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DISCUSSION PAPER SERIES

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ABSTRACT

Polluted Job Search: The Impact of Poor Air Quality on Reservation Wages

This paper investigates the impact of air pollution on reservation wages. We use rich survey data on unemployed job seekers in Germany and exploit variation in individual exposure to fine particulate matter (PM10) based on the quasi-random allocation of interview slots to individuals. Our results show that an increase in PM10 by one standard deviation (corresponding to 12 μg/m3) reduces the reservation wage by approximately 1.2%. We further provide evidence that PM10 pollution decreases job seekers' search effort, risk tolerance and patience, which serve as potential mechanisms through which PM10 exposure negatively affects the reservation wage of unemployed job seekers.

JEL Classification: Q53, J64

Keywords: reservation wage, air pollution, job search

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1 Introduction

Fighting unemployment is a key policy goal as unemployment affects the financial stability, health and well-being of individuals, and has broader economic, social, and societal impacts that can hinder overall growth and development. In 2020 alone, EU Member States spent approximately EUR 383 billion (2.9% of their GDP) on active labour market polices, that support a smooth and durable transition to employment for unemployed job seekers (European Comission, 2023). Despite these substantial investments, there is still limited understanding of factors influencing job seekers' search behaviour, restricting the effectiveness of such policies. Therefore, it is crucial to get a better understanding of job seekers' search behaviour that these policies address.

Many labour market policies address wage expectations with the aim to adjust individuals' reservation wage, which is the lowest wage at which a job seeker is willing to accept a job offer. While reservation wages are a key determinant of the job search process and its outcomes, current knowledge about factors influencing the reservation wage is still limited. Previous studies focused on directly related factors arising from job search theory, such as unemployment duration (Deschacht and Vansteenkiste, 2021) and the generosity of unemployment benefits (Le Barbanchon et al., 2019), or individuals' personality, including the locus of control (Caliendo et al., 2015), risk preferences (Pannenberg, 2010) and one's degree of patience (DellaVigna and Paserman, 2005). In our study, we show that the reservation wage is also affected by a seemingly unrelated, random factor, which can influence the effectiveness of current policies addressing the reservation wage, such as counselling, wage subsidies or benefit levels.

This paper analyses whether reservation wages of job seekers are significantly affected by ambient levels of particulate matter pollution (PM_{10}), underlining the important role of random, seemingly unrelated factors altering job search behaviour. The adverse effect of even moderate levels of air pollution on individuals' health, productivity and cognition is clearly documented (see, e.g., Aguilar-Gomez et al., 2022, for a review). We adopt those insights from the environmental economics literature and estimate the impact of poor air quality on reservation wages. Ex ante, the relationship between elevated levels of air pollution and reservation wages is ambiguous, because the impairment in health, productivity and cognition might trigger opposing effects on the reservation wage.

We use survey data providing information on the reservation wages of a random sample of unemployed job seekers in Germany between June 2007 and May 2008. Besides detailed information on individual job search behaviour, the data contain the exact starting time of the interview, allowing us to accurately match the survey information to the PM_{10} levels at the time of the interview. We exploit the quasi-random timing of the interviews to identify changes in search behaviour associated with air pollution. Individuals are drawn from a pool of available addresses of workers entering unemployment between June 2007 and May 2008 and called to participate in a telephone interview about their labour market activities without prior notice. Hence, these individuals are exposed to exogenously varying levels of PM_{10} pollution based on the quasi-random timing of their interview, allowing us to identify a causal effect of exposure to PM_{10} concentration on the reservation wage of unemployed job seekers. Additionally, we control for individual characteristics as well as weather conditions and regional factors which might simultaneously affect job search behaviour and PM_{10} pollution concentrations. A falsification test based on future values of PM_{10} concentrations as well as an instrumental variable strategy, exploiting exogenous variation in wind speed, confirm the validity of our identification strategy. In addition, a replication exercise using the *German Socio-Economic Panel*, covering a much larger time window, confirms the external validity of our results.

Our findings show that PM_{10} pollution reduces the reservation wages of job seekers. We find that a 12 $\mu g/m^3$ increase in PM_{10}, corresponding to one standard deviation (SD) in our sample, reduces the reservation wage by approximately 1.2%, corresponding to 0.034 SDs in the reservation wage. In addition, we find that PM_{10} decreases job seekers' risk tolerance and patience, as well as search intensity, which may serve as potential mechanisms through which PM_{10} exposure leads to a reduction in the reservation wage.

This paper makes the following contributions to the literature. First, we contribute to the scarce literature on the determinants of reservation wages. As explained above, this literature focuses on directly related factors, while we now consider a seemingly unrelated, random factor which has not been considered before but significantly affects individuals' reservation wages.[1] While Pannenberg (2010) finds that a one SD increase in risk aversion lowers the reservation wage by approximately 7%, (DellaVigna and Paserman, 2005) finds no effect for patience, and Bloemen and Stancanelli (2001) and Caliendo et al. (2015) find that a one SD increase in financial assets and internal locus of control increase the reservation wage by 1.2% and 1.3%, respectively. This clearly shows that the effect of PM_{10} pollution (1.2%) is of similar magnitude as those of directly related factors.

Second, this study contributes to the growing literature on the social and economic impacts of air pollution exposure. Borgschulte et al. (2022) examines the impact of air pollution on core labour market outcomes, such as labor income and employment. Exploiting variation in air quality induced by wildfire smoke, they find that exposure to wildfire smoke leads to significant losses in labor income, employment, and labor force participation. Earlier studies on the

[1] One exception is Doerrenberg and Siegloch (2014) analysing the effect of international soccer tournaments on the motivation of unemployed individuals. Yet, this is a very specific and rare event, while our study focuses on an external factor that people are exposed to every day. Moreover, this external shock affecting unemployed individuals cannot be addressed by policy, in contrast to the external shock analysed in our study.

behavioural responses to air pollution took place outside the labour markets or focused on the working population with the main focus on labour supply and productivity (see, e.g., Aguilar-Gomez et al., 2022, for a review). Hence, the understanding of the impact of air pollution on the most vulnerable population of the labour market, the unemployed, is still missing. This is particularly important given that the environmental justice literature documents disproportionate exposure to air pollution for individuals with less financial means (Banzhaf et al., 2019), making the unemployed even more disadvantaged. Our study adds evidence on the impact of air pollution on unemployed job seekers, contributing to a broader understanding of the (social) costs of air pollution on the labour market.

The remainder of the paper is structured as follows. In the next section, we present our conceptual framework linking the impact of air pollution on cognitive performance, preferences and activity levels to job search behaviour. Section 3 describes the data and discusses the empirical strategy. The results are presented in section 4 together with several robustness checks. Section 5 presents evidence on the potential mechanisms. Section 6 concludes.

2 Conceptual Framework

This section provides the theoretical foundation for the empirical analysis by explaining the link between air pollution and individuals' reservation wage. We start with a brief introduction to job search theory, explaining the key role of reservation wages and its determinants. Based on the environmental literature, we then discuss how air pollution is likely to affect the different determinants of reservation wages.

2.1 Job Search Theory and Determinants of the Reservation Wage

Job search theory focuses on the job seekers' probability of finding employment by describing the job search process of (unemployed) job seekers under imperfect information and uncertainty about future wage offers (McCall, 1970; Mortensen, 1986; Petrongolo and Pissarides, 2001). In the basic job search model, job seekers are continuously looking for a job and receive a certain number of job offers in every period depending on the general state of the labour market as well as their own search effort. The job seeker then evaluates job offers and accepts one if the offered wage exceeds the reservation wage. The reservation wage is the lowest wage at which a job seeker is willing to accept the offer and stop searching for better offers, i.e., where the job seeker is indifferent between remaining unemployed or accepting the job. Therefore, the reservation wage is a key parameter in job search models, determining the optimal search strategy as well as the search outcomes. This is supported by empirical evidence showing that the reservation wage drives the duration of unemployment as well as the wage of job seekers (Jones, 1988; Krueger and Mueller, 2016).

Given the key role of the reservation wage in the job search process, it is important to understand its determinants. In this regard, a first stream of literature investigates the impact of characteristics of the unemployment spell on the formation of reservation wages. For instance, Deschacht and Vansteenkiste (2021) show that reservation wages decline with unemployment duration, while Le Barbanchon et al. (2019) do not find any impact of unemployment benefit duration on reservation wages.

A second stream of literature investigates the impact of individuals' personality and behavioural aspects on reservation wages. Job seekers set their reservation wage based on their beliefs about the wage offer distribution and the job offer arrival rate, where the latter can be influenced by the search effort of the job seeker. A higher search effort increases the job offer arrival rate, which, in turn, increases reservation wages as the likelihood of receiving a better job offer, and thus the value of searching, increases. Spinnewijn (2015) shows that job seekers tend to overestimate their job offer arrival rate, leading to higher reservation wages and lower search effort. Caliendo et al. (2015) investigate the idea that the locus of control affects individuals' beliefs about the job offer arrival rate and, in turn, their search behaviour. Consistently, they find that individuals with a more external locus of control search less intensively and have lower reservation wages.

Job search theory also proposes risk and time preferences as determinants of the reservation wage. Risk averse job seekers prefer the certainty of being employed and receiving a fixed income. Therefore, they would be willing to decrease their reservation wage to increase their probability of finding a job in the near future. Pannenberg (2010) provides empirical evidence supporting this inverse relationship between risk aversion and reservation wages. Impatient job seekers are also expected to lower their reservation wage, because they assign a higher value to present benefits compared to future benefits. Moreover, impatient job seekers have a lower incentive to invest in the future and are, therefore, more likely to reduce their search effort, which negatively affects the reservation wage. Yet, DellaVigna and Paserman (2005) find that the effect of patience on the reservation wage is essentially zero.

To sum up, for our study most importantly, individuals' believes, preferences and search effort are likely to play a role in the formation of reservation wages. In the next step, we establish a link between air pollution and reservation wages by explaining how air pollution directly affects the identified determinants of reservation wages.

2.2 The impact of air pollution on reservation wages

Search effort Numerous studies show an adverse effect of air pollution on workers' effort and physical productivity. Evidence from physically demanding occupations shows a significant negative impact of air pollution on the productivity of workers (Graff Zivin and Neidell, 2012; Chang et al., 2016). In addition, more recent studies explored the effect of air pollution on the productivity of office workers, showing that higher levels of particulate matter decrease their productivity too, through a decrease in up-time Meyer and Pagel (2017), an increase in judges' decision time (Kahn and Li, 2019) and an increase in the amount of time spent on breaks (Chang et al., 2019). Moreover, Hoffmann and Rud (2024) show that workers reduce their hours worked on high polluted dates, but compensate for these lost hours by increasing their labour supply in the subsequent days.

