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Abstract

Ill-health is commonly believed to be detrimental for labor market outcomes. Yet, causal evidence mostly comes from analyses of severe shocks, whereas minor variations in health are not only more common but also a better target for prevention measures. This study makes use of data from the German Socio-Economic Panel merged with data on regional weather conditions prior to the date of a survey interview. Weather conditions are capable of affecting peoples' health. While bad weather leads to minor reductions in health, the effect on working hours is, surprisingly, positive. Comprehensive survey data on time-use and subjective assessments of people's working lives allows discussing the mechanisms behind these findings, such as whether the weather manipulates people's allocation of working time and leisure. The evidence seems to support the idea that less healthy individuals compensate the potential impairments on labor productivity by spending some additional time at the workplace. Analyzing effect heterogeneity across subgroups, the study shows that there is only little variation across industries, but stronger increases in working time among people in part-time jobs. While there are no gender-specifics in the health impairments due to bad weather, the increase in working hours is driven by women.

JEL classification codes

I12, J22, Q50

Keywords

Quasi-experiment, weather, health, labor supply, SOEP, gender differences

Whoever would study medicine aright must learn of the following subjects. First he must consider the effect of the seasons of the year and the differences between them. Secondly he must study the warm and the cold winds, both those which are in common to every country and those peculiar to a particular locality.
(Hippocrates, taken from 'Airs, Waters, and Places')

1. Introduction

Labor market and health economists have produced a large literature on the economic implications of health. Accordingly, there is a widespread belief based on many studies that lower health is a detriment to individual economic outcomes (for early reviews, see e.g. Currie and Madrian 1999, Smith 1999). On closer inspection, however, the number of studies providing causal evidence is comparatively small, given that the question whether health is important for labor market success is very basic and relevant. An explanation for this may lie in the difficulty for researchers to establish credible evidence. Triggers of health changes are required, which are plausibly determined exogenously. So far, researchers rely on the analysis of major health shock events, which massively reduce the health of affected individuals in comparison to other individuals who are not experiencing the shock. The list of incidences includes acute hospitalizations (García-Gómez et al. 2013), disabilities (Campolieti and Krashinsky 2006), sizeable losses in body mass index (Wagstaff 2007), commuting accidents (Halla and Zweimüller 2013), severe road accidents (Møller Danø 2005), and other severe health shocks like cancer (Wu 2003). While the investigation of such fatal events may deliver the quasi-random setup for which the researcher is looking, there is an important aspect, however, that arguably has not received the attention it deserves. In fact, health is not a binary phenomenon, according to which workers are either completely healthy or in very bad shape. Instead, most of the variation in people's health is minor, such as having a cold for a few days. Importantly, people can exercise agency in regard to small health problems, e.g. by taking preventative measures or exhibiting healthy behaviors. People do not choose to have a car crash, whereas they can very well decide upon, for instance, the amount of alcohol they consume or the quality of food that they eat. The unanswered question so far is, therefore, whether avoiding small health problems is a promising way to improve labor market outcomes or not.

The starting point for this paper is the realization of a gap in the literature concerning the important phenomenon of mild variations in health. These are much more common than major health shocks, possibly affecting everyone at almost every time, and hence are arguably more relevant from a policy perspective. For example, interventions at the firm level aimed at increasing workers' health and avoiding sickness in the workforce during particular seasons of the year sound like a reasonable policy. However, this relies on the existence of credible evidence for economic gains from such policy-induced improvements in health, for instance, in the form of increased working hours. Arguably, it would be misleading to extrapolate the previous evidence on major health shocks and its negative implications to the issue of minor variations in health by concluding that small health problems are also capable of impairing labor outcomes, although probably to a smaller extent. However, this conclusion may be wrong, as in case of small health issues it might be possible for people to compensate the possible implications for job performance, for instance, by increasing their workplace presence. In fact, while suffering from lower productivity due to lower health, a worker could simply stay longer at the workplace in order to get the job done.

This empirical study is the first specifically focusing on the role of minor health variations in labor market behavior. To gather evidence, this paper makes use of data on regional weather conditions, as those allow for plausibly exogenous and quasi-random manipulation of people's health status. A large literature by epidemiologists and other scientists examines the how weather conditions like temperatures affect people's health (see e.g. Kunst et al. 1993, Braga et al. 2001, Basu and Samet 2002, Curriero et al. 2002, Yang et al. 2009). In recent years, economists have also become interested in the weather, for a variety of reasons, one of which certainly is its attractiveness from a methodological standpoint.[1] Longitudinal weather data collected on a daily basis allows for considering seasonal and regional trends, promising a clean empirical identification by analyzing deviations from region- and time-adjusted averages. Such setups that promise to provide credible evidence by using such exogenous variation over time and within spatial areas (e.g. Deschênes and Greenstone 2011) are part of a burgeoning body of research that Dell et al. (2014) in their comprehensive review describe as the 'New Climate–Economy Literature'. Among many objectives, this research aims at shedding light on possible implications of climate change by analyzing historical weather data. One outcome of interest is health, measured typically via mortality information. While there are also some studies that examine the effects of weather on labor market behavior (e.g. Conolly 2008, Graff Zivin and Neidell 2014, Lee at al. 2014), the role of weather-induced changes of people's health as a potential aspect in this context has, thus far, received no attention. To study the implications of less severe variations in health, most datasets do not provide any indication. When people are sick and go to work without reporting this to their doctors or employers, there is no record at all about their lower health. The only way to learn about minor health problems, such as having a cold, and its possible implications for labor market outcomes is to ask people about it directly.

[1] Economic studies based on weather data contribute to a variety of different topics. In many cases, researchers are interested in the way that weather affects decision-making, such as in the context of education (Simonsohn 2010), consumption (Busse et al. 2015) and politics (Fujiwara et al. 2016).

The German Socio-Economic Panel Study (SOEP) offers exactly this research opportunity. It is Europe's longest running representative panel survey of households (Wagner et al. 2007) and allows studying both health and labor market behavior comprehensively, using various pieces of information and large sample sizes. In addition to self-assessed health, the longitudinal survey includes information on people's actual working hours, which many researchers use to study individual labor supply (e.g. Bell and Freeman 2001, Doorley and Pestel 2016, Pestel 2017, Schurer 2017). Most importantly, the data can be separated according to its regional origin, based on the availability of information on the region of each interviewee, and to its date of collection. This allows merging the rich SOEP data with information on regional weather conditions on the interview date and, more importantly, weather conditions in the weeks prior to the day of survey participation. Weather data for Germany comes from the German weather service and is available for all regions in the country, thanks to stations that are operating across the country, allowing exploitation of both regional- and time-based variation in weather conditions.

The country of Germany offers an interesting research setting for the analysis of labor-related implications from being a victim of bad weather conditions. Predominantly around the end of winter, many Germans become sick. While this may be related to a variety of factors, weather conditions are famously among those and are not subject to individual manipulation. Depending on time and region, some people are lucky and are in better shape, while in other cases health is reduced via persistent forms of bad weather in the past. Ways to protect oneself against this exogenous influence do exist, but large enough sample sizes of individuals allow for detecting substantial numbers of cases when people do indeed have different health compared to people in other weather contexts. In other words, some people get the sniffles, in quasi-experimental fashion, while others do not because of having experienced better weather conditions.

Germany also provides a promising institutional setup for the investigation of exogenously triggered health impacts on economic outcomes, as argued in other papers (see e.g. Schurer 2017). In fact, a generous social security system with universal access to health care allows individuals to stop working or reduce hours of work when having health issues, without expecting immediate economic repercussions. Instead, workers maintain regular income levels in absence, which generates incentives for people to shirk (e.g. Puhani and Sonderhof 2010, Ziebarth and Karlsson 2010). Especially minor health problems could be reason to take some days off, while the homogeneous healthcare system allows the researcher to study the effects of ill health on labor supply based on individual choices that are plausibly unrelated to the economic background and budget constraints of the individual.

The main finding of this paper stands in contrast to previous interpretations of the evidence on the role of health in labor market behavior. Bad weather, which for the beginning of the year in Germany can be defined as cold and windy, is capable of reducing people's health in significant ways, while the impact on working hours turns out to be positive. Hence, workers who are likely experiencing minor health problems due to bad weather are working longer hours, and not fewer, as indicated by previous research. While intriguing at first glance, there are plausible explanations that the analysis of potential mechanisms using the rich SOEP data can shed light upon. Two explanations emerge from the economic literature on the implications of weather: a macroeconomic demand effect, according to which weather affects production and thus the demand for work, and a microeconomic substitution effect, according to which workers have incentives to increase working time when bad weather decreases the utility gain from leisure. The results from analyzing the data however provide no convincing support for these two arguments, which brings us back to the role of health and suggests a novel explanation for the behavioral responses of workers to health problems. Accordingly, the health impairment may directly affect workplace presence as people with lower health increase working time in order to compensate for the potentially lower productivity. Finally, the representativeness of the dataset allows conducting subsample analyses to study effect heterogeneity. While there is only little variation across industries, the positive effect of health-threatening weather on working time is particular strong among people in part-time jobs. Connected to that, the increase in working hours is clearly driven by women, which is interesting given that both men and women suffer similar impairments in their health due to past bad weather. It seems that part-time employed females exploit the possibility to compensate possible health impairments via increased workplace presence, while full-time working men cannot do that as easily. As a contribution to the ongoing debate on gender differences in labor market outcomes, the paper concludes that health may not play a decisive role, as women compensate health problems with more working hours and thereby can avoid implications for their labor market outcomes.[2]

The paper is structured as follows. Section 2 introduces the dataset that combines the SOEP data with the weather data and illustrates the empirical approach. Section 3 presents the results of the empirical analysis, including the discussion of mechanisms. Section 4 concludes.

