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Inflation expectations and climate concern

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Non-technical summary

Research question

Risks arising from climate change have featured prominently in discussions among central bankers recently. So far, little is known about their implications for the conduct of monetary policy. Against this background, this study provides a first analysis of the empirical relationship between households' perception of climate change and their inflation expectations.

Contribution

Inflation expectations play a key role in the transmission of the monetary policy stance. We use unique microdata from the Bundesbank Online Panel Households (BOP-HH) – a regular monthly survey of German households – to assess the relationship between households' perception of climate change and their inflation expectations. Our study may be useful in highlighting the challenges and trade-offs that arise when central banks take into account issues surrounding climate change.

Results

We find a strong negative correlation between climate concern – a variable measuring households' perception of the overall seriousness of climate change on a 1 to 10 scale – and expected inflation. A one-notch decrease in climate concern goes along with an increase of 24 basis points in expected inflation over the next twelve months. Evaluating candidate explanations, we find that part of the link between climate concern and inflation expectations can be associated with individuals' perceived exposures to climate-related risks and with their distrust in the central bank. Overall, our results suggest that climate change perceptions matter for inflation expectations.

Nichttechnische Zusammenfassung

Fragestellung

Risiken, die sich aus dem Klimawandel ergeben, waren zuletzt Gegenstand intensiver Diskussionen unter Zentralbanken. Insbesondere über ihre Auswirkungen auf die Wirkungskanäle geldpolitischer Entscheidungen ist bislang wenig bekannt. Vor diesem Hintergrund präsentieren wir in dieser Studie eine erste Analyse des empirischen Zusammenhangs zwischen der Sensibilität privater Haushalte für den Klimawandel und ihren Inflationserwartungen.

Beitrag

Den Inflationserwartungen kommt bei der Transmission der Geldpolitik eine Schlüsselrolle zu. Wir untersuchen den Zusammenhang zwischen der Klimasensibilität privater Haushalte einerseits und ihren Inflationserwartungen andererseits. Als Grundlage hierfür dienen Mikrodaten aus dem Bundesbank-Online-Panel-Haushalte (BOP-HH), einer regelmäßigen monatlichen Umfrage unter deutschen Privathaushalten. Mithilfe unserer Studie lassen sich bestimmte Herausforderungen und Zielkonflikte aufzeigen, die sich ergeben, wenn Zentralbanken dem Klimawandel zukünftig stärker Rechnung tragen.

Ergebnisse

Die Sorge privater Haushalte hinsichtlich des Klimawandels – gemessen anhand der Antwort auf die Frage, inwieweit der Klimawandel aktuell ein ernstes Problem darstellt – ist negativ korreliert mit ihren Inflationserwartungen. Eine um eine Stufe niedriger ausgeprägte Besorgnis über den Klimawandel geht mit einer um 24 Basispunkte höheren erwarteten Inflation über die nächsten zwölf Monate einher. Dieser Zusammenhang kann teilweise durch die Wahrnehmung individueller klimabedingter Risiken sowie durch allgemeines Misstrauen gegenüber der Zentralbank erklärt werden. Insgesamt deuten unsere Resultate darauf hin, dass die Sensibilität privater Haushalte für den Klimwandel eine Rolle für Inflationserwartungen spielt.

Deutsche Bundesbank Discussion Paper No 12/2022

Inflation Expectations and Climate Concern

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Abstract: Using survey data from German households, we find that individuals with lower climate concern tend to have higher inflation expectations up to five years ahead. This correlation is most pronounced among individuals with extremely high inflation expectations. Evaluating candidate explanations, we find that part of the link between climate concern and inflation expectations can be associated with individuals' perceived exposures to climate-related risks and with their distrust in the central bank. Overall, our results suggest that climate change perceptions matter for inflation expectations.

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 transmission of the monetary policy stance. Expectations influence households' decisions regarding savings and consumption as well as firms' decisions regarding production and investment (ECB (2021)). Therefore central banks carefully monitor factors that could potentially impact or disrupt expectations. Risks arising from climate change have featured prominently in discussions among central bankers recently. So far, however, little is known about their links to inflation expectations. Against this background, this study provides a first analysis of the empirical relationship between households' perception of climate change and their inflation expectations.

To do so, 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 (September 2020 and February 2021), the survey also asked questions designed to elicit households' overall climate concern as well as their perception of their individual climate-related risks.

As the key contribution of our paper, we find 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.[1] In our sample, a one-notch decrease in climate concern goes along with an increase of 24 basis points in expected inflation over the next 12 months. In other words, individuals with lower climate concern tend to have higher inflation expectations. This result becomes even stronger when excluding outliers from our sample, and it remains significant when controlling for unemployment expectations as a proxy for expectations concerning the development of the economy. In our regressions, we also control for demographics and other economic or political concerns. 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 find that a one-notch decrease in climate concern is associated with an increase 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.

We then elaborate on a few potential explanations for our key result. First and foremost, we analyze the link between expected inflation and climate concern through households' perception of their individual exposure to climate-related risks. 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

[1] 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.

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 to a partial extent. Respondents who fear losses in income due to climate policies have lower climate concern. The same is true for respondents who do not feel exposed to disruptive climate-related weather events (or disregard this risk altogether). 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 climate-related risks. Taken together, this means that the explanatory power of climate concern for expected inflation goes beyond individually attributable climate-related risks.

