

A Breath of Change: Can Personal Exposures Drive Green Preferences?*

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Abstract

Are investors’ preferences for responsible investing affected by their idiosyncratic personal experiences? Using a comprehensive dataset with hospital visits and information on portfolio holdings by retail investors in Denmark, we show that when an investor’s child is diagnosed with a respiratory disease, the investor decreases (increases) portfolio weights of “brown” (“green”) stocks but does not alter their holdings of ESG funds. Consistent with parents attributing respiratory diseases to air pollution, we find no effects for non-respiratory diseases. The results are stronger for more severe diseases and are driven by parents who live with their children.

JEL Classification: D91, G11, G41, Q51, Q53

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Recent years have seen an unprecedented rise in the importance of Environmental (E), Social (S), and Governance (G) factors for investment decision-making. According to Morningstar, at the beginning of 2023, the assets under management of ESG funds reached \$2.5 trillion (Bioy et al. (2023)) showing more than 150% growth over the past three years. As a survey of investors by BlackRock reports that 88% of investors cite the environment as the primary focus in ESG investing (BlackRock (2020)), it is important to understand how investors form preferences towards the E-factor and whether these preferences can change due to personal experiences. While a growing body of research documents the importance of non-pecuniary consideration driven by ethical or green values for ESG investment, evidence on the factors that determine individuals’ attitudes towards responsible investing remains scant.

In this study, we examine whether significant life events alter investors’ preference for responsible investing.¹ Using administrative data from Denmark, we show that when investors’ children get admitted to hospitals with respiratory diseases, they decrease the weight of “brown” stocks in their portfolios and increase the portfolio weight of “green” stocks. The degree of portfolio rebalancing is economically significant: After the shock, investors decrease their holdings of “brown” stocks by 9% to 12% of the pre-treatment mean, while the weight on “green” stocks increases by 2% of the pre-treatment mean (relative to the control group).² This effect is stronger for more serious medical conditions and is driven by parents who are living with their children at the time of the incident. We find similar changes, albeit of smaller magnitude, for the extended family — including grandparents, aunts and uncles of the diagnosed child. Our findings suggest that investors’ experiences of idiosyncratic health shocks related to air pollution affect their allocation to sustainable assets, and, as a result, the relative fraction of “green” versus “brown” stocks in their portfolios.

Our interpretation of the results is the following. The connection between air pollution

¹In keeping with prior literature, and for ease of reference, we interchangeably refer to responsible investments, and green investments, although our classification of stocks into “brown” and “green” stocks focuses on the energy sector to ensure that we rely on a classification that is salient to retail investors. See Section 2.1 for details about our classification of “brown” and “green” stocks.

²In further tests, we examine the allocation to “green” minus “brown” stocks to rule out that our results are driven by unclassified stocks.

and respiratory diseases, which has been long established by the medical literature, is getting more salient with the global rise in ecological awareness. When a child is diagnosed with a respiratory disease, parents (as well as the extended family) experience a shock they might plausibly associate with the effect of air pollution. This perceived exposure to air pollution can influence investors’ stock selection. Since personal affection and loyalty to the company are important factors for individual stockholders (e.g., Fama and French (2007), Cohen (2009), and Keloharju et al. (2012)), an increase in the “green” sentiment coming from personal experience undermines the investor’s loyalty towards “brown” stocks that she holds. While revising the investment portfolio may not be the parent’s immediate response, when later rebalancing their holdings, the parent pays more attention to the “greenness” of the stocks, carefully evaluating new selections and being more likely to sell previously held “brown” stocks. In line with this interpretation, we find that the treatment effect is not immediate but is rather spread over time, consistent with retail investors slowly revising their portfolios.

Our identification strategy exploits idiosyncratic health shocks to children to isolate the effect of individual experiences from household wealth shocks. Our focus on health shocks to a non-working member of the household in a setting with free universal healthcare (Denmark), ensures that the shock does not tighten the budget constraint, but exposes the family members to a personal experience. We then test our main hypothesis that personal exposures to respiratory diseases alter family members’ attitude towards green investing. Importantly, our health shocks are relatively rare (i.e., relatively few investors are treated simultaneously) and idiosyncratic, which makes them plausibly unrelated to any systematic events that could potentially affect current or future stock prices. Our key identifying assumption is that the timing of the health shock is random relative to the timing of investment decisions.

To rule out the possibility that the treatment effect is driven by unobservable factors that might correlate with the likelihood of getting a disease, such as lifestyle, social connections, living conditions, or informational environment, we conduct our analysis in a (staggered)

difference-in-differences setting, following the approach of Sun and Abraham (2021). We match treatment and control groups on a range of personal characteristics such as age, number of children, geography, wealth, etc. One possible concern with our use of health shocks is that it is difficult to rule out the possibility that differences between the treatment and control groups are affected by confounding factors, such as health (in general), lifestyle, or the investor’s personal experience of having a child admitted to a hospital. To address these concerns, we conduct placebo tests using other diseases. The results of the placebo tests confirm that our findings are specific to respiratory diseases. This further supports our conjecture that the salience of the connection between respiratory diseases and air pollution is important for our results. In further, tests we show that the treatment group does not reduce their risk taking measured by their risky asset share or their labor supply measured by personal income, suggesting that our main result on portfolio rebalancing is not an artifact of changing attitudes to risk or changing preferences for leisure.

We then turn to studying whether the effect of shocks to investors’ personal experiences is limited to stocks or whether it is also present for other asset categories. Looking at individuals’ investment in mutual funds, we find no effect on the probability of holding an ESG fund or the weight of ESG funds in the portfolio after the treatment. One potential explanation is that the investors view “brown” and “green” stock holdings as assets directly related to addressing air pollution, while ESG is a broader term and may be rather associated with climate risk, global warming, social impact, or governance standards.

In further tests we show that the effect on portfolio allocation depends on the severity of the child’s medical condition. If personal exposures drive green preferences, then the strength of the effect should be related to how serious the child’s medical condition is, as well as to how much the parent is personally affected by this experience. Consistent with this hypothesis, we find that the effect is stronger for a) children who are hospitalized with a respiratory disease for a longer time period, b) children that are diagnosed with multiple respiratory diseases, and c) children with multiple hospital visits due to respiratory diseases.

We also examine the effect of personal exposures among other members of the family. We find that the response is strongest for parents, but that it is also statistically and economically significant for extended family members, namely the child’s aunts, uncles, and grandparents. Moreover, the effect for parents is mainly driven by the parents who are living with the child that is diagnosed with a respiratory disease. Further studying the cross-sectional variation of the effect, we document that while the results are stronger for the sample of more educated individuals, we find little evidence that the investor’s age, gender, or geographical location influences the treatment effect.

By examining the impact of health shocks on “green” investing in a country with moderate levels of air pollution, such as Denmark, we demonstrate that the salience of pollution is important. Within our sample period, the decreasing level of air pollution in Denmark is accompanied by an increase in social interest towards environmental problems. In line with this trend, we document stronger results in the end of our sample period compared to earlier periods. We conclude that idiosyncratic personal experiences and the perceived importance of the pollution problem have a strong effect on individuals’ investment decisions.

Our main contribution is to the literature on the determinants of ESG or green preferences by showing that idiosyncratic experiences can change investors’ environmental preferences. Prior studies document that the increased allocation to sustainable investments is driven by investors with green or ethical values (Bauer and Smeets (2015); Riedl and Smeets (2017); Briere and Ramelli (2020); Bauer et al. (2021); Barber et al. (2021); Bonnefon et al. (2022); Hong and Shore (2023); Degryse et al. (2023); Giglio et al. (2023); and Andersen et al. (2023)), high financial literacy (Anderson and Robinson (2022) and Degryse et al. (2023)), high wealth (Andersen et al. (2023)), and high subjective beliefs about returns to responsible investments (Giglio et al. (2023)). Two closely related studies to ours are Choi et al. (2020), who show that attention to local temperatures affects investors’ holding of carbon intensive stocks, and Fisman et al. (2023) who show that attention to local air pollution levels affects investors’ holdings of “brown” stocks. In comparison to these studies, we focus

on an idiosyncratic health shock related to air pollution that is uninformative about current or future stock prices, which ensures that investors are reacting to their personal experience rather than market movements. Our setting also ensures that the change in portfolio allocation is not caused by confounding government policies or general time trends in investors' allocation to responsible assets. In addition, our focus on investors in Denmark highlights that the effect of ecological problems on investors' holdings as documented in [Fisman et al. \(2023\)](#), also manifests itself in regions with high air quality.

We also contribute to the literature on the effect of health and expected lifetime on financial decisions ([Rosen and Wu \(2004\)](#), [Døskeland and Kvaerner \(2022\)](#), [Kárpáti \(2022\)](#), and [Kvaerner \(2023\)](#)). An important finding in these studies is that health shocks might lead to changes in individuals' portfolio allocation due to two distinct channels: The effect of health on expected wealth, as well as the effect of health on expected lifetime. To convincingly identify the effect of personal experiences on green preferences, we analyze how family members react to health shocks to children. By focusing on parents' (and other family members') reactions rather than their own health shocks, we address the concern that changes in the individuals' portfolio allocations are confounded by changes to expected wealth and/or expected lifetime. Thus, we contribute to the literature on the effect of health on financial decision by documenting that shocks to investors' "green" sentiment through personal exposure to respiratory diseases cause strong effects on environmental preferences.

Our paper is also related to the vast and growing literature on the effects of personal experiences for financial decisions. Prior literature shows that personal experiences are important in the context of IPO participation ([Kaustia and Knüpfer \(2008\)](#)), risk taking ([Malmendier and Nagel \(2011\)](#), [Malmendier and Nagel \(2016\)](#), [Koudijs and Voth \(2016\)](#), [Knüpfer et al. \(2017\)](#), [Andersen et al. \(2019\)](#), and [Malmendier et al. \(2021\)](#)), house purchases ([Happel et al. \(2022\)](#)), or defaults ([Kalda \(2020\)](#) and [Kleiner et al. \(2021\)](#)). A common theme in these studies is that people tend to overweight own experiences, as suggested by [Kaustia and Knüpfer \(2008\)](#), consistent with reinforcement learning. We add to this literature by

studying the effect of idiosyncratic experiences on investors’ environmental preferences.

Our final contribution is to the literature on non-financial determinants of individuals’ stock holdings. Well-documented facts about individuals’ portfolio allocations such as home bias (French and Poterba (1991)), political bias (Hong and Kostovetsky (2012)), and over-investment in local stocks (Coval and Moskowitz (1999)), own employers’ stock (Massa and Simonov (2006), Cohen (2009)), stocks of companies one frequents as a customer (Keloharju et al. (2012)) and socially responsible stocks (Hong and Kacperczyk (2009), Geczy et al. (2021)) stress that the assumption that investment assets share no common properties with consumption goods is unrealistic (Fama and French (2007)). We add to the literature on non-financial determinants of individuals’ stock holdings by showing that idiosyncratic exposures to health problems associated with air pollution affect their environmental preferences, ultimately changing their portfolio compositions.

The paper proceeds as follows. Section 1 discusses the relationship between air quality and respiratory diseases; Section 2 describes the data; Section 3 introduces our main results; Section 4 shows the heterogeneity of results across different groups of investors and different health outcomes; Section 5 shows the effects of investors’ own respiratory diseases on their stock holdings; Section 6 concludes.

1 Air pollution and respiratory diseases

The link between air pollution and respiratory diseases has long been established by the medical literature. A large body of evidence documents the connection between air pollution, associated diseases and mortality, for Denmark as well as globally.

To provide an overview of the evidence we start by discussing the studies that outline the effect of air pollution on respiratory diseases. We then provide evidence suggesting that although the level of air pollution in Denmark has been declining during our sample period, there is a notable increase in concerns related to air quality by the general population. As

such these observations suggest an increasing salience of the link between air pollution and respiratory diseases.³

1.1 General evidence

The connection between air pollution and cardiopulmonary diseases (an aggregate category comprised of cardiovascular and respiratory diseases) has been generally accepted by medical scholars since the 1970-1980s (Pope III and Dockery (2006)). The early evidence provides detailed case studies of increasing mortality rates associated with severe pollution episodes from Meuse Valley (Belgium), Donora (United States), and London (United Kingdom). These studies highlight a relation between air pollution and cardiovascular and respiratory diseases. A more recent study of the effects of air pollution in six US cities shows that air pollution increases mortality and morbidity from cardiopulmonary diseases, but not from other types of diseases (Dockery et al. (1993)).⁴ Later studies have been able to separate the two causes and to demonstrate that both respiratory and cardiovascular diseases are related to air pollution.⁵

Importantly, multiple studies detect significant effects of unexpectedly low concentration levels of particle omissions on daily mortality rates (e.g., Schwartz and Marcus (1990) and Schwartz (1991)). Since 2009, the Environmental Protection Agency (EPA) estimates the connection between particulate matter (PM) pollution and respiratory mortality and morbidity as “*likely to be causal*”, highlighting the “strong evidence for a relationship between short-term $PM_{2.5}$ exposure and several respiratory-related endpoints” (EPA (2019)).⁶ The health effects of PM pollution pointed out by the EPA “range from inflammation and

³The Online Appendix A2 provides additional information about the types of substances that are considered to cause air pollution to have negative health effects.

⁴As cross-coding difficulties and diagnoses misspecification often obscured the exact cause of death, the two types of disease, cardiovascular and respiratory, were often aggregated in earlier studies (Pope III and Dockery (2006)).

⁵See Table 1 in Pope III and Dockery (2006) for a review of different studies. A more recent synthesis is presented in EPA (2019).

⁶The difficulty of proving the causal relationship partially comes from the effect of the gaseous co-pollutants. Interestingly, the EPA estimates the relationship between $PM_{2.5}$ and cardiovascular mortality and morbidity as “*causal*”.

changes in lung function to respiratory-related emergency department visits and hospital admissions.”

General morbidity is positively associated with respiratory diseases for different age categories, including children and young adults (MacIntyre et al. (2014), Chen et al. (2015), and EPA (2019)).⁷ Overall, the medical literature provides substantial evidence on the link between air pollution and respiratory diseases, and thus, confirms an important premise of our study.⁸

1.2 Air pollution and awareness in Denmark

The institutional setting in Denmark might be counterintuitive for a study of the link between respiratory diseases and green preferences, given that Denmark is a country with low to moderate levels of air pollution, combined with the fact that air pollution has declined since 2010 (see Panel A of Figure 1).