[2] There is a huge literature on possible explanations for the gender gap in labor market outcome, which Azmat and Petrongolo (2014) in a recent survey group into the three major topics preferences (Croson and Gneezty 2009), discrimination (Altonji and Blank 1999) and productivity. As a factor related to the latter, there is a heated debate on the role of health in this context and the idea that women's career success is impaired by their susceptibility to health problems (e.g. Ichino and Moretti 2009, Herrmann and Rockoff 2012, 2013, Chadi and Goerke 2015).

2. Empirical framework

2.1 SOEP

The SOEP is Europe's longest running representative panel survey of households and has been used for numerous empirical investigations in a broad set of research areas. The annual survey started in the year of 1984 and thus covers German re-unification, which has led to an increase in the SOEP's overall sample size in 1990. In addition, several refreshments have ensured a large sample size over the entirety of its existence. Over several months in each year, but predominantly at the end of winter, interviews take place and participants report comprehensively on their life situation. In spring, most of the fieldwork is done and almost all of the annual survey interviews are completed.

For studying the role of health in the labor market, the variable of health satisfaction is of particular interest, as it is the only question in the SOEP always included in the questionnaire since its beginning in the 1980s. The information is observed on a scale ranging from 0 ("completely dissatisfied") to 10 ("completely satisfied") via this question: "How satisfied are you with your health?" The SOEP offers alternative health indicators, all of which have the limitation of restricted availability across survey waves. Still, in order to compare findings based on subjective self-assessments of health, a variable on people's doctor visits in the last three months (prior to the interview) appears to be very informative. The combination of evidence on perceived health status with information on doctor visits is particular promising, as this variable comes from a completely different question at a very different place in the SOEP questionnaire and is arguably an objective fact. Either somebody went to the doctor recently, or not. It is certainly not hard to correctly report on this simple fact. Nevertheless, while arguably free of subjective influences and thus useful for comparisons of findings, this variable may not show the same picture as health satisfaction because of people's varying attitudes towards doctors, especially when having minor health problems. Because visiting the doctor was (almost) free for the German people in most of the investigation period, some may have exploited the opportunity to access medical care, while others did not, despite being on the same level of (ill-)health.[3] In consequence, one can expect huge heterogeneity in how health problems translate into doctor visits in Germany, and the subjective assessment of people's satisfaction with their health appears to be the superior variable for the research context here, in which the entire spectrum of health problems, including minor problems, is of interest.

[3] For a period of several years, starting in 2004, Germans covered by national health insurance had to pay a minor sum of money for consulting their doctor. This unpopular fee was abolished in 2012.

To study people's labor market behavior, the SOEP offers several pieces of information. One variable that is particularly promising for analyzing behavioral implications of minor health problems is people's actual working hours. This survey item inquires a two-digit number of hours via this question: "And how many hours do you generally work, including any overtime?" Whereas minor health issues may not affect the employment contract and the contractually agreed upon hours of work, the actual working hours can be affected. Imagine someone is asked first about the number of contractual working hours and then asked about the actual working hours, while, because of health problems, this person has actually spent more or less time at work in recent time.

Expanding the set of information on peoples' working time, there are additional questions in the SOEP that promise to illustrate the mechanisms behind the results. People report on their daily time-use in the course of a battery on several activities, such as work and leisure activities. A separate question interrogates the actual number of overtime hours at work. Finally, there is a subjective question on people's work life, as people are asked whether they want to work more or less (wording: "If you could choose your own working hours, taking into account that your income would change according to the number of hours: How many hours would you want to work?").

Apart from the main variables of interest, the SOEP contains a rich set of information on people's lives in general as well as on their working lives. Contrary to the additional variables on health and workplace behavior, all variables used as controls are regularly included in the SOEP questionnaire and can be seen in Appendix Table A1. These descriptive statistics illustrate the main dataset that emerges after merging the SOEP data, using version 30 (SOEP 2014), with the available weather data. The next subsection provides more information concerning that data.

2.2. Regional weather conditions and construction of the dataset

The country of Germany is one of the largest in Europe and shows significant variation in weather conditions, both throughout the year and across regions. This heterogeneity allows researchers to conduct empirical analyses based on variations in weather by distinguishing the situation between given dates and between regions, though the latter cannot be extraordinarily large. While there are of course larger countries that allow for analyzing a more regionally diverse spectrum of weather conditions, the country of Germany can be split into about a hundred different areas, with meaningful variation in weather conditions. Instead of using federal states, of which there are sixteen in Germany, a suitable option for the given research context appears to be the level of the so-called regional policy regions (German: Raumordnungsregionen, ROR).

One ROR typically consists of several counties, the exceptions being big city counties like Hamburg, while federal states typically consist of several ROR. About a million people on average live in one ROR. In regard to SOEP participants, this translates into about a hundred persons on average, which allows for a meaningful analysis while capturing the regional heterogeneity in German weather conditions.[4] Another advantage to using data at the ROR level is that most people live and work within such larger region, which reduces the possible influences of cross-regional aspects like commuting. Note that there was a significant reform of regions in Germany during the investigation period in the mid-1990s, in the course of which some regions got larger and others smaller. To deal with this, the empirical analysis takes about a hundred regions before and after into account, which affects the use of regional control variables in the model. Also this needs to be considered when conducting clustering of standard errors at the regional level, which is a common robustness check for findings once those are obtained in the empirical analysis.

Regional weather conditions in Germany are comprehensively measured by the German weather service. For all regions in the country, there are datasets available collected by regional weather stations. This weather data includes several factors, of which temperature and wind speed are of particular interest in the following to examine the influence of bad weather conditions at the beginning of the year, i.e. in winter and in early spring. Note that while many of the latest contributions to the weather and climate literature focus on heat as a weather phenomenon, for this particular season of the year in the country of Germany, health can only be at risk when temperatures are very cold, whereas warm temperatures are rather beneficial in this period of the year. Most of the SOEP data is gathered in the first 20 weeks of each year and only few interviews take place afterwards. It thus appears reasonable to drop the data from the remaining time of the year after calendar week 20. Restricting the sample to this investigation period goes along with only a very small loss of observations, but fosters the accuracy of the weather-based identification.[5]

Regarding the merger between weather and SOEP data, the availability of regional identifiers restricts the analysis to the period of 1985 to 2013. The weather data used in this study has been created based on a pre-selected set of weather stations for which data from the German weather

[4] ROR identifier allows researchers to merge the SOEP data with other regional datasets after signing a data protection agreement. Note that the identifiers are available for all households since the SOEP wave of 1985.

[5] Additional analyses show that the findings of this paper are robust to changes of the decision of choosing 20 weeks. Note that all results mentioned but not presented in this paper are available from the author upon request.

service could be obtained. In the case of missing information, data from the geographically nearest weather stations for the same date is used in order to avoid losses of observations. Merging takes place on the basis of two pieces of information: the (interview) day and the ROR where the interviewee’s household is located. A small loss of information results from not having interview date information, which is essential for this merger. Moreover, some of the standard variables used in the analysis have some item-nonresponse. Using further outcome variables, however, especially alternative health data, would lead to much smaller sample sizes, since not all SOEP variables are gathered annually throughout the period of investigation. Thus, further analyses using such additional variables (like doctor visits) require separate samples. Those analyses are included in Appendix B, whereas Appendix A focuses on output established on the basis of the main sample shown in Appendix Table A1.

Finally, there are some additional restrictions on the main dataset using further information on individuals. First, to minimize the role of movers and possibly endogenous migration (see Dell et al. 2014) as well as to allow for robustness checks using clustered standard errors at the ROR level, no moving between regions is allowed. To still make use of data from individuals who are observed in more than one ROR, the data from the region in which one person is most often observed is used.[6] Second, all individuals are required to be of working age, which is defined as 21 to 65 years of age. Third, unemployed persons are excluded and all individuals in the sample are working according to their reported employment status, either full-time or part-time, while apprentices are also dropped from the sample.

2.3 Empirical approach

The aim of the following empirical investigation is to identify weather conditions that are capable of influencing people’s health status and to then test for potential implications of this exogenous influence on labor market behavior. Thus, there are basically two main outcome variables in a reduced-form context. This appears to be a reasonable option when the exogenous influence may affect the second outcome but the first outcome is not necessarily the only channel at play.[7] If this would be different, one could imagine using weather factors as instrumental variables for health as the endogenous variable on the second stage, while labor supply is the outcome on the second stage. Since there are potentially other channels through

[6] In cases of interviewees with more than one region with the maximum number of participations, preference is given to earlier observations.

[7] A recent example for a very similar methodological approach is a study by Kearney and Wilson (2017) who are interested in fertility outcomes as a result of changes in the economic position of workers. For this purpose, the authors study local-area fracking production as an exogenous trigger of increases in labor market outcomes, while the reduced-form effects on fertility are positive as well, thereby offering novel insights on an otherwise hard-to investigate empirical relationship.

which weather may affect the economic outcome (see discussion in Section 3.3), this approach is not superior to a simple reduced-form analysis, which requires “relatively few identification assumptions and allows unusually strong causative interpretation” (Dell et al. 2014). The following model serves as the basis for this empirical analysis:

$$Y_{irt} = \beta PastWeather_{rt} + \gamma' PC_{it} + \chi' WC_{it} + \delta_r + \tau_t + \varepsilon_{irt} \quad (1)$$

To analyze both the impact of weather on health and on economic behavior, the outcome variable Y_{irt} takes the form of different outcomes, in particular health and working hours. Variations in these outcomes can differ between individuals i who live in regions r at time t. The source of exogenous variation is past weather, which is measured for individuals in their region and at the exact date on which they participated in the SOEP survey. As laid out in detail below, the interviewee is interviewed at time t but the weather phenomenon of interest (i.e. the ‘treatment’ in experimental parlance) took place in the time prior to the interview in t.