A source of high (possibly de-anchored) inflation expectations that has been identified in the literature is the overall level of distrust in the institutional setup of the economy, in particular in central banks (Christelis, Georgarakos, Jappelli, and Van Rooij (2020)). We thus include proxies for households' overall distrust in the ability of the European Central Bank (ECB) to ensure price stability. We find a strong negative association between climate concern and our proxies of distrust. However, despite the strong and significant correlation, the two variables are not interchangeable: climate concern remains a significant predictor of expected inflation even when controlling for ECB distrust. Overall, our results suggest that climate concern has explanatory power above and beyond climate-related risks and ECB distrust. However, there is also evidence that climate concern is intertwined with these two variables.

To address model uncertainty, we also seek to confirm our main results using cluster analysis. Specifically, regressions can – by construction – only uncover marginal effects. In parallel, the encountered non-linearities in the basic relation may point towards the existence of clusters. In line with our main results, the cluster analysis provides evidence for a distinct set of individuals who have high inflation expectations (around 5.5%), low climate concern (around 4.5), transition risk fears (with respect to future income and expenses), and high distrust in the ECB (around 6.7 out of 10).

While our research design does not allow for any causal statements, we still believe that our study increases our understanding of inflation expectations. Specifically, we provide empirical evidence that climate change perceptions play a role in this context. Recently, different links have been theoretically discussed by Batten, Sowerbutts, and Tanaka (2020) and McKibbin, Morris, Wilcoxen, and Panton (2020). Our study shows that lower climate concern and higher distrust in the abilities of a central bank to ensure price stability are associated with higher inflation expectations. As suggested by the cluster analysis, there appears to be a set of individuals with high inflation expectations who (i) distrust monetary policy more generally and (ii) have low climate concern, but also transition risk fears. Interestingly, we find that even above and beyond central bank distrust and individual climate-related risks, there is a link between climate concern and inflation expectations.

The remainder of the paper is structured as follows. Section 2 discusses related literature. Thereafter, Section 3 introduces the BOP-HH data and draws the main link between expected inflation and climate concern. Section 4 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 5. Section 6 discusses the results from the cluster analysis, the analysis of long-term inflation expectations, the correction for outliers, and the analysis controlling for unemployment expectations. Finally, Section 7 concludes.

2 Related literature

Our paper has links to several strands of research that have been largely unconnected so far. First of all, there is empirical literature on inflation expectations. For instance, Galati, Moessner, and Van Rooij (2020) argue that inflation expectations are much less anchored among consumers as compared to professional forecasters, and they explain the extent to which consumer expectations surveys can provide additional information beyond surveys of professional forecasters or market-based measures. Ehrmann, Pfajfar, and Santoro (2017) and Blanchflower and MacCoille (2009) study determinants of consumers' inflation expectations. They find that consumers' expectations differ substantially from those of professional forecasters. Souleles (2004), Coibion and Gorodnichenko (2015) and Carroll (2003), among others, argue that consumer expectations are biased and inefficient. Furthermore, there is a growing body of work studying in detail the micro determinants of how inflation expectations are formed, how central banks can affect them, and how inflation expectations affect households' consumption, saving and debt choices using microdata. Recent examples are D'Acunto, Hoang, Paloviita, and Weber (2021), D'Acunto, Fuster, and Weber (2021), D'Acunto, Malmendier, Ospina, and Weber (2021), D'Acunto, Malmendier, and Weber (2021), D'Acunto, Hoang, and Weber (2022), and Coibion, Gorodnichenko, and Weber (2019).

Distrust in central banks as an explanatory variable for inflation expectations has been analyzed empirically by Christelis et al. (2020) and Ehrmann, Soudan, and Stracca (2013), and theoretically by Lamla, Pfajfar, and Rendell (2019). Their findings are broadly supported by our results. Besides the focus on climate-related risks and climate concern, we also add to this literature by (i) focusing on consumer expectations, (ii) studying both short-term and long-term inflation expectations, and (iii) taking into account the cross-section of consumers' inflation expectations (i.e. the entire distribution) and not just the mean.

Second, there is ample literature on consumers' expectations regarding climate change in general. Dietrich, Mueller, and Schoenle (2020) analyze consumers' expectations of the frequency of natural disasters both empirically and in a theoretical model, but without an explicit focus on inflation. Baker, McElroy, and Sheng (2020) analyze the interaction between economic survey data for professional forecasters, their inattentiveness to disaster risk, and the occurrence of natural disasters.[2] Baldauf, Garlappi, and Yannelis (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. Consumers' perception of climate risks has also featured prominently in psychology literature. A key insight of, for example, Van der Linden (2017) and Lee, Markowitz, Howe, Ko, and Leiserowitz (2015) is that the notion of

[2]Note there are also other studies on expectations regarding climate change using survey data. For instance, Krueger, Sautner, and Starks (2020) analyze the importance of climate risks for institutional investors.

risk is a human invention and as such, it does not exist independently from our minds and culture. Van der Linden (2015) corroborates this insight by developing a climate change risk model based on cognitive factors (knowledge), experience (emotions and personal experience), socio-demographics, and socio-cultural influences (values and social norms), which is able to explain up to 70% of variation in risk perception. He also documents that trust in institutions, experts, and media is an important predictor of an individual's belief in climate change.

