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

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Abstract

This paper analyses whether there is a causal relationship between work-related mental health problems and multitasking, the number of tasks performed at work. The data comes from two cross sectional surveys on the German working population. The empirical strategies uses technological change as an instrument for multitasking. In the first stage, the introduction of new production and information technologies is associated with increases in multitasking. Production technology adoption has larger associations to manual multitasking and informational technology adoption to cognitive multitasking. There is evidence for a causal effect of multitasking on emotional strain, emotional exhaustion and burnout.

Keywords: work-related mental health, multitasking, job satisfaction

JEL Classification: I10, J28

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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 2 gives an overview over the relevant literature. Section 3 is dedicated to data, section 4 explains the methodology. Results are presented in sections 5 and 6 and discussed in section 7. The last section concludes.

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

[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.

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 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 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

[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.

(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]

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 1 shows the categorization.

[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.

Table 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.

4 Estimation procedure

The relationship between multitasking and work-related health outcomes can be formalized as in equation 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 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 A.1).[4] For the binary outcomes absenteeism and presenteeism, equation 1 is a

[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 A.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

linear probability model.

$$Y_i = \alpha + \beta multitasking_i + \mathbf{X}_i' \delta + u_i \quad (1)$$

Estimating equation 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 technological 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 restric-

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.

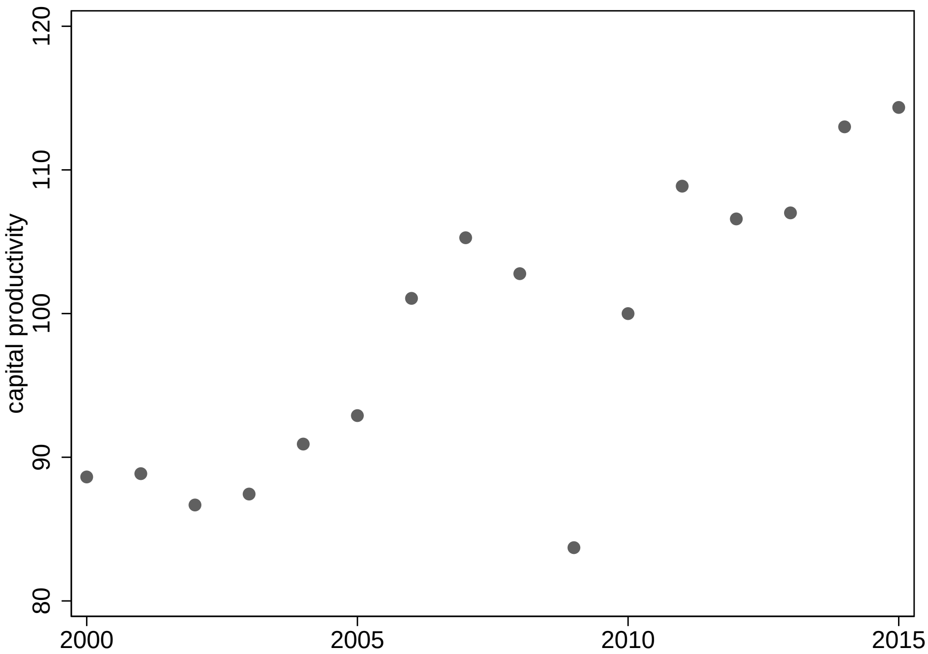
[5]Some workers may still have some leeway of deciding whether or not to adopt a particular technology in their specific job.

tion. 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 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 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 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 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 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 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

Figure 1: Capital productivity in manufacturing



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

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). 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%).