Adopting this evidence on worker productivity, we expect a reduction in search effort among unemployed job seekers in response to elevated levels of ambient air pollution. Sending out less applications will have a negative impact on the job offer arrival rate and, inducing individuals to lower their reservation wage. Hence, air pollution is expected to have a negative effect on the reservation wage.

Cognitive Performance and Risk and Time Preferences A growing number of studies report harming effects of air pollution on the brain and cognitive performance. The inhalation of particles smaller than 200 nanometers can enter the nose and travel into the brain and lungs, causing systemic inflammatory reactions, damaging the brain and hampering cognition (Calderón-Garcidueñas et al., 2015; Underwood, 2017). These adverse effects on cognition are shown to have severe consequences for the performance of individuals in cognitive tasks (Zhang et al., 2018). Empirical evidence shows that students perform worse in high-stake examinations (Ebenstein et al., 2016) and obtain lower test scores (Roth, 2018) in case of exposure to high concentrations of particulate matter. Moreover, Künn et al. (2023) show that air pollution impairs the quality of individuals' performance in cognitive tasks, in particular when individuals are acting under time pressure.

The harming effects of air pollution on cognitive performance are also suggested to affect risk and time preferences, as cognition is shown to be related to risk preferences and patience (Dohmen et al., 2010). Studies show that exposure to air pollution induces a decrease in risk tolerance and patience (Heyes et al., 2016; Bondy et al., 2020; Chew et al., 2021; Klingen and van Ommeren, 2020). This relationship is likely to be mediated by an air pollution induced increase in stress hormones (Li et al., 2017; Niu et al., 2018), which is shown to increase both risk aversion and the subjective discounting rate (Cornelisse et al., 2013; Kandasamy et al., 2014; Riis-Vestergaard et al., 2018).

The adverse effects of air pollution on cognitive performance and time and risk preferences are expected to impact the job search process. First, cognitive decline is likely to exacerbate a general misinterpretation of labour market information by the job seekers. For instance, job seekers overestimating their job finding probability are likely to set higher reservation wages, whereas they are also expected to reduce their search effort which would lead to lower reservation wages. Second, job search theory suggests that risk averse job seekers set a lower reservation wage to increase their job finding probability. Similarly, an increase in impatience is suggested to lower the job seeker's reservation wage. Hence, the change in risk and time preferences driven by air pollution exposure is expected to have a negative effect on the reservation wage of job seekers.

While the effect of air pollution on reservation wages is theoretically ambiguous, most of the mechanisms suggest a negative impact, i.e., exposure to elevated levels of air pollution is likely to reduce individuals' reservation wages.

3 Data and Empirical Strategy

3.1 Data Sources

The main empirical analysis relies on extensive survey data on job search behaviour which is combined with data on local air pollution and weather conditions. First, we use the *IZA Evaluation Dataset Survey*, which comprises survey information on 17,396 individuals who entered unemployment between June 2007 and May 2008 (see Arni et al., 2014, for details on the data).[2] The selected individuals were interviewed multiple times. The first interview took place shortly after entry into unemployment (on average after 10 weeks). A second and third interview took place after 12 and 36 months, respectively. Besides an extensive set of socio-demographic and household characteristics, the survey contains information about labour market histories and detailed information on individuals' job search behaviour as well as their risk preferences and degree of patience. Most importantly, the date and time of the interview are observed, allowing us to accurately match the survey data to the pollution levels at the exact time of the interview.

Second, pollution data is provided by the German Federal Environment Agency (*Umweltbundesamt*). It comprises geo-coded hourly measures of ground-level concentration of multiple pollutants from several measuring stations. Our measure for air pollution is the hourly concentration of particulate matter with particles smaller than ten micrometers (μm) in ambient air (PM_{10}). Particulate matter is a mixture of solid and liquid particles with different compositions that vary in size, which are mainly generated by construction, combustion or traffic. In addition, we merge ozone (O_3) levels which emerge from photochemical reactions of nitrogen oxide stimulated by the sun's ultraviolet light, and can be considered a proxy for general air pollution.

Third, since weather conditions are important environmental confounders of air pollution,

[2]The survey data can be accessed via the International Data Service Center (IDSC) of the Institute of Labor Economics (IZA).

we further include a rich set of weather controls provided by the German Meteriological Service (*Deutscher Wetterdienst*). Temperature, humidity and wind speed are measured as 24-hour averages, whereas precipitation is measured as the total amount over 24 hours.

We link the survey, pollution and weather data based on the date and time of the interview and respondent's home county centroid.[3] Specifically, the pollution values are linked to the survey by calculating the inverse distance-weighted averages for the pollution and weather measures across all monitoring stations within a 30km radius from the centroid of the participants' county of residence (similar to Bellani et al., 2024; Hoffmann and Rud, 2024).[4]

For the purpose of the study, we impose the following restrictions to the dataset. We focus on the first interview wave of the IZA Evaluation Dataset Survey because most respondents were still unemployed at this time (and hence reporting a reservation wage). We then restrict the analysis to individuals still being unemployed and actively searching for employment at the time of the interview, as only those received the questions on job search behaviour. This leaves us with an sample comprising 9,144 individuals who reported their reservation wage. Next, we link the survey data with the weather and pollution measures and exclude observations with missing information on our control variables. Lastly, we exclude outliers with reservation wages above 25 euro/hour, corresponding to 0.3% of our sample.[5] The final estimation dataset comprises 7,254 individuals for whom we can analyse the effect of air pollution on their reservation wage.

Table 1 reports the descriptive statistics of the main variables in the dataset. We have a balanced sample of men and women who were, on average, 35 years old at entry into unemployment. The individuals in our sample were on average unemployed for 63 days before their first interview and the majority experienced a previous unemployment spell and receive unemployment benefits. Furthermore, we observe substantial variation in their reported hourly reservation wage during the interview as well as their search intensity, which is measured as the average number of applications sent per day since entry into unemployment. Finally, the descriptive statistics on the ambient concentrations of PM_{10}[6] and O_3 indicate a strong variation in air pollution exposure which we exploit in our empirical analysis.

[3] We link the survey response to pollution and weather data based on county level, because the IZA Evaluation Dataset Survey only provides information on the place of residence of the respondents at the county level.

[4] We test the sensitivity of our results to this radius by estimating our main specification using the pollution and weather measures taken within a radius of 20km from the county centroid which confirms the validity of our main results (see Figure A.1 in the Appendix).

[5] A net reservation wage of 25 euro/hour corresponds to a monthly net wage of approximately 4500 euro.

[6] Figure A.2 in the Appendix presents the full distribution of the mean concentrations of PM_{10} the last 24 hours before the interview and the hourly reservation wage.

Table 1: Descriptive statistics

	Mean	SD	Min	Max	N
Panel A: IZA Evaluation Dataset					
Reservation Wage[a]					
Hourly Reservation Wage	7.26	2.70	0.01	24.93	7,254
Potential Mechanisms[a]					
Patience[b]	6.08	2.40	0	10	3,033
Risk Tolerance[b]	5.37	2.33	0	10	3,036
Search Intensity[c]	0.32	0.42	0.01	10	7,713
Individual characteristics[d]					
Age	35.35	10.45	17	55	7,254
Female	0.50	0.50	0	1	7,254
Vocational education	0.61	0.49	0	1	7,254
Higher education	0.17	0.38	0	1	7,254
With partner	0.69	0.46	0	1	7,254
Children in household	0.31	0.46	0	1	7,254
Migration background	0.23	0.42	0	1	7,254
Previous unemployment spell[e]	0.68	0.46	0	1	7,142
Previous employment full time[e]	0.65	0.48	0	1	7,180
Last income (in euro)[e]	1,075.06	858.89	0	23,000.00	7,051
Unemployment benefit recipient[e]	0.80	0.40	0	1	7,211
Days of unemployment	63.43	26.29	25	150	7,254
Panel B: Environmental Data					
Air Pollution indicators					
PM_{10} 24h. average before interview (in $\mu g/m^3$)	25.05	12.29	1.46	113.59	7,254
O_3 24h. average before interview (in $\mu g/m^3$)	41.86	22.75	0.85	141.52	7,254
Average PM_{10} since unempl. (in $\mu g/m^3$)	24.68	4.90	5.25	45.08	7,713
Average O_3 since unempl. (in $\mu g/m^3$)	43.72	16.70	9.97	97.91	7,713
Weather indicators					
Temperature 24h. average before interview (in °C)	9.95	6.25	-13.57	25.19	7,254
Humidity 24h. average before interview (in %)	76.95	10.76	34.05	100	7,254
Wind speed 24h. average before interview (in m/s)	3.65	1.71	0.10	15.01	7,254
Precipitation 24h. before interview (in mm/m^2)	2.23	4.71	0	73.28	7,254
Panel C: Regional Characteristics[f]					
Unemployment Rate (in %)	10.10	3.64	3	17	7,254
Vacancy Rate (in %)	10.43	6.37	2	24	7,254
Urban Area	0.85	0.36	0	1	7,254
GDP per Capita	32.76	14.21	14.00	93.20	7,254

Notes: This table displays the descriptive statistics for the estimation sample with the reservation wage as its dependant variable. Pollution and weather measurements are computed based on a radius of 30km.
[a] The exact questions for the reservation wage and potential mechanisms are described in Section A.3 in the Appendix.
[b] Patience and risk tolerance are measured on a scale from 0 (very impatient/risk averse) to 10 (very patient/risk tolerant).
[c] Search intensity is measured by the average daily number of applications sent since unemployment entry.
[d] Individual characteristics are measured at time of the interview.
[e] Some individuals did not report information about previous unemployment spells, previous job being full time, last income and unemployment benefits. An additional category is created for these missing observations to keep these approximately 400 observations in our sample. Our results are robust to leaving these observations out.
[f] Regional characteristics are measured as a yearly average during the year of unemployment entry.

3.2 Study Design and Identification Strategy

Our goal is to estimate the causal effect of ambient PM_{10} pollution at the residence of the job seeker on the reservation wage of unemployed job seekers as reported during the interview. Therefore, we need to accurately link the reported reservation wages to PM_{10} concentrations that unemployed job seekers were exposed to just before the interview. The interviewed job seekers were asked to report their marginal minimum monthly wage for which they would be willing to work as well as the number of hours per week they think they would have to work for this wage (see Section A.3 in the Appendix for the exact survey questions). Based on this information, we constructed the hourly reservation wage for each respondent at the time of the interview. In addition, we observe the exact starting time of the interview, allowing us to accurately match the reported reservation wage to the air pollution concentration measured in the county of residence just before the interview took place.