Finally, there is a new, growing body of literature on the impact of climate-related risks (i.e. physical risk and transition risk) on the transmission of monetary policy. This topic has become very prominent among central bankers recently (ECB (2021)). 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 seems to increase the frequency of 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 tries to come up with forthright evidence by focusing on consumers' expectations directly.

3 Inflation expectations and climate concern

3.1 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).[3] 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

[3] The survey has been conducted monthly since January 2020.

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 6.1.

Finally, the BOP-HH also provides rich socio-demographic information as well as perceptions of economic developments, 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 refugee situation and of Covid-19, current region of residence[4], education, and employment. 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 B. Additional information about the controls is also provided in Appendix E.

3.2 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?"[5]

with the different developments or topics being Covid-19, the refugee/migration situation, the economic situation, climate change, and Brexit.[6] 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".

3.3 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.[7] Table 1 shows the results from an OLS regression of expected inflation on climate concern. Columns (1a), (1b) and (1c) refer

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

[5]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?"

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

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

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.[8]

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, a decrease in climate concern by one notch is associated with an increase of 24 basis in expected inflation. In other words, people who find that climate change is not a serious problem tend to have higher inflation expectations. Climate concern accounts for 0.3% of the cross-sectional variation in the pooled sample. Including the large set of controls, the explanatory power of the regression increases to 5.2%. Notably, in this last regression, we also control for other concern variables, such as concern regarding Covid-19, that may arguably be correlated with climate concern. However, the relation between climate concern and expected inflation remains highly significant.

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 strongly 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. Not being concerned about the consequences of climate change is thus associated with very high conditional inflation expectations among those who are located in the highest quantiles, in particular, i.e. those who have high conditional inflation expectations in general.

[8] We do not restrict the sample in any way in our baseline setup. Robustness checks for subsamples in Section 6.3 show that the impact of potential outliers in the data is only marginal.

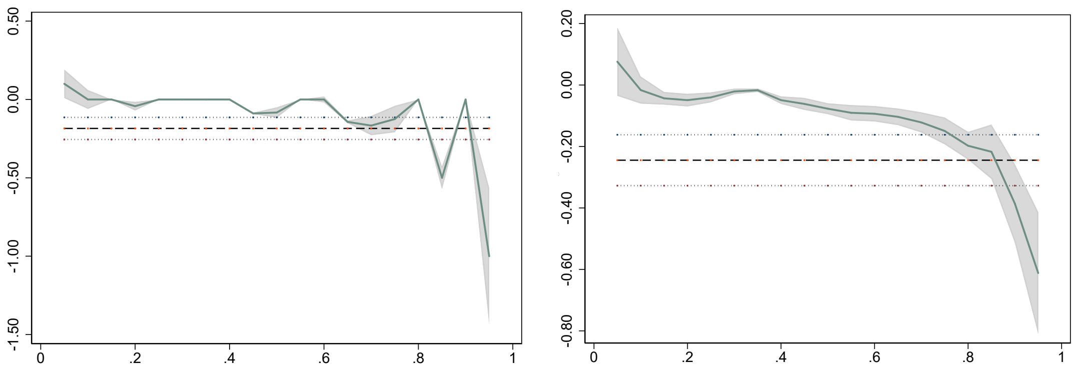

Figure 1: Quantile regressions of expected inflation on climate concern

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.

4 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.

4.1 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."[9]

Thereafter, respondents are presented the following question:

[9] 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."

> "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.)"[10]

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".[11]

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."[12]

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.)"[13]

[10]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."

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

[12]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."

[13]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."

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 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.)"[14]

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.

4.2 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) 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:[15]

> "On a scale from 0 to 10, how much do you trust that the European Central Bank can ensure price stability?"[16]

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. 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

[14] 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."

[15] 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.

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

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.

4.3 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.[17]

Columns (1) and (2) report the coefficients of the perception of physical risk for the pooled 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 hold climate-sensitive assets). Not considering oneself exposed to more frequent extreme weather events is thus associated with a reduced 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 do not expect more frequent extreme weather events have a lower 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.

[17]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.

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) 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 3 in the sense that the perception of the seriousness of climate change is correlated with higher inflation expectations via a distrust channel. 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 channel and the central bank distrust channel capture different dimensions of climate concern.[18] 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.

5 Relative importance of the channels

Next, we combine the previous results and analyze the extent to which the link between climate concern and expected inflation (Section 3) can be explained through the covariates introduced in Section 4. 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, while 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 impacts inflation expectations beyond an individual's climate concern.

Columns (7) and (8) report coefficients when we include central bank distrust in Wave 14.[19]

[18] 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.

[19] 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 4.2, 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.

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 bank distrust, i.e. the two variables seem to constitute two separate but important channels for expected inflation.[20] 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 3.

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.[21] A possible interpretation is that the correlation of climate concern with expected inflation works through two channels. The first channel is via central bank distrust, which is captured by including this variable. The second, albeit weaker, channel is via climate-related risks. Controlling for central bank distrust, the climate-related risk questions appear to explain expected inflation in a similar way to climate concern, rendering the coefficient on climate concern insignificant.