Despite the relatively low level of air pollution, studies from Denmark show that long-term exposure even to low levels of air pollutants is associated with elevated levels of mortality in the Danish population (Raaschou-Nielsen et al. (2023)). A recent nationwide study by Kaspersen et al. (2023) documents that exposure to air pollution is associated with a higher probability of getting a respiratory tract infection. Thus, although the number of deaths caused by air pollution in Denmark is declining (Panel B of Figure 1), the estimated total average annual external health-related costs for Denmark during 2014-2016 amounted to 3.9 billion EUR (Ellermann et al. (2016)), equivalent to around 13.8% of the total health expenditures.

These large numbers are reflected in the growing interest towards ecological problems as evidenced by the growing number of Google searches of “air quality” (Panel A of Figure 1).

⁷Williams et al. (2002) document that acute respiratory infections are among the leading causes of childhood mortality. The authors estimate that around 1.9 million children died from acute respiratory infections in 2000, 70% of which were in Africa and Southeast Asia.

⁸See Schüepp and Sly (2012) for an overview of the possible reasons making children especially vulnerable to PM pollution.

Similarly, Panel A of Figure 2 shows that the news coverage of issues related to air quality and greenhouse gases (such as CO_2) substantially increased since 2011. Interestingly, as suggested by the decrease in the number of deaths associated with air pollution, the trend for the public interest towards air quality does not appear to be grounded in worsening health. Panel B of Figure 2 shows that if anything, the number of articles covering such common respiratory diseases such as asthma and Chronic Obstructive Pulmonary Disease (COPD) has decreased since 2010. This surprising disconnect between pollution levels and public concern suggests that the general dynamics of air pollution and its health consequences are poor predictors of the public interest in environmental problems.

2 Institutional details, data, and methodology

We assemble a dataset of individual investors above the age of 21 with detailed information on wealth, income, demographic variables, and their holdings of stocks and mutual funds. We also use information on their children at ages below 18. The dataset is constructed based on different administrative registries made available by Statistics Denmark, as we describe below.

Income, wealth, and portfolio holdings are from the official records of The Danish Tax Agency (SKAT). These records give us comprehensive information on individuals' income and wealth at the yearly level and include personal identification numbers (CPR), which are equivalent to the US social security numbers. SKAT obtains the data on income and wealth from relevant sources: Employers provide statements about the wages paid to their employees, while financial institutions similarly provide information on amounts of deposits, interests, and dividends received, as well as interests paid.

Similarly, SKAT receives the portfolio holdings directly from financial institutions (e.g., brokerage houses and banks) at an individual asset level, which allows us to observe the International Securities Identification Number (ISIN) of individual securities in investors'

portfolios. We later use these ISIN codes to identify “brown” and “green” stocks as we describe further.

Our data on income, wealth and portfolio holdings cover the time period from 2011 to 2021. Unless stated otherwise, all monetary values are in 2015 Danish kroner (DKK).⁹

Educational records are from the Ministry of Higher Education and Research (Uddannelses- og Forskningsministeriet). All completed years of education, both formal and informal, as well as degrees’ fields, are recorded and made available through Statistics Denmark.

Individual and family data are from the Danish Civil Registration System (Det Centrale Personregister). These records contain CPRs, gender, dates of birth, CPR numbers of nuclear family members (parents, children, and siblings), as well as the marital history (the marital status and the CPR of the spouse) and address ID. In addition to providing useful demographic control variables, this dataset helps us link investors to their children in order to study the effect of pediatric health shocks on parents’ portfolio holdings. We further use the link between parents and children to identify close family members (grandparents, aunts, and uncles of the diagnosed child).

Individual health data are from the National Patient Registry (Landspatientregisteret) at the Danish National Board of Health (Sundhedsstyrelsen). This registry records interactions with the Danish hospital system either for an examination or for a treatment. The part of the registry available to us through Statistics Denmark covers both outpatient and inpatient hospitalizations from 1995 to the first quarter of 2019. We observe the time of the hospital visit, the CPR number, as well as the detailed diagnosis made according to the 10th addition of the International Classification of Diseases (ICD-10), which is the medical classification list provided and updated by the World Health Organisation.

Most of the data described above is assembled for the purpose of individual tax collection or research within medical and social sciences, and is therefore of very high quality.¹⁰ In

⁹One euro equals 7.45 Danish kroner.

¹⁰The data on income, wealth, and portfolio holdings are comparable to that of other Nordic countries: Sweden (Calvet et al. (2007), Calvet et al. (2009a), Calvet et al. (2009b)), Finland (Grinblatt and Keloharju (2001), Grinblatt et al. (2012)), and Norway (Hvide and Östberg (2015), Døskeland and Hvide (2011)).

addition to the registry data from Statistics Denmark, we use Compustat and MSCI to identify industry codes, and Morningstar and Nasdaq Nordic to identify the mutual fund names and characteristics.

2.1 Classification of stocks

Following Andersen et al. (2023), we take a conservative approach to stock classification and define “brown” stocks as those that belongs to an industry directly related to traditional energy production (such as extraction and processing of fossil fuels: coal, oil, and gas). Similarly, we label a stock as “green” if it belongs to an industry related to alternative energy production (i.e., wind and solar). This partitioning is mutually exclusive but not collectively exhaustive, leaving the vast majority of stocks unclassified.

The advantage of this approach is in its intuitiveness to retail investors, whose behavior we study. While the attribution of broader industries to “brown” or “green” categories depends on the informativeness of a specific investor and may therefore be imprecise, the connection between combustion of fossil fuels and air pollution is well-known to the general audience.¹¹

To identify “brown” stocks, we zoom in on the energy sector and look at such industries as oil and gas extraction, petroleum refining, gas production and distribution, electric and gas and other utility (SIC codes 13, 29, 492, and 493). We manually check the business scope of each stock to ensure that its business activity corresponds to the assigned classification. To ascertain that we identify “brown” and “green” stocks outside the industry codes listed above, we search for such keywords as “green”, “solar”, or “wind” in the company names. Again, we manually verify the business activity of each company to ensure that we correctly classify the stock. Overall, we identify 108 unique “green” stocks and 75 “brown”

¹¹As an alternative, one could use an ESG rating such as the one provided by MSCI ESG (former KLD). The coverage of Danish stocks by MSCI ESG ratings over the sample years is scant. In 2021, when the MSCI coverage was the highest within our sample, the average MSCI environmental pillar was 4.82 for the “brown” stocks we classify compared to 6.96 for “green” stocks. By contrast, the average score for an unclassified stock is 5.74.

stocks. Note that our “green–brown” classification is mutually exclusive but not collectively exhaustive.

2.2 Classification of mutual funds

Following the existing literature, we classify ESG mutual funds by names (Gaspar et al. (2006), Lapanan (2018), Hellström et al. (2020), Curtis et al. (2021), Michaely et al. (2021), Li et al. (2021)). To identify ESG funds, we use historical fund names from Morningstar and Nasdaq Nordic. We take the keywords list from Michaely et al. (2021) (such as “sustain,” “social,” “impact,” “ESG,” “green,” etc) and translate these keywords in Danish since local investors tend to hold Danish funds.¹² We further augment this list with typical Danish keywords related to responsible investment.¹³

Overall, out of 7,490 unique funds, we label 561 funds, that is, 7.6% as ESG at some point in time. This label is time-varying, as funds’ names can change. Indeed, 76 out of 561 funds are labeled as ESG after a renaming.

2.3 Sample formation

We start by finding all hospital visits by all patients under the age of 18 from 1995 to 2019 with a ICD-10 diagnosis codes DJ00-DJ99 (respiratory diseases). For each patient, we find their first case of getting admitted to a hospital with a respiratory diagnosis. We merge the patients to both of their parents by using the family links. For “treated” parents, we identify the first time that one of their children is admitted to the hospital. We then connect the sample of parents with the demographic data and their financial portfolios in the year before their child is admitted to a hospital, retaining only those parents who hold financial assets, stocks or mutual funds. If both parents participate in the financial market, we keep them

¹²Approximately 95% of all mutual fund holdings in our dataset are kept in Danish funds.

¹³Alternatively, one could use Morningstar Sustainability Rating (MSR), which is only available starting 2018. In 2021, when the coverage is the highest, the average MSR for funds classified as socially responsible by our name-based measure was 0.95 as compared to 0.18 for funds that were not classified as socially responsible.

both in the dataset as separate observations.

Figure 3 shows the distribution of respiratory cases in the final sample across years. Our sample ends in the beginning of 2019, which is reflected by the low number of observations in the last year. The jump in the number of cases in 2014 is driven by changing procedures of treatment for emergency cases. Before 2014, general care practitioners provided out-of-hours primary medical services for acute cases either as home visits or in centralized clinics. Since 2014, patients started to get directed to emergency departments in local hospitals (Fløjstrup et al. (2020)), which explains the increase in the number of patients in our data.

2.4 Summary statistics

The summary statistics for the population of stock market participants in Denmark together with the sample of investors whose children are diagnosed with a respiratory disease is given in Table 1. Panel A presents the summary statistics of individual characteristics for the entire sample of investors (column 1) and the treated sample (column 2). By construction, as our focus is on parents with children under the age of 18, treated investors are younger than the typical Danish investor who is, on average, 53 years old. Similarly, more investors in the treatment group are male, married, have longer education, and more children living at home. It is important to mention that the number reported in Panel A is the number of children in the current household, not the number of children that the individual investor had over her lifespan. Finally, we note that treated investors have higher income than the average investor but smaller financial wealth.

Panel B shows the summary statistics for the portfolio characteristics. Remarkably, investors in the treated sample have comparable portfolio weights of “brown” stocks and more “green” stocks than the average investor. Similarly, the average investor has a lower portfolio weight of ESG funds than investors from the treated sample.

2.5 Methodology

We conduct staggered difference-in-differences analysis. For each treatment unit, we choose a matching “control” unit and estimate the change in the differences between the treatment and the control groups.

As is documented in the econometric literature, staggered difference in differences can produce biased estimates under heterogeneous treatment effects (Goodman-Bacon (2021)). Following the recommendation of Baker et al. (2022), we use the dynamic difference-in-differences estimator designed by Sun and Abraham (2021). We estimate the coefficients of the model

$$Y_{i,t} = \alpha_i + \lambda_t + \sum_{m=-K}^{-2} \mu_m D_{i,t}^m + \sum_{m=0}^L \mu_m D_{i,t}^m + \nu_{i,t}, \quad (1)$$

where $Y_{i,t}$ measures responsible investments of individual i at time t . The specification includes individual fixed effects α_i to control for time-invariant individual heterogeneity like lifestyles or investment style, time fixed effects, λ_t , to control for time trends and macroeconomic conditions. The variables of interest, $D_{j,s}$, are indicator variables such that $D_{j,s} = 1$ if $i = j$ and $t = s$, otherwise $D_{j,s} = 0$. We use an estimation window of five years in event time relative to the treatment, that is, $K = L = 5$ while year $t-1$ is the year of reference. The Average Treatment effect for the Treated (ATT) is defined as the average of the post-treatment coefficients: $ATT = \left(\sum_{m=1}^K \mu_m \right) / K$.

The matching is done at the year preceding the treatment. To obtain the matching sample, for each treatment investor we find a set of control investors with the same age, gender, marital status, and number of children in the household, who live in the same municipality, and have the same education level. Similar to the treatment group, potential control investors are also required to hold financial assets, either stocks or mutual funds. In this set of potential control investors, we select the nearest neighbor i.e. the investor who has the closest level of total wealth to the treatment investor.

3 Respiratory diseases and investors’ portfolios

In this section we present our main results. We start by studying the change in investors’ holdings of “brown” and “green” stocks after her child gets diagnosed with a respiratory disease. We then introduce our measure of “green minus brown” as a way to summarize our findings, and we further use it for comparisons of different specifications. We accompany our findings with results for placebo groups, that is, other diseases that have comparable numbers of treated patients. We conclude this section by presenting the results related to another asset type: mutual fund holdings.

3.1 “Brown” stocks

If idiosyncratic health shocks affect green preferences, we expect the investors to decrease their holdings of brown stocks (relative to the control group) after their children get diagnosed with a respiratory disease. We begin our analysis by estimating the treatment effect on two variables: (i) the weight of “brown” stocks in the investor’s portfolio and (ii) the indicator taking the value one if the investor holds a “brown” stock. The change in the portfolio weight can signalize that the investor is adjusting her portfolio at the intensive margin, while the indicator captures changes at the extensive margin.

The results of estimating equation 1 for both variables are presented in Table 2. Significant negative ATTs indicate that both variables decrease after the treatment. The effect on the portfolio weight becomes statistically significant in the first year after the treatment, while the indicator reacts with a time lag of one year, consistent with a gradual liquidation of “brown” stocks as opposed to a quick exit. The evolution of the treatment effects over time is shown in Figure 4. Both panels A and B show no pre-trend. The treatment effect is lasting, surviving for over 5 years after the investor gets the first-time experience.

The largest single-year effect on the portfolio weight is -27 bps in year 4, while the average effect is -19 bps. Given the average pre-treatment level of 220 bps, the treatment effect ranges

from 9% to 12% of the pre-treatment mean, which is economically significant. Similarly, the effect on the probability of holding a “brown” stock ranges from -42 bps to -58 bps, which — compared to the pre-treatment average of 610 bps — gives an estimate of the effect from 7% to 10% relative to the mean.

For a correct interpretation of the results, it is necessary to remember that the estimates of the treatment effect are obtained relative to a matched control group. One potential interpretation of the results is that investors actively sell off “brown” stocks in response to the children’s diagnoses. Alternatively, some part of the effect can be explained by the treatment group decreasing the probability of buying new “brown” stocks compared to the control group. Each of the two stories is consistent with our general hypothesis that treated investors change their approach to portfolio formation after receiving shocks to their individual experiences. However, the exact way in which investors adjust their portfolios compared to the control group is of separate interest. To further study this question, in Figure 5 we plot the raw averages of the portfolio weight on the “brown” stock and the indicator of holding a “brown” stock for the treated and control groups separately. Panel A shows that while the overall weight on “brown” stocks in the portfolios of the control group is constant or mildly decreasing, the treatment group has a stronger negative trend. While this result is consistent with treated investors actively selling “brown” stocks, it can also be a result of the time trend in “brown” stock prices or the treated investors’ tendency to buy more “non-brown” stocks post treatment. To correctly interpret our finding, we repeat the graph in Panel A using constant stock prices throughout the sample.¹⁴ Figure A-1 shows the results. Both groups increase their fractions of “brown” stock holdings measured in fixed prices, but the trend in the treated investors’ holdings becomes flat after the treatment. The comparison of the two graphs suggests that since the portfolio weight of “brown” stocks decreases post treatment, either the treated investors decrease their purchase of new “brown” stocks as a group or some fraction of treated investors actively decreases their portfolio weights on

¹⁴For each stock, we find the average end-of-year price and use it to compute the portfolio value and the fraction of “brown” stocks for each investor-year combination.

