Households' Inflation Expectations and Concern about Climate Change

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Abstract: Using survey data from German households, we find that individuals with higher concern about the consequences of climate change have lower inflation expectations up to five years ahead. We show that the link between climate concern and inflation expectations goes above and beyond individuals' perception of their personal exposures to climate-related risks, their distrust in the central bank, and a broad range of socio-demographic and socio-economic control variables.

Keywords: Climate change, inflation expectations, physical risk, transition risk, central bank distrust, household surveys

JEL: E31, E50, Q54, Q58

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1 Introduction

Inflation expectations play a key role in the monetary policy transmission. They influence households' decisions regarding savings and consumption as well as firms' decisions regarding production and investment (ECB (2021b)). Therefore central banks carefully monitor factors that could potentially impact or disrupt inflation expectations. In tandem, risks arising from climate change have featured prominently in discussions among central bankers.[1] So far, however, little is known about their links to inflation, let alone inflation expectations. Against this background, this study provides a first correlational analysis of the relationship between households' perception of climate change and their inflation expectations, therefore, giving novel insights and contributing to the broader debate among central bankers on how climate-related risks affect price stability.

In light of little guidance offered by theories, our study takes a simple and straightforward approach. We use microdata from the Bundesbank Online Panel Households (BOP-HH), a regular monthly survey of about 4,000 German households. It comprises a set of questions concerning expectations about inflation and other macroeconomic developments as well as socio-demographic questions. In two waves, the survey also asked questions to elicit households' overall concern about climate change (hereafter *climate concern*) as well as their perception of their individual climate-related risks.

As the key contribution of our paper, we document an economically and statistically significant negative correlation between climate concern and expected inflation. We measure climate concern through a household's reported perception of the overall seriousness of climate change on a 1 (no problem) to 10 (serious problem) scale.[2] In our sample, a one-notch increase in climate concern goes along with a decrease of 24 basis points in expected inflation over the next 12 months. In other words, individuals with higher climate concern have lower inflation expectations.

This result becomes even stronger when excluding outliers from our sample. It also remains significant when controlling for unemployment expectations as a proxy for expectations concerning the development of the economy and, more generally, when including a battery of other control

[1] See, e.g., ECB (2021a).

[2] We purposefully use the term "climate concern" and not "climate belief" throughout the paper when referring to this survey question. In public debates, the term climate belief often refers to the assessment whether human activities contribute to global warming. This notion differs from concerns about the seriousness of climate change.

variables that measure sociodemographics or other economic and political concerns. The link also remains significant when splitting the sample along socio-demographic dimensions, such as gender, age, or education. Furthermore, we provide evidence for non-linearity in this basic relation: in quantile regressions, the slope coefficient reaches up to -60 basis points for respondents with very high conditional expected inflation.

We also run our main analysis with a subsample of respondents for whom we have longer-term inflation expectations. We find that the association between climate concern and expected inflation is even stronger when looking five years ahead. For this horizon, we document that a one-notch increase in climate concern is associated with a decrease of 49 basis points in expected inflation. The regression coefficient, therefore, doubles in magnitude, corroborating our main result. For the ten-year horizon, the significance of the correlations deteriorates, however.

The findings from our quantile regressions indicate that climate concern is especially relevant for the right tail of inflation expectations. The literature has identified the overall level of distrust in the institutional setup of the economy, in particular in central banks, as one source of high (possibly de-anchored) inflation expectations (see, e.g., Christelis et al. (2020), Brouwer and de Haan (2022)). In line with this literature, we find that households with lower climate concern have significantly higher distrust in the ability of the European Central Bank (ECB) to ensure price stability. Obviously, distrust may also relate to political attitudes. We confirm this link in regressions on a subsample for which we have information on individuals' political party affiliation. On a more general level, these findings highlight the importance of socio-cultural factors for explaining climate concern (see also Van der Linden (2015)) as well as its link to inflation expecations. Finally, a cluster analysis provides evidence for the existence of two distinct sets of individuals whose centroids differ strongly in the climate concern dimension (4.5 as opposed to 8.8). Individuals in the high climate concern cluster have lower inflation expectations and lower distrust in the ECB than individuals in the low climate concern cluster. Importantly, however, our regression exercises suggest that climate concern has explanatory power for inflation expectations above and beyond ECB distrust.

To better understand the mechanism behind the link between climate concern and inflation expectations, a deeper look at our climate concern variable is instructive. Social and behavioral research (see, e.g., Van der Linden (2017) for a survey) has long shown that people's perceptions of climate change risks are complex, as they cannot be explained by a few co-variates only, which we also find in our study. Furthermore, individuals have both a personal and a societal understanding of climate-related risks. A common theme in this research is *optimism bias*, meaning that people tend to underestimate their own risk while believing that others are more likely to be affected.

Arguably, we find evidence for such optimism bias in our study as well. More precisely, we show that the explanatory power of climate concern for expected inflation goes beyond individually perceived climate-related risks. To do so, we follow the standard concept of separating climate-related risks into physical and transition risk. Whereas the term physical risk refers to the exposure to disruptive climate-related weather events, transition risk is about the challenges that can arise from the shift towards a low-carbon economy in the medium to long term. We find that individually perceived climate-related risks explain climate concern, but only partially. For instance, respondents who feel exposed to disruptive climate-related weather events or expect more frequent extreme weather events have higher climate concern. However, the explanatory power of households' perception of climate-related risks for climate concern does not exceed 20%. Similarly, in a multivariate regression of expected inflation on these variables, we find that climate concern remains significant, even when controlling for these individually perceived climate-related risks.

Potential mechanisms to explain our main result should thus relate to the link between inflation expectations and the societal, not personal, exposures to climate-related risks. Based on research on the effects of climate change on *realized* inflation[3], we propose three possible mechanisms, all leading to lower expectations of aggregate demand and hence, to lower inflation *expectations*. The first mechanism is associated with physical risk. Households with higher climate concern might fear damage to physical capital - such as property, land or infrastructure - due to climate-induced natural disasters or persistent changes in temperature and precipitation levels. Such instances could lead to wealth loss, which in turn, reduces aggregate demand and, consequently, lowers inflation. This idea complements the findings of Dietrich et al. (2020). These authors find that US households assign a much higher probability to natural disasters than what would seem justified given historical records. Feeding such expectations into a New Keynesian model, they show that higher expected losses from natural disasters can lead to a decrease in consumption and subsequently, lower realized inflation, which they label as an expectations channel of climate

[3] A comprehensive overview of recent developments in the respective macroeconomic literature is given in Batten et al. (2020), McKibbin et al. (2020) or ECB (2021a).

change.

The second mechanism relates to transition risk. The shift towards a carbon-neutral economy – driven by technological change, climate policies or changes in consumer behavior – is associated with the risk of asset stranding. If carbon emissions are to be reduced drastically, certain assets like fossil fuel resources or particular machinery will lose their value entirely. Heightened climate concern may signify increased worry about asset stranding and a perceived expected loss in aggregate wealth, which would decrease aggregate demand and, thus, lower realized inflation. This idea is supported by the research of Meinerding et al. (2023), who find that shocks increasing the likelihood of asset stranding resemble negative demand shocks, putting deflationary pressure on the economy.

Third, households with greater climate concern could perceive the future economy as more unstable due to the presence of both physical and transition risks. An extensive literature (see, e.g., Bloom (2009); Jurado et al. (2015); Baker et al. (2016)) has documented that increased uncertainty is associated with lower aggregate demand and higher aggregate savings, again exerting downward pressure on inflation. Coibion et al. (2023) provide causal evidence for such a channel by evaluating randomized information treatments within the ECB Consumer Expectations Survey.

Our paper contributes to the literature on inflation expectations (e.g. Ehrmann et al. (2017); Christelis et al. (2020); D'Acunto et al. (2021)) by providing first evidence that climate concern relates to it. We also add to the literature on central bank distrust (e.g. Ehrmann et al. (2013); Christelis et al. (2020); Brouwer and de Haan (2022)) by revealing a complex interrelation of this variable with climate concern and inflation expectations. On the other hand, we contribute to research on economic expectations regarding climate change. As discussed, Dietrich et al. (2020) analyze consumers' expectations of the frequency of natural disasters both empirically and in a theoretical model. Baker et al. (2020) explore the interaction between economic survey data for professional forecasters, their inattentiveness to disaster risk, and the occurrence of natural disasters. Krueger et al. (2020) analyze the importance of climate risks for institutional investors. Baldauf et al. (2020) find that house prices mirror differences in beliefs about climate change: houses projected to be flooded sell at a discount in neighborhoods populated by climate change believers. We add to this literature showing that a correlation exists between concern about climate change and inflation expectations that goes above and beyond a broad range of control variables.

Furthermore, we contribute to a new, growing body of literature on the impact of climate-related risks (i.e. physical risk and transition risk) on the monetary policy transmission. This topic has gained importance among central bankers recently (ECB (2021a)). If the perception of climate risks distorts expected inflation, there might be room for interventions, for instance, from central banks. According to an NGFS (2020) report, climate change risks affect the expectation channel of monetary policy in three ways. In the short term, the perception of physical risk can increase the frequency of forecast revisions and the homogeneity of expected inflation (see, for example, Baker et al. (2020)). In the medium term, the perception of physical risk may lead households to adjust expectations about the future price level, in particular of energy and food. In the long term, the perception of transition risk might affect expectations about future changes in taxation and economic policy. Our study seeks to obtain forthright evidence by focusing on consumers' expectations directly.

Lastly, one might hypothesize that households overlook climate concern because they are rationally inattentive and have other, more salient issues to worry about. This would dilute the quantitative importance of our suggested mechanisms. However, the growing prominence of climate change in public discourse challenges this view. For instance, Tzamourani (2022) illustrates that climate concern remained high and distinguished from other concerns even amidst the Covid-19 pandemic. Lee et al. (2015) highlighted the salience of climate change across advanced economies even more than a decade ago, using data from 2007 and 2008. If anything, as documented by Van der Linden (2017), rational inattention should apply to the assessment of households' personal exposure to climate-related risk rather than the societal dimension, which seems to drive our results to a large extent.

The remainder of the paper is structured as follows. Section 2 introduces the BOP-HH data and draws the main link between expected inflation and climate concern. Section 3 introduces climate-related risks and ECB distrust, relating these variables to climate concern. The relationship between expected inflation and all those variables is presented in Section 4. Section 5 discusses the results from the cluster analysis, the sample splits, the analysis of long-term inflation expectations, the correction for outliers, and the analysis controlling for unemployment expectations. Finally, Section 6 concludes.

2 Inflation expectations and climate concern

2.1 The Bundesbank Online Panel Households

We use data from the BOP-HH, a monthly online survey designed by the Deutsche Bundesbank in collaboration with Forsa. The BOP-HH collects granular information about inflation expectations from a representative sample of more than 4,000 German households. Individuals are German-speaking and aged 14 years and older.

On top of the standard set of questions about inflation expectations, respondents are asked a number of specific questions that differ across the various waves of the survey. Our study employs both baseline survey questions and project-specific questions, where the latter are supposed to elicit respondents' concern regarding climate change, their expectations about climate-related risks and the level of trust in central banks. We introduce these questions as we go along throughout the rest of the paper.

Our pooled estimation sample includes a total of 8,544 individuals. The questions regarding households' perception of climate change were posed to 4,054 respondents in September 2020 (Wave 9) and to 4,490 respondents in February 2021 (Wave 14).[4] Each wave contains a mix of new respondents as well as respondents from previous waves. Our study does not exploit the longitudinal nature of the survey – which in our case would yield 600 panel observations – but only two repeated cross-sections. Panel observations are, therefore, dropped from Wave 14. In addition, the number of observations may also shrink due to randomization exercises, i.e. not all survey participants receive exactly the same set of questions. Summary statistics on all project-specific survey questions as well as on expected inflation are provided in Appendix A. Descriptive scatter plots regarding the joint distribution of expected inflation and climate concern are contained in Appendix D.2 and are also discussed in more detail in Section 5.1.

The BOP-HH also provides rich socio-demographic information as well as other economic or political concerns capturing political attitudes more generally, which enter our regressions as controls. Our study employs the following variables as controls: gender, homeowner/renter, age, household size, household income, size of the city of residence, perception of the severity of the

[4] We wish to emphasize that the two survey waves we consider in this study were conducted before the end of the ECB's monetary policy strategy review in July 2021. Although the strategy review covered climate change considerations, the respective material was published on the ECB website only afterwards, implying that the households in our surveys were not exposed to it.

refugee situation and of Covid-19[5], current region of residence[6], education, and employment.[7] Additional information about the controls is also provided in Appendix B. For the sake of brevity, we do not report any coefficients for controls in the main text. The full set of results is, however, shown in Appendix C.

Given that the BOP-HH only surveys households in Germany, one may question whether our results carry over to other countries. While we leave precise answers to future research, we can at least draw comparisons to household surveys from other countries. For instance, Duca-Radu et al. (2021), Georgarakos and Kenny (2022), or Coibion et al. (2023) provide insights on household expectations across European countries based on the ECB's Consumer Expectations Survey, suggesting minimal heterogeneity in the general economic mindset of households across countries. Of course, European countries differ in their levels of wealth, income or unemployment and in their exposure to economic shocks, but the resulting effects are in line with standard intuition. Regular surveys conducted by the European Commission suggest a correlation of about 80-90% between aggregate inflation expectations in Germany and in the rest of the Euro area.[8] Regarding climate-related risks, evidence suggests that the characteristics of climate concern are broadly similar across advanced economies as well (see, e.g., Lee et al. (2015); Poortinga et al. (2019)).