For completeness, we also regress ECB distrust on the climate-related questions (Table 4). In 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,

[20] 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.

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

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 lower a person's climate concern and the higher their transition risk fears, the more they distrust in the central bank.

Table 4: 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.

6 Complementary analysis and robustness

6.1 Cluster analysis

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. Specifically, we document in the following that there is indeed a cluster of individuals characterized by low climate concern and very high expected inflation, together with a strong view on central bank distrust and climate-related risks.

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.[22]

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.[23] In the specifications with categorical variables like the climate-related risk questions, we use K-prototypes.[24] The respective results, which are reported in Appendix D.2, by and large confirm the findings reported here in the main text.

Table 5: 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.

K-means detects two clusters. Their centroids and the numbers of observations are reported in Table 5. 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 differ along all three dimensions: distrust in the ECB, expected inflation, and climate concern. More precisely, the centroids reported in Table 5 reveal that there is a distinct set of individuals who have low climate concern (clustering around 4.5), low trust in the central bank (around 6.7), and high expected inflation (around 5.5%). 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. Finally, including the climate-related risk dummies into the cluster analysis supports the findings that transition risk fears also play a role. Specifically, Table 11 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

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

[23] 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.

[24] 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)).

to a lower-carbon economy.

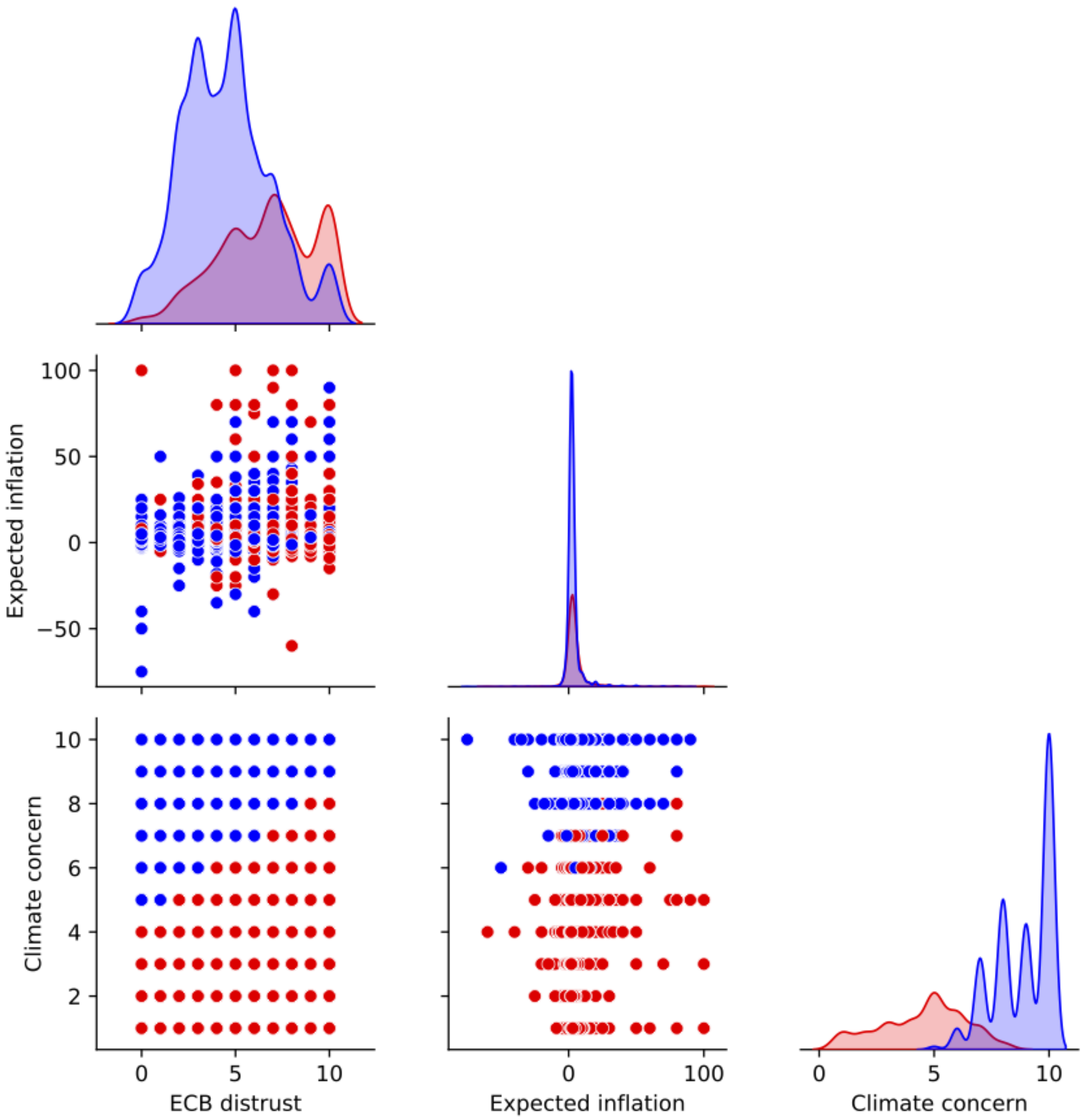

Figure 2: Pairplot

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.