Figure 1 illustrates how the reported reservation wage is linked to the pollution and weather indicators. We match the observed average of PM_{10} concentrations 24 hours before the interview with the reported reservation wage to allow for a potential lagged effect of PM_{10} pollution (as found by e.g. Künn et al., 2023; Bellani et al., 2024). In this example, Individual A is interviewed on October 24, 2007, at 10:00 AM. Thus, we match the calculated average concentration of PM_{10} pollution from October 23 at 10:00AM to 10:00 AM at October 24 to the reported reservation wage. The same procedure is applied to the weather controls using a weighted average of the daily values.

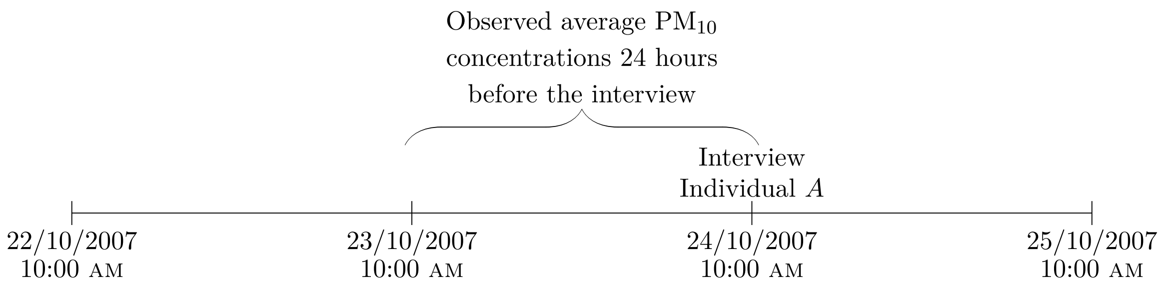


Figure 1: Study design

Applying this study design, we can identify a causal effect of PM_{10} pollution on the reported reservation wage under the assumption that individuals' exposure to PM_{10} pollution levels is as good as random. We argue that this assumption is likely to hold in our setting because of the way how the interviews were collected. First, the interviewed job seekers are resident in different counties in Germany which are all subject to different levels of air pollution. This allows us to exploit spatial variation in the exposure to PM_{10} pollution across counties around the time of the interview. Next to the spatial variation in PM_{10} levels, we also exploit temporal variations in PM_{10} concentrations within counties, because interviews took place over one entire calendar year.

Second, and most importantly, respondents had no perfect control over the exact timing of the interview. Between June 2007 and May 2008, the interview company received every month a randomly drawn pool of addresses of individuals entering unemployment in the month before. Those potential respondents were then notified by a generic letter that they have been selected for an interview and will be contacted within the next weeks. The interview company contacted the participants in a random order without further notice (beyond this generic announcement letter). Hence, the participants could not influence the timing of the interview. Individuals who did not answer their phone were returned to the pool of potential subjects and contacted again at another random point in time. Individuals who answered but were not available for the interview at that moment in time, had the option to reschedule the call to a different date and time. This would violate our identification if respondents did select their interview time based on air pollution concentrations. We show in Section 4.1.3 below that restricting the sample to individuals without a fixed appointment does not lead to any significant changes of the results, confirming the assumption that the timing of interviews can be considered to be random. In sum, the randomness of the timing of the interview ensures a random exposure to PM_{10} concentrations during the interview within their county of residence.

3.3 Regression Model

To exploit the spatial and temporal variation in PM_{10} concentrations, we follow a fixed effects strategy and estimate the following regression model,

$$RW_{ijt} = \alpha + \beta PM_{10_{jt}} + \delta X_{ijt} + \gamma_{ijt} + \mu W_{jt} + \nu R_{jt} + \eta_j + \epsilon_{ijt}, \tag{1}$$

where the dependent variable, RW_{ijt}, is the hourly reservation wage of individual i in county j at interview time t measured in natural logarithms. We measure our variable of interest, $\mathrm{PM}_{10_{jt}}$, as a linear function of mean PM_{10} concentrations 24 hours before the interview. The vector X_{it} controls for individual (labour market) characteristics and R_{jt} contains regional control variables (GDP, urban area, unemployment and vacancy rate). In addition, we control for weather and environmental conditions, W_{jt}, which are shown to influence both PM_{10} concentrations and individual behaviour. We further include month and hour-by-day fixed effects γ_{it} as well as county fixed effects, η_j. The standard errors are clustered at the county level, ϵ_{ijt}. Moreover, we weight the regression by the number of active PM_{10} monitors at the hour of the interview within the 30km radius of the county centroid to reduce measurement error.

The relationship between the reservation wage and exposure to PM_{10} concentrations is measured by β, our parameter of interest. In this analysis, we exploit the exogenous variation in the respondents' exposure to particulate matter up to 24 hours before the interview took place.

Hence, our main identifying assumption is that concentrations of PM_{10} are randomly assigned to the individuals conditional on the included control variables and fixed effects.

A challenge to our identification strategy are potentially remaining unobserved confounding factors, such as local economic activity, which could be correlated with both the level of air pollution exposure and the reservation wage of job seekers. We address this concern by including county fixed effects as well as time-varying economic indicators in the regression model. In addition, we run a falsification test showing regression estimates of PM_{10} concentrations around the hour of the interview (see Section 4.1.1). The underlying assumption is that the levels of air pollution after the interview should not affect respondents' answers. In addition, we instrument for PM_{10} concentrations with the variation in wind speed at the day of the interview to further test the robustness of our estimates to potential confounding factors (see Section 4.1.2). The falsification test as well as the IV estimation confirm the validity of our identification strategy.

4 The Impact of Air Pollution on Reservation Wages

Table 2 presents the main results showing the effect of exposure to PM_{10} on the reservation wages of unemployed job seekers. Column (1) shows the effect using a specification including individual controls only. We then subsequently add environmental controls, regional characteristics as well as time and county fixed effects.

Table 2: Effect of PM_{10} on the reservation wage

	(1)	(2)	(3)	(4)	(5)
PM_{10} (in $\mu g/m^3$)	-0.0012**	-0.0014***	-0.0015***	-0.0009**	-0.0010**
	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0004)
Observations	7,700	7,268	7,257	7,257	7,254
Adjusted R-squared	0.3060	0.3041	0.3165	0.3305	0.3271
Individual characteristics	YES	YES	YES	YES	YES
Environmental controls	NO	YES	YES	YES	YES
Month FE	NO	NO	YES	YES	YES
Hour-by-day FE	NO	NO	YES	YES	YES
Regional characteristics	NO	NO	NO	YES	YES
County FE	NO	NO	NO	NO	YES

Notes: Dependent variable: log of hourly reservation wage. Standard errors clustered on county level in parentheses. */**/*** indicate statistical significance at the 10%/5%/1% levels. Individual characteristics: age, female, education level, with partner, children in household, migration background, previous unemployment spell, previous employment full time, last income, unemployment benefit recipient, days of unemployment. Environmental controls: O_3, temperature, humidity, wind speed, precipitation. Regional characteristics: unemployment rate, vacancy rate, urban area, GDP per capita.

It can be seen that the estimated coefficient is very robust to the inclusion of additional controls. The results of our preferred specification in column (5) show that a 12 $\mu g/m^3$ increase in PM_{10}, one SD, results in a 1.2% reduction of the reservation wage, corresponding to 0.034 SDs in the reservation wage. Therefore, the effect size is comparable to existing estimates on the impact of individuals' wealth (1.2%) and personality (1.3%) on the reservation wage (Bloemen and Stancanelli, 2001; Caliendo et al., 2015).

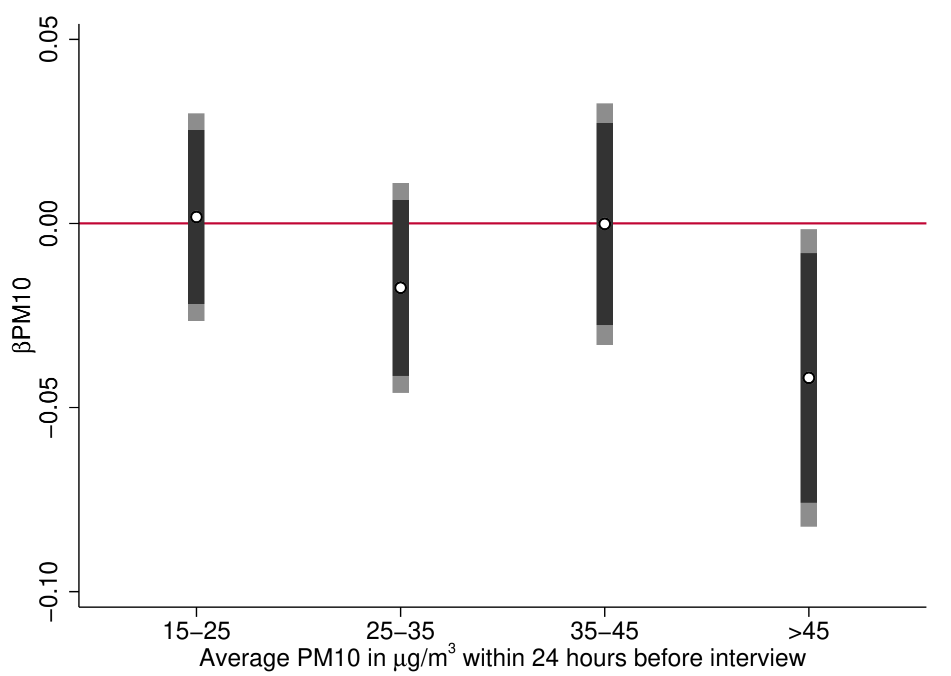
In a next step, we deviate from the linearity assumption in the regression model above and investigate whether higher levels of PM_{10} pollution generates a relatively larger negative effect on the reservation wage compared to lower levels of air pollution. The non-linearity of the effect of air pollution has been shown with respect to several outcomes, including productivity, labour supply and cognitive performance (see e.g. Chang et al., 2016; Ebenstein et al., 2016; Hoffmann and Rud, 2024). Therefore, we re-estimate equation (1) replacing the linear specification of PM_{10} with a step-wise linear function of PM_{10}. Specifically, we create different categories for every 10 $\mu g/m^3$ of PM_{10}, with concentrations below 15 $\mu g/m^3$ as the reference category and concentrations above 45 $\mu g/m^3$ as the highest category.

Figure 2 presents the estimated coefficient $\hat{\beta}$ showing the relationship between the exposure to the different categories of PM_{10} and the hourly reservation wage. We indeed find the effect of PM_{10} to be nonlinear. In particular, it can be seen that the effect is mainly driven by observations being exposed to PM_{10} concentrations above 45 $\mu g/m^3$, indicating a reduction in the hourly reservation wage of approximately 4.2%, compared to the reference category.

