Seeing Green: The Effects of Financial Exposures on Support for Climate Action*

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Abstract

Despite the large common net benefits of climate mitigation, broad-based political consensus for large-scale policy action remains elusive. We hypothesize that financial exposure to energy stocks central to the green transition can induce learning and greater support for climate mitigation policies. We conduct a RCT which randomizes both the presence of financial market exposure to the energy sector, as well as which type of portfolio—fossil-fuel (brown) or renewable energy (green)—is given to an individual. Treatment increases support for mitigation action and intent to undertake adaptation, with positive support caused by ownership of both green and brown assets. The effects are particularly pronounced among individuals who are initially more climate-skeptic, and persist eight months after treatment. We present evidence consistent with learning as the primary mechanism: treated respondents are more likely to consume financial news and become more financially knowledgeable, less likely to obtain news from polarized sources, and better able to accurately predict the environmental impacts of green and brown firms.

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1 Introduction

The costs of unchecked climate change are potentially devastating to the world economy, causing large reductions in global income and worsening global income inequality (Burke, Hsiang and Miguel, 2015), as well as significantly increasing mortality risk (Carleton et al., 2022). Even in the United States, the poorest third of counties are projected to experience damages due to climate change as high as 20% of county income by the late 21st century in absence of mitigation (Hsiang et al., 2017). Thus, the global economic benefits of mitigating climate change are substantial, while costs of mitigation are likely to rise if action is not taken (IPCC, 2022).

Despite the large common net benefits of climate mitigation, broad-based political consensus for large-scale mitigation action has been elusive (Gazmararian and Tingley, 2023). The United States is not an exception to these patterns. Though in the past, strong bipartisan political support pushed through crucial climate protection legislation such as the establishment of the Environmental Protection Agency (EPA), and the Clean Air Act, more recently, support for climate mitigation policies have become increasingly polarized (Chinn, Hart and Soroka, 2020; Falkenberg et al., 2022).[1] A crucial question then is how to build broad policy support for climate action despite rises in political polarization.

Important recent studies find that providing information about climate change science and impacts, or delivering persuasive climate-related messages, can widen support for mitigation policies (Ranney and Clark, 2016; Bolsen and Druckman, 2018; Dechezleprêtre et al., 2025; Voelkel et al., 2026). However, in increasingly polarized environments, providing information that contradicts individuals' existing priors and emphasizes the threatening consequences of climate change may increasingly be ignored or forgotten (Golman, Hagmann and Loewenstein, 2017; Sunstein et al., 2016; Feinberg and Willer, 2011). Thus, finding scalable ways to encourage individuals with widely heterogeneous baseline beliefs to learn on their own, process information in new ways, and reach their own conclusions about the costs and benefits of climate action, could complement informational approaches in overcoming these barriers and increase broad-based consensus about the returns to mitigation.

In this paper, we present a novel approach for building broad support for climate action, namely, giving individuals exposure to, and curated opportunities to trade in, financial market assets that are impacted by the green transition (i.e. equity participation in energy sector stocks). In particular, using a randomized control trial, we estimate the causal impacts of financial exposure to equity ownership in energy-sector companies on individuals' beliefs, preferences, and behaviors related to climate change. The cash flows, and thus stock prices of energy-sector stocks, both fossil-fuel and renewable, are directly affected by policies targeted at addressing climate change. We argue that exposure to such stocks in terms of ownership and trading opportunities encourage individuals to learn about the factors that affect the value of these assets, which include climate change risks and the returns to mitigation policies.

[1] In our baseline sample, only 30% of Republicans agree or strongly agree that "human activities are a significant cause of climate change", compared to 49% of independents and 71% of Democrats. These shares are comparable to the Energy Policy Institute (2024), which finds the proportions believing that climate change was "mostly or entirely" caused by human activities to be 34%, 46% and 67% respectively.

It is possible that the type of financial exposure that individual experience may shape both the information they choose to seek and what they ultimately learn. In particular, exposure to renewable energy assets *may* induce a different learning process, and therefore lead individuals to form different opinions about climate change, than exposure to a fossil fuel asset, if individuals selectively seek out and interpret information in ways that align with their financial interests (i.e., motivated reasoning is an important determinant of learning). Our experimental design allows us to directly test for this mechanism, by varying both the presence of financial market exposure to the energy sector, as well as which type of portfolio (i.e., fossil-fuel related or renewable energy related) is given to an individual. We are also able to test whether the impacts of financial exposure persist after individuals are divested from their assets, up to eight months post-treatment.