“brown” stocks.¹⁵

Panel B of Figure 5 shows that both treatment and control groups experience a common trend in the probability of holding a “brown” stock. After the shock, the slope of the time trend for the treated group decreases compared to the control group but remains positive. Taken together with Panel A, this evidence suggests that over time more people choose to hold “brown” stocks, for example, for diversification purposes. Then after receiving the treatment, parents of children suffering from respiratory conditions, are more aware of their holdings and are less likely to diversify into “brown” stocks, ultimately decreasing their portfolio weight on “brown” stocks either due to their active decision or to the time trend in prices.

The change in the investment approach after the treatment is surprising given the retail investors’ inertia documented in previous studies (e.g., Calvet et al. (2009a), Biliias et al. (2010)). One potential explanation for the decrease in brown stock holdings is a liquidity shock. If the medical bills are not fully covered by the social security scheme or if parents incur some additional health-related costs, this may induce them to liquidate some of their stock holdings. When divesting the stock portfolio due to a liquidity shock, “brown” stocks may be a natural starting point given the intuitive association between health, pollution, and “brown” companies.

Although theoretically plausible, this explanation, however, is unlikely to be the main driver for the divestment of “brown” stocks since the social security coverage in Denmark is very generous.¹⁶ Prescription medicines in Denmark are also substantially subsidized.¹⁷ However, parents may incur additional costs that go beyond the necessary medical expenses.

¹⁵Note that retail investors are likely to rebalance their holdings using contemporary prices as weights as opposed to constant historical prices. Therefore, treated investors likely perceive the change in the fraction of “brown” stocks in their portfolio as a result of their (active) decision.

¹⁶For children and adolescents under the age of 18, healthcare services are entirely free, which covers general practitioner (GP) visits, hospital stays, and any treatments, including those for chronic and acute diseases. Pediatric care is comprehensive and fully funded by the state.

¹⁷Prescription medicines in Denmark are subsidized to varying degrees based on a progressive self-payment structure, where the subsidy increases as one’s annual expenditure on prescribed medicines rises. For children, many prescribed medications are either free or available at a very low cost, further reducing the financial burden on families for the treatment of children’s diseases.

For example, they may adjust their consumption and take additional costs to best accommodate their children’s needs. In this case, even after the social security coverage, health shocks may cause liquidity shortages.

If pediatric health shocks cause liquidity shocks, parents will first deplete their most liquid source of funds, which is the bank account. Panel A of Figure 6 shows the difference-in-differences analysis for the investors’ bank deposits. There is no economically significant change in deposit amounts after the treatment, suggesting that the treated group does not experience liquidity shortage. Similarly, we find no evidence that treatment induces investors to divest stocks in general. Panel B of Figure 6 shows that the risky asset share (proportion of stocks and funds in the investor’s financial wealth) does not decrease after the investor’s child gets a respiratory disease.¹⁸ This evidence suggests that in response to the treatment, parents adjust their preferences across different types of risky assets rather than redirect their investment focus towards relatively safer assets.

3.2 “Green” stocks

Similarly to “brown” stocks, investors’ holdings of “green” stocks may be adjusted following the treatment. The results for the proportion of “green” stocks and the probability of holding a “green” stock are displayed in Table 3. The proportion of “green” stocks slightly increases after the shock, while the probability of holding a green stock does not change post-treatment. The ATT for the portfolio weight is significant and amounts to 2% of the pre-treatment mean.

It is important to contrast the results for the “brown” and “green” stocks. First, the effect on the “brown” stock fraction is strong and immediate as compared to the “green” stocks, suggesting that investors are more concerned about contributing to the air pollution than about failing to support the “green” energy industry. The treatment effect on the “green”

¹⁸Furthermore, Figures A-2, A-3, and A-4, respectively, show that the treated investors do not become less wealthy, do not decrease their working income, and are relatively less likely to move to a new residence after the treatment. This evidence is inconsistent with treatment constituting a wealth shock or a significant liquidity shock. The corresponding coefficients are provided in Table A-2.

stock holding is building up over time, potentially driven by diseases that continue to develop over time. Second, comparing the results for the portfolio weight and the indicator of holding “green,” we conclude that the effect is present at the intensive margin, that is, possibly driven by those who already hold “green” stocks. Finally, even though the probability of holding “green” stocks does not increase post-treatment, it is perhaps even more important that it does not decrease. The absence of the effect means that our results for “brown” stocks are not driven by investors simply divesting all energy stocks, switching the investment industry or consolidating their holdings in a smaller number of stocks.

3.3 “Green” minus “brown”

A natural question arising from the difference-in-differences tests of investments in “brown” stocks and “green” stocks is whether the changes in portfolio weights are caused by active changes to portfolio weights on “unclassified” stocks. To address this possibility, we present results for investments in “green” minus “brown” stocks. It follows that changes to the portfolio weight on “green” minus “brown” stocks cannot be attributed to changing portfolio weights on “unclassified” stocks as this change will net out. Thus, analyzing the change to the “green” and “brown” stock holdings isolates the tilt in the investors’ portfolios towards ecologically sustainable stock investing. We use the difference of (i) portfolio weights and (ii) indicators of holding “green” and “brown” stocks to compare the results across different groups of diseases, health conditions, and investors.¹⁹ Figure 8 shows difference-in-differences results for “green” stocks minus “brown” stocks for the portfolio weights (Panel A) and the indicator of holding (Panel B) for the investors whose children visit a hospital with a respiratory disease relative to the control group. We note that the treatment group increases the portfolio weight on “green” minus “brown” stocks by 30 to 50 bps., depending on the evaluation horizon. The changing portfolio weights on “green” minus “brown” stocks are statistical as well as economically significant. The results for the indicator of holding a

¹⁹Note that for the indicators we take the difference between the indicator for holding “green” stocks and the indicator for holding “brown” stocks, leading to 1, 0, and -1 as possible outcomes.

“green” stock minus the indicator of holding a “brown” stock also shows a positive and statistically significant effect. Thus, we conclude that the decreasing (increasing) allocation to “brown” stocks (“green” stocks) is not driven by an increasing allocations to “unclassified” stocks.

3.4 Placebo tests

An alternative explanation of our findings is that the parents’ reaction is not specific to respiratory diseases as the category most saliently connected to air pollution. Several studies find that responsible investments are related to the warm-glow effect (Riedl and Smeets (2017), Andersen et al. (2023)). Consistent with this effect, hospital visits and first-hand exposure to pediatric diseases might create a desire to personally contribute to the public good via charitable donations or investment in sustainable assets. It follows that the warm-glow effect might cause an decrease in “brown” investments and a increase in “green” investment not only for respiratory diseases, but for other diseases as well.

To check to what extent our findings extrapolate to other groups of diseases, we repeat the same procedure for other types of diseases.²⁰ Table 4 shows the results for major groups of diseases, starting with the most frequent disease and ending with the least frequent. Among the 19 major groups of diseases, only the respiratory group demonstrates positive and statistically significant results. This result suggests that the salience of the connection between respiratory diseases and air pollution is important for the investors.

In Section 1, we note that the effect of air pollution on the frequency of cardiopulmonary diseases, the group comprised of cardiovascular and respiratory diseases. The connection between air pollution and cardiovascular hospitalizations is well-known in medicine but not as salient to people without a medical degree. One likely explanation for the lack of awareness is that cardiovascular diseases stem from multiple cause of which one is air pollution. The absence of the treatment effect for circulatory system diseases as well as for blood diseases in

²⁰Table A-1 provides the full list of disease categories with their ICD-10 codes. We exclude diseases in the residual group “Abnormal findings IKA” as it might involve potential misclassifications.

Table 4 suggests that investors are more likely to make intuitive connections between air pollution and illnesses related to breathing. We conclude that the placebo tests, which show no effect for non-respiratory diseases, bolster our interpretation that personal experiences with respiratory diseases make investors alter their preference for responsible investing, resulting in decreasing (increasing) portfolio weights of “brown” (“green”) stocks.

3.5 Mutual fund holdings

We now turn to looking at a different class of assets — mutual funds. If investors’ environmental concerns extend beyond individual stocks, we expect them to increase their holdings of ESG funds after the treatment. Alternatively, if investors do not consider ESG funds as a means of decreasing air pollution but rather associate them with addressing global warming and the improvement of S- and G-related factors, we will not see a positive effect.

Analysing the results for mutual funds presented in Table 5, we find that investors with children suffering from a respiratory disease do not increase their holdings of ESG funds neither at the intensive, nor at the extensive margin, relative to a control group. This evidence suggests that investors do not associate ESG funds with decreasing air pollution. It also speaks against the warm glow explanation of our findings, as research shows that investing in ESG funds is often value-driven (Riedl and Smeets (2017), and Giglio et al. (2023)), and identifies the effect of warm glow on ESG fund holdings (Riedl and Smeets (2017), and Andersen et al. (2023)). We conclude that the effect is strongest for such assets as “brown” and “green” stocks, which are most directly related to the factor potentially driving the experience (i.e., air pollution).

4 Heterogenous treatment effects

In this section, we start by describing how the severity of the health condition affects the results. Then we show to what extent our results vary with investors’ characteristics.

4.1 Severity of disease

In our study, parents, whose children get admitted into a hospital with a respiratory disease, experience a shock that affects their preferences for green investing. If this interpretation is correct, the result should be stronger for those patients whose condition at the moment of the hospital visit is more serious or who have respiratory diagnoses with long-lasting health consequences and the potential to return to an acute stage.

As proxies for the seriousness of health condition, we use a) children who are hospitalized with a respiratory disease for a longer time period, b) children that are diagnosed with multiple respiratory diseases, and c) children with multiple hospital visits due to respiratory diseases, and d) an indicator for children that are admitted to the hospital with a chronic diagnosis. For each of these measures, we separate the data in two subsamples and estimate the results separately. If our interpretation is correct, we expect to see stronger treatment effects for more serious conditions (that is, higher numbers of days in hospital, higher number of respiratory diagnoses, and higher number of hospital visits). We expect that parents of children admitted with chronic diagnoses will have a stronger reaction as chronic conditions may have long-term effect on patients' lives. At the same time, if a patient is hospitalized with a chronic diagnosis, it is possible that this diagnosis is a known pre-existent condition of the patient, which has developed prior to the hospitalization. In this case, the effect of the "chronic" subsample will be difficult to identify due to the uncertain timing of the treatment.

Table 6 shows the results. The effects are stronger for the non-chronic diseases, consistent with chronic patients knowing their conditions prior to the hospital visit. Most patients in our sample come to the hospital with acute respiratory tract infections (mostly of the upper respiratory tract). These cases can be early signs of other respiratory diseases or aggravations of pre-existing conditions. Since our data does not track the entire medical history for each patient but only records hospital visits, we do not observe whether a patient has a respiratory diagnosis established by a general practitioner prior to the hospital visit. However, since the response of the sample that is admitted with a chronic diagnosis is weaker, it is possible that

they are aware of their pre-existing respiratory condition, which means that the actual time of treatment happened before the first hospital visit we observe.

Columns 3 to 8 of Table 6 show that the results are stronger for parents of the patients who make several hospital visits in our data sample and those who get several respiratory diagnoses. Splitting the sample by the number of days spent in the hospital, we see that those who spent more than one day during the year of the first respiratory visit demonstrate a stronger effect than the rest of the sample. Overall, the results are consistent with more severe cases causing stronger reactions.

4.2 Geographic proximity

One interpretation of the connection between the severity of children’s medical conditions and the strength of the parents’ responses is that parents relate health consequences to local air pollution. In this case, one can expect to see a stronger effect for domestic (as opposed to foreign) “brown” and “green” stocks as investors are more likely to associate their health conditions with the activity of local firms.

To test this hypothesis, we use stock ISINs to partition the sample into domestic and foreign stocks.²¹ Since Denmark is a relatively small country, we focus on comparing Nordic stocks (that is, the stocks that were first registered in Finland, Denmark, Iceland, Norway, or Sweden) to stocks that were registered in other countries. Table 7 shows the results.

While both fractions and probabilities of holding “green” minus “brown” stocks increases for both samples, the results are economically and statistically significant only for domestic stocks. Therefore, we conclude that investors are more likely to adjust their holdings of stocks that are more likely to affect the health of their children.

²¹The first two symbols of an ISIN code correspond to the country where this stock was first registered. This country does not have to coincide with the country of incorporation.

4.3 Investors' characteristics

We proceed to testing whether investors' characteristics influence our results. Table 8 shows a stronger effect for more educated investors consistent with more educated investors perceiving themselves as more competent, and thus trading more often and putting more weight on their own information and views (Graham et al. (2009), Anderson and Robinson (2022), and Degryse et al. (2023)).

We find little evidence that investors' age and location affect our results: The outcome is similar for younger and older and for investors living in and outside of big (that is, top-10) Danish cities. Separating the sample into mothers and fathers, we see a somewhat stronger result at the intensive margins for fathers. However, the interpretation of this finding is obscured by the possibility that only one partner is investing on behalf of the entire family. Meanwhile, the extensive margin outcomes for both samples are very close.

4.4 Family Ties

We continue by studying the influence of family ties on the magnitudes of the treatment effect in Table 9. Interestingly, our results are driven by parents who live with their children (i.e., have the same living address) at the time of the health shock. This finding can be consistent with the first-hand experience being necessary for the reaction to the child's disease on the stock holdings to be pronounced. Alternatively, it may be that parents who do not live with their children do not maintain tight connections with their families and will not be the first people with whom the important health news will be shared.

