the change in the level of unemployment is associated with work-related mental health (first two panels). Point estimates are zero. This suggests that the absolute magnitude does not play a role for the relationship between work-related mental health and unemployment.

A simplification of the relative change measure could be to distinguish between decreasing and increasing unemployment only and not take the magnitude into account. The last panel shows the results with a dummy for increasing versus decreasing/constant unemployment. All coefficients are significant (strain at the 10% level). Increasing compared to constant or decreasing unemployment is associated with a 0.1 standard deviation increase in any work-related mental health problem. The coefficient for strain (0.074) is smaller than the one for exhaustion (0.099). Absenteeism increases by 3.7 percentage points and presenteeism by 3.3 percentage points. The binary measure is easier to interpret but considerably reduces variation in the regressor of interest. In the following, I therefore continue to use the continuous measure.

Table 5.6: OLS estimates for work-related mental health outcomes with alternative unemployment measures

	combined	strain	exhaustion	absenteeism	presenteeism
level					
unemployment	-0.000**	-0.000*	-0.000***	-0.000*	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
constant	-0.625***	-0.515***	-0.537***	0.120*	0.099
	(0.173)	(0.188)	(0.166)	(0.070)	(0.071)
level change					
unemployment	0.000***	0.000**	0.000***	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
constant	-0.697***	-0.577***	-0.595***	0.102	0.082
	(0.174)	(0.185)	(0.167)	(0.071)	(0.072)
dummy increasing					
unemployment	0.100***	0.074*	0.099***	0.037***	0.033***
	(0.038)	(0.041)	(0.025)	(0.010)	(0.010)
constant	-0.746***	-0.608***	-0.651***	0.081	0.062
	(0.175)	(0.188)	(0.166)	(0.070)	(0.072)
N	11307	11325	11311	11308	11304

Standardized dependent variable given in column header (absenteeism and presenteeism: binaries). Combined: emotional exhaustion and/or emotional strain. Full model contains job demands and resources, sociodemographic and job covariates according to table 5.1. Standard errors clustered on federal state and occupation in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA, IAB. Own calculations.

The lag between the change in unemployment and work-related mental health outcomes was chosen to be of on average one year. Individuals need to observe unemployment changes and react in their work-related mental health. Table 5.7 presents evidence on the sensitivity to lag choices. More recent unemployment changes from lag $t-1$ to t are not significant. Panels two and three take larger time frames (two years). Panel two uses unemployment changes from $t-2$ to t. The point estimates are highly significant but between half and one third the size of the ones in table 5.2. More recent unemployment changes seem to bias the effect of the ones from the earlier period. Panel three uses changes from $t-3$ to $t-1$. The coefficient for emotional strain is negative and highly significant. This suggests that earlier unemployment changes confound the effect of more recent ones. All in all, the initial choice appears to successfully balance the trade-off between too recent and too early changes. [13]

Table 5.7: OLS estimates for work-related mental health outcomes, lag choice

	combined	strain	exhaustion	absenteeism	presenteeism
t-1 to t					
unemployment	0.006	0.009	-0.001	0.002	0.003
	(0.008)	(0.008)	(0.005)	(0.002)	(0.002)
constant	-0.659***	-0.538***	-0.575***	0.112	0.091
	(0.176)	(0.188)	(0.167)	(0.071)	(0.072)
t-2 to t					
unemployment	0.023***	0.025***	0.010*	0.005***	0.006**
	(0.008)	(0.008)	(0.006)	(0.002)	(0.002)
constant	-0.647***	-0.528***	-0.564***	0.114	0.093
	(0.175)	(0.187)	(0.167)	(0.071)	(0.072)
t-3 to t-1					
unemployment	-0.013***	-0.015***	-0.003	-0.000	-0.001
	(0.004)	(0.005)	(0.003)	(0.001)	(0.001)
constant	-0.665***	-0.547***	-0.573***	0.110	0.088
	(0.173)	(0.186)	(0.166)	(0.071)	(0.072)
N	11307	11325	11311	11308	11304

Standardized dependent variable given in column header (absenteeism and presenteeism: binaries). Combined: emotional exhaustion and/or emotional strain. Full model contains job demands and resources, sociodemographic and job covariates according to table 5.1. Standard errors clustered on federal state and occupation in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA, IAB. Own calculations.

The results could be driven by the measurement of work-related mental health. The first three columns in table 5.8 use binary measures instead of standardized variables. About 4,000 individuals report frequent emotional strain. Defining a narrow measure for strain as equal to 1 if strain is frequent and 0 otherwise

[13] Using an earlier wave, the 2006 survey, allows conducting a falsification test, i.e. to regress work-related mental health on future unemployment changes from lag t to $t+1$. This is not possible for the 2012 survey since the unemployment data ends in 2011. The 2006 survey is not used for the main analysis because it does not contain information on past unemployment. Significant results in the falsification test would indicate that the relationship assumed so far is random. Using the 2006 data, there is no descriptive evidence for any clear relationship between future unemployment and mental health. Not surprisingly the point estimates are insignificant (not displayed).

yields an insignificant unemployment coefficient in the full model. Including individuals experiencing emotional strain sometimes (about 5,000 individuals), an increase in the relative change of unemployment of 10 percentage points is associated with an increase in strain of 1.2 percentage points (5% level). Since 61% of the sample frequently or sometimes feel strained, this corresponds to an increase of 2%. Emotional exhaustion was standardized assuming physician consultation as an indicator for severeness. The binary measure does not distinguish between consultation and no consultation. The unemployment point estimate is highly significant (2.2 percentage points or 8.8%). The relative increase is larger as 25% report emotional exhaustion.

The four outcomes emotional exhaustion, emotional strain, absenteeism, and presenteeism were chosen based on the literature (work-related) and the data (availability). Two questions arising from this choice are: 1) Do the measures chosen represent a common underlying factor (work-related mental health problems) or do they measure entirely different things? and 2) Is the focus on explicitly work-related mental health necessary? Factor analysis addresses the first question. One factor had an eigenvalue larger than 1 in an analysis with iterated principal factor. The common factor was predicted after rotation and is the dependent variable in the fourth column of table 5.8 (“common”). The point estimate is highly significant and comparable in size to the estimate for standardized exhaustion (0.05).

Table 5.8: OLS estimates for alternative work-related mental health outcomes

	strain	strain (broad)	exhaustion	common
unemployment	-0.008	0.012^{**}	0.022^{***}	0.050^{***}
	(0.005)	(0.006)	(0.004)	(0.010)
constant	0.244^{***}	0.375^{***}	0.034	-0.460^{***}
	(0.093)	(0.100)	(0.079)	(0.175)
N	11325	11325	11314	11276
R^2 adj.	0.025	0.053	0.163	0.177

Binary dependent variable given in column header. Common factor determined in factor analysis from emotional exhaustion, emotional strain, absenteeism, and presenteeism. Binary strain: sometimes/often (1), rarely/never (0). Binary exhaustion: emotional exhaustion (1), no exhaustion (0). Model contains job demands and resources, sociodemographic and job covariates according to table 5.1. Standard errors clustered on federal state and occupation in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/ BAuA, IAB. Own calculations.

To answer the second question, columns one to five of table 5.9 display the results for mental health outcomes frequently arising during or immediately after work but which are not conceptually related to work.[14] Contrary to emotional strain, they can also arise in a work-free context. Headaches, night-time sleeping disorders, general tiredness, nervousness or irritability, and the blues could arise from stress at work but also in private life, due to physical health problems, personality, genetic predisposition etc. All dependent variables are binaries. Unemployment is not significant for the probability of suffering from sleeping disorders and general tiredness. A 10 percentage point increase is significantly associated with an increase in headaches of 1.7 percentage points and in nervousness of 1.5 percentage points. The point estimates are similar in size to the estimate for binary emotional strain but since prevalence is higher, the relative importance is smaller: 35% report headaches and 29% nervousness. The relative increases are 5%. Rising unemployment is associated with a lower risk for blues but the coefficient is significant at the 5% level only and rather small (0.008). Overall, increasing unemployment does not seem to be related to mental health as clearly and unambiguously as it is to work-related mental health.

A positive association between absenteeism and unemployment stands in contrast to the literature on the disciplinary effect of unemployment, e.g. Leigh (1985): employees reduce voluntary absenteeism (shirking) to prevent from being laid off. In this literature, rising unemployment is associated with lower absenteeism. To address this issue, the last two columns of table 5.9 use general absenteeism and presenteeism as outcomes. Unemployment is not significantly related to these measures suggesting that there is no shirking reduction in absenteeism.

Table 5.9: OLS estimates for general (mental) health outcomes

	headaches	sleeping	tired	nervous	blues	absenteeism	presenteeism
unemployment	0.017***	-0.001	0.005	0.015***	-0.008*	0.005	0.003
	(0.005)	(0.005)	(0.006)	(0.005)	(0.004)	(0.007)	(0.006)
constant	0.385***	0.008	0.206**	0.096	0.037	0.505***	0.599***
	(0.099)	(0.073)	(0.100)	(0.083)	(0.075)	(0.100)	(0.101)
N	11321	11316	11322	11317	11321	11308	11304
R^2 adj.	0.089	0.135	0.152	0.158	0.153	0.036	0.116

Binary dependent variable given in column header. During work or on working days: headaches, sleeping disorder, general tiredness, nervousness/irritability, blues. Model contains job demands and resources, sociodemographic and job covariates according to table 5.1. Standard errors clustered on federal state and occupation in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/ BAuA, IAB. Own calculations.

Finally, the results may be confounded by small city states which typically attract more commuters or by missing unemployment information in some federal states due to different patronage of employment offices (see footnote 4 on page 107). Table 5.10 addresses these concerns. Excluding city states (Berlin, Hamburg, Bremen) or federal states with partially missing information on unemployment (the option

[14]The models use the full set of controls. Since the dependent variables are not intrinsically work-related, job demands and resources may not play the same role as for work-related mental health. Excluding these controls does not substantially alter the results. Point estimates are affected marginally.

states Brandenburg, Hessen, and Niedersachsen) does not affect the relationship between mental health and unemployment (panels one and three). The estimates for city states only are largely insignificant (panel two). All standard errors are larger due to a smaller sample size and point estimates are smaller except for emotional strain. In option model states (last panel), the effect is comparable for emotional exhaustion, emotional strain, and absenteeism but somewhat larger for presenteeism. All in all, the positive relationship between mental health and rising unemployment is confirmed.

Table 5.10: OLS estimates for work-related mental health outcomes, different samples

	combined	strain	exhaustion	absenteeism	presenteeism
excl. city states					
unemployment	0.072***	0.070***	0.044***	0.016***	0.016***
	(0.013)	(0.015)	(0.010)	(0.004)	(0.004)
constant	-0.711***	-0.555***	-0.665***	0.082	0.039
	(0.179)	(0.191)	(0.171)	(0.072)	(0.072)
city states					
unemployment	0.102**	0.097**	0.065	0.026	0.013
	(0.044)	(0.043)	(0.045)	(0.020)	(0.017)
constant	-0.683	-1.002	0.156	0.313	0.548*
	(0.647)	(0.641)	(0.620)	(0.231)	(0.284)
excl. option states					
unemployment	0.066***	0.061***	0.045***	0.017***	0.015***
	(0.015)	(0.016)	(0.011)	(0.004)	(0.004)
constant	-0.760***	-0.588***	-0.714***	0.047	0.063
	(0.192)	(0.200)	(0.192)	(0.078)	(0.081)
option states					
unemployment	0.110***	0.121***	0.041*	0.019*	0.021*
	(0.023)	(0.025)	(0.023)	(0.010)	(0.011)
constant	-0.561	-0.584	-0.285	0.228	0.137
	(0.395)	(0.434)	(0.321)	(0.153)	(0.152)
N excl. city	10382	10398	10385	10384	10379
N city	925	927	926	924	925
N excl. option	9007	9020	9010	9007	9004
N option	2300	2305	2301	2301	2300

Standardized dependent variable given in column header (absenteeism and presenteeism: binaries). Combined: emotional exhaustion and/or emotional strain. Full model contains job demands and resources, sociodemographic and job covariates according to table 5.1. Standard errors clustered on federal state and occupation in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA, IAB. Own calculations.

5.5 Mechanism

This section aims at shedding more light on the mechanism of the relationship between unemployment and work-related mental health. The first subsection asks whether occupational or regional unemployment is the driving force. The second subsection analyses whether own unemployment experiences in the past play a role.