This approach is notable for two primary reasons. First, we offer a non-paternalistic intervention for learning about climate change and forming policy preferences on the topic. Rather than telling citizens about the risks of climate change and the benefits they should expect from mitigation reforms—an approach which past research suggests may be modestly effective (Vlasceanu et al., 2024; Voelkel et al., 2026), or even counterproductive (Mildenberger et al., 2024)—we allow individuals to learn and draw their own conclusions about the effects and remedies of this increasingly politicized issue. Our evidence suggests that this approach is not only incentive compatible and engaging, but also effective in generating sustained support for mitigation that lasts long after investors are divested from their assets. Second, our focus on financial markets—which serve as a tangible signal of investors' beliefs regarding the market, the broader economy, and the risks and benefits associated with climate change and mitigation reforms—allows us to sidestep the polarized nature of many policy debates on this topic. Using financial markets as an information source and specific assets to incentivize personal learning, the intervention increases support for mitigation action, with larger effects on individuals with lower baseline support for mitigation. This underscores the potential promise of financial market exposure to increase consensus about mitigation action.

We recruited 3,806 American adults with diverse socioeconomic backgrounds and political beliefs, oversampling participants from states that are particularly exposed to climate change or the transition away from fossil fuels. The study was implemented using two parallel surveys. First, all participants in our study completed a baseline survey on an online platform measuring demographics and climate-related beliefs, preferences, and behaviors. These surveys also included questions on financial literacy and confidence, as well as media consumption. We administer the same survey three more times during the course of our study: three-weeks following the commencement of treatment (henceforth *midline*), seven weeks following the commencement of treatment (*endline*), and eight months post-treatment, to estimate long-term effects.

In parallel, we invited a randomly selected subset of respondents to participate in a in a six-week trading module (henceforth, '*treated*' respondents). As part of the module, treated participants received a financial portfolio, which they could track and trade with other assets from a curated list on a weekly basis. Specifically, treated participants were randomly assigned a portfolio of energy stocks with an initial value of $50 or $100, or, for a subset of the treatment arm, the fantasy treatment arm, with $0 real value but the same access to the trading platform and information about the assets as the treatment arms with monetary asset allocation. These are nontrivial amounts for this sample, with \$100 representing about 20% of liquid assets for the first tercile of respondents, and 5% of liquid assets for the median respondent.[2] We chose to focus on the energy sector because it is among the most directly affected by the green transition and climate mitigation policies, not to mention a key component of the economy at large. We further randomized the portfolio type to which treated respondents were initially assigned. Portfolios consisted of three companies or exchange traded funds (ETFs) (this assignment was also randomized) that were either renewable energy (mainly solar) companies at the forefront of the green transition (henceforth *'green'*) or companies that are more fossil-fuel dependent, with varying reliance on oil, coal, and natural gas following the fracking revolution (henceforth *'brown'*, see also Coglianese, Gerarden and Stock (2020); Gazmararian (2025)).

During the first three weeks of trading, treated respondents completed a weekly survey in which they could choose to hold or trade their initially assigned set of green or brown assets, and purchase an additional fourth asset within their treatment condition. Beginning in the fourth week, participants were allowed to trade beyond their initial portfolio and could choose any subset of the eight green and brown assets included in the study. The overall trading period encompassed the 2024 presidential election, which we anticipated could significantly affect the direction of climate policies, their projected efficacy, and the prices of green and brown stocks. After six weeks of treatment, the respondents received the full value of their portfolios.

We test our predictions by comparing the changes in climate beliefs over the course of treatment (measured at baseline, midline, and endline) between respondents in the treated and control groups. The experimental design allows us to causally identify the overall effects of tailored exposure to financial markets, as well as heterogeneity in these effects by asset type and value, and to examine whether initial exposure to green versus brown assets has differential effects across the political spectrum.

Importantly, to forestall social desirability or experimenter demand effects, the climate attitudes surveys were administered anonymously and entirely separately from the trading surveys. We present survey evidence that this was successful: the participants did not connect the two when asked what they believed was the study's purpose.