6.2 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 6.

Table 6: 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 decrease in climate concern is now associated with an increase of 49 basis points in expected inflation. The impact 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.[25] Our results can be seen as a prerequisite for such a deeper analysis. According to ECB (2021), de-anchoring can, for instance, be measured through the responsiveness of longer-

[25] 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 (2021))

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 more relevant 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 impact of this variable becomes progressively stronger. A one-notch increase in the level of distrust translates into 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.

6.3 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 9 and 10 in Appendix C 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.

6.4 Unemployment expectations

Finally, recent papers such as Andre, Pizzinelli, Roth, and Wohlfart (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. Results with fixed effects for these five categories are shown in Table 7.[26] 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. However, we notice an increase of the explanatory power by one order of magnitude (reaching up to 25%). Moreover, we observe a non-monotonicity of the slope coefficients. This could be in line with Andre et al. (2022): individuals who expect a large change (either strong decrease or strong increase) in unemployment have higher inflation expectations.

Table 7: OLS regressions of expected inflation on climate concern, unemployment expectations and ECB distrust with robust standard errors

	(1)	(2)	(3)
Climate concern	-0.147***	-0.200***	-0.158**
Unemployment expectations: strong decrease (dummy)	7.171***	8.768***	8.230***
Unemployment expectations: decrease (dummy)	4.278***	5.997***	4.976***
Unemployment expectations: no change (dummy)	4.579***	6.176***	4.779**
Unemployment expectations: increase (dummy)	4.419***	5.969***	5.076***
Unemployment expectations: strong increase (dummy)	6.330***	7.307***	6.165***
ECB distrust			0.277***
Controls	No	Yes	Yes
R-squared	0.222	0.256	0.238
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.

7 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 the first 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 find 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. A one-notch decrease in climate concern is associated with

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

an increase of 24 basis points in expected inflation over the next 12 months and of up to 49 basis points for the five-year time horizon. We also provide evidence of strong non-linearity in the cross-sectional distribution: the regression coefficient goes up to about 60 basis points for respondents with extremely high 12-month-ahead conditional expected inflation. In line with this, a cluster analysis uncovers a set of individuals with high inflation expectations (expected inflation of around 5.5%) who distrust the ECB (score of around 6.7 out of 10) and have low climate concern (score of around 4.5), which makes up about one third of our sample.

We find that individually perceived climate-related risks explain climate concern to only a partial extent. Furthermore, the explanatory power of climate concern for expected inflation goes beyond individually attributable climate-related risks. Central bank distrust, too, which has been identified as a source of de-anchored inflation expectations, only partially explains climate concern. Climate concern remains a significant predictor of expected inflation even when controlling for central bank distrust. Overall, our results suggest that climate change perceptions matter for inflations expectations.

Well-anchored inflation expectations are key for the transmission of monetary policy through the expectations channel. They influence households' decisions regarding saving and consumption as well as firms' decisions regarding price and wage setting, production and investment. When expectations are not firmly anchored, they become unresponsive to the monetary policy stance. While our research design does not allow for any causal statements, we still believe that our study increases our understanding of extremely high inflation expectations by showing that lower climate concern, above and beyond central bank distrust and climate-related risks, strongly correlates with high inflation expectations. Future efforts should be directed towards understanding whether (and to what extent) low climate concern and climate risk perceptions de-anchor inflation expectations upwards. The stronger association between low climate concern and high expected inflation in the medium term provides a starting point for such deeper analyses.

Our results give rise to some policy interpretations. Clearly, there are limitations to our study, in particular a lack of any causal evidence (for instance, due to an omitted variable). Still, we show that the perception of climate-related risks, climate concern, 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. On the one hand, our results do not exclude the possibility of decreasing the extreme inflation expectations of some individuals by raising awareness of climate change. On the other hand, the strong interdependence of central bank distrust and climate concern may actually exacerbate the problem: if central banks take into account issues related to climate change, they might end up increasing the inflation expectations of some individuals by lowering trust in the central bank.

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Appendix A Summary statistics

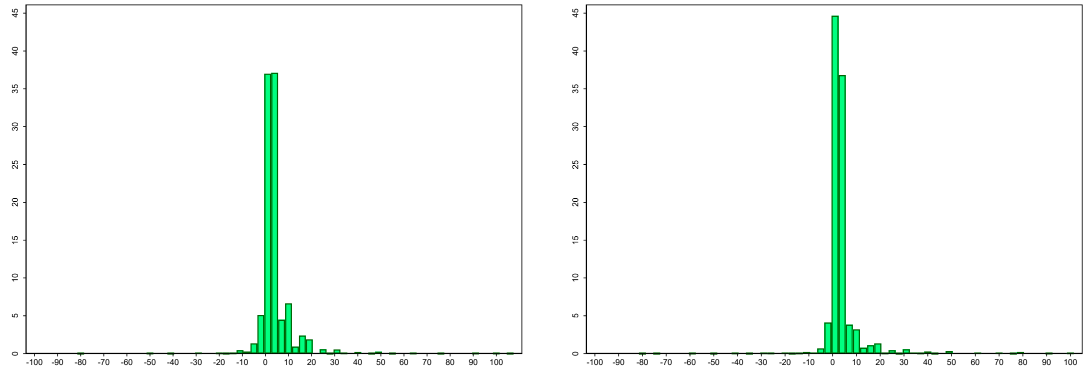

Figure 3: Distribution of expected inflation in Wave 9 (left) and Wave 14 (right)