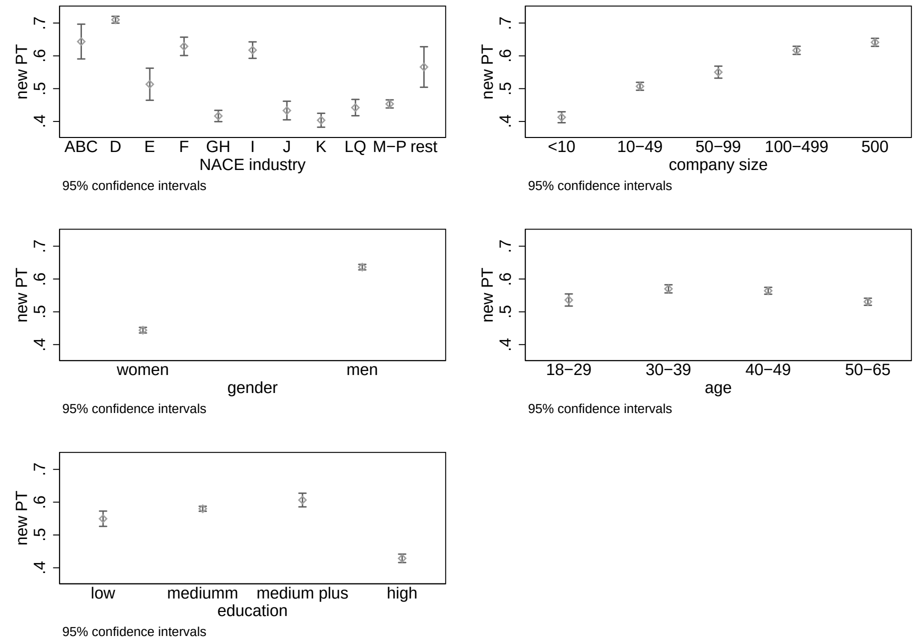
Both figures suggest that technological change is not random across the working population but differs across industries, company size, age, gender, and education. Instrumenting multi-tasking with PT/IT adoption in the full sample might still deliver somewhat biased estimates if there is selection into 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 5). Then, I focus on the smaller subsamples (section 6).

Table 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 2: Production technology adoption by company and individual characteristics



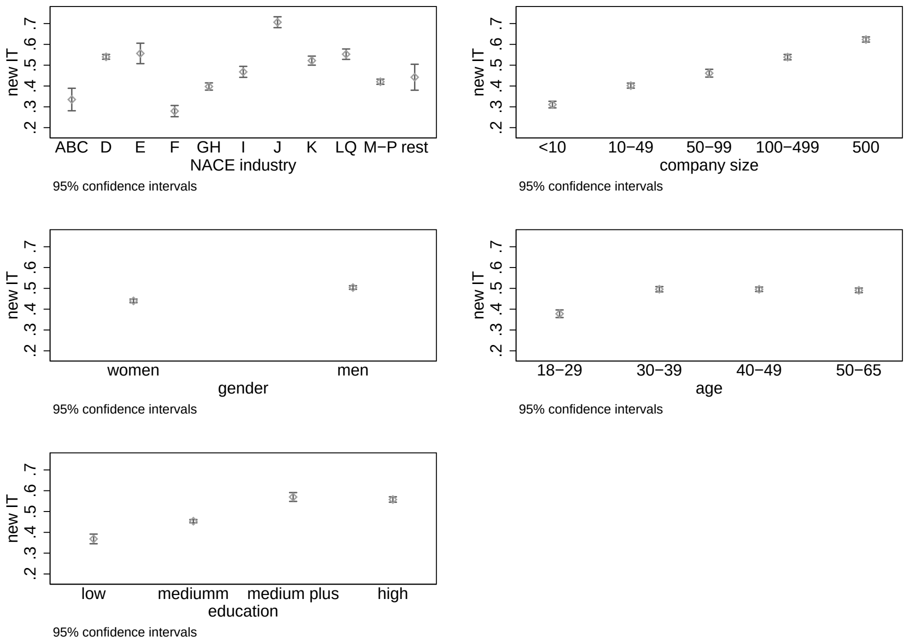
NACE industries: ABC: Agriculture, fishery, mining, D: Manufacturing, E: Energy & water supply, F: Construction, G&H: Commerce and hotels, I: Transport, J: Finance, K: Real estate etc., L&Q: Public administration, M-P: Public & private services, rest not elsewhere allocated. Data sources: BIBB/BAuA.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

5 Full sample results

5.1 Descriptives and general multitasking

Figures 4 and 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-

Figure 3: Information technology adoption by company and individual characteristics