5.5.1 Level of aggregation of unemployment

Table 5.11 shows the results for more aggregate unemployment changes. Panels one and two use rising occupation specific unemployment on the federal level and in West/East Germany separately.[15] The point estimates for occupation but not state specific unemployment changes ("specific Germany") are highly significant and slightly larger for all outcomes but absenteeism. The coefficients for occupation specific unemployment changes in East or West Germany ("specific East/West") are marginally smaller except for emotional strain (slightly larger). Commuting to other federal states could bias the results. Panel three uses the federal state of the company location instead of the individual state of residence. Merging occupation and federal state specific unemployment data based on this definition yields 612 occupation-federal state combinations. The points estimates are very similar to the original ones except for emotional strain (smaller).[16]

The last panel displays coefficients for federal state specific but occupation unspecific unemployment changes on the federal state level. Unemployment decreased in all federal states. Schleswig-Holstein's decrease from 2009 to 2010 was largest (29%), Mecklenburg Vorpommern's smallest (2.8%). Standard errors increase by a factor of two to four. A 10 percentage points increase in the relative change in unemployment is significantly associated with higher absenteeism (4.6 percentage points). Point estimates are insignificant for all other outcomes. This suggests that occupation is more important than region for the relationship between unemployment and work-related mental health.

[15] Different sample sizes arise because unemployment information is available for more occupations on a higher level of aggregation.

[16] Another possibility to address commuting would be to include the unemployment in federal states which are attractive to commuters, e.g. due to proximity. One could for example include adjacent federal states and calculate the mean of residential and surrounding federal states unemployment changes. There are two problems with this approach. First, while proximity is clearly given for all city states residents, this is different for larger federal states. For example, Saxony is close for East Lower Saxons but not for West Lower Saxons. Second, Hesse and Thuringia have five to six neighbors which would cover half of Germany's area. A more narrow measurement unit than federal states would be required for this analysis.

Table 5.11: OLS estimates for work-related mental health outcomes, level of aggregation prior unemployment

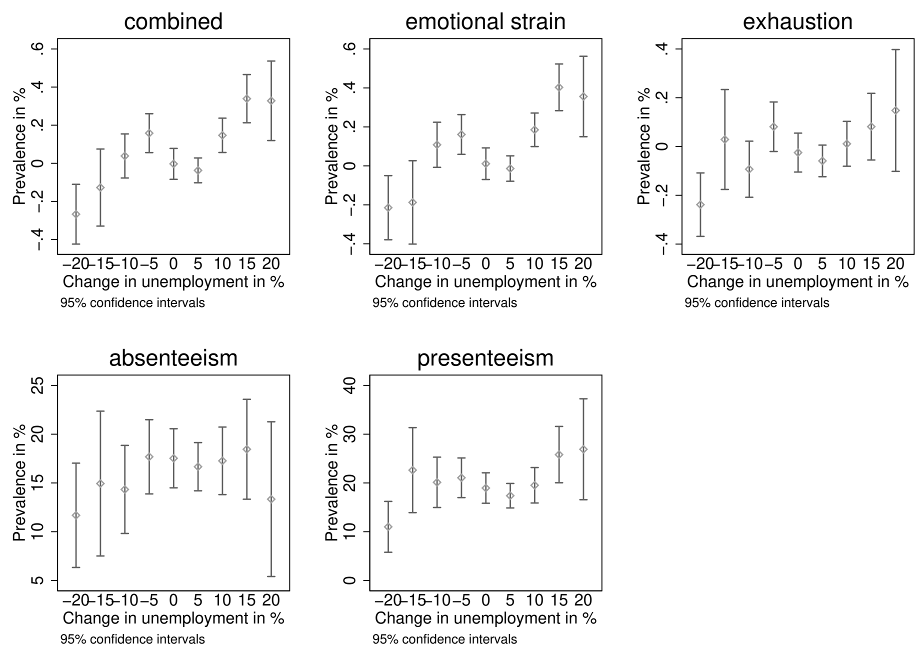
	combined	strain	exhaustion	absenteeism	presenteeism
specific Germany					
unemployment	0.093***	0.095***	0.048***	0.015***	0.019***
	(0.028)	(0.032)	(0.017)	(0.005)	(0.007)
constant	-0.682***	-0.574***	-0.591***	0.073	0.093*
	(0.184)	(0.211)	(0.138)	(0.063)	(0.054)
specific East/West					
unemployment	0.081***	0.082***	0.044***	0.014***	0.016***
	(0.024)	(0.026)	(0.014)	(0.005)	(0.006)
constant	-0.693***	-0.585***	-0.597***	0.071	0.091
	(0.181)	(0.205)	(0.147)	(0.065)	(0.067)
specific company					
unemployment	0.066***	0.060***	0.046***	0.016***	0.017***
	(0.015)	(0.016)	(0.011)	(0.005)	(0.004)
constant	-0.701***	-0.579***	-0.598***	0.101	0.080
	(0.174)	(0.188)	(0.166)	(0.069)	(0.071)
unspecific federal state					
unemployment	0.039	0.007	0.073	0.046***	0.008
	(0.041)	(0.033)	(0.048)	(0.015)	(0.016)
constant	-0.637***	-0.544***	-0.519**	0.144*	0.094
	(0.143)	(0.142)	(0.243)	(0.075)	(0.096)
N Germany, East/West, company	12409	12433	12413	12415	12411
N unspecific	11307	11325	11311	11308	11304

Standardized dependent variable given in column header (absenteeism and presenteeism: binaries). Combined: emotional exhaustion and/or emotional strain. Full model contains job demands and resources, sociodemographic and job covariates according to table 5.1. Specific: occupation and federal state of residence specific unemployment. Germany: occupation specific unemployment. East/West: occupation and East/West German specific unemployment. Company: occupation and federal state of company specific unemployment. Unspecific: federal state of residence unemployment. Standard errors clustered on federal satate and occupation in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA, IAB. Own calculations.

5.5.2 Own unemployment experience in the past

Individuals who have been unemployed in the past might react differently to increasing unemployment compared to individuals who have no own experience with unemployment. Unemployment experience could a) scar people and make them more vulnerable to worse outside options or b) toughen them (habituation) and make them less vulnerable as in (Clark et al., 2001). Information on prior unemployment experience is not available for all individuals. Sample sizes reduce to around 3,000 people who have never been unemployed and about 5,000 people who have been unemployed at some point in their work life. There are 411 occupation-federal state combinations in the sample with no past unemployment experience and 546 in the sample with past unemployment experience. Figure 5.4 shows the relationship between unemployment changes and work-related mental health for people who have never been unemployed. Confidence intervals overlap and no clear pattern emerges. Strain is larger for unemployment increases of 10% and more compared to decreases of 15% and more. Exhaustion and presenteeism are very low for large decreases in unemployment (20%) but even there, confidence intervals overlap. Figure 5.5 demonstrates that the group of people with unemployment experience was driving the joint figure 5.3. All graphs suggest a linear positive relationship between rising unemployment and work-related mental health problems.[17]

Figure 5.4: Work-related mental health outcomes by changes in unemployment, individuals without prior unemployment experience

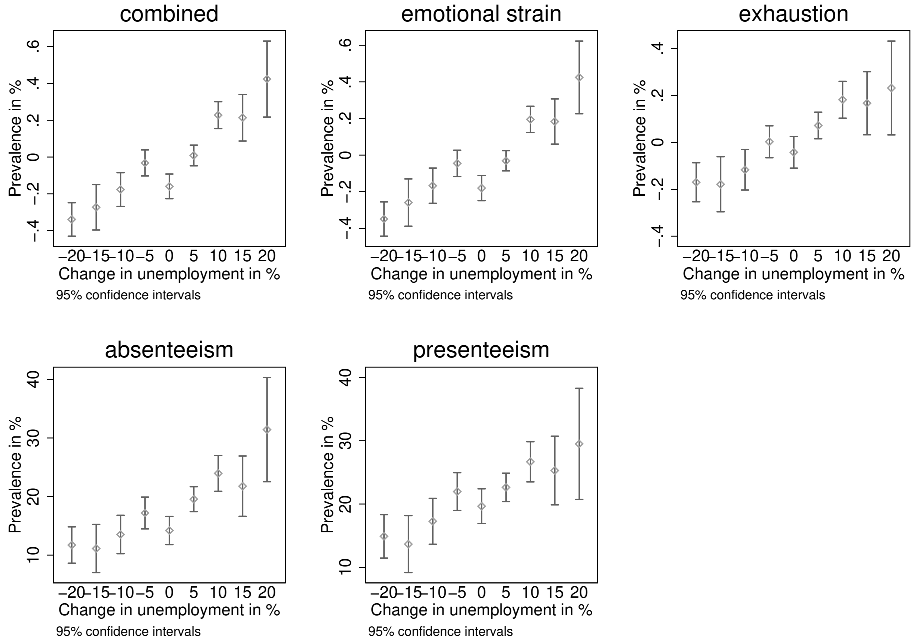


The x-axis shows one period lagged changes in occupation specific unemployment on federal state level. 95% confidence intervals. Data sources: BIBB/BAuA, IAB. Own figure.

Estimating equation 5.2 separately for both samples confirms the descriptive evidence: the relationship between rising unemployment and higher work-related mental health problems is driven by individuals with past unemployment experience. For individuals without own unemployment experience, there is no relationship between rising unemployment and work-related mental health (table 5.12). Standard errors are larger than in the full sample but point estimates are often less than half the original size. The unemployment coefficient is significant for strain in the base model at the 10% level but insignificant with

[17]One could argue that people with weaker mental health selected into the group of people with unemployment experience and that this is driving the above relationship. In this case, weak mental health made people lose their job in the first place and could result in a more violent reaction to rising unemployment. Prevalence of emotional exhaustion and strain should then also be higher among people with unemployment experience. Emotional exhaustion is indeed significantly higher among people with unemployment experience (0.05 standard deviations, 5% level), while emotional strain is lower (0.125 standard deviations). Some selection can thus not be ruled out entirely. However, selection would also occur out of unemployment, i.e. individuals with better mental health select back into employment and thus into the sample.

Figure 5.5: Work-related mental health outcomes by changes in unemployment, individuals with prior unemployment experience



The x-axis shows one period lagged changes in occupation specific unemployment on federal state level. 95% confidence intervals. Data sources: BIBB/BAuA, IAB. Own figure.

all control variables. The point estimates in the sample with past unemployment experience are highly significant and slightly larger than for the whole sample (table 5.13). A 10 percentage point increase in the relative change of unemployment is associated with an increase in emotional exhaustion and strain of 0.065 standard deviations. Absenteeism and presenteeism increase 2.3 and 2.6 percentage points which equals 12% at a 17% absenteeism rate and 11% at a presenteeism rate of 21%. All in all, unemployment scars in the sense that it makes individuals more vulnerable to later unemployment threats.

Table 5.12: OLS estimates for work-related mental health outcomes, individuals without past unemployment experience

	combined	strain	exhaustion	absenteeism	presenteeism
base model					
unemployment	0.065*	0.069*	0.029	0.011	0.011
	(0.033)	(0.037)	(0.023)	(0.009)	(0.009)
constant	0.043	0.074	-0.029	0.170***	0.189***
	(0.044)	(0.048)	(0.024)	(0.009)	(0.010)
full model					
unemployment	0.031	0.028	0.022	0.012	0.011
	(0.025)	(0.029)	(0.020)	(0.008)	(0.008)
constant	-0.720*	-0.511	-0.752**	0.118	0.013
	(0.390)	(0.415)	(0.357)	(0.150)	(0.164)
N	2386	2387	2387	2383	2384
R^2 adj. base	0.005	0.006	0.001	0.001	0.001
R^2 adj. full	0.325	0.267	0.202	0.158	0.203

Standardized dependent variable given in column header (absenteeism and presenteeism: binaries). Combined: emotional exhaustion and/or emotional strain. Full model contains job demands and resources, sociodemographic and job covariates according to table 5.1. Standard errors clustered on federal state and occupation in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA, IAB. Own calculations.

Table 5.13: OLS estimates for work-related mental health outcomes, individuals with past unemployment experience

	combined	strain	exhaustion	absenteeism	presenteeism
base model					
unemployment	0.145***	0.135***	0.098***	0.035***	0.034***
	(0.024)	(0.026)	(0.017)	(0.006)	(0.007)
constant	0.011	-0.018	0.055**	0.197***	0.226***
	(0.039)	(0.041)	(0.023)	(0.010)	(0.010)
full model					
unemployment	0.079***	0.066***	0.065***	0.023***	0.026***
	(0.019)	(0.020)	(0.017)	(0.006)	(0.007)
constant	-1.038***	-1.038***	-0.591	0.078	0.146
	(0.320)	(0.328)	(0.365)	(0.129)	(0.154)
N	3941	3947	3943	3944	3937
R^2 adj. base	0.029	0.024	0.013	0.012	0.010
R^2 adj. full	0.304	0.271	0.154	0.126	0.147

Standardized dependent variable given in column header (absenteeism and presenteeism: binaries). Combined: emotional exhaustion and/or emotional strain. Full model contains job demands and resources, sociodemographic and job covariates according to table 5.1. Standard errors clustered on federal state and occupation in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA, IAB. Own calculations.