Since individual outcomes like health and working hours can be effected by a variety of factors other than the weather, several control variables are used and separated into a standard set of personal control variables PC_{it} and work-related controls WC_{it} to leave as little as possible unexplained variation to the error term ε_{irt}. Care needs to be taken with control variables, since when using weather data there is always a potential for over-controlling (Dell et al. 2014). One could argue for instance that the weather affects people’s work lives so strongly that typically fixed aspects of their employment contract may get adjusted. Using fluctuations in year-to-year within-region weather conditions in Germany, this appears unlikely, but still the results of the analyses are routinely shown with and without work-related covariates. To mitigate the role of possible anticipation of weather conditions and adaptation behaviors, the model also considers time-fixed effects τ_t and fixed differences between regions δ_r. The former picks up variation across years via wave dummy variables and within years via dummy variables for the week of the year when the interview took place. While a month-based identification would technically be possible, and computationally less demanding, weeks are considered more precise and are thus preferred. Regarding the main determinant of $PastWeather_{rt}$, several issues have to be addressed, as discussed in the following subsection.

2.4 Analyzing weather conditions

To exploit weather data for an investigation into the possible implications of health impairments, the first important decision is the selection of weather factors to be studied. Temperatures and wind speed are potentially relevant determinants of health for a mid-

European country like Germany, especially if data is available primarily for winter and early spring months. Common wisdom and some of the previous literature on comparable backgrounds (e.g. Martens 1998, Mercer 2003, Deschênes and Moretti 2009, Barreca 2012) suggests looking at those factors.[8] While various explanations on reasons for the implications on health implications are given, ranging from thermoregulation to bronchoconstriction, researcher also discuss the possible impairment of the immune system and reduced resistance to infections (e.g. Keatinge et al. 1997, Otrachshenko et al. 2017). This suggests looking at prior weather conditions several weeks before a certain date in order to examine health implications that happened recently.

Accordingly, as a second point, the time window of interest needs to be defined. In contrast to the five weeks just prior to the date of the data collection, which is referred to in the following as 'recent' weather, the main focus is on the five weeks before that, i.e. the 35 days in week 6 to 10 prior to the interview date. Two reasons speak for going back several weeks. One is that very recent weather variations close to the date of the interview could affect self-reporting without causing changes in real health. The other reason is the potential delay in the impact of weather influences. Deschênes and Greenstone (2011) argue in reference to other research that the weather impact takes time to accumulate, and a particular phenomenon on a certain day takes time to manifest itself. It thus makes sense to use a time window of several weeks to capture a concentrated impact of weather conditions.

Specifically, the idea in the following is to count the number of bad vs. good weather days within the time window of 35 days, starting six week prior to the survey interview. Counting days with good vs. bad weather has the advantage to avoid discussions of the functional form of weather influences. Still, even in the case of a count variable, the relationship may not be linear and outliers may play a role. To tackle the fact that after some days of bad weather, the additional bad weather day affects health differently, a logarithm of this count variable appears to be a suitable option.

Finally, the adjustment of the weather conditions is another important aspect of how to use the weather data best for studying labor market implications. Instead of absolute weather measures, the superior option for clean identification is to rely on relative conditions, which takes place by adjusting given values in temperatures and wind speed with average weather conditions for a given region and at a given time. Specifically, for each ROR and each calendar week, the average temperature and the average wind speed is determined first, which then serves as the

[8] Note that other weather factors are generally available in the weather data. Analyzing those alternatively however does not lead to consistent findings in regard of implications for people's health when using the dataset at hand.

basis for the adjustment that then yields a deviation from this mean. In consequence, the fluctuation in weather is independent of both regional characteristics and seasonal effects.

Note that in consequence of this adjustment, taking away both fixed regional heterogeneity in weather and any seasonal effects, the full impact of the weather is not reflected in the outcomes of the following analysis. Yet, the effect identified promises to be as good as random, which in the given research context appears preferable, as otherwise it would be difficult to disentangle the actual effects from time trends or regional influences in the second main outcome of interest, i.e. working hours. Thus, focusing on a small part of the variation, i.e. the deviation from region-time averages, fosters clean identification of the effects and is therefore given priority. Moreover, there are further reasons justifying the region-time adjustment of weather conditions, such as the fact that this type of variation in weather is less easy to predict in advance. As recent research discusses, people anticipate certain weather phenomena during certain times of the year and adapt to those conditions by preparing themselves (e.g. Barreca et al. 2015, 2016). While such forms of counter-behaviors cannot be ruled out completely, the issue is at least mitigated by focusing on deviations from regional and seasonal averages in weather conditions.[9]

3. Empirical analysis

3.1. Main results

3.1.1 Health

Table 1 shows the results for the effects of weather conditions on people's perceived health. The evidence comes from specifications (1), (2) and (3) with different sets of covariates each. Further included are different panels A, B and C that show results for different definitions of past weather conditions, whereas the preferred approach is shown in the final panel at the bottom of the table. Panel A shows the effects when both weather factors (temperatures and wind speed) are considered as distinct influences. The variables reflect the number of days with above-average temperatures, respectively wind speed, during the time window of interest prior to the interview. Panel B combines these two factors by counting days on which both temperatures are below average and wind speed is above average, which reflects particular bad weather and relies on the idea that health impairments are stronger when both phenomena come

[9] Another advantage is that the adjustment of weather conditions by regional averages addresses the potential issue that in some cases weather stations may not perfectly reflect average weather conditions for a certain region. For example, some stations are positioned on a mountain where only a few people live, so that the majority of region inhabitants may experience different weather than indicated by the data collected by the station for this region. By adjusting the daily variation in weather via regional and time-point averages, the relative weather indicator cannot be influenced by region-fixed or, in this example, station-fixed effects.

together. Panel C shows the results when the logarithm of this latter combined weather variable is used. Importantly, these past weather influences are always determined based on the same time window that ranges from week six to week ten prior to the interview, and thus includes 35 days with either more or less bad weather days.[10] A variable on recent weather in the time window immediately before (i.e. in the last five weeks prior to the SOEP survey interview) can be added to the main specifications of panel C for some additional analyses (see Appendix Table A2). This reveals that the main findings are robust to consideration of recent weather, which itself turns out to be insignificant for self-reported health satisfaction. Note finally that the complete set of results including the display of covariates for the two main specifications (2) and (3) of panel C are given in Appendix Table C1.

[Table 1]

The findings in Table 1 are straightforward. Warmer temperatures in the investigation period of winter and early spring are positively influencing the health of the people in Germany. Ten additional warm days, defined as above-average temperatures, within a period of 35 days going back five weeks ago, increases health satisfaction by 0.03 points on the scale. This is a minor effect, which for this large dataset is clearly statistically significant. In similar fashion, panel A shows that days with above-average wind speed decrease people's health satisfaction. The combination of the two weather factors strengthens the impact, as health satisfaction declines by 0.06 points when there are 10 additional days of bad weather, defined as having both above-average windiness and below-average temperatures. Finally, the log of this count variable shows the strongest effect of weather on health (with t-statistics above 4 in the two main specifications). The interpretation is that SOEP participants who are interviewed after a period of bad weather have more likely experienced minor health issues in recent time, contrary to those who are interviewed on a date and in a region with better weather conditions prior to the survey participation.

Regarding control variable influences, it is important to point out the role of the time dummy variables. Calendar week controls are important as there is a positive time trend in people's health status over the first weeks of the year, so these variables are routinely added to the specifications, starting in column 1. Other available variables added to the model in column 2 do not seem to play a large role in the relationship between weather and health. This also seems

[10] This means that the basic variables shown in panels A and B have values from zero to 35 at most. In regard of the variable in panel C, the special case of zero bad weather days is treated as one bad weather day in order to generate log variables without any loss of data. The underlying idea is that the accumulation of certain bad weather days affects people's health, and not just one 'bad' day alone.

to be the case for work-related controls that complement the last specification in column 3, despite many of these variables seeming significant for people's health, as can be seen in Appendix Table C1.

The analyses in Table 1 can be replicated with dummy variables instead of linear health satisfaction. By distinguishing between being healthy or unhealthy, defined at different levels of the satisfaction scale, the evidence shows that the effect of weather on health is driven by healthy types of people. Persons with high levels of health respond to the influence of bad weather with declining health, rather than the very sick individuals are getting in even worse shape. This is in line with the research idea to use such weather fluctuations for the inspection of regular types of workers and the possible role of minor variations in health, ranging from being in good shape to not so good, rather than studying those with severe health problems. Nevertheless, disability is an issue of relevance in this context, as for instance, the disabled stay indoors more often and might not be affected by the weather. A minority of individuals in the SOEP data reports a disability degree of more than zero. Just like a variable on hospital stays in the last year prior to the survey interview, these additional pieces of information serve as control variables in the analyses based on the additional health data presented in Appendix B.

Appendix Table B1 presents results for doctor visits as a second health indicator and an alternative to health satisfaction. As argued above, such an alternative outcome variable helps fostering the credibility of the finding that weather matters for people's health. The information is used in two different ways; first, as a binary variable for no doctor visit at all, and, second, as a log variable of the number of visits. Results in all cases show negative effects of past bad weather and clearly support the idea that bad weather can make a difference for people's health. This finding holds when taking the other health information on hospital stays and disability into account (last column). The finding is also robust when, in additional analyses, the sample is restricted a) by exclusion all disabled persons, and b) by focusing only on data starting in the mid-1990s. Recall that these additional health questions are included regularly in the SOEP only since then and irregularly beforehand (see Appendix Table B1).

3.1.2 Working hours

Having detected a bad weather influence which decreases people's health and checked its robustness, the aim in the following is to analyze the impact of this exogenous factor on labor market behavior. Using the same approach as before, Table 2 presents the results for individual working hours as the second major outcome variable in this paper. As actual working hours vary quite strongly, with a few outliers reporting extraordinary workloads, there are different options on how to deal with this particular variable. In a first attempt, the raw information is used, which leads to the results presented in the first two columns of Table 2. Capping this variable at 50 hours and recoding all the values above as 50 as well as simply excluding all these values above 50 are options that lead to the results presented in Appendix Table A3. While the results from this exercise support the main finding, the preferred alternative is to avoid any arbitrary decisions on certain thresholds by making use of the log of actual working hours. This variable allows taking all observations into account, but mitigates the role of outliers. Results are in the last two columns of Table 2. Complete results (for the main specifications 3 and 4) are given in Appendix Table C1.