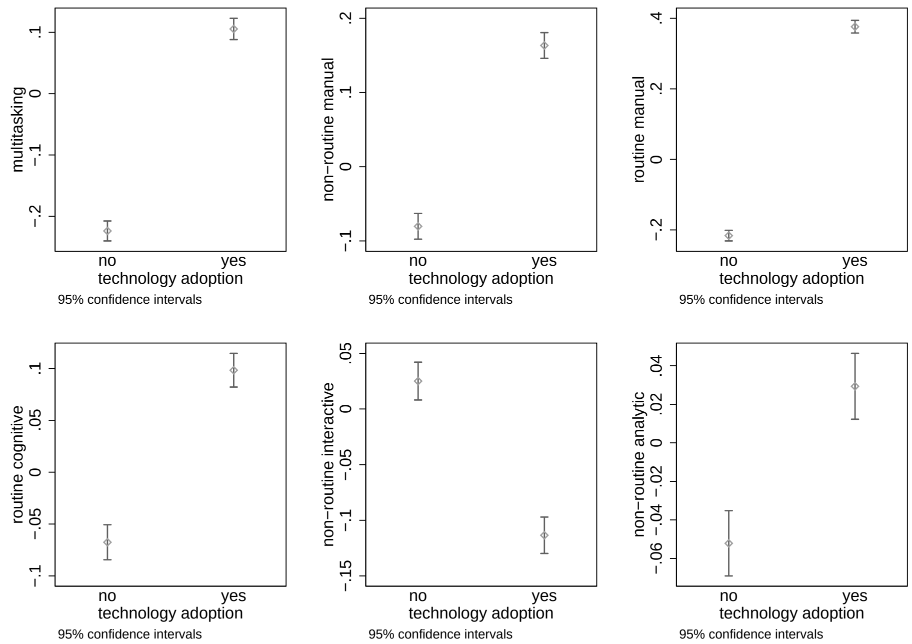


NACE industries: ABC: Agriculture, fishery, mining, D: Manufacturing, E: Energy & water supply, F: Construction, G&H: Commerce and hotels, I: Transport, J: Finance, K: Real estate etc., L&Q: Public administration, M-P: Public & private services, rest not elsewhere allocated. Data sources: BIBB/BAuA.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

routine analytic tasks, too, but the 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 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.

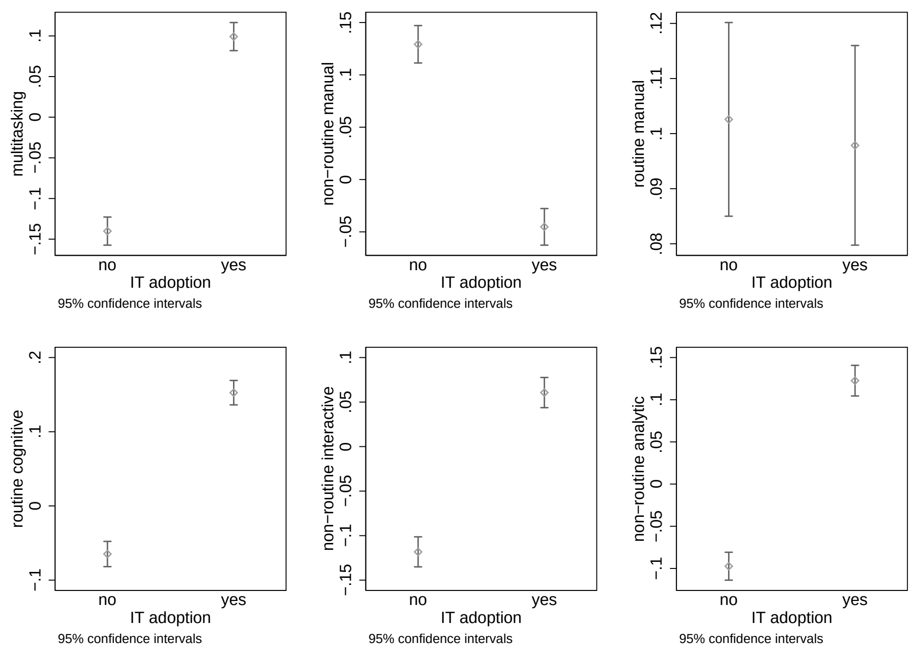
Table 3 displays OLS results in the first panel and IV results with both instruments in the second and third panel. First stage coefficients and their t-statistics can be found at the bottom of the table. A rule of thumb is that the first stage is weak when the F-statistics of the excluded instrument 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

Figure 4: Multitasking by production technology adoption



Data sources: BIBB/BAuA. Own figure.

Figure 5: Multitasking by information technology adoption



Data sources: BIBB/BAuA. Own figure.

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 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: 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.

5.2 Multitasking within task categories

Multitasking in non-routine manual tasks is significantly associated with worse work-related mental health in OLS (table 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 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 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 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 5, routine manual multitasking is not significantly affected by the adoption of new IT. First stages are insignificant.