4.1 Validation of Identifying Assumptions

As discussed in the previous section, our identification strategy faces some challenges because of the absence of an experimental setting. Although we control for county fixed effects as well as local economic conditions in our main specification, there might be still a concern that remaining unobserved confounding factors bias the results. To mitigate such concerns, we run a falsification test showing regression estimates of lag and lead values of PM_{10} around the hour of the interview and we instrument for PM_{10} concentrations with the variation in wind speed at the day of the interview. A detailed explanation and the results are shown in Section 4.1.1 and 4.1.2, respectively. A final concern with our identification strategy addresses the timing of the interview. As explained, respondents were contacted at a random day and time. However, in case respondents answer the call but were unable to conduct the interview at that particular moment, they were allowed to reschedule the call to a later day or time. This option could theoretically make the treatment endogenous. Therefore, we re-estimate the results based on a restricted sample including only individuals without a fixed appointment in Section 4.1.3.

Figure 2: Nonlinear effect of PM_{10} on the reservation wage



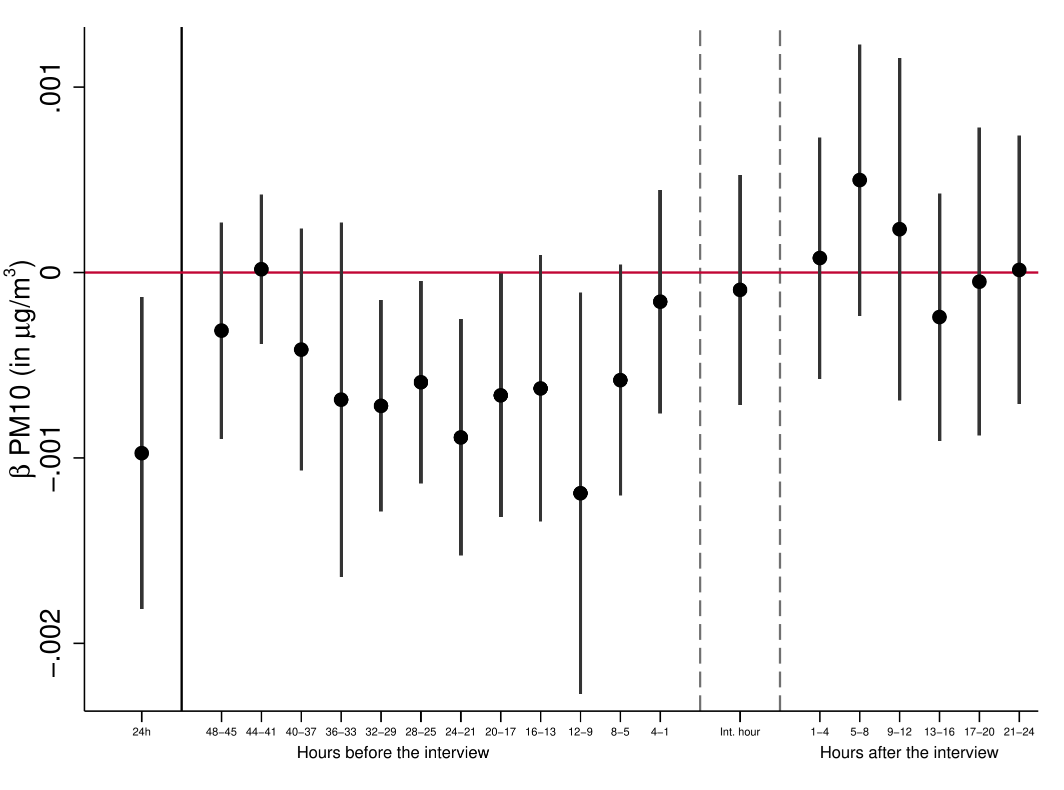
Note: Dependent variable: log of hourly reservation wage. Reference group: Days with PM_{10} pollution below 15 $\mu g/m^3$. Dots represent point estimates. Black (gray) bars show the 90% (95%) confidence intervals calculated based on standard errors clustered at the state level. All regressions include the full set of fixed effects and control variables. The total number of observations is 7254: baseline category (N=1757), 15-25 $\mu g/m^3$ (N=2872), 25-35 $\mu g/m^3$ (N=1606), 35-45 $\mu g/m^3$ (N=613), >45 $\mu g/m^3$ (N=406).

4.1.1 Lag and Lead PM_{10} values

We conduct a falsification test by examining the effect of PM_{10} concentrations occurring after the interview took place to show that our results are not driven by remaining confounding factors. We estimate a modified version of equation (1), varying the time of measurement of PM_{10} concentrations from 48 hours before the interview to 24 hours after the interview in intervals of 4 hours. The coefficients displayed in Figure 3 are the result of separate regressions, where the estimated coefficient on the very left (24h) corresponds to the estimate of PM_{10} in column (5) of Table 2.

The underlying idea is that PM_{10} concentrations before the interview affect the reported reservation wage, whereas future concentrations of PM_{10} should not affect the answers given during the interview. Indeed, we find that PM_{10} concentrations between 5 and 32 hours before the interview negatively affect the reservation wage, indicating a lagged effect of PM_{10} on the reservation wage. This lagged effect has also been shown in several studies evaluating the effect of air pollution on cognitive performance and decision making (see e.g. Künn et al., 2023; Bellani et al., 2024). Moreover, we find no evidence of a relationship between PM_{10} concentrations measured after the interview and the reported reservation wage. The absence of an effect

Figure 3: Lagged and lead values of PM_{10}



Note: Dependent variable: log of hourly reservation wage. The graph shows the estimated coefficient of separate regressions with a 95% confidence interval based on the clustered standard errors.

for lead PM_{10} concentrations strongly supports that our results are not driven by unobserved confounding factors.

4.1.2 IV Estimation

In addition to the sensitivity test presented above, we perform an instrumental variable analysis to further assess the robustness of our results. Although we include a rich set of control variables, our estimates might still be biased by confounding factors that simultaneously affect the concentrations of PM_{10} and the reservation wages of job seekers, such as the level of economic activity in the different regions. Similar to Hoffmann and Rud (2024), we address this concern more generally and perform an instrumental variable estimation exploiting the variation in wind speed around the time of the interview.

The instrument has to fulfil two main conditions in order to identify a causal effect. First, the instrument should be sufficiently correlated with concentrations of PM_{10}. The intuition behind this instrument is that wind speed transports PM_{10} emissions across space affecting the level of ground air pollution in a given location. In general, higher wind speeds would result in a greater dispersion of air pollutants, thereby reducing the concentration of PM_{10} in that area. In contrast, low wind speeds are correlated with higher concentrations of PM_{10}. Consistently, we do find a strong first stage, i.e., wind speed impacts PM_{10} measurements negatively, see Table 3.

Second, the instrument has to fulfill the exclusion restriction requiring that the instrument has no direct impact on the outcome variable, but only through its effect on PM_{10} concentrations. We argue that this condition holds because we only observe very low to modest wind speeds. Figure A.5 in the Appendix shows the exact distribution of wind speed in our sample.[7] It can be seen that the vast majority of observations experienced only a light breeze at the day of the interview. While high wind speeds, causing storms, might influence individuals' mood and behaviour, it is very unlikely that the observed levels of wind speed in our sample have a direct effect on the reservation wages of individuals.

Assuming the validity of the instrument, we estimate the effect of PM_{10} pollution on reservation wages using a two stage OLS estimation. In the first stage, we regress our treatment variable PM_{10} on the instrument:

$$PM_{10_{jt}} = \theta SPEED_{jt} + \phi X_{ijt} + \tau_{it} + \psi W_{jt} + \zeta R_{jt} + \upsilon_j + \xi_{jt}, \tag{2}$$

where PM_{10_j} pollution is measured as the average PM_{10} concentration 24 hours before the interview. Consistently, our instrument $SPEED_j$ is measured as a weighted average of the hourly wind speed during the last 24 hours before the interview. We further include individual (labour market) characteristics, X_{ijt}, the timing of the interview, τ_{it}, environmental, W_{jt}, and regional characteristics, R_{jt} as well as county fixed effects υ_j. The second stage estimation is identical to Equation 1 with the exception that $PM_{10_{jt}}$ is replaced by the predicted values $\widehat{PM}_{10_{jt}}$ resulting from the first stage.

Table 3 presents the results of the IV estimation. In column (1), we show the first-stage estimate. We find that wind speed significantly impacts PM_{10} concentrations, where higher wind speeds lead to lower concentration of PM_{10}. Moreover, the first stage F-statistic is 645.4, indicating that our instrument is sufficiently strong. The second stage estimation of the parameter of interest shows a clear negative effect of exposure to PM_{10} concentrations on the reservation wage (column 2). The result implies that an increase in PM_{10} exposure of 12 $\mu g/m^3$, one SD, leads to a 4% reduction in the reservation wage.[8] Therefore, the IV estimation underlines the existence of a negative impact of PM_{10} exposure on the reservation wages of unemployed job seekers.

[7] See https://www.dwd.de/DE/service/lexikon/Functions/glossar.html?lv2=100310&lv3=100390 for more information about the classification of wind speeds following the Beaufort scale.

[8] We find similar results when restricting our analysis to individuals who were interviewed at a day with a maximum wind speed below 5.5 m/s, which is classified as a moderate breeze on the Beaufort scale. Results using this restricted sample are shown in Table A.1 in the Appendix.

Table 3: PM_{10} pollution and the reservation wage: IV estimation

	(1) First stage	(2) Second stage
Wind speed (in m/s)	-2.4765***	
	(0.0975)	
PM_{10} (in $\mu g/m^3$)		-0.0033***
		(0.0013)
Observations	7221	7221
First stage F-stat	645.4	
Environmental controls	X	X
Month of year	X	X
Day of week	X	X
Hour of day	X	X
Individual characteristics	X	X
Regional characteristics	X	X
County FE	X	X

Note: Dependent variable: column (1) PM_{10} and column (2) log of reservation wage. Standard errors clustered on county level in parentheses. */**/*** indicate statistical significance at the 10%/5%/1% levels.

4.1.3 Appointments

Our main identifying assumption is based on the random timing of the interview. The individuals in our sample are randomly drawn out of a pool of available addresses and called for an interview. Moreover, our subjects could not influence the timing of the interview. Yet, some individuals who answered the phone were not available for the interview at the time of the call. They were allowed to reschedule the interview to a different date and time, which threatens the validity of our main identifying assumption because individuals could have selected their interview time based on expected air pollution concentrations. Therefore, we test the sensitivity of our estimates to the quasi-randomness of the call by restricting our sample to individuals that made no (clear) appointment. Examples of unclear appointments are calling back during the evening or at a particular day of the week without specifying the exact date or time. Hence, the timing of their interviews could still be regarded as quasi-random.