The climate attitudes surveys included a range of questions to capture support for climate action. These begin with the fundamental belief about whether human agency is a significant cause of climate change, an arguably important determinant of the reciprocal belief that humans have the agency to also act in mitigation. We further measure the perceived benefits and tradeoffs of mitigation policies, intentions for individual decisions on adaptation and mitigation, and elicit an incentivized revealed preference measure of mitigation support (donation to a prominent and nonpartisan nonprofit working on mitigation). Our primary outcome combines all of these dimensions into a single z-score *Climate Action Support Index, or CASI*, (following Kling, Liebman and Katz (2007)), before presenting the results component by component. As prespecified, our primary analyses focus on the effects of allocating any stock portfolio with real (i.e., non-fantasy)

[2] To increase compliance in the fantasy condition, respondents endowed with a fantasy portfolio were informed that a single respondent will be randomly selected to receive the true value of their portfolio at the end of the study. It is further worth noting that, in contrast, an important recent study in the U.S. that had a much greater financial component– providing a basic income of \$ 1,000 a month– had no effect on political attitudes (Broockman et al., 2024).

initial value on climate attitudes, relative to the control group. We also estimate treatment effects by initial assignment to green or brown assets, to test whether the type of financial exposure matters.[3]

Our main result is that the intent to treat (ITT) effect pooling all financial exposure treatments, including the fantasy treatment, raises the overall *CASI* by 0.036 standard deviations (SD) at midline (p-value 0.015), rising to 0.065 SD by the end of the experimental treatment (p-value < 0.001). Further, and as anticipated, the endline increases are particularly marked for those endowed with real assets (0.072 SD) compared to the fantasy treatments (0.035 SD). The increased ITT effect from midline to endline is consistent with the learning channel. Specifically, longer exposure to financial assets and trading facilitates greater learning about the factors that affect the prices of energy sector stocks. Both green and brown treatments show positive support for mitigation action, with those initially endowed with real green assets showing effects of 0.089 SD while those with real brown assets showing effects of 0.057 SD. This finding suggests that motivated beliefs is unlikely to explain our findings.

Our main results, measured in distinct surveys that eliminate demand effects by design, are substantively comparable to the top end of results from a recent megastudy (Voelkel et al., 2026), suggesting that the average *immediate* effect of the ten most-cited messaging strategies on climate-related beliefs, concerns, policy preferences, and behavioral intentions ranges between 0.03-0.07 of an SD. Notably, top-cited climate messages do not appear to impact costly behavior, are equally effective for climate skeptics and enthusiasts, and their long-term effects remain underexplored (Voelkel et al., 2026). In contrast, exposure to financial markets meaningfully shifts beliefs, preferences *and* behaviors, especially among ex-ante climate skeptics, and these effects endure up to eight-months post-treatment. Indeed, exposure to real assets increases support for mitigation action (our main *CASI* index) by 0.038 SDs (p-value$<$0.10), indicating that this support is long-lasting, although its magnitude decays over time.

Breaking the effect down component by component, we find that at endline, the real asset treatments have positive and significant ITT effects on increasing support for climate action across most of the nine different sub-dimensions we use to form the overall index. In particular, those egiven opporunities to trade in energy stocks increased support for mitigation along several dimensions. This includes sub-indices of beliefs regarding costs imposed by climate change on the quality of life in the U.S., perceptions about the potential benefits of a green transition, and of their support for not only government and business action to counter climate change but also personal willingness to donate to climate causes as well. Respindents report a greater influence of climate change on their personal decisions going forward, including where to work and in which companies to invest in the future. Further, most of these effects tend to strengthen in magnitude between midline and endline, with the positive effect of the pooled treatment on the *CASI* almost doubling from 0.036 SD (p-value 0.015) to 0.065 SD (p$<$0.001).