The duration of the unemployment spell could matter. The direction of this effect is not a priori clear. Longer past unemployment could make individuals even more vulnerable due to continued exposure to unemployment or make them less vulnerable due to habituation (Clark et al., 2001). Mean past unemployment is 1.6 years with a standard deviation of 1.9 years. Most individuals needed up to a year to leave unemployment (1,800). For 1,600 people, unemployment lasted not longer than half a year. 700 became re-employed after up to two years and 800 needed three years or longer. As figures A5.3 to A5.7 in the appendix show, the prevalence of emotional exhaustion over unemployment changes does not differ over earlier unemployment duration. The prevalences of emotional strain, absenteeism, and presenteeism appear to be higher for large unemployment increases among people who have been unemployed longer than one year. Due to large confidence intervals however, this difference does not seem to be significant. Table 5.14 confirms this except for absenteeism in the full model.[18] Unemployment duration does not linearly mediate the relationship between work-related mental health and changing unemployment. The interaction term is insignificant, and duration is not significant individually. If both scarring and habituation occur, the effects cancel out.[19]

[18]Neither duration nor the interaction are significant in the base model. Adding controls slightly increases both coefficients so that they become significant at the 10% and 5% level. An additional year of unemployment experience is associated with an increase in absenteeism of 0.6 percentage points. The unemployment coefficient of 1.4 percentage points increases by 0.5 percentage points for each year. At the mean duration of 1.6 years, the increase equals 2.1 percentage points.

[19]A factor which could bias this finding is how long ago the unemployment spell occurred. The importance of events from the remote past might fade out over time and result in the insignificant estimates. Unfortunately, the data does not contain information on the time of the unemployment spell.

Table 5.14: OLS estimates for work-related mental health outcomes, unemployment duration

	combined	strain	exhaustion	absenteeism	presenteeism
base model					
unemployment	0.135***	0.124***	0.090***	0.029***	0.033***
	(0.025)	(0.027)	(0.020)	(0.007)	(0.008)
duration	-0.008	-0.017	0.014	0.005	-0.000
	(0.011)	(0.012)	(0.011)	(0.004)	(0.004)
interaction	0.006	0.006	0.005	0.003	0.001
	(0.009)	(0.009)	(0.009)	(0.003)	(0.003)
constant	0.025	0.010	0.034	0.189***	0.227***
	(0.039)	(0.041)	(0.028)	(0.010)	(0.011)
full model					
unemployment	0.060***	0.048**	0.051**	0.014**	0.023***
	(0.021)	(0.022)	(0.020)	(0.007)	(0.008)
duration	0.011	0.007	0.016	0.006*	0.001
	(0.009)	(0.009)	(0.011)	(0.004)	(0.003)
interaction	0.011*	0.011	0.009	0.005**	0.002
	(0.007)	(0.007)	(0.008)	(0.003)	(0.003)
constant	-1.047***	-1.047***	-0.596	0.070	0.145
	(0.321)	(0.329)	(0.367)	(0.129)	(0.155)
N	3941	3947	3943	3944	3937
R^2 adj. base	0.028	0.025	0.013	0.011	0.009
R^2 adj. full	0.306	0.272	0.156	0.127	0.148

Standardized dependent variable given in column header (absenteeism and presenteeism: binaries). Combined: emotional exhaustion and/or emotional strain. Full model contains job demands and resources, sociodemographic and job covariates according to table 5.1. Standard errors clustered on federal state and occupation in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA, IAB. Own calculations.

5.6 Conclusion

This paper contributes to the literature on the effects of unemployment, job insecurity, and aggregate unemployment on individual well-being in a twofold way: First, it focuses on clearly work-related mental health problems and thereby concentrates on the channel of worse outside options deterring employees in stressful jobs. Second, it uses occupation- and region-specific unemployment. Aggregate unemployment changes can affect employed individuals mental health through three channels: increases job insecurity, feelings of guilt (others lost their job), and worse outside options. Worse outside option discourage employees from leaving stressful job due to fear of unemployment. If an employee is unsatisfied with her job, e.g. because she faces high job demands but has few job resources, she might consider leaving this job for a more balanced one. Before leaving, she assesses her outside options taking the economic situation into account. Rising aggregate (occupation-specific) unemployment worsens her outside options because her probability of finding a new job is lower. Unemployment is more likely. This discourages employees to quit. They continue to work in imbalanced jobs and their work-related mental health suffers. The findings are first, a significant relationship between rising unemployment and work-related mental health problems. The relationship is stronger for mild problems such as emotional strain. Second, occupation specific unemployment drives this relationship. The spatial dimension (region) of unemployment is less relevant. Third, the relationship is driven by past unemployment experience. This suggests a scarring effect of unemployment similar to the one for life satisfaction in Clark et al. (2001). There is no habituation or continued exposure effect as the duration of past unemployment does not play a role.

The analysis is subject to three limitations. First, while worse outside options are the suggested underlying driver of the found relationship, there is no final proof of this due to lacking data on the time of exposure to high job demands and low job resources. The data is cross-sectional and collected every sixth year only. A yearly panel would be necessary to infer exposure time. This limitation does not substantially decrease the findings' relevance. Even being agnostic about the exact channel, the important take away is that there exists a link between rising unemployment and worse work-related mental health. Second, the analysis does not explicitly account for geographic and occupational mobility. Individuals might have broader employment prospects than their current federal state and occupation. The first is not problematic as the spatial dimension is less important. Occupational mobility might arise from similarities between occupations or earlier employment in a different occupation. Data on individual occupational mobility is not recorded. Third, the paper remains descriptive in the sense that it does not identify a causal effect of aggregate unemployment on work-related mental health. Individuals select into occupations and federal states. This could be correlated with mental health vulnerability. Experience could also induce more healthy individuals to leave for occupations or federal states with better conditions. Less healthy individuals might be left behind and "stuck" in unfavorable occupation-federal state cells.

Despite these limitations, the findings are relevant when assessing the costs of economic downturns. These calculations are often limited to monetary losses because non-monetary losses, e.g. reductions in well-being, are harder to measure. The same is true for work-related mental health decreases. Data is sparse. One of the main reasons for this is the problematic measurement of for example burnout, the only work-related mental health problem for which there is some consensus and some, albeit inaccurate data. Even less is known for milder work-related mental health problems such as emotional strain and exhaustion. The practical implication of this paper's findings remain music of the future until better measurement of work-related mental health and data on treatment, work incapacity, and early retirement are available.

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Appendices

Appendix for chapter 2

Table A2.1: Descriptive statistics

	mean	sd	min	max
combined	-0.1	1.0	-1.3	3.2
emotional strain	-0.1	1.0	-1.3	1.7
exhaustion	-0.1	0.9	-0.6	2.8
burnout	-0.0	0.9	-0.3	5.1
absenteeism	0.1	0.3	0.0	1.0
presenteeism	0.2	0.4	0.0	1.0
common factor 2012	-0.1	0.9	-0.6	1.8
common factor 2006	-0.0	0.9	-0.3	3.5
exhaustion	-0.1	0.9	-0.6	2.8
burnout	-0.0	0.9	-0.3	5.1
multitasking	-0.0	1.0	-1.7	3.6
above average multitasking	0.4	0.5	0.0	1.0
extreme multitasking	0.1	0.3	0.0	1.0
above average occupation multitasking	0.4	0.5	0.0	1.0
extreme occupation multitasking	0.2	0.4	0.0	1.0
occupational multitasking	-0.0	1.0	-3.1	3.7
reach limits of own capacity	-0.0	1.0	-1.6	1.5
interrupted during work	-0.1	1.0	-2.6	0.9
deadline/performance pressure	-0.0	1.0	-3.0	0.8
work fast	-0.0	1.0	-2.3	1.0
minimum performance	0.0	1.0	-1.3	1.3
overstrained	0.2	0.4	0.0	1.0
risk of financial loss	0.0	1.0	-1.2	1.7
no timely information about future	-0.0	1.0	-1.5	1.6
do not receive all information necessary	-0.0	1.0	-1.4	1.9
details predetermined	0.0	1.0	-1.5	1.4
repetition	0.0	1.0	-2.0	0.9
plan, schedule own work	-0.1	1.0	-2.9	0.5
influence own workload	-0.0	1.0	-1.5	1.1
decide when to break	-0.1	1.0	-1.9	0.7
good collaboration	-0.0	1.0	-6.5	0.3
perform tasks independently	0.7	0.5	0.0	1.0
supervisor for somebody	0.3	0.5	0.0	1.0
get familiar with tasks	-0.0	1.0	-2.7	1.0
improve methods	-0.0	1.0	-2.3	1.2
demanded unknown things	-0.0	1.0	-1.3	2.0
men	0.6	0.5	0.0	1.0
married or registered partnership	0.6	0.5	0.0	1.0
having children	0.6	0.5	0.0	1.0
low education	0.1	0.3	0.0	1.0

Table A2.1 – continued on next page

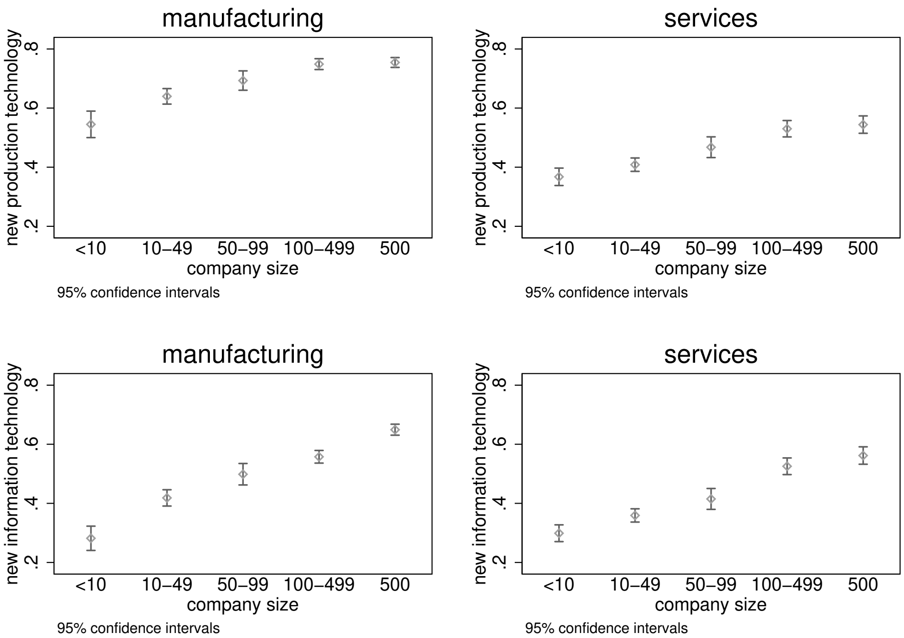
Table A2.1 – continued from previous page

medium+ education	0.1	0.3	0.0	1.0
higher education	0.2	0.4	0.0	1.0
age	42.1	10.7	18.0	65.0
age squared	1883.5	892.3	324.0	4225.0
working hours main job	38.8	11.4	10.0	120.0
hours squared	1635.0	913.9	100.0	14400.0
tenure in years	11.9	10.1	0.0	51.0
atypical	0.1	0.3	0.0	1.0
night	0.2	0.4	0.0	1.0
shift	0.2	0.4	0.0	1.0
weekend	0.7	0.5	0.0	1.0
standby	0.2	0.4	0.0	1.0
work is important	-0.0	1.0	-4.6	0.4
successful work life balance	0.6	0.5	0.0	1.0

Weighted according to census data. Data sources: BIBB/BAuA.