To generalize, we also need to consider how the German economy compared to other economies during the survey periods (September 2020 and February 2021). Germany, like all other Euro area countries, was hit by the first Covid-19 winter wave and experienced a deflationary recession. We argue that our findings are useful and representative for two main reasons. First, climate change and the Covid-19 pandemic may arguably be perceived as two distinct problems with different economic effects. In the analysis that we present in the following, we also control for households' concern about other major issues (namely Covid-19, Brexit, the migration crisis and the overall economic situation). Moreover, Tzamourani (2022) documents that climate concern remained high and distinguished from other concerns even amidst the Covid-19 pandemic.

[5]These control variables supposedly capture political attitudes more generally. In Wave 9 of the BOP-HH survey, however, individuals were also asked directly about their affiliation to a political party. Results for these variables are in line with the ones for distrust in the ECB. Detailed results are available upon request.

[6]When included, this variable replaces the dummy for residence before 1989 given the high correlation between the two covariates.

[7]Unfortunately, the survey waves that we use do not include questions about personal experience with natural disasters (or climate change, more generally). We also do not know whether respondents have recently migrated to Germany, a fact that could conceivably be linked to climate change and to households' concern about it (see Van der Linden (2017) for a discussion on this topic). We thus cannot analyze the extent to which personal experience with climate change shapes inflation expectations, and leave this question open for future research.

[8]See `https://economy-finance.ec.europa.eu/economic-forecast-and-surveys_en`

Second, the aggregate economic effects of the pandemic for Germany were similar to those for the Euro area as a whole. For instance, the headline (HICP) inflation rate in Germany was −0.4% in September 2020 and +1.6% in February 2021, which is fairly close to the Euro area means (−0.3% and +0.9% respectively). In September 2020, Germany was actually the median country, while it ranked second within the Euro area in February 2021. GDP growth in Germany was −2.5% in 2020Q3, which is again close to the Euro area mean (−3.9%) and median (−3.2%). In the subsequent winter, GDP growth in the Euro area was somewhat heterogeneous, reflecting a wide dispersion in national policy responses to the pandemic. Germany was a bit on the low side here, with GDP growth remaining at −2.2% as opposed to a Euro area average of −0.8% in 2021Q1. But altogether, we view our setup as representative in this respect as well.

2.2 Measuring climate concern

The survey asks individuals to quantify their concern about certain political or economic issues on a scale from 1 ("no serious problem") to 10 ("serious problem"):

> "To what extent do you think that the following developments/topics currently constitute a serious problem?"[9]

with the different developments or topics being Covid-19, the refugee/migration situation, the economic situation, climate change, and Brexit.[10] The survey does not specify the question any further, so to avoid influencing the answers. For the very same reason, the question is posed before all other climate-related questions.

We wish to emphasize that the question does not necessarily elicit whether respondents "believe" in the existence of climate change or in the contribution of human activities to it, but rather to what extent respondents are concerned about potential consequences of climate change. In fact, an individual can believe that anthropogenic climate change is real and still perceive the consequences for their own environment or activities as being very limited. Therefore, throughout the paper, we label the answer to this question as "climate concern" rather than, for instance, "climate belief" or "climate skepticism".

[9] All survey questions are formulated in German because all respondents are German. The question thus actually reads: "Was denken Sie, inwieweit stellen die folgenden Entwicklungen/Dinge aktuell ein ernstes Problem dar?"

[10] This question was introduced in the BOP-HH for the research project of Bernard et al. (2022). We would like to thank our colleagues for sharing their data with us.

2.3 Results

As part of the standard set of questions, respondents are asked to report a point estimate of their expected level of inflation over the subsequent 12 months.[11] Table 1 shows the results from an OLS regression of expected inflation on climate concern. Columns (1a), (1b) and (1c) refer to the data from Wave 9, Wave 14 and the pooled sample, respectively. In Column (2), we add the set of controls listed above for the pooled sample. The statistical significance in all regression tables throughout the paper is evaluated based on robust standard errors.[12]

Table 1: OLS regressions of expected inflation on climate concern

	(1a)	(1b)	(1c)	(2)
Climate concern	-0.153**	-0.225***	-0.185***	-0.240***
Constant	5.425***	5.675***	5.541***	6.431***
Controls	No	No	No	Yes
R-squared	0.002	0.004	0.003	0.052
Observations	3,970	4,854	8,251	6,724

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

Notes: The table shows coefficients from OLS regressions of 12-month-ahead expected inflation on climate concern: $\text{expinf}_i = \beta_0 + \beta_1 \text{climateconcern}_{i,1} + \beta_p \text{controls}_{i,p} + \varepsilon_i$. Column (1a) refers to Wave 9, Column (1b) refers to Wave 14 and Column (1c) refers to the pooled sample. In Column (2), we add controls to the pooled sample. Controls included in Column (2) are: gender, age, education, employment, size of the city of residence, household income, household size, region of residence, perception of the seriousness of Covid-19, perception of the seriousness of the refugee crisis, and homeownership. Statistical significance is evaluated based on robust standard errors.

The table highlights the main finding of our paper, namely a highly significant negative correlation between climate concern and expected inflation. With controls and in the pooled sample, an increase in climate concern by one notch is associated with a decrease of 24 basis points in expected inflation. In other words, people who find that climate change is a serious problem tend to have lower inflation expectations. Notably, in the last regression, we also control for other concern variables, such as concern regarding Covid-19 and the refugee situation, that may arguably be correlated with climate concern and may capture political attitudes more generally. However, the relationship between climate concern and expected inflation remains highly significant.

[11] For reference, Figure 3 in Appendix A shows the cross-sectional distribution of this point estimate.

[12] We do not restrict the sample in any way in our baseline setup. Robustness checks for subsamples in Section 5.3 show that the impact of potential outliers in the data is only marginal.

The explanatory power of our regressions may appear low. But it aligns well with a large number of studies on expected inflation across various surveys, which observe R-squared values ranging from about 2% to 9% when controlling for a broad range of demographic and socio-economic variables (see, e.g., Galati et al. (2020); D'Acunto et al. (2021); Afunts et al. (2023)). We find that climate concern explains around 0.3% of the cross-sectional variation in expected inflation (Columns (1a)-(1c)). Including our large set of controls, the explanatory power of the regression increases to 5.2%.[13]

Focusing on the conditional mean of expected inflation via OLS regressions might lead to inaccurate predictions if the relationship with the explanatory variable is non-linear. Therefore, we also run cross-sectional quantile regressions. Figure 1 plots the coefficients of climate concern across the different quantiles of the conditional cross-sectional distribution of expected inflation. As in the OLS setting, we show coefficients without (left) and with controls (right), but only for the pooled sample. The figure reinforces our main finding above, but points towards a non-linear relationship. The slope coefficient goes up to about -60 basis points for respondents in the right tail of the conditional cross-sectional distribution, but is close to zero in the left tail. The negative correlation between climate concern and inflation expectations is thus stronger among those households, which have high conditional inflation expectations, relative to those with low conditional inflation expectations.

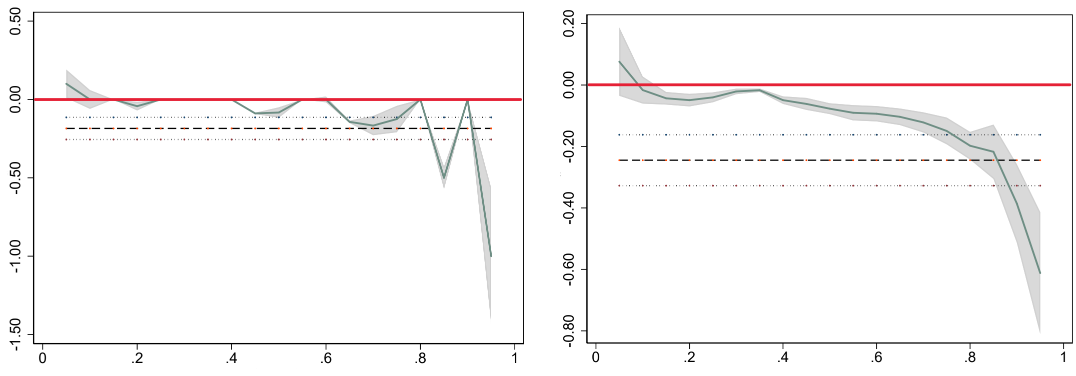

Figure 1: Quantile regressions of expected inflation on climate concern

Notes: The figure shows slope coefficients from quantile regressions of 12-month-ahead expected inflation (solid line) on climate concern and the corresponding OLS coefficient from Table 1 (dashed line). The x-axis indicates the different quantiles (5% to 95% quantile) for which the regression is estimated. The figure shows results for the pooled sample without controls (left graph) and with controls (right graph). Controls included are the same as in Table 1. The shaded areas indicate 95% confidence intervals.

[13]The R-squared from a regression with only the controls, excluding climate concern, is 4.9% (not shown in this paper, for brevity). This means that climate concern accounts for 0.3 percentage points of the overall R-squared in Column (2).

3 Understanding households' climate concern

Given the strong link between climate concern and expected inflation, it is instructive to analyze the explanatory variable, climate concern, in more detail. To this end, we consider its relation to climate-related risks, central bank distrust, and other control variables contained in the survey.

3.1 Measuring climate-related risks

First, we want to understand the relationship between respondents' climate concern and their perception of their individual climate-related risks. In this regard, we rely on the standard separation of climate risks into physical and transition risk. Whereas the former refers to risks connected to disruptive climate-related weather events, the latter are risks that can arise from the shift towards a low-carbon economy.

We add three additional project-specific questions to the survey. The first one is designed to elicit expectations about physical risk, and the remaining two are dedicated to transition risk. The pooled estimation sample is 4,256 observations for the physical risk question and 4,262 observations for each transition risk question.

Respondents are introduced to the concept of physical risk by means of the following statement:

> "Many scientists argue that climate change will lead to more frequent extreme weather events. By extreme weather events we mean, for example, extreme heat, extreme drought, floods, heavy rain, storms, tornadoes, hail or avalanches."[14]

Thereafter, respondents are presented the following question:

> "Do you expect asset losses due to more frequent extreme weather events within the next five years?
> (By asset losses, we mean value losses (e.g. due to damage) of your real assets (e.g. real estate, land, valuables), but also losses of securities portfolios, company shares or other financial investments.)"[15]

[14]In German: "Viele Wissenschaftler argumentieren, dass durch den Klimawandel extreme Wetterereignisse häufiger auftreten werden. Mit extremen Wetterereignissen meinen wir z.B. extreme Hitze, extreme Trockenheit, Überschwemmungen, Starkregen, Stürme, Tornados, Hagel oder Lawinen."

[15]In German: "Rechnen Sie aufgrund häufigerer extremer Wetterereignisse mit Vermögensverlusten innerhalb der nächsten fünf Jahre? Mit Vermögensverlusten meinen wir Wertverluste (z.B. durch Schäden) von Wirtschaftsgütern (z.B. Immobilien, Grundstücke, Wertgegenstände). Mit Vermögensverlusten meinen wir aber auch Verluste von Wertpapierportfolios, Unternehmensanteilen oder sonstigen Geldanlagen."

We offer three answers to this question: (1) "No, as my assets are not affected by more frequent extreme weather events"; (2) "No, as my assets are generally not affected by extreme weather events"; (3) "Yes, I expect asset losses".[16]

We convert the answers into two dummy variables. The variable "physical risk: no increasing frequency" takes the value of 1 if the respondent picks answer (1), i.e. if they do not expect there to be more frequent extreme weather events in the next five years, and zero otherwise. The variable "physical risk: no exposure" takes the value of 1 if the respondent picks answer (2), i.e. if they do not consider themselves exposed to extreme weather events at all, and zero otherwise.

Respondents' perception of transition risk is elicited with two separate questions on changes in income and changes in expenses. The following statement introduces the concept of transition risk:

> "To protect the climate, more and more measures are being taken that are supposed to lead to a climate-neutral economy. By measures we mean, for example, the coal phase-out, the CO2 tax for fuels, purchase premiums for electric cars, lowering the VAT on train tickets, investment in public transportation, subsidies for energy-efficient housing or renewable energies."[17]

The first question concerns income:

> "Do you expect these or similar measures to result in a higher or lower regular household income within the next five years?
> (By regular household income, we mean, for example, income from self-employed or employed work, renting, leasing, interest, dividends or pensions.)"[18]

The resulting dummy variable "transition risk: decreasing income" takes the value of 1 if respondents expect a decrease in their regular household income and 0 if they expect no change

[16] In German: 1) "Nein, da meine Vermögenswerte durch häufigere extreme Wetterereignisse nicht verstärkt betroffen sind"; 2) "Nein, da meine Vermögenswerte generell nicht von extremen Wetterereignissen betroffen sind."; "Ja, ich rechne mit Vermögensverlusten."

