Fresh Air Eases Work –
The Effect of Air Quality on Individual Investor Activity

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ABSTRACT

This paper shows that air quality has a significantly negative effect on the willingness of individual investors to sit down, log in, and trade in their brokerage accounts controlling for investor-, weather-, traffic-, and market-specific factors. In perspective, a one standard deviation increase in fine particulate matter leads to the same reduction in the probability of logging in and trading as a one standard deviation increase in sunshine. We document this effect for low levels of pollution that are commonly found throughout the developed world. When individual investor trading is seen as engagement in a cognitively-demanding task similar to office work, our findings suggest that the negative effects of pollution on white-collar productivity may be much more severe than previously thought. To our knowledge, this is the first study to demonstrate a negative impact of pollution on a measure of white-collar work productivity at the individual level in western countries rather than historically polluted places.

JEL classification: D14, G11, J22, J24, Q51, Q53

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1. Introduction

This paper builds on an emerging economic literature that links air pollution to a wide range of human impacts, including cognition, mood, and worker productivity (Graff Zivin and Neidell, 2012; Chang et al., 2016; Lavy et al., 2014). We show that individual investors are significantly more likely to sit down, log in, and trade in their brokerage accounts when air quality improves (in a generally high air-quality environment). This effect is comparable in magnitude to the effects of weather, i.e., incarceration due to precipitation or going out because of sunshine. This study relies on the interpretation of individual investor trading, an indoor activity that requires some skill and cognitive but no physical exertion, as a proxy for willingness and ability to engage in office work and thereby white-collar productivity. The large significant negative effect we find implies that the detrimental impact of pollution on workplace performance may be far more widespread than previously believed.

A handful of recent papers are closely related to our study. First, Chang et al (2016) show that pollution affects call-center worker productivity, building on previous studies showing that pollution affects productivity in physically arduous jobs (Graff Zivin and Neidell, 2012; Chang et al., 2014). Second, Heyes et al. (2016) provide empirical evidence of a relationship between air pollution and financial markets, linking short-term variations in fine particulate matter in New York City to movements in the S&P 500. Furthermore, Lavy, Ebenstein, and Roth (2014) show that air pollution is significantly negatively correlated with student exam performance in Israeli high school exit exams and Archsmith, Heyes, and Saberian (2016) find evidence that short-term exposure to air pollution is negatively associated with the work performance of a sample of professional baseball umpires whose jobs are brain-intensive and quality-focused. Additionally, Huang et al. (2016) analyze individual investors from 28 cities in China and find a negative relation between air pollution and portfolio performance.

Relative to all these previous empirical studies, we analyze behavior and pollution at the individual and much more disaggregated level by using individuals' zip code location and the nearest of 1600 air, weather, and traffic stations. Beyond providing evidence at the individual level, we look at a western economy, where the service and knowledge sectors account for most of the economic output, but in which the low levels of air pollution are not commonly seen as a problem. This allows us to generalize our findings to all over Europe and North America.

To investigate the effect of air quality on individual investors, we use a unique panel dataset on the daily trading of private investors in Germany. This approach has three advantages. First, we precisely measure each trader's daily activity (Bloom et al., 2014) by his log in and trading behavior. Second, air quality measures such as particulate matter (PM) pollution easily penetrate indoors (Thatcher and Layton, 1995; Vette et al., 2001) and feature considerable variation across Germany. Exposure could impair trading activity through changes in cardiovascular and lung functioning (Seaton et al., 1995), irritation of the ear, nose, throat, and lungs (Pope, 2000), as well as through direct impact on cognitive performance (Lavy et al., 2014). Third, we use a fixed-effects approach to compare the same individuals in the same place at the same time in the presence of different levels of air quality. Unlike Heyes et al. (2016), we utilize variation at the individual level, which makes our findings difficult to reconcile with competing hypotheses. Additionally, we use a range of other time and meteorology controls to address alternative explanations. For instance, air quality is correlated with sunshine or precipitation which affects time spent on outside activities. To combat this concern, we control for weather directly. Beyond weather, it could be that traffic—a major contributor to pollution—can distort the results of the study. A nightmare commute could reduce productivity by raising stress and causing late arrivals to home and less willingness to sit down and trade. Again, we control for traffic directly at an even more disaggregated level.

In Europe, emissions of many air pollutants have decreased substantially in recent decades, resulting in improved air quality across the region. However, air pollutant concentrations are still too high, and air quality problems persist. Germany of all countries---seen internationally as a forerunner in environment protection---is not innocuous in respect to air pollution. A historically strong faith in individual transportation, unlimited speed highways, a powerful car industry, and widespread fossil fuel combustion contribute to the ongoing pollution. The primary pollutant in Germany is particulate matter. Even without obvious symptoms, fine particulate matter is affecting cognitive function by translocating through the nose to the brain. In 2014, Stuttgart, Germany exceeded the legal limit of fine particulate matter concentrate on 64 days, more days per year than any other German city. Like Stuttgart, other German cities such as Leipzig violate EU-wide standards (that are less stringent than US ones) on a regular basis. Thus, we can exploit quite considerable local variation to analyze how air quality affects willingness to trade and sentiment. Moreover, we are empowered to identify an effect even for cities with very low levels of pollution in which individuals are not suffering any obvious symptoms.