Table 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 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 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 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 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 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 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.

6 Subsample results

6.1 Subsample definitions

Figures 2 and 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 A.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 (A.4). 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)

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 A.5 to A.8. 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 A.5 and A.6, 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 A.7). 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 A.8). 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 A.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 A.4). First stages in the IT 1 sample are insignificant or come with low t-statistics for all outcomes except general multitasking (table A.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 A.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 A.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 A.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 A.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 A.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 A.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 A.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.

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

[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.

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.

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.

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.

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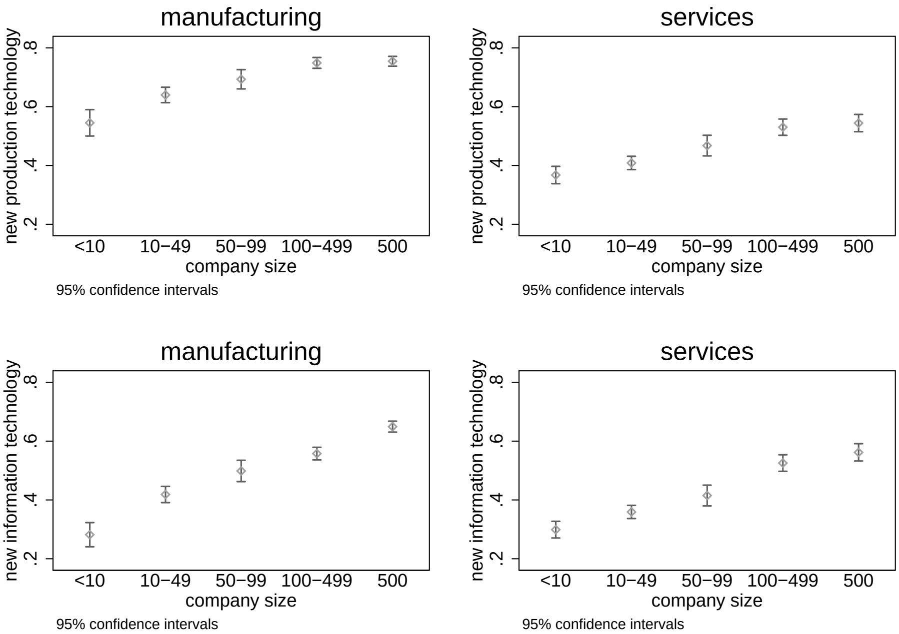
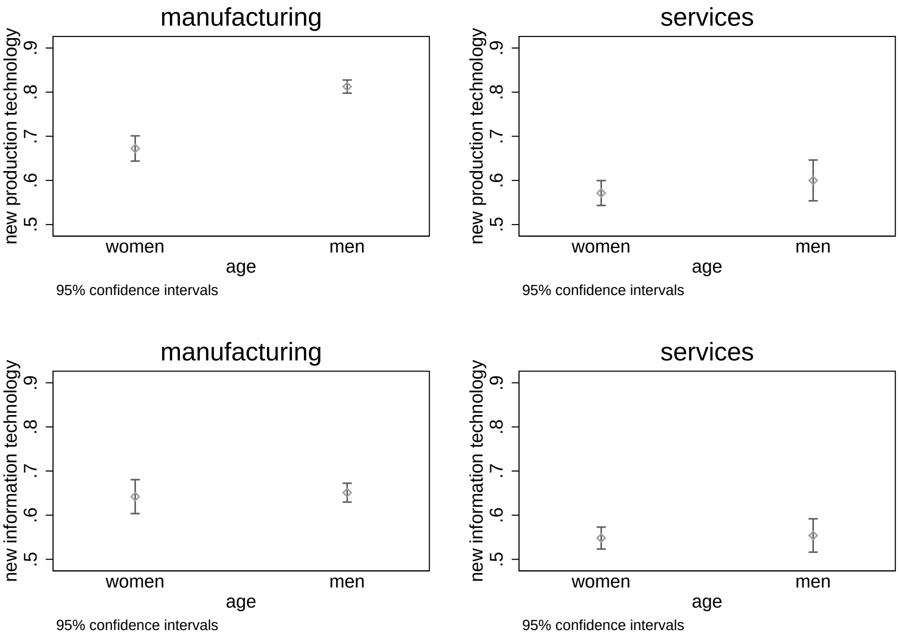
Figures

