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DISCUSSION PAPER SERIES

IZA DP No. 14137

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ABSTRACT

Cognitive Load and Occupational Injuries[1]

We investigate the relationship between cognitive load and occupational injuries. Cognitive load is defined in the literature as a tax on bandwidth which reduces cognitive resources. We proxy cognitive load with the number of non-professional tasks that individuals perform during weekdays. The underlying assumption is that when individuals perform many of those tasks, this requires mental organization which reduces available cognitive resources. We show that being cognitively loaded is associated with an increase in the risk of occupational injury for both males and females. The effect is stronger for individuals in high-risk occupations and, among those, for low-educated workers.

JEL Classification: J28, J81, D91

Keywords: work injury, cognitive load, time-use data

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I. Introduction

A growing body of literature in psychology, economics and cognitive sciences investigates the impact of cognitive load on individuals' abilities and preferences.

The concept of cognitive load builds on the two-system model of the brain (Kahneman, 2002, 2011). In this framework, people have a fast system (system 1) that governs automatic and effortless thoughts and a slow system (system 2) which is deliberate and costly (Schilbach et al., 2016). When required to make a decision, system 1 quickly reaches a decision but is prone to biases and errors. System 2 is more accurate but overriding an intuitive decision made by system 1 comes at a cost. Individuals have a mental reserve, called bandwidth (Mullainathan and Shafir, 2013), for the effortful thought required to use system 2. Cognitive load acts as a tax on bandwidth which reduces the amount of cognitive resources available for engaging in logical reasoning.

Several studies have estimated the impact of cognitive load on a number of individual outcomes. The vast majority of the research manipulates cognitive load in the lab. A widespread method to impair cognitive resources is to have subjects hold a 7-or-more digit number or letter sequence in their memory while making choices (Miller, 1956). The impact on bandwidth can be readily measured using, for example, Raven's matrices which capture fluid intelligence, i.e. the capacity to think logically and solve problems in novel situations independent of acquired knowledge (Mani et al. 2013). Alternatively, the effect on bandwidth can also be measured via arithmetic mistakes or the reduced ability to spot flawed logical arguments in syllogisms (De Neys, 2006). Under cognitive load, individuals perform significantly worse on all these cognitive tasks, thus suggesting that the effort made to memorize the number/letter sequence reduces the amount of "working memory" (De Jong, 2010) and hence, the cognitive resources available for deliberation.

The tax on bandwidth imposed by cognitive load has been shown to have consequences both in terms of preferences and quality of judgement – see Schilbach et al. (2016) for a review of the literature.

The literature has shown that preferences are altered by cognitive load. Individuals are typically more risk averse (Benjamin et al., 2013; Deck and Jahedi, 2015; Gerhardt et al., 2016), more impatient over money and have a greater likelihood to anchor (Deck and Jahedi, 2015) when facing high levels of cognitive load. They also make more random decisions (Franco-Watkins et al., 2006) and poorer dietary choices (Zimmerman and Shimoga, 2014). Mentally burdened individuals indeed favor immediate gratification at the expense of long-term costs. Shiv and Fedorikhin (1999) show that undergraduate students under high cognitive load are more likely to choose chocolate cake over a fruit salad than students under lower cognitive load. Similarly, female undergraduates self-reporting themselves as restrained eaters are found to consume more ice cream than unrestrained eaters when cognitively loaded (Boon et al. 2002). More recently, Byrd-Bredbenner et al. (2016) confirm that individuals under cognitive load are more likely to eat few fruit and vegetables and to eat in response to external cues or emotions. Another strand of literature suggests that cognitive burden may also affect generosity in a dictator game although, the direction of this effect is ambiguous: Benjamin et al. (2013) find individuals to be more selfish under cognitive load while Schulz et al. (2014) find the opposite effect and Hauge et al. (2016) do not find any significant effect.

Beyond preferences, the quality of judgement also turns out to be affected by cognitive load. Hon et al. (2013) show that working memory load reduces the sense of agency, i.e. the extent to which individuals perceive whether they may be responsible or not for a given outcome. More importantly, experiments run by Kleider and Parrott (2009) show that when subject to high cognitive load, individuals are more likely to shoot unarmed targets. In their review of the literature, Kleider-Offutt et al. (2016) suggest that it is due to the fact that these individuals lack the cognitive resources necessary to engage in controlled processing so that they rely on automatic processing. Similarly, Correll et al. (2007) show that cognitive load increases the racial bias against black people in shooting decisions. They conclude that cognitive resources are needed to override the use of automatic stereotypes. Kleider et al. (2012) also find that mock-jurors rely more on stereotypes when mentally burdened. This suggests that unbiased decisions require processing resources that are less available under cognitive load.

If cognitive load deteriorates the ability to solve problems, retain information and engage in logical reasoning, it is likely to affect individual performance. In this paper, we investigate a dimension of performance that has not been studied yet, i.e. individual productivity. We focus on one particular aspect of productivity, i.e. occupational injuries. These incur enormous costs both to employees and employers. Estimates from the National Safety Council suggest that the overall cost of work injuries in the USA amounted to $171 billion in 2018, of which $52.4 due to wage and productivity losses.[2] A most common cause of occupational injury is distraction (European Commission, 2009). Now, one of the components of bandwidth is executive control which determines our ability to focus and shift attention to work with information in our memory. So, one can hypothesize that reduced bandwidth due to cognitive load is likely to generate distraction thereby increasing the risk of work accident.

Given that we are interested in occupational injuries on the job, ethical as well as legal concerns prevent us from manipulating cognitive load in an experimental setting. We thus rely on survey data. Of course, manipulation of working memory in the lab has the key advantage of generating within-subject variation while being strictly exogenous. We replicate this set-up as closely as we can with our data. We consider that individuals are mentally burdened when they have to keep in mind non-professional preoccupations while working. This is, in some sense, equivalent to what Mani et al. (2013) do with their experiment where they induce rich and poor subjects

[2] See https://injuryfacts.nsc.org/work/costs/work-injury-costs/

to think about everyday financial demands. For the rich, these demands have no consequence, while for the poor, they trigger distracting concerns that reduce their bandwidth as measured by Raven's matrices. The idea that preoccupation induces a reduction in bandwidth is central to our measure of cognitive load. Using time-use information provided by the German Socio-Economic Panel (SOEP), we proxy cognitive load with the number of non-professional tasks (e.g. housework, child care etc.) performed by individuals each day, independent of the time spent on them. The underlying assumption is that when individuals perform a large number of those tasks, this requires mental organization and hence generates preoccupation which keeps part of the individual's working memory busy. In turn, this may create distraction thereby increasing the risk of work injury. Our empirical strategy is based on linear probability models in which the individual probability of occupational injury is modelled as a function of the number of non-professional tasks performed on weekdays, controlling for a number of individual characteristics. These models are estimated using Ordinary Least Squares (OLS) and Fixed Effects (FE) estimators. To the extent that we include individual fixed effects in our preferred specification, our identification strategy relies on within-individual variations. Our results suggest that cognitive load is associated with a higher risk of occupational injury for both males and females. The effect is driven by benign injuries that do not require hospitalization. It is stronger for individuals in high-risk occupations and, among those, for low-educated workers.