To further our understanding of how personal experience affect investor decisions, we test the treatment effect for other family members. The results in column 3 of Table 9 show that grandparents display a significant treatment effect, although roughly 50% smaller than that of parents. At the same time, comparing the effect for parents and aunts/uncles in column 4, we see that the latter are as likely to increase the probability of holding at least one green stock (decrease the probability of holding at least one brown stock) but are less likely to

substantially adjust their portfolio in response to the shock. These findings suggest that the exposure to the news about the child’s sickness is transmitted through social channels and affects other family members holdings, albeit to a smaller degree. To this end, these results suggest that the effect of idiosyncratic health shocks extend beyond first-hand experiences to other family members.

4.5 Time effect

In Section 1.2, we show that despite the improvement of the ecological situation in Denmark, the population is becoming more interested in the news about air quality and global warming. If the strength of the treatment effect on the holding of “green” minus “brown” stocks depends on the actual level of pollution and the associated health effects, we would expect the treatment effect to be stronger in the first part of the sample (for children who fell sick before 2015). However, if the driving power of the effect is the social interest, we expect to see stronger results in the later part of the sample (that is, after 2015).

Upon testing these two hypotheses, as shown in Table 10, we find that investors exhibit a stronger reaction in the later part of the sample. This trend is more consistent with social interest in environmental issues (rather than pollution itself) playing a key role in investors’ responses to pollution-related problems. This finding is crucial for interpreting pollution-related studies, including ours, suggesting that the dynamics of the documented effects are likely to strengthen in response to increasing public demand for higher living standards.

5 Shocks to investors’ own health

Up until this point, we focused exclusively on the shocks that are unrelated to the health of the investor herself or any of the working family members. In doing so, our motivation is to explore a strong shock to preferences that is unrelated to the investor’s budget constraint and/or liquidity needs. However, even taking into account potential identification issues, it

is useful to know whether investors’ own health shocks induce a comparable effect on their holdings.

To estimate this effect, we start by forming the sample of investors’ own respiratory health shocks in the same way as we did for the children. The limitation here is that we do not observe the entire history of hospital visits for grown-ups as our dataset starts in 1995. We proceed assuming that by 2010 the effect of investors’ experiences from hospital visits prior to 1995 on their stock holdings becomes negligibly small.

Table 11 shows the results. The ATT is insignificant for all four variables, as well as for the differences between “green” and “brown” holdings (unreported). We conclude that investors do not significantly react to their own health shocks.

This has several potential explanations. First, our assumptions about the irrelevance of the medical history prior to 1995 may be wrong. Second, grown-up investors know much more about their own health, which makes a “surprise” hospital visit less likely. Third, grown-up individuals are potentially more likely to attribute their conditions to their own actions (such as smoking, which we do not observe). Finally, if investors perceive their own health shock as impacting their budget constraint, they will consider themselves less wealthy. If “green” investing is a luxury good as suggested by Andersen et al. (2023), this may give rise to an effect of the opposite sign, which can cancel out the influence of own health shock.

6 Conclusion

In this paper, we establish that individual experiences affect investors’ preferences for responsible investing. When a child gets admitted to a hospital with a respiratory disease, her parents decrease (increase) the portfolio weights of “brown” (“green”) stocks, and are less likely to invest in “brown” stocks. The effect stems from both an active divestment in “brown” stocks and a reduced likelihood of selecting a “brown” stock after the treatment. Consistent with the conjecture that parents associate pediatric respiratory diseases with air

pollution we find no such effects for non-respiratory diseases.

The tightness of social connections is important for the results. We show that although our findings are strongest for the parents, the results also hold for uncles and aunts and for grandparents of the sick children. The effect on the parents is driven by those who are living with their children at the moment of the hospital visit.

We find stronger effects for more severe health conditions: Parents of children with higher numbers of respiratory diagnoses and longer hospital stays display stronger results. Looking at investors' own health outcomes, we find no significant effect on stock holdings.

Regarding the effects for other asset types, we document no effect of the shocks on the investors' holdings of ESG funds, which can mean that individuals do not perceive investment in ESG funds as a way to address air pollution.

By examining the impact of health shocks on “green” investing in Denmark — a country with moderate levels of air pollution — we demonstrate that the salience of pollution is more influential than its absolute level. While air pollution in Denmark decreases, social interest in environmental problems increases. This trend aligns with the significant role that public interest, rather than the relative severity of environmental issues, plays in shaping outcomes. Our findings reveal a stronger effect post-2015 compared to earlier periods. Consequently, we conclude that preferences for responsible investing are increasingly important in shaping investors' portfolios, regardless of the absolute levels of pollution.

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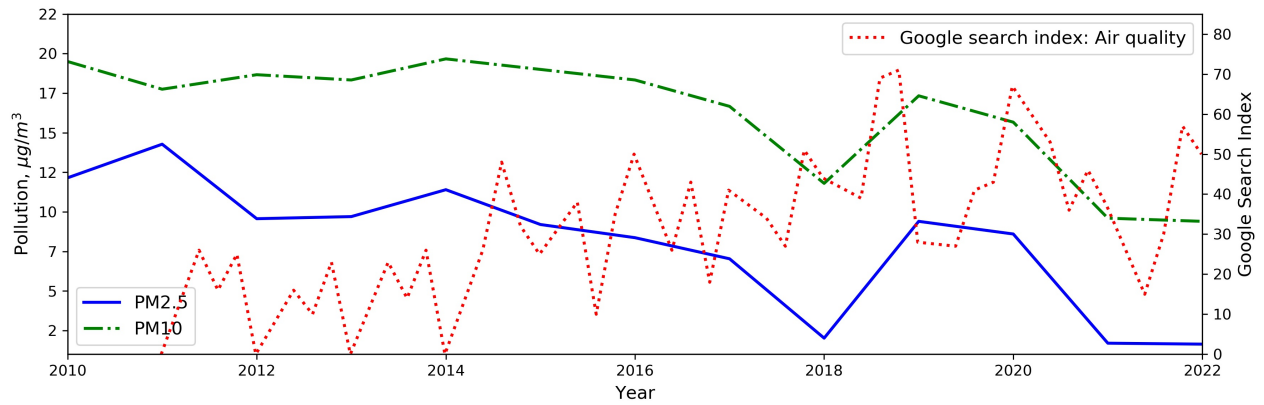
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Figure 1: Air pollution, awareness, and social costs

Panel A shows yearly average particulate matter (PM) pollution levels in Denmark (in $\mu\text{g}/\text{m}^3$) across all measurement stations (left axis, source: Aarhus University Air Quality Measurement Database) and the Google search “Interest over time” index for “air quality” (right axis). PM_{10} is defined as particulate matter of 10 micrometers in diameter or less; $\text{PM}_{2.5}$ is particulate matter of less than 2.5 micrometers in diameter. The Google Interest over time index measures the number of Google searches of a certain combination of words (“air quality”) from a specific location (Denmark), where the maximal number of searches is normalized to 100. Panel B shows the number of deaths attributable to air pollution in Denmark from 2010 to 2019 (in total and for PM and ozone pollution separately). Source: Health Effects Institute, *State of Global Air 2020*, Global Burden of Disease Study 2019.

Panel A: Air pollution and awareness



Panel B: Social costs of air pollution

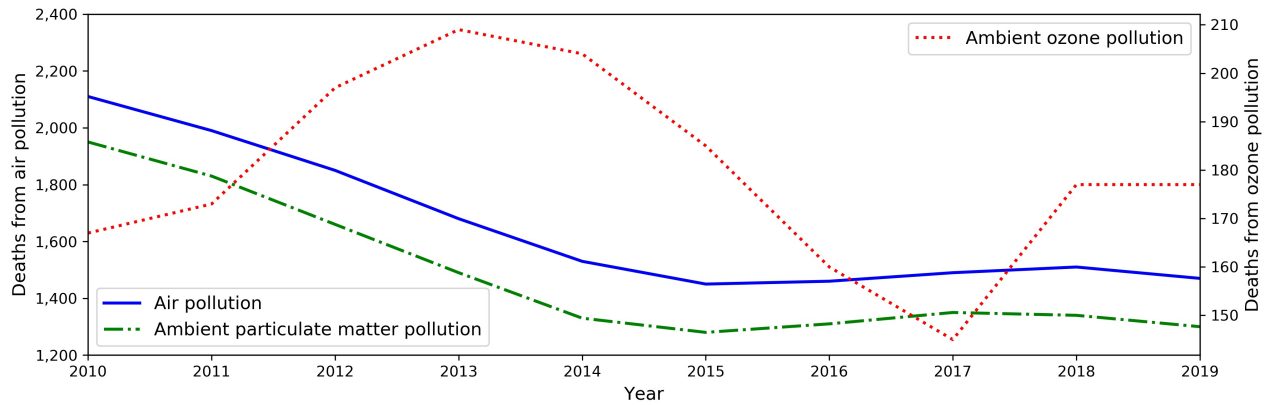
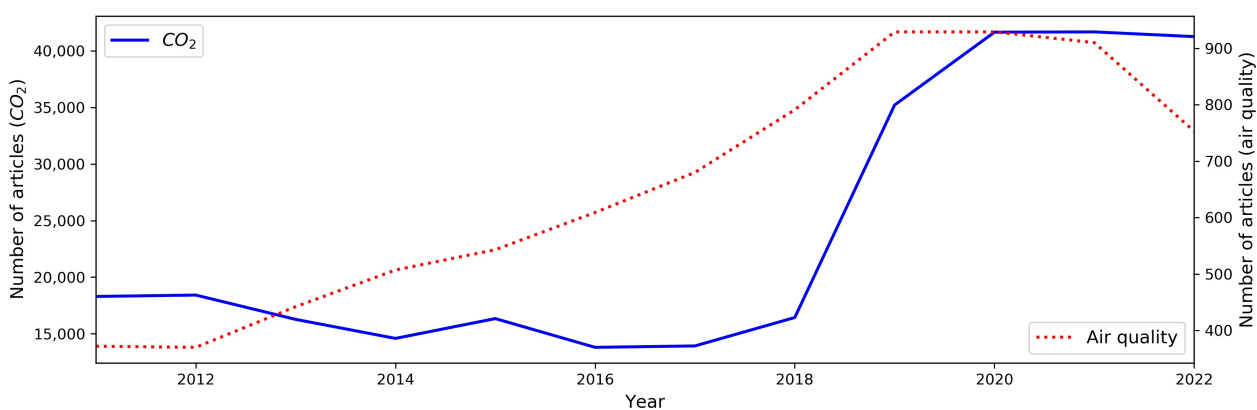


Figure 2: News coverage of air pollution and respiratory diseases

Panel A shows the yearly number of articles in Danish media covering CO_2 and “Air quality” (Luftkvalitet). Panel B shows the yearly number of articles in Danish media (print media (newspapers and magazines), broadcast media (TV and radio), online news, and social media platforms) covering Chronic obstructive pulmonary disease (COPD — KOL in Danish), asthma, and “Clean air” (ren luft) or “Cleaner air” (renere luft). Source: www.infomedia.org.

Panel A: News coverage of air quality and CO_2 emissions



Panel B: News coverage of air quality and respiratory diseases

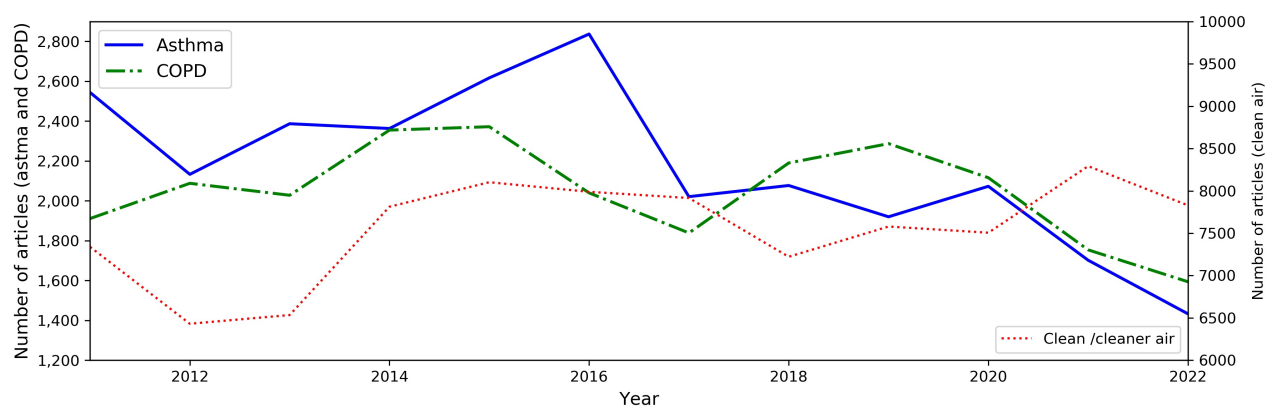


Figure 3: Pediatric hospital admittance with respiratory diseases in Denmark

This figure shows the distribution of the number of children admitted to hospitals in Denmark with respiratory diseases from 1 January 2011 to 4 July 2019 (in the treated sample). Starting in 2014, patients are directed to local hospitals rather than receiving home visits, resulting in an increasing number of hospitalizations in our data (see [Fløjstrup et al. \(2020\)](#) for details). For 2019, our data ends on 4 July 2019, decreasing the number of observations in 2019 relative to other years.