Figure A.4 in the Appendix presents the results. The different sample specifications follow the same pattern, showing a significant negative effect of PM_{10} concentrations before the interview on the reported reservation wage. This indicates that our results presented in section 4 are not driven by individuals who made an appointment for the interview. Hence, the interview participants did not select their interview time based on potential air pollution concentrations, supporting our assumption of the as good as random exposure to PM_{10} concentration during the interview.

4.2 Replication based on the Socio-Economic Panel

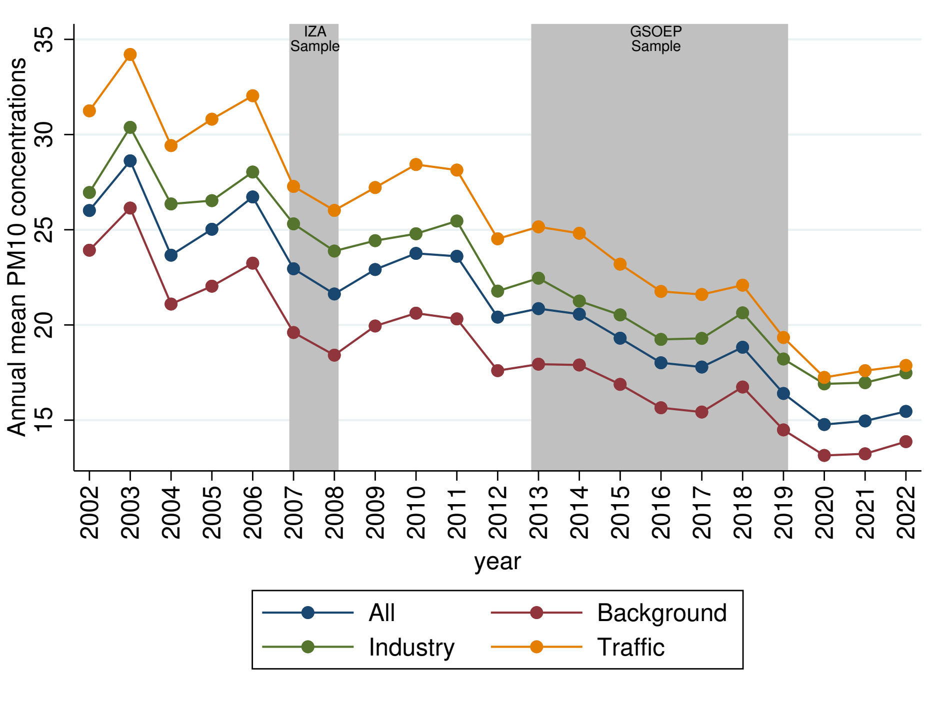
Finally, we run a replication study based on a different sample, overlapping a much larger time window, to show the strong external validity of our findings. The main analysis uses data (*IZA Evaluation Dataset*) on unemployed job seekers in the years 2007 and 2008. While using these data has clear advantages (quasi-randomness of interview timing and detailed information on job search strategy), it might raise concerns about how representative the results for 2007/2008 are for more recent years. This is because governments have implemented several measures to reduce ambient air pollution during the last decades. As a results, Figure 4 shows that PM_{10} pollution constantly decreased over time, with an average reduction of about 30% since 2007. This development might raise doubts about the validity of our results. Therefore, we complement our results based on the *IZA Evaluation Dataset* using a more recent sample (2013-2017) of job seekers drawn from the *German Socio-Economic Panel* (SOEP) (see Figure 4). In addition to assessing the external validity of our results with respect to the restricted time frame, this exercise will also help to more generally evaluate to what degree our results are specific and only detectable in our main sample or whether it is a rather general effect which also holds in a different sample and period.

The SOEP is a long-running representative German household survey (see Goebel et al., 2019, for details on the SOEP). Every year, households are interviewed about a wide range of topics, including their labour market histories and job search behaviour. Most importantly for our purpose, the SOEP contains information on the exact timing of the interview and measures the reservation wage of unemployed job seekers in a very similar way as it is measured in the *IZA Evaluation Dataset*.[9] Hence, we can apply the same estimation strategy as before, which allows for a reliable comparison of the estimated effect in both samples.

We construct the estimation sample based on the SOEP data as follows. First, we restrict our analysis to the years 2013-2020, for which we observe the hour of the interview to exploit a similar identification strategy to our main analysis. In addition, we drop all individuals interviewed in 2020, because the COVID-19 pandemic might bias our results through its potential effects on air quality, the labour market and individual preferences. Second, we restrict the analysis to individuals being unemployed at the time of the interview. In addition, we drop reservation wages above 25 Euro/hour, corresponding to approximately 2% of our sample. Next, we link the survey with the weather and pollution measures based on the county centroid of individuals' residence and the hour of the interview in order to be consistent with the analysis using the

[9] In both surveys, the respondents were asked to report the minimum income or wage for which they would be willing to accept a position as well as the hours they would have to work for this income (see A.3 in the Appendix). The similarity in questions allows for a reliable comparison between samples.

Figure 4: PM_{10} concentrations over time



Note: This graph displays the yearly average concentrations of air pollution over time using data from the German Federal Environment Agency (*Umweltbundesamt*).

IZA Evaluation Dataset. Finally, we exclude observations with missing information on any of our control variables. The final SOEP dataset comprises 6,355 observations.[10]

Similarly to the *IZA Evaluation Dataset*, the interviewed job seekers are resident in different counties in Germany which are all subject to different pollution levels. This enables us to exploit spatial variation in PM_{10} concentrations around the time of the interview. Next to this, we exploit the variation in PM_{10} concentrations across the different interview dates. Households receive a letter at the beginning of a survey year, announcing that their interviewer will call them in a few days for making an appointment. This appointment could be made for the next day or for a date in a couple of months. We assume that these appointments are made without prior knowledge on the levels of air pollution on the agreed date.[11] The exposure to PM_{10} concentrations before and during the interview is therefore assumed to be as good as random, which is a key identifying assumption.

We then estimate equation (1) using the SOEP sample. Table 4 shows the results. Again, the estimates are very robust to the inclusion of additional controls and fixed effects, as shown in columns (1) to (5). Moreover, the estimated effect is negative, statistically significant and very similar in magnitude as compared to the estimated effect based on the *IZA Evaluation Dataset* sample (column 6). We consider this striking similarity between the estimates of both samples

[10] The descriptive statistics are reported in Table A.2 of the Appendix.

[11] The strong robustness of our estimates in the main analysis to prior interview appointments (Section 4.1.3) makes us confident that the timing of appointments are not endogenously selected.

as strong evidence of a negative effect of PM_{10} pollution on the reported reservation wage of unemployed job seekers.

Table 4: Effect of PM_{10} on the reservation wage (II)

	SOEP					IZA ED
	(1)	(2)	(3)	(4)	(5)	(6)
PM_{10} (in $\mu g/m^3$)	-0.0014***	-0.0018***	-0.0012**	-0.0012**	-0.0009*	-0.0010**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.0004)
Observations	6523	6405	6385	6385	6355	7254
Adjusted R-squared	0.0995	0.0992	0.1463	0.1545	0.1719	0.3271
Individual characteristics	YES	YES	YES	YES	YES	YES
Environmental controls	NO	YES	YES	YES	YES	YES
Month FE	NO	NO	YES	YES	YES	YES
Hour-by-day FE	NO	NO	YES	YES	YES	YES
Regional characteristics	NO	NO	NO	YES	YES	YES
County FE	NO	NO	NO	NO	YES	YES

Notes: Dependent variable: log of hourly reservation wage. Standard errors clustered on county level in parentheses. */**/*** indicate statistical significance at the 10%/5%/1% levels.

Similar to the main analysis, we also analyse the effect of PM_{10} concentrations several hours before and after the interview to test for the presence of confounding factors. Figure 5 shows the corresponding estimates for both datasets. Again, we find a very similar pattern for both estimation samples, underlining the strong external validity of finding, which is robust across different samples and time.

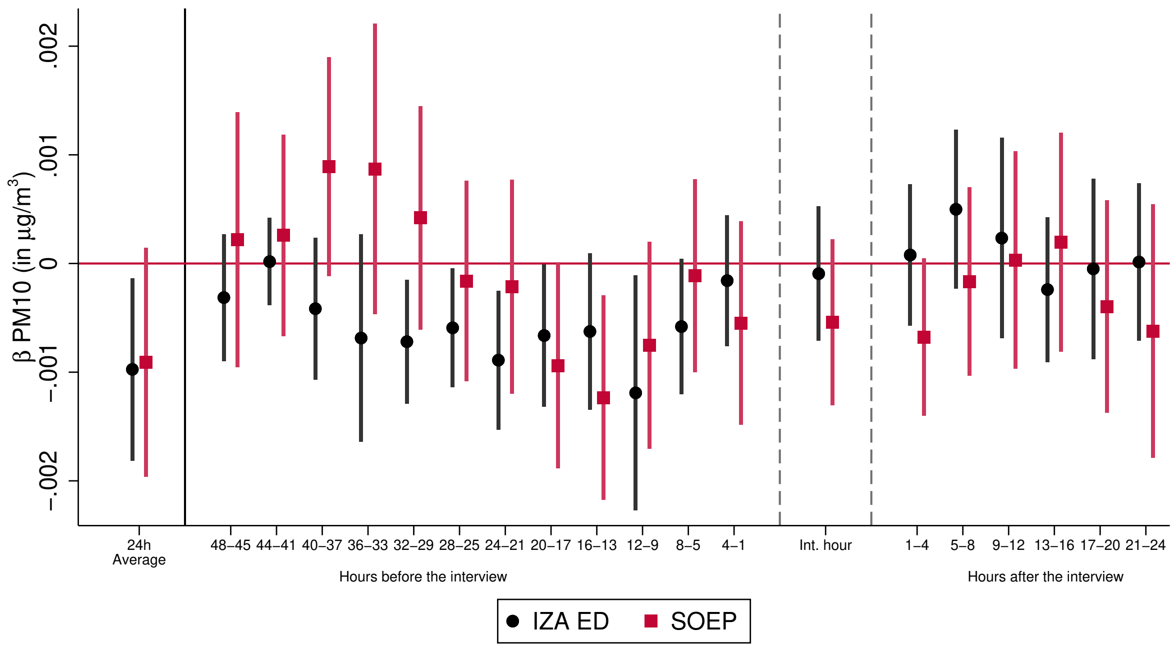
5 Mechanisms

As a last step, we aim to provide evidence on underlying mechanisms explaining the negative effect of PM_{10} pollution on the reservation wage. This helps to underline the importance of the discussed channels in the theoretical foundation in Section 2. It would be difficult to argue the negative effect of PM_{10} pollution on the reservation wage in case we would find no consistent effect of PM_{10} pollution on such mechanisms. The data allow us to investigate two potential mechanisms: individuals' preferences as well as the search effort.