Our paper relates to the small literature on the impact of cognitive load on individuals' ability to perform a secondary task. This has been particularly investigated in transport studies where researchers study in the lab the impact of cognitive load on the quality of driving as evaluated using a driving simulator. Participants typically have to travel in a 3-vehicle column as the middle car. They must keep a constant distance with the preceding car which is driving at a moderate speed. The quality of the driving is measured by the standard deviation in the traffic lane position and standard speed deviations. The primary memory task consists in the so-called "n-back" task, i.e. recalling a series of numbers that the speaker told earlier. In this context, the impact of high cognitive load is ambiguous. Kruszewski et al. (2017) find that the quality of driving deteriorates under high cognitive load, while Li et al. (2018) find the opposite: lane-keeping increases, and the timing of events suggests that cognitive load improves gaze concentration and physical arousal which positively affect the quality of driving. We complement this literature by considering another secondary task, i.e. one's professional activity, and measure the performance on this task by the occurrence of occupational injuries in real life situations. Our results suggest that beyond road traffic accidents, cognitive load also represents a risk factor for occupational safety.

Our research also relates to the literature on occupational injuries. Several determinants have been uncovered in the vast literature on work accidents, among which the most prominent are the worker's educational level, the economic sector, the type of work contract, firm size and the characteristics of the job such as long hours of work, monotony, lack of autonomy at work and job dissatisfaction – see Oh and Shin (2003), Pouliakas and Theodossiou (2013) and Picchio and Van Ours (2017). Our paper adds to this literature by emphasizing the role of cognitive load in jeopardizing health and safety at work. Our findings are also consistent with the literature accounting for the Monday Effect – i.e. the fact that work injury claims are more numerous on Monday, in particular for hard-to-diagnose injuries – based on physiological mechanisms – see Section V below.

The rest of the paper is structured as follows. Section II describes the data and presents summary statistics. Section III lays out our empirical strategy. Section IV presents the empirical results. Section V discusses our results in view of the Monday Effect literature and Section VI concludes.

II. The Data

To investigate the relationship between cognitive load and occupational injuries, we need data containing information on work accidents on the one hand, and that allow us to build a proxy for cognitive load on the other hand. The German Socio-Economic Panel (*SOEP)* provides such data. It is a longitudinal survey that follows households and all their members aged 16 and above since 1984, first in the Federal Republic of Germany, and since 1990 in the whole of Germany – see Wagner et al. (2007).

Over the period 1987-1999 (except in 1990 and 1993), individuals who reported they worked during the previous year were asked the following question: " During the previous year, did you receive a treatment by a doctor or in hospital because of a work injury?" Possible answers are: "Yes, treated by a doctor", "Yes, in hospital", "No". When the individual answered "yes" by a doctor or in hospital at survey year $t+1$, we code her as having a work accident during year t. We then define a dummy variable equal to 1 at year t when the individual reported having a work accident during that year. All other variables are based on the survey that took place at year t.

A key challenge for us is, of course, to measure cognitive load in our survey data. We proxy cognitive load by the number of non-professional tasks performed by individuals every day. Our data contains time-use information for weekdays for all years starting in 1987. Since 1991, the various non-professional activities an individual can engage in are consistently listed in six groups: errands (shopping, trips to government agencies, etc.), housework (washing, cooking, cleaning), child care, education or further training (also school, university), repairs on and around the house (including car repairs and garden work) and hobbies and other free-time activities. We consider that hobbies and free-time activities are unlikely to tax bandwidth. In contrast, having to handle several chores and education or training programs every day does. Therefore, our proxy for cognitive load consists in the number of different tasks to which an individual reports dedicating a positive number of hours on a typical weekday – excluding hobbies but including education and training. Given that we want to capture the brain burden generated by the variety of tasks one has to think of contemporaneously, we proxy cognitive load by the number of those tasks, conditional on the time that the individual spends on them. By doing so, we can estimate the impact of the number of different tasks one has to handle every day on the risk of occupational injuries, independent of the total amount of time dedicated to those tasks. Our preferred measure includes education and training since we believe that it contributes to the reduction in working memory to the extent that individuals have to think about it. But, given that it is different in nature from household chores, we also run a robustness check excluding it.

SOEP also contains information on a large variety of individual characteristics, namely gender, age, the number of years of education, marital status, whether individuals are in employment or not, occupation and industry, the daily number of hours worked and of hours dedicated to non-professional activities, tenure, the number of children under 16, the number of adults in the household and whether individuals live in East or West Germany. We control for these variables in our regressions.

Overall, we have consistent information on occupational injuries and the number of non-professional activities for years 1991 to 1998 (excluding 1992).[3] Given that we are interested in work accidents, we only keep individuals in employment, aged 18 to 64, who answered the question on occupational injuries the year after. We drop individuals in the armed forces.[4] Our final sample contains 46,452 observations belonging to 12,057 individuals.

- Insert Figures 1 and 2 about here -

[3] This is due to the fact that the question on work accident last year was asked for the last time in 1999 and was not asked in 1993.

[4] They represent 0.47% of our sample. Their inclusion does not affect our results.

Appendix Table A.1 provides descriptive statistics. The average proportion of employees with at least one occupational injury during the year is 5.8%; it is higher for males than for females (7.3% and 3.6%, respectively). Part of this difference is due to the fact that females are underrepresented in high-risk occupations, in particular skilled and unskilled blue-collar ones as shown on Figure 1. But, within these occupations, females also face a lower risk of occupational injury, suggesting that they hold different types of jobs – see Figure 2. Females also work fewer hours than males do while spending more time on non-professional activities – see Appendix Table A.1. As expected, the number of non-professional tasks performed by females is on average larger than for males (2.73 and 2.12, respectively on a scale ranging from 0 to 5). As evidenced on Figure 3, a very small proportion of females do not perform any task (1.3% as compared to 9.9% of males). 16.7% of females perform 4 tasks as compared to only 11.2% of males. Interestingly, the proportion of individuals performing the maximum number of tasks (i.e. 5) is very small for both genders: 2.3% of females and 1.7% of males.[5] Given that individuals performing all 5 tasks are very few and that females not involved in any task are likely to be highly selected, our preferred measure of cognitive load is based on a dummy variable capturing a large number of tasks performed.[6] To the extent that performing 4 or 5 tasks seems to be particularly harmful to occupational injuries – see Figure 4 –, we define this dummy variable as equal to 1 if the individual performs more than 3 tasks and 0 otherwise. In our sample 12.9% of males and 19% of females perform a large number of tasks.

- Insert Figures 3 and 4 about here –

[5] This overall pattern of tasks across gender is very similar if we exclude education and training from the list of non-professional tasks. In this case, 24.7% of males perform 3 tasks as compared to 41% for females with the corresponding figures being respectively 8.3% and 12.9% for males and females performing the maximum number of tasks, i.e. 4.

[6] We also perform some robustness checks using the total number of non-professional tasks carried out.

III. The Empirical Approach

To investigate the relationship between cognitive load – as measured by performing a large number of non-professional tasks – and the risk of occupational injuries, we first estimate the following equation using a linear probability model:

$$OI_{it} = \beta_0 + \beta_1 Many\_Tasks_{it} + X_{it}\beta_2 + \gamma_t + \varepsilon_{it} \qquad [1]$$

where OI_{it} is a dummy variable equal to 1 if individual *i* had to be treated for an occupational injury at year *t* and 0 otherwise. $Many\_Tasks_{it}$ is a dummy indicator equal to 1 if individual *i* performed a large number of non-professional tasks on weekdays at year *t* and 0 otherwise. X_{it} is a vector of individual characteristics – including the total number of hours worked and of hours dedicated to non-professional activities – and γ_t are time fixed effects. Standard errors are adjusted for clustering at the individual level and for heteroskedasticity. Given the potential negative effect of cognitive load on individual attention highlighted in the literature, we expect $\hat{\beta}_1$ to be positive.