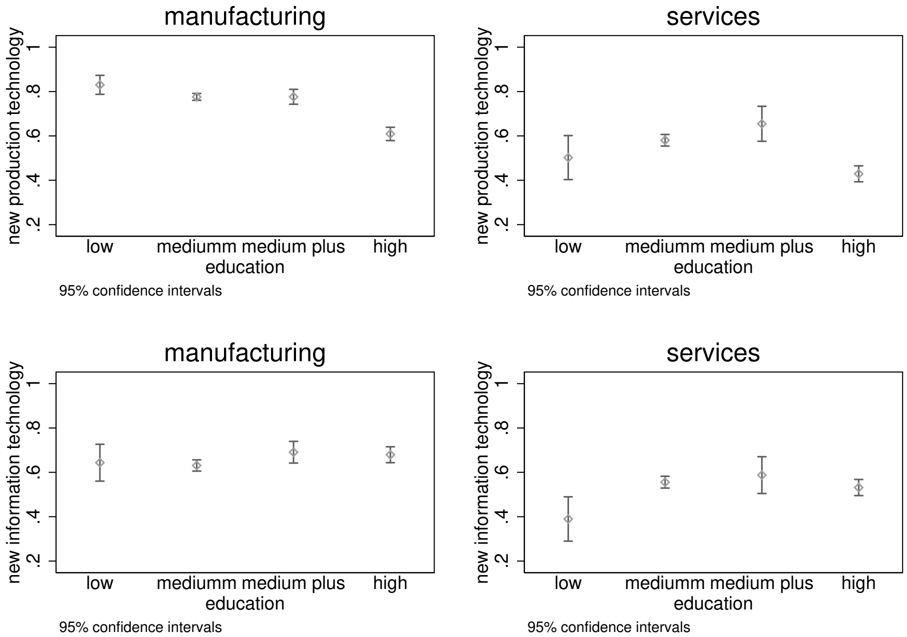
Appendix for chapter 3

Figure A3.1: PT and IT adoption in manufacturing and services companies by company size



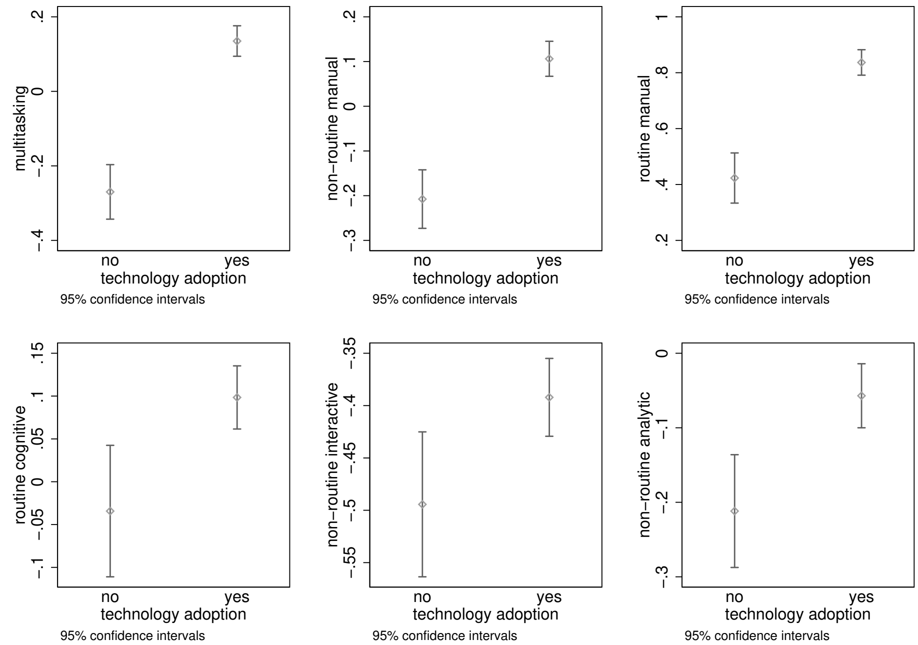
Data sources: BIBB/BAuA. Own figure.

Figure A3.2: PT and IT adoption in manufacturing and services companies by level of education



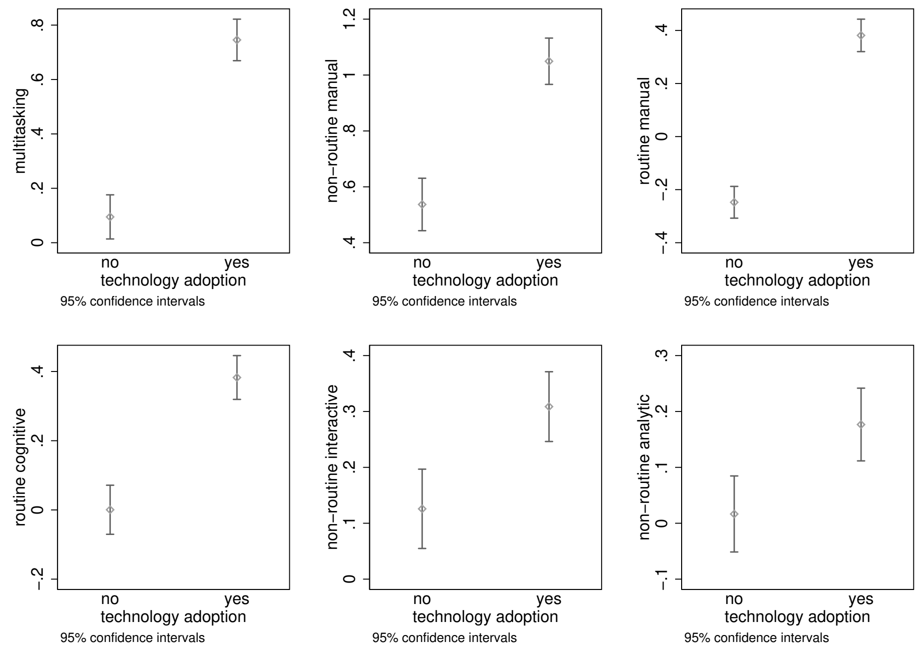
Data sources: BIBB/BAuA. Own figure.

Figure A3.3: Standardized multitasking by technology adoption for low to medium plus educated men in manufacturing companies with 100 and more employees



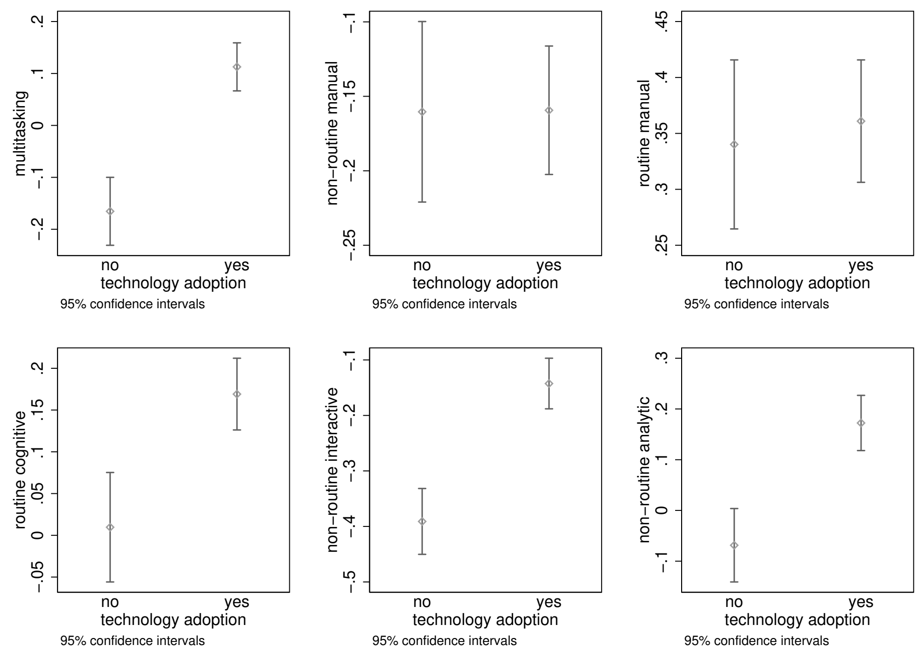
Data sources: BIBB/BAuA. Own figure.

Figure A3.4: Standardized multitasking by technology adoption for low to medium plus educated employees in service companies with 100 and more employees



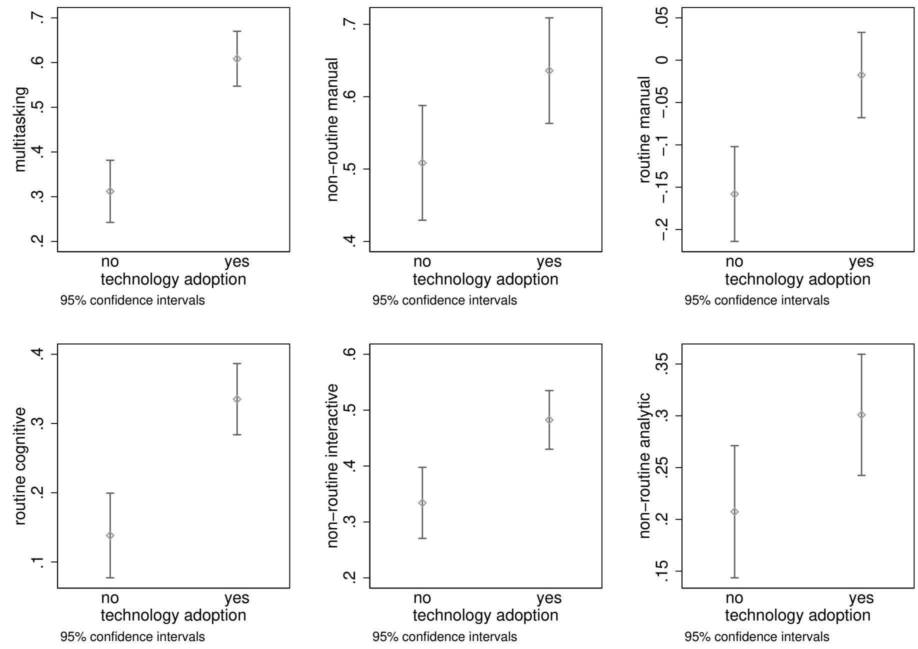
Data sources: BIBB/BAuA. Own figure.

Figure A3.5: Standardized multitasking by IT adoption for employees in manufacturing companies with 500 and more employees



Data sources: BIBB/BAuA. Own figure.

Figure A3.6: Standardized multitasking by IT adoption for medium to higher educated employees aged 30 and older in service companies with 100 and more employees



Data sources: BIBB/BAuA. Own figure.

Table A3.1: Descriptive statistics

	mean	sd	min	max
combined	-0.075	0.979	-1.3	3.2
emotional strain	-0.064	0.997	-1.3	1.7
exhaustion	-0.072	0.938	-0.6	2.8
burnout	-0.042	0.922	-0.3	5.1
absenteeism	0.110	0.313	0.0	1.0
presenteeism	0.186	0.390	0.0	1.0
age	42.056	10.713	18.0	65.0
men	0.561	0.496	0.0	1.0
low education	0.080	0.271	0.0	1.0
medium education	0.660	0.474	0.0	1.0
medium+ education	0.077	0.267	0.0	1.0
higher education	0.183	0.386	0.0	1.0
company size smaller than 10	0.135	0.341	0.0	1.0
company size between 11 and 49	0.274	0.446	0.0	1.0
company size between 50 and 99	0.115	0.319	0.0	1.0
company size between 100 and 499	0.239	0.426	0.0	1.0
company size larger than 500	0.238	0.426	0.0	1.0
A&B: Agriculture, fishery & mining	0.015	0.122	0.0	1.0
E: Energy & water supply	0.016	0.125	0.0	1.0
F: Construction	0.058	0.233	0.0	1.0
G&H: Commerce and hotels	0.131	0.337	0.0	1.0
I: Transport	0.060	0.237	0.0	1.0
J: Finance	0.038	0.191	0.0	1.0
K: Real estate etc.	0.072	0.259	0.0	1.0
L&Q: Public administration	0.054	0.227	0.0	1.0
M-P: Public & private services	0.213	0.410	0.0	1.0
not elsewhere allocated	0.011	0.102	0.0	1.0
subsample 1 (PT 1)	0.171	0.376	0.0	1.0
subsample 2 (PT 2)	0.054	0.225	0.0	1.0
subsample 3 (IT 1)	0.111	0.314	0.0	1.0
subsample 4 (IT 2)	0.072	0.258	0.0	1.0

Weighted according to census data. Data sources: BIBB/BAuA.

Table A3.2: Multitasking estimates for work-related mental health outcomes, additional controls

	combined	strain	exhaustion	burnout	absenteeism	presenteeism
OLS						
multitasking	0.144***	0.150***	0.069***	0.047***	0.016***	0.033***
	(0.008)	(0.008)	(0.010)	(0.012)	(0.003)	(0.004)
constant	-1.507***	-1.404***	-1.169***	-0.714***	-0.174***	-0.189***
	(0.121)	(0.128)	(0.144)	(0.158)	(0.037)	(0.061)
IV PT						
multitasking	0.215***	0.194***	0.207***	0.056	0.046***	0.082***
	(0.047)	(0.048)	(0.063)	(0.063)	(0.016)	(0.027)
constant	-1.432***	-1.356***	-1.010***	-0.705***	-0.142***	-0.131*
	(0.134)	(0.140)	(0.166)	(0.177)	(0.041)	(0.069)
IV IT						
multitasking	0.358***	0.349***	0.151*	0.214*	0.053**	0.079**
	(0.075)	(0.077)	(0.087)	(0.124)	(0.025)	(0.037)
constant	-1.304***	-1.193***	-1.090***	-0.648***	-0.151***	-0.140*
	(0.146)	(0.154)	(0.173)	(0.178)	(0.045)	(0.076)
N	23702	23743	13232	10486	23724	13263
			first stage IV PT			
new PT	0.321	0.321	0.313	0.330	0.321	0.314
t-statistic	21.09	21.10	15.16	14.78	21.09	15.18
model F-statistic	107.04	107.30	57.99	59.34	107.33	58.34
			first stage IV IT			
new IT	0.206	0.207	0.232	0.171	0.206	0.233
t-statistic	13.36	13.41	11.09	7.51	13.38	11.13
model F-statistic	90.73	90.98	50.35	50.53	90.92	50.68

Standardized dependent variable given in column header (absenteeism, presenteeism: binary). Combined: emotional exhaustion, burnout and/or emotional strain. Models include controls for age, age square, gender, level of education, tenure, tenure square, hours, hours square, industry, and company size. IV PT: production technology adoption as instrument. IV IT: information technology adoption as instrument. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