[17] In German: "Zum Schutz des Klimas werden vermehrt Maßnahmen getroffen, die zu einer klimaneutralen Wirtschaft führen sollen. Mit Maßnahmen meinen wir z.B. den Kohleausstieg, die CO2-Steuer für Brennstoffe, Kaufprämien für Elektroautos, die Senkung der Mehrwertsteuer für Bahntickets, den Ausbau des öffentlichen Nahverkehrs, die Förderung energetischer Gebäudesanierung oder erneuerbarer Energien."

[18] In German: "Erwarten Sie durch diese oder ähnliche Maßnahmen ein höheres oder niedrigeres regelmäßiges Haushaltseinkommen innerhalb der nächsten fünf Jahre? Mit regelmäßigem Haushaltseinkommen meinen wir z.B. Einkommen aus selbständiger oder nichtselbständiger Arbeit, Vermietung, Verpachtung, Zinsen, Dividenden oder Renten."

or an increase. Similarly, we ask the following question about future changes in expenses:

> "Do you expect these or similar measures to result in higher or lower regular expenses within the next five years?
> (By regular expenses we mean, for example, rent, ancillary costs (e.g. gas, water, electricity), insurance costs, living costs or mobility costs.)"[19]

Again, we create a dummy variable "transition risk: increasing expenses" that takes the value of 1 if respondents expect an increase in their regular expenses and 0 if they expect no change or a decrease. Summary statistics of these variables are provided in Appendix A.

3.2 Measuring distrust in the ECB

Besides these variables targeting climate-related risks, we add two variables that proxy general distrust in the expertise and abilities of the central bank. Recent studies such as Christelis, Georgarakos, Jappelli, and Van Rooij (2020), Brouwer and de Haan (2022), and Ehrmann et al. (2013) stress the importance of trust in and knowledge of the central bank in determining household inflation expectations. In Wave 14 (February 2021), respondents are asked to directly quantify their trust in the ECB:[20]

> "On a scale from 0 to 10, how much do you trust that the European Central Bank can ensure price stability?"[21]

Out of the 5,075 respondents from Wave 14, 40 respondents skipped this question because they did not know what the ECB is. The distribution of the variable is shown in Appendix A. In this paper, we invert the scale of this variable such that a 10 indicates "no trust" and a 0 "high trust", allowing us to call the variable "ECB distrust".

The question about central bank distrust was not included in Wave 9 (September 2020) because of limited space in the questionnaire. For Wave 9, we therefore construct an indirect proxy of distrust from additional survey questions that elicit respondents' uncertainty about inflation.

[19] In German: "Erwarten Sie durch diese oder ähnliche Maßnahmen höhere oder niedrigere regelmäßige Ausgaben innerhalb der nächsten fünf Jahre? Mit regelmäßigen Ausgaben meinen wir z.B. Miete, Wohnnebenkosten (z.B. Gas, Wasser, Strom), Versicherungskosten, Lebenshaltungskosten oder Mobilitätskosten."

[20] Again, this question was originally included in the survey for a different research project at the Deutsche Bundesbank. We would like to thank Mathias Hoffmann, Lora Pavlova, Emanuel Mönch and Guido Schultefrankenfeld for sharing their data with us.

[21] In German: "Auf einer Skala von 0-10, wie sehr vertrauen Sie darauf, dass die Europäische Zentralbank für Preisstabilität sorgen kann?

More precisely, we take the absolute value of the difference between the maximum level of inflation deemed possible by each respondent 12 months ahead and the ECB's inflation target of 2%. Naturally, this proxy suffers from several limitations. First, it assumes a certain level of literacy about the ECB and its target. Second, the number of observations is restricted to 1,794 because not all respondents are asked the questions about inflation distribution. Third, the sizeable and significant correlation with respondents' expected inflation might raise endogeneity concerns, although conceptually the two measures are arguably different. Given the different nature of the two proxies, we present results for the two waves separately and do not report results for the pooled sample in the following.[22]

3.3 Results

Table 2: OLS regressions of climate concern on climate-related risks and ECB distrust

	(1)	(2)	(3)	(4)	(5a)	(5b)	(6a)	(6b)	(6c)
P-risk: no exposure (dummy)	-0.451***						-0.410*	-1.058***	-0.825***
P-risk: no incr. frequency (dummy)		0.081					-0.456**	-0.510***	-0.451***
T-risk: decr. income (dummy)			-0.592***				-0.732***	-0.397***	-0.669***
T-risk: incr. expenses (dummy)				-0.148					
ECB distrust					-0.028***	-0.160***	-0.031***	-0.163***	
Constant	3.510***	3.396***	3.613***	3.534***	4.289***	4.131***	5.421***	4.830***	4.064***
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.190	0.184	0.199	0.185	0.162	0.248	0.201	0.286	0.210
Observations	3,806	3,806	3,813	3,811	1,708	3,710	850	1,873	3,801

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

Notes: The table shows coefficients from OLS regressions of climate concern on climate-related risks and ECB distrust. $\text{climateconcern}_i = \beta_0 + \beta_1 \text{question}_{i,1} + \beta_p \text{controls}_{i,p} + \varepsilon_i$. Columns (5a) and (6a) refer to Wave 9. Columns (5b) and (6b) refer to Wave 14. The other columns report results for the pooled sample. Statistical significance is evaluated based on robust standard errors. The labels "P-risk" and "T-risk" refer to physical risk and transition risk, respectively. Controls include gender, age, education, employment, city size, household income, household size, region of residence, perception of the seriousness of Covid-19, perception of the seriousness of the refugee crisis, and homeownership.

The results from the OLS regressions of climate concern on all the aforementioned variables are shown in Table 2. We present results for both univariate and multivariate regressions.[23]

Columns (1) and (2) report the coefficients of the perception of physical risk for the pooled

[22] In Wave 9 of the BOP-HH survey, individuals were also asked directly about their affiliation to a political party. Results for parties which are generally more skeptical about the ECB's monetary policy are in line with the ones for distrust in the central bank presented in the following. Detailed results are available upon request.

[23] For the sake of clarity and consistency of the exposition, we decide to run OLS regressions in this section. Ordinal logit regression would be an alternative since the dependent variable is ordinal. In robustness checks not shown here, we have verified that our results do not change qualitatively with ordinal logit regressions.

sample. The dummy "physical risk: no exposure" is negatively correlated with climate concern. Remember that this dummy takes the value of 1 if a respondent does not fear wealth losses because they do not consider themselves exposed to extreme weather events (i.e. they do not consider that they hold climate-sensitive assets). Considering oneself exposed to more frequent extreme weather events is thus associated with an increased perception of the seriousness of climate change.

The dummy "physical risk: no increasing frequency" takes the value of 1 if a respondent does not expect more frequent extreme weather events. It is uncorrelated with climate concern in the univariate regression (2), but negatively correlated once we control for the exposure dummy in Column (6). Respondents who expect more frequent extreme weather events have a higher climate concern.

Columns (3) and (4) refer to the transition risk dummies, which take the value of 1 if respondents expect a decrease in their regular household income or an increase in their regular expenses. Expecting decreases in income is negatively correlated with climate concern. Put differently, a person can still believe that policymakers will enforce climate policies affecting their future income, despite, or maybe because of, opposing personal views on climate change.

The coefficients for distrust in the ECB are reported in Columns (5a) and (5b). In both waves, our distrust measures are negatively correlated with climate concern: the less a person trusts in the ECB, the less they are also concerned about climate change. Studies such as Christelis et al. (2020), Brouwer and de Haan (2022), and Ehrmann et al. (2013) provide evidence that distrust in central banks is associated with higher inflation expectations. Hence, a correlation between climate concern and central bank distrust could potentially contribute to an explanation of our main result from Section 2 in the sense that the perception of the seriousness of climate change is correlated with higher inflation expectations via a distrust factor channel. Specifically, as outlined by Brouwer and de Haan (2022), ECB distrust may capture pessimism and low trust in policy institutions more generally and explain climate concern as well as its link to inflation expectations. We shed more light on this hypothesis in the next section.

Interestingly, the regression results change only marginally when we run multivariate regressions on the dummies for climate-related risks and central bank distrust (Columns (6a) and (6b)), indicating that the climate risk factor and the distrust factor capture different dimensions of climate concern.[24] The explanatory power of the regressions, reaching up to 29% (Column (6b)), suggests that climate concern represents a comprehensive, generalized concept of the challenges arising from climate change. It goes beyond the individual exposure to or perception of climate-related risks. The term “concern” thus seems indeed very appropriate.

4 Relative importance of the factors

Next, we combine the previous results and analyze the extent to which the link between climate concern and expected inflation (Section 2) can be explained through the covariates introduced in Section 3. Results are shown in Table 3. We copy Column 1 from Table 1 as a reference and then add the dummy variables for transition and physical risk and for central bank distrust one by one. Because of this step-by-step approach, the sample sizes vary considerably across the different columns. However, we wish to emphasize that this variation is the result of different randomization exercises in the BOP-HH survey and therefore does not bias our results.

As indicated in the previous section, climate concern and the perception of individual climate-related risks are not fully interchangeable. We find that the coefficient on climate concern remains negative and highly significant across Columns (1)-(6), while most of the coefficients on the climate-related risk dummies are insignificant. Still, we observe that not expecting more frequent extreme weather events (e.g. physical risk frequency) is negatively correlated with expected inflation. On the other hand, expecting declines in household income due to transition risk is significantly positively correlated with expected inflation. We interpret this as weak evidence that the perception of transition risk and physical risk is associated with inflation expectations beyond an individual's climate concern.

Columns (7) and (8) report coefficients when we include central bank distrust in Wave 14.[25] There are two main takeaways here. First, distrust the in central bank is positively correlated with expected inflation, confirming previous findings in the literature. A one-notch increase in the distrust level is associated with an increase of 32 basis points in expected inflation (Column (7)). Second, climate concern remains significant even when we control for central

[24] Note that the two transition risk dummies are highly collinear. Therefore, we do not include them jointly here. A logit regression of transition risk income on transition risk expenses yields a highly significant slope coefficient of 10, meaning that expecting changes in expenses increases the odds of expecting changes in income by a factor of 10.

[25] The results for Wave 9, for which only the proxy of central bank distrust is available, are qualitatively similar, but weaker. Given the statistical difficulties that come with this proxy, as outlined in Section 3.2, we therefore do not discuss them any further at this stage.

Table 3: OLS regressions of expected inflation on climate concern, climate-related risks, and ECB distrust

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Climate concern	-0.240***	-0.219**	-0.218**	-0.206**	-0.223**	-0.211**	-0.180**	-0.169
P-risk: no exposure (dummy)		0.034				-0.390		0.011
P-risk: no incr. frequency (dummy)			-0.430			-0.622*		0.084
T-risk: decr. income (dummy)				0.492*		0.443		-0.351
T-risk: incr. expenses (dummy)					-0.223			
ECB distrust							0.320***	0.373***
Constant	6.431***	3.809**	4.092**	3.563**	3.996**	4.010**	5.154***	1.015
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.053	0.047	0.047	0.047	0.046	0.048	0.057	0.061
Observations	6,724	3,382	3,382	3,388	3,386	3,378	3,250	1,648

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

Notes: The table shows the coefficients from OLS regressions of 12-month-ahead expected inflation on climate concern, climate-related risks, and ECB distrust. The regression equation is $\text{expinf}_i = \beta_0 + \beta_1 \text{climateconcern}_{i,1} + \beta_2 \text{question}_{i,2} + \beta_p \text{controls}_{i,p} + \varepsilon_i$. Columns (1), (2), (3), (4), (5), and (6) refer to the pooled sample. Columns (7) and (8) refer to Wave 14. Statistical significance is evaluated based on robust standard errors. The labels "P-risk" and "T-risk" refer to physical risk and transition risk, respectively. Controls include gender, age, education, employment, city size, household income, household size, region of residence, perception of the seriousness of Covid-19, perception of the seriousness of the refugee crisis, and homeownership.

bank distrust, i.e. the two variables seem to constitute two separate but important factors for expected inflation.[26] In additional quantile regressions, which we do not report here for the sake of brevity, we also confirm that the effects are generally more pronounced among those respondents who have high conditional expected inflation, similar to what we find in Section 2.

Interestingly, when we finally add the climate-related risk dummies (Column (8)), climate concern and the climate-related risk dummies all turn insignificant, while ECB distrust remains significant.[27] To gain more insights into this result, we orthogonalize climate concern with respect to ECB distrust. Specifically, we regress climate concern on ECB distrust and use the residuals as an explanatory variable (see Table 4). Importantly, we find that orthogonalized climate concern is statistically significant, both without (Column (2a)) and with controls (Column (2b)). Furthermore, the slope coefficient has the same sign as in our benchmark analysis (which is copied in Column (1) of Table 4 for convenience), i.e., the higher orthogonalized climate concern, the lower is expected inflation. We interpret this as evidence that climate concern explains expected inflation beyond central bank distrust.