We can illustrate the magnitude of the findings by assuming that the same relationship applies to office work. We estimate that a one standard-deviation increase in the air quality index reduces willingness to log in, or engage in other cognitively-demanding activities, by 8.5 percent relative to what it would have been if the pollution levels were lower. To put this number in perspective, a one standard deviation increase in sunshine has an effect of approximately the same magnitude. Thus, the negative impacts of air quality may well be larger than previously thought in high air-quality countries for high-skilled occupations that form the backbone of the service and information economies. Conditional on logging in, we find an additional effect of trading in the range of 1 percent; again, in line with the effect of sunshine or precipitation. Nevertheless, in a labor context and in contrast to Chang et al. (2016), we find effects for both labor supply than the marginal product of labor.[2] However, we also find large effects on the internal margin when we look at the absolute value of trades conditional on trading as an outcome. Again, we find that a one standard deviation increase in pollution induces the same reduction in the absolute value of trades as one standard deviation in sunshine.

We analyze daily trading records of individual investors that span the years 2003 to 2015, controlling for various investor-, time-, market-, traffic-, and weather-specific factors. Our data set consists of security trading for a sample of more than 103,000 private investors of one of the largest retail brokerages in Germany. An advantage of our data set is that we are able to exclude quasi-automatic trades that cannot be related to air quality, such as savings plan transactions. Additionally, trading decisions in our sample are not moderated by any influence from third parties, such as financial advisors. Our sample includes only self-directed online investors who make decisions on their own. Given these attributes, our data set has the potential to clearly identify any effect of air quality on the trading behavior of individual investors. Moreover, we obtain data on customer demographics such as gender or age as well as detailed information on traded securities such as asset class, risk class, issuer or issue date of a security.

In line with Schmittmann et al. (2014), who analyze the effect of weather on trading decisions of private investors, we use panel regressions with investor fixed effects and follow their

[2] One has to keep in mind that the effect on trade is on a sample of traders that logged in on a poor air pollution day. Thus, the trade regression suffers from selection bias.

approach in defining the weather measures. As the outcome variable of interest is whether individuals sit down, log in, and trade. Thus, we estimate a linear probability model, which allows to interpret the coefficients straightforwardly. Our primary air-quality variables are particulate matter pollution and ozone.[3] We can use either PM 10, that is, particulate matter 10 micrometers or less in diameter, or PM 2.5, that is, particulate matter 2.5 micrometers or less in diameter. Especially PM 2.5 is believed to have detrimental cognitive effects. But because PM 2.5 is contained in our PM 10 data, the two are highly correlated. Our main weather variables are sunshine and air pressure but we can also include temperature, cloud cover (roughly the inverse of sunshine), and precipitation. To avoid spurious correlation due to common seasonality in air quality, weather, and trading measures, we demean the daily variables using the mean of the closest calendar day (of the day-of-week for the pollution measures, or the annual average for trading measures) under consideration over 10 years and control for month and year fixed effects. Additionally, we control for various calendar and other effects that are known to affect trading such as preceding market returns to control for momentum, wealth, school and public holidays, closed-market days, turn of the month and year, day of week, seasonal affective disorder, and changes daylight saving time. The inclusion of controls for weather, traffic, and various calendar effects provides a second safeguard against spurious correlations and helps to differentiate between novel and already known effects.

To further analyze the effects of air quality on the willingness to sit down and trade and assess the robustness of the baseline result, we split our sample in various ways. We first partition our data by gender. However, we do not find that women are more affected by air pollution but the effects are strongly significant and large in both subsamples. Additionally, we split our sample by average pollution levels. We find that effects are stronger in more polluted areas but again significant and large in both subsamples. Finally, we split the sample by the trading frequency of individual investors and sophistication, as measured by their average diversification. We find that effects are larger for more frequent traders than less frequent ones, while sophistication does not make a big difference. We argue that these results lend additional credibility to our extrapolation from willingness to trade to white-collar productivity.

[3] Air pollutants such as fine particulate matter can translocate from the upper respiratory tract to the brain, causing brain inflammation and cognitive deficits (e.g., Pope and Dockery, 2006; Block and Calderón-Garcidueñas, 2009). Exposure to air pollutants can also reduce the capacity of red blood cells' hemoglobin to transport oxygen, leading to reduced availability of oxygen to the brain and impaired concentration and confusion (Badman and Jaffe, 1996; Kampa and Castanas, 2008).

Air quality's potential influence on financial markets and investors can be relevant to the existing literature in climate change, labor, and behavioral finance as an example of how air pollution can influence productivity and market efficiency. Beyond the recent studies in labor economics mentioned above that find negative effects of air pollution on worker productivity, our paper is also related and contributes to the behavioral-finance literature studying how individual investor trading is influenced by environmental conditions.

In this strand of literature, cognitive ability and sophistication have shown to influence investment behavior and outcomes in Calvet, Campbell, and Sodini (2009a, 2009b) and Seru, Shumway, and Stoffman (2010). Moreover, Korniotis and Kumar (2011) show that older investors make worse trades, and Grinblatt, Keloharju, and Linnainma (2012) find that trades by high-IQ investors outperform those by low-IQ investors. Our study is also related to the literature that analyses investor attention and sentiment. Barber and Odean (2008) show that investors trade because a security has caught their attention by news, because past day's returns were large (Barber and Odean (2008), Grinblatt and Keloharju (2001)), because the weather is bad (Schmittmann et al. (2014)) or because of superstition (Bhattacharya et al. (2014)). In terms of sentiment, Kostopoulos and Meyer (2016) apply the results of textual and acoustic analysis to daily top-10 music downloads in iTunes to derive a novel and direct measure for investor sentiment, which has a significantly negative effect on trading activity. Da, Engelberg, and Gao (2011) and Da, Engelberg, and Gao (2015) analyze Google search volume and Siganos, Vagenas-Nanos, and Verwijmeren (2014) look at social media mood for Facebook and Bollen, Mao, and Zeng (2011) for Twitter.