[Table 2]

The finding presented in Table 2 appears to be both robust and probably unexpected. In fact, health-reducing weather conditions in the past lead to increases in working hours, not decreases. Using the log of actual working hours produces significant positive effects (column 3 and 4). This holds for the absolute number of hours, especially when using all control variables (column 2), which, in the case of work-related controls, appears to be important. Relevant factors here are the large difference in hours between full-time and part-time employment contracts as well as differences in earnings. These factors make a substantial difference for how much of the working hours variation can be explained.

Just like in the case of the health effect, the impact is not economically strong but it clearly counters the expectation one could initially have when thinking about people with minor health problems at the beginning of the year. Recall that the sample includes all individuals who generally report to be part of the labor market, which is defined by not reporting to be out of the labor force and instead reporting either full-time or part-time employment. As some of the individuals report on having very few actual working hours, checks and sample restrictions promise to be informative. Subsample analyses of that kind are discussed in Section 3.2.2, as part of the extensive sensitivity analyses that follow next.

3.2. Sensitivity analyses

3.2.1 Robustness checks

To first check the robustness of the finding on health towards the choice of method, the main analysis as presented in Table 1 can be re-run employing ordered probit. While this leads to no other insight, treating health satisfaction as a linear variable has the advantage that it is easily possible to switch from pooled OLS to fixed-individual effects analyses. These are presented for both main outcomes, health and working hours, in Appendix Table A4. Here, the regressions take into account that individuals are observed more than once in the panel dataset and any between-person differences are ignored. Instead, the results show how a variation in weather conditions lead to changes in the outcome variables for a given person living in a given region. This certainly makes it very difficult to establish evidence for the effects of a particular determinant, since persons without observable changes in their variables drop out, thereby reducing the de facto sample size. Still, the results are supportive of the main conclusions in the paper, as past bad weather again reduces health and the same exogenous weather influence increases working hours. This finding is also robust to clustering standard errors at the region level, which can be implemented in the fixed-effects analyses because of the exclusion of 'movers' (i.e. observations from persons when those are observed in a different region than in their main one).

Appendix Table A4 also shows results in the last column of each panel, when recent bad weather, i.e. weather conditions in the last five weeks prior to the SOEP interview, are considered. This variable may be informative but care needs to be taken here regarding its unclear role in the given context. On the one hand, weather conditions closer to the interview date could be suspected to trigger potential measurement issues, as some researchers argue that weather could manipulate people's response in surveys in ways undesired by the empiricist.[11] On the other hand, recent and past weather may be connected, so that inclusion of recent weather takes away some of the exogenous influence on people's lives in recent time. Be it as it may, the recent weather variable is insignificant in both cases, which at least could be interpreted as evidence against a potential measurement error, because otherwise the effect should be larger the closer the time of measuring to the actual interview date.[12] There are other ways in which survey-related aspects could play a role in this context. For instance, the interview-date identification strategy certainly works best if the exogenous event does not influence survey participation itself.[13] In the setting here, the identification relies on previous and long-period weather measures over more than five weeks in the past, which clearly reduces concerns about this type of selection.

Finally, of the many robustness checks one can think of, the last one deals with the issue of time trends in weather conditions and the possible implications for individuals. Undoubtedly, the decision to capture the time trend via week dummy variables ensures higher precision than the

[11] The claim that weather itself can effectively manipulate survey responses goes back to a study on life satisfaction by Schwarz and Clore (1983). In recent years, there has been an increasingly hot debate about this issue, with more and more studies arguing against significant influences of weather on self-reports (see e.g. Lucas and Lawless 2013, Simonsohn 2015). In line with this, adding weather controls for the interview date does not produce significant effects in the outcomes, nor does the consideration of these variables change the findings.

[12] Note that the recent bad weather is also insignificant for working hours in the pooled OLS regressions above.

[13] In one of the most recent empirical studies based on interview-date identification using SOEP data, Goebel et al. (2016) argue in this way in their paper on the implications of the Fukushima incidence for Germany.

commonly used month variables. The calculation of the region-based deviation from the mean could of course also be carried out based on monthly instead of weekly averages. Having a smaller number of within-year trend variables allows, in a second step, checking for a potential role of within-region time trends by adding time-region interactions to the model. All of these additional inspections lead to the same findings as presented in the main results section beforehand.

3.2.2 Subgroups and effect heterogeneity

The following subgroups analyses aim at further inspecting the sensitivity of the results, but also at providing preliminary insights on the possible mechanisms that are at play. While many aspects may be of interest, the focus is restricted to three different areas, the first of which deals with socio-demographics, followed by employment status and industry. To learn more about how subgroups respond to the influence of bad weather conditions in the past, interaction variables can be added to the estimation models.

3.2.2.1 Socio-demographics

In the case of people's age, previous research suggests interactions in the way that the implications of bad weather may be stronger for the elderly for whom health risk factors pose an additional threat to their already impaired well-being. Due to the focus on working people in the age of 21 to 65, this is probably less of an issue, though lower health of older workers is certainly an important topic. Additionally, gender differences in both health as well as labor market outcomes are of special interest.[14]

[Table 3]

The subgroup analysis on the role of age and gender is presented in Table 3. The left two columns show the results for health satisfaction, the right two columns show results for working hours. It turns out that neither the implications of bad weather for health, nor those for labor market behavior interact with the age variable in significant ways. The subgroup of older people, defined as 45 years of age or higher, respond insignificantly different to past bad weather regarding health (column 1) and working hours (column 3), compared to the reference group of younger individuals.

[14] Further analyses of standard socio-demographic factors reveal no significant subgroup differences as response to variations in weather. For instance, interactions between weather and marital status, education level, and childlessness are insignificant for both of the two outcomes on health and working hours.

In contrast, there is evidence for gender differences in these relationships. The last column reveals that the finding of increased working hours as a consequence of health-threatening weather is driven by women. This is remarkable, given the non-finding on gender-specifics in the effect of bad weather on health (column 2). Thus, both groups suffer lower health from bad weather conditions in the past, but in particular women may be able to compensate possible implications of this negative health effect for labor market outcomes. An interpretation is that women, more than men, have the option to spend additional time at the workplace when suffering from lower health because of more flexible and on average lower working time.

3.2.2.2 Employment status

Given the fact that part-time is much more common among women, the finding on gender differences in the effect of weather on working hours suggests taking a closer look at the role of employment status and contractual working time. Additional results come from restricting the main sample (as shown in Appendix Table A1) regarding working hours and are presented in Appendix Table A5. First, the minimum of working hours is raised to 15. In another step, the data is restricted to only full-time jobs with a minimum of 35 hours. While the main finding holds, the effect on the working hours gets smaller. The result from using an interaction for full-time employment based on the full sample confirms that the increase in working hours appears to be driven by part-time employees.

An interpretation is that more flexible individuals can respond to lower health by increasing working hours. The evidence does not comply with the idea that the overly exhausted worker, who already works full-time, increases workplace presence in exchange for more leisure when the weather is good, which could be a different explanation for the main finding, as discussed deeper below. Most strikingly, the health implications of bad weather do not vary with job characteristics, indicating that people get their negative health ‘treatment’ outside of their workplaces, which is an interpretation that also aligns with the results from the following subsample analyses.

3.2.2.3 Industry sectors

In the last set of subsample analyses, the focus is on the role of the actual job. The implications of bad weather for labor market behavior may depend on what people are actually doing for a living. Therefore, Appendix Table A6 provides results using interactions with the industry sector of a person's job.[15]

The first observation is a lack of evidence on industry-related heterogeneity in the health effects, as demonstrated by the many insignificant interaction terms. These check whether the industry effect differs from the impact on people working in the reference sector of retail. Retail is particularly interesting and thus chosen as the reference here, since there is arguably no direct weather impact on the job as such. The demand for products and services can be seen as independent of weather conditions, while the work itself is typically done indoors. This is different for sectors like manufacturing, for which one could expect a direct economic effect coming from variations in weather conditions.

Indeed, while the impact of bad weather on health is constant and does not vary significantly across the sectors, the workplace behavior response to it varies in a few cases. Interestingly, those sectors for which a direct weather effect is plausible do indeed respond differently and are not subject to a positive effect in working hours. By excluding the sectors of manufacturing, energy and transport, the picture remains the same and shows that weather-robust jobs drive the main pattern of reduced health and more working hours.

Interpreting the evidence of the industry-specific analysis, it seems that the health problems do not emerge during work, which is substantiated by the lack of significant interactions terms in the health regressions. Rather, people may get sick in their free time, which makes this particular health impairment caused by bad weather even more attractive for studying its implications on labor market behavior.[16] Regarding the effect of bad weather on the situation at the workplace, it seems that the positive impact on working hours is mitigated by a direct negative effect on labor market activity, which makes sense for a sector like manufacturing. However, this does not explain why there is on average a positive effect of health-threatening weather conditions on working hours in the first place. Overall, these additional findings do not support the idea that the increase in working hours is a direct consequence of weather effects on the occupation as such, which is one of the potential mechanisms discussed deeper in the following.

3.3. Discussion and further analyses

The finding that bad weather decreases health but increases working hours deserves a deeper

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[15] Deviating from the official NACE-1 classification, two large sectors of trade and services have been split into subsectors, while maintaining sufficient observation numbers. Trade is split into two sectors of 'retail' and 'other trade' sectors, while services is split into 'public administration', 'education', 'health/social' and 'other services'.