A problem in estimating equation [1] by OLS arises from the fact that omitted individual characteristics may be correlated both with the probability of occupational injury and with our measure of cognitive load. To deal with this issue, we estimate an augmented version of equation [1], including individual fixed effects. We thus decompose the error term (ε_{it}) into a time-invariant unobserved heterogeneity (α_i) that is allowed to be correlated with $Many\_Tasks_{it}$ and X_{it} and an idiosyncratic time-varying error term (τ_{it}). $\hat{\beta}_1 > 0$ then suggests that an increase in the probability of performing a large number of tasks is associated with an increase in the risk of occupational injury.

IV. Results

IV.1 Main Results

We first estimate the relationship between cognitive load and the risk of occupational injury by OLS. Based on our full sample – see Table 1, col (1) –, we confirm that females experience a lower risk of occupational injury than men. The risk of work accident also decreases with age – although at a decreasing rate –, with the number of years of education and with tenure – although at a very small pace. It does not seem to vary with marital status nor with the composition of the household. It is significantly higher for all blue-collar and unskilled white-collar occupations than for managers, with the larger difference being for craft and related trade workers. It is also higher in Eastern than in Western Germany in the whole sample and for males. Unsurprisingly, the risk of occupational injuries increases with the number of hours worked per day. Similarly, performing a large number of non-professional tasks is positively and significantly associated with the risk of occupational injuries. Interestingly, conditional on the number of non-professional tasks, the time spent doing them does not seem to affect the risk of work accident. This suggests that, rather than the number of hours dedicated to non-professional activities, it is their variety that matters. Having to think about many different tasks contemporaneously indeed reduces the amount of brain resources that employees can use to develop health-preserving strategies on the job, thus increasing the risk of occupational injuries. When splitting our sample across gender, the results turn out to be very similar for males with a slightly larger gap in the risk of work accidents between managerial occupations on the one hand, and blue and unskilled white-collar occupations on the other hand – see Table 1, col (2) –. Here again, the number of hours worked increases the risk of occupational injury, as does performing a large number of non-professional tasks. For females too, the number of hours worked has a positive effect on the risk of occupational injury – see Table 1, col (3) –. Performing a large number of non-professional tasks is also associated with a higher risk of work accident among females. This may seem at odds with the evidence provided on Figure 4 that did not show any relation between the number of non-professional tasks and the risk of occupational injury for females. However, both findings can be reconciled if noting that women who perform few non-professional tasks are also working longer hours. So, when conditioning on the number of hours worked – as in Table 1, col (3) – we uncover a positive correlation between a large number of non-professional tasks and the risk of occupational injury among women. Contrary to men, the type of occupation does not seem to be related to the probability to have a work accident. This first set of results suggests that the relationship between having to handle many non-professional tasks and the risk of occupational injury is not particularly driven by either males or females and is large in magnitude.[7] Relative to the sample average, working under cognitive load increases the risk of occupational injury by 30.1% and 30.6% for males and females respectively.

- Insert Table 1 about here -

One concern when estimating equation [1] by OLS is that omitted individual characteristics could bias our results. To overcome this problem, we re-estimate our model including individual fixed effects – see Table 1, cols (4) to (6). The risk of occupational injury still increases with the number of hours worked, at least in the whole sample. Similarly, being involved in many non-professional tasks is associated with a higher risk of occupational injury, both in the whole sample (at the 1% significance level) and for males (at the 10% level) and females (at the 5% level) separately.[8] To the extent that occupational injury is a binary variable, we check that our results are robust to estimating a fixed effects logit model. When doing so,

[7] Results of OLS estimates of a model where the dummy variable « Woman » is interacted with each of the explanatory variables included in Table 1 does not reject the hypothesis that the point estimates of “Many non-professional tasks” are equal for men and women at the 5%-level (p-value: 0.172).
[8] Results of FE estimates of a model where the dummy variable « Woman » is interacted with each of the explanatory variables included in Table 1 does not reject the hypothesis that the point estimates of “Many non-professional tasks” are equal for men and women at the 5%-level (p-value: 0.923).

the coefficient estimates (resp. standard errors) on the cognitive load variable are: 0.270 (0.090) in the full sample, 0.216 (0.108) for males and 0.378 (0.165) for females, thus confirming that an increase in cognitive load is significantly correlated with a higher risk of occupational injury.

To better characterize the effect of cognitive load, we then investigate its differential effect on the type of occupational injuries according to their seriousness. To do so, we exploit the distinction available in the *SOEP* survey between work injuries that had to be treated in hospital (the most serious ones) and work injuries that could be treated by a doctor (the most benign ones). More specifically, we estimate a fixed effects multinomial logit model (Chamberlain, 1980) that allows testing whether the effect of cognitive load differs across both types of injuries. The results are presented in Table 2. They show that having to handle many non-professional tasks is positively associated with the probability to have a work injury that was treated by a doctor (relative to having no work injury) but that it is not significantly associated with the risk of having a work injury that required being treated in hospital. These findings hold both in the whole sample – Panel A – and for men and women separately – Panels B and C. They suggest that an increase in cognitive load is associated with a higher risk of benign – rather than serious – occupational injuries.

- Insert Table 2 about here -

IV.2 Robustness Checks

The equations estimated so far do not control for income. However, given that income could be correlated with the number of domestic tasks performed and with the risk of occupational injury, we add the log of monthly after-tax household income as an additional control in a robustness check. As evidenced in Appendix Table A.2 – Panel A, the effect of performing a large number of non-professional tasks is unchanged as compared to Table 1. Similarly, individual health status could be associated with having to handle many non-professional tasks, while it turns out to be negatively correlated with occupational injuries. However, controlling for health satisfaction in our regression leaves the coefficient of interest unchanged – Appendix Table A.2 – Panel B. Finally, one could wonder whether our results are driven by changes in the work status of one's partner since we observe in our data that moving from being single to having a partner working either part time or full time increases the number of non-professional tasks that an individual performs, in particular for women. We thus run a robustness check adding the partner's working status as an additional control. As evidenced in Table A.2 – Panel C, this status has no effect on the risk of work accident and the relationship between performing a large number of non-professional tasks and the risk of occupational injury is virtually identical to our baseline results shown in Table 1. The same holds if controlling for household income, health satisfaction and partner's work status contemporaneously – see Table A.2 – Panel D.

Our baseline regression controls for the number of children in the household. Nonetheless, one could imagine that the main change in the number of non-professional tasks comes with the first child and that this could be correlated with the risk of work accident as this major change in family life generates some distraction. To investigate this possibility, we modify our specification to introduce a set of dummy variables for each possible number of children in the household. Our results are unchanged with the fixed effects point estimates (resp. standard errors) on a large number of non-professional tasks being 0.013 (0.004) in the whole sample, 0.013 (0.007) for males and 0.012 (0.005) for females.

So far, we have used a binary indicator of many/few non-professional tasks to capture high rather than low cognitive burden. However, it is interesting to test the robustness of our results to alternative specifications. We first consider a linear specification where the variable of interest is the total number of tasks performed. Second, we use a non-parametric specification which does not make any functional form assumption about the relationship between the total number of non-professional tasks performed by an individual each day and the probability to have a work injury. When doing so, we estimate a model including a set of dummies corresponding to the number of non-professional tasks (which varies from 0 to 5, 3 tasks being the reference category). The results obtained with these two alternative specifications are presented in Appendix Table A.3, together with those from our baseline specification (reported in Table 1). The linear fixed effects estimates suggest that handling one more non-professional task is associated with an increase in the probability of occupational injury by 0.4 percentage points (i.e. +6.9% at sample average), significant at the 5% level – see column (5). When turning to the non-parametric fixed effects estimates, we find that performing four or five non-professional tasks every day (as compared to 3 tasks) is positively associated with a higher risk of occupational injuries, with the effect being significant at least at the 5% level – column (6). These findings confirm that cognitive load is associated with a higher risk of occupational injury, whatever specification we use.