Table 4: OLS regressions of expected inflation on orthogonalized climate concern

	(1)	(2a)	(2b)
Climate concern	-0.169		
P-risk: no exposure (dummy)	0.011		0.192
P-risk: no incr. frequency (dummy)	0.084		0.172
T-risk: decr. income (dummy)	-0.351		-0.287
ECB distrust	0.373^{***}		
Orthogonalized climate concern		-1.875^{***}	-1.637^{***}
Constant	1.015	17.937^{***}	14.498^{***}
Controls	Yes	No	Yes
R-squared	0.061	0.020	0.059
Observations	1,648	4,821	1,648

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

Notes: The table shows the coefficients from OLS regressions of 12-month-ahead expected inflation on orthogonalized climate concern (orthogonalized with respect to ECB distrust). The regression equation is $\text{expinf}_i = \beta_0 + \beta_1 \text{orthclimateconcern}_{i,1} + \beta_p \text{controls}_{i,p} + \varepsilon_i$. All Columns refer to Wave 14. Statistical significance is evaluated based on robust standard errors. The labels "P-risk" and "T-risk" refer to physical risk and transition risk, respectively. Controls include gender, age, education, employment, city size, household income, household size, region of residence, perception of the seriousness of Covid-19, perception of the seriousness of the refugee crisis, and homeownership.

For completeness, we also regress ECB distrust on the climate-related questions (Table 5). In

[26] In regressions not shown here, we have also tested an interaction term between central bank distrust and climate concern, but the coefficient is small and statistically insignificant.

[27] Again, in regressions not shown here, interaction terms between central bank distrust and climate-related questions are all statistically insignificant.

line with previous results, we find that climate concern is an ~~important~~ explanatory variable for ECB distrust, being significant at the 1% level. A fall in climate concern goes along with a rise in ECB distrust. When including all climate-related questions (except for transition risk expenses, due to the collinearity) as explanatory variables (Column (6)), each has significant explanatory power. Not being exposed or not expecting more frequent weather events is actually associated with lower ECB distrust. In contrast, expecting a decrease in income goes along with an increase in ECB distrust. These results hold both with and without climate concern (Columns (4a), (4b), (5a), and (5b)). Putting the pieces together, we conclude that the higher a person's climate concern and the lower their transition risk fears, the less they distrust in the central bank.

Table 5: OLS regressions of ECB distrust on climate concern and climate-related risks

	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)	(6)
Climate concern	-0.258***	-0.208***		-0.232***		-0.223***		-0.208***		-0.224***	-0.220***
P-risk: no exposure (dummy)			0.003	-0.320**							-0.533***
P-risk: no incr. frequency (dummy)					-0.174*	-0.042					-0.366**
T-risk: decr. income (dummy)							0.963***	0.748***			0.689***
T-risk: incr. expenses (dummy)									0.388***	0.415***	
Constant	7.116***	7.480***	5.175***	7.787***	5.262***	7.724***	4.764***	7.121***	4.862***	7.378***	7.533***
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	Yes
R-squared	0.062	0.076	0.000	0.086	0.001	0.083	0.034	0.103	0.003	0.087	0.107
Observations	5,033	3,710	2,514	1,874	2,514	1,874	2,519	1,876	2,518	1,875	1,873

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

Notes: The table shows the coefficients from OLS regressions of the Wave 14 proxy of ECB distrust on climate concern and climate-related risks: $\text{CBdistrust}_i = \beta_0 + \beta_1 \text{question}_{i,1} + \beta_p \text{controls}_{i,p} + \varepsilon_i$. Statistical significance is evaluated based on robust standard errors. The labels "P-risk" and "T-risk" refer to physical risk and transition risk, respectively. Controls include gender, age, education, employment, city size, household income, household size, region of residence, perception of the seriousness of Covid-19, perception of the seriousness of the refugee crisis, and homeownership.

5 Complementary analysis and robustness

5.1 Cluster analysis and sample splits

Linear regressions can by construction only uncover marginal effects of climate concern on expected inflation. Moreover, the quantile regressions shown in Figure 1 indicate that the explanatory power of climate concern is especially strong for the right-hand tail of the conditional cross-sectional distribution of expected inflation. We thus complement the previous exercises with a cluster analysis. The cluster analysis provides evidence for two distinct sets of individuals whose centroids differ strongly in the climate concern dimension (4.5 as opposed to 8.8). In line with our main results, individuals in the high climate concern cluster have lower inflation expectations and lower distrust in the ECB than individuals in the low climate concern cluster.

Specifically, we make use of two machine learning algorithms: K-means and K-prototypes. The purpose of both algorithms is to aggregate data into groups. Needless to say, there are numerous clustering algorithms, but they all trade off minimizing the heterogeneity of characteristics within a cluster and maximizing the heterogeneity of characteristics between clusters. The decision to employ K-means and K-prototypes is mostly guided by our preference for simplicity and clarity of exposition over complexity. K-means and K-prototypes are easily interpretable and implementable algorithms. Conceptually, K-prototypes represents an evolution of the standard K-means for clustering numerical data by integrating the features of K-modes for clustering categorical data. A critical aspect is the number of clusters K, which must be chosen in advance. We loop the algorithms over a range of values for K and choose the optimal number ex post, based on an optimization criterion. We provide a detailed explanation of the algorithms, our choices regarding the features, and the optimization criterion in Appendix D.1.[28]

Since K-means is the standard algorithm for continuous variables, we use it in our first exercise with expected inflation, climate concern, and ECB distrust with data from Wave 14.[29] In the specifications with categorical variables like the climate-related risk questions, we use K-prototypes.[30] The respective results, which are reported in Appendix D.2, by and large confirm the findings reported here in the main text.

K-means detects two clusters. Their centroids and the numbers of observations are reported in Table 6. A graphical representation of the clusters using pairplots is available in Figure 2. It depicts scatterplots of our data for each combination of variables as well as the distributions of our variables within each cluster. Consistent with our main result, the two clusters seem to

[28]We wish to thank Nelis J. de Vos for making the Python code for these algorithms available in a public library.

[29]As a benchmark, we report the results from K-means without including the climate-related risk dummies. For this benchmark analysis, we also drop the control variables because it would render the interpretation more complex.

[30]The heterogeneity of data types – a mix of categorical and numerical variables – generally constrains the range of applicable algorithms. Clustering algorithms for numerical variables largely rely on Euclidean distances in the objective function, but these are difficult to evaluate for categorical variables. Clustering algorithms for mixed data types exist, but they are notably unpopular, especially for large data sets because of quadratic computational cost (Huang (1998)). The traditional approach is to convert categorical variables into a series of dummy variables (Ralambondrainy (1995)) and then apply standard algorithms for clustering of continuous variables, such as K-means. However, this approach has been criticized for being difficult to interpret and delivering often meaningless results (Huang (1997a)).

Table 6: Cluster centroids

	Cluster	
	1	2
Expected inflation	5.5%	3.7%
Climate concern	4.5	8.8
ECB distrust	6.7	4.5
Number of observations	1,569	3,251

Notes: The table reports the cluster centroids resulting from an application of K-means to expected inflation, climate concern, and ECB distrust, with data from Wave 14 only. We apply min-max feature scaling and the number of clusters is chosen endogenously. We run K-means 100 times with different starting values.

differ along all three dimensions: distrust in the ECB, expected inflation, and climate concern. More precisely, the centroids reported in Table 6 reveal that there are two distinct sets of individuals, where one set has higher climate concern (clustering around 8.8), less distrust in the central bank (around 4.5), and lower expected inflation (around 3.7%) relative to the other set (clustering around 4.5, 6.7, and 5.5%, respectively). Interestingly, the separation between clusters is most pronounced for climate concern, for instance, looking at Figure 2. This emphasizes that climate concern is indeed very useful for classifying the respondents of the survey into different categories. Furthermore, including the climate-related risk dummies into the cluster analysis supports the findings that transition risk fears also play a role. Specifically, Table 10 in Appendix D.2 suggests that the individuals with high expected inflation, low climate concern, and high central bank distrust also expect a decrease in income and an increase in expenses due to a transition to a lower-carbon economy. Finally, Table 11 in Appendix D.2 suggests that individuals in the low climate concern cluster also have low concern about Covid-19. In this last exercise, we also include further control variables. However, the results do not point towards any further systematic differences between the high and low climate concern clusters.

Generally speaking, the clustering algorithm sorts all datapoints into clusters by optimizing a specific objective function. A more widely used way of doing this are standard sample splits. These, of course, are subject to the limitations of linear regressions again. However, in order to put our results a bit more into perspective, we complement our analysis with sample splits along the lines of socio-demographic variables like age, gender, education. Tables 12-14 in Appendix E present the results from regressions of expected inflation on climate concern and all other

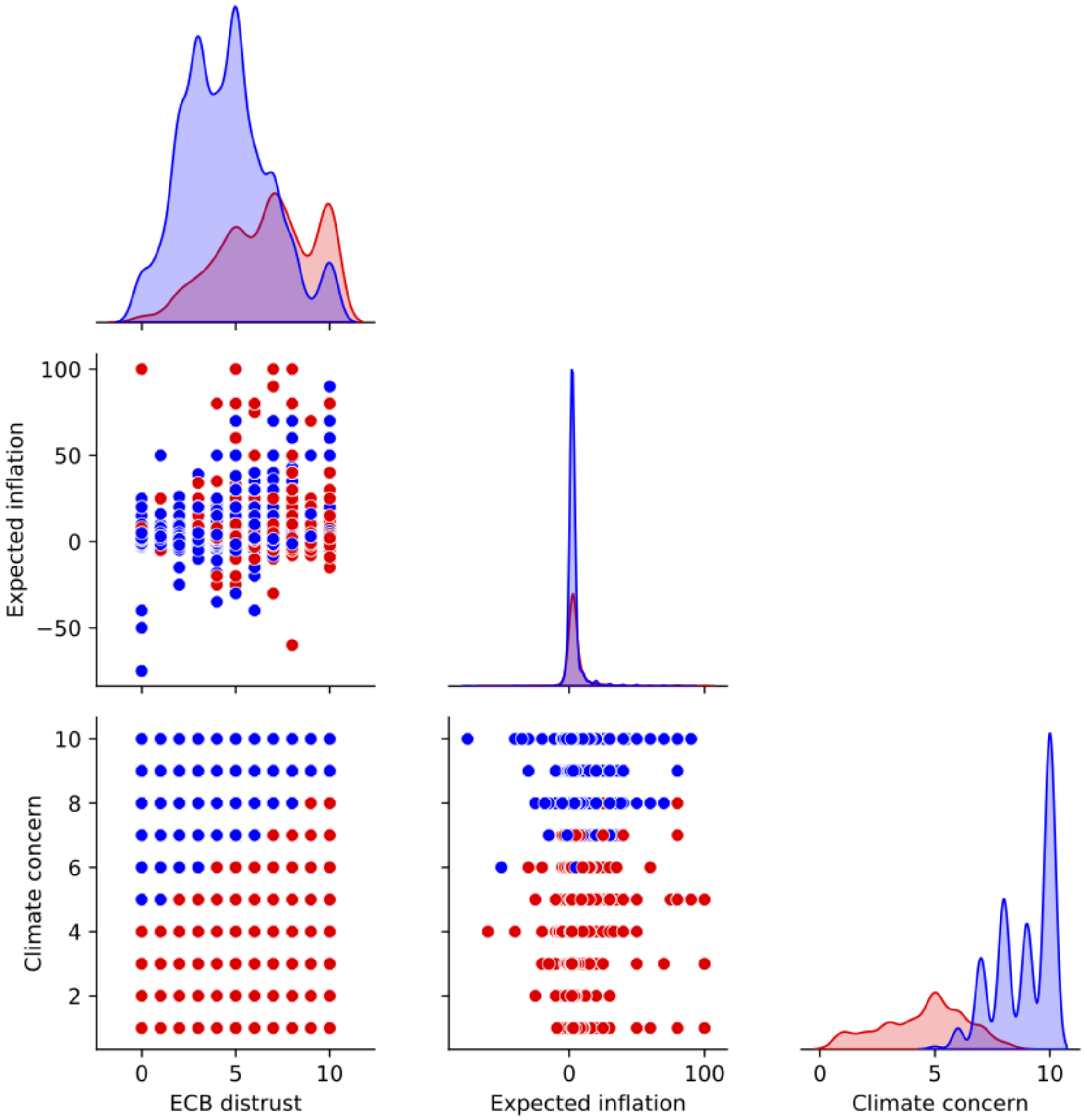

Figure 2: Pairplot

Notes: The figure shows the pairplot resulting from an application of K-means to expected inflation, climate concern, and ECB distrust, with data from Wave 14 only. We apply min-max feature scaling and the number of clusters is chosen endogenously. We run K-means 100 times with different starting values.

control variables for various subsamples of our dataset. The columns are set up like the ones in Table 1, i.e. Columns (1a), (1b) and (1c) refer to the data from Wave 9, Wave 14 and the pooled sample, respectively. In Column (2), we add controls for the pooled sample. Of course, in each column, we exclude the respective control variable which is used to split the sample. The results confirm our baseline findings discussed above. Climate concern remains by and large significant across sample splits.

5.2 Medium and long-term inflation expectations

The consequences of climate change are usually associated with risks over the medium or long term. An interesting question, therefore, is whether household perceptions about climate change affect longer-term inflation expectations. In the previous sections, we presented results for expected inflation 12 months ahead, since this is the standard horizon of the BOP-HH. In Wave 14, however, the BOP-HH survey also includes questions about expected inflation five and ten years ahead, which is much more in line with the horizon in our climate-related risk questions. Results for these medium and long-term expectations are reported in Table 7.