Table A3.3: First stage estimates for work-related mental health outcomes for low to medium plus educated employees in manufacturing companies with 100 and more employees

	combined	strain	exhaustion	burnout	absenteeism	presenteeism
multitasking						
new technology	0.327***	0.327***	0.276***	0.403***	0.327***	0.276***
	(0.042)	(0.042)	(0.054)	(0.065)	(0.042)	(0.054)
constant	-0.543***	-0.554***	-0.552***	-0.612***	-0.542***	-0.565***
	(0.093)	(0.093)	(0.113)	(0.151)	(0.093)	(0.113)
non-routine manual						
new technology	0.267***	0.267***	0.280***	0.250***	0.267***	0.281***
	(0.039)	(0.039)	(0.050)	(0.063)	(0.039)	(0.050)
constant	-0.305***	-0.310***	-0.257**	-0.348**	-0.304***	-0.264**
	(0.091)	(0.091)	(0.113)	(0.155)	(0.091)	(0.112)
routine manual						
new technology	0.445***	0.444***	0.426***	0.481***	0.445***	0.424***
	(0.049)	(0.049)	(0.064)	(0.075)	(0.049)	(0.064)
constant	0.255**	0.250**	0.275**	0.421**	0.256**	0.269**
	(0.105)	(0.105)	(0.136)	(0.163)	(0.105)	(0.136)
routine cognitive						
new technology	0.120***	0.120***	0.077	0.189***	0.121***	0.078
	(0.042)	(0.042)	(0.055)	(0.061)	(0.042)	(0.055)
constant	-0.158*	-0.164*	-0.203*	-0.189	-0.158*	-0.209*
	(0.086)	(0.086)	(0.113)	(0.134)	(0.086)	(0.112)
non-routine interactive						
new technology	0.010	0.010	-0.001	0.026	0.011	-0.002
	(0.037)	(0.037)	(0.049)	(0.057)	(0.037)	(0.049)
constant	-0.668***	-0.675***	-0.716***	-0.785***	-0.668***	-0.725***
	(0.085)	(0.085)	(0.115)	(0.125)	(0.085)	(0.115)
non-routine analytic						
new technology	0.090**	0.091**	0.058	0.129**	0.089**	0.061
	(0.040)	(0.040)	(0.053)	(0.061)	(0.040)	(0.053)
constant	-0.394***	-0.401***	-0.295**	-0.589***	-0.393***	-0.303**
	(0.088)	(0.088)	(0.118)	(0.136)	(0.088)	(0.118)
N	3683	3691	2028	1657	3685	2036
t-statistics						
multitasking	7.85	7.86	5.09	6.23	7.85	5.10
non-routine manual	6.83	6.85	5.62	3.95	6.83	5.64
routine manual	9.10	9.09	6.65	6.41	9.09	6.63
routine cognitive	2.89	2.90	1.40	3.09	2.91	1.41
non-routine interactive	0.27	0.26	-0.03	0.45	0.28	-0.04
non-routine analytic	2.23	2.28	1.09	2.13	2.22	1.15

Second stage standardized dependent variable given in column header (absenteeism, presenteeism: binary). Combined: emotional exhaustion, burnout and/or emotional strain. Models include controls for age and company size. IV PT: production technology adoption as instrument. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

Table A3.4: First stage estimates for work-related mental health outcomes for low to medium plus educated employees in service companies with 100 and more employees

	combined	strain	exhaustion	burnout	absenteeism	presenteeism
multitasking						
new technology	0.633***	0.632***	0.629***	0.622***	0.634***	0.628***
	(0.068)	(0.067)	(0.089)	(0.103)	(0.068)	(0.088)
constant	0.684***	0.681***	0.590***	0.993***	0.683***	0.584***
	(0.159)	(0.159)	(0.212)	(0.245)	(0.159)	(0.212)
non-routine manual						
new technology	0.522***	0.520***	0.489***	0.555***	0.523***	0.486***
	(0.074)	(0.074)	(0.095)	(0.117)	(0.074)	(0.094)
constant	1.205***	1.206***	1.333***	1.456***	1.205***	1.329***
	(0.182)	(0.182)	(0.221)	(0.311)	(0.182)	(0.220)
routine manual						
new technology	0.633***	0.634***	0.657***	0.593***	0.632***	0.658***
	(0.053)	(0.053)	(0.069)	(0.081)	(0.053)	(0.069)
constant	-0.312***	-0.312***	-0.274*	-0.295	-0.314***	-0.275*
	(0.120)	(0.120)	(0.153)	(0.210)	(0.120)	(0.153)
routine cognitive						
new technology	0.371***	0.369***	0.392***	0.336***	0.373***	0.388***
	(0.059)	(0.059)	(0.076)	(0.091)	(0.059)	(0.076)
constant	0.043	0.039	-0.134	0.339	0.042	-0.141
	(0.141)	(0.141)	(0.191)	(0.212)	(0.141)	(0.191)
non-routine interactive						
new technology	0.162***	0.164***	0.181**	0.124	0.163***	0.183**
	(0.057)	(0.057)	(0.073)	(0.088)	(0.057)	(0.073)
constant	0.709***	0.711***	0.570***	0.956***	0.711***	0.571***
	(0.142)	(0.142)	(0.188)	(0.222)	(0.142)	(0.187)
non-routine analytic						
new technology	0.134**	0.135**	0.096	0.185**	0.135**	0.097
	(0.058)	(0.058)	(0.076)	(0.089)	(0.058)	(0.076)
constant	0.290**	0.290**	0.179	0.418**	0.290**	0.176
	(0.138)	(0.138)	(0.186)	(0.212)	(0.138)	(0.186)
N	1616	1623	1007	609	1619	1013
t-statistics						
multitasking	9.36	9.38	7.10	6.06	9.39	7.12
non-routine manual	7.06	7.04	5.17	4.73	7.07	5.15
routine manual	11.99	12.05	9.46	7.33	11.99	9.54
routine cognitive	6.32	6.30	5.15	3.68	6.34	5.12
non-routine interactive	2.86	2.90	2.47	1.42	2.88	2.51
non-routine analytic	2.31	2.33	1.25	2.07	2.33	1.27

Second stage standardized dependent variable given in column header (absenteeism, presenteeism: binary). Combined: emotional exhaustion, burnout and/or emotional strain. Models include controls for age, gender, level of education, and company size. IV PT: production technology adoption as instrument. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

Table A3.5: First stage estimates for work-related mental health outcomes for employees in manufacturing companies with 500 and more employees

	combined	strain	exhaustion	burnout	absenteeism	presenteeism
multitasking						
new technology	0.263***	0.266***	0.259***	0.265***	0.263***	0.265***
	(0.045)	(0.045)	(0.059)	(0.069)	(0.045)	(0.059)
constant	-0.579***	-0.593***	-0.546***	-0.581***	-0.578***	-0.563***
	(0.103)	(0.103)	(0.125)	(0.166)	(0.103)	(0.125)
non-routine manual						
new technology	0.027	0.028	-0.010	0.090	0.027	-0.008
	(0.042)	(0.042)	(0.055)	(0.065)	(0.042)	(0.055)
constant	-0.240**	-0.244**	-0.192	-0.323**	-0.240**	-0.196
	(0.100)	(0.100)	(0.129)	(0.160)	(0.100)	(0.129)
routine manual						
new technology	0.045	0.046	-0.009	0.130*	0.045	-0.006
	(0.051)	(0.051)	(0.068)	(0.073)	(0.051)	(0.068)
constant	0.365***	0.360***	0.356**	0.508***	0.365***	0.350**
	(0.131)	(0.131)	(0.175)	(0.191)	(0.131)	(0.175)
routine cognitive						
new technology	0.150***	0.153***	0.137**	0.185***	0.152***	0.142**
	(0.045)	(0.045)	(0.059)	(0.065)	(0.045)	(0.059)
constant	-0.170*	-0.180*	-0.239*	-0.077	-0.168	-0.249*
	(0.102)	(0.102)	(0.138)	(0.149)	(0.102)	(0.138)
non-routine interactive						
new technology	0.191***	0.193***	0.200***	0.179***	0.192***	0.204***
	(0.040)	(0.040)	(0.052)	(0.062)	(0.040)	(0.051)
constant	-0.946***	-0.957***	-1.039***	-0.996***	-0.944***	-1.052***
	(0.091)	(0.091)	(0.114)	(0.149)	(0.091)	(0.114)
non-routine analytic						
new technology	0.213***	0.217***	0.254***	0.137*	0.212***	0.260***
	(0.049)	(0.049)	(0.062)	(0.077)	(0.049)	(0.062)
constant	-0.348***	-0.359***	-0.156	-0.590***	-0.348***	-0.169
	(0.116)	(0.117)	(0.153)	(0.182)	(0.116)	(0.153)
N	2516	2521	1391	1126	2517	1396
t-statistics						
multitasking	5.82	5.89	4.39	3.86	5.83	4.49
non-routine manual	0.64	0.67	-0.18	1.38	0.64	-0.14
routine manual	0.88	0.91	-0.13	1.79	0.88	-0.09
routine cognitive	3.36	3.43	2.31	2.84	3.40	2.39
non-routine interactive	4.77	4.83	3.89	2.87	4.80	3.96
non-routine analytic	4.37	4.45	4.11	1.78	4.36	4.20

Second stage standardized dependent variable given in column header (absenteeism, presenteeism: binary). Combined: emotional exhaustion, burnout and/or emotional strain. Models include controls for age and gender. IV IT: information technology adoption as instrument. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

Table A3.6: First stage estimates for work-related mental health outcomes for medium to higher educated employees in service companies with 100 and more employees

	combined	strain	exhaustion	burnout	absenteeism	presenteeism
multitasking						
new technology	0.287***	0.288***	0.316***	0.228***	0.288***	0.318***
	(0.057)	(0.057)	(0.073)	(0.088)	(0.057)	(0.073)
constant	0.686***	0.687***	0.548***	1.052***	0.686***	0.546***
	(0.136)	(0.135)	(0.179)	(0.211)	(0.136)	(0.178)
non-routine manual						
new technology	0.122**	0.118*	0.110	0.119	0.123**	0.104
	(0.061)	(0.060)	(0.077)	(0.096)	(0.061)	(0.077)
constant	1.287***	1.290***	1.360***	1.468***	1.288***	1.358***
	(0.150)	(0.150)	(0.184)	(0.244)	(0.150)	(0.184)
routine manual						
new technology	0.126***	0.125***	0.130**	0.112	0.126***	0.128**
	(0.045)	(0.045)	(0.058)	(0.071)	(0.045)	(0.058)
constant	0.046	0.044	0.067	0.074	0.044	0.064
	(0.104)	(0.104)	(0.141)	(0.163)	(0.104)	(0.141)
routine cognitive						
new technology	0.182***	0.182***	0.219***	0.116	0.183***	0.220***
	(0.050)	(0.050)	(0.064)	(0.078)	(0.050)	(0.064)
constant	0.108	0.109	-0.158	0.471**	0.108	-0.159
	(0.122)	(0.122)	(0.163)	(0.193)	(0.122)	(0.162)
non-routine interactive						
new technology	0.158***	0.160***	0.177***	0.126	0.158***	0.180***
	(0.049)	(0.049)	(0.062)	(0.080)	(0.049)	(0.061)
constant	0.443***	0.446***	0.324**	0.694***	0.444***	0.328**
	(0.120)	(0.120)	(0.151)	(0.196)	(0.120)	(0.151)
non-routine analytic						
new technology	0.087*	0.091*	0.029	0.169**	0.088*	0.036
	(0.053)	(0.053)	(0.070)	(0.079)	(0.053)	(0.070)
constant	0.227*	0.227*	0.109	0.406**	0.227*	0.110
	(0.127)	(0.127)	(0.169)	(0.199)	(0.127)	(0.169)
N	2202	2210	1363	839	2205	1370
t-statistics						
multitasking	5.05	5.09	4.32	2.60	5.08	4.36
non-routine manual	2.02	1.96	1.44	1.23	2.03	1.36
routine manual	2.79	2.77	2.24	1.57	2.80	2.21
routine cognitive	3.63	3.65	3.40	1.48	3.65	3.42
non-routine interactive	3.21	3.26	2.87	1.58	3.23	2.93
non-routine analytic	1.65	1.74	0.42	2.14	1.67	0.52

Second stage standardized dependent variable given in column header (absenteeism, presenteeism: binary). Combined: emotional exhaustion, burnout and/or emotional strain. Models include controls for age, gender and company size. IV IT: information technology adoption as instrument. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