The remainder of this paper proceeds as follows: In section 2 we provide an overview of our data set. Section 3 discusses our empirical approach. Section 4 presents the effects of air quality on retail investors. Section 5 concludes.

2. Data

2.1. AIR QUALITY AND WEATHER DATA

We obtain hourly pollution data from all German air stations measuring ozone and fine particulate matter (PM 10) and daily weather data from all German weather stations. 153 air stations and 197 weather stations are located across Germany and can be mapped exactly to investors' zip codes for controls in a given locale. The data on air pollution is provided by the

UBA (German Federal Environmental Agency) and the data on weather is obtained from the German weather sevice (DWD).

[Insert Figure 1 about here]

Incorporated seasonality can be an important issue when considering our time-series data. Seasonality effects could cause spurious correlations of our air quality measures and applied trading measures. For example, ozone is generally more of a problem in the summer. To avoid spurious correlations affecting our results, we include month fixed effects in our panel regressions. Furthermore, we include year fixed effects to account for potential spurious relationships in the data due to long-term trends in our time-series. Finally, we demean the daily variables using the mean of the closest calendar day for weather data or of the day-of-week for the pollution measures under consideration over our sample period of 10 years.

2.2. TRAFFIC DATA

Traffic data is used as a control from BASt, a German research institute on federal highways. Data are available from 2003 to 2015 and include hourly total traffic volume of all vehicles passing through designated checkpoints in each direction. About 1300 checkpoints are located across Germany and can be mapped exactly to investors' zip codes for controls in a given locale. We also demean the traffic data using the mean of the day-of-week for the traffic data.

2.3. INVESTOR DATA

In cooperation with a large German discount broker, we get information on a daily basis regarding logins (from 2012 onwards), trades, and portfolio holdings of approximately 103,000 customers and match this data with our air quality, weather, and traffic data from 2003 through 2015. One important characteristic of our investor data is that we are able to identify self-directed customers. To ensure that we are looking at self-driven behavior of investors, we exclude all customers who are not self-directed. Further, we exclude transfers among personal accounts, saving plans and trades from limit orders[4], because this type of transactions do not reflect current trading decisions of investors.[5] We keep only private

[4] See Linnainmaa (2010).

[5] Saving plan transactions and trades from limit orders do represent trading decisions. However, these decisions are made in the past or are influenced from other sources than the daily air quality, which we are analyzing.

investors that reside in Germany, as only these individuals' trading decisions can be influenced by German air quality. In online brokerages, silent attribution is a common phenomenon, as usually there is no charge for having an account. Therefore, in order to not analyze accounts of investors who stopped trading, we require that households execute at least 1 trade per year. Table I highlights that these restrictions leave us with a sample of 103,000 investors and a total number of trades of approximately 23 million.

[Insert Table I about here]

2.4. OUTCOME VARIABLES

We estimate a linear probability model for both logins and trades, i.e., the variable log in is 1 if the investor logged in on a given day and 0 otherwise and the variable trade is 1 if the investor traded on a given day and 0 otherwise. This model allows us to interpret the coefficients straightforwardly.

2.5. CONTROL VARIABLES

Following Schmittmann et al. (2014) we include several control variables to our panel regression of air quality on different trading variables in order to avoid picking up effects that have already been found in previous studies.

The first group of controls consists of variables that generally explain trading patterns of private investors. Preceding stock market returns may affect trading behavior of households (Gervais, Kaniel, and Mingelgrin (2001), Barber and Odean (2008)). In addition, Garcia (2013) shows that investors react to news with a certain time lag. Both findings lead to the conclusion that momentum could play a role in decision making of households. Therefore, we include two momentum control variables on the right hand side of our regressions. First, a preceding-one-day realized market return variable and second a preceding-three-month realized market return variable. Since our investor data cover German retail investors (see Section 2.3) we use the CDAX. CDAX is a German composite stock market index that captures all stocks tradeable on German's Frankfurt stock exchange.

Wealth plays a major role in decision making of households (Carroll (2002), Wachter and Yogo (2010)). For instance, Carroll (2002) generates evidence that risk aversion decreases in wealth. In order to account for wealthy investor's trading patterns and to not allow few huge orders of wealthy investors to drive our results we control for wealth. We measure wealth as the natural logarithm of the sum of all assets an investor holds at the end of the preceding month.

Our second group of control variables is related to calendar-dates, such as public holidays. Additionally, school holidays may have an impact on trading behavior of private investors. In fact, Hong and Yu (2009) show that during school holidays, trading volume is significantly lower. Therefore, we add a holiday dummy that varies across states, as different states in Germany have different holiday periods. To control for abnormal trades just before going on vacation or just after arriving from vacations, we insert two more dummies – one for the last trading day before and one for the first trading day after school holidays.[6] Since public holidays could also have the same effect as school holidays, we include one more dummy accounting for public holidays.

In the data we find investors to trade predominantly on German exchanges. It could be that on days with no trading at the Deutsche Börse in Frankfurt, investors trade significantly less. To control for this effect, we append a dummy for days with no trading at the Deutsche Börse in Frankfurt.

Previous studies find anomalies on capital markets that are associated with the turn of the month (Ariel (1987), Lakonishok and Smidt (1988)) and the turn of the year (Rozeff and Kinney (1976), Reinganum (1983), Jones, Pearce, and Wilson (1987), Ritter (1988), Ritter and Chopra (1989)). Therefore, we add dummies for the first and last trading day of the month and year. Likewise, French (1980), Lakonishok and Maberly (1990), Gibbons and Hess (1981), Keim and Stambaugh (1984), Rogalski (1984) find anomalies on Mondays and Fridays. Thus, we insert day-of-the-week dummies.