One could worry that our measure of cognitive load based on multi-tasking aggregates heterogeneous non-professional tasks. In particular, considering participation in education and training as generating the same kind of cognitive load as domestic chores may be disputable. One the one hand, when individuals have to dedicate brain resources to continuous education and training this is likely to reduce the amount of working memory that they can dedicate to make decisions and, in particular, to engage in health-preserving strategies on the job. On the other hand, whether this tax on bandwidth is of the same nature or amount as the one generated by chores remains unclear. To make sure that our results are not driven by a specific effect of education and training, we re-estimate our model using the total number of tasks performed excluding education and training as a measure of cognitive load – see Appendix Table A.4. The results are very similar to those in Appendix Table A.3, columns (3) and (6). The OLS estimates suggest that performing a limited number of tasks as compared to the reference level (i.e. 3) is associated with a lower risk of occupational injuries in the whole sample and for males. Here again, performing the maximum number of tasks (i.e. 4) is associated with a higher risk of work accidents. This holds both in the whole sample and for males and females separately. Fixed effects estimates yield similar results: increasing the number of tasks performed from 3 to 4 increases the risk of occupational injuries (at the 1% level of significance for the full sample and at the 10% level for males). For females, the effect is positive, although not significant at conventional levels. This confirms that, overall, our results are not driven by education and training and that having to handle a variety of tasks in parallel to a working activity is likely to be harmful to occupational health. The cognitive load that this generates reduces the ability to make appropriate decisions and pay attention that would allow employees to protect themselves against injuries.

Beyond education and training, one could wonder whether our results are driven by one specific task rather than by the number of different tasks. To investigate this possibility, we add one control for each task at a time to our main equation that is estimated controlling for individual fixed effects. When doing so, none of the single tasks is ever significant at conventional levels, and the effect of performing a large number of tasks is unchanged with the point estimate ranging from 0.011 to 0.013 on the full sample, always significant at least at the 5% level. In a last check we include all five tasks together along with our indicator of performing many professional tasks. The latter is still identified since it is a non-linear variable taking value 1 if the individual performs 4 tasks or more. Here again, none of the individual tasks is significant and the point estimate on our measure of cognitive load is 0.010 (with standard error 0.005). This suggests that what matters in terms of occupational injury is not each single task per se but rather the number of different tasks that the individual performs to the extent that this requires mental organization and hence increases the tax exerted on bandwidth, i.e. cognitive load.

A last test consists in controlling for the number of non-professional tasks performed during weekends, in addition to our variable of interest which captures the number of non-professional tasks carried out on a typical weekday.[9] Our assumption is that tasks carried out on weekdays are a source of cognitive load since they require mental organization that reduces the amount of cognitive resources the individual can dedicate to her secondary task, i.e. working. In contrast, the number of tasks performed during weekends should not generate as much cognitive load since individuals can concentrate on them given that they have no secondary task to perform at the same time. When re-estimating our model controlling for a dummy variable indicating whether the individual performed many non-professional tasks during weekends and the time spent on them, this dummy variable is not significantly different from zero.[10] In contrast, the correlation between the number of tasks performed on weekdays and the risk of occupational injury remains positive and, if anything larger, with a fixed effects point estimate of 0.028 in the whole sample, significant at the 1% level.

IV.3 Heterogeneity

Presumably, cognitive load does not affect occupational injuries in the same way according to the type of occupations. As evidenced in Figure 2 and Table 1, some occupations are more exposed to work accidents. This is the case of elementary occupations, plant and machine operators, craft and trade workers, skilled agricultural workers and service and sales workers. We define these as high-risk occupations. In contrast, managers, professionals, technicians (and associate professionals) and clerks represent low-risk occupations. To compare the relationship between the number of non-professional activities and work accidents according to the level of occupational risk, we split our sample between high and low-risk occupations and re-estimate our baseline fixed effects model. The results are presented in Table 3. In low-risk occupations – see Panel A – having many non-professional activities to handle is uncorrelated with the risk

[9] Note that the information about the time use during weekends is only available in our sample for 1993, 1995 and 1997.
[10] It is even negative and significant at the 10 percent level when the model is estimated for men only.

of occupational injury. In contrast, in high-risk occupations – see Panel B.1 – it is associated with a higher risk of occupational injuries both in the whole sample and for males and females separately.[11] This suggests that the negative effect of cognitive load on work injury is concentrated on jobs in which the occupational risk is initially high. In those jobs, the lack of attention and/or of ability to efficiently develop health-preserving strategies that is induced by cognitive load constitutes an additional cause of accidents.

Whether or not cognitive load generates the same type of threat for all individuals in high-risk occupations is an important question, in particular when coming to the targeting of prevention campaigns. An important dimension of potential heterogeneity is education. To investigate this issue, we split our sample of individuals in high-risk occupations across individuals with high (i.e. above-average[12]) versus low education. As evidenced in Table 3 – Panel B.2, individuals with a high level of education are not significantly affected by cognitive load. The positive correlation between having to handle many non-professional activities and occupational injuries in high-risk occupations is entirely driven by employees with a low level of education – see column (1). This result holds on the full sample of workers. The point estimates we obtain are very close when splitting the sample across gender, but our model reaches its limits in terms of statistical power so that the results are not significant at conventional levels.

- Insert Table 3 about here -

Overall, our findings suggest that handling a large number of non-professional activities generates a threat for health at work for individuals in high-risk occupations and with a low level of education. For this subgroup of population, the necessity to keep in mind considerations related to a large number of non-professional activities while working generates a tax on

[11] If adding managers to the group of high-risk occupations for women, our results are unchanged with OLS and fixed effects estimates (standard errors) being respectively 0.024 (0.009) and 0.025 (0.012).
[12] In our sample, this corresponds to individuals with 12 years of education or more.

bandwidth which prevents individuals from ensuring the safety of their working environment. This suggests that when an individual is employed in a high-risk job, distraction is a problem but that a high-enough educational level may help coping with the cognitive burden imposed by multi-tasking.

V. Discussion: Cognitive Load and the Monday Effect

A number of papers studying the time pattern of work accidents have shown that claims for work injuries are more numerous on Monday than on any other workdays and that this so-called Monday Effect is particularly large for hard-to-diagnose injuries such as sprains and strains. How do our findings relate to this literature?[13] If cognitive load is one of the determinants of work injuries, why should we observe that these are more frequent on Monday?

The Monday Effect was first evidenced by Smith (1990). He found that the mix of injuries giving rise to a compensation claim on Monday was significantly more oriented towards sprains and strains – the treatment of which can be somewhat delayed –, while cuts and lacerations – which treatment is more urgent – were a significantly higher share of injuries claimed on Tuesdays to Fridays. He interpreted these results as providing evidence of moral hazard in work injury reporting: individuals would tend to report as work injuries minor injuries that actually took place off-the-job, since in the USA, workers' compensation insurance provides more generous medical coverage than health insurance, as well as partial income replacement for lost wages. More recent evidence on California (Hansen, 2016) and Spain (Martin-Roman and Moral, 2016) goes in the same direction.