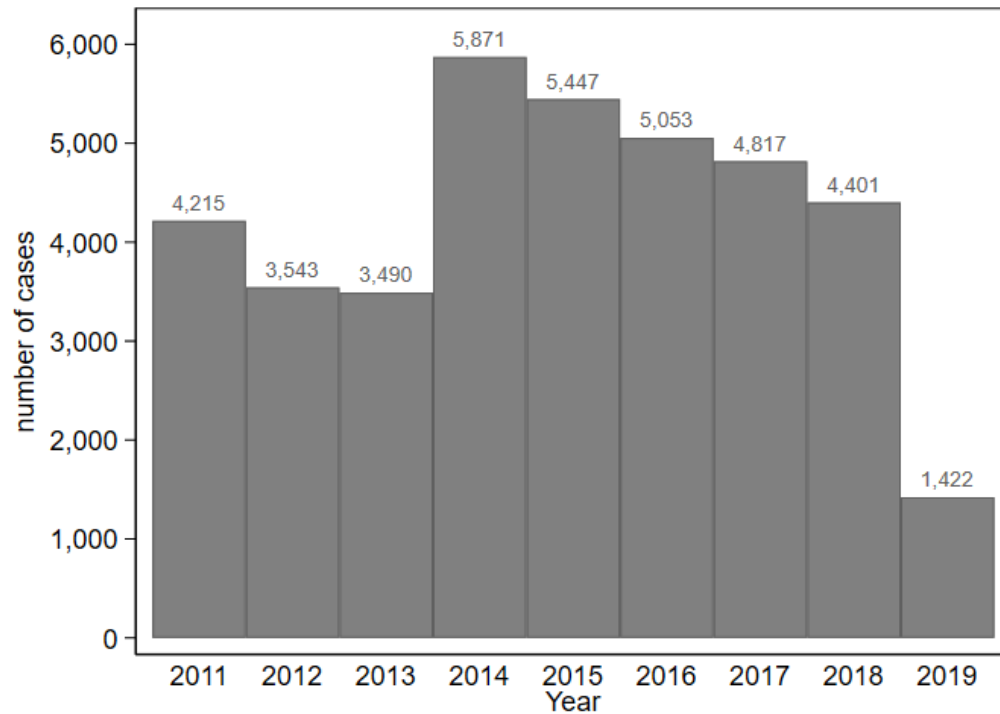
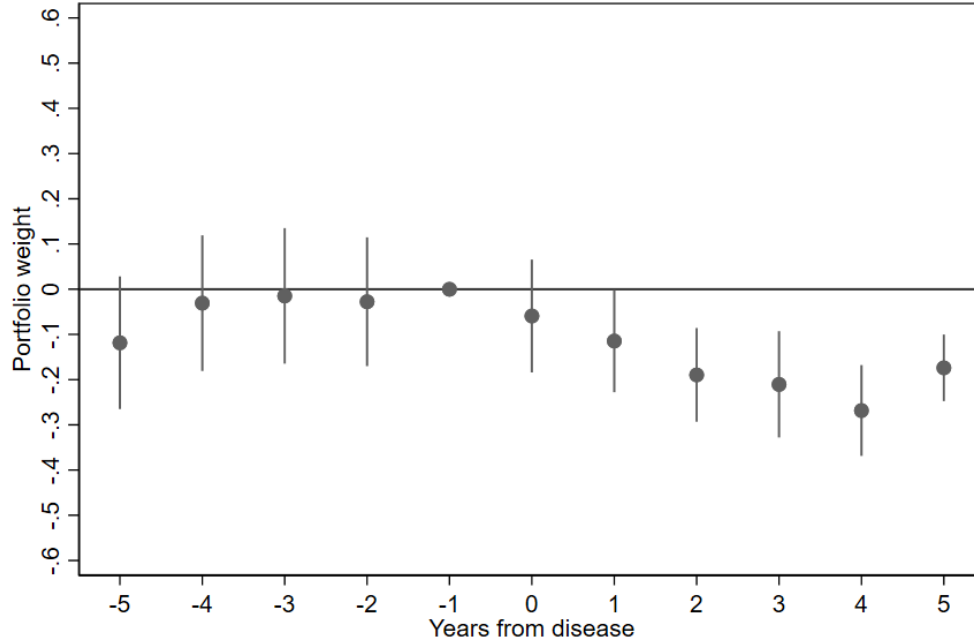


Figure 4: “Brown” stock holdings

This figure plots the difference-in-differences results (coefficients $\mu_{-5} - \mu_5$ in equation (1)) for the portfolio weight (Panel A) and the probability of holding “brown” stocks (Panel B) for traders, whose children get diagnosed with a respiratory disease. The year preceding the treatment is omitted. 95% two-sided confidence intervals are plotted using standard errors clustered at the municipality level.

Panel A: Portfolio weight of “brown” stock



Panel B: Indicator of holding a “brown” stock

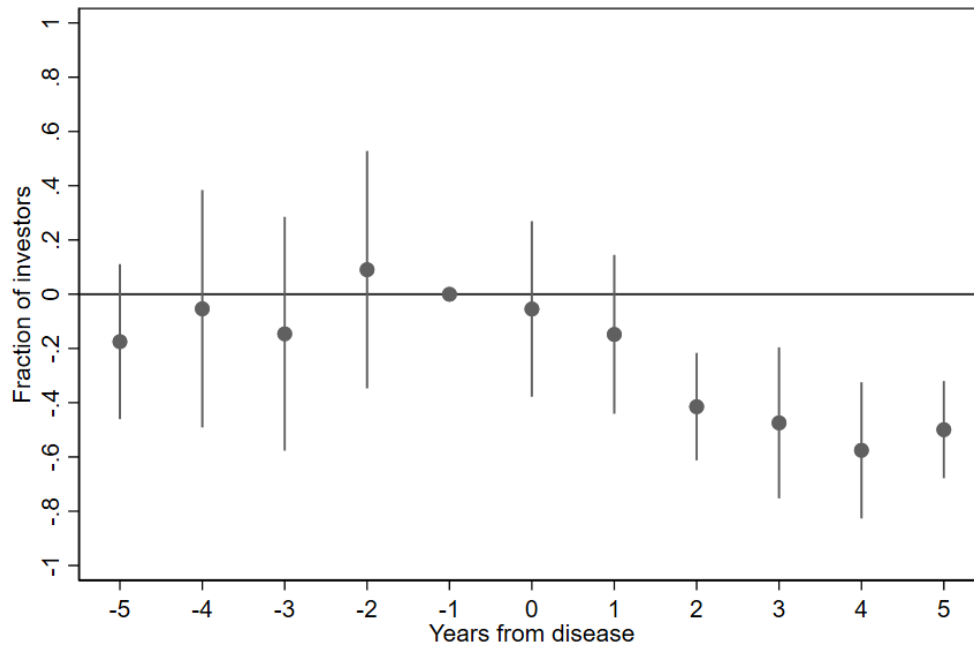
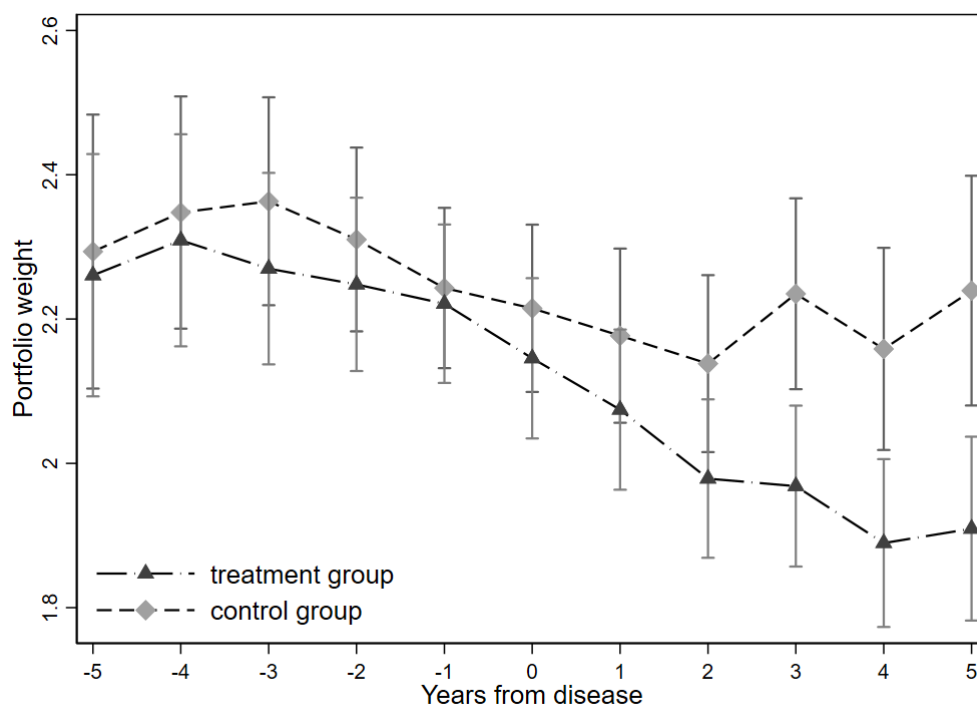


Figure 5: Unadjusted sample averages (“brown” stocks)

This figure shows sample averages for the portfolio weight (Panel A) and the probability of holding “brown” stocks (Panel B) for traders, whose children get diagnosed with a respiratory disease (treatment group), and control samples separately with 95% two-sided confidence intervals.

Panel A: Portfolio weight of “brown” stock



Panel B: Indicator of holding a “brown” stock

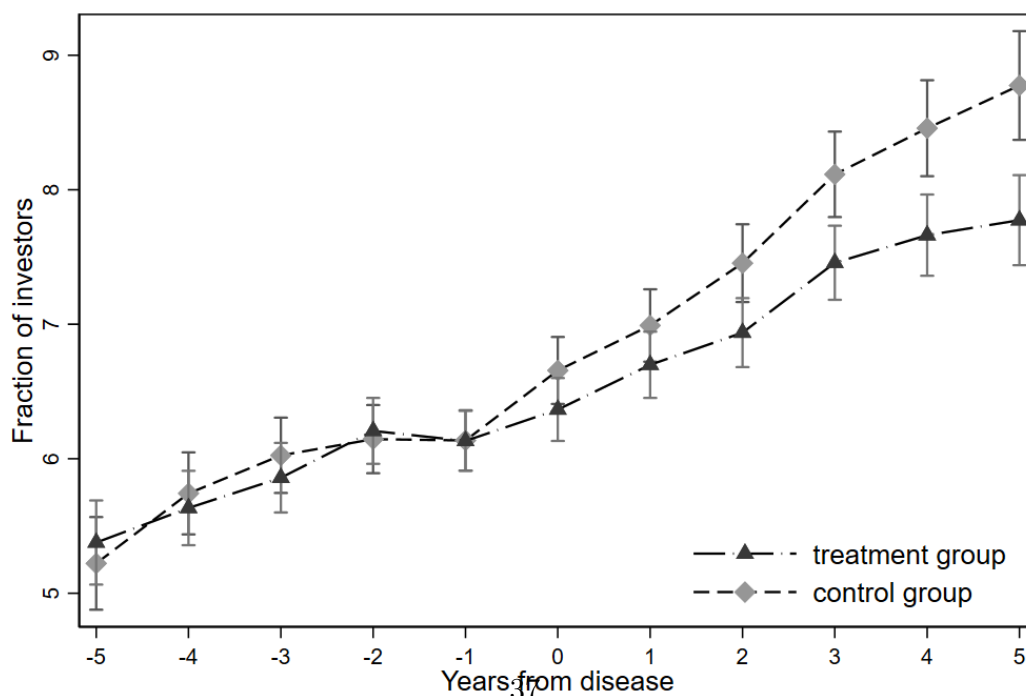
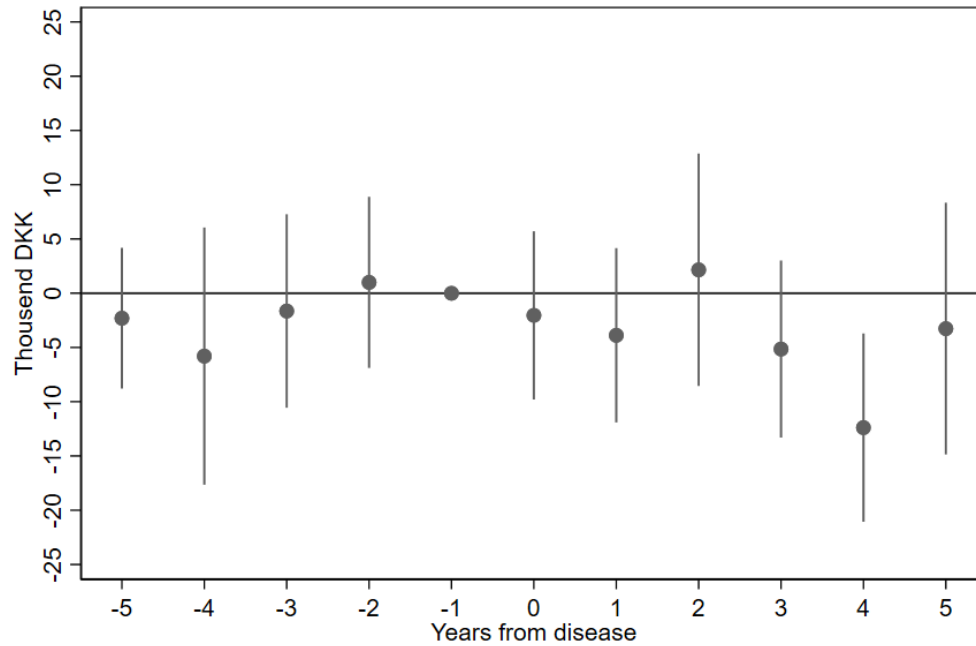


Figure 6: Financial assets

This figure plots the difference-in-differences results (coefficients $\mu_{-5} - \mu_5$ in equation (1)) for the amount of investors' bank deposits (Panel A) and the ratio of risky assets (stocks and mutual funds) to financial wealth (Panel B) for traders, whose children get diagnosed with a respiratory disease. The year preceding the treatment is omitted. 95% two-sided confidence intervals are plotted using standard errors clustered at the municipality level.