Another well-known set of anomalies is related to human biorhythm (Kamstra, Kramer, and Levi (2000), Kamstra, Kramer, and Levi (2003), Pinegar (2002)). Therefore, we control for the seasonal affective disorder (SAD). We measure SAD as in Kamstra, Kramer, and Levi (2003). Further we include two dummy variables for Mondays following changes in day light saving time – one for advancing clocks and one for adjusting them backwards.

Lastly, we incorporate year and month fixed effects. By doing so, we ensure that our results are not driven by slow moving trends or single months-of-year, or any other slow-moving

[6] One could for instance sell all risky positions just before going on vacation and rebuy risky positions right after returning from vacations, because of limited access to accounts for instance.

seasonality effects. In addition, months fixed effects control for tax-induced trading behavior of retail investors (Rozeff and Kinney (1976), Keim (1983), Roll (1983), Grinblatt and Keloharju (2001)).

2.6. HYPOTHESES AND EMPIRICAL APPROACH

We develop three main hypotheses. Our first hypothesis is rather straightforward: when air quality is bad individuals tend to be less willing and able to engage in a cognitively-demanding task such as trading unconditionally. We define our two main hypotheses as follows:

Hypothesis 1 (H1): When air quality is poor, retail investors are less likely to log in.

Hypothesis 2 (H2): When air quality is poor, retail investors are less likely to trade.

Hypothesis 3 (H3): When air quality is poor, retail investors trade less in value.

We test these hypotheses by performing investor fixed effects panel regressions that look as follows:

$$TM(i,t) = \alpha + \beta\, AQI(i,t) + \gamma\, C(i,t) + \varepsilon(i,t) \qquad (1)$$

TM represents the dummy for logging in and/or trading or the natural logarithm of absolute trade value. *AQI* are ozone and fine particulate matter. *C* is the set of weather and traffic variables and the set of control variables discussed in Section 2.5. *i* stands for an individual investor and *t* stands for a certain trading day. The effect we are interested in is β. If our hypotheses hold, β should have the expected sign and be statistically significant. We cluster standard errors at the individual investor level or alternatively at the treatment level, i.e., the zip code level. The latter increases standard errors marginally but all results remain highly significant.

We perform regressions in the manner of Equation (1) in several ways. In order to test our main hypotheses *H1 – H3,* we run these regressions with logins and/or trading (value). In Section 3.2 we test all three hypotheses for particular subsamples of our data. More precisely, we test whether *H1-H2* hold for male or female or both groups of investors and how effects differ. Moreover, we differentiate between frequent and less frequent traders. We run all these additional model specifications, because it sheds further light to the question how air quality affects the behavior of individual investors on capital markets and because it helps to check robustness of our main results.

3. Results

3.1. EFFECTS OF AIR QUALITY ON THE AVERAGE INDIVIDUAL INVESTOR

Table II shows effects on the unconditional probability to log in and trade.

[Insert Table II about here]

We find evidence that when air quality is poor, private investors are less likely to log in and trade. We are able to comfortably reject the null hypothesis that the change in the likelihood of logging in or trading equals to zero at less than the 1%-level for ozone and less than the 1%-level for fine particulate matter, consistent with *H1* and *H2*.

To facilitate the interpretation of the coefficients, we consider the percentage effect on the unconditional means of logging in and trading of a one standard deviation increase in ozone or PM 10 in Table III. For instance, when PM 10 increases by one standard deviation, around 12 points, then the likelihood of logging in decreases by 0.37 percent which is approximately 8.5 percent of the baseline probability of logging in on a given day. Given that investors can trade only after logging in, the coefficient on trade is the additional likelihood that investors do not trade at all conditional on having logged in. In turn, the coefficient on trade implies that a standard deviation increase in PM 10 makes investors 1 percent less likely to trade, conditional on logging in. Overall, investors are thus 9.5 percent less likely to engage in trading on poor air quality days. Here, one has to keep in mind that the effect on trade is on a sample of traders that logged in on a poor air pollution day. Thus, the trade regression suffers from selection bias.

With respect to ozone, both effects are in the magnitude of 1 percent. This appears in line with the evidence that ozone has less detrimental cognitive effects than PM 10. To put the coefficients on pollution in perspective, we also report the decrease in the probability of logging in and trading from a one standard deviation increase in sunshine and air pressure. Clearly, additional sunshine makes investors less likely to stay home and trade in a country with mediocre weather and limited sunshine such as Germany. It turns out, that the effect of a one standard deviation increase in sunshine is almost the same in magnitude as PM 10 for both logins and trading. This underlines how important and large the effects of air quality are on individual engagement in cognitively-demanding tasks.

Beyond controlling for sunshine and air pressure, we can also include temperature and precipitation. After all, we may be concerned that our pollution measures are picking up residual variation from weather fluctuations. However, inclusion of additional weather variables strengthens the previous results if anything, as can be seen in Table IV. This table presents coefficients and the magnitudes as described above. Again, pollution appears to have a strong negative effect on logins and trading similar in magnitude to a one-standard deviation increase in temperature or decrease in precipitation.

[Insert Table III and Table IV about here]

The larger coefficient on logins than trade suggests that pollution and weather affects the external margin more so than the internal margin or labor supply more so than labor productivity. To shed additional light on this question, we run a conditional regression, i.e., conditional on trading at all, of the log trade value, i.e., the natural log of the value of all buys and the absolute value of all sells. It can be seen in Table V that pollution and sunshine reduce the value of trades significantly. In terms of magnitudes, the coefficient of sunshine is approximately 1.5 that of PM 10 which is in line with the previous results and suggests that one standard deviation increase in sunshine reduces the value of trades by the same amount as one standard deviation increase in PM 10. This, again, suggests that the detrimental effects of pollution are large and hypothesis *H3* holds too.