However, a competing explanation of the Monday Effect has been put forward, based on physiology. Workers would be more prone to sprains and strains on Monday after a weekend

[13] We are grateful to an anonymous referee for raising this point and drawing our attention to this literature.

off from work (Card and McCall, 1996; Campolieti and Hyatt, 2006), either because they need to warm up (Choi et al., 1996; Martin-Roman and Moral, 2016) or because they dislike working on Mondays, which makes them more likely to notice soft-tissue injuries (Butler et al., 2014; Poland et al., 2019).

Our results are consistent with this literature emphasizing the role of physiology in accounting for the Monday effect. We find that cognitive load is associated with higher probabilities of work injuries, in particular minor ones that did not require being hospitalized. This is consistent with the finding that returning to work after a resting period may increase the risk of work injury. Cognitive load is indeed likely to be higher on Monday than on other weekdays if individuals have to plan on that day the organization of their non-professional tasks over the whole week. Individuals may also be more sensitive to cognitive load after resting periods – and, in particular weekends – if their ability to carry out professional duties while mentally organizing domestic tasks is reduced since it has not been used for a few days. The idea that cognition too may have to be warmed-up after weekends is in fact emphasized by Butler et al. (2014).

Our findings also show that handling many non-professional tasks during weekends has no significant impact on the risk of occupational injuries. This is consistent with the idea that these tasks do not generate substantial cognitive load since individuals can concentrate on them to the extent that they have no secondary task to perform at the same time. In contrast, coming back to work on Monday is likely to induce a discontinuous change in cognitive load that may raise the risk of injury since individuals are back to a situation in which they must perform a secondary task (namely work) while having their mental bandwidth taxed by the organization of their non-professional tasks over the coming week.

Our data do not allow us testing whether cognitive load is higher on Monday since we do not have information on the exact date of the injury. However, our findings are definitely consistent with this possibility.

VI. Conclusion

In this paper, we complement the standard analyses of cognitive load in the lab, by investigating its relationship with occupational injuries, using survey data. We consider that individuals are mentally burdened when they have to keep in mind non-professional preoccupations while working. So, we proxy cognitive load with the number of non-professional tasks that individuals perform every day, conditional on the time they spend on them. The underlying assumption is that when individuals perform a large number of those tasks, this requires mental organization which keeps part of their working memory busy.

We show that having to handle many non-professional activities is associated with a higher risk of occupational injury for both males and females. The effect is driven by benign injuries that do not require hospitalization. It is stronger for individuals in high-risk occupations and, among the latter, for low-educated workers. These findings suggest that, in high-risk jobs, distraction increases the risk of occupational injury, but that a high-enough educational level may help individuals cope with the cognitive burden imposed by multi-tasking.

Our research is, to our knowledge, the first to study the effects of cognitive load using survey data. Although non-experimental measures of cognitive load have drawbacks since they are not as neat as experimental ones, they also have some advantages in that they allow to study the impact of cognitive burden on outcomes that are difficult to reproduce in the lab, e.g. occupational injuries.

One limitation of this research is that our data do not allow us to estimate causal effects. By estimating fixed effects models we rule out that the correlation between cognitive load and occupational injuries is due to time-invariant heterogeneity. However, if some unobserved characteristics vary over time and are correlated both with the number of non-professional activities and with work accidents, they could in principle account for the relationship that we highlight. Although it is not easy to conjecture what such characteristics could be, we cannot rule out that they exist, strictly speaking.

A second limitation of this research lies in the fact that, due to data limitations, we cannot investigate whether long-term effects may be different from short-term ones. Our brain is known to be highly plastic. So, one could expect that when people have been subject to a high cognitive load for a long period of time, they get better at dealing with it, so that the potential consequences in terms of safety at work should be reduced. However, our fixed effects specification only captures the instantaneous impact of changes in cognitive load. Thus doing, we do not capture any long-term effect and cannot exclude that they could be quite different. This limitation also applies to existing experimental research manipulating cognitive load in the lab. This calls, of course, for more research investigating the impact of cognitive load on individual performance in working tasks, be it experimental or based on survey data.