5.1 Risk and Time Preferences

As discussed in Section 2, the environmental literature finds evidence that PM_{10} pollution affects individuals' risk and time preferences, while job search theory and related evidence identifies such preferences as key determinants of the reservation wage. Given the negative effect on reservation wages, we would expect a negative effect of PM_{10} pollution on risk tolerance and

Figure 5: Lagged and lead values PM_{10} using the SOEP



Note: Dependent variable: log of hourly reservation wage. The graph shows the estimated coefficient of separate regressions with a 95% confidence interval based on the clustered standard errors.

patience because, according to job search theory, more risk averse (impatient) job seekers tend to reduce their reservation wage in order to increase the probability of finding a job soon.

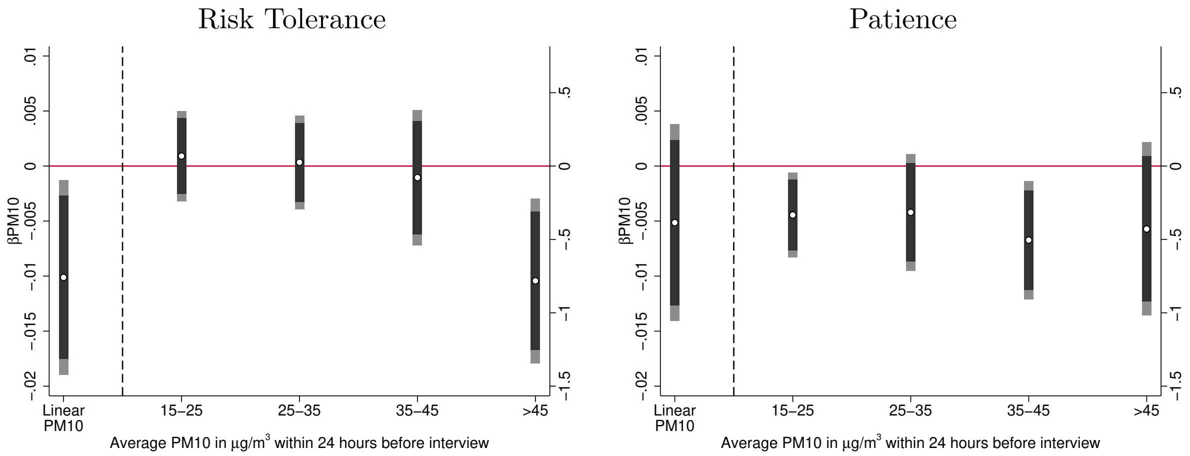
To test this hypothesis, we use two additional questions from the *IZA Evaluation Dataset Survey* that were asked to a 25% subsample of survey respondents. These individuals were asked to self-report their general willingness to take risks on a scale from 0 (not willing to take risks) to 10 (very willing to take risks), which is shown to be a good predictor of the actual risk behaviour of individuals (Dohmen et al., 2011). Similarly, the respondents were asked to grade themselves with respect to their degree of patience on a scale from 0 (very impatient) to 10 (very patient). Importantly, the respondents report their perception of their risk preference and patience at the time of interview. Hence, identical to the analysis on the reservation wage, we can accurately match the average concentrations of PM_{10} 24 hours before the interview with the reported preferences. We then estimate a modified version of equation (1) replacing the dependent variable by the reported risk tolerance and degree of patience. Moreover, we do not restrict the analysis to unemployed job seekers, but include all individuals to have sufficient statistical power because the risk and time preference questions are only asked to a 25% subsample. We add the respondents' employment status at the time of the interview as a control variable.

Figure 6 presents the corresponding results. The left panel shows the impact of PM_{10} concentrations on the reported risk preferences, where the estimate on the left shows the linear relationship and the estimates on the right of the dotted line display the step-wise linear effect. We find a significant negative effect of PM_{10} pollution on risk tolerance. This effect is driven by PM_{10} concentrations above 45 $\mu g/m^3$, indicating that individuals who are exposed to high levels of PM_{10} concentrations report themselves to be more risk averse, compared to individuals who are exposed to levels of PM_{10} below 15 $\mu g/m^3$.

The right panel displays the relationship between the exposure to PM_{10} concentrations and the reported level of patience. The overall effect on patience is negative but not statistically significant. The stepwise-linear point estimates are throughout negative and partially statistically significant. Already low concentrations of PM_{10} trigger a reduction in one's patience. Individuals who are exposed to concentrations of PM_{10} between 15-25 and 35-45 $\mu g/m^3$ report a lower level of patience than individuals exposed to level of PM_{10} below 15 $\mu g/m^3$.

Both findings are in line with previous studies showing that air pollution reduces the willingness to take risks and increases impatience (Heyes et al., 2016; Chew et al., 2021; Klingen and van Ommeren, 2020), and are in line with the expected mediation effect as discussed above. Hence, the PM_{10} induced reduction in risk tolerance and patience could serve as a potential mechanism for the negative effect of PM_{10} concentrations on the reservation wage.

Figure 6: Mechanisms



Note: Dots represent point estimates. Reference group: Days with PM_{10} pollution below 15 $\mu g/m^3$. Black (gray) bars show the 90% (95%) confidence intervals calculated based on standard errors clustered at the county level. The vertical axis on the left corresponds to the linear estimates, whereas the vertical axis on the right reflects the values for the step-wise linear estimates. All regressions include the full set of fixed effects and control variables. Number of observations are 3028 and 3027 for risk and patience, respectively: baseline category (N=870), 15-25 $\mu g/m^3$ (N=1247/1246), 25-35 $\mu g/m^3$ (N=582), 35-45 $\mu g/m^3$ (N=197), >45 $\mu g/m^3$ (N=132). Figure A.3 shows the distribution of PM_{10} concentrations for the estimation sample.

5.2 Search Intensity

Section 2 discusses compelling evidence that air pollution reduces individuals' productivity. Hence, job seekers are likely to search less when exposed to higher concentrations of PM_{10} pollution. A lower search intensity has a negative effect on the job offer arrival rate, which leads to a lower reservation wage. Hence, the search intensity of job seekers could serve as another potential mechanism through which air pollution affects the reservation wage.

We test this hypothesis by constructing a measure of search intensity using the average daily number of applications sent since entry into unemployment as reported by the survey respondents.[12] The measurement period since entry into unemployment does not allow for a precise match between the reported number of applications and PM_{10} concentrations the job seeker was exposed to while searching for employment opportunities, because we do not observe the exact time and date when the applications were sent. Therefore, we match PM_{10} pollution with the reported search intensity by calculating the average value of PM_{10} in the individual's county of residence since entry into unemployment.[13] This measure allows us to explore the relationship between exposure to PM_{10} concentrations and the search activity of unemployed job seekers. However, one has to be cautious with causal interpretations, because the rough measurement makes it difficult to single out the effect of air pollution on search intensity.

We re-estimate equation (1) where the dependent variable changes to the average daily number of applications sent since entry into unemployment measured in natural logarithms. Moreover, we measure our variable of interest, PM_{10_j}, both as linear and step-wise linear function of the average concentration of PM_{10} since entry into unemployment. In this case, we consider only four categories of PM_{10} with the highest category being PM_{10} concentrations above 35 $\mu g/m^3$, because we lose some variation in the upper part of the distribution of PM_{10} pollution by taking the average over a longer period of time.[14] Figure 7 shows the estimated coefficients with respect to the average number of applications sent since entry into unemployment.

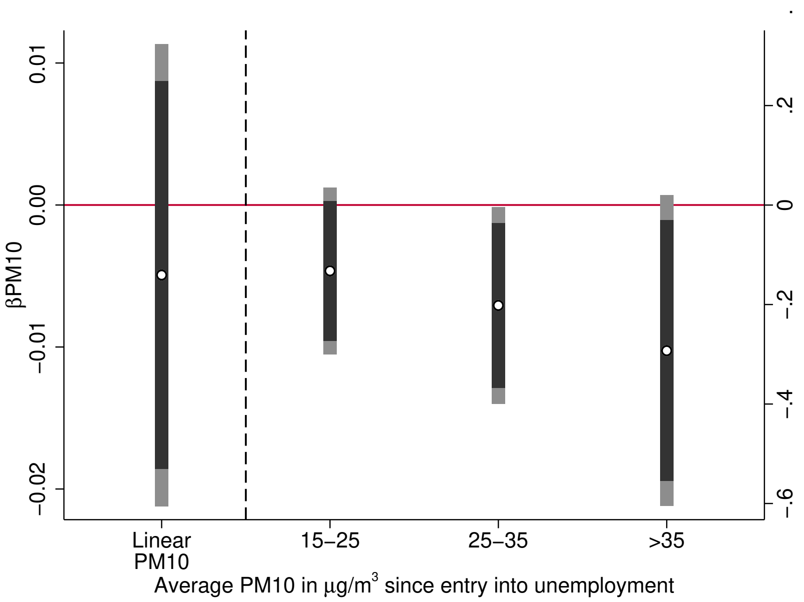
The overall effect of PM_{10} pollution on search intensity is negative but very imprecisely estimated. The linear stepwise estimations show a clear negative relationship between PM_{10} pollution and the number of applications sent, which is already statistically significant for lower concentrations of PM_{10}. The magnitude of this effect becomes more pronounced for higher concentrations of PM_{10}, where we find the largest effect for concentrations of PM_{10} above 35 $\mu g/m^3$. Specifically, exposure to concentrations of PM_{10} above 35 $\mu g/m^3$ is associated with a decrease of approximately 30% in the average daily number of applications sent, compared to the reference category. This PM_{10} induced reduction in search intensity could, therefore, serve as a mechanism for the negative effect of PM_{10} concentrations on the reservation wage.

[12] See Section A.3 in the Appendix for the exact wording of the question. We divide the reported number of applications by the days of unemployment for each individual separately, giving us the average daily number of applications sent since entry into unemployment.

[13] This matching design is illustrated in Figure A.7 in the Appendix.

[14] See Figure A.3 for the distribution of PM_{10} concentrations since entry into unemployment compared to our previous measure of average PM_{10} concentrations over the last 14 hours before the interview.

Figure 7: Search Intensity in natural logarithm



Note: Dots represent point estimates. Reference group: Days with PM_{10} pollution below 15 $\mu g/m^3$. Black (gray) bars show the 90% (95%) confidence intervals calculated based on standard errors clustered at the county level. The vertical axis on the left corresponds to the linear estimates, whereas the vertical axis on the right reflects the values for the step-wise linear estimates. All regressions include the full set of fixed effects and control variables. The total number of observations is 7713: baseline category (N=411), 15-25 $\mu g/m^3$ (N=4555), 25-35 $\mu g/m^3$ (N=2580), >35 $\mu g/m^3$ (N=167).