[16] Additional analyses using information on commuting in the SOEP also support this, as there are no significant interaction effects, suggesting that commuters and non-commuters are similarly affected by bad weather.

discussion of the potential mechanisms at play. First of all, it could be that the two observations have no connection to each other and weather separately affects labor market behavior, resulting in this probably somewhat paradox picture. Previous research and additional considerations suggest explanations that can be inspected more closely with the available SOEP data.

According to the idea of a leisure-work substitution effect (see Connolly 2008), workers have an incentive to increase working time when bad weather decreases the utility gain from leisure. Thanks to a time-use battery in the SOEP, it is possible to test this idea of whether bad weather makes it less attractive to enjoy leisure, while indirectly making it more attractive to spent time at work.

[Figure 1]

The results of this analysis on people's weekly time-use are presented visually in Figure 1. The illustration shows bars that reflect the direction and the size of all seven coefficients from each time-use variable after running regressions on past bad weather conditions in the same manner as the main analyses above (using model (1) from Section 2). Most of the time-use variables do not respond at all and show no significant changes. This is also true for the item 'hobbies and other leisure activities' (short: leisure) that shows no significant decrease following past bad weather. As the only exception, time for activities aggregated under the term 'work' increase. While the effect is statistically significant, providing an additional check for the main finding of increased working hours, the effect size is again rather small with about twenty minutes more working time for ten additional bad weather days.

One has to keep in mind that there are many reasons explaining the small size of the effect. First, underreporting of the actual effect could be an issue, since people are likely describing their ideal day, not necessarily considering actual deviations from that in the recent past. Arguably, the same argument could also be relevant for the main working hours variable; in any case, the conclusions of the paper would not change even if underestimation is a large concern. Second, all activities provided in the SOEP time-use battery are defined rather broadly, so that, for instance, the job category includes commuting and even side jobs.[17] Thirdly, there are several outliers, again suggesting application of log hours, as more appropriate from a methodological standpoint. Note also that the information shown is based on biennial SOEP data, since for the establishment of time-use information for the whole week, responses to time-

[17] Other survey-based studies consider more than ten daily activities (see e.g. Knabe et al. 2010), while researchers using smartphones to gather data are able to study almost forty activities (see e.g. Bryson and MacKerron 2017). Note that changes in the SOEP time-use battery questionnaire over the years are another limitation of the data here. During the period of investigation, a time-use activity on taking 'care and support for persons in need of care' was added in 2001, and an item on 'physical activities' in 2013, both of which are ignored here.

use on weekends is needed, which are only included in the questionnaire every two years. To maximize the dataset and to provide an additional check of the findings in Figure 1, Appendix Table B2 provides results for log hours of activities per weekday, leading to similar insights. The effect for time spent on work again aligns with the finding for the main variable of actual working hours, while the effect of past bad weather on leisure activities becomes even weakly positive, rejecting the notion of a work-leisure substitution.

When interpreting the evidence for a potential substitution of work and leisure as a result of weather conditions, one has to take the seasonal background and the definition of bad weather into account. It could be, for instance, that the leisure-substitution effect does indeed play a role for the people of Germany, but not in the examined period at the beginning of the year. A lack of bad weather in this season does not necessarily mean people perceive the weather as being good. In this sense, the period of investigation here might help to shut down this additional channel of how the weather affects labor market behavior, leaving the question open what the mechanism at play actually is.

A second explanation for a possible direct effect of weather on working hours considers macroeconomic aspects, according to which weather may affect production and thus the demand for work directly. Certainly, the weather can affect an economy (see e.g. Hsiang 2010, Jones and Olken 2010, Dell et al. 2012), and thereby the demand for labor. In consequence, one would expect a negative effect in working hours, however, not the reverse.[18] In fact, the results from the industry-specific analysis in the previous subsection suggests a negative macroeconomic effect on working hours in weather-susceptible sectors like manufacturing, which may compensate any positive effect. In turn, however, macroeconomic influences do not seem capable of explaining why bad weather increases working hours in jobs of other industries.

Further evidence against the idea of a labor demand effect as the explanation for increased working hours due to past bad weather comes from the inspection of overtime hours. If a lack of labor demand was responsible for a reduced need to go to work, one would expect the working hours to deviate from the agreed upon hours of work by being lower. Instead, the evidence presented in Appendix Table B3 suggests that the variation takes place above the contractually agreed level of working hours. In fact, using overtime as the outcome variable shows significant effects for both the incidence, as past bad weather reduces the likelihood of having no overtime, and the magnitude. For the latter, log overtime is analyzed as the outcome

[18] In this context, one may ask whether bad weather several weeks ago is linked to better weather in recent time. This however is not the case as the two are positively correlated.

variable, both on the full and on a restricted sample that excludes people reporting no overtime work at all, in both cases showing a positive impact of past bad weather.

So, why do people then increase working hours and even overtime when the weather has been bad and they might as a result suffer lower health? A third explanation picks up the latter finding and relates health to productivity. The basic idea is that a small reduction of health makes it a bit more difficult to get the job done in the same amount of time as otherwise in good health. In other words, workers' output per time unit declines, which raises the question if workers respond by increasing time at work to maintain the same output level. Given the opportunity for many German workers, it appears to be a plausible consequence when faced with minor health problems to just compensate lacking productivity by increasing the time spent at work. Being aware of the fact that a job needs to be done sooner or later, people might increase working hours and stay longer at work, thereby finishing their task at the expense of some free time.[19] A similar phenomenon could emerge if people have to compensate an additional sickness-absence day with longer working time on the other days when being present at work. Again, a compensation pattern emerges that the literature on the nexus between health and labor market outcomes certainly has not taken into account so far.

Several factors would be interesting to observe at this point, such as productivity or sickness absence behavior.[20] What the data can do here is inform about the voluntariness of the working time increase. The SOEP questionnaire offers a variety of subjective assessments of people's lives and working lives in specific, one of which is the desired number of working hours. This variable is used for an analysis of working hours mismatch (in Appendix Table B4) that is defined by how strongly the desired working hours deviate from the actual working hours.[21] If there was an exogenous macroeconomic effect, leading to less working time as a consequence of a lack of labor demand, people should report underemployment as a form of working hours mismatch. However, the evidence suggests that people treated by bad weather in the past instead report overemployment, compared to situations with better weather conditions in the past. It seems that they are rather unhappy about spending more time than usual at work and thus report a desire to have less workplace presence. While this finding also speaks against the idea of a voluntary substitution of time, it fits very well with the idea that people feel forced to stay a bit

[19] Note that there is evidence for a negative effect of working hours on productivity (Collewet and Sauermann forthcoming.

[20] Sickness-related absence is available in the SOEP but only at a yearly basis, so that it does not appear to be useful for investigating the implications of within-year variation from changing weather conditions.

[21] A few outlier cases in which the working hours mismatch exceeds 40 hours are excluded from the analysis here. For research on working hours mismatch using SOEP data, see Kugler et al. (2014).

longer at their workplace due to their lower health and possible implications for the output goals of their jobs when being less productive.

4. Conclusion

Health economic research so far focuses on severe health shocks to analyze employment effects of (ill-)health. The analysis of minor changes in health is arguably of higher interest from a policy perspective, but such analyses are lacking so far. Importantly, as long as health problems are minor, people could be able to compensate reduced productivity by increasing working hours, which is certainly not possible in the case of major health shocks, such as disabilities and hospitalizations. In consequence, the present paper may have revealed a novel and important argument for the discussion on why health might not be a key determinant of labor market success.

To provide empirical evidence, this paper uses weather data to analyze people's labor market behavior when changes in their health status are plausibly due to an exogenous influence. Thanks to having long-run survey data on people's subjective health from the German Socio-Economic Panel Study (SOEP), it is possible to detect minor health implications as a result of cold temperatures and windiness. The evidence on the lagged effects of this type of weather phenomena for winters in Germany might be novel itself, though in line with findings for similar research contexts. Using year-to-year within-region variation in weather conditions, the dataset merged on the basis of regional identifiers and exact interview dates allows for a clean identification of the effects.

Regarding the main research question on the labor market implications, the finding for a standard measure of individual labor supply, working hours, reveals an intriguing and very different picture than the one suggested by previous research in health economics. The same bad weather influence that mildly reduces people's health does not reduce their labor supply. Instead, there is a small but robust positive effect on working hours. While multiple channels might be at play, the SOEP data allows for a broad discussion of the potential mechanisms of this effect. A microeconomic interpretation, according to which bad weather makes leisure less and thus work more attractive, and a macroeconomic interpretation, according to which weather has direct effects on the economy and thus changes overall demand for labor, are both discussed based on additional evidence. The latter seems to play a certain role in some sectors, such as manufacturing. To explain the overall pattern however, it appears to be more promising to go back to the finding on health and to the explanation from above, according to which people may compensate negative health impacts on labor productivity by increasing workplace presence.

To draw policy conclusions, attempts to extrapolate from the previous evidence on major health shocks that minor health problems also affect labor market outcomes in negative ways does not seem to work. In consequence of the findings here, one conclusion is that policies aimed at fostering workers' health with the purpose of increasing labor market outcomes do not appear as promising as previously thought. Firms financing healthy behaviors of their workers, as an example, might not see the higher employee output that such measures seem to promise. People suffering from mild health problems are potentially capable of compensating lower productivity implications on their own, especially if they have the time to do so.

Another conclusion of this paper relates to the discussion on gender differences in labor market outcomes. Obviously, health is a suspect here, as males not only have better health on average but also better labor market outcomes, which has been linked together in some contributions to labor market research (e.g. Ichino and Moretti 2009). When minor differences in health can be compensated with longer workplace presence, however, this means that the overall lower health of women may not be a major contributing factor to the emergence of these gender differences.