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Tables and Figures

Figure 1 – Occupational structure by gender

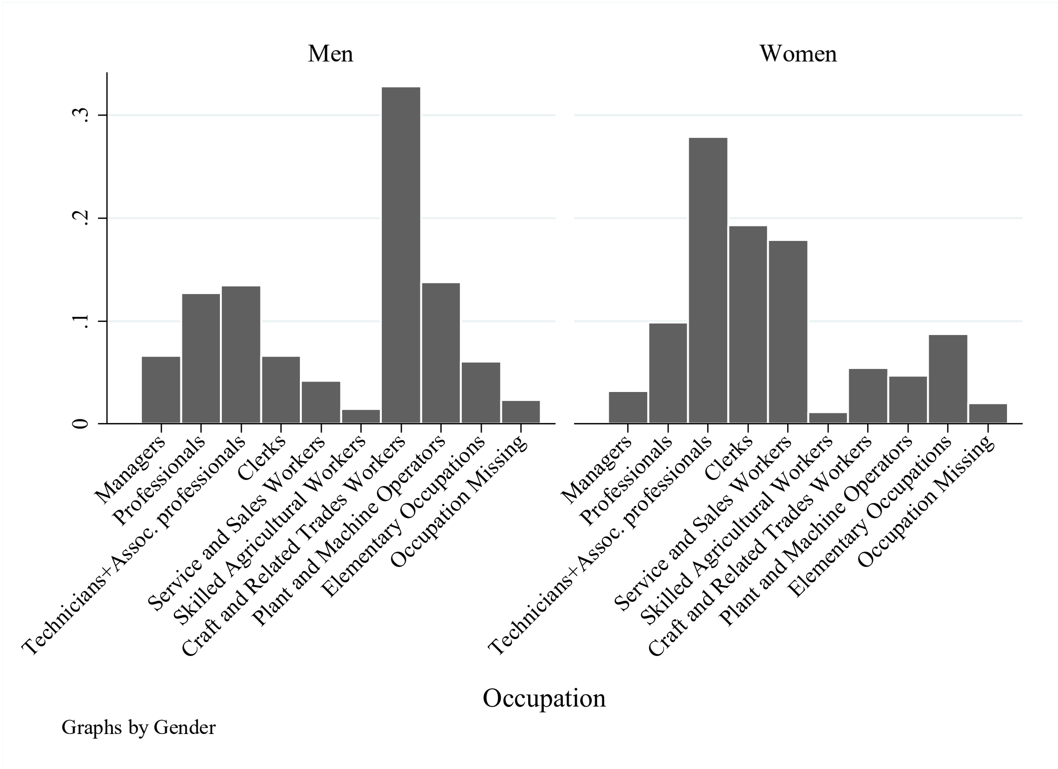

Figure 2 – Occupational injuries by gender and occupation

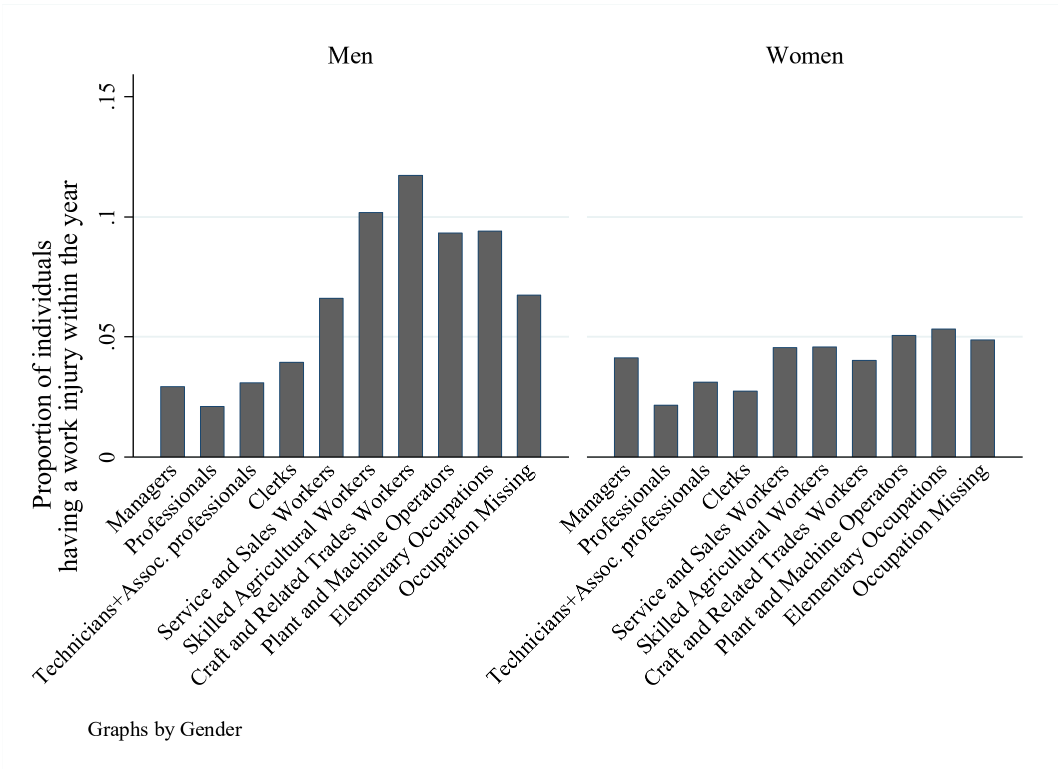

Figure 3 – Distribution across the number of non-professional tasks, by gender

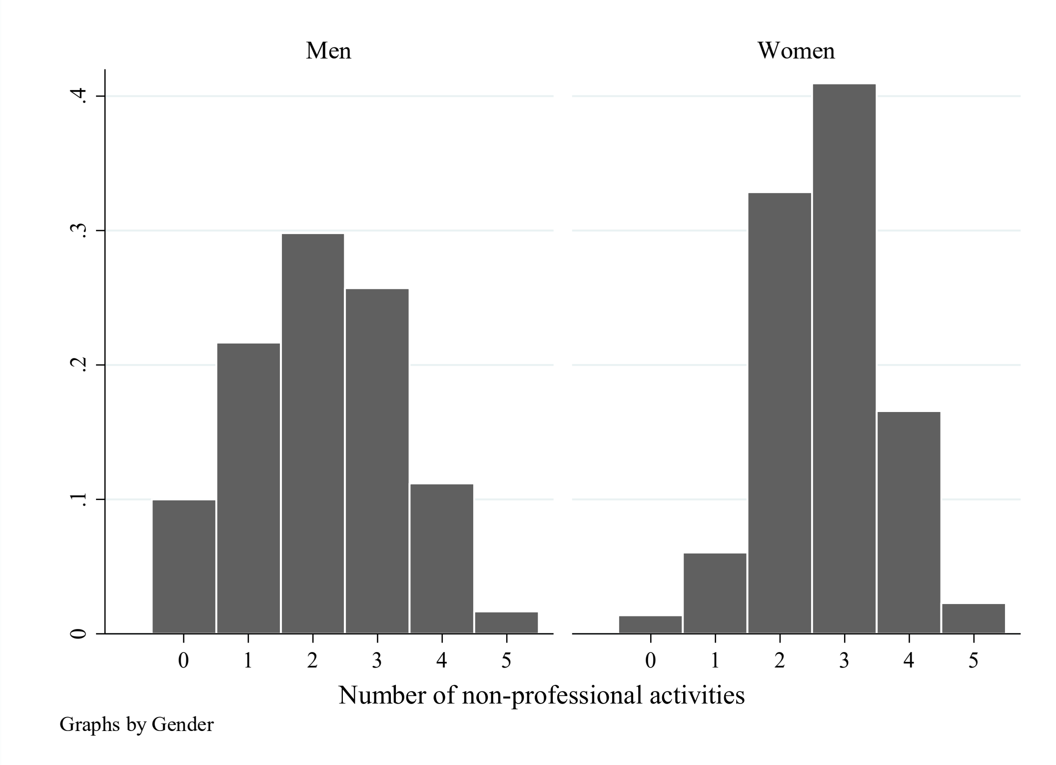

Figure 4 – Occupational injuries by number of tasks and gender

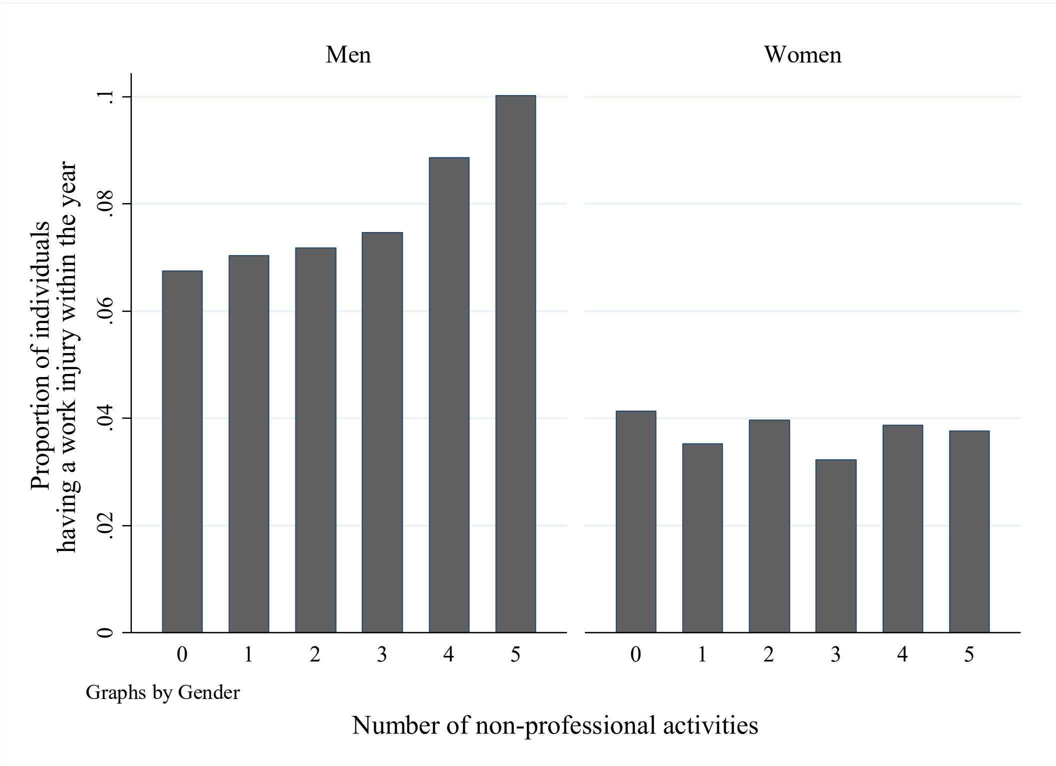

Table 1 Occupational injuries and cognitive load (large number of non-professional tasks)