Table A3.7: OLS and second stage estimates for work-related mental health outcomes for low to medium plus educated employees in manufacturing companies with 100 and more employees

	combined	strain	exhaustion	burnout	absenteeism	presenteeism
OLS						
multitasking	0.098***	0.113***	0.012	0.030	0.004	0.002
	(0.021)	(0.021)	(0.026)	(0.026)	(0.006)	(0.011)
constant	-0.638***	-0.665***	-0.281***	-0.095	-0.011	0.136***
	(0.087)	(0.097)	(0.098)	(0.085)	(0.026)	(0.044)
IV PT						
multitasking	0.372***	0.349**	0.408**	-0.033	0.060	0.120
	(0.138)	(0.145)	(0.201)	(0.125)	(0.040)	(0.081)
constant	-0.549***	-0.586***	-0.137	-0.118	0.007	0.180***
	(0.098)	(0.109)	(0.131)	(0.105)	(0.030)	(0.055)
OLS						
non-routine manual	0.016	0.016	0.001	0.023	-0.001	0.001
	(0.022)	(0.023)	(0.027)	(0.028)	(0.006)	(0.012)
constant	-0.667***	-0.701***	-0.286***	-0.101	-0.012	0.135***
	(0.088)	(0.097)	(0.098)	(0.084)	(0.026)	(0.044)
IV PT						
non-routine manual	0.455***	0.427**	0.402**	-0.053	0.074	0.118
	(0.176)	(0.185)	(0.195)	(0.201)	(0.049)	(0.080)
constant	-0.612***	-0.647***	-0.259**	-0.117	-0.003	0.144***
	(0.098)	(0.107)	(0.109)	(0.102)	(0.028)	(0.046)
OLS						
routine manual	-0.042**	-0.047***	-0.024	0.007	-0.004	-0.004
	(0.017)	(0.018)	(0.021)	(0.022)	(0.005)	(0.008)
constant	-0.646***	-0.677***	-0.272***	-0.111	-0.010	0.137***
	(0.088)	(0.097)	(0.097)	(0.087)	(0.026)	(0.044)
IV PT						
routine manual	0.273***	0.257**	0.264**	-0.027	0.044	0.078
	(0.101)	(0.107)	(0.125)	(0.104)	(0.029)	(0.051)
constant	-0.821***	-0.844***	-0.435***	-0.087	-0.037	0.092*
	(0.111)	(0.117)	(0.123)	(0.103)	(0.030)	(0.054)
N	3683	3691	2028	1657	3685	2036

Standardized dependent variable given in column header (absenteeism, presenteeism: binary). Combined: emotional exhaustion, burnout and/or emotional strain. Models include controls for age and company size. IV PT: production technology adoption as instrument. First stage results in appendix table A3.3. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

Table A3.8: OLS and second stage estimates for work-related mental health outcomes for low to medium plus educated employees in service companies with 100 and more employees

	combined	strain	exhaustion	burnout	absenteeism	presenteeism
OLS						
multitasking	0.254***	0.275***	0.087**	0.057	0.017*	0.049***
	(0.026)	(0.024)	(0.034)	(0.054)	(0.010)	(0.014)
constant	0.168	0.191	0.134	-0.282	0.062	0.267***
	(0.141)	(0.135)	(0.196)	(0.255)	(0.051)	(0.080)
IV PT						
multitasking	0.056	0.095	0.031	-0.208	-0.009	0.050
	(0.096)	(0.090)	(0.131)	(0.194)	(0.036)	(0.053)
constant	0.387**	0.390**	0.190	0.088	0.090	0.266***
	(0.180)	(0.168)	(0.241)	(0.374)	(0.066)	(0.095)
OLS						
non-routine manual	0.256***	0.265***	0.088***	0.126***	0.034***	0.050***
	(0.020)	(0.019)	(0.031)	(0.039)	(0.009)	(0.013)
constant	0.051	0.084	0.075	-0.432	0.028	0.234***
	(0.139)	(0.135)	(0.202)	(0.265)	(0.052)	(0.082)
IV PT						
non-routine manual	0.068	0.115	0.040	-0.233	-0.010	0.065
	(0.116)	(0.108)	(0.168)	(0.226)	(0.044)	(0.068)
constant	0.343	0.316	0.155	0.221	0.097	0.210
	(0.232)	(0.217)	(0.350)	(0.486)	(0.086)	(0.136)
OLS						
routine manual	0.052	0.062*	0.013	0.005	0.012	0.025
	(0.032)	(0.032)	(0.042)	(0.051)	(0.012)	(0.018)
constant	0.443***	0.488***	0.218	-0.203	0.079	0.312***
	(0.145)	(0.140)	(0.195)	(0.261)	(0.051)	(0.081)
IV PT						
routine manual	0.056	0.095	0.030	-0.218	-0.009	0.048
	(0.098)	(0.093)	(0.126)	(0.200)	(0.036)	(0.052)
constant	0.442***	0.484***	0.216	-0.182	0.082	0.309***
	(0.146)	(0.140)	(0.196)	(0.261)	(0.051)	(0.081)
OLS						
routine cognitive	0.193***	0.217***	0.035	0.038	-0.002	0.024
	(0.032)	(0.030)	(0.041)	(0.060)	(0.011)	(0.017)
constant	0.392***	0.433***	0.216	-0.224	0.081	0.313***
	(0.140)	(0.133)	(0.195)	(0.258)	(0.051)	(0.081)
IV PT						
routine cognitive	0.095	0.162	0.050	-0.385	-0.015	0.081
	(0.165)	(0.155)	(0.211)	(0.365)	(0.061)	(0.088)
constant	0.421***	0.448***	0.215	0.013	0.085	0.307***
	(0.151)	(0.140)	(0.197)	(0.341)	(0.054)	(0.082)
N	1616	1623	1007	609	1619	1013

Standardized dependent variable given in column header (absenteeism, presenteeism: binary). Combined: emotional exhaustion, burnout and/or emotional strain. Models include controls for age, gender, level of education, and company size. IV PT: production technology adoption as instrument. First stage results in appendix table A3.4. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

Table A3.9: OLS and second stage estimates for work-related mental health outcomes for employees in manufacturing companies with 500 and more employees

	combined	strain	exhaustion	burnout	absenteeism	presenteeism
OLS						
multitasking	0.109***	0.119***	0.033	0.035	0.012	0.010
	(0.024)	(0.025)	(0.032)	(0.025)	(0.007)	(0.014)
constant	-0.428***	-0.455***	-0.218*	0.025	0.033	0.107**
	(0.102)	(0.111)	(0.119)	(0.099)	(0.032)	(0.048)
IV IT						
multitasking	0.338*	0.248	0.251	0.593***	0.160***	0.104
	(0.176)	(0.182)	(0.217)	(0.214)	(0.059)	(0.090)
constant	-0.312**	-0.379***	-0.117	0.259	0.102**	0.146**
	(0.126)	(0.135)	(0.161)	(0.161)	(0.045)	(0.066)
N	2516	2521	1391	1126	2517	1396

Standardized dependent variable given in column header (absenteeism, presenteeism: binary). Combined: emotional exhaustion, burnout and/or emotional strain. Models include controls for age and gender. IV IT: information technology adoption as instrument. First stage results in appendix table A3.5. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

Table A3.10: OLS and second stage estimates for work-related mental health outcomes for medium to higher educated employees in service companies with 100 and more employees

	combined	strain	exhaustion	burnout	absenteeism	presenteeism
OLS						
multitasking	0.243***	0.259***	0.107***	0.036	0.021**	0.050***
	(0.022)	(0.021)	(0.031)	(0.045)	(0.009)	(0.012)
constant	0.181	0.184	0.033	0.038	0.074*	0.245***
	(0.124)	(0.118)	(0.168)	(0.234)	(0.043)	(0.068)
IV2						
multitasking	0.226	0.269	-0.109	0.272	-0.060	-0.009
	(0.178)	(0.167)	(0.228)	(0.437)	(0.068)	(0.090)
constant	0.205	0.175	0.205	-0.238	0.149**	0.293***
	(0.204)	(0.192)	(0.248)	(0.546)	(0.072)	(0.094)
N	2202	2210	1363	839	2205	1370

Standardized dependent variable given in column header (absenteeism, presenteeism: binary). Combined: emotional exhaustion, burnout and/or emotional strain. Models include controls for age, gender and company size. IV2: information technology adoption as instrument. First stage results in appendix table A3.6. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/ BAuA. Own calculations.

Appendix for chapter 4

Table A4.1: Descriptive statistics

	mean	sd	min	max
combined	0.0	1.0	-1.2	2.9
emotional strain	0.0	1.0	-1.3	1.7
emotional exhaustion	-0.0	1.0	-0.5	3.0
burnout	0.0	1.0	-0.3	5.3
low education	0.1	0.3	0.0	1.0
medium education	0.6	0.5	0.0	1.0
medium+ education	0.1	0.2	0.0	1.0
higher education	0.2	0.4	0.0	1.0
years of education	13.1	2.8	7.0	18.0
age	41.6	11.0	18.0	65.0
men	0.5	0.5	0.0	1.0
deadline/performance pressure	-0.0	1.0	-2.8	0.8
reach limits of own capacity	0.0	1.0	-1.5	1.5
do different things simultaneiously	-0.0	1.0	-2.6	0.7
interrupted during work	-0.0	1.0	-2.4	0.9
overstrained	0.2	0.4	0.0	1.0
multitasking	-0.0	1.0	-1.5	3.3
no timely information about the future	-0.0	1.0	-1.5	1.7
working hours main job	38.3	11.7	10.0	120.0
details predetermined	-0.0	1.0	-1.5	1.4
repetition	-0.0	1.0	-2.0	0.9
risk of financial loss	-0.0	1.0	-1.1	1.7
do not receive all information necessary for correct work	-0.0	1.0	-1.4	1.9
work fast	0.0	1.0	-2.2	1.0
minimum performance	0.0	1.0	-1.2	1.2
plan/schedule own work	-0.0	1.0	-2.7	0.6
influence own workload	0.0	1.0	-1.4	1.1
plan and schedule own breaks	0.0	1.0	-1.7	3.9
good collaboration	-0.0	1.0	-6.2	0.3
feel as part of community	0.0	1.0	-4.0	0.4
receive help from colleagues	-0.0	1.0	-4.3	0.4
receive help from supervisor	0.0	1.0	-2.6	0.7
perform tasks independently	0.7	0.5	0.0	1.0
get familiar with tasks	0.0	1.0	-2.6	1.0
improve methods	-0.0	1.0	-2.2	1.2
demanded unknown things	0.0	1.0	-1.2	1.9
supervisor for somebody	0.3	0.5	0.0	1.0
married or registered partnership	0.6	0.5	0.0	1.0
having children	0.6	0.5	0.0	1.0
monthly income	2602.9	1677.2	1.0	50000.0
working hours main job	38.3	11.7	10.0	120.0
experience in years	21.8	11.8	0.0	52.0
high risk of layoff	0.1	0.3	0.0	1.0

Table A4.1 – continued on next page

Table A4.1 – continued from previous page

work is important	0.0	1.0	-4.4	0.5
work life balance	0.6	0.5	0.0	1.0
perform tasks independently	0.7	0.5	0.0	1.0
atypical	0.1	0.3	0.0	1.0
night	0.2	0.4	0.0	1.0
shift	0.2	0.4	0.0	1.0
weekend	0.7	0.5	0.0	1.0
standby	0.2	0.4	0.0	1.0
A-C: Agriculture, fishery & mining	0.0	0.1	0.0	1.0
E: Energy & water supply	0.0	0.1	0.0	1.0
F: Construction	0.1	0.2	0.0	1.0
G&H: Commerce and hotels	0.1	0.3	0.0	1.0
I: Transport	0.1	0.2	0.0	1.0
J: Finance	0.0	0.2	0.0	1.0
K: Real estate etc.	0.1	0.3	0.0	1.0
L&Q: Public administration	0.1	0.3	0.0	1.0
M-P: Public & private services	0.2	0.4	0.0	1.0
not elsewhere allocated	0.0	0.1	0.0	1.0
mild strain (binary)	0.1	0.3	0.0	1.0
strain (binary)	0.0	0.0	0.0	0.0
exhaustion (binary)	0.2	0.4	0.0	1.0
burnout (binary)	0.1	0.3	0.0	1.0
depression	0.0	0.2	0.0	1.0
night-time sleeping disorder	0.2	0.4	0.0	1.0
general tiredness	0.4	0.5	0.0	1.0
nervousness or irritability	0.3	0.4	0.0	1.0
blues	0.2	0.4	0.0	1.0
mental health problem	0.5	0.5	0.0	1.0
physical health problem	0.7	0.5	0.0	1.0
bad health	0.1	0.3	0.0	1.0
stressful: deadline/performance pressure	0.6	0.5	0.0	1.0
stressful: reach limits of own capacity	0.6	0.5	0.0	1.0
stressful: different things simultaneously	0.3	0.4	0.0	1.0
stressful: interrupted during work	0.5	0.5	0.0	1.0
stressful: no timely info abt future	0.6	0.5	0.0	1.0
stressful: details predetermined	0.3	0.4	0.0	1.0
stressful: repetition	0.1	0.3	0.0	1.0
stressful: financial loss	0.4	0.5	0.0	1.0
stressful: don't receive all info for necessary for correct work	0.7	0.4	0.0	1.0
stressful: work fast	0.4	0.5	0.0	1.0
stressful: minimum performance	0.4	0.5	0.0	1.0
stressful: plan, schedule own work	0.1	0.3	0.0	1.0
stressful: influence own workload	0.2	0.4	0.0	1.0
stressful: decide when to break	0.2	0.4	0.0	1.0
stressful: good collaboration	0.5	0.5	0.0	1.0
stressful: feel as part of community	0.3	0.4	0.0	1.0
stressful: receive help, support from colleagues	0.4	0.5	0.0	1.0
stressful: receive help, support from supervisor	0.4	0.5	0.0	1.0
stressful: think through, get familiar w/ tasks	0.1	0.3	0.0	1.0
stressful: demanded unknown things	0.4	0.5	0.0	1.0
overall job satisfaction	0.0	1.0	-3.7	1.4