[Insert Table V about here]

3.2. EFFECTS OF AIR QUALITY ON SUBSAMPLES OF INVESTORS

In order to explore whether demographics play a crucial role for our results, we partition our data in multiple different ways and rerun the analysis of Section 3.1 for each of the formed subsamples. First, we partition by gender. It can be seen in Table VI that men and women are both affected by air quality in a strongly significant way. Thus, our effects are robust to partitioning by gender. Some medical research finds that women are more affected by particulate matter. To reconcile our findings with this hypothesis, it seems important to keep in mind that our sample of German women trading in discount brokerage accounts is selective.

[Insert Table VI about here]

Beyond splitting the sample by gender, we can also split the sample by pollution levels. We find that those traders living in relatively more polluted areas are more affected than those living in less polluted areas. However, it is noticeable that the coefficients are highly significant and of the same magnitude as the baseline in both sample splits, as can be seen in Table IV.

[Insert Table VII about here]

Beyond splitting the sample by gender and pollution levels, we can also split the sample by trading frequency, which is of special interest given that we are trying to extrapolate our findings to daily office work productivity. Heavy traders trade on more days than the median number of days per year, 52. If heavy traders, who trade in a more professional manner similar to office work, would be less affected, we would wonder whether our findings are more relevant for leisure activities rather than labor. However, we find that heavy traders are more affected than infrequent traders as can be seen in Table VIII.

[Insert Table VIII about here]

Beyond trading frequency, we can also split the sample by investor sophistication, which again may be informative about the extrapolation to daily office work productivity. Sophisticated investors on average belong to the top 20% of best diversified investors at the end of the month. We find that sophisticated investors are slightly less affected than less sophisticated traders as can be seen in Table IX. Overall, the difference is very small relative to splitting by trading frequency for instance.

[Insert Table IX about here]

Overall, it is noticeable that the coefficients from pollution are highly significant in all sample splits and have a large impact on investor behavior that ranges around the same magnitudes as changes in weather.

3.3. ADDITIONAL ROBUSTNESS CHECKS

In the previous section, we saw that the negative effects of pollution on investor's willingness to sit down, log in, and trade are robust and uniform in terms of coefficient sizes throughout sample splits and the inclusion of additional weather controls. Nevertheless, in the following we will address a number of other robustness concerns.

Pollution and weather monitors are subject to measurement error (Sullivan, 2016). In principle, measurement error would bias our estimates towards zero. Nevertheless, to address potential concerns we run a specification that only uses distance to air stations of one kilometer. It is reassuring that the magnitudes of the coefficients are unchanged for both logins and trades, thus the significance of the trade coefficients is affected. However, we also slash the number of observations which is thus not surprising. Moreover, for each zip code the longitude and latitude is the focal-point rather than the most population-dense point and many individuals log in and trade during the day while at the office. The size of each zip codes varies considerably depending on how remote the area is. When we split the sample according to average levels of pollution, probably a good proxy for rurality, we find smaller coefficients for low levels of pollution which may be driven by larger measurement error due to larger zip code areas. Nevertheless, all are significant individually.

[Insert Table IX about here]

We notice that the coefficients on log in, for both weather and pollution, tend to be much larger than the coefficients for trade. We first check whether this is driven by the fact that logins are only available for a part of the sample period. However, when we run the trade regression using the same sample period for which we have log in data available we do not find a difference in the coefficients, neither in terms of the magnitude nor significance even though the number of observations is slashed, which is reassuring. The results can be seen in Table X.

4. Conclusion

We use individual investor trading as a measure of white-collar work productivity to assess the effects of air quality on willingness to engage in a cognitively-demanding task. We link highly disaggregated air, traffic, and weather data with daily trading records and socio-demographic information of investors. To the best of our knowledge, this paper is the first to test whether air quality affects investors willingness to sit down and trade, controlling for investor-, environment-, and market-specific factors in a commonly-found low-pollution environment. When air quality is poor, investors are significantly less likely to log in and trade. The one-standard deviation effect on trading is similar in magnitude to the effect of a one-standard deviation increase in sunshine and thus appears not only statistically but also economically significant.