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Table 1 Weather and health

Panel A)	(1)	(2)	(3)
Dependent variable:		Health satisfaction	
Past good weather:	0.003***	0.003***	0.003***
Number of warm days	(0.001)	(0.001)	(0.001)
Past bad weather:	-0.002**	-0.003***	-0.004***
Number of windy days	(0.001)	(0.001)	(0.001)
Week controls	X	X	X
Wave controls		X	X
Region controls		X	X
Personal controls		X	X
Work-related controls			X
N	126028	126028	126028
R^2	0.001	0.079	0.083
Panel B)	(1)	(2)	(3)
Dependent variable:		Health satisfaction	
Past bad weather:	-0.005***	-0.006***	-0.006***
Number of cold and windy days	(0.002)	(0.002)	(0.002)
Week controls	X	X	X
Wave controls		X	X
Region controls		X	X
Personal controls		X	X
Work-related controls			X
N	126028	126028	126028
R^2	0.001	0.079	0.083
Panel C)	(1)	(2)	(3)
Dependent variable:		Health satisfaction	
Past bad weather:	-0.024***	-0.033***	-0.033***
Log number of cold and windy days	(0.008)	(0.008)	(0.008)
Week controls	X	X	X
Wave controls		X	X
Region controls		X	X
Personal controls		X	X
Work-related controls			X
N	126028	126028	126028
R^2	0.001	0.079	0.083

Source: SOEP and German Weather Service data (years: 1985 to 2013)

Levels of statistical significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Standard OLS regressions are used. Robust standard errors are in parentheses. Cold (warm) days are days with below-(above-)average temperatures, in comparison to the mean for the same calendar week in the same region. Windy days are days with above-average wind speed, in comparison to the mean for the same calendar week in the same region. Log number of days takes the value of zero in all cases of no past bad weather day during the time window. The time window for past weather conditions refers to weeks six to ten prior to the survey interview. Personal control variables are for gender, age (5-year brackets), German nationality, education levels, log equivalent household income, home ownership, size of dwelling, number of household members, no child in household, person needing care in household, partnership, and recent life events (moving in with partner, marriage, divorce, separation, death of partner, child birth). Work-related control variables are for regular part-time employment, irregular part-time employment, further education, side job, part-time employment experience, full-time employment experience, unemployment experience, recent job change, tenure (u-shape), public sector, industry sector, firm size, log net earnings, occupation (blue-collar, white-collar, civil servant), and hierarchical rank.

Table 2 Weather and working hours

	(1)	(2)	(3)	(4)
Dependent variable:	Actual working hours		Log actual working hours	
Past bad weather:	0.078*	0.086***	0.003**	0.004***
Log number of cold and windy days	(0.043)	(0.028)	(0.002)	(0.001)
Week controls	X	X	X	X
Wave controls	X	X	X	X
Region controls	X	X	X	X
Personal controls	X	X	X	X
Work-related controls		X		X
N	126028	126028	126028	126028
R^2	0.276	0.669	0.241	0.703

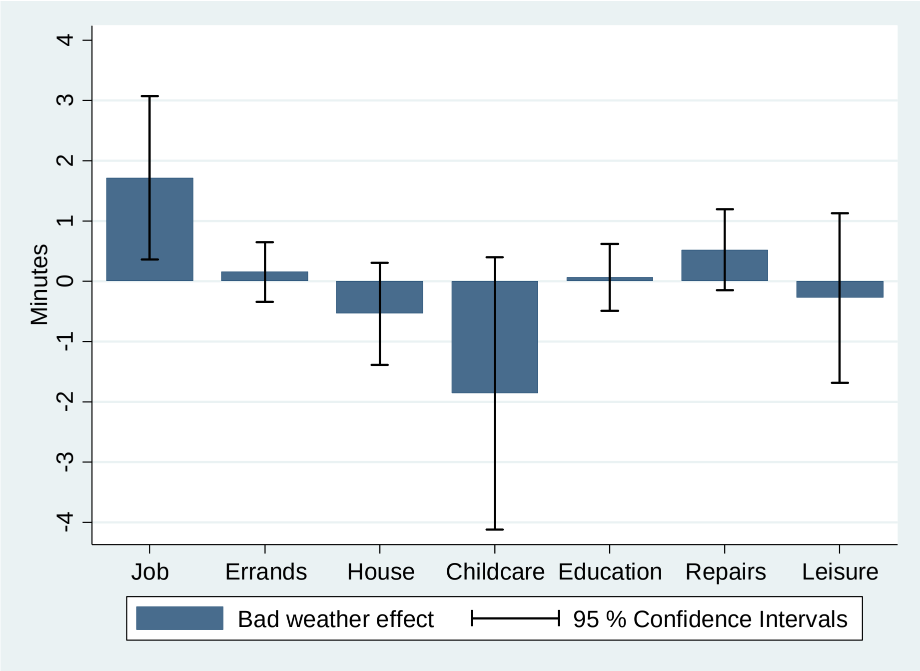
Source: SOEP and German Weather Service data (years: 1985 to 2013)
Levels of statistical significance: * p < 0.1, ** p < 0.05, *** p < 0.01
Notes: Standard OLS regressions are used. Robust standard errors are in parentheses. See Table 1 for more information on variables used.

Table 3 Weather, health and working hours: Interactions (socio-demographics)

	(1)	(2)	(3)	(4)
Dependent variable:	Health satisfaction		Log actual working hours	
Past bad weather:	-0.026***	-0.034***	0.004***	0.002*
Log number of cold and windy days	(0.010)	(0.010)	(0.001)	(0.001)
Interaction:	-0.016		-0.001	
Past bad weather X age at least 45	(0.014)		(0.002)	
Interaction:		0.001		0.004**
Past bad weather X female		(0.014)		(0.002)
Week controls	X	X	X	X
Wave controls	X	X	X	X
Region controls	X	X	X	X
Personal controls	X	X	X	X
Work-related controls	X	X	X	X
N	126028	126028	126028	126028
R^2	0.083	0.083	0.703	0.703

Source: SOEP and German Weather Service data (years: 1985 to 2013)
Levels of statistical significance: * p < 0.1, ** p < 0.05, *** p < 0.01
Notes: Standard OLS regressions are used. Robust standard errors are in parentheses. See Table 1 for more information on variables used.

Figure 1 Weather and time-use



Source: SOEP and German Weather Service data (years: 1993 to 2013, every second year)
Notes: Bars denote the impact of past bad weather (i.e. an additional bad weather day with both below-average temperatures and above-average wind speed) on several activities, as included in the SOEP time-use battery. Estimates come from OLS regressions controlling for all control variables as shown in the last specification of Table 1 (i.e. week, wave, region, personal, and work-related controls). Time-use variables are defined for the entire week, adding self-reported information on time-use for Sundays, Saturdays and weekdays (times five). The sample includes 56884 observations. See Table 1 for more information on variables used.

Appendix A

Table A1 Descriptive statistics (main sample, SOEP waves 1985-2013)

	Mean	Std. deviation	Min	Max
Female	0.451	0.498	0	1
Migrant background	0.195	0.396	0	1
Age	42.646	10.663	21	65
German	0.904	0.295	0	1
Education: primary	0.130	0.337	0	1
Education: secondary	0.640	0.480	0	1
Education: tertiary	0.230	0.421	0	1
Log equivalent real income	7.481	0.436	1.888	11.839
Owner of dwelling	0.515	0.500	0	1
Size of dwelling	105.241	43.540	8	540
Number of persons in household	2.953	1.251	1	17
No children in household	0.581	0.493	0	1
Person needing care in household	0.018	0.132	0	1
Partnership	0.863	0.344	0	1
Recently married	0.020	0.140	0	1
Recently moved together with partner	0.023	0.149	0	1
Recently divorced	0.006	0.078	0	1
Recently separated from partner	0.016	0.126	0	1
Recent death of partner	0.001	0.037	0	1
Recently had a child	0.025	0.156	0	1
Part-time experience	2.577	5.298	0	45.2
Full-time experience	16.917	11.398	0	50.3
Unemployment experience	0.468	1.265	0	27
Employment: full-time	0.777	0.416	0	1
Employment: regular part-time	0.181	0.385	0	1
Employment: irregular part-time	0.042	0.200	0	1
Further education	0.036	0.187	0	1
Side job	0.065	0.247	0	1
Occupation: self-employment	0.047	0.212	0	1
Occupation: blue-collar	0.340	0.474	0	1
Occupation: white-collar	0.532	0.499	0	1
Occupation: civil servant	0.081	0.273	0	1
Recent job change	0.146	0.353	0	1
Tenure	11.338	9.948	0	51.6
Public sector job	0.275	0.447	0	1
Industry: agriculture	0.013	0.115	0	1
Industry: energy	0.011	0.105	0	1
Industry: mining	0.004	0.067	0	1
Industry: manufacturing	0.206	0.404	0	1
Industry: construction	0.138	0.345	0	1
Industry: retail	0.086	0.281	0	1
Industry: trade	0.052	0.222	0	1
Industry: transport	0.053	0.224	0	1
Industry: banking, insurance	0.040	0.196	0	1
Industry: public administration	0.092	0.289	0	1
Industry: education	0.073	0.261	0	1
Industry: health, social	0.111	0.315	0	1
Industry: other services	0.120	0.325	0	1
Firm size: small (<20)	0.256	0.436	0	1
Firm size: medium (20-200)	0.288	0.453	0	1
Firm size: large (200-2000)	0.221	0.415	0	1
Firm size: big (>2000)	0.236	0.424	0	1
Log net earnings	7.153	0.673	0.693	11.593
Autonomy (rank level: 1-5)	2.710	1.109	1	5
Health satisfaction	6.939	1.992	0	10
Actual working hours	39.004	12.118	1	80

Table A2 Role of past and recent weather

	(1)	(2)	(3)
Dependent variable:		Health satisfaction	
Recent bad weather:	0.007	0.002	0.001
Log number of cold and windy days	(0.008)	(0.008)	(0.008)
Past bad weather:	-0.027***	-0.033***	-0.033***
Log number of cold and windy days	(0.008)	(0.008)	(0.008)
Week controls	X	X	X
Wave controls		X	X
Region controls		X	X
Personal controls		X	X
Work-related controls			X
N	126028	126028	126028
R^2	0.001	0.079	0.083

Source: SOEP and German Weather Service data (years: 1985 to 2013)
Levels of statistical significance: * p < 0.1, ** p < 0.05, *** p < 0.01
Notes: Standard OLS regressions are used. Robust standard errors are in parentheses. Recent weather conditions refer to the last five weeks prior to the survey interview. See Table 1 for more information on variables used.