We present three pieces of evidence that further support a learning-based mechanism underlying the main effects. First, we examine participants' media consumption and show that treated respondents substitute away from polarizing sources, including social media (Braghieri et al., 2024) and towards financial

[3] As described below, we also subsequently cross-randomized the provision of environmental disclosure, which we study in a companion paper.

news. This pattern is consistent with the treatment inducing learning, which respondents pursue through the financial media - an information source better suited than general news for understanding an asset's value, as it emphasizes fundamentals, cash flows, and market implications. Second, we show that respondents' ability to correctly predict the environmental impact (carbon emissions) of the energy firms included in the treatment is greater, as is their subjective expectation of how environmentally impactful each of these firms is (treatment increases the perceived environmental impact of brown firms, and reduces it for green firms). Thus, treated respondents learn about and retain knowledge about the environmental impact of firms included in our study. Consistent with a knowledge mechanism, we also find an overall increase in financial literacy in the treatment group. Third, a final test of learning is examining whether those who were ex-ante more skeptical about the economic consequences of climate change have greater treatment effects (consistent with Bayesian updating with greater information acquisition). Indeed, we find effects that are significantly larger among those who have below median support for climate action at baseline (i.e., lower prior support for mitigation). This last result shows that this intervention did not only build support for mitigation action, but expanded the coalition of policy support.

The paper builds on three strands of literature. The first is the literature on the determinants of climate-related beliefs, preferences, and behaviors and how to build support for climate action. Prior work shows that political orientation, moral values, and demographic characteristics are correlated with belief in climate change and support for mitigation policies (Feinberg and Willer, 2013; Hornsey et al., 2016; Drews and Van den Bergh, 2016; Dechezleprêtre et al., 2025). There is also evidence that exposure to weather shocks and extreme weather events increases salience of climate change (Hilbig and Riaz, 2024; Bernstein, Gustafson and Lewis, 2019), belief in climate change (Arias and Blair, 2024), and support for mitigation policies (Baccini and Leemann, 2021; Hazlett and Mildenberger, 2020). In addition, interventions that try to change beliefs about climate change have focused on communicating the scientific consensus regarding climate change (Ranney and Clark, 2016; Bolsen and Druckman, 2018), providing moral messaging to motivate belief change (Feinberg and Willer, 2013), and exposing people to varying messaging about the impacts of climate change and the potential benefits of various mitigation actions (Jones, Hine and Marks, 2017; Loy and Spence, 2020; Dechezleprêtre et al., 2025). However, meta-analyses and cross-country experiments show that it remains challenging to identify precisely what type of messaging approaches are effective in facilitating broad mitigation support (Vlasceanu et al., 2024), and even the most effective messages appear to yield modest short-term effects (Voelkel et al., 2026). Moreover, there is some evidence that even theoretically informed and contextually sound messages may at times also have unintended negative *backlash* impacts on beliefs about climate change and support for mitigation action (Bosetti et al., 2025; Zhou, 2016; Mildenberger et al., 2024; Voelkel et al., 2026). We contribute to this literature by developing an approach which incentivizes learning through financial exposure to and trading in climate-relevant assets instead of trying to optimize over the type of messaging, which may vary depending on individuals' context, priors, and willingness to update. We show that our approach is effective in shifting beliefs on a broad range of outcomes, and that our primary effects persist even when the assets are divested.

The second literature to which we contribute is on the impacts of financial market exposure on policy preferences. Jha and Shayo (2019) randomly assign Israeli participants to opportunities to trade small amounts of Israeli and Palestinian stocks. They find that this treatment affects individuals' political attitudes, with treated participants increasing their support for restarting the peace process, and reevaluating the economic costs of the conflict and the potential gains from a peace settlement to society. Margalit and Shayo (2021) and Jha (2025) assigned British voters to hold and trade financial assets in the run-up to the Brexit referendum, finding that treated individuals become more self-reliant in their economic attitudes (Margalit and Shayo, 2021), and were more likely to counter populist narratives and vote to remain in the EU.[4] This paper estimates whether and how exposure to financial markets, and specifically different types of assets in the energy sector, impact individuals' beliefs in climate change and support for mitigation policies. Climate support is a substantively different policy issue, with mitigation costs largely accruing in the short-term while benefits largely accruing in the longer-term, and requiring sustained global co-operation on a portfolio of mitigation strategies (Keohane and Victor, 2016). We show that financial market exposure can serve as a tractable, market-driven, non-paternalistic way to incentivize learning, and ultimately increase support for mitigation policies and behaviors.