6 Conclusion

This paper analyses the impact of ambient air pollution (PM_{10}) on reservation wages of unemployed job seekers. Using rich survey data combined with air pollution and meteorological data, we identify a causal effect by exploiting quasi-experimental variation in PM_{10} concentrations based on the random allocation of interviews to unemployed job seekers across different German counties over time. Thereby, this study contributes to the scarce literature on the determinants of reservation wages, shedding light on a seemingly irrelevant factor affecting the job search process of individuals. In addition, we add to the existing literature on the social and economic impacts of air pollution, which so far only focused on settings outside the labour market or on the working population.

We find that exposure to elevated levels of PM_{10} pollution reduces the reservation wages of unemployed job seekers. Moreover, we find that this effect is likely to be driven by the negative impacts of PM_{10} exposure on job seekers' search effort, risk tolerance and patience.

To our knowledge, this is the first study of random shocks affecting reservation wages, illustrating how exposure to air pollution disrupts job search behaviour. These findings have important implications for policymakers aiming to inform and incentivize job seekers to find new employment promptly, as their efforts may be hindered by poor environmental conditions.

In addition, the PM_{10} induced reduction in the reservation wage is likely to have important implications for job match quality. While a lower reservation wage is expected to have a positive effect on the probability of finding employment, it could lead to individuals being pushed into lower paid jobs, causing them to become at risk of being persistently low paid. Moreover, it might increase the risk of repeated unemployment due to a lower job match quality. Future research should further investigate the effects of air pollution exposure on the job search outcomes of unemployed job seekers to enhance our understanding of the implications of air pollution for one of the most vulnerable groups in the labour market.

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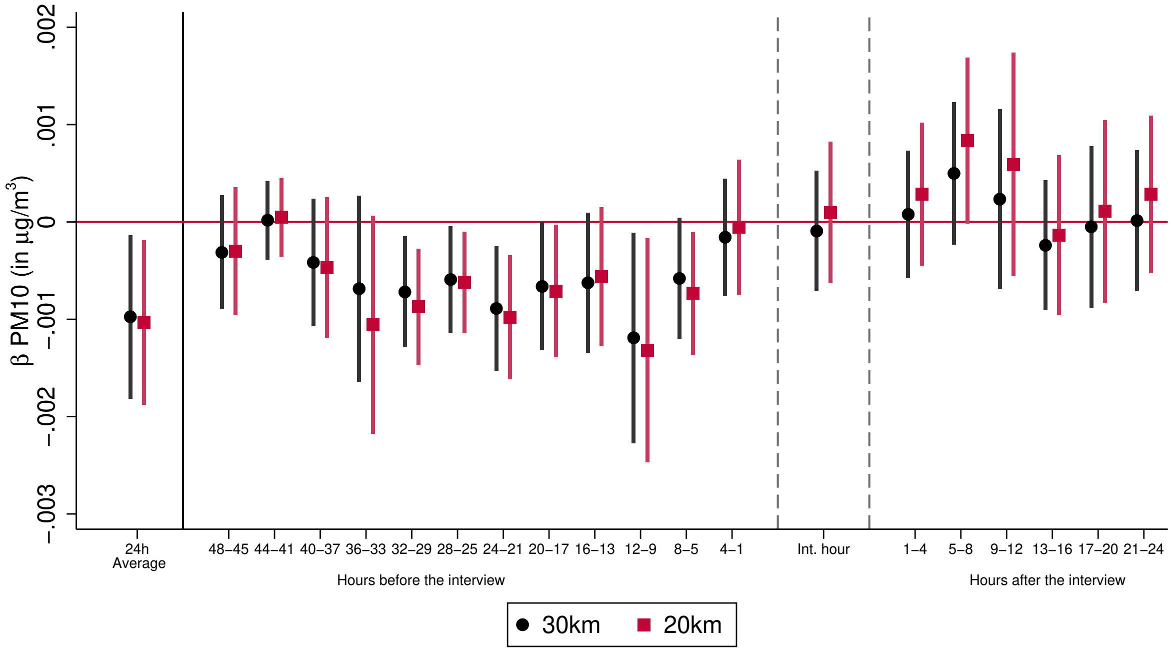
A Appendix

A.1 Robustness to distance monitors to county centroid

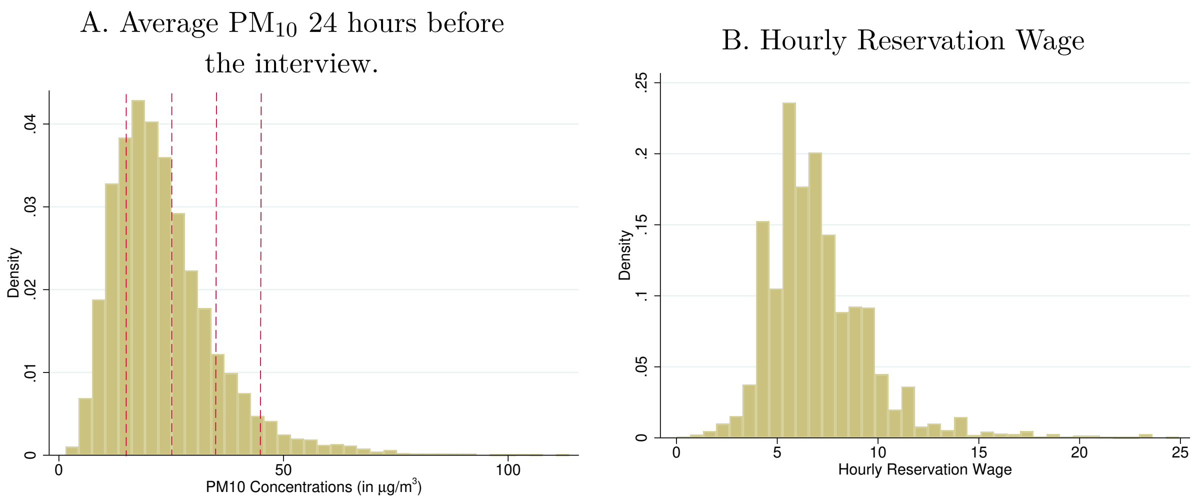
Figure A.1: Robustness distance monitors to county centroid



Note: Dependent variable: log of hourly reservation wage. The graph shows the estimated coefficient of separate regressions with a 95% confidence interval based on the clustered standard errors. N=7254 taking the 30km radius and N=5730 for the 20km radius sample.

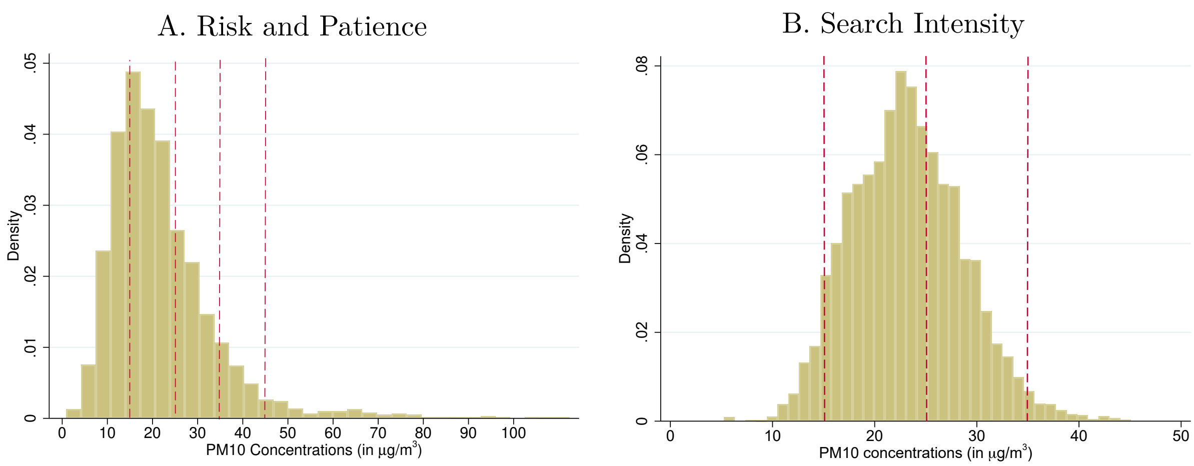
A.2 Descriptive Statistics: Distribution Graphs

Figure A.2: Distribution of mean PM_{10} concentrations and hourly reservation wage



Note: The figure shows the distribution of PM_{10} concentrations and the reservation wage in our estimation samples using the *IZA Evaluation Dataset*. The vertical red lines indicate the different categories of PM_{10} used in our analysis.

Figure A.3: Distribution of mean PM_{10} concentrations Mechanisms and Search Intensity



Note: The figure shows the distribution of PM_{10} concentrations in our estimation samples using the *IZA Evaluation Dataset*. The vertical red lines indicate the different categories of PM_{10} used in our analysis.

A.3 Survey questions

A.3.1 IZA Evaluation Dataset

The following questions regarding our dependent variables were asked in the questionnaire of wave 1 of the IZA Evaluation Dataset Survey.

Reservation Wage:

Q144: "What is the marginal minimum wage for which you would still be willing to work?"

Q145: "Given this marginal wage of (fade in from question 144) Euro/month; what do you think, how many hours per week do you have to work for this?"

We constructed our measure of the hourly reservation wage as follows. First we multiplied the hours per week the respondent expects to work by 4.35 to convert the weekly hours into monthly hours. Then we divided the reported marginal minimum monthly wage by the expected monthly working hours.

Risk Tolerance and Patience

Q320: "Are you generally willing to take risks or do you try to avoid risks? Please use the numbers from 0 to 10: 0 means that you regard yourself as not willing to take risks at all, and 10 means that you regard yourself as willing to take risks. You can gauge your evaluations with the in between values."

Q322: *"Are you a person who generally gets impatient or someone who always has a lot of patience. Please use the numbers from 0 to 10: 0 means that you regard yourself as very impatient, and 10 means that you regard yourself as very patient. You can gauge your evaluations with the in between values."*

Respondents were asked to rate their patience and risk tolerance on a scale from 0 to 10. The variables risk and patience in our main analysis kept the same format.

Search intensity

Q135: *"And how often did you apply for jobs during this time which were not offered by the Employment Agency?"*

The respondents were asked how many applications they sent since entry into unemployment ("this time"). We divided this number by their unemployment duration to construct our measure of average daily applications since entry into unemployment.