	(1)	(2)	(3)	(4)	(5)	(6)
Method	OLS	OLS	OLS	FE	FE	FE
Sample	All	Males	Females	All	Males	Females
Dependent variable	Occupational Injury	Occupational Injury	Occupational Injury	Occupational Injury	Occupational Injury	Occupational Injury
Many non-professional tasks	0.019***	0.022***	0.011***	0.013***	0.013*	0.012**
	(0.004)	(0.006)	(0.004)	(0.004)	(0.007)	(0.005)
Females	-0.017***	-	-	-	-	-
	(0.003)	-	-	-	-	-
Age	-0.004***	-0.006***	-0.001	-0.014	-0.026	0.005
	(0.001)	(0.001)	(0.001)	(0.012)	(0.017)	(0.015)
$Age^2/100$	0.004***	0.007***	0.002	0.003	0.004	0.001
	(0.001)	(0.002)	(0.001)	(0.003)	(0.004)	(0.004)
Years of education	-0.001*	-0.001	-0.001	-	-	-
	(0.001)	(0.001)	(0.001)	-	-	-
Eastern Germany	0.011***	0.012**	0.005	-0.028	-0.024	-0.031
	(0.003)	(0.005)	(0.004)	(0.024)	(0.036)	(0.027)
Couple	0.002	0.006	-0.000	-0.004	-0.010	0.003
	(0.003)	(0.006)	(0.004)	(0.007)	(0.011)	(0.008)
# Adults in household	-0.002	-0.003	-0.001	0.001	0.001	0.001
	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)
# Children in household	0.001	0.003	-0.001	-0.007*	-0.007	-0.004
	(0.002)	(0.003)	(0.003)	(0.004)	(0.005)	(0.005)
Tenure	-0.000**	-0.000	-0.000**	-0.000	-0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Hours worked	0.004***	0.005***	0.004***	0.002*	0.002	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Hours on non-prof tasks	0.000	0.001	0.000	-0.000	0.001	-0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Occupations (ref. Managers) :						
Professionals	-0.005	-0.005	-0.015	0.003	0.009	-0.016
	(0.005)	(0.006)	(0.011)	(0.009)	(0.010)	(0.018)
Technicians + Associate Professionals	0.005	0.003	-0.008	-0.001	0.008	-0.025
	(0.005)	(0.006)	(0.009)	(0.008)	(0.010)	(0.016)
Clerks	0.010*	0.015**	-0.010	0.012	0.029**	-0.017
	(0.005)	(0.007)	(0.009)	(0.009)	(0.013)	(0.017)
Service + shop workers	0.026***	0.031***	0.008	0.013	-0.008	0.004
	(0.006)	(0.010)	(0.009)	(0.011)	(0.017)	(0.017)
Skilled agricultural workers	0.037**	0.052**	0.004	0.027	0.039	-0.004
	(0.016)	(0.022)	(0.020)	(0.026)	(0.032)	(0.046)
Craft and trade workers	0.068***	0.078***	0.002	0.040***	0.053***	-0.004
	(0.006)	(0.007)	(0.012)	(0.011)	(0.012)	(0.023)
Plant + machine operators	0.052***	0.062***	0.011	0.030**	0.046***	-0.016
	(0.007)	(0.008)	(0.012)	(0.012)	(0.014)	(0.023)
Elementary occupations	0.050***	0.064***	0.019*	0.035***	0.054***	-0.002
	(0.007)	(0.009)	(0.011)	(0.012)	(0.016)	(0.020)
Occupation missing	0.020**	0.024**	0.004	0.003	0.005	-0.008
	(0.009)	(0.012)	(0.014)	(0.015)	(0.020)	(0.022)
1-digit industry dummies	yes	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes	yes
Observations	46,452	26,803	19,649	46,452	26,803	19,649
(Within) R-squared	0.025	0.028	0.007	0.002	0.004	0.002

Note. Robust standard errors clustered at the individual level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2 Cognitive load and work injury seriousness (fixed effects multinomial logit).

	(1)	(2)
Outcome (Ref = No Occupational Injury)	Injury treated by a doctor (coef.)	Injury treated at hospital (coef.)
	Panel A – All	
Many non-professional tasks	0.286***	0.111
	(0.096)	(0.223)
Observations	9,418	
	Panel B – Women	
Many non-professional tasks	0.397**	0.145
	(0.177)	(0.456)
Observations	2,721	
	Panel C – Men	
Many non-professional tasks	0.229**	0.095
	(0.116)	(0.269)
Observations	6,697	

Note: Control variables include, age and age squared, Eastern/Western Germany, marital status, the number of children and of adults in the household, 9 occupational dummies, tenure, the number of hours worked, the number of hours spent on non-professional activities, 1-digit industry and year dummies. 10,246 individuals (37,034 observations) dropped because no change in the dependent variable occurred during the observation period. Robust standard errors clustered at the individual level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3 Occupational injuries and cognitive load, by level of risk and education – Fixed effects estimates

Sample	All		Males		Females	
Dependent variable	Occupational Injury		Occupational Injury		Occupational Injury	
			Panel A - Low-risk occupations			
Many non-professional tasks	0.004		0.001		0.005	
	(0.005)		(0.008)		(0.006)	
Individual controls	yes		yes		yes	
1-digit industry dummies	yes		yes		yes	
Year dummies	yes		yes		yes	
Observations	22,473		10,616		11,857	
Within R-squared	0.002		0.005		0.002	
			Panel B.1 - High-risk occupations			
Many non-professional tasks	0.023***		0.021*		0.024*	
	(0.009)		(0.012)		(0.013)	
Individual controls	yes		yes		yes	
1-digit industry dummies	yes		yes		yes	
Year dummies	yes		yes		yes	
Observations	22,987		15,577		7,410	
Within R-squared	0.003		0.005		0.006	
			Panel B.2 - High-risk occupations, by level of education			
	Low educ.	High educ.	Low educ.	High educ.	Low educ.	High educ.
Many non-professional tasks	0.026**	0.016	0.023	0.019	0.028	0.010
	(0.012)	(0.013)	(0.016)	(0.017)	(0.017)	(0.018)
Individual controls	yes	yes	yes	yes	yes	yes
1-digit industry dummies	yes	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes	yes
Observations	15,623	7,364	10,507	5,070	5,116	2,294
Within R-squared	0.006	0.005	0.009	0.007	0.010	0.015

Note. Individual controls include, age and age squared, Eastern/Western Germany, marital status, the number of children and of adults in the household, 9 occupational dummies, tenure, the number of hours worked and the number of hours spent on non-professional activities. Robust standard errors clustered at the individual level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix (for online publication only)

Table A.1 – Descriptive statistics

Variables	Whole sample (n=46,452)		Men (n=26,803)		Women (n=19,649)	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
Occupational Injuries	0.058	0.233	0.073	0.261	0.036	0.187
Number of non-professional tasks (0 to 5)	2.37	1.14	2.12	1.21	2.73	0.93
Many non-professional tasks (≥4)	0.154	0.361	0.129	0.335	0.190	0.392
Hours worked per day	8.89	2.22	9.59	1.73	7.93	2.46
Total number of hours spent on non-professional tasks per day	4.00	3.20	2.98	2.23	5.39	3.76
Gender (Woman=1)	0.423	0.494	-	-	-	-
Age	38.45	11.10	38.91	11.20	37.83	10.94
Couple	0.773	0.419	0.787	0.409	0.754	0.431
Years of education	11.73	2.57	11.78	2.65	11.65	2.46
Number of children in household	0.77	0.98	0.84	1.03	0.68	0.90
Number of adults in household	3.12	1.30	3.22	1.35	2.98	1.22
Years of tenure	9.36	9.40	10.39	10.06	7.95	8.23
Lives in Eastern Germany	0.286	0.452	0.267	0.442	0.312	0.463
	0.154	0.361	0.129	0.335	0.190	0.392
Occupations						
Managers	0.052	0.222	0.066	0.249	0.032	0.176
Professionals	0.116	0.320	0.128	0.334	0.099	0.299
Technicians+Associate professionals	0.196	0.397	0.135	0.342	0.279	0.449
Clerks	0.120	0.325	0.066	0.249	0.193	0.395
Service + shop workers	0.099	0.299	0.042	0.201	0.177	0.382
Skilled agricultural workers	0.013	0.114	0.015	0.120	0.011	0.105
Craft and trade workers	0.210	0.407	0.325	0.468	0.054	0.226
Plant + machine operators	0.100	0.300	0.138	0.345	0.047	0.212
Elementary occupations	0.073	0.259	0.061	0.240	0.088	0.283
Occupation missing	0.021	0.145	0.023	0.149	0.019	0.138