Finally and most broadly, we contribute to the literature that aims to increase the supply of environmentally friendly behaviors using price and non price interventions. One strand in this literature focuses on interventions to increase conservation of energy or water, such as providing usage information (Jessoe and Rapson, 2014), peer comparison information (Allcott, 2011; Knittel and Stolper, 2019; Ferraro and Price, 2013), performance feedback and monitoring (Gosnell, List and Metcalfe, 2020), moral suasion (Ito, Ida and Tanaka, 2018), and religious messaging (Buccione, 2023). Another strand focuses on how changing the price of energy impacts energy use (Ito, Ida and Tanaka, 2018; Jessoe and Rapson, 2014). We contribute to this literature by providing evidence that financial market participation can provide a force for increased knowledge about, and support for, climate policies.

2 Research Design

Examining how exposure to financial markets causally affects climate-related beliefs, preferences, and behaviors requires a research design to overcome endogeneity on two dimensions. The first is the decision to participate in financial markets at all, which is correlated with characteristics such as gender, education, and income (Jha and Shayo, 2025; Bucher-Koenen et al., 2023; Lusardi and Mitchell, 2014). The second is the fact that even conditional on participating in financial markets, portfolio allocation choice is endogenous. Specifically, retail investors' climate beliefs, cultural values, and political preferences inform trading behavior and investment in renewable energy (Anderson and Robinson, 2019; Briere and Ramelli, 2020; Meeuwis et al., 2022).

To overcome these challenges, we designed and implemented a large-scale RCT in the run-up to the 2024 elections, in which we endowed treated participants with financial portfolios, randomized the emis-

[4] Tailored financial exposure has also been shown to increase generalized trust in Israel (Jha, Shayo and Weiss, 2025) and Mexico (Rivera, Seira and Jha, 2025).

sions intensity of these portfolios, and then elicited outcomes of interest in unrelated surveys. Our design followed six steps described below. First, we recruited 3,806 U.S.-based survey respondents to participate in a longitudinal survey on economic, social, and climate-related issues, oversampling participants from states exposed to climate risks due to energy transitions and extreme weather events (see Appendix B.1 for more information).[5] Second, we block-randomized study participants into treatment and control conditions.[6] Third, we invited 2,406 treated respondents to participate in a six-week trading module, receiving a \$50, \$100, or a 'fantasy' financial portfolio with either three green ($n = 1,209$) or brown ($n = 1,197$) assets.[7] In both the green and brown asset conditions, 80% of participants were assigned to either \$50 or \$100 portfolios, and remaining 20% were assigned to \$100 fantasy condition (this arm received the trading platform, and \$100 in fantasy dollars (i.e., no real value), and could trade just like the other treatment groups could. To increase compliance, fantasy respondents were informed that one participant will be randomly selected to receive the real value of their portfolio in the end of the study.).

Individuals assigned to the green treatment assets arm received a randomly chosen three of four different green assets, each of equal value. These assets consisted of stocks in First Solar Inc, Enphase Energy, Clearway Energy Inc, as well as a green energy ETF (Invesco Solar ETF), for which First Solar Inc. is a top holding. Similarly, individuals assigned to the brown treatment assets arm received a randomly selected set of three of four brown assets, each of equal value. These assets consisted of stocks in Haliburton, Exxon Mobil Corp, ConocoPhillips, as well as a brown energy ETF (Strive U.S. Energy ETF), for which Exxon Mobil Corp. is a top holding. We provided respondents with a one-line description of each firm (included in Table A4). In Appendix A, we show that in a pilot study with about 100 respondents on the same platform, respondents' beliefs were that firms in the green portfolio had a significantly lower environmental impact than firms in the brown portfolio.[8] Thus, these stocks were perceived differently on average in terms of environmental impact. A description of all asset prices against the timeline of our experiment is reported in Figure 1b.

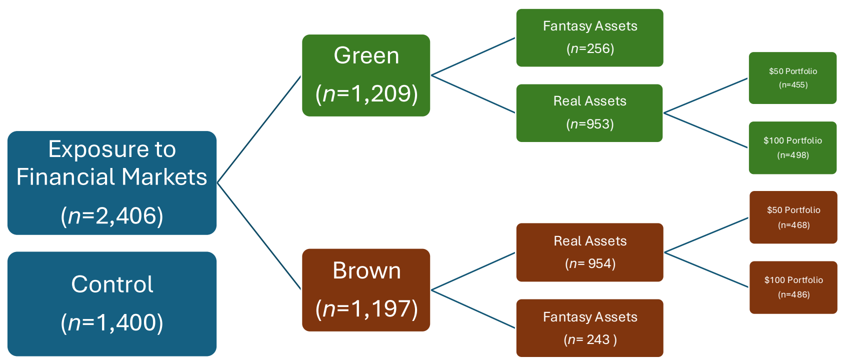
The RCT design allows us to both estimate the causal impacts of financial exposure and trading on climate beliefs, as well as to test for underlying mechanisms. By randomizing the respondents to financial exposure vs. control (our primary comparison of interest), we identify the general causal effects of financial exposure and trading. By randomizing participants into green and brown portfolios, we can estimate