Table A3 Weather and working hours (different definitions)

	(1)	(2)	(3)	(4)
Dependent variable:	Actual working hours ‘cap 50’		Actual working hours	
Past bad weather:	0.079**	0.087***	0.093**	0.100***
Log number of cold and windy days	(0.037)	(0.022)	(0.039)	(0.023)
Week controls	X	X	X	X
Wave controls	X	X	X	X
Region controls	X	X	X	X
Personal controls	X	X	X	X
Work-related controls		X		X
Data restriction:			<= 50 working hours	
N	126028	126028	114906	114906
R^2	0.294	0.741	0.280	0.746

Source: SOEP and German Weather Service data (years: 1985 to 2013)
Levels of statistical significance: * p < 0.1, ** p < 0.05, *** p < 0.01
Notes: Standard OLS regressions are used. Robust standard errors are in parentheses. Actual working hours ‘cap 50’ takes the value of 50 in all cases of actual working hours above 50. See Table 1 for more information on variables used.

Table A4 Individual-fixed effects analyses

Panel A)	(1)	(2)	(3)
Dependent variable:		Health satisfaction	
Recent bad weather:			0.011
Log number of cold and windy days			(0.007)
Past bad weather:	-0.015**	-0.015**	-0.016**
Log number of cold and windy days	(0.007)	(0.007)	(0.007)
Week controls	X	X	X
Wave controls	X	X	X
Region controls	X	X	X
Personal controls	X	X	X
Work-related controls		X	X
N	126028	126028	126028
R^2	0.027	0.029	0.029
Panel B)	(1)	(2)	(3)
Dependent variable:		Log actual working hours	
Recent bad weather:			0.001
Log number of cold and windy days			(0.001)
Past bad weather:	0.002**	0.002***	0.002***
Log number of cold and windy days	(0.001)	(0.001)	(0.001)
Week controls	X	X	X
Wave controls	X	X	X
Region controls	X	X	X
Personal controls	X	X	X
Work-related controls		X	X
N	126028	126028	126028
R^2	0.042	0.366	0.366

Source: SOEP and German Weather Service data (years: 1985 to 2013)

Levels of statistical significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: OLS regressions with consideration of fixed-individual effects are used. Standard errors are clustered at the regional level and are in parentheses. Recent weather conditions refer to the last five weeks prior to the survey interview. See Table 1 for more information on variables used.

Table A5 Weather, health and working hours: employment status and minimum working hours

Panel A)	(0)	(1)	(2)	(3)
Dependent variable:	Health satisfaction			
Past bad weather:	-0.033***	-0.033***	-0.034***	-0.033**
Log number of cold and windy days	(0.008)	(0.008)	(0.009)	(0.015)
Interaction:				0.000
Past bad weather X full-time				(0.017)
Week controls	X	X	X	X
Wave controls	X	X	X	X
Region controls	X	X	X	X
Personal controls	X	X	X	X
Work-related controls	X	X	X	X
Data restriction:		>= 15 hours	>= 35 hours & full-time	
N	126028	119633	95443	126028
R^2	0.083	0.083	0.088	0.083
Panel B)	(0)	(1)	(2)	(3)
Dependent variable:	Log actual working hours			
Past bad weather:	0.004***	0.002**	0.001**	0.009***
Log number of cold and windy days	(0.001)	(0.001)	(0.001)	(0.003)
Interaction:				-0.007**
Past bad weather X full-time				(0.003)
Week controls	X	X	X	X
Wave controls	X	X	X	X
Region controls	X	X	X	X
Personal controls	X	X	X	X
Work-related controls	X	X	X	X
Data restriction:		>= 15 hours	>= 35 hours & full-time	
N	126028	119633	95443	126028
R^2	0.703	0.663	0.284	0.703

Source: SOEP and German Weather Service data (years: 1985 to 2013)
Levels of statistical significance: * p < 0.1, ** p < 0.05, *** p < 0.01
Notes: Standard OLS regressions are used. Robust standard errors are in parentheses. See Table 1 for more information on variables used.

Table A6 Weather, health and working hours: industry sectors

	(1)	(2)	(3)	(4)
Dependent variable:	Health satisfaction	Log actual working hours	Health satisfaction	Log actual working hours
Past bad weather:	-0.051**	0.009**	-0.053**	0.008**
Log number of cold and windy days	(0.024)	(0.003)	(0.024)	(0.003)
Interaction:	0.008	0.003	0.007	0.004
Past bad weather X Agriculture	(0.063)	(0.010)	(0.063)	(0.010)
Interaction:	0.036	-0.010		
Past bad weather X Energy	(0.079)	(0.006)		
Interaction:	0.048	0.001	0.054	0.002
Past bad weather X Mining	(0.101)	(0.011)	(0.101)	(0.011)
Interaction:	0.016	-0.009**		
Past bad weather X Manufacturing	(0.029)	(0.004)		
Interaction:	0.028	-0.006	0.028	-0.006
Past bad weather X Construction	(0.030)	(0.004)	(0.030)	(0.004)
Interaction:	0.039	-0.001	0.039	0.000
Past bad weather X Other trade	(0.039)	(0.005)	(0.039)	(0.005)
Interaction:	0.032	-0.010*		
Past bad weather X Transport	(0.039)	(0.005)		
Interaction:	-0.040	-0.003	-0.044	-0.003
Past bad weather X Bank/Insurance	(0.042)	(0.006)	(0.042)	(0.006)
Interaction:	0.029	-0.002	0.029	-0.001
Past bad weather X Public admin.	(0.034)	(0.004)	(0.034)	(0.004)
Interaction:	0.049	-0.006	0.049	-0.005
Past bad weather X Education	(0.036)	(0.005)	(0.036)	(0.005)
Interaction:	-0.001	0.001	-0.001	0.001
Past bad weather X Health/Social	(0.032)	(0.004)	(0.032)	(0.004)
Interaction:	0.015	-0.007	0.016	-0.007
Past bad weather X Other services	(0.031)	(0.005)	(0.031)	(0.005)
Week controls	X	X	X	X
Wave controls	X	X	X	X
Region controls	X	X	X	X
Personal controls	X	X	X	X
Work-related controls	X	X	X	X
Data restriction:			Energy, Manufacturing, Transport excluded	
N	126028	126028	92057	92057
R^2	0.083	0.703	0.083	0.716

Source: SOEP and German Weather Service data (years: 1985 to 2013)

Levels of statistical significance: * p < 0.1, ** p < 0.05, *** p < 0.01

Notes: Standard OLS regressions are used. Robust standard errors are in parentheses. See Table 1 for more information on variables used.

Appendix B

Table B1 Alternative health data

Panel A)	(1)	(2)	(3)
Dependent variable:		Health satisfaction	
Past bad weather:	-0.035^{***}	-0.035^{***}	-0.037^{***}
Log number of cold and windy days	(0.008)	(0.008)	(0.008)
Degree of disability in percentage			-0.026^{***}
			(0.001)
Nights in hospital last year			-0.048^{***}
			(0.003)
Week controls	X	X	X
Wave controls	X	X	X
Region controls	X	X	X
Personal controls	X	X	X
Work-related controls		X	X
N	115293	115293	115293
R^2	0.078	0.082	0.124
Panel B)	(1)	(2)	(3)
Dependent variable:		No doctor visit in the last three months	
Past bad weather:	-0.005^{***}	-0.005^{***}	-0.006^{***}
Log number of cold and windy days	(0.002)	(0.002)	(0.002)
Degree of disability in percentage			-0.004^{***}
			(0.000)
Nights in hospital last year			-0.007^{***}
			(0.000)
Week controls	X	X	X
Wave controls	X	X	X
Region controls	X	X	X
Personal controls	X	X	X
Work-related controls		X	X
N	115293	115293	115293
R^2	0.043	0.051	0.065
Panel C)	(1)	(2)	(3)
Dependent variable:		Log number of doctor visits in the last three months	
Past bad weather:	0.007***	0.007***	0.008***
Log number of cold and windy days	(0.003)	(0.003)	(0.003)
Degree of disability in percentage			0.008***
			(0.000)
Nights in hospital last year			0.021***
			(0.001)
Week controls	X	X	X
Wave controls	X	X	X
Region controls	X	X	X
Personal controls	X	X	X
Work-related controls		X	X
N	115293	115293	115293
R^2	0.044	0.052	0.099

Source: SOEP and German Weather Service data (years: 1988, 1989, 1991, 1992, and 1995 to 2013)
Levels of statistical significance: * p < 0.1, ** p < 0.05, *** p < 0.01
Notes: Standard OLS regressions are used. Robust standard errors are in parentheses. Log number of doctor visits in the last three months takes the value of zero in all cases of no doctor visit at all in the last three months. See Table 1 for more information on variables used.

Table B2 Weather and time-use (per weekday)

Dependent variable:	(0) Log actual working hours	(1) Log hours: Job	(2) Log hours: Errands	(3) Log hours: Housework
Past bad weather: Log number of cold and windy days	0.004*** (0.001)	0.004*** (0.001)	0.000 (0.001)	0.000 (0.001)
Week controls	X	X	X	X
Wave controls	X	X	X	X
Region controls	X	X	X	X
Personal controls	X	X	X	X
Work-related controls	X	X	X	X
N	114450	114450	114450	114450
R^2	0.724	0.620	0.068	0.459

Dependent variable:	(4) Log hours: Childcare	(5) Log hours: Education	(6) Log hours: Repair	(7) Log hours: Leisure
Past bad weather: Log number of cold and windy days	-0.004** (0.002)	-0.000 (0.001)	0.001 (0.001)	0.003* (0.002)
Week controls	X	X	X	X
Wave controls	X	X	X	X
Region controls	X	X	X	X
Personal controls	X	X	X	X
Work-related controls	X	X	X	X
N	114450	114450	114450	114450
R^2	0.409	0.397	0.100	0.113

Source: SOEP and German Weather Service data (years: 1991 to 2013)

Levels of statistical significance: * p < 0.1, ** p < 0.05, *** p < 0.01

Notes: Standard OLS regressions are used. Robust standard errors are in parentheses. Log number of hours always takes the value of zero in all cases of zero hours reported. See Table 1 for more information on variables used.