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



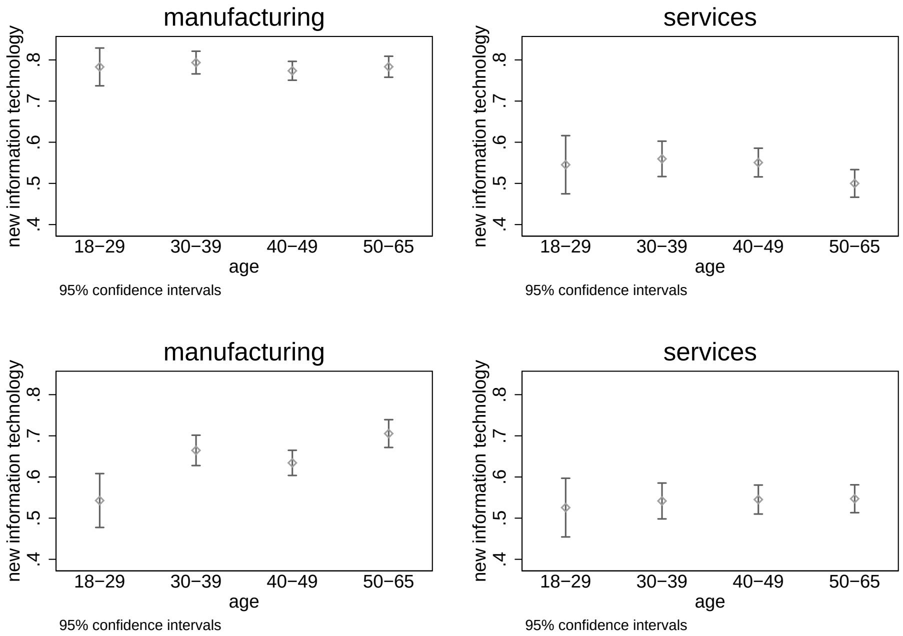
Data sources: BIBB/BAuA. Own figure.

Figure A.2: PT and IT adoption in manufacturing and services companies with 100 and more employees by gender[a]



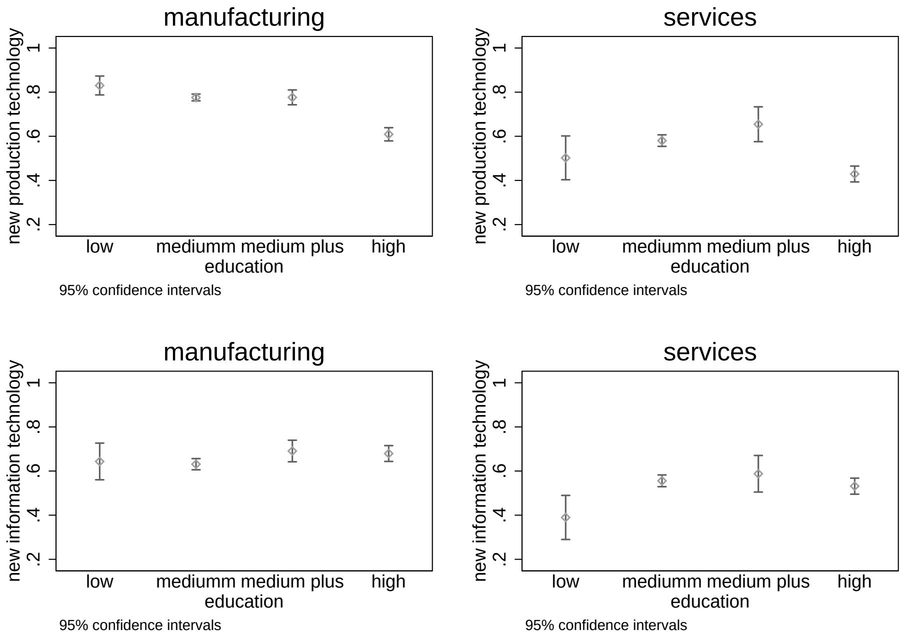
[a] IT adoption in manufacturing companies with 500 and more employees.
Data sources: BIBB/BAuA. Own figure.