Table A4.1 – continued on next page

Table A4.1 – continued from previous page

satisfaction with income	0.0	1.0	-2.3	1.6
satisfaction with tasks	-0.0	1.0	-3.7	1.4
satisfaction with application of skills	0.0	1.0	-3.2	1.3
satisfaction with further training	0.0	1.0	-2.4	1.5
satisfaction with physical working conditions	0.0	1.0	-3.0	1.5
satisfaction with career opportunities	0.0	1.0	-2.0	1.8
satisfaction with working atmosphere	-0.0	1.0	-2.9	1.1
satisfaction with supervisor	0.0	1.0	-2.8	1.2
satisfaction with work equipment	0.0	1.0	-2.8	1.5
satisfaction with hours	-0.0	1.0	-2.7	1.5
log of hourly income	2.7	0.5	-5.3	5.7
work life balance	0.6	0.5	0.0	1.0
dream job	0.8	0.4	0.0	1.0
work is important	0.0	1.0	-4.4	0.5
high risk of layoff	0.1	0.3	0.0	1.0
atypical	0.1	0.3	0.0	1.0
night	0.2	0.4	0.0	1.0
shift	0.2	0.4	0.0	1.0
weekend	0.7	0.5	0.0	1.0
standby	0.2	0.4	0.0	1.0

Weighted according to census data. Data sources: BIBB/BAuA.

Table A4.2: Model specifications

sparse model	full model		
	job demands and resources	sociodemographics	job characteristics
education	**job demands**	having a partner	experience
low	reach limits of own capacity	having children	feel work is important
medium plus	interrupted during work	income	successful work life balance
higher	deadline/performance pressure		atypical work
(base: medium)	work fast		night work
	minimum performance		shift work
age	overstrained		work on weekends
gender	risk of financial loss		standby duty
survey dummy	no timely information about future		
	do not receive all necessary information		
	details predetermined		
	repetition		
	multitasking		
	working hours		
	job resources		
	plan/schedule own work		
	influence own workload		
	decide when to break		
	good collaboration		
	feel as part of community		
	get help from colleagues		
	get help from supervisor		
	perform tasks independently		
	ambiguous factors		
	supervisor for somebody		
	get familiar with tasks		
	improve methods		
	demanded unknown things		

Own table.

Table A4.3: OLS estimates for work-related mental health outcomes – occupation controls

	combined		strain		exhaustion		burnout	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
low education	-0.159***	-0.068**	-0.174***	-0.077**	-0.032	-0.004	-0.060	-0.042
	(0.037)	(0.033)	(0.038)	(0.035)	(0.042)	(0.040)	(0.062)	(0.061)
medium plus	0.182***	0.105***	0.180***	0.097***	0.077*	0.054	0.021	0.020
	(0.032)	(0.028)	(0.031)	(0.028)	(0.043)	(0.040)	(0.058)	(0.056)
higher education	0.170***	0.108***	0.180***	0.105***	0.050	0.045	0.039	0.058
	(0.024)	(0.023)	(0.023)	(0.023)	(0.035)	(0.037)	(0.039)	(0.042)
constant	0.059	-0.221***	-0.864*	-0.557	-0.578***	-1.157***	-0.373***	-0.051
	(0.037)	(0.075)	(0.502)	(0.386)	(0.042)	(0.110)	(0.082)	(0.152)
N	18418	18418	18441	18441	12532	12532	5892	5892
Adj. R^2	0.107	0.326	0.121	0.302	0.039	0.169	0.008	0.083

Standardized dependent variable given in column header. Combined: emotional exhaustion, burnout and/or emotional strain. Model specifications: (1) full model according to table A4.2 and industry dummies, (2) full model and occupation dummies. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

Table A4.4: OLS estimates for work-related mental health outcomes – one-digit occupation controls

	combined		strain		exhaustion		burnout	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
low education	-0.183***	-0.080**	-0.204***	-0.092***	-0.037	-0.005	-0.032	-0.013
	(0.037)	(0.034)	(0.038)	(0.035)	(0.041)	(0.040)	(0.060)	(0.058)
medium plus	0.205***	0.110***	0.201***	0.097***	0.101**	0.067*	0.044	0.045
	(0.032)	(0.027)	(0.031)	(0.028)	(0.042)	(0.039)	(0.057)	(0.055)
higher education	0.167***	0.083***	0.173***	0.077***	0.067**	0.043	0.026	0.064
	(0.021)	(0.022)	(0.021)	(0.022)	(0.029)	(0.034)	(0.036)	(0.040)
constant	-0.341***	-0.288***	-0.247***	-0.206***	-0.174***	-0.199**	-0.013	0.217*
	(0.042)	(0.071)	(0.042)	(0.071)	(0.047)	(0.088)	(0.062)	(0.132)
N	18418	18418	18441	18441	12532	12532	5892	5892
Adj. R^2	0.083	0.311	0.095	0.285	0.027	0.160	0.002	0.081

Standardized dependent variable given in column header. Combined: emotional exhaustion, burnout and/or emotional strain. Model specifications: (1) full model according to table A4.2 and industry dummies, (2) full model and occupation dummies. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

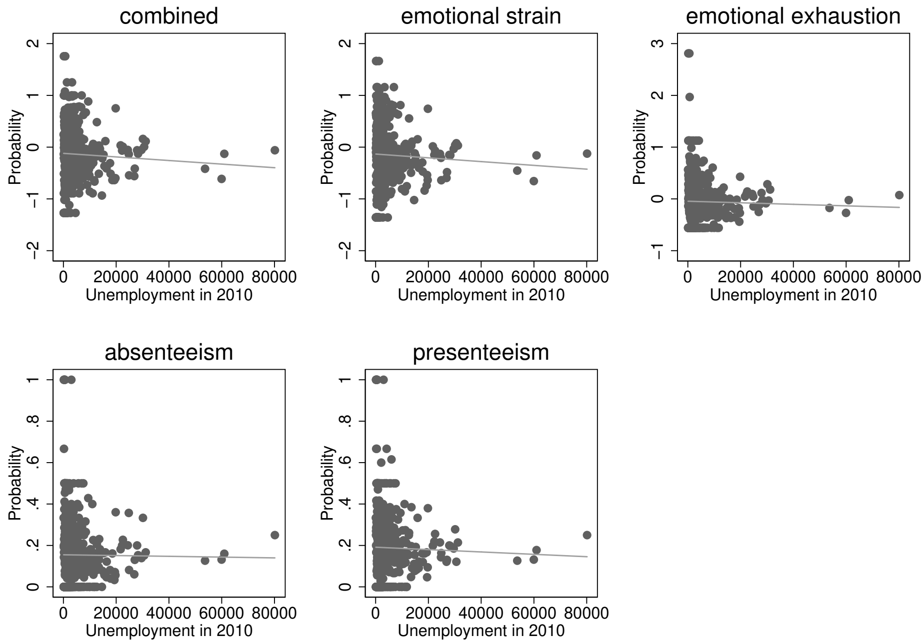
Table A4.5: OLS estimates for work-related mental health outcomes – industry controls

	combined		strain		exhaustion		burnout	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
low education	-0.209***	-0.075**	-0.230***	-0.087**	-0.057	-0.016	-0.034	-0.009
	(0.036)	(0.033)	(0.037)	(0.035)	(0.042)	(0.041)	(0.052)	(0.050)
medium plus	0.197***	0.106***	0.197***	0.096***	0.100**	0.074*	0.028	0.026
	(0.031)	(0.027)	(0.030)	(0.027)	(0.042)	(0.039)	(0.050)	(0.048)
higher education	0.216***	0.096***	0.222***	0.089***	0.092***	0.059*	0.057*	0.051
	(0.020)	(0.021)	(0.019)	(0.021)	(0.028)	(0.035)	(0.031)	(0.036)
constant	-0.419***	-0.540***	-0.316***	-0.461***	-0.186***	-0.268***	-0.163***	-0.052
	(0.040)	(0.067)	(0.040)	(0.068)	(0.050)	(0.091)	(0.053)	(0.109)
N	19651	19651	19674	19674	12135	12135	7522	7522
Adj. R^2	0.085	0.312	0.100	0.289	0.023	0.157	0.004	0.086

Standardized dependent variable given in column header. Combined: emotional exhaustion, burnout and/or emotional strain. Model specifications: (1) full model according to table A4.2 and industry dummies, (2) full model and occupation dummies. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

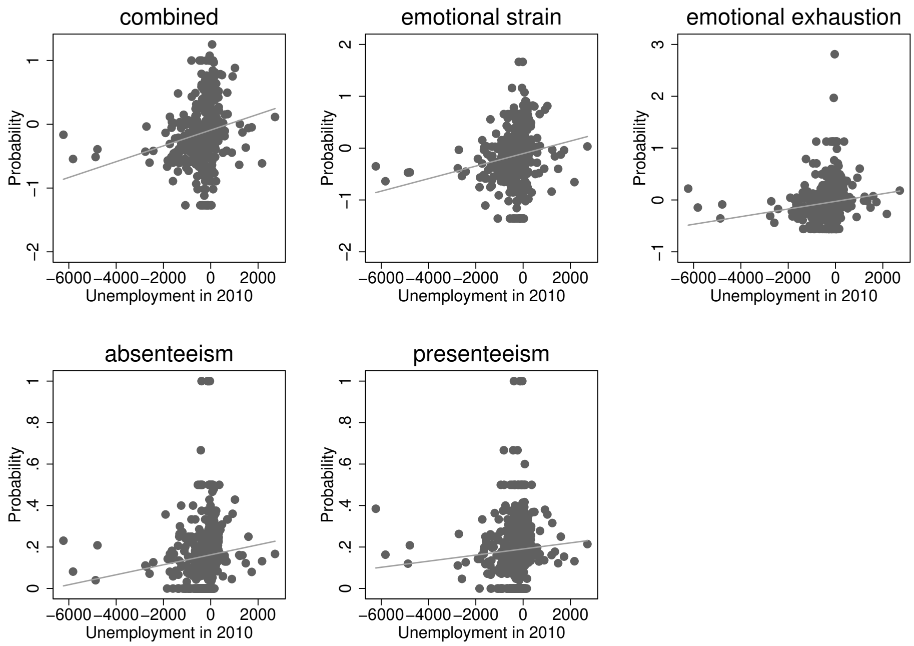
Appendix for chapter 5

Figure A5.1: Prevalence of work-related mental health problems over level of unemployment



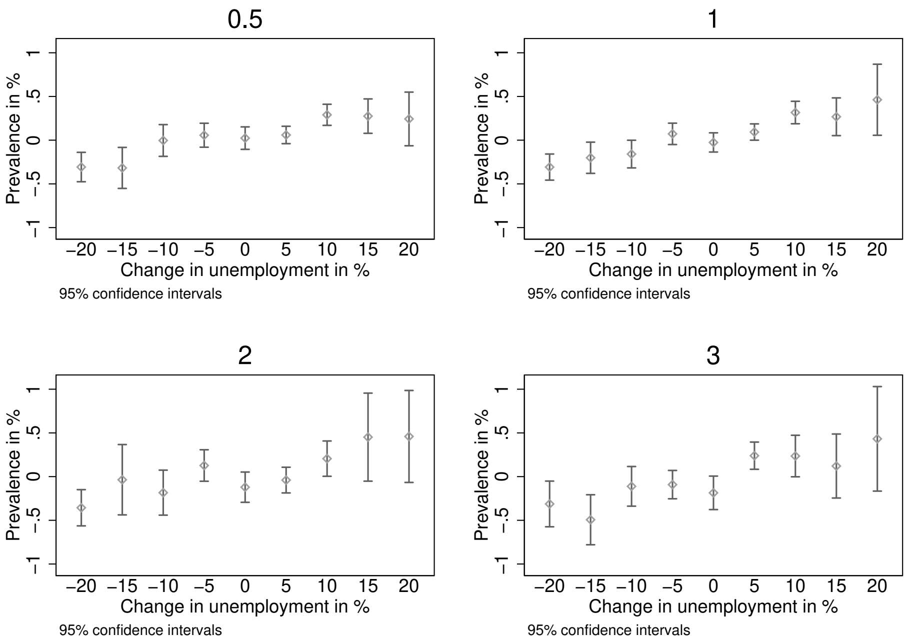
The x-axis shows one period lagged occupation specific unemployment on federal state level (2010). One dot represents one occupation-federal state combination. Data sources: BIBB/BAuA, IAB. Own figure.