Panel A: Bank deposits



Panel B: Risky assets share

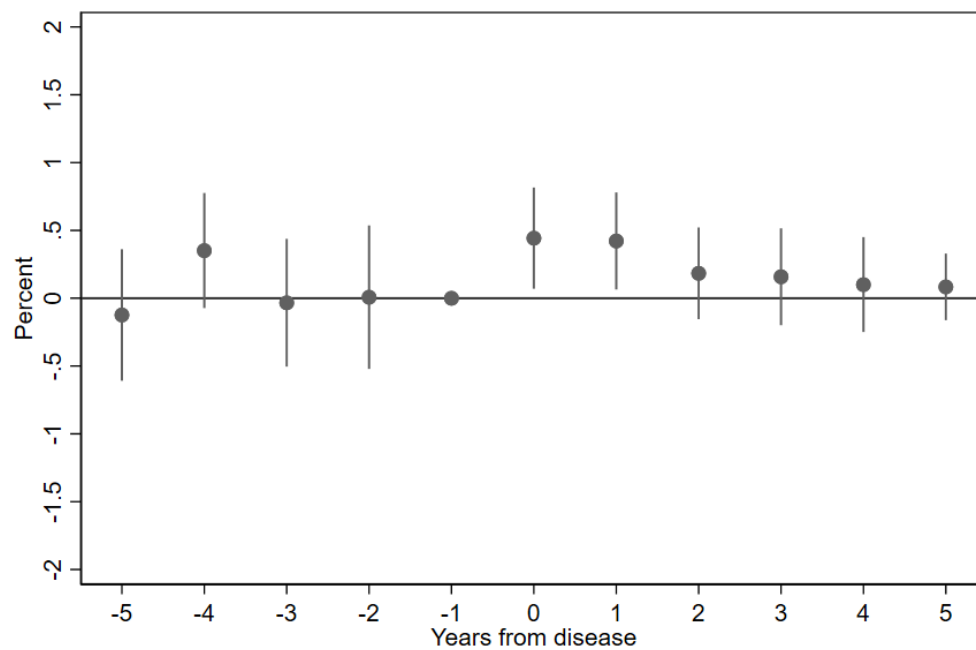
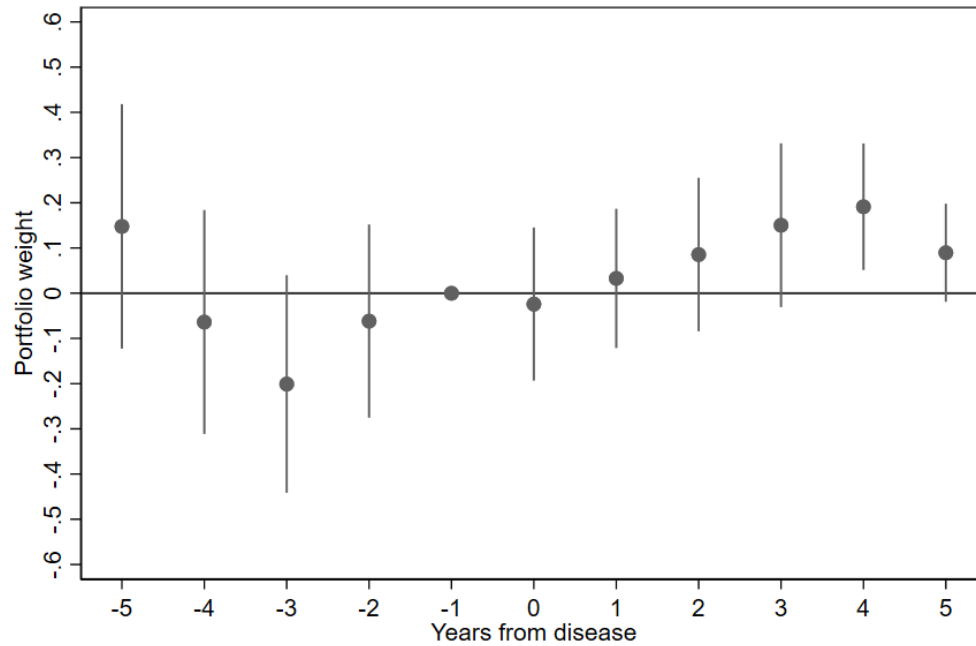


Figure 7: “Green” stock holdings

This figure plots the difference-in-differences results (coefficients $\mu_{-5} - \mu_5$ in equation (1)) for the portfolio weight (Panel A) and the probability of holding “green” stocks (Panel B) for traders, whose children get diagnosed with a respiratory disease. The year preceding the treatment is omitted. 95% two-sided confidence intervals are plotted using standard errors clustered at the municipality level.

Panel A: Portfolio weight of “green” stock



Panel B: Indicator of holding a “green” stock

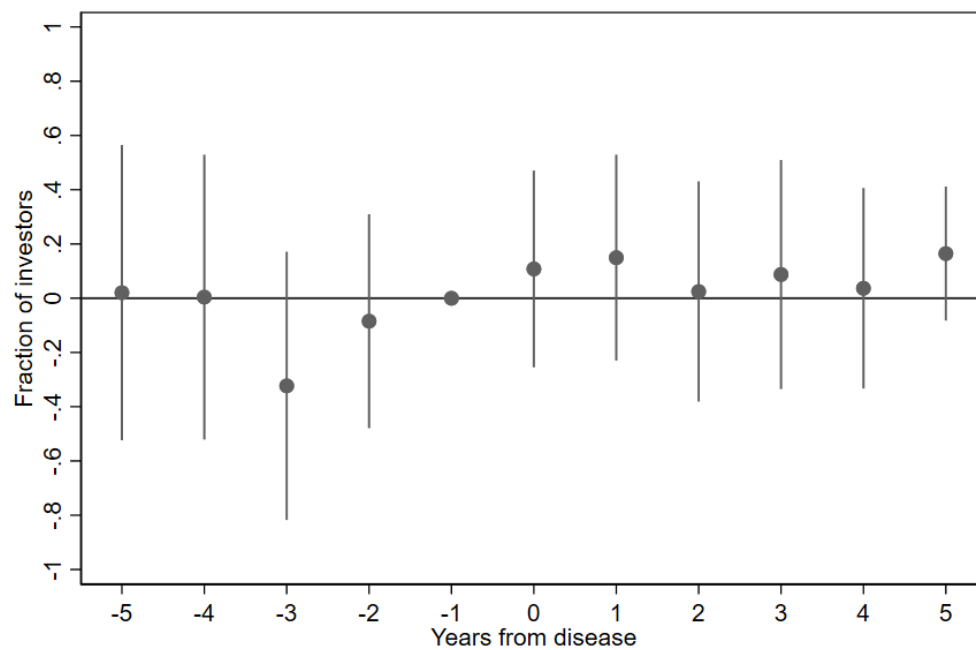
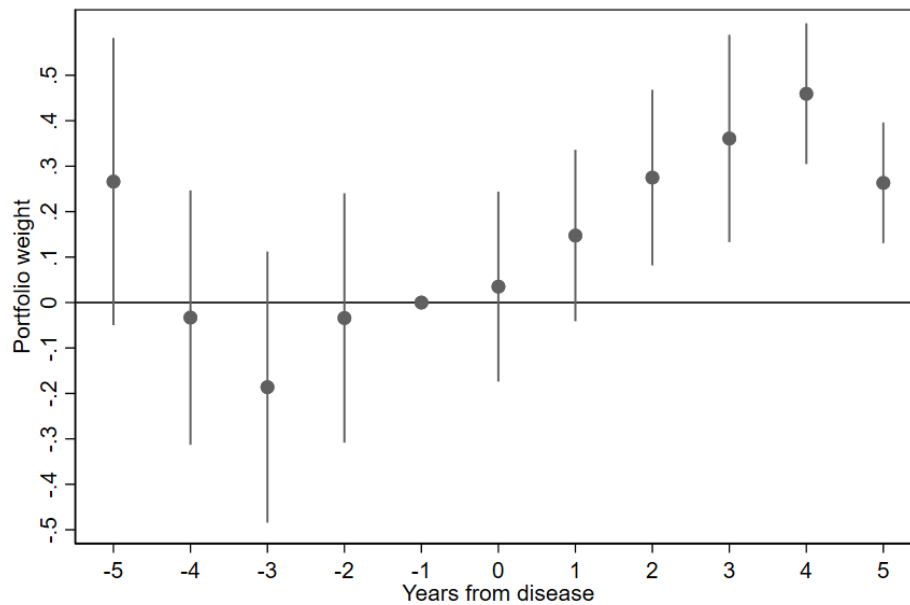


Figure 8: Holdings or “green” minus “brown” stocks

This figure plots the difference-in-differences results (coefficients $\mu_{-5} - \mu_5$ in equation (1)) for the difference in portfolio weight of “green” and “brown” stocks (Panel A) and for the difference in the probability of holding “green” and “brown” stocks (Panel B) for traders, whose children get diagnosed with a respiratory disease. The year preceding the treatment is omitted. 95% two-sided confidence intervals are plotted using standard errors clustered at the municipality level.

Panel A: Portfolio weight of “green” stocks minus the portfolio weight of “brown” stocks



Panel B: Indicator of holding a “green” stock minus the indicator of holding a “brown” stock

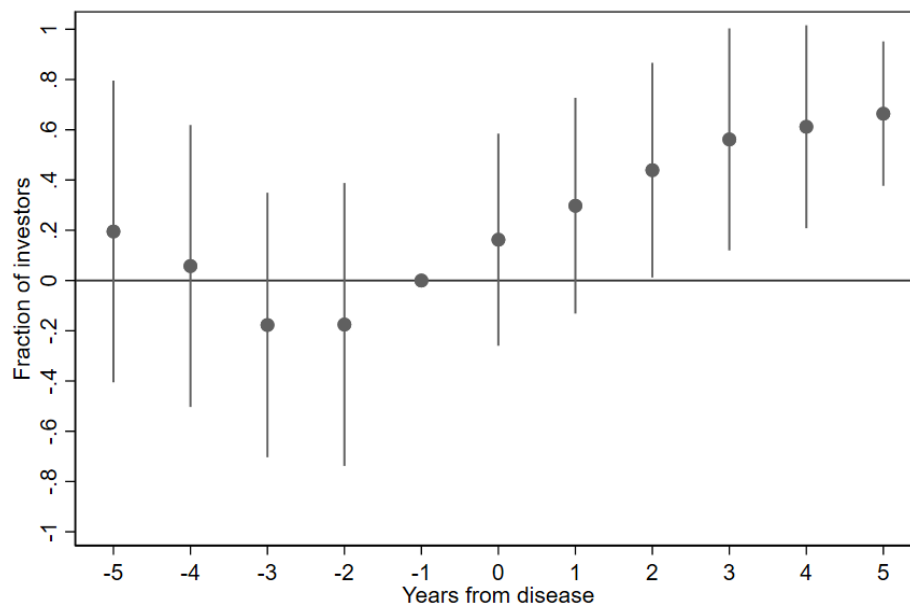


Table 1: Summary statistics

This table shows summary statistics for investors' demographic characteristics (Panel A) and portfolio characteristics (Panel B). Column 1 describes all traders who hold risky assets (stocks or mutual funds) from 2010 to 2018 while column 2 focuses on the treated sample in the year before the treatment (2010 to 2018). All amounts are in thousand year-2015 Danish kroner (DKK). One euro equals 7.45 DKK. Standard deviations are in the parenthesis.

Panel A: Individual characteristics

	All	Sample
Age (years)	51.5 (21.2)	37.4 (7.8)
Gender (% male)	52.8 (49.9)	58.6 (49.3)
Married (%)	50.8 (50.0)	59.4 (49.1)
Education (years)	13.7 (3.1)	15.5 (2.2)
Number of children	0.5 (0.9)	1.3 (0.9)
Income (1,000 DKK)	336.6 (624.8)	513.4 (637.7)
Financial wealth (1,000 DKK)	560.1 (1394.7)	367.6 (1138.9)
<i>N</i>	11,442,067	50,065

Panel B: Portfolio characteristics

	All	Sample
Market value of risky assets (1,000 DKK)	162.3 (14,281.3)	167.7 (7,289.4)
Risky asset share (%)	34.8 (68.9)	32.1 (45.1)
Invest in brown stocks (%)	5.8 (23.3)	6.1 (23.9)
Portfolio weight on brown stocks (%)	2.1 (11.5)	2.2 (11.8)
Invest in green stocks (%)	9.7 (29.7)	13.1 (33.7)
Portfolio weight on green stocks (%)	3.7 (15.7)	5.2 (18.6)
Invest in ESG fund (%)	2.4 (15.4)	2.8 (16.6)
Portfolio weight in ESG funds (%)	0.6 (5.8)	0.9 (7.8)
<i>N</i>	11,442,067	50,065

Table 2: “Brown” stock holdings

This table shows the results for the difference-in-differences estimation results (coefficients $\mu_{-5} - \mu_5$ in equation (1)) for the portfolio weight (column 1) and the probability of holding “brown” stocks (column 2) for the investors, whose children got diagnosed with a respiratory disease. The year preceding the treatment is omitted. The table provides treatment estimates in event time relative to the treatment as well as the overall ATT. We define ATT as the average of post-treatment coefficients (for periods from $t+1$ to $t+5$), where t is the treatment year. The category indicator $\mathbb{1}\{x\} = 1$ if the investor holds at least one stock of category x in her portfolio, otherwise $\mathbb{1}\{x\} = 0$. Standard errors clustered at the municipality level are given in parentheses.

Event time	Portf. weight	$\mathbb{1}\{\text{holds “brown”}\}$
t+5	-0.174*** (0.038)	-0.501*** (0.091)
t+4	-0.269*** (0.051)	-0.577*** (0.128)
t+3	-0.211*** (0.060)	-0.476*** (0.142)
t+2	-0.190*** (0.053)	-0.416*** (0.101)
t+1	-0.115** (0.058)	-0.149 (0.150)
t	-0.059 (0.064)	-0.055 (0.166)
t−2	-0.028 (0.073)	0.091 (0.224)
ATT, p.p.	-0.192*** (0.042)	-0.424*** (0.096)
Num. obs.	758,697	758,697
Num. treated	46,184	46,184

Table 3: “Green” stock holdings

This table shows the results for the difference-in-differences estimation results (coefficients $\mu_{-5} - \mu_5$ in equation (1)) for the portfolio weight (column 1) and the probability of holding “green” stocks (column 2) for the investors, whose children got diagnosed with a respiratory disease. The year preceding the treatment is omitted. The table provides treatment estimates in event time relative to the treatment as well as the overall ATT. We define ATT as the average of post-treatment coefficients (for periods from $t+1$ to $t+5$), where t is the treatment year. The category indicator $\mathbb{1}\{x\} = 1$ if the investor holds at least one stock of category x in her portfolio, otherwise $\mathbb{1}\{x\} = 0$. Standard errors clustered at the municipality level are given in parentheses.

Event time	Portf. weight	$\mathbb{1}\{\text{holds “green”}\}$
t+5	0.90 (0.055)	0.167 (0.126)
t+4	0.092** (0.071)	0.040 (0.189)
t+3	0.151 (0.092)	0.091 (0.216)
t+2	0.086 (0.087)	-0.027 (0.208)
t+1	0.033 (0.079)	0.151 (0.194)
t	-0.024 (0.086)	0.108 (0.186)
t-2	-0.062 (0.109)	-0.085 (0.202)
ATT, p.p.	0.110* (0.061)	0.095 (0.157)
Num. obs.	758,697	758,697
Num. treated	46,184	46,184

Table 4: Results for different categories of diseases

This table shows the ATT (defined as the average of post-treatment difference-in-differences coefficients ($\mu_1 - \mu_5$ in equation (1)) for different groups of diseases sorted by the number of treated individuals. The year preceding the treatment is omitted. *Difference in weight* is the difference in portfolio weights of “green” and “brown” stocks in the investor’s portfolio, and *difference in indicators* is defined as $\mathbb{1}\{\text{“green”}\} - \mathbb{1}\{\text{“brown”}\}$. The category indicator $\mathbb{1}\{x\} = 1$ if the investor holds at least one stock of category x in her portfolio, otherwise $\mathbb{1}\{x\} = 0$. Standard errors clustered at the municipality level are given in parentheses.