Figure A.3: PT and IT adoption in manufacturing and services companies with 100 and more employees by age category[a]



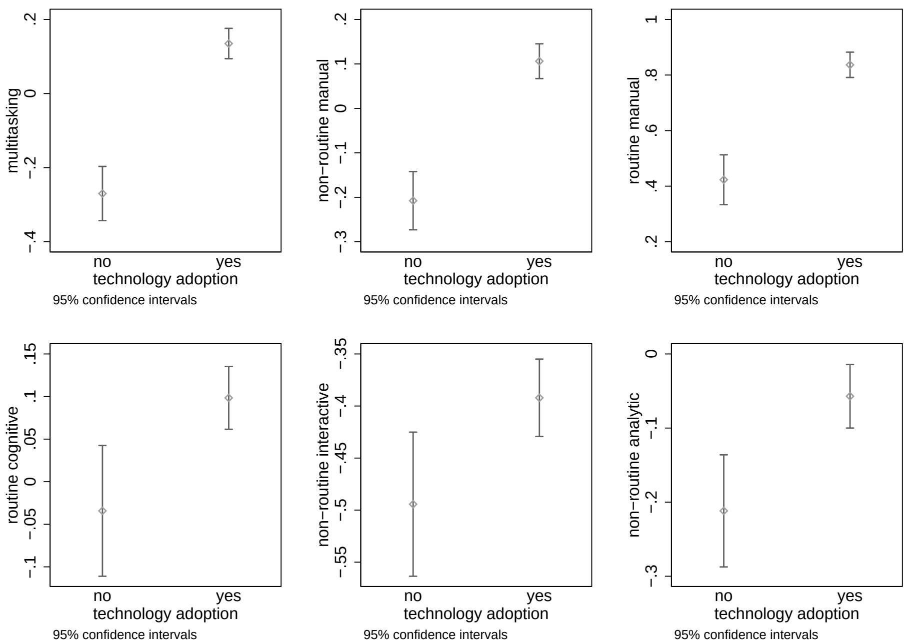
[a] Technology adoption for men in manufacturing companies with 100 and more employees. IT adoption in manufacturing companies with 500 and more employees.
Data sources: BIBB/BAuA. Own figure.

Figure A.4: PT and IT adoption in manufacturing and services companies by level of education



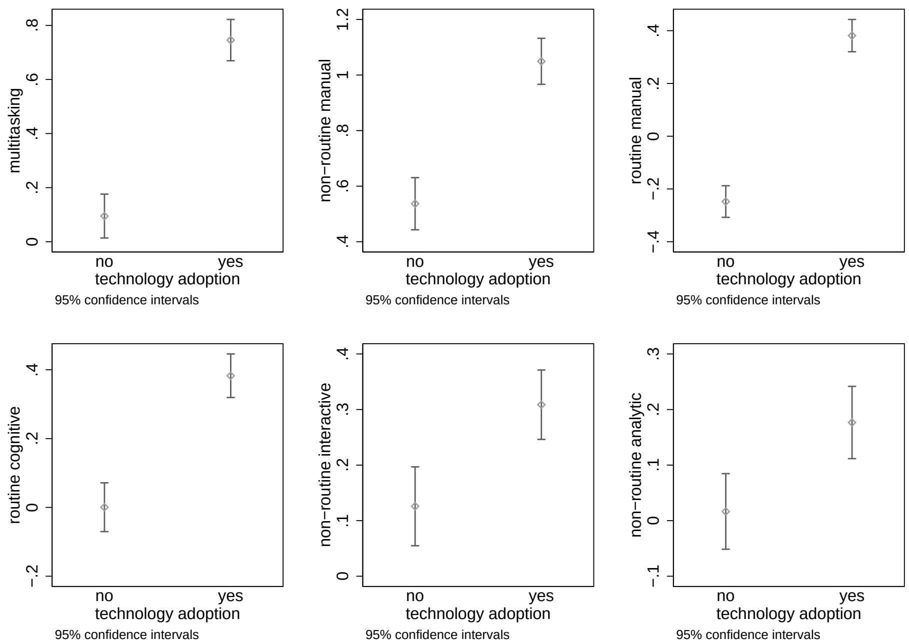
Data sources: BIBB/BAuA. Own figure.