Table 7: OLS regressions of medium and long-term expected inflation on climate concern, climate-related risks, and ECB distrust

	5-year horizon							10-year horizon	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Climate concern	-0.490***	-0.515***	-0.556***	-0.562***	-0.543***	-0.428***	-0.425**	-0.270*	-0.032
P-risk: no exposure (dummy)		1.492*					2.363***		-0.672
P-risk: no incr. frequency (dummy)			-0.538				0.941		-1.080
T-risk: decr. income (dummy)				0.033			-0.065		0.201
T-risk: incr. expenses (dummy)					-1.774				
ECB distrust						0.389***	0.419***		0.422***
Constant	7.185**	10.520**	11.226**	10.779**	11.911**	4.564	6.233	9.144***	4.530
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.046	0.067	0.063	0.062	0.067	0.055	0.082	0.069	0.095
Observations	1,624	822	822	822	822	1,613	818	1,640	829

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

Notes: The table shows the coefficients from OLS regressions of long-term expected inflation on climate concern, climate-related risks, and ECB distrust: $\text{longtermexpinf}_i = \beta_0 + \beta_1 \text{question}_{i,1} + \beta_p \text{controls}_{i,p} + \varepsilon_i$. Columns (1)-(7) refer to the five-year horizon, Columns (8) and (9) to the ten-year horizon. All columns refer to Wave 14 only. Statistical significance is evaluated based on robust standard errors. The labels "P-risk" and "T-risk" refer to physical risk and transition risk, respectively. Controls include gender, age, education, employment, city size, household income, household size, region of residence, perception of the seriousness of Covid-19, perception of the seriousness of the refugee crisis, and homeownership.

There are three main takeaways. First, climate concern is highly statistically significant for five-year-ahead expected inflation (Column (1)). The magnitude of the coefficients is twice as large as in the baseline setup, increasing from -0.24 to -0.49, i.e. a one-notch increase in climate concern is now associated with a decrease of 49 basis points in expected inflation. The association of climate concern is thus even more pronounced for long-term inflation expectations than for short-term ones, also when we add climate-related risk questions and central bank distrust (Columns (2)-(7)). On the other hand, the significance deteriorates and the coefficients are again much smaller for a horizon of ten years (Columns (8) and (9)).

Although the limited number of observations and the setup do not allow for a rigorous analysis of de-anchoring, the strong increase in the slope coefficient for climate concern and inflation expectations in the medium term - hence, close to the inflation anchor - motivates further research to understand whether (and to what extent) individuals with low climate concern have upward de-anchored inflation expectations.[31] Our results can be seen as a prerequisite for such a deeper analysis. According to ECB (2021b), de-anchoring can, for instance, be measured through the responsiveness of longer-term inflation expectations to shorter-term economic developments. However, such a test should only be applied conditional on ex ante evidence for extreme levels of expected inflation.

Second, considering the five-year horizon, climate concern remains significant in the multivariate regression with ECB distrust and the climate-related risks (Column (7)). In contrast to Table 3, climate concern thus explains variation in expected inflation above and beyond distrust in central bank and climate risk exposure. Moreover, physical risk exposure turns significant, emphasizing that physical risk issues become linked over the medium-term horizon.

The third result is that distrust in the central bank remains positively associated with expected inflation across all horizons. In terms of magnitude, the marginal effect of this variable becomes progressively stronger. A one-notch increase in the level of distrust goes along with an increase of 34 basis points in higher expected inflation in the short term (see Table 3) and of 42 basis points in the long term.

[31] We acknowledge that five-year-ahead inflation expectations might not be a universally accepted reference for the ECB target, given that the length of the medium-term horizon has never been definitively clarified (ECB (2021b))

5.3 Dealing with outliers

A natural concern when it comes to survey research is robustness to outliers. This is also true for the BOP-HH since a survey about inflation expectations requires at least a minimum level of economic literacy. Our pooled sample, for instance, contains more than 900 respondents with inflation expectations above 10%.

Tables 15 and 16 in Appendix F show results for the subsample of survey participants with expected inflation between -0.1% and 20%. The size of this reduced sample is still very large (7,438 observations) and, most importantly, the main results of our paper are corroborated or even strengthened. The coefficients from the regression of expected inflation on climate concern are even more significant than in Table 3, although they are about half as large as in the full sample analysis. The smaller coefficients are in line with the quantile regressions in Figure 1: the link between expected inflation and climate concern is particularly strong among respondents with high expected inflation. But our overall findings are robust, even when we disregard these respondents. Concerning climate-related risks, we notice an overall increase in the significance of coefficients across almost all specifications. If anything, removing outliers reinforces this part of the results.

We also perform an additional robustness check where we exclude respondents that have either anchored (at 2%) or extreme (below -0.1% or above 20%) inflation expectations. Table 17 in Appendix F shows the results for this subsample. Overall, we find slightly larger regression coefficients and larger R-squared values. Again, this supports our takeaway from the quantile regressions in Figure 1, namely that the marginal effect becomes stronger when we focus on households with higher conditional expected inflation.

5.4 Unemployment expectations

Finally, recent papers such as Andre et al. (2022) find that associative memory plays an important role in the formation of forecasts and thoughts. Put differently, there is evidence that survey participants employ heuristic methods when forming economic expectations. Somewhat simplified, for instance, there may be households who form their economic expectations based on narratives that resemble New-Keynesian demand shocks. This could imply that they expect high inflation to occur along with high growth and low unemployment. On the other hand, there may be households that rather think of standard supply-side narratives. Such households may be more likely to connect high inflation to low growth and high unemployment.

We control for such heuristics by adding unemployment expectations fixed effects. Specifically, the BOP-HH asks individuals whether they expect (i) a strong decrease, (ii) a decrease, (iii) no change, (iv) an increase, or (v) a strong increase in unemployment over the next 12 months. We create four dummy variables out of the five possible answers, such that category (iii) becomes the reference category, which is captured by the constant. Results with fixed effects for these categories are shown in Table 8.[32] Columns (1) and (2) refer to the pooled sample and should be compared to Column (1c) and Column (2) of Table 1, respectively. Column (3) refers to Wave 14 only, and should be compared to Column (7a) of Table 3. We find that climate concern retains its significance. The magnitude and significance of the slope coefficients for climate concern are about the same as in Tables 1 and 3.

Table 8: OLS regressions of expected inflation on climate concern, unemployment expectations and ECB distrust

	(1)	(2)	(3)
Climate concern	-0.147***	-0.200***	-0.158**
Unemployment expectations: strongly decrease (dummy)	2.591***	2.593***	3.451***
Unemployment expectations: decrease (dummy)	-0.301	-0.178	0.197
Unemployment expectations: increase (dummy)	-0.160	-0.206	0.298
Unemployment expectations: strongly increase (dummy)	1.751***	1.131***	1.386***
ECB distrust			0.277***
Constant	4.579***	6.176***	4.779**
Controls	No	Yes	Yes
R-squared	0.017	0.060	0.063
Observations	8,249	6,723	3,249

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

Notes: The table shows coefficients from OLS regressions of 12-month-ahead expected inflation on climate concern, unemployment expectations and ECB distrust: $\text{expinf}_i = \beta_0 + \beta_1 \text{climateconcern}_{i,1} + \beta_2 \text{question}_{i,1} + \beta_p \text{controls}_{i,p} + \varepsilon_i$. Columns (1) and (2) refer to the pooled sample, Column (3) to Wave 14. Controls included in Columns (2) and (3) are: gender, age, education, employment, size of the city of residence, household income, household size, region of residence, perception of the seriousness of Covid-19, perception of the seriousness of the refugee crisis, and homeownership. Statistical significance is evaluated based on robust standard errors.

[32] We also consider an alternative binning based on 3 categories: (i) decrease (ii) no change (iii) increase. Results do not change qualitatively.

6 Conclusion

Risks arising from climate change have featured prominently in discussions among central bankers recently. However, little is known about their impact on inflation, let alone inflation expectations. This study provides empirical evidence on the relationship between households' perception of climate change and their inflation expectations using microdata from the BOP-HH.

As the key contribution, we document a strong negative correlation between climate concern – a variable measuring households' perception of the overall seriousness of climate change on a 1-10 scale – and expected inflation. In other words, individuals with higher concern about the consequences of climate change have lower inflation expectations. A one-notch increase in climate concern is associated with a decrease of 24 basis points in expected inflation over the next 12 months and of up to 49 basis points for the five-year horizon. We show that the link between climate concern and inflation expectations goes above and beyond individuals' perception of their personal exposures to climate-related risks, their distrust in the central bank, and a broad range of socio-demographic and socio-economic control variables. Furthermore, it survives a range of robustness checks.

While our research design does not allow for any causal statements, we still believe that our study increases our understanding of inflation expectations by showing that higher climate concern is associated with lower inflation expectations. Future efforts should be directed towards understanding related mechanisms more deeply, such as those associated with physical risk, transition risk, and uncertainty highlighted above. Furthermore, studies should examine whether and in what way our main result carries over to other countries, time periods, or policy regimes. Future research could also examine how climate concern relates to the formation of inflation expectations and whether it is linked to systematic behavioral biases. Such an analysis would require longer time series of households' inflation forecast errors, which could be obtained by eliciting climate concern repeatedly over multiple periods.

Finally, our results give rise to some policy interpretations. Most importantly, our findings provide evidence that climate change perceptions may matter for inflation expectations, contributing to the broader debate among central bankers on how climate-related risks affect price stability. Moreover, we find that climate concern, the perception of individual climate-related risks, trust in the central bank and inflation expectations are interrelated in very complex, possibly non-linear ways. In this sense, our results may be useful in highlighting the challenges and trade-offs that arise when central banks take into account issues surrounding climate change.

References

Afunts, G., M. Cato, and T. Schmidt (2023). Inflation Expectations in the Wake of the War in Ukraine. *Deutsche Bundesbank Discussion Paper 03/2023*.

Andre, P., C. Pizzinelli, C. Roth, and J. Wohlfart (2022). Subjective Models of the Macroeconomy: Evidence from Experts and a Representative Sample. *Review of Economic Studies, forthcoming*.

Baker, S., N. Bloom, and S. Davis (2016). Measuring Economic Policy Uncertainty. *Quarterly Journal of Economics 131*, 1593–1636.

Baker, S. R., T. S. McElroy, and X. S. Sheng (2020). Expectation Formation Following Large, Unexpected Shocks. *Review of Economics and Statistics 102*, 287–303.

Baldauf, M., L. Garlappi, and C. Yannelis (2020). Does Climate Change Affect Real Estate Prices? Only If You Believe in It. *Review of Financial Studies 33*, 1256–1295.

Batten, S., R. Sowerbutts, and M. Tanaka (2020). Climate Change: Macroeconomic Impact and Implications for Monetary Policy. *Ecological, Societal, and Technological Risks and the Financial Sector*, 13–38.

Bernard, R., P. Tzamourani, and M. Weber (2022). Climate Change and Individual Behavior. *Deutsche Bundesbank Discussion Paper 01/2022*.

Bloom, N. (2009). The Impact of Uncertainty Shocks. *Econometrica 77*, 623–685.

Brouwer, N. and J. de Haan (2022). Trust in the ECB: Drivers and Consequences. *European Journal of Political Economy 74*, 102262.

Cao, F., J. Liang, and L. Bai (2009). A New Initialization Method for Categorical Data Clustering. *Expert Systems with Applications 36*, 10223–10228.

Christelis, D., D. Georgarakos, T. Jappelli, and M. Van Rooij (2020). Trust in the Central Bank and Inflation Expectations. *International Journal of Central Banking 16*, 1–37.

Coibion, O., D. Georgarakos, Y. Gorodnichenko, G. Kenny, and M. Weber (2023). The Effect of Macroeconomic Uncertainty on Household Spending. *ECB Working Paper 2557*.

D'Acunto, F., U. Malmendier, J. Ospina, and M. Weber (2021). Exposure to Grocery Prices and Inflation Expectations. *Journal of Political Economy 129*, 1615–1639.

Dietrich, A., G. Mueller, and R. Schoenle (2020). The Expectations Channel of Climate Change: Implications for Monetary Policy. *Working Paper*.

Duca-Radu, I., G. Kenny, and A. Reuter (2021). Inflation Expectations, Consumption and the Lower Bound: Micro Evidence from a Large Multi-Country Survey. *Journal of Monetary Economics 118*, 120–134.

ECB (2021a). Climate Change and Monetary Policy in the Euro Area. *ECB Occasional Paper 271 (September 2021)*.

ECB (2021b). Inflation Expectations and their Role in Eurosystem Forecasting. *ECB Occasional Paper 264 (September 2021)*.

Ehrmann, M., D. Pfajfar, and E. Santoro (2017). Consumers' Attitudes and their Inflation Expectations. *International Journal of Central Banking 47*, 225–259.

Ehrmann, M., M. Soudan, and L. Stracca (2013). Explaining European Union Citizens' Trust in the European Central Bank in Normal and Crisis Times. *Scandinavian Journal of Economics 115*, 781–807.

Galati, G., R. Moessner, and M. Van Rooij (2020). The Anchoring of Long-Term Inflation Expectations of Consumers: Insights from a New Survey. *DNB Working Paper 688*.