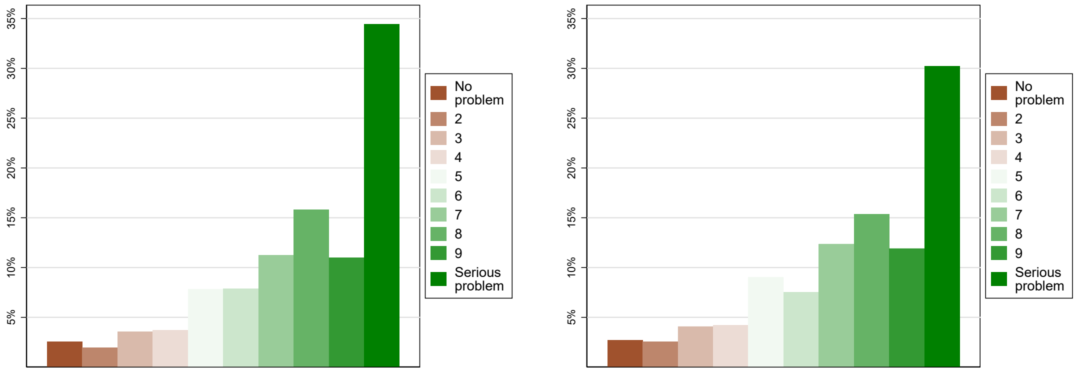

Figure 4: Distribution of climate concern in Wave 9 (left) and Wave 14 (right)

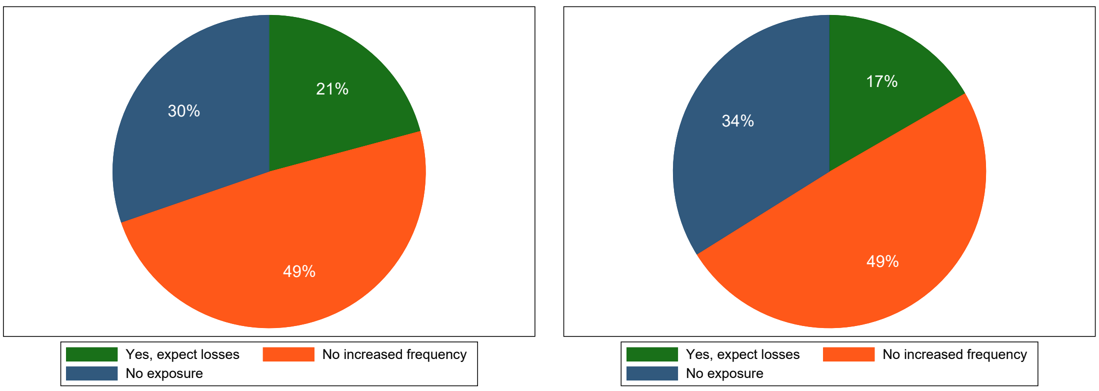

Figure 5: Distribution of perception of physical risk in Wave 9 (left) and Wave 14 (right)

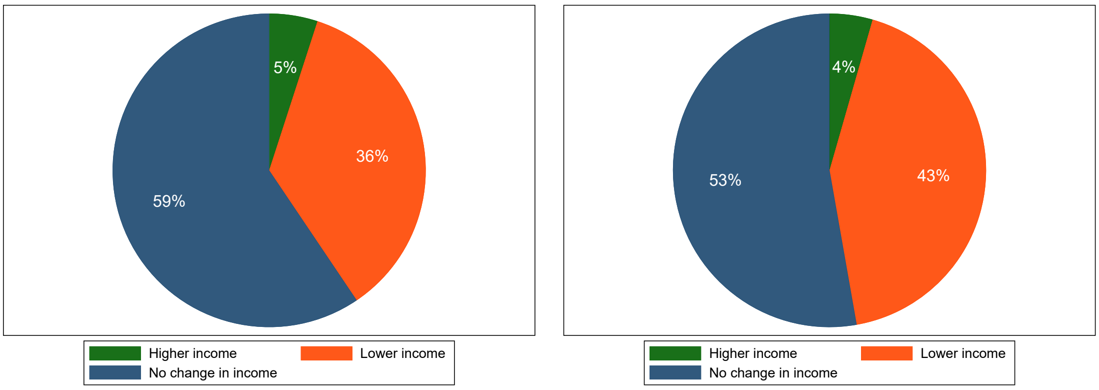

Figure 6: Distribution of perception of transition risk (income) in Wave 9 (left) and Wave 14 (right)