Disease gr.	Diff. weight	Diff. indic.	num. obs.	num. treated
Lesions, poisonings, etc.	-0.007 (0.080)	0.138 (0.146)	1,193,877	73,313
Respiratory	0.302*** (0.072)	0.519*** (0.165)	758,697	46,184
Bones, muscles, and connective tissue	-0.045 (0.093)	0.238 (0.186)	658,805	38,853
Digestive organs	0.001 (0.123)	0.265 (0.223)	546,507	32,363
Infectious and parasitic	0.031 (0.097)	-0.208 (0.201)	476,210	28,986
Urinary and genital organs	-0.126 (0.143)	-0.137 (0.325)	373,095	22,255
Congenital and chromosomal	-0.037 (0.114)	0.208 (0.262)	357,480	21,601
Skin and subcutaneous tissue	0.143 (0.116)	0.006 (0.338)	331,864	19,749
Ear and mastoid process	0.170 (0.184)	0.012 (0.322)	263,365	15,952
Endocrine, nutritional, and metabolic	-0.043 (0.18)	-0.219 (0.403)	261,290	15,604
Eye	0.288 (0.176)	-0.210 (0.33)	225,412	13,449
Nervous system	0.163 (0.215)	-0.018 (0.397)	171,817	10,261
Mental and behavioral disorders	-0.283 (0.197)	-0.017 (0.421)	149,967	9,029
Neoplasms	-0.044 (0.215)	0.475 (0.388)	127,929	7,548
Circulatory organs	-0.189 (0.245)	0.066 (0.594)	78,586	4,713
Diseases in the perinatal period	0.003 (0.364)	-0.287 (0.698)	60,416	3,828
Blood and blood-forming organs	0.174 (0.369)	-0.001 (0.807)	52,737	3,123
Pregnancy, childbirth, and maternity	-0.577 (0.363)	-0.588 (0.656)	40,435	2,521
External causes of injury	-0.316 (2.274)	1.145 (3.347)	1,550	102

Table 5: ESG fund holdings

This table shows the results for the difference-in-differences estimation results (coefficients $\mu_{-5} - \mu_5$ in equation (1)) for the portfolio weight (column 1) and the probability of holding ESG funds (column 2) for the investors, whose children got diagnosed with a respiratory disease. The year preceding the treatment is omitted. The table provides treatment estimates in event time relative to the treatment as well as the overall ATT. We define ATT as the average of post-treatment coefficients (for periods from $t+1$ to $t+5$), where t is the treatment year. The category indicator $\mathbb{1}\{x\} = 1$ if the investor holds at least one stock of category x in her portfolio, otherwise $\mathbb{1}\{x\} = 0$. Standard errors clustered at the municipality level are given in parentheses.

Event time	Portf. weight	$\mathbb{1}\{\text{holds ESG fund}\}$
t+5	0.132 (0.160)	-0.365 (0.382)
t+4	-0.023 (0.214)	-0.630 (0.485)
t+3	-0.008 (0.262)	-0.987* (0.531)
t+2	0.043 (0.252)	-0.548 (0.491)
t+1	-0.017 (0.232)	-0.231 (0.427)
t	0.028 (0.252)	0.162 (0.463)
t-2	-0.116 (0.290)	-0.098 (0.580)
ATT, p.p.	0.025 (0.187)	-0.557 (0.377)
Num. obs.	236,126	236,126
Num. treated	20,137	20,137

Table 6: Health conditions

This table shows the ATT for the difference between the portfolio weights of “green” and “brown” stocks and for the difference in indicators of holding “green” and “brown” stocks for patients with different medical conditions. The ATT is defined as the average of post-treatment difference-in-differences coefficients ($\mu_1 - \mu_5$ in equation (1)). The year preceding the treatment is omitted. *Portfolio weight difference* is the difference in portfolio weights of “green” and “brown” stocks in the investor’s portfolio. The category indicator $\mathbb{1}\{x\} = 1$ if the investor holds at least one stock of category x in her portfolio, otherwise $\mathbb{1}\{x\} = 0$. Standard errors clustered at the municipality level are given in parentheses.

ATT	Chronic		Num. hosp. visits		Num. diag		Bed days	
	no	yes	1	> 1	1	> 1	≤ 1	> 1
Portf. weight diff.	0.347*** (0.084)	0.119 (0.166)	0.282*** (0.1)	0.345* (0.19)	0.243** (0.12)	0.363*** (0.113)	0.200* (0.102)	0.421*** (0.145)
$\mathbb{1}\{\text{“green”}\} - \mathbb{1}\{\text{“brown”}\}$	0.534*** (0.19)	0.308 (0.325)	0.433* (0.224)	0.712** (0.333)	0.310 (0.258)	0.706*** (0.214)	0.356 (0.250)	0.674*** (0.265)
Num. obs.	534,047	224,650	543,811	214,886	356,414	402,283	443,641	315,056
Num. treated	32,534	13,650	32,922	13,262	21,463	24,721	26,904	19,280

Table 7: Geographic proximity

This table shows the ATT for the difference between the portfolio weights of “green” and “brown” stocks and for the difference in indicators of holding “green” and “brown” stocks separately for stocks registered (i) in Nordic countries (Denmark, Finland, Iceland, Norway, and Sweden) or (ii) in other countries. The ATT is defined as the average of post-treatment difference-in-differences coefficients ($\mu_1 - \mu_5$ in equation (1)). The year preceding the treatment is omitted. *Portfolio weight difference* is the difference in portfolio weights of “green” and “brown” stocks in the investor’s portfolio. The category indicator $\mathbb{1}\{x\} = 1$ if the investor holds at least one stock of category x in her portfolio, otherwise $\mathbb{1}\{x\} = 0$. Standard errors clustered at the municipality level are given in parentheses.

ATT	Region of stock registration	
	Nordic	Other
Portf. weight diff.	0.291*** (0.07)	0.1 (0.02)
$\mathbb{1}\{\text{“green”}\} - \mathbb{1}\{\text{“brown”}\}$	0.489*** (0.163)	0.053 (0.087)
Num. obs.	758,681	758,692
Num. treated	46,184	46,184

Table 8: Parents’ characteristics.

This table shows the ATT for the difference between the portfolio weights of “green” and “brown” stocks and for the difference in indicators of holding “green” and “brown” stocks for different investor characteristics. The ATT is defined as the average of post-treatment difference-in-differences coefficients ($\mu_1 - \mu_5$ in equation (1)). The year preceding the treatment is omitted. The *Portfolio weight difference* is the difference in portfolio weights of “green” and “brown” stocks in the investor’s portfolio. The category indicator $\mathbb{1}\{x\} = 1$ if the investor holds at least one stock of category x in her portfolio, otherwise $\mathbb{1}\{x\} = 0$. Standard errors clustered at the municipality level are given in parentheses.

ATT	Educ. length		Parent		Big city		Parent’s age	
	< 15.5 years	> 15.5 years	father	mother	no	yes	≤ 36	> 36
Portf. weight diff.	0.114 (0.109)	0.291** (0.142)	0.395*** (0.089)	0.176 (0.108)	0.290*** (0.098)	0.311** (0.141)	0.227** (0.113)	0.338*** (0.110)
$\mathbb{1}\{\text{“green”}\} - \mathbb{1}\{\text{“brown”}\}$	0.111 (0.253)	0.484* (0.276)	0.502** (0.214)	0.565** (0.234)	0.396* (0.204)	0.489 (0.328)	0.573** (0.28)	0.360 (0.252)
Num. obs.	417,360	341,337	452,217	306,480	495,017	259,160	400,431	358,266
Num. treated	26,006	20,178	27,682	18,502	33,525	20,499	25,509	20,675

Table 9: Family relationships

This table shows the ATT for the difference between the portfolio weights of “green” and “brown” stocks and for the difference in indicators of holding “green” and “brown” stocks dependent on the “proximity” of the investor to the affected child. The ATT is defined as the average of post-treatment difference-in-differences coefficients ($\mu_1 - \mu_5$ in equation (1)). The year preceding the treatment is omitted. *Portfolio weight difference* is the difference in portfolio weights of “green” and “brown” stocks in the investor’s portfolio. The category indicator $\mathbb{1}\{x\} = 1$ if the investor holds at least one stock of category x in her portfolio, otherwise $\mathbb{1}\{x\} = 0$. Standard errors clustered at the municipality level are given in parentheses.

ATT	Live together		Other relatives	
	no	yes	grandparents	aunts/uncles
Portf. weight diff.	-0.620*	0.390***	0.115**	0.157*
	(0.370)	(0.089)	(0.051)	(0.092)
$\mathbb{1}\{\text{“green”}\} - \mathbb{1}\{\text{“brown”}\}$	-0.4511	0.628***	0.189*	0.583***
	(0.773)	(0.188)	(0.114)	(0.203)
Num. obs.	73,108	685,589	736,770	607,792
Num. treated	5,975	40,209	81,389	37,169

Table 10: Time subsamples

This table shows the ATT for the difference between the portfolio weights of “green” and “brown” stocks and for the difference in indicators of holding “green” and “brown” stocks for two time periods — before and after 2015. The ATT is defined as the average of post-treatment difference-in-differences coefficients ($\mu_1 - \mu_5$ in equation (1)). The year preceding the treatment is omitted. *Portfolio weight difference* is the difference in portfolio weights of “green” and “brown” stocks in the investor’s portfolio. The category indicator $\mathbb{1}\{x\} = 1$ if the investor holds at least one stock of category x in her portfolio, otherwise $\mathbb{1}\{x\} = 0$. Standard errors clustered at the municipality level are given in parentheses.

ATT	Time period	
	before 2015	after 2015
Portf. weight diff.	0.102	0.363**
	(0.134)	(0.136)
$\mathbb{1}\{\text{“green”}\} - \mathbb{1}\{\text{“brown”}\}$	0.550*	0.518
	(0.330)	(0.309)
Num. obs.	331,200	427,497
Num. treated	20,983	25,201

Table 11: Investors' own health

This table shows the results for the difference-in-differences estimation results (coefficients $\mu_{-5} - \mu_5$ in equation (1)) for the portfolio weight (columns 1 and 3) and the probability of holding “brown” and “green” stocks (columns 2 and 4) for the investors, who got diagnosed with a respiratory disease. The year preceding the treatment is omitted. The table provides treatment estimates in event time relative to the treatment as well as the overall ATT. We define ATT as the average of yearly post-treatment coefficients (for periods from $t + 1$ to $t + 5$), where t is the treatment year. The category indicator $\mathbb{1}\{x\} = 1$ if the investor holds at least one stock of category x in her portfolio, otherwise $\mathbb{1}\{x\} = 0$. Standard errors clustered at the municipality level are given in parentheses.

Event time	“Brown” stocks		“Green” stocks	
	Portf. weight	$\mathbb{1}\{\text{holds category}\}$	Portf. weight	$\mathbb{1}\{\text{holds category}\}$
t+5	-0.027 (0.033)	-0.084 (0.075)	0.088 (0.054)	0.065 (0.107)
t+4	0.007 (0.037)	-0.063 (0.105)	0.102* (0.060)	0.119 (0.113)
t+3	0.014 (0.034)	0.002 (0.108)	0.105* (0.063)	0.038 (0.01)
t+2	-0.033 (0.039)	-0.078 (0.108)	0.085 (0.055)	0.103 (0.119)
t+1	-0.015 (0.045)	-0.109 (0.094)	-0.004 (0.058)	-0.029 (0.132)
t	0.009 (0.052)	-0.094 (0.103)	-0.001 (0.062)	-0.008 (0.127)
t-2	0.036 (0.051)	-0.005 (0.106)	0.006 (0.072)	0.030 (0.166)
ATT, p.p.	-0.011 (0.031)	-0.066 (0.081)	0.075 (0.049)	0.059 (0.092)
Num. obs.	1,286,231	1,286,231	1,286,231	1,286,231
Num. treated	90,370	90,370	90,370	90,370

Appendix

A-1 Additional tables and figures

Figure A-1: Unadjusted sample average portfolio weights of “brown” stocks (using constant stock prices)

This figure shows sample averages for the portfolio weight (Panel A) and the probability of holding “brown” stocks (Panel B) for traders, whose children get diagnosed with a respiratory disease (treatment group), and control samples separately with 95% two-sided confidence intervals. Portfolio weights are computed using constant stock prices (fixed at the average price level over the sample period).

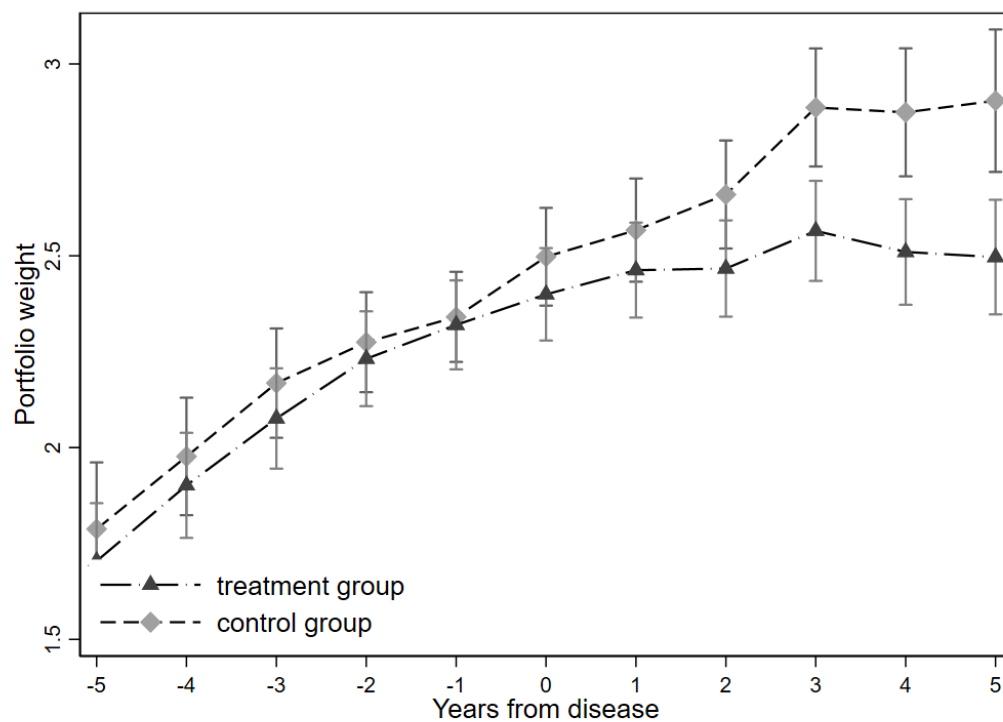


Figure A-2: Total assets

This figure plots the difference-in-differences results (coefficients $\mu_{-5} - \mu_5$ in equation (1)) for the amount of total assets (in th. DKK) for investors, whose children get diagnosed with a respiratory disease. The year preceding the treatment is omitted. 95% two-sided confidence intervals are plotted using standard errors clustered at the municipality level. This figure shows the diff-in-diff results for the investors' total assets in th. DKK. 95% two-sided confidence intervals are plotted using standard errors clustered at the municipality level.