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Figures and Tables

Figure **1. Air (blue), Weather (red), and Traffic (green) Stations**

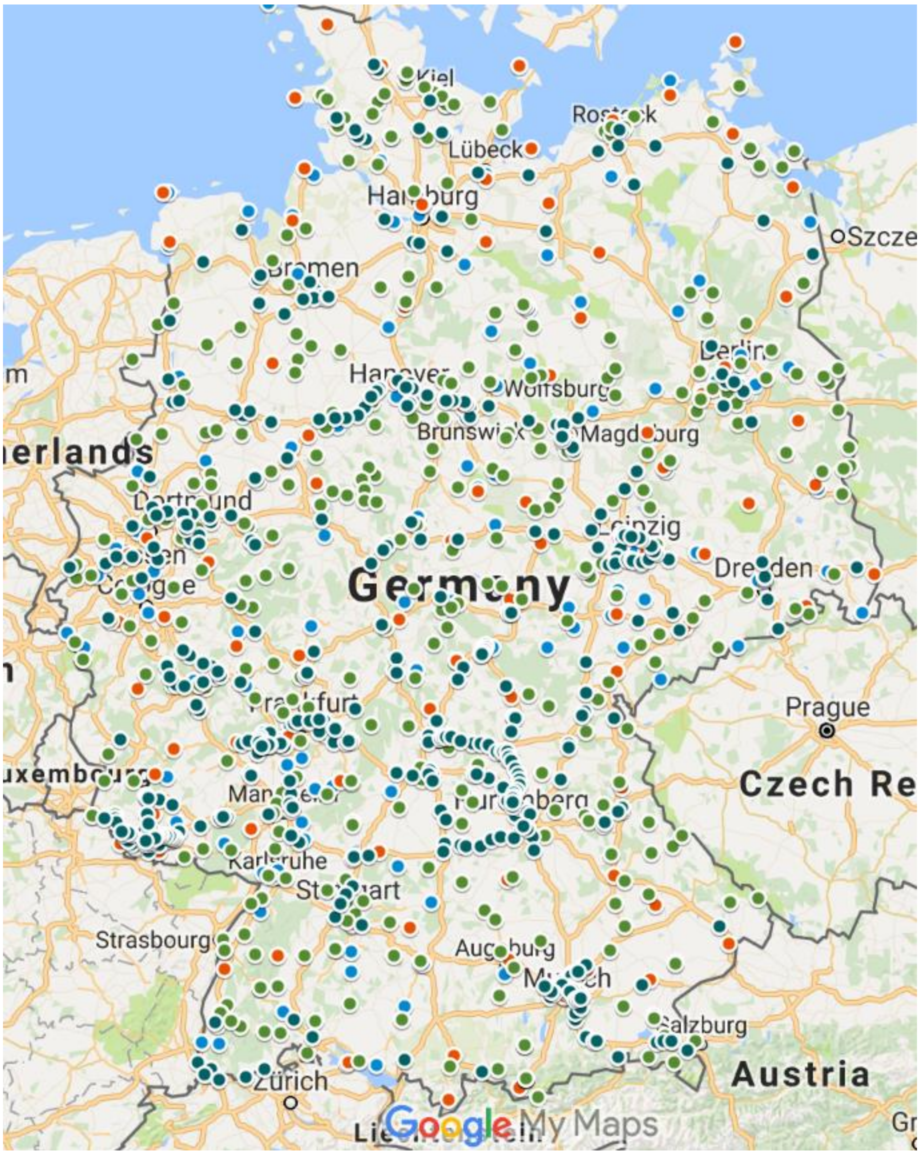

Table I. Investor data description

This table presents summary statistics for our retail investor data. Data are obtained from one of the largest German discount brokerages. We exclude customers that are not self-directed, do not reside in Germany and execute less than 10 trades per year. Further, we exclude transfers among personal accounts, saving plans and bonus shares.

Individual Investors and Transactions	
Number of individual investors	103,373
Total number of trades	23,387,906
Total number of buys	12,636,217
Total number of sales	10,751,689
Total transaction value	1,159,868,416
Total value of buys	62,282,993,664
Total value of sells	(61,123,125,248)

Individual Investor Characteristics	
Number of male investors	85,860
Number of female investors	17,513
Average age	53
Age (1. quartile)	44
Age (median)	52
Age (3. quartile)	61

Table II. The impact of air quality on the average investor

This table presents results from investor fixed effects panel regressions on ozone and fine particulate matter for the average investor. Panel 1 uses the linear probability of at least one trade and Panel 2 uses the linear probability of logging in as the dependent variable. All regressions control for a set of calendar-, weather-, traffic-, and market-specific factors through the following variables: wealth, measured by the natural logarithm of preceding month's asset holdings; preceding-one-day realized market return (CDAX); preceding-three-month realized market return (CDAX); seasonal affective disorder, measured as in Kamstra, Kramer, and Levi (2003); dummies for school vacations, public holidays, trading days before school vacations, trading days after school vacations, trading days for closed exchange, first trading days of the months, last trading days of the months, first trading days of the years, last trading days of the years, day-of-week, Mondays following forward changes in daylight saving time, Mondays following backward changes in daylight saving time, year and month fixed effects. We use White (1980) standard errors clustered at the individual level that are robust to heteroskedasticity and report them in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
	trade	log in	trade	log in	trade	log in
Ozone	-5.52e-05***	-0.000156***	-5.14e-05***	-0.000182***	-3.15e-05***	-9.39e-05***
	(2.43e-06)	(5.26e-06)	(2.35e-06)	(5.30e-06)	(2.36e-06)	(5.26e-06)
PM 10	4.20e-06	-0.000367***	-4.20e-05***	-0.000390***	-2.46e-05***	-0.000288***
	(3.32e-06)	(6.99e-06)	(2.97e-06)	(7.14e-06)	(2.98e-06)	(7.03e-06)
Traffic controls	✓	✓	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓	✓	✓
Wealth					✓	✓
Calendar controls			✓	✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓	✓
Observations	52,374,915	24,234,197	52,374,915	24,234,197	52,110,450	23,969,732
R-squared	0.136	0.287	0.140	0.289	0.141	0.293

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table III. The impact of air quality on the average investor

This table presents the coefficients results in interpretable format. We consider the effect of one standard deviation on the unconditional means of logging in and trading in percent.

	standard deviation	(5)	(6)
		trade	log in
Unconditional mean		3.87%	4.38%
Ozone	16.12	-1.31%	-3.46%
PM 10	12.95	-0.82%	-8.52%
Air pressure	8.41	-0.12%	7.28%
Sunshine	3.72	-1.22%	-8.27%

Table IV. The impact of air quality on the average investor

This table presents the coefficients results in raw and interpretable format of all air quality, weather, and traffic measures. We consider the effect of one standard deviation on the unconditional means of logging in and trading in percent.