Table A.2 – Occupational injuries and cognitive load (additional controls) – Fixed effects estimates

Sample	All	Males	Females
Dependent variable	Occupational Injury	Occupational Injury	Occupational Injury
	Panel A – Controlling for income		
Many non-professional tasks	0.013***	0.012*	0.013**
	(0.005)	(0.007)	(0.005)
Log(Household income)	0.010*	0.013*	0.004
	(0.006)	(0.008)	(0.007)
Basic controls	yes	yes	yes
Observations	44,783	25,862	18,921
Within R-squared	0.002	0.004	0.003
	Panel B – Controlling for health		
Many non-professional tasks	0.013***	0.013*	0.012**
	(0.004)	(0.007)	(0.005)
Satisfaction with health	-0.002**	-0.002*	-0.001
	(0.001)	(0.001)	(0.001)
Basic controls	yes	yes	yes
Observations	46,38	26,762	19,618
Within R-squared	0.003	0.004	0.003
	Panel C – Controlling for Partner's working status (ref. no partner)		
Many non-professional tasks	0.013***	0.012*	0.013**
	(0.005)	(0.007)	(0.005)
Partner not working	-0.012	-0.021	0.003
	(0.009)	(0.013)	(0.011)
Partner working part time	-0.007	-0.014	-0.002
	(0.009)	(0.013)	(0.013)
Partner working full time	-0.003	-0.009	0.005
	(0.007)	(0.012)	(0.009)
Basic controls	yes	yes	yes
Observations	44,294	25,589	18,705
Within R-squared	0.003	0.004	0.003
	Panel D – Controlling for income, health and partner's working status		
Many non-professional tasks	0.014***	0.012*	0.014**
	(0.005)	(0.007)	(0.006)
Basic controls	yes	yes	yes
Health+Income+Partner controls	yes	yes	yes
Observations	42,690	24,683	18,007
Within R-squared	0.003	0.004	0.003

Note. Basic controls include age and age squared, Eastern/Western Germany, marital status, the number of children and of adults in the household, 9 occupational dummies, tenure, the number of hours worked, the number of hours spent on non-professional activities 1-digit industry dummies and year dummies. Robust standard errors clustered at the individual level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.3 – Cognitive load and occupational injuries – Binary, linear and non-parametric measures of the number of non-professional tasks.

	(1)	(2)	(3)	(4)	(5)	(6)
Method	OLS	OLS	OLS	FE	FE	FE
Sample			All			
Dependent variable: Occupational injury						
Many non-professional tasks	0.019***	-	-	0.013***	-	-
	(0.004)	-	-	(0.004)	-	-
Number of non-professional tasks	-	0.007***	-	-	0.004**	-
	-	(0.002)	-	-	(0.002)	-
Number of non-professional tasks – 0 to 5 (Ref = 3 tasks)						
0 tasks	-	-	-0.011*	-	-	-0.009
	-	-	(0.006)	-	-	(0.007)
1 task	-	-	-0.009**	-	-	-0.000
	-	-	(0.004)	-	-	(0.005)
2 tasks	-	-	-0.001	-	-	0.001
	-	-	(0.003)	-	-	(0.004)
4 tasks	-	-	0.016***	-	-	0.012**
	-	-	(0.004)	-	-	(0.005)
5 tasks	-	-	0.035***	-	-	0.035***
	-	-	(0.009)	-	-	(0.011)
Control variables	yes	yes	yes	yes	yes	yes
Observations	46,452	46,452	46,452	46,452	46,452	46,452

Note. In fixed effects specifications, control variables include, age and age squared, Eastern/Western Germany, marital status, the number of children and of adults in the household, 9 occupational dummies, tenure, the number of hours worked, the number of hours spent on non-professional activities 1-digit industry and year dummies. OLS specifications also control for gender and the number of years of education. Robust standard errors clustered at the individual level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.4 – Occupational injuries and cognitive load (Total number of non-professional tasks – Excluding education and training)

	(1)	(2)	(3)	(4)	(5)	(6)
Method	OLS	OLS	OLS	FE	FE	FE
Sample	All	Males	Females	All	Males	Females
Dependent variable	Occupational Injury	Occupational Injury	Occupational Injury	Occupational Injury	Occupational Injury	Occupational Injury
Number of non-professional tasks – 0 to 4 (Ref = 3 tasks)						
0 tasks	-0.014**	-0.019**	-0.001	-0.009	-0.008	0.012
	(0.006)	(0.008)	(0.011)	(0.007)	(0.010)	(0.015)
1 task	-0.012***	-0.016***	-0.001	-0.002	-0.000	0.000
	(0.004)	(0.006)	(0.006)	(0.005)	(0.007)	(0.008)
2 tasks	-0.004	-0.008*	0.003	0.001	0.002	0.002
	(0.003)	(0.005)	(0.004)	(0.004)	(0.006)	(0.005)
4 tasks	0.019***	0.025***	0.010**	0.015***	0.017*	0.011
	(0.005)	(0.008)	(0.005)	(0.006)	(0.009)	(0.007)
Females	-0.018***	-	-	-	-	-
	(0.003)	-	-	-	-	-
Age	-0.004***	-0.007***	-0.001	-0.013	-0.026	0.006
	(0.001)	(0.001)	(0.001)	(0.012)	(0.017)	(0.015)
$Age^2/100$	0.005***	0.008***	0.002	0.003	0.004	0.001
	(0.001)	(0.002)	(0.001)	(0.003)	(0.004)	(0.004)
Years of education	-0.001	-0.001	-0.001	-	-	-
	(0.001)	(0.001)	(0.001)	-	-	-
Eastern Germany	0.010***	0.011**	0.006	-0.028	-0.024	-0.031
	(0.003)	(0.005)	(0.004)	(0.024)	(0.036)	(0.027)
Couple	0.002	0.006	-0.001	-0.004	-0.010	0.003
	(0.003)	(0.006)	(0.004)	(0.007)	(0.011)	(0.008)
# Adults in household	-0.001	-0.002	-0.001	0.001	0.002	0.001
	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)
# Children in household	0.000	0.002	-0.001	-0.007*	-0.008	-0.004
	(0.002)	(0.003)	(0.003)	(0.004)	(0.005)	(0.005)
Tenure	-0.000**	-0.000	-0.000**	-0.000	-0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Hours worked	0.004***	0.005***	0.004***	0.002*	0.002*	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Hours on non-prof tasks	-0.000	-0.001	0.001	-0.000	0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Occupational dummies	yes	yes	yes	yes	yes	yes
1-digit industry dummies	yes	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes	yes
Observations	46,452	26,803	19,649	46,452	26,803	19,649
(Within) R-squared	0.025	0.028	0.007	0.003	0.004	0.002

Note. All specifications include 9 occupational dummies. Robust standard errors clustered at the individual level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.