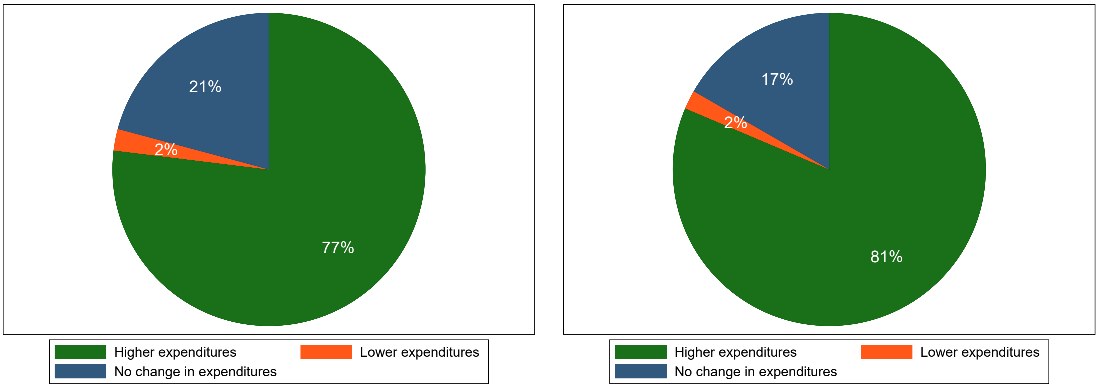

Figure 7: Distribution of perception of transition risk (expenses) in Wave 9 (left) and Wave 14 (right)

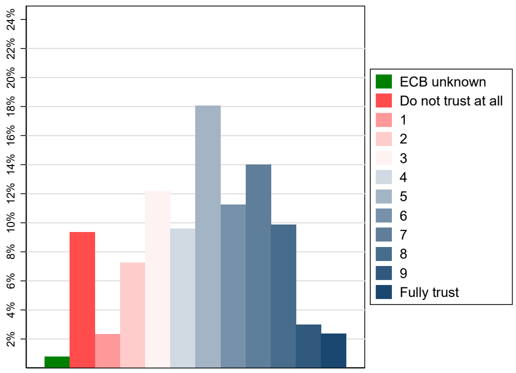

Figure 8: Distribution of trust in ECB in Wave 14

Appendix B Complete regression results

Table 8: 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 C Subsample analysis

Table 9: Subsample analysis

	(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 10: Subsample analysis

	(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.

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.[27]

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

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.[28] 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[29] nor on the initialization method[30]. 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.

D.2 Results

Table 11: 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.

[28] 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.

[29] 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.

[30] Initialization defines the way in which the starting centroids of K-prototypes clusters are selected. There are two available methods: Huang (1998) and Cao, Liang, and Bai (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.