Georgarakos, D. and G. Kenny (2022). Household Spending and Fiscal Support During the COVID-19 Pandemic: Insights from a New Consumer Survey. *Journal of Monetary Economics 129*, S1–S14.

Huang, Z. (1997a). A Fast Clustering Algorithm to Cluster Very Large Categorical Data Sets in Data Mining. *Research Issues on Data Mining and Knowledge Discovery 3*, 34–39.

Huang, Z. (1997b). Clustering Large Data Sets with Mixed Numeric and Categorical Values. *Proceedings of the 1st Pacific-Asia Conference on Knowledge Discovery and Data Mining*, 21–34.

Huang, Z. (1998). Extensions to the k-Means Algorithm for Clustering Large Data Sets with Categorical Values. *Data Mining and Knowledge Discovery 2*, 283–304.

Jurado, K., S. Ludvigson, and S. Ng (2015). Measuring Uncertainty. *American Economic Review 105*, 1177–1216.

Krueger, P., Z. Sautner, and L. Starks (2020). The Importance of Climate Risks for Institutional Investors. *Review of Financial Studies 33*, 1067–1111.

Lee, T. M., E. M. Markowitz, P. D. Howe, C. Y. Ko, and A. A. Leiserowitz (2015). Predictors of Public Climate Change Awareness and Risk Perception Around the World. *Nature Climate Change 5*, 1014–1020.

McKibbin, W. J., A. C. Morris, P. J. Wilcoxen, and A. J. Panton (2020). Climate Change and Monetary Policy: Issues for Policy Design and Modelling. *Oxford Review of Economic Policy 36*, 579–603.

Meinerding, C., Y. Schüler, and P. Zhang (2023). Shocks to Transition Risk. *Deutsche Bundesbank Discussion Paper 04/2023*.

NGFS (2020). Climate Change and Monetary Policy: Initial Takeaways. Technical report.

Poortinga, W., L. Whitmarsh, L. Steg, G. Böhm, and S. Fisher (2019). Climate Change Perceptions and their Individual-Level Determinants: A Cross-European Analysis. *Global Environmental Change 55*, 25–35.

Ralambondrainy, H. (1995). A Conceptual Version of the K-means Algorithm. *Pattern Recognition Letters 16*, 1147–1157.

Tzamourani, P. (2022). Climate Change Concerns and Actions – Can Provision of Information Motivate People to Fight Climate Change? *Deutsche Bundesbank Research Brief No. 47*.

Van der Linden, S. (2015). The Social-Psychological Determinants of Climate Change Risk Perceptions: Towards a Comprehensive Model. *Journal of Environmental Psychology 41*, 112–124.

Van der Linden, S. (2017). Determinants and Measurement of Climate Change Risk Perception, Worry, and Concern. *The Oxford Encyclopedia of Climate Change Communication*.

Appendix A Summary statistics

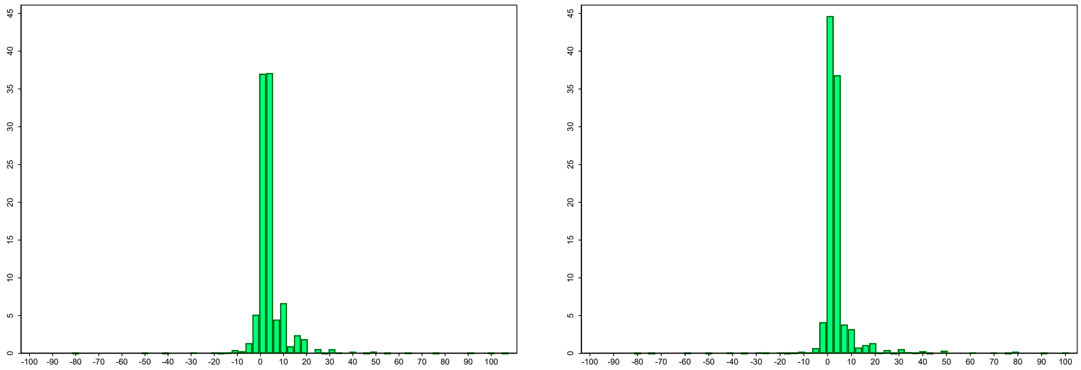

Figure 3: Distribution of expected inflation in Wave 9 (left) and Wave 14 (right)

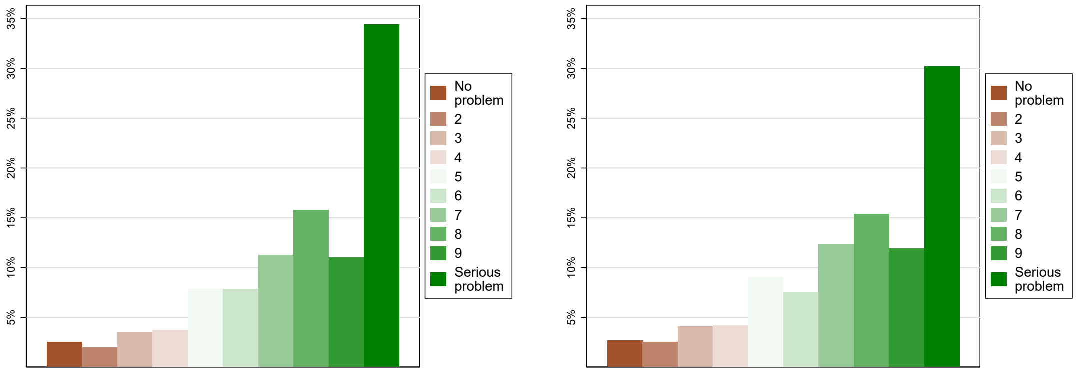

Figure 4: Distribution of climate concern in Wave 9 (left) and Wave 14 (right)

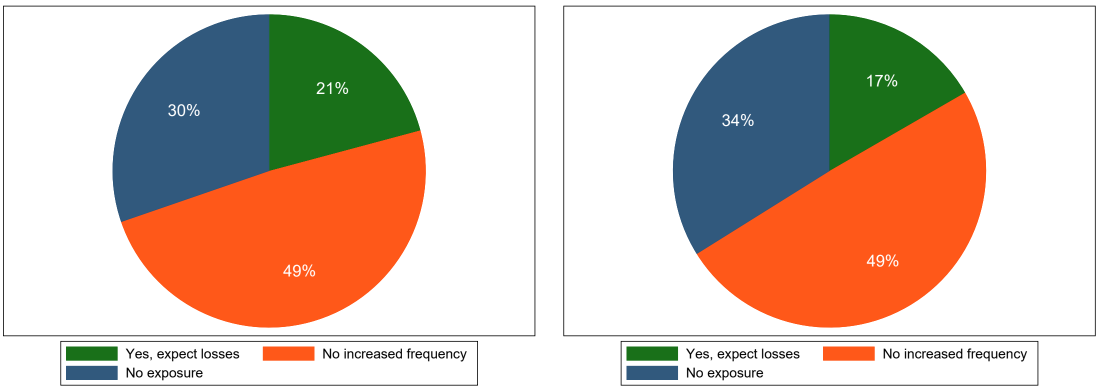

Figure 5: Distribution of perception of physical risk in Wave 9 (left) and Wave 14 (right)

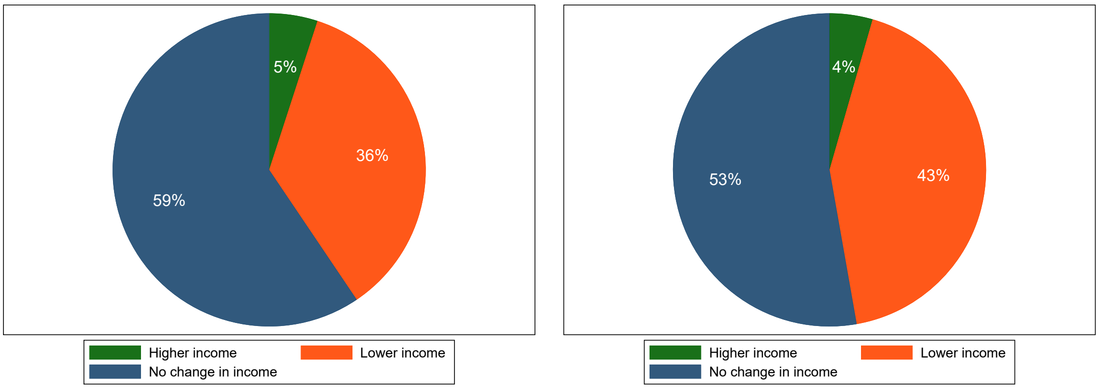

Figure 6: Distribution of perception of transition risk (income) in Wave 9 (left) and Wave 14 (right)

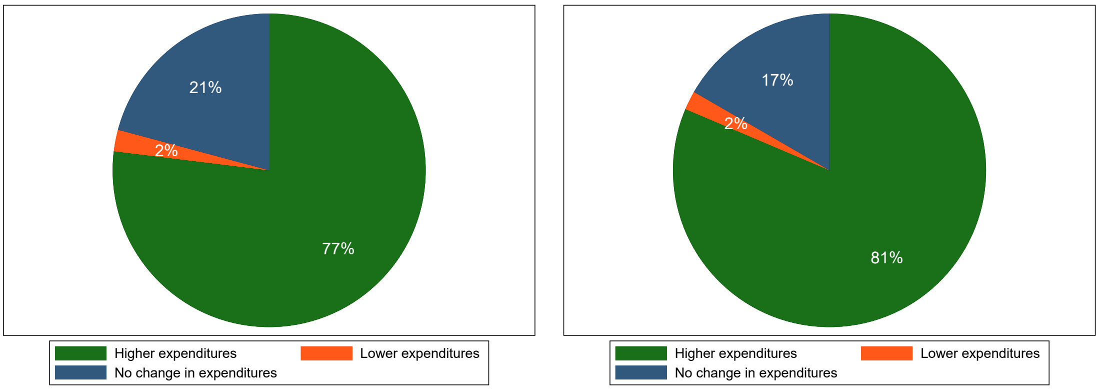

Figure 7: Distribution of perception of transition risk (expenses) in Wave 9 (left) and Wave 14 (right)

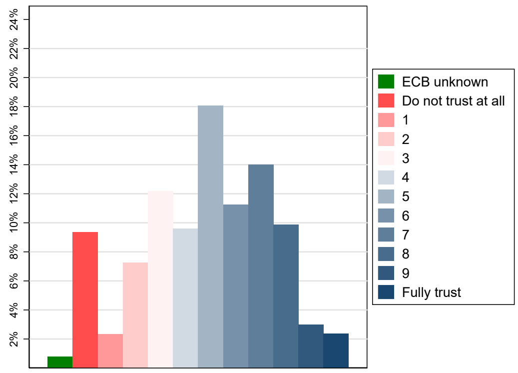

Figure 8: Distribution of trust in ECB in Wave 14

Appendix B Control variables

The purpose of this section is to provide an overview of control variables, grouped by statistical type of data.

Our dataset contains three categorical, dichotomous variables. The first identifies whether the respondent is the owner of a house or apartment, or a renter. The second is gender. The third distinguishes whether a person lived in East or West Germany before German reunification in 1989-90.

Age, household size, household income, size of the city of residence, perception of the severity of the refugee crisis and of Covid-19 are treated as continuous variables for the sake of clarity of exposition. These variables have a minimum of five categories and the categories have a clear order.[33] Age goes from 16 to 80+ years, and household size goes from 1 to 6 or more members. Household income is grouped in 13 categories, the first being below €500 and the last being above €10,000 net per month.[34] City size comprises five categories, ranging from small villages (population below 5,000) to big cities (population above 500,000). The remaining two variables are designed similarly to our main climate concern variable: respondents are asked to quantify their perception of the seriousness of the issue on a scale from 1 to 10.

The remaining variables can be classified as (categorical) polytomous variables. We have information about the current region of residence (North, South, East, West Germany), education (university, college, high school, other/no degree) and employment (full-time, part-time, retired, unemployed, casual/irregular, other/student/intern/parental leave).

[33] We have checked that our results are robust to this choice and do not change when these variables enter the regressions as categorical variables, too.

[34] Every category increases the range of income by €499 up until the threshold of €3,999 net per month, from here, every notch accounts from an increase of €999 net per month.