Figure A5.2: Prevalence of work-related mental health problems over level changes in unemployment



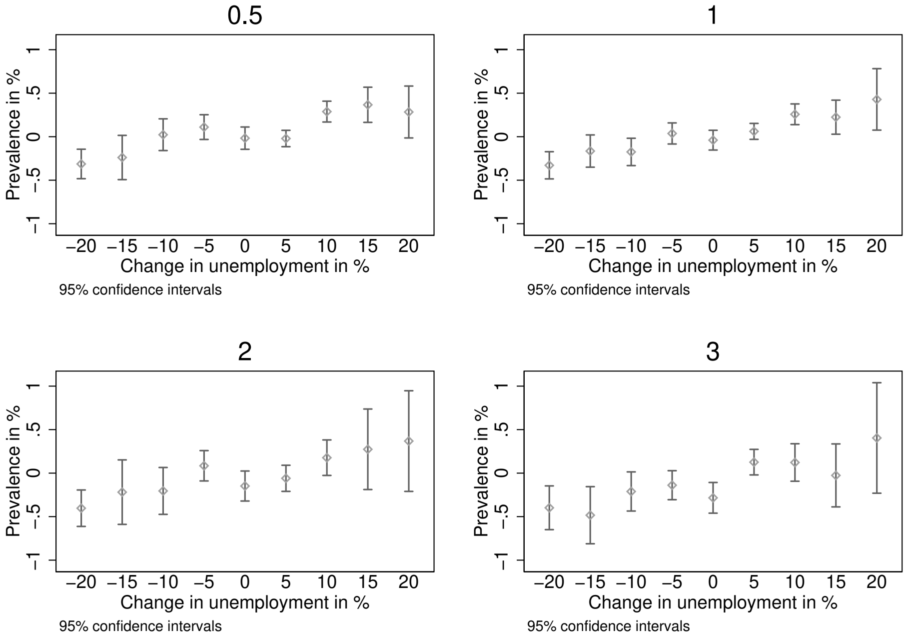
The x-axis shows one period lagged changes in occupation specific unemployment on federal state level (change from 2009 to 2010). One dot represents one occupation-federal state combination. Data sources: BIBB/BAuA, IAB. Own figure.

Figure A5.3: Prevalence of standardized combined measure over changes in unemployment by unemployment duration



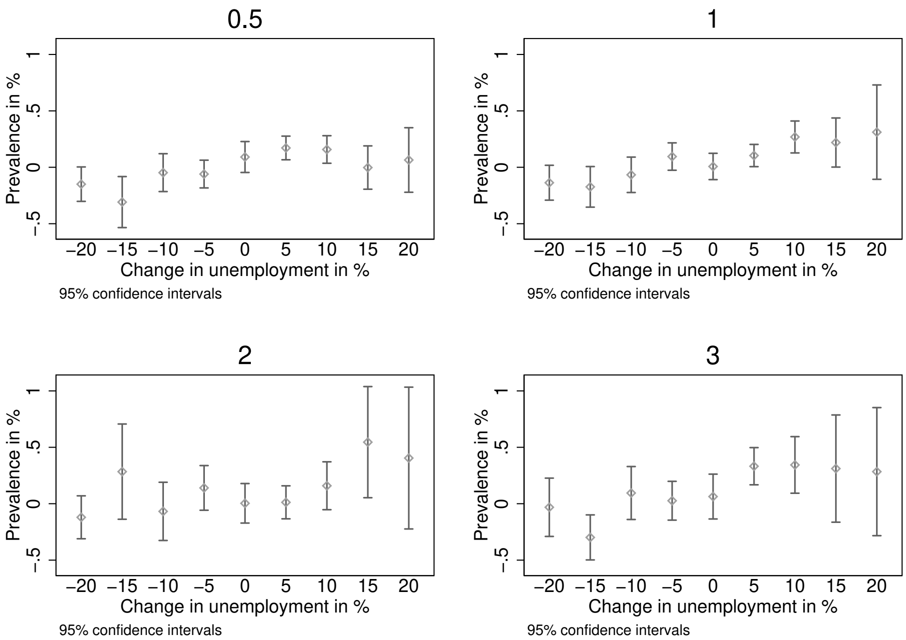
Combined measure: emotional exhaustion an/or emotional strain. The x-axis shows one period lagged changes in occupation specific unemployment on federal state level. Duration: 0.5 years, 1 year, 2 years, 3 years and longer. Data sources: BIBB/BAuA, IAB. Own figure.

Figure A5.4: Prevalence of standardized emotional strain over changes in unemployment by unemployment duration



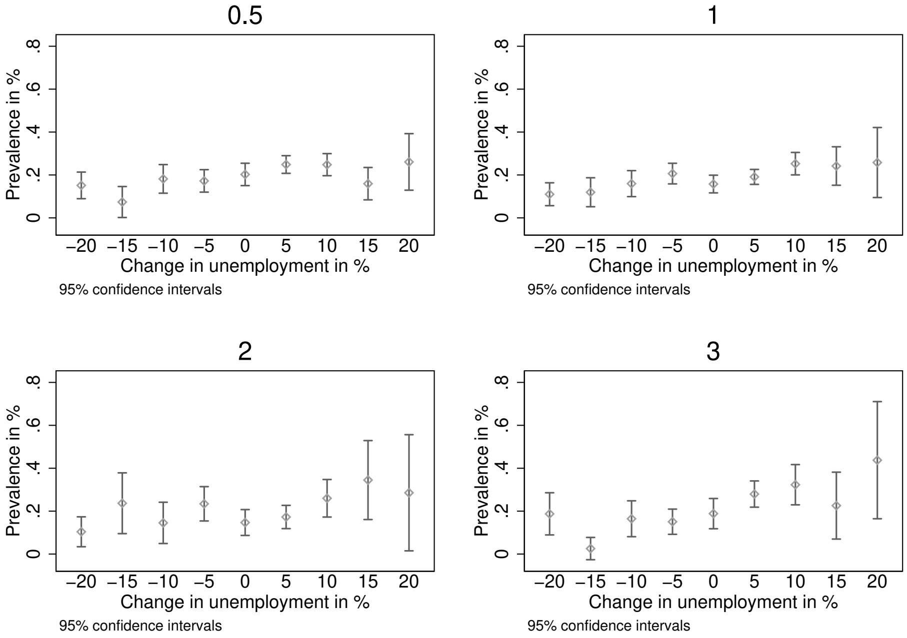
The x-axis shows one period lagged changes in occupation specific unemployment on federal state level. Duration: 0.5 years, 1 year, 2 years, 3 years and longer. Data sources: BIBB/BAuA, IAB. Own figure.

Figure A5.5: Prevalence of standardized emotional exhaustion over changes in unemployment by unemployment duration



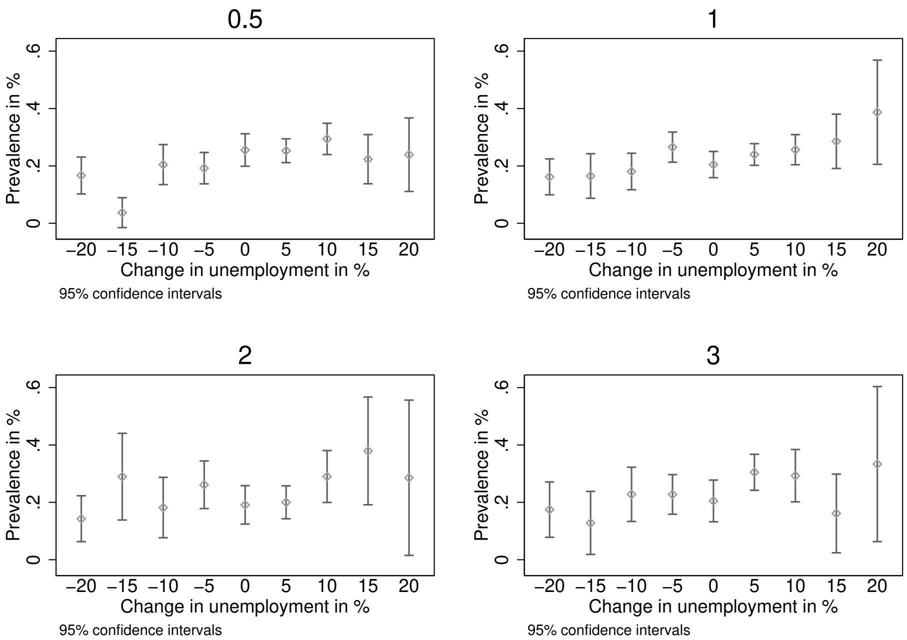
The x-axis shows one period lagged changes in occupation specific unemployment on federal state level. Duration: 0.5 years, 1 year, 2 years, 3 years and longer. Data sources: BIBB/BAuA, IAB. Own figure.

Figure A5.6: Prevalence of absenteeism over changes in unemployment by unemployment duration



The x-axis shows one period lagged changes in occupation specific unemployment on federal state level. Duration: 0.5 years, 1 year, 2 years, 3 years and longer. Data sources: BIBB/BAuA, IAB. Own figure.

Figure A5.7: Prevalence of presenteeism over changes in unemployment by unemployment duration



The x-axis shows one period lagged changes in occupation specific unemployment on federal state level. Duration: 0.5 years, 1 year, 2 years, 3 years and longer. Data sources: BIBB/BAuA, IAB. Own figure.

Table A5.1: Descriptive statistics

	mean	sd	min	max
combined	-0.047	0.990	-1.3	2.5
emotional strain	-0.038	1.001	-1.4	1.7
exhaustion	-0.041	0.960	-0.6	2.8
absenteeism	0.160	0.367	0.0	1.0
presenteeism	0.193	0.395	0.0	1.0
combined (0-2, std.)	-0.033	0.981	-0.6	1.7
strain, binary	0.284	0.451	0.0	1.0
strain (broad), binary	0.613	0.487	0.0	1.0
exhaustion (ordinal)	0.251	0.434	0.0	1.0
common factor	-0.033	0.953	-0.6	1.9
unemployment change from t-2 to t-1 in %	-0.033	0.118	-0.4	0.3
unemployment change from t-1 to t in %	-0.157	0.190	-1.0	1.8
unemployment change from t-3 to t-2 in %	0.136	0.281	-0.5	2.0
unemployment change from t-3 to t-1 in %	-0.178	0.214	-1.0	0.9
ever unemployed	0.635	0.481	0.0	1.0
unemployment duration	1.579	1.916	0.5	30.0
reach limits of own capacity	-0.021	0.994	-1.5	1.5
interrupted during work	-0.053	1.013	-2.4	0.9
deadline/performance pressure	-0.016	1.009	-2.9	0.8
work fast	-0.012	1.003	-2.1	1.0
do different things simultaneously	-0.068	1.044	-2.7	0.7
minimum performance	0.058	1.003	-1.2	1.3
overstrained	0.202	0.401	0.0	1.0
risk of financial loss	0.025	1.007	-1.1	1.7
no timely information about future	-0.014	1.002	-1.5	1.7
do not receive all information necessary	-0.006	1.000	-1.4	2.0
details predetermined	0.018	0.996	-1.4	1.4
repetition	0.006	0.996	-1.9	0.9
plan, schedule own work	-0.052	1.028	-3.0	0.5
influence own workload	-0.009	0.997	-1.5	1.1
decide when to break	-0.050	1.026	-1.9	0.7
good collaboration	-0.014	1.040	-6.5	0.3
perform tasks independently	0.711	0.454	0.0	1.0
supervisor for somebody	0.308	0.462	0.0	1.0
get familiar with tasks	-0.018	1.026	-2.7	1.0
improve methods	-0.007	1.020	-2.3	1.2
demanded unknown things	0.001	1.004	-1.1	2.0
men	0.526	0.499	0.0	1.0
married or registered partnership	0.566	0.496	0.0	1.0
having children	0.642	0.479	0.0	1.0
low education	0.075	0.263	0.0	1.0
medium+ education	0.084	0.277	0.0	1.0
higher education	0.237	0.425	0.0	1.0
age	43.004	11.092	18.0	65.0
age squared	1972.327	935.797	324.0	4225.0
working hours main job	38.951	12.180	10.0	120.0
hours squared	1665.517	1013.441	100.0	14400.0

Table A5.1 – continued on next page

Table A5.1 – continued from previous page

tenure in years	12.411	10.537	0.0	50.0
atypical	0.133	0.340	0.0	1.0
night	0.200	0.400	0.0	1.0
shift	0.154	0.361	0.0	1.0
weekend	0.660	0.474	0.0	1.0
standby	0.178	0.382	0.0	1.0
work is important	-0.024	1.033	-4.5	0.5
successful work life balance	0.586	0.493	0.0	1.0
working in dream job	0.791	0.406	0.0	1.0

Weighted according to census data. Data sources: BIBB/BAuA, IAB.