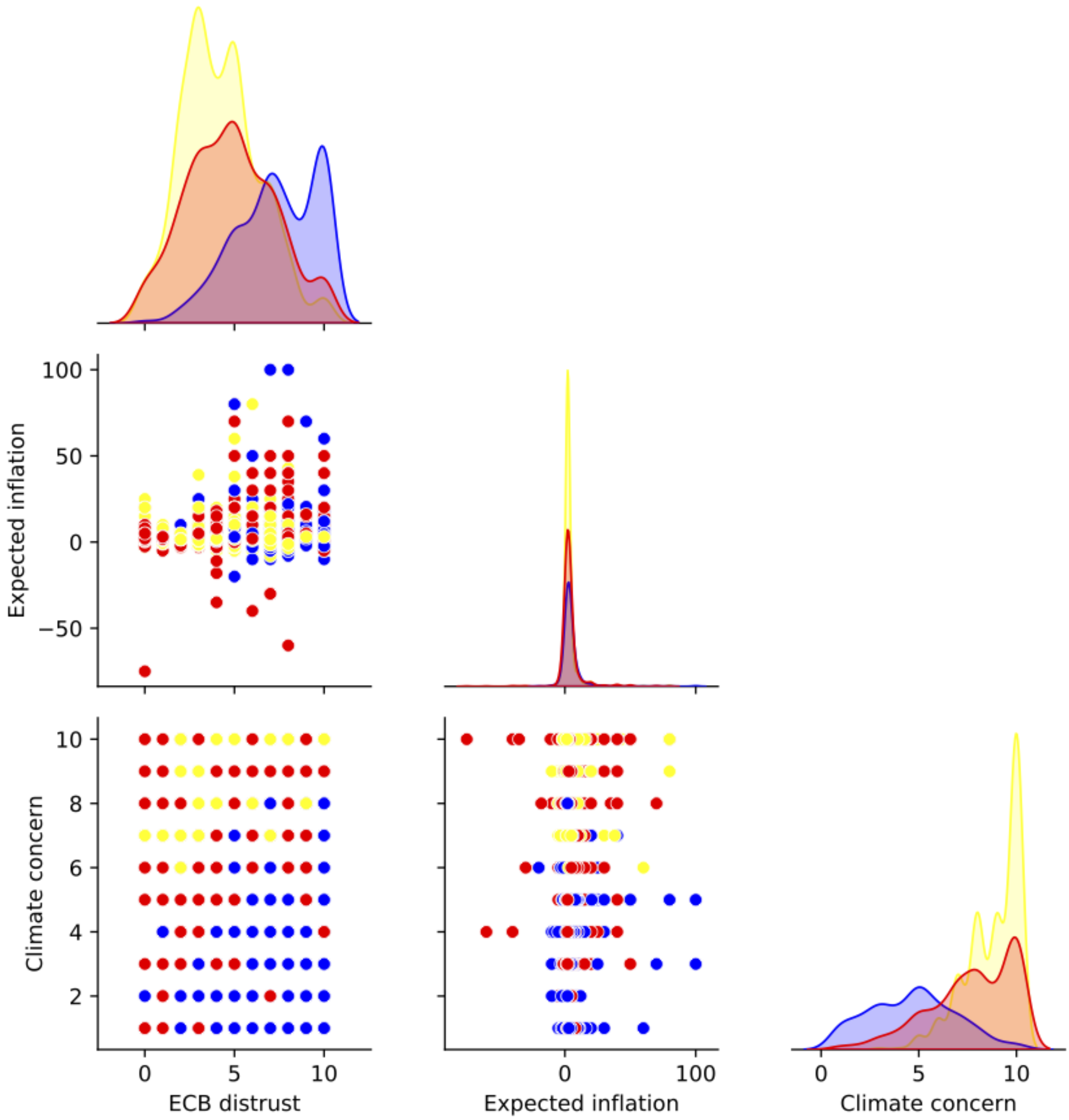

Figure 9: Pairplot with K-prototypes

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.

Table 12: 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.

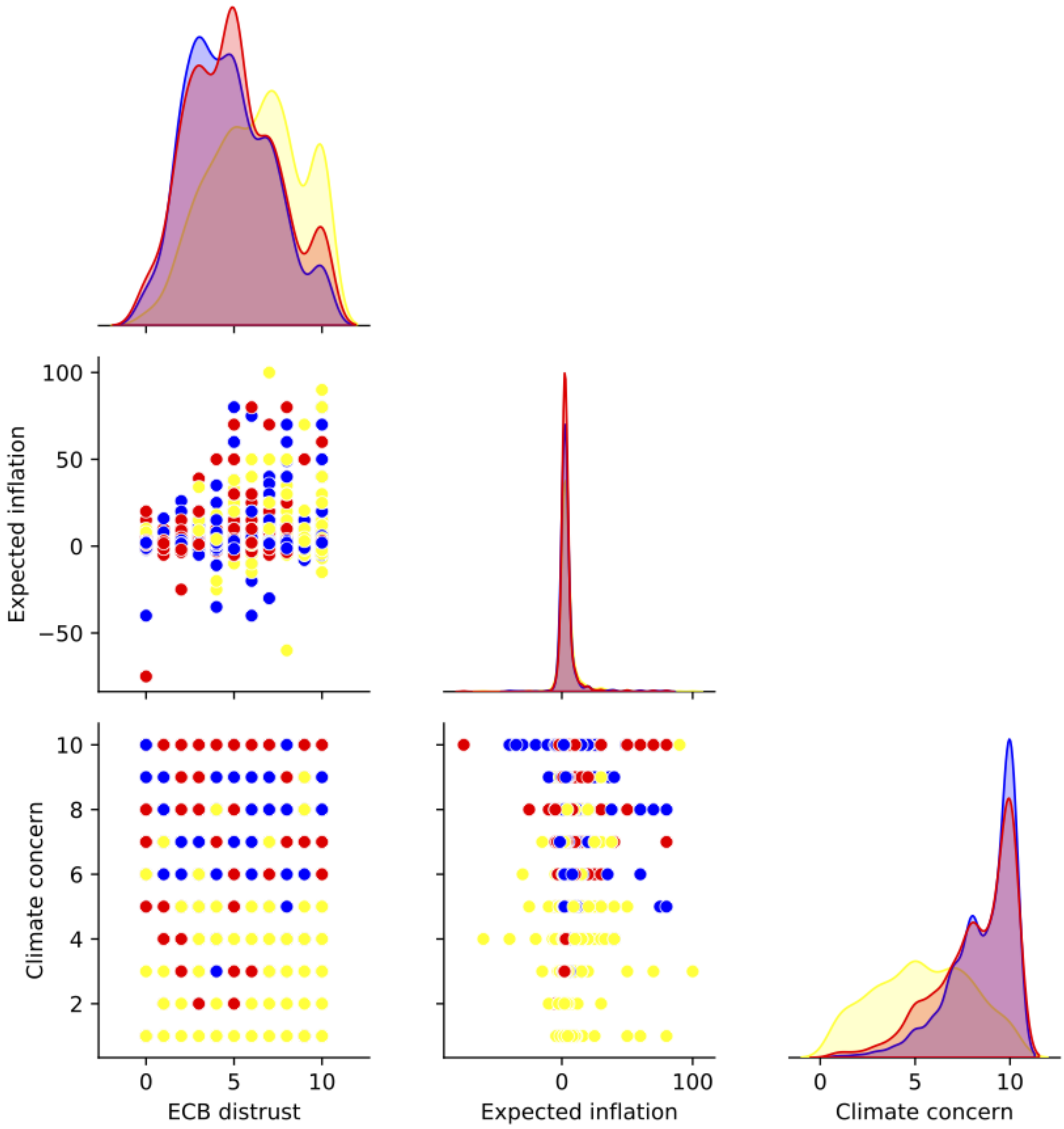

Figure 10: Pairplot with K-prototypes

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 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.[31] 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.[32] 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).

[31] 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.

[32] 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.