Table B3 Weather and overtime

Dependent variable:	(1) No overtime	(2) Overtime in hours	(3) Log overtime	(4) Log overtime
Past bad weather:	-0.006***	0.047***	0.012***	0.010**
Log number of cold and windy days	(0.002)	(0.014)	(0.003)	(0.004)
Week controls	X	X	X	X
Wave controls	X	X	X	X
Region controls	X	X	X	X
Personal controls	X	X	X	X
Work-related controls	X	X	X	X
Data restriction:				Overtime > 0
N	117769	117769	117769	52978
R^2	0.140	0.138	0.160	0.129

Source: SOEP and German Weather Service data (years: 1985 to 2013)
Levels of statistical significance: * p < 0.1, ** p < 0.05, *** p < 0.01
Notes: Standard OLS regressions are used. Robust standard errors are in parentheses. Log overtime takes the value of zero in all cases of no overtime. See Table 1 for more information on variables used.

Table B4 Weather and working hours mismatch

Dependent variable:	(1) Working hours mismatch	(2) Under-employment	(3) Over-employment
Past bad weather:	-0.072**	-0.002*	0.007***
Log number of cold and windy days	(0.030)	(0.001)	(0.002)
Week controls	X	X	X
Wave controls	X	X	X
Region controls	X	X	X
Personal controls	X	X	X
Work-related controls	X	X	X
N	122359	122359	122359
R^2	0.195	0.144	0.153

Source: SOEP and German Weather Service data (years: 1985 to 1995, 1997 to 2013)
Levels of statistical significance: * p < 0.1, ** p < 0.05, *** p < 0.01
Notes: Standard OLS regressions are used. Robust standard errors are in parentheses. Working hours mismatch is the difference between the desired number of working hours, as reported by the interviewees, and their actual working hours. Underemployment (overemployment) is 1 if the desired number of working hours is larger (smaller) than the actual working hours and 0 otherwise, i.e. the working hours mismatch is positive (negative). See Table 1 for more information on variables used.

Appendix C

Table C1 Weather, health and working hours (complete results)

	(1)	(2)	(3)	(4)
Dependent variable:	Health satisfaction	Health satisfaction	Log actual working hours	Log actual working hours
Female	-0.070***	-0.116***	-0.367***	0.001
	(0.022)	(0.029)	(0.005)	(0.003)
Migrant background	0.090**	0.126***	0.030***	-0.002
	(0.038)	(0.039)	(0.008)	(0.004)
Age: 26-30	-0.202***	-0.172***	0.035***	-0.021***
	(0.031)	(0.033)	(0.009)	(0.005)
Age: 31-35	-0.464***	-0.400***	0.037***	-0.041***
	(0.035)	(0.041)	(0.009)	(0.005)
Age: 36-40	-0.702***	-0.604***	0.045***	-0.050***
	(0.036)	(0.049)	(0.009)	(0.006)
Age: 41-45	-0.956***	-0.828***	0.063***	-0.052***
	(0.036)	(0.057)	(0.009)	(0.007)
Age: 46-50	-1.142***	-0.988***	0.046***	-0.064***
	(0.036)	(0.066)	(0.009)	(0.008)
Age: 51-55	-1.343***	-1.168***	0.015	-0.082***
	(0.038)	(0.076)	(0.009)	(0.010)
Age: 56-60	-1.475***	-1.287***	-0.026**	-0.098***
	(0.042)	(0.087)	(0.010)	(0.011)
Age: 61-65	-1.359***	-1.163***	-0.174***	-0.140***
	(0.052)	(0.103)	(0.014)	(0.014)
German	-0.095*	-0.134***	-0.012	0.001
	(0.051)	(0.051)	(0.011)	(0.005)
Education: primary	-0.159***	-0.101***	-0.019**	0.007*
	(0.035)	(0.036)	(0.008)	(0.004)
Education: tertiary	0.159***	0.097***	0.063***	-0.022***
	(0.028)	(0.034)	(0.006)	(0.004)
Log equivalent real income	0.368***	0.294***	0.154***	-0.057***
	(0.027)	(0.028)	(0.006)	(0.004)
Owner of dwelling	0.033	0.022	-0.036***	-0.015***
	(0.025)	(0.025)	(0.005)	(0.003)
Size of dwelling	0.001***	0.001***	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Number of persons in household	0.029***	0.032***	-0.025***	-0.003**
	(0.011)	(0.011)	(0.002)	(0.001)
No children in household	-0.069***	-0.042	0.045***	0.046***
	(0.026)	(0.026)	(0.005)	(0.003)
Person needing care in household	-0.339***	-0.332***	-0.014	0.022**
	(0.073)	(0.074)	(0.018)	(0.009)
Partnership	-0.110***	-0.111***	-0.031***	-0.001
	(0.031)	(0.031)	(0.006)	(0.003)
Recently married	0.041	0.046	0.042***	0.010**
	(0.038)	(0.038)	(0.007)	(0.004)

(*continued on the next page*)

Recently moved together with partner	0.042	0.036	0.058***	0.010**
	(0.038)	(0.038)	(0.007)	(0.005)
Recently divorced	-0.003	-0.013	0.006	-0.001
	(0.073)	(0.073)	(0.013)	(0.009)
Recently separated from partner	-0.038	-0.054	0.024***	-0.010*
	(0.049)	(0.049)	(0.009)	(0.005)
Recent death of partner	-0.448**	-0.451**	-0.059*	-0.022
	(0.187)	(0.183)	(0.035)	(0.025)
Recently had a child	0.117***	0.100***	0.028***	-0.020***
	(0.036)	(0.036)	(0.008)	(0.005)
Part-time experience		0.001		0.002***
		(0.004)		(0.000)
Full-time experience		-0.006**		0.002***
		(0.003)		(0.000)
Unemployment experience		-0.058***		0.006***
		(0.010)		(0.001)
Employment: regular part-time		0.041		-0.385***
		(0.034)		(0.005)
Employment: irregular part-time		0.143***		-0.920***
		(0.055)		(0.012)
Further education		-0.036		-0.035***
		(0.039)		(0.006)
Side job		-0.061*		0.001
		(0.034)		(0.004)
Occupation: blue-collar		-0.066		-0.093***
		(0.058)		(0.009)
Occupation: white-collar		0.014		-0.095***
		(0.050)		(0.008)
Occupation: civil servant		0.051		-0.116***
		(0.072)		(0.010)
Recent job change		0.008		0.001
		(0.020)		(0.003)
Tenure		-0.005		-0.003***
		(0.004)		(0.000)
Tenure squared		0.000		0.000***
		(0.000)		(0.000)
Public sector job		-0.061*		-0.004
		(0.034)		(0.004)
Industry: agriculture		-0.044		0.053***
		(0.107)		(0.012)
Industry: energy		-0.049		-0.086***
		(0.110)		(0.009)
Industry: mining		-0.052		-0.075***
		(0.135)		(0.013)
Industry: manufacturing		-0.007		-0.050***
		(0.041)		(0.005)
Industry: construction		0.007		-0.054***
		(0.044)		(0.005)
Industry: trade		-0.000		0.024***
		(0.051)		(0.007)
Industry: transport		-0.016		-0.005
		(0.058)		(0.007)

(*continued on the next page*)

Industry: banking, insurance		0.011		-0.070***
		(0.064)		(0.007)
Industry: public administration		0.030		-0.057***
		(0.061)		(0.007)
Industry: education		0.028		-0.092***
		(0.061)		(0.008)
Industry: health, social		0.071		-0.053***
		(0.048)		(0.006)
Industry: other services		0.036		-0.059***
		(0.043)		(0.006)
Firm size: medium (20-200)		-0.041		-0.004
		(0.027)		(0.003)
Firm size: large (200-2000)		-0.074**		-0.024***
		(0.031)		(0.004)
Firm size: big (>2000)		-0.078**		-0.043***
		(0.032)		(0.004)
Log net earnings		0.085***		0.280***
		(0.025)		(0.005)
Autonomy: rank level 2		0.119***		0.005
		(0.035)		(0.004)
Autonomy: rank level 3		0.132***		0.010**
		(0.044)		(0.005)
Autonomy: rank level 4		0.088*		0.019***
		(0.052)		(0.006)
Autonomy: rank level 5		0.172**		0.031***
		(0.073)		(0.008)
Past bad weather:	-0.033***	-0.033***	0.003**	0.004***
Log number of cold and windy days	(0.008)	(0.008)	(0.002)	(0.001)
Week controls	X	X	X	X
Wave controls	X	X	X	X
Region controls	X	X	X	X
N	126028	126028	126028	126028
R^2	0.079	0.083	0.241	0.703

Source: SOEP and German Weather Service data (years: 1985 to 2013)

Levels of statistical significance: * p < 0.1, ** p < 0.05, *** p < 0.01

Notes: Standard OLS regressions are used. Robust standard errors are in parentheses. Cold days are days with below-average temperatures, in comparison to the mean for the same calendar week in the same region. Windy days are days with above-average wind speed, in comparison to the mean for the same calendar week in the same region. Log number of days takes the value of zero in all cases of no past bad weather day during the time window. The time window for past weather conditions refers to weeks six to ten prior to the survey interview.

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