	standard deviation	coefficients		magnitudes	
		trade	log in	trade	log in
Unconditional mean				3.87%	4.38%
Ozone	15.91	-2.74e-05***	-4.60e-05***	-1.13%	-1.67%
		(2.47e-06)	(5.42e-06)		
PM 10	13.14	-2.58e-05***	-0.000307***	-0.88%	-9.21%
		(2.97e-06)	(7.03e-06)		
Vehicle count highways	7326.43	2.25e-08	8.99e-08***	0.43%	1.50%
		(2.34e-08)	(1.89e-08)		
Vehicle count interstate	2878.51	5.65e-08	-9.83e-08**	0.42%	-0.65%
		(4.73e-08)	(4.85e-08)		
Temperature	3.66	-8.16e-05***	-0.00129***	-0.77%	-10.79%
		(1.05e-05)	(2.23e-05)		
Sunshine	3.74	-0.000111***	-0.000598***	-1.07%	-5.11%
		(9.33e-06)	(2.15e-05)		
Air pressure	8.50	-8.66e-06**	0.000358***	-0.19%	6.95%
		(4.16e-06)	(1.02e-05)		
Precipitation	5.12	3.24e-06	0.000351***	0.04%	4.11%
		(6.61e-06)	(1.62e-05)		

Table V. The impact of air quality on the value of trades

This table presents results from investor fixed effects panel regressions on ozone and fine particulate matter for the average investor. Panel 1 uses the natural log of the absolute value of all trades, i.e., log(buys+abs(sells)), as the dependent variable. All regressions control for a set of calendar-, weather-, traffic-, and market-specific factors through the following variables: wealth, measured by the natural logarithm of preceding month's asset holdings; preceding-one-day realized market return (CDAX); preceding-three-month realized market return (CDAX); seasonal affective disorder, measured as in Kamstra, Kramer, and Levi (2003); dummies for school vacations, public holidays, trading days before school vacations, trading days after school vacations, trading days for closed exchange, first trading days of the months, last trading days of the months, first trading days of the years, last trading days of the years, day-of-week, Mondays following forward changes in daylight saving time, Mondays following backward changes in daylight saving time, year and month fixed effects. We use White (1980) standard errors clustered at the individual level that are robust to heteroskedasticity and report them in parentheses.

	total value of trades	value of buys	absolute values of sells
Ozone	-0.00112***	-0.000913***	-0.00130***
	(1.30e-05)	(1.23e-05)	(1.47e-05)
PM 10	-0.000815***	-0.000678***	-0.000988***
	(1.85e-05)	(1.74e-05)	(2.09e-05)
Sunshine	-0.00172***	-0.00249***	-0.00106***
	(5.15e-05)	(5.09e-05)	(5.72e-05)
Traffic controls	✓	✓	✓
Weather controls	✓	✓	✓
Wealth	✓	✓	✓
Calendar controls	✓	✓	✓
Individual fixed effects	✓	✓	✓
Observations	2,395,918	2,395,918	2,395,918
R-squared	0.553	0.564	0.507

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table VI. The impact of air quality for male and female investors

This table presents results from investor fixed effects panel regressions on ozone and fine particulate matter for the average investor. Panel 1 uses the linear probability of at least one trade and Panel 2 uses the linear probability of logging in as the dependent variable. All regressions control for a set of calendar-, weather-, traffic-, and market-specific factors through the following variables: wealth, measured by the natural logarithm of preceding month's asset holdings; preceding-one-day realized market return (CDAX); preceding-three-month realized market return (CDAX); seasonal affective disorder, measured as in Kamstra, Kramer, and Levi (2003); dummies for school vacations, public holidays, trading days before school vacations, trading days after school vacations, trading days for closed exchange, first trading days of the months, last trading days of the months, first trading days of the years, last trading days of the years, day-of-week, Mondays following forward changes in daylight saving time, Mondays following backward changes in daylight saving time, year and month fixed effects. We use White (1980) standard errors clustered at the individual level that are robust to heteroskedasticity and report them in parentheses.

	men		women	
	trade	log in	trade	log in
Ozone	-3.16e-05***	-9.95e-05***	-3.11e-05***	-6.28e-05***
	(2.62e-06)	(5.90e-06)	(5.32e-06)	(1.08e-05)
PM 10	-2.49e-05***	-0.000307***	-2.28e-05***	-0.000182***
	(3.34e-06)	(7.89e-06)	(6.26e-06)	(1.44e-05)
Traffic controls	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓
Wealth	✓	✓	✓	✓
Calendar controls	✓	✓	✓	✓
Individual fixed effects	✓	✓	✓	✓
Observations	44,030,600	20,231,249	8,079,850	3,738,483
R-squared	0.141	0.289	0.133	0.285

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table VII. The impact of air quality for high and low pollution areas

This table presents results from investor fixed effects panel regressions on ozone and fine particulate matter. Panel 1 uses the linear probability of at least one trade and Panel 2 uses the linear probability of logging in as the dependent variable. All regressions control for a set of calendar-, weather-, traffic-, and market-specific factors through the following variables: wealth, measured by the natural logarithm of preceding month's asset holdings; preceding-one-day realized market return (CDAX); preceding-three-month realized market return (CDAX); seasonal affective disorder, measured as in Kamstra, Kramer, and Levi (2003); dummies for school vacations, public holidays, trading days before school vacations, trading days after school vacations, trading days for closed exchange, first trading days of the months, last trading days of the months, first trading days of the years, last trading days of the years, day-of-week, Mondays following forward changes in daylight saving time, Mondays following backward changes in daylight saving time, year and month fixed effects. We use White (1980) standard errors clustered at the individual level that are robust to heteroskedasticity and report them in parentheses.