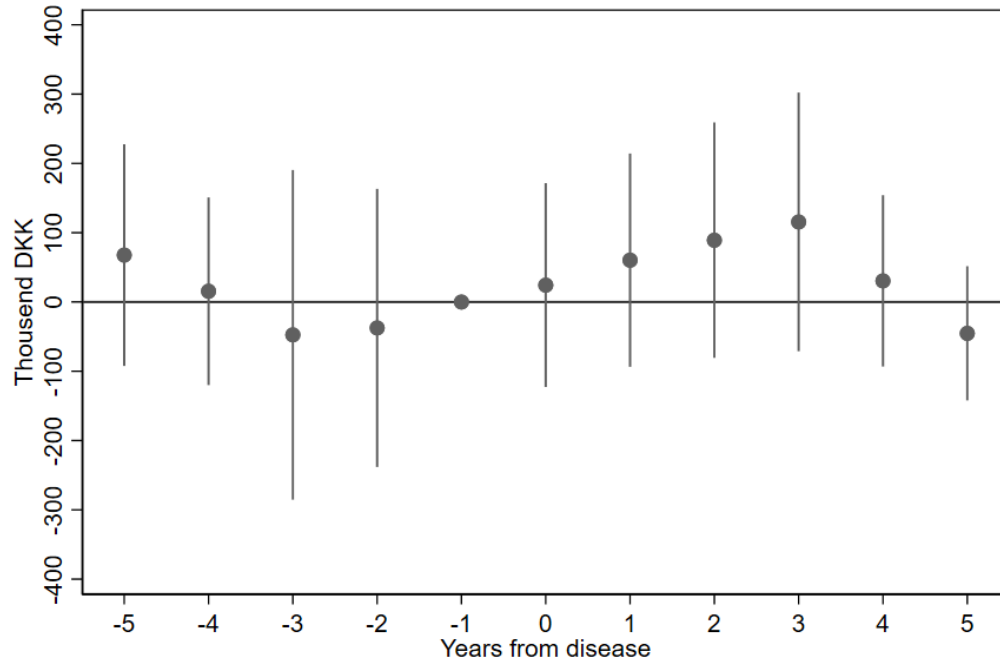


Figure A-3: Labor income

This figure plots the difference-in-differences results (coefficients $\mu_{-5} - \mu_5$ in equation (1)) for the labor income of investors, whose children get diagnosed with a respiratory disease. The year preceding the treatment is omitted. 95% two-sided confidence intervals are plotted using standard errors clustered at the municipality level.

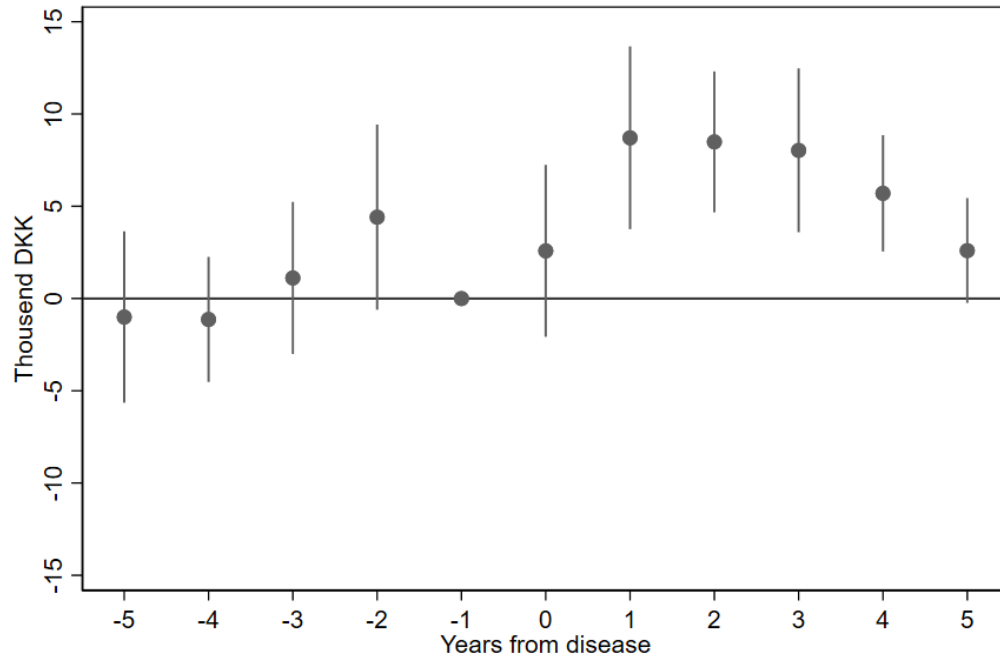


Figure A-4: Probability of moving

This figure plots the difference-in-differences results (coefficients $\mu_{-5} - \mu_5$ in equation (1)) for the probability of relocating to a new house or apartment for investors, whose children get diagnosed with a respiratory disease. The year preceding the treatment is omitted. 95% two-sided confidence intervals are plotted using standard errors clustered at the municipality level.

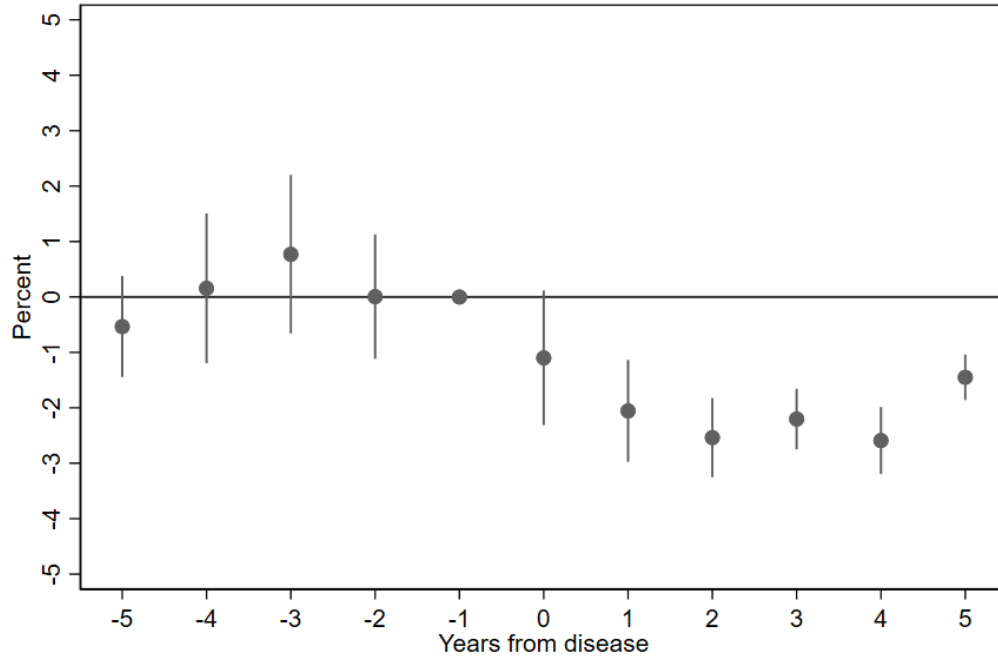


Table A-1: ICD-10 codes of disease groups

This table lists disease groups classified according to ICD-10, along with the average annual number of hospital visits for patients aged 18 years and older, and those aged below 18 years. The number of cases is averaged over the period 2011-2018 (excluding 2019 since the data for this year is incomplete) and sorted by the number of cases for the group below 18 years old.

Disease gr.	ICD-10 code	Cases (age>18)	Cases (age≤18)
Lesions, poisonings, etc.	DS00-DT98	630,613	224,189
Respiratory	DJ00-DJ99	189,152	53,226
Bones, muscles, and connective tissue	DM00-DM99	411,620	27,788
Digestive organs	DK00-DK93	268,948	23,982
Congenital and chromosomal	DQ00-DQ99	17,088	20,882
Infectious and parasitic	DA00-DB99	74,271	20,376
Urinary and genital organs	DN00-DN99	224,321	16,306
Ear and mastoid process	DH60-DH95	66,147	13,453
Nervous system	DG00-DG99	118,868	13,066
Endocrine, nutritional, and metabolic	DE00-DE90	123,221	12,897
Skin and subcutaneous tissue	DL00-DL99	70,432	12,458
Neoplasms	DC00-DD48	279,841	9,019
Eye	DH00-DH59	104,581	8,913
Mental and behavioral disorders	DF00-DF99	33,991	5,175
Blood and blood-forming organs	DD55-DD89	32,569	3,492
Circulatory organs	DI00-DI99	317,875	2,688
Diseases in the perinatal period	DP00-DP96	14,630	2,269
Pregnancy, childbirth, and maternity	DO00-DO99	114,618	1,260
External causes of injury	DX60-DY09	274	47

Table A-2: Wealth and liquidity

This table shows the results of the difference-in-differences estimation (coefficients $\mu_{-5} - \mu_5$ in equation (1)) for (i) the amount of bank deposits, th. DKK; (ii) the portion of an individual's financial wealth allocated to risky assets (funds and stocks), p.p.; (iii) the amount of total assets, th. DKK; (iv) the amount of yearly working income, th. DKK; and the probability of moving to a new residence (in p.p.) after the treatment. The table provides treatment estimates in event time relative to the treatment as well as the overall ATT. We define ATT as the average of post-treatment coefficients (for periods from $t + 1$ to $t + 5$), where t is the treatment year. Standard errors clustered at the municipality level are given in parentheses.

Event time	Bank depos.	% of risky assets	Tot. assets	Work. income	Prob. of moving
t+5	2.698 (1.788)	0.084 (0.126)	-45.243 (49.421)	2.632* (1.449)	-1.445*** (0.211)
t+4	1.516 (2.165)	0.101 (0.179)	30.507 (63.133)	5.738*** (1.607)	-2.588*** (0.309)
t+3	-0.022 (1.529)	0.159 (0.183)	115.561 (95.235)	8.068*** (2.263)	-2.200*** (0.28)
t+2	-3.544 (3.733)	0.184 (0.173)	89.178 (86.676)	8.518*** (1.943)	-2.535*** (0.365)
t+1	-3.816 (4.728)	0.422** (0.182)	60.391 (78.525)	8.726*** (2.519)	-2.055*** (0.47)
t	0.856 (2.347)	0.443** (0.19)	24.333 (75.053)	2.591 (2.371)	-1.099* (0.62)
t-2	0.975 (3.269)	0.008 (0.27)	-37.418 (102.416)	4.407* (2.546)	0.006 (0.573)
ATT	-0.634	0.190	50.079	6.736***	-2.165***
Num. obs.	848,601	849,709	849,814	849,964	849,970
Num. treated	46,184	46,184	46,184	46,184	46,184

A-2 Criteria air pollutants

Since air pollution is subject to monitoring and regulation by the government in most countries, we turn to regulatory documents for the classification of relevant pollutants. The US Clean Air Act describes the so-called “criteria pollutants” that are known or suspected to influence human mortality and/or morbidity or negatively affect the environment (Clean Air Act (1971)). This group includes five elements: particulate matter (PM), ozone, sulfur dioxide, nitrogen dioxide, carbon monoxide, and lead. The concentration of each of each of these pollutants in the air is monitored and compared to the safe amounts stated in the National Ambient Air Quality Standards (NAAQS).²²

Regulatory standards and guidelines often focus on particulate matter due to its well-documented health effects and its association with visible pollution. Moreover, monitoring and measuring gaseous pollutants can be more complex and expensive compared to measuring particulate matter. However, gaseous pollutants such as nitrogen dioxide (NO_2), sulfur dioxide (SO_2), ozone (O_3), carbon monoxide (CO), and volatile organic compounds ($VOCs$) also pose significant health and environmental risks (EPA (2019)).

Particulate Matter (PM) refers to air-suspended mixture of solid and liquid particles that appear due to the emission of combustion proceeds, condensation of liquid pollutants, or from the suspension of dust, seas salt, soil, and other firm substances in the air. These particles vary by origin, air concentration, size, shape, and composition. The common classification distinguishes coarse particles (with an aerodynamic diameter greater than $2.5 \mu m$), fine particles (diameter between $0.1 \mu m$ and $2.5 \mu m$), and ultrafine particles (diameter less than $0.1 \mu m$)²³ The usual sampling convention relies on nested groups; for example, the category PM_{10} includes all particles with a diameter below $10 \mu m$ (even the ultrafine ones).

The efforts of regulators such as the EPA aim to reduce the pollution levels to protect public health and the environment by limiting exposure to harmful air pollutants. In the

²²See Suh et al. (2000) for a detailed comparison between criteria air pollutants with other toxic substances.

²³See, for example, Pope III and Dockery (2006) and Donaldson et al. (2001) for the classification.

Integrated Science Assessment for Particulate Matter 2019, the EPA conducts a review of research articles by the pollutants that were found to be related to respiratory diseases (EPA (2019)). The majority of these studies focused on the role of nitrate, sulfate, organic carbon, elemental carbon, and black carbon. Although most of them come to the form of PM pollution from combustion-related processes, some can appear as products of chemical reactions in the atmosphere or due to biogenic emission.