A.3.2 Socio-Economic Panel

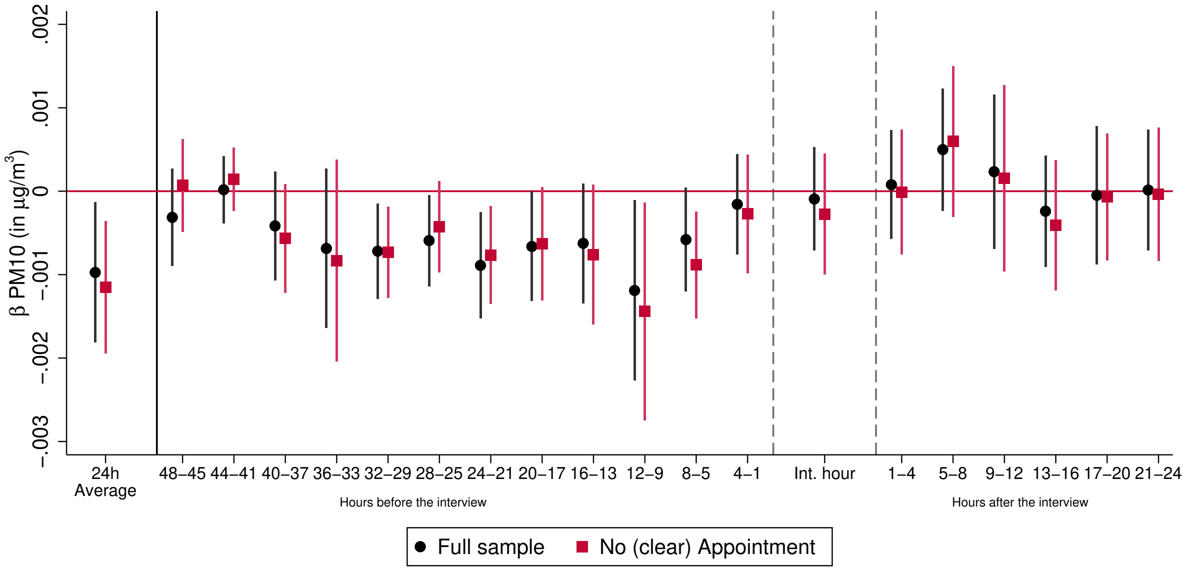
plb0420_v2: "What would your net income have to be for you to accept a position?"

plb0422: "How many hours per week would you have to work to earn this net income?"

Our measure of the hourly reservation wage is constructed in the same way as described above for the *IZA Evaluation Dataset.*

A.4 Robustness to interview appointments

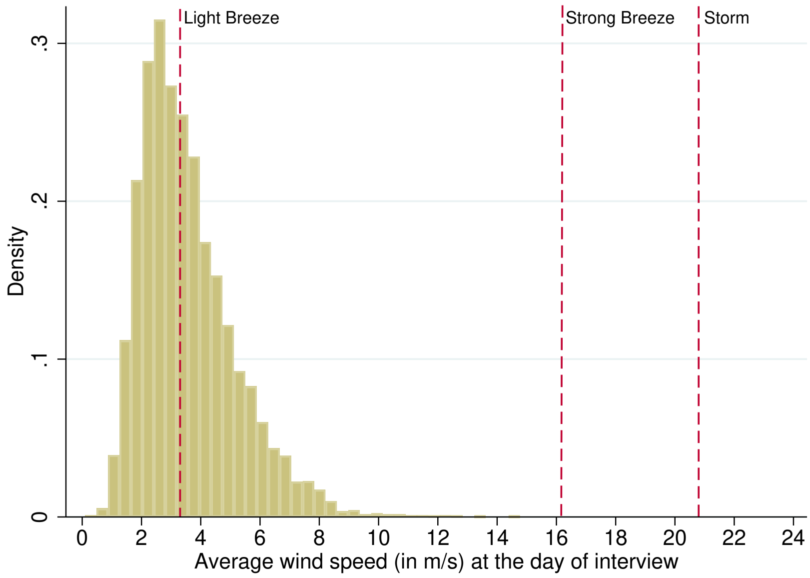
Figure A.4: Robustness to interview appointments



Note: Dependent variable: log of hourly reservation wage. The graph shows the estimated coefficient of separate regressions with a 95% confidence interval based on the clustered standard errors. N=7254 for the full sample, N=4969 for the sample including individuals with no (clear) appointment.

A.5 Wind-IV estimation

Figure A.5: Distribution wind speed (in m/s)



Note: The figure shows the distribution of wind speed in m/s of our estimation sample. The vertical red lines indicate the category of wind speed as described by the Deutscher Wetterdienst.

Table A.1: PM_{10} pollution and the reservation wage: IV estimation restricted sample

	(1) First stage	(2) Second stage
Wind speed (in m/s)	-3.3382***	
	(0.1441)	
PM_{10} (in $\mu g/m^3$)		-0.0049***
		(0.0014)
Observations	6267	6267
First stage F-stat	536.8	
Environmental controls	X	X
Month of year	X	X
Day of week	X	X
Hour of day	X	X
Individual characteristics	X	X
Regional characteristics	X	X
County FE	X	X

Notes: Dependent variable: column (1) PM_{10} and column (2) log of reservation wage. The sample is restricted to observations experiencing a wind speed below 5.5 m/s. Standard errors clustered on county level in parentheses. */**/*** indicate statistical significance at the 10%/5%/1% levels.

A.6 Descriptive Statistics SOEP

Table A.2: Descriptive Statistics SOEP sample

	(1) Mean	(2) SD	(3) Min	(4) Max	(5) N
Panel A: SOEP					
Reservation Wage [a]					
Hourly Reservation Wage	9.64	3.5	0.26	24.91	6,355
Individual Characteristics					
Age	34.83	9.82	18	55	6,355
Female	0.6	0.49	0	1	6,355
Years of Education	10.71	2.56	7	18	6,355
Married	0.48	0.5	0	1	6,355
Single	0.38	0.48	0	1	6,355
Widowed	0.01	0.11	0	1	6,355
Divorced	0.09	0.28	0	1	6,355
Separated	0.04	0.2	0	1	6,355
Children	0.66	0.47	0	1	6,355
Migration Background	0.56	0.5	0	1	6,355
Expected Employment Contract	1.72	0.78	1	4	6,355
Unemployment Benefit Recipient	0.1	0.3	0	1	6,355
Unemployment Benefit Amount	70.86	264.74	0	2,600.00	6,355
Unemployment Duration	1	0.02	0	1	6,355
Actively Searching	0.34	0.48	0	1	6,355
Panel B: Environmental Data					
Air Pollution Indicators					
Average PM_{10} 24h. before interview (in $\mu g/m^3$)	20.75	11.22	0.59	131.9	6,355
Average O_3 24h. before Interview (in $\mu g/m^3$)	49.05	21.7	0.03	144.19	6,355
Weather Indicators					
Average temperature 24h. before interview (in ^{o}C)	11.53	6.91	-11.98	29.46	6,355
Average humidity 24h. before interview (in %)	74.93	11.18	39.77	99.39	6,355
Average wind speed 24h. before interview (in m/s)	3.41	1.35	0.67	13.68	6,355
Average precipitation 24h. before interview (in mm/m^2	2.06	3.6	0	41.68	6,355
Panel C: Regional Characteristics [b]					
Regional Characteristics					
Unemployment Rate (in %)	8.2	2.77	1.29	15.12	6,355
Population Density	1,977.20	1,364.99	35.61	4,777.04	6,355
Urban area	0.91	0.29	0	1	6,355
GDP per Capita	42.11	18.75	15.75	194.7	6,355

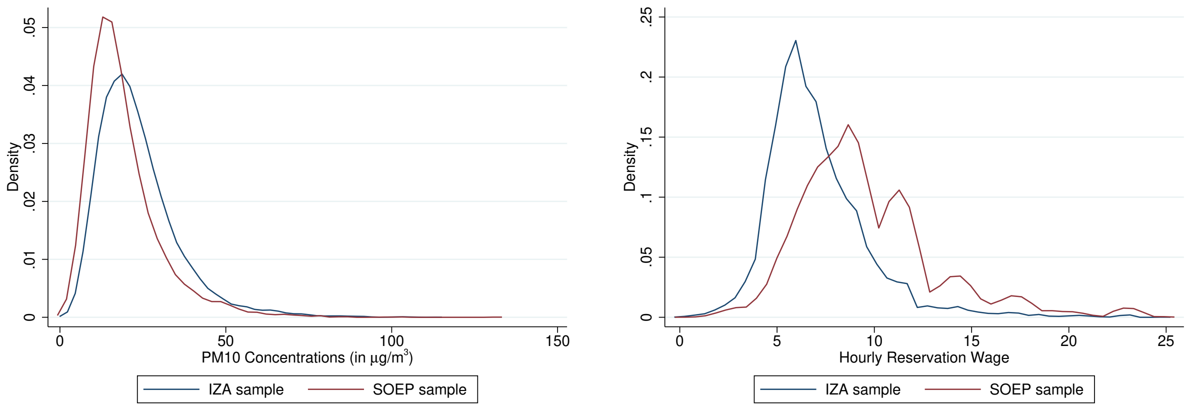
Notes: This table displays the descriptive statistics for the estimation sample based on the SOEP. Pollution and weather measurements are computed based on a radius of 30km.

[a] The exact questions for the reservation wage and potential mechanisms are described in Section A.3 in the Appendix.

[b] Regional characteristics are measured as a yearly average during the year of unemployment entry.

Figure A.6: Distribution of PM_{10} concentrations in both samples

(a) PM_{10} Concentrations (b) Hourly Reservation Wage



Note: The figure shows the distribution of PM_{10} concentrations and the hourly reservation wage in both of our estimation samples restricted to hourly reservation wages below 25 euro.

A.7 Matching design PM_{10} to reported search intensity

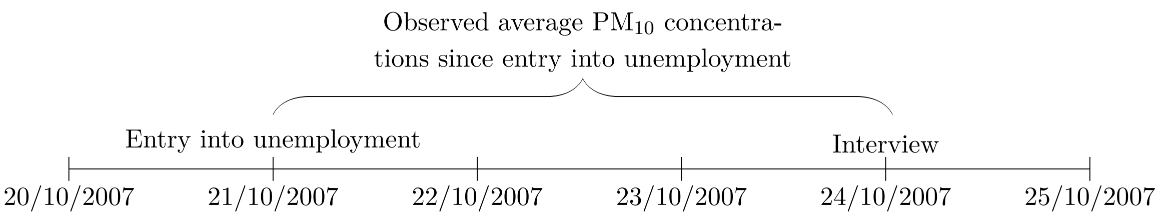


Figure A.7: Matching PM_{10} with the reported search intensity