	more polluted areas		less polluted areas	
	trade	log in	trade	log in
Ozone	-3.89e-05***	-0.000119***	-8.87e-06***	-1.28e-05
	(3.05e-06)	(6.40e-06)	(1.50e-06)	(8.21e-06)
PM 10	-2.90e-05***	-0.000339***	-1.09e-05***	-0.000124***
	(3.86e-06)	(8.55e-06)	(1.83e-06)	(1.09e-05)
Traffic controls	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓
Wealth	✓	✓	✓	✓
Calendar controls	✓	✓	✓	✓
Individual fixed effects	✓	✓	✓	✓
Observations	39,816,835	18,332,466	12,293,615	5,637,266
R-squared	0.137	0.288	0.003	0.223

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table VIII. The impact of air quality for frequent and infrequent traders

This table presents results from investor fixed effects panel regressions on ozone and fine particulate matter. Panel 1 uses the linear probability of at least one trade and Panel 2 uses the linear probability of logging in as the dependent variable. All regressions control for a set of calendar-, weather-, traffic-, and market-specific factors through the following variables: wealth, measured by the natural logarithm of preceding month's asset holdings; preceding-one-day realized market return (CDAX); preceding-three-month realized market return (CDAX); seasonal affective disorder, measured as in Kamstra, Kramer, and Levi (2003); dummies for school vacations, public holidays, trading days before school vacations, trading days after school vacations, trading days for closed exchange, first trading days of the months, last trading days of the months, first trading days of the years, last trading days of the years, day-of-week, Mondays following forward changes in daylight saving time, Mondays following backward changes in daylight saving time, year and month fixed effects. We use White (1980) standard errors clustered at the individual level that are robust to heteroskedasticity and report them in parentheses.

	frequent traders		infrequent traders	
	trade	log in	trade	log in
Ozone	-5.05e-05***	-0.000150***	-1.40e-05***	-3.93e-05***
	(4.52e-06)	(8.54e-06)	(1.38e-06)	(6.17e-06)
PM 10	-3.91e-05***	-0.000413***	-1.13e-05***	-0.000170***
	(5.75e-06)	(1.13e-05)	(1.69e-06)	(8.33e-06)
Traffic controls	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓
Wealth	✓	✓	✓	✓
Calendar controls	✓	✓	✓	✓
Individual fixed effects	✓	✓	✓	✓
Observations	25,821,099	11,872,759	26,289,351	12,096,973
R-squared	0.133	0.286	0.007	0.237

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table IX. The impact of air quality for sophisticated and less sophisticated investors

This table presents results from investor fixed effects panel regressions on ozone and fine particulate matter. Panel 1 uses the linear probability of at least one trade and Panel 2 uses the linear probability of logging in as the dependent variable. All regressions control for a set of calendar-, weather-, traffic-, and market-specific factors through the following variables: wealth, measured by the natural logarithm of preceding month's asset holdings; preceding-one-day realized market return (CDAX); preceding-three-month realized market return (CDAX); seasonal affective disorder, measured as in Kamstra, Kramer, and Levi (2003); dummies for school vacations, public holidays, trading days before school vacations, trading days after school vacations, trading days for closed exchange, first trading days of the months, last trading days of the months, first trading days of the years, last trading days of the years, day-of-week, Mondays following forward changes in daylight saving time, Mondays following backward changes in daylight saving time, year and month fixed effects. We use White (1980) standard errors clustered at the individual level that are robust to heteroskedasticity and report them in parentheses.

	sophisticated traders		less sophisticated traders	
	trade	log in	trade	log in
Ozone	-2.16e-05***	-4.55e-05***	-3.37e-05***	-7.70e-05***
	(4.57e-06)	(9.58e-06)	(2.30e-06)	(3.09e-06)
PM 10	-1.72e-05***	-0.000112***	-2.44e-05***	-0.000163***
	(5.56e-06)	(1.30e-05)	(2.93e-06)	(4.24e-06)
Traffic controls	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓
Wealth	✓	✓	✓	✓
Calendar controls	✓	✓	✓	✓
Individual fixed effects	✓	✓	✓	✓
Observations	4,428,672	4,428,672	59,900,720	59,900,720
R-squared	0.088	0.231	0.144	0.265

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table X. The impact of air quality for the post 2012 period and short distances to air stations

This table presents results from investor fixed effects panel regressions on ozone and fine particulate matter. Panel 1 uses the linear probability of at least one trade and Panel 2 uses the linear probability of logging in as the dependent variable. All regressions control for a set of calendar-, weather-, traffic-, and market-specific factors through the following variables: wealth, measured by the natural logarithm of preceding month's asset holdings; preceding-one-day realized market return (CDAX); preceding-three-month realized market return (CDAX); seasonal affective disorder, measured as in Kamstra, Kramer, and Levi (2003); dummies for school vacations, public holidays, trading days before school vacations, trading days after school vacations, trading days for closed exchange, first trading days of the months, last trading days of the months, first trading days of the years, last trading days of the years, day-of-week, Mondays following forward changes in daylight saving time, Mondays following backward changes in daylight saving time, year and month fixed effects. We use White (1980) standard errors clustered at the individual level that are robust to heteroskedasticity and report them in parentheses.

	restriction to post 2012		short distance to air stations	
	trade	log in	trade	log in
Ozone	-3.29e-05***	-7.13e-05***	-3.91e-05**	-0.000121***
	(2.38e-06)	(4.47e-06)	(1.74e-05)	(3.41e-05)
PM 10	-1.34e-05***	-0.000308***	-1.34e-05	-0.000300***
	(3.33e-06)	(6.43e-06)	(2.47e-05)	(4.80e-05)
Traffic controls	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓
Wealth	✓	✓	✓	✓
Calendar controls	✓	✓	✓	✓
Individual fixed effects	✓	✓	✓	✓
Observations	31,532,591	31,532,591	552,213	552,213
R-squared	0.200	0.304	0.171	0.286

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1