Appendix C Complete regression results

Table 9: OLS regressions of expected inflation on climate concern, climate-related risks, and ECB distrust

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Climate concern	-0.240***	-0.219**	-0.218**	-0.206**	-0.223**	-0.211**	-0.180**	-0.169
P-risk: no exposure (dummy)		0.034				-0.390		0.011
P-risk: no incr. frequency (dummy)			-0.430			-0.622*		0.084
T-risk: decr. income (dummy)				0.492*		0.443		-0.351
T-risk: incr. expenses (dummy)					-0.223			
ECB distrust							0.320***	0.373***
Female (dummy)	1.769***	1.704***	1.686***	1.716***	1.696***	1.721***	1.832***	2.160***
University education (dummy)	-1.081***	-1.217***	-1.195***	-1.216***	-1.207***	-1.203***	-0.719***	-0.758**
Other/no degree (dummy)	1.106	2.098	2.040	2.121	2.113	2.072	2.558	3.573
Part-time (dummy)	0.384	-0.029	-0.024	0.010	-0.006	0.008	0.435	-1.123
Casual or irregular (dummy)	0.507	1.663	1.635	1.716	1.661	1.668	-0.356	-1.210
Other, student, intern, or parental leave (dummy)	3.027**	3.304*	3.291*	3.416**	3.317*	3.389*	3.062*	1.534
Unemployment (dummy)	3.109**	2.360	2.315	2.217	2.271	2.299	1.825	3.588
Retirement (dummy)	0.276	-0.061	-0.055	-0.010	-0.045	-0.014	0.686	-0.655
Residence in East Germany before 1989 (dummy)	1.400***	1.457***	1.439***	1.439***	1.452***	1.430***	0.948*	0.667
Renter (dummy)	0.771***	0.555	0.486	0.567	0.542	0.571	0.795**	0.468
Age	-0.028**	-0.005	-0.006	-0.007	-0.005	-0.007	-0.039*	0.004
City size	-0.087	-0.063	-0.060	-0.051	-0.062	-0.047	-0.091	-0.096
Household income	-0.218***	-0.120	-0.115	-0.110	-0.120	-0.105	-0.140**	-0.091
Perception Covid-19	0.078	0.139	0.138	0.133	0.138	0.136	0.067	0.247*
Perception refugee crisis	0.149***	0.141*	0.137*	0.137*	0.142*	0.135*	0.064	0.026
Household size	0.053	0.098	0.096	0.094	0.103	0.088	-0.192	0.088
Constant	6.431***	3.809**	4.092**	3.563**	3.996**	4.010**	5.154***	1.015
R-squared	0.053	0.047	0.047	0.047	0.046	0.048	0.057	0.061
Observations	6,724	3,382	3,382	3,388	3,386	3,378	3,250	1,648

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

Notes: The table shows the coefficients from OLS regressions of 12-month-ahead expected inflation on climate concern, climate-related risks, and ECB distrust. The regression equation is $\text{expinf}_i = \beta_0 + \beta_1 \text{climateconcern}_{i,1} + \beta_2 \text{question}_{i,2} + \beta_p \text{controls}_{i,p} + \varepsilon_i$. Columns (1), (2), (3), (4), (5), and (6) refer to the pooled sample; Columns (7) and (8) refer to Wave 14. Statistical significance is evaluated based on robust standard errors. The labels "P-risk" and "T-risk" refer to physical risk and transition risk, respectively.

Appendix D K-means and K-prototypes

D.1 Algorithms

We first describe the basic functioning of K-means through pseudo-code:

1. For a fixed number of clusters K, pick k observations randomly. These observations constitute the initial centroids (e.g. means).
2. Calculate the distance of each data point from the centroids, using the square of the Euclidean distance.
3. Assign each point to the nearest centroid.
4. Select a new centroid for each cluster. Among all observations within a cluster, pick the one for which the distance between observations and the previous centroid is closest to the mean distance.
5. Repeat steps 2. and 3.
6. Iterate until no further changes are made in the assignment of observations to clusters after a full cycle test of the dataset

As noted before, the mean and Euclidean distance have no meaning with categorical data. The K-modes algorithm (Huang (1997a)) addresses this challenge by using modes and a simple frequency-based dissimilarity measure. The pseudo-code is:

1. For K number of clusters, pick k observations randomly. Their records constitute the initial cluster centroids (e.g. modes).
2. Compare each cluster centroid with the remaining records, feature by feature, assign $+1$ for each dissimilar feature in the record, assign 0 for each equal feature. Compute the sum of dissimilar features for each records. This is what is referred to as Hamming distance.
3. Assign each observation to the cluster with the lowest Hamming distance.
4. Compute the mode for each feature in each cluster.
5. Use these mode records as new cluster centroids, and repeat steps 2. to 4.

6. Iterate until no changes are made in the assignment of observations to clusters after a full cycle test of the dataset.

To combine K-means and K-modes into K-prototypes, it suffices to combine the dissimilarity measures for numerical data (e.g. Euclidean distance) and categorical data (e.g. Hamming distance) in step 2. The sum of the dissimilarity measures is weighted to avoid favoring either of them.[35]

The final step consists of pinning down the optimal number of clusters. Of the many tools available, we employ the elbow method. We calculate a cost function to assess the extent of heterogeneity within each cluster.[36] and sum up the costs of all clusters. As we increase the number of clusters, the total costs decrease by construction as we tend to create smaller - hence, more homogeneous - clusters. The extreme case would be to have zero cost - i.e. one cluster per observation. The trade-off is therefore between number of clusters and heterogeneity. The optimal number is the point at which the second derivative of the cost function has the highest value. Beyond this point, increasing the number of clusters would lead to diminishing returns.

We emphasize that the results presented in our paper do not depend on the normalization of the data[37] nor on the initialization method[38]. Notably, certain initial selection of centroids may lead to local solutions (Huang (1997b)), so it is therefore standard practice to run K-prototypes several times with different starting points for the clusters and choose the run that ends up with the lowest costs. The combination of a "smart choice" of centroids and a large number of runs - in our study, we set the number of runs to 100 - should increase the chance of finding a global solution.

Table 10: Cluster centroids with K-prototypes

	Cluster		
	1	2	3
Expected inflation	4%	3%	3%
Climate concern	4	7	8
T-risk: decr. income (dummy)	1	0	0
T-risk: incr. expenses (dummy)	1	1	1
P-risk: no exposure (dummy)	0	1	0
P-risk: no incr. frequency (dummy)	1	0	1
ECB distrust	7	4	4
Number of observations	586	809	1,018

Notes: The table reports the cluster centroids resulting from an application of K-prototypes to expected inflation, climate concern, physical risk frequency, physical risk exposure, transition risk income, transition risk expenses, and ECB distrust, with data from Wave 14 only. We apply min-max feature scaling and Huang initialization. The number of clusters is set to three exogenously. We run K-prototypes 100 times with different starting values.

D.2 Results

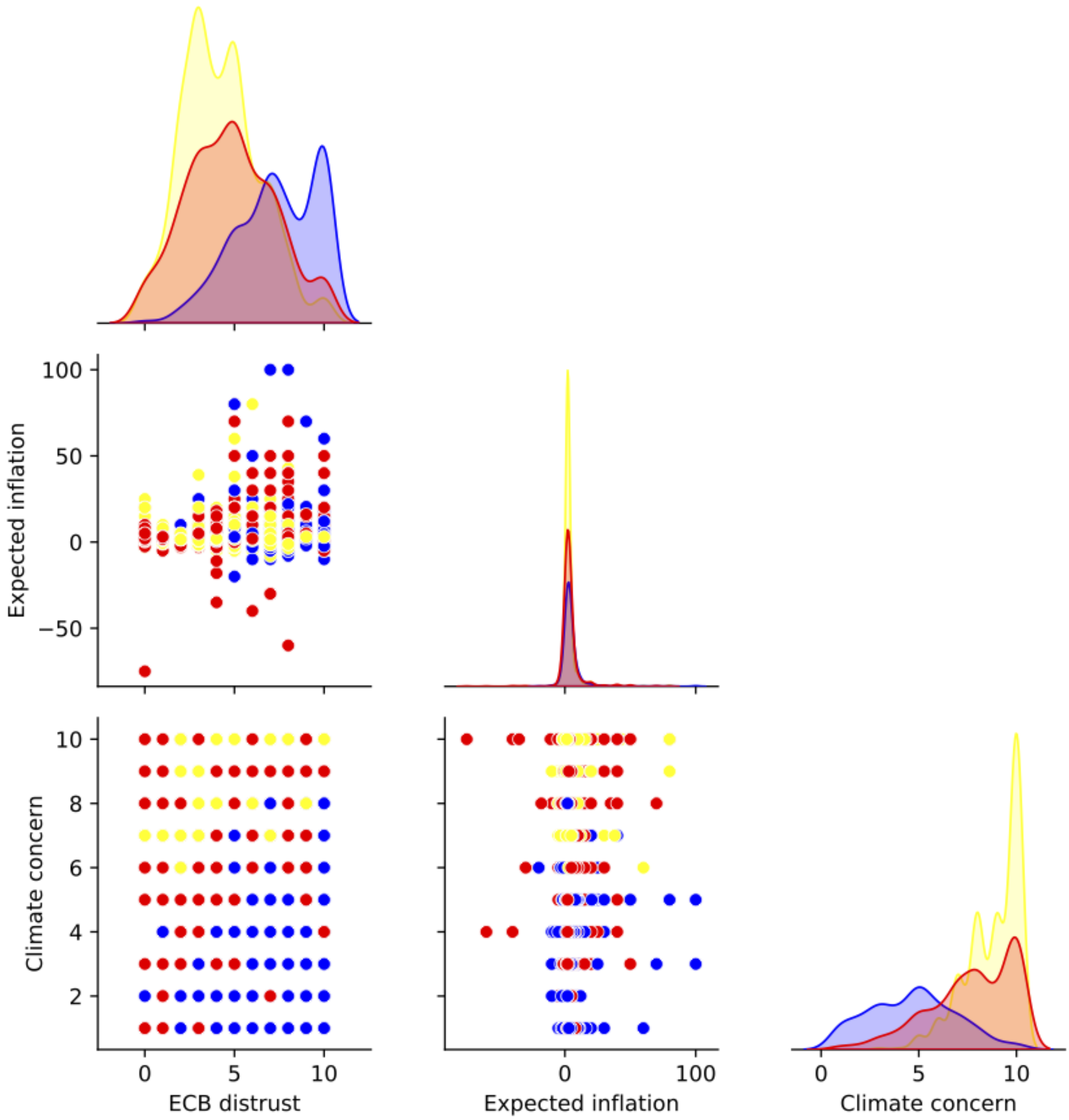

Figure 9: Pairplot with K-prototypes

Notes: The figure shows the pairplot resulting from an application of K-prototypes to expected inflation, climate concern, physical risk frequency, physical risk exposure, transition risk income, transition risk expenses, and ECB distrust. Results are for Wave 14 only. The K-prototypes algorithm employs min-max feature scaling and Huang initialization. The number of clusters is set to three exogenously. We run K-prototypes 100 times with different starting values.

[35]See Huang (1997b) for a detailed discussion.

[36]In K-means, this is equivalent to computing inertia or the sum of squared errors within each cluster (i.e. the variance). In K-prototypes, the cost is similarly defined as the sum of the distances of all points to their respective cluster centroids.

[37]We test K-prototypes and K-means with two different normalizations: simple feature scaling applies the following normalization $X' = \frac{X}{X_{max}}$ and min-max feature scaling is obtained with the formula $X' = \frac{X - X_{min}}{X_{max} - X_{min}}$. Our baseline results employ min-max feature scaling.

[38]Initialization defines the way in which the starting centroids of K-prototypes clusters are selected. There are two available methods: Huang (1998) and Cao et al. (2009). Huang selects k distinct objects from the dataset as initial modes and then assigns the most frequent categories equally to the initial modes (see Huang (1997b, 1998)). The Cao method selects prototypes for each data object based on the density of the data point and the dissimilarity value. Results do not change when Cao is used instead of Huang.

Table 11: Cluster centroids with K-prototypes

	Cluster		
	1	2	3
Expected inflation	3%	3%	4%
Climate concern	8	8	5
ECB distrust	4	4	6
Perception Covid-19	7	7	5
Perception refugee crisis	8	8	7
Household size	2	3	2
City size	5k-20k	20k-100k	5k-20k
Income	€2,500-2,999	€2,500-2,999	€2,500-2,999
Age	66 years old	43 years old	49 years old
Employment	retirement	full-time	full-time
Higher education	non-university education (e.g. vocational training)	university education	non-university education (e.g. vocational training)
Gender	male	female	male
Homeownership	owner	owner	owner
Region	West Germany	South Germany	South Germany
Lower education	high school education	technical school education	high school education
Number of observations	955	897	823

Notes: The table reports the cluster centroids resulting from an application of K-prototypes to expected inflation, climate concern, ECB distrust, age, perception of the seriousness of Covid-19, perception of the seriousness of the refugee crisis, city size, household size, income, employment type, higher education, gender, homeownership, region, and lower education, with data from Wave 14 only. We apply min-max feature scaling and Huang initialization. The number of clusters is set to three exogenously. We run K-prototypes 100 times with different starting values.