Figure A.5: Standardized multitasking by technology adoption for low to medium plus educated men in manufacturing companies with 100 and more employees



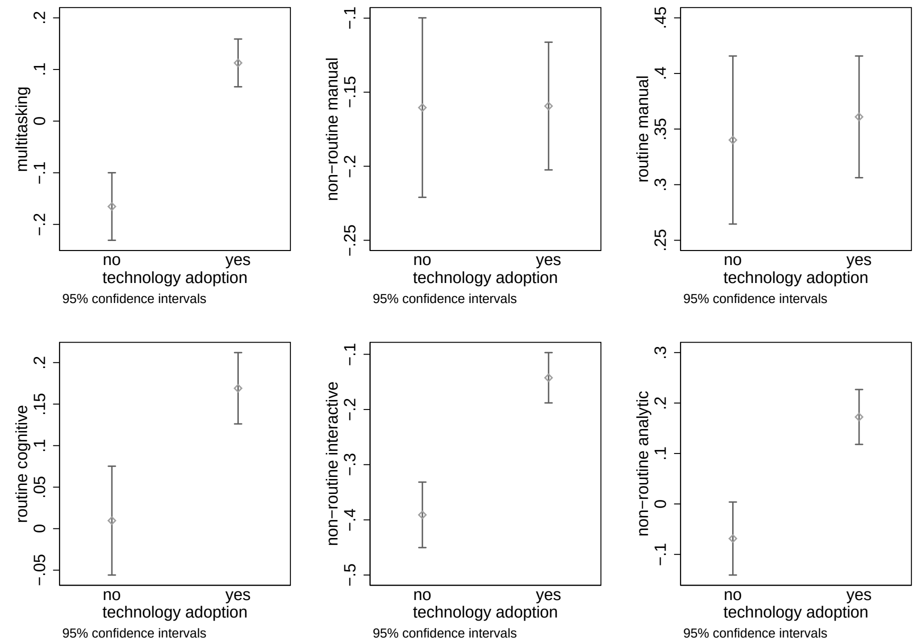
Data sources: BIBB/BAuA. Own figure.

Figure A.6: Standardized multitasking by technology adoption for low to medium plus educated employees in service companies with 100 and more employees



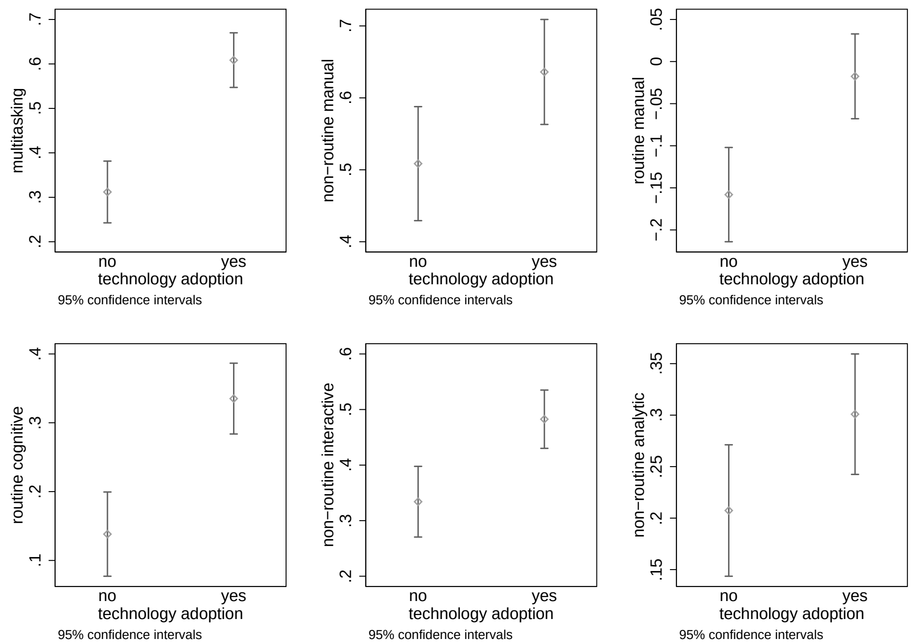
Data sources: BIBB/BAuA. Own figure.

Figure A.7: Standardized multitasking by IT adoption for employees in manufacturing companies with 500 and more employees



Data sources: BIBB/BAuA. Own figure.

Figure A.8: 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.

Tables

Table A.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 A.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 A.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 A.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 A.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 A.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 A.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 A.3. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

Table A.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 A.4. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

Table A.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 A.5. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/BAuA. Own calculations.

Table A.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 A.6. Standard errors in parentheses. Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: BIBB/ BAuA. Own calculations.