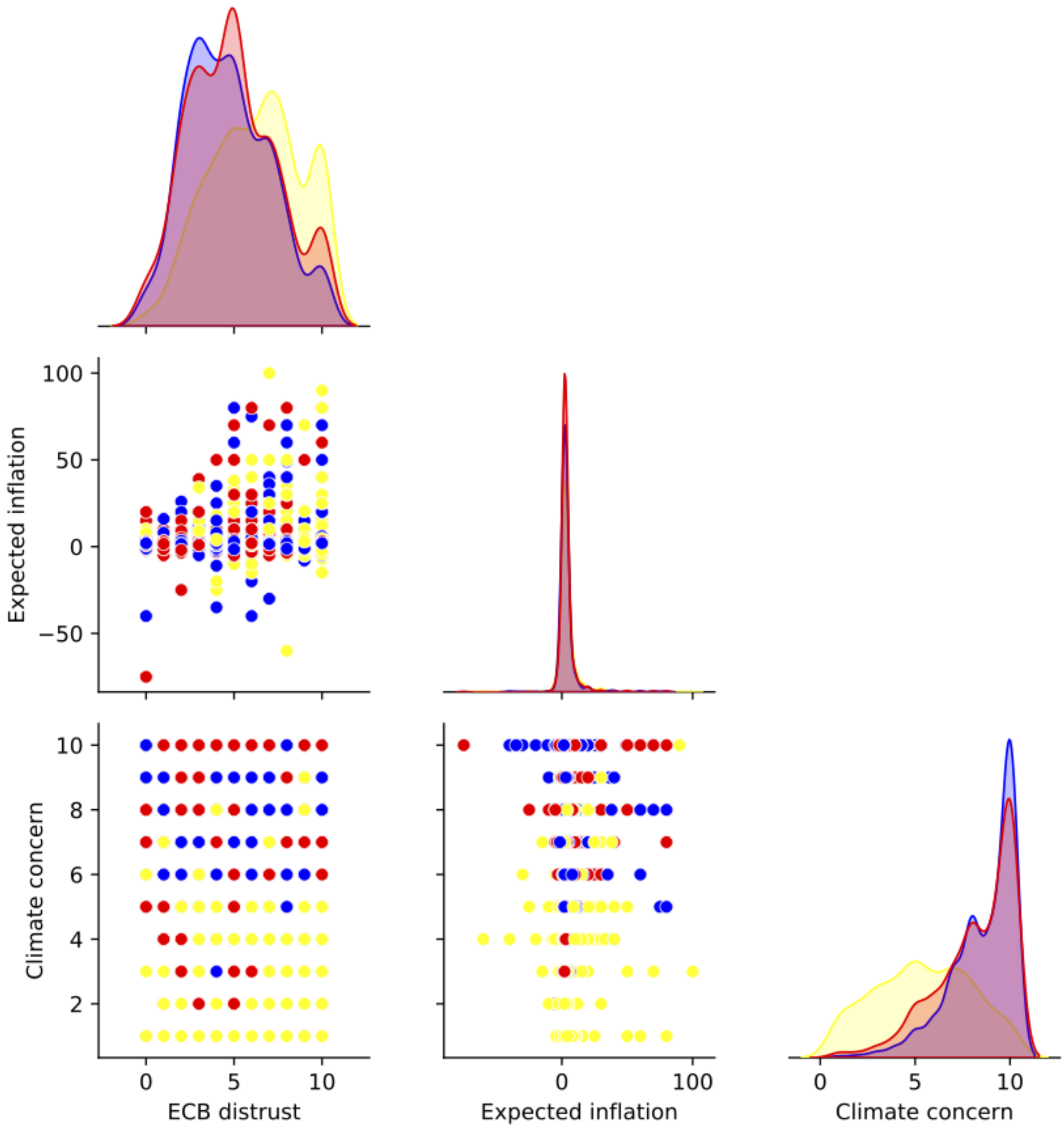

Figure 10: Pairplot with K-prototypes

Notes: The figure shows the pairplot resulting from an application of K-prototypes to expected inflation, climate concern, ECB distrust, age, perception of the seriousness of Covid-19, perception of the seriousness of the refugee crisis, city size, household size, income, employment type, higher education, gender, homeownership, region, and lower education, with data from Wave 14 only. We apply min-max feature scaling and Huang initialization. The number of clusters is set to three exogenously. We run K-prototypes 100 times with different starting values.

Appendix E Subsample analysis: socio-demographics

Table 12: Subsample analysis: gender

	Male				Female			
	(1a)	(1b)	(1c)	(2)	(1a)	(1b)	(1c)	(2)
Climate concern	-0.234***	-0.199***	-0.208***	-0.203***	-0.179	-0.429***	-0.308***	-0.295**
Constant	5.165***	4.530***	4.757***	5.195***	6.795***	8.466***	7.707***	9.557***
Controls	No	No	No	Yes	No	No	No	Yes
R-squared	0.009	0.006	0.007	0.040	0.002	0.009	0.005	0.046
Observations	2,284	2,700	4,589	3,791	1,686	2,154	3,662	2,933

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

Notes: The table shows coefficients from OLS regressions of 12-month-ahead expected inflation on climate concern for the male and the female subsample: $\text{expinf}_i = \beta_0 + \beta_1 \text{climateconcern}_{i,1} + \beta_p \text{controls}_{i,p} + \varepsilon_i$. Column (1a) refers to Wave 9, Column (1b) refers to Wave 14 and Column (1c) refers to the pooled sample. In Column (2), we add controls to the pooled sample. Controls included in Column (2) are: age, education, employment, size of the city of residence, household income, household size, region of residence, perception of the seriousness of Covid-19, perception of the seriousness of the refugee crisis, and homeownership. Statistical significance is evaluated based on robust standard errors.

Table 13: Subsample analysis: age

	Age 34 and below				Age 35-59				Age 60 and above			
	(1a)	(1b)	(1c)	(2)	(1a)	(1b)	(1c)	(2)	(1a)	(1b)	(1c)	(2)
Climate concern	-0.209	-0.442	-0.363**	-0.837**	-0.197	-0.358***	-0.268***	-0.297***	-0.043	-0.039	-0.034	-0.077*
Constant	5.756***	8.389***	7.540***	3.670	6.214***	6.637***	6.314***	6.125***	4.062***	4.015***	4.036***	3.181***
Controls	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes
R-squared	0.007	0.007	0.007	0.109	0.003	0.011	0.006	0.055	0.0004	0.0002	0.0002	0.0510
Observations	472	558	976	280	1,851	2,223	3,806	3,393	1,647	2,073	3,469	3,051

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

Notes: The table shows coefficients from OLS regressions of 12-month-ahead expected inflation on climate concern for different age cohorts: $\text{expinf}_i = \beta_0 + \beta_1 \text{climateconcern}_{i,1} + \beta_p \text{controls}_{i,p} + \varepsilon_i$. Column (1a) refers to Wave 9, Column (1b) refers to Wave 14 and Column (1c) refers to the pooled sample. In Column (2), we add controls to the pooled sample. Controls included in Column (2) are: gender, education, employment, size of the city of residence, household income, household size, region of residence, perception of the seriousness of Covid-19, perception of the seriousness of the refugee crisis, and homeownership. Statistical significance is evaluated based on robust standard errors.

Table 14: Subsample analysis: education

	University degree				No unversity degree			
	(1a)	(1b)	(1c)	(2)	(1a)	(1b)	(1c)	(2)
Climate concern	-0.131*	-0.141***	-0.124***	-0.151***	-0.138	-0.219***	-0.174***	-0.267***
Constant	4.274***	4.066***	4.086***	4.710***	5.765***	6.057***	5.909***	6.801***
Controls	No	No	No	Yes	No	No	No	Yes
R-squared	0.004	0.006	0.004	0.049	0.002	0.003	0.003	0.051
Observations	1,264	1,520	2,581	2,072	2,706	3,334	5,670	4,652

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

Notes: The table shows coefficients from OLS regressions of 12-month-ahead expected inflation on climate concern for survey respondents with and without a university degree: $\text{expinf}_i = \beta_0 + \beta_1 \text{climateconcern}_{i,1} + \beta_p \text{controls}_{i,p} + \varepsilon_i$. Column (1a) refers to Wave 9, Column (1b) refers to Wave 14 and Column (1c) refers to the pooled sample. In Column (2), we add controls to the pooled sample. Controls included in Column (2) are: gender, age, employment, size of the city of residence, household income, household size, region of residence, perception of the seriousness of Covid-19, perception of the seriousness of the refugee crisis, and homeownership. Statistical significance is evaluated based on robust standard errors.

Appendix F Subsample analysis: expected inflation

Table 15: Subsample analysis: expected inflation between -0.1% and 20%

	(1a)	(1b)	(1c)	(2)
Climate concern	-0.129***	-0.113***	-0.105***	-0.160***
Constant	5.294***	4.333***	4.701***	4.457***
Controls	No	No	No	Yes
R-squared	0.006	0.008	0.005	0.083
Observations	3,539	4,431	7,436	6,054

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

Notes: The table shows the coefficients from OLS regressions of 12-month-ahead expected inflation on climate concern. The regression equation is $\text{expinf}_i = \beta_0 + \beta_1 \text{climateconcern}_{i,1} + \beta_p \text{controls}_{i,p} + \varepsilon_i$. The sample is restricted to individuals with expected inflation between -0.1% and 20%. Column (1a) refers to Wave 9, Column (1b) refers to Wave 14 and Column (1c) refers to the pooled sample. In Column (2), we add controls to the pooled sample. Statistical significance is evaluated based on robust standard errors. Controls include gender, age, education, employment, city size, household income, household size, region of residence, perception of the seriousness of Covid-19, perception of the seriousness of the refugee crisis, and homeownership.

Table 16: Subsample analysis: expected inflation between -0.1% and 20%

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Climate concern	-0.160***	-0.124***	-0.126***	-0.112***	-0.130***	-0.119***	-0.072***	-0.055
P-risk: no exposure (dummy)		0.115				-0.404*		-0.180
P-risk: no incr. frequency (dummy)			-0.553***			-0.751***		-0.374
T-risk: decr. income (dummy)				0.522***		0.454***		0.194
T-risk: incr. expenses (dummy)					-0.263			
ECB distrust							0.170***	0.182***
Female (dummy)	1.212***	1.248***	1.232***	1.264***	1.243***	1.266***	1.086***	1.367***
University education (dummy)	-0.623***	-0.633***	-0.611***	-0.639***	-0.629***	-0.619***	-0.300**	-0.239
Other/no degree (dummy)	0.011	-0.458	-0.534	-0.414	-0.439	-0.489	-0.441	-0.605
Part-time (dummy)	0.153	0.041	0.046	0.077	0.063	0.078	-0.100	-0.388
Casual or irregular (dummy)	-0.047	-0.068	-0.085	-0.030	-0.070	-0.055	-0.482	-0.566
Other, student, intern, or parental leave (dummy)	0.526	0.840	0.816	0.933	0.855	0.895	0.365	0.740
Unemployment (dummy)	0.728	0.058	-0.012	-0.036	0.034	-0.013	1.217*	-0.083
Retirement (dummy)	0.285*	0.306	0.316	0.358	0.319	0.364	0.275	0.248
Residence in East Germany before 1989 (dummy)	0.689***	0.780***	0.760***	0.769***	0.783***	0.749***	0.230	0.108
Renter (dummy)	0.446***	0.326**	0.255*	0.366**	0.335**	0.346**	0.484***	0.546***
Age	-0.010*	-0.008	-0.009	-0.010	-0.007	-0.010	-0.004	-0.002
City size	-0.036	-0.014	-0.011	-0.001	-0.013	0.004	-0.039	-0.042
Household income	-0.148***	-0.114***	-0.109***	-0.107***	-0.116***	-0.100***	-0.059**	-0.049
Perception Covid-19	0.061**	0.086**	0.085**	0.078**	0.084**	0.081**	0.014	0.025
Perception refugee crisis	0.113***	0.075***	0.070**	0.072**	0.078***	0.068**	0.009	-0.033
Household size	0.160***	0.106	0.103	0.106	0.111	0.101	0.082	0.093
Constant	4.457***	3.960***	4.362***	3.713***	4.190***	4.275***	2.908***	2.838***
R-squared	0.083	0.072	0.077	0.076	0.072	0.082	0.079	0.086
Observations	6,054	3,064	3,064	3,069	3,067	3,060	2,966	1,505

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

Notes: The table shows coefficients from OLS regressions of 12-month-ahead expected inflation on climate concern, climate-related risks, and ECB distrust. The regression equation is $\text{expinf}_i = \beta_0 + \beta_1 \text{climateconcern}_{i,1} + \beta_2 \text{question}_{i,2} + \beta_p \text{controls}_{i,p} + \varepsilon_i$. The sample is restricted to individuals with expected inflation between -0.1% and 20%. Columns (1), (2), (3), (4), (5), and (6) refer to the pooled sample; Columns (7) and (8) refer to Wave 14. Statistical significance is evaluated based on robust standard errors. The labels "P-risk" and "T-risk" refer to physical risk and transition risk, respectively.

Table 17: Subsample analysis: expected inflation between -0.1% and 20%, but not equal to 2%

	(1a)	(1b)	(1c)	(2)
Climate concern	-0.159***	-0.140***	-0.130***	-0.196***
Constant	6.102***	5.173***	5.516***	5.712***
Controls	No	No	No	Yes
R-squared	0.009	0.009	0.006	0.091
Observations	2,825	3,093	5,581	4,572

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

Notes: The table shows the coefficients from OLS regressions of 12-month-ahead expected inflation on climate concern. The regression equation is $\text{expinf}_i = \beta_0 + \beta_1 \text{climateconcern}_{i,1} + \beta_p \text{controls}_{i,p} + \varepsilon_i$. The sample is restricted to individuals whose expected inflation is between -0.1% and 20%, but not anchored at 2%. Column (1a) refers to Wave 9, Column (1b) refers to Wave 14 and Column (1c) refers to the pooled sample. In Column (2), we add controls to the pooled sample. Statistical significance is evaluated based on robust standard errors. Controls include gender, age, education, employment, city size, household income, household size, region of residence, perception of the seriousness of Covid-19, perception of the seriousness of the refugee crisis, and homeownership.