[5]Specifically, we increased the representation of respondents from the following states by 1.5 times relative to their population share: Alabama, Georgia, Kentucky, Mississippi, North Carolina, South Carolina, Ohio, Pennsylvania, Tennessee, and West Virginia. Despite their climate-related vulnerabilities, we did not over-sample respondents from California, Florida, and Texas, given their large population relative to other states.

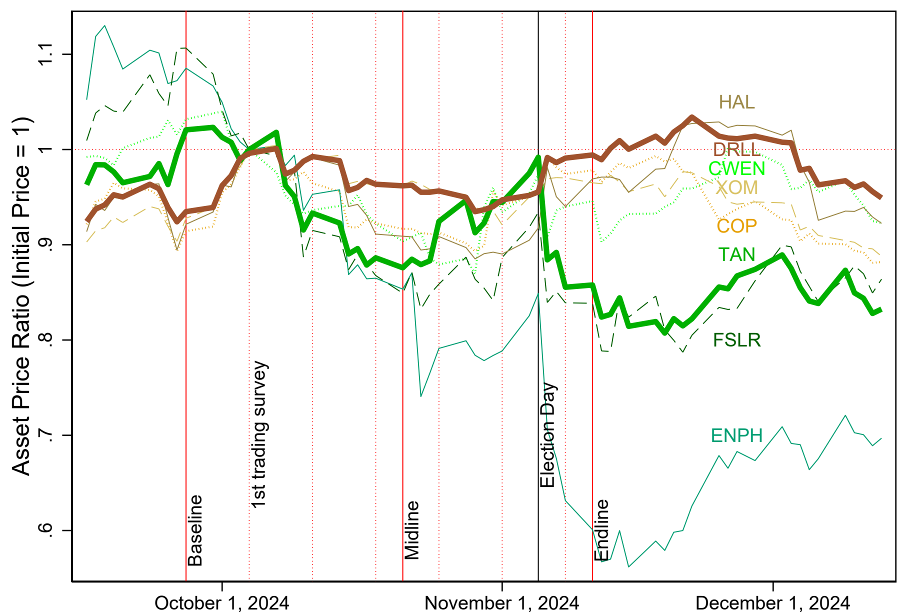
[6]We created blocks by stratifying sequentially on party identity (Democrat, Republican, Independent, Other), geographical region (Northeast, Midwest, South, West), prioritization of climate as a top policy issue ("Yes" if a respondent identifies climate as a first or second policy priority, "No" otherwise), and trading experience ("Experienced" if a respondent reports past experience investing in stocks, bonds, mutual funds, or other financial assets outside of their 401K, "Inexperienced" otherwise.). This results in a total of 64 blocks, ranging in sample size from 1-294 study participants.

[7]In Appendix A, we describe our asset selection procedure, as well as a pilot survey conducted to validate our selection of eight financial assets for the purpose of this experiment.

[8]We further randomly assigned 1,206 treated respondents to receive financial and climate-related disclosures after four weeks of trading, which we study in a companion paper. All treated respondents received financial disclosures at that time. We control for the receipt of climate disclosure in all endline regressions.



(a) Overview of experimental design.



Note: Dashed red lines represent start of a 3-day trading survey period. Stock price data from investing.com.

(b) Financial assets included in our experiment.

Figure 1: **Description of Experimental Design.** Panel (a) reports the experimental groups in our study. Panel (b) reports the asset price ratios of all assets over the different periods of our experiment, wth the initial price normalized to 1 (HAL=Haliburton, DRLL=Strive U.S. Energy ETF, CWEN=Clearway Energy, XOM= Exxon Mobil, TAN=Invesco Solar ETF, FSLR=First Solar, ENPH=Enphase Energy, COP=ConocoPhillips). The solid green and brown lines track the value of the green and brown ETF, respectively.

whether exposure to brown vs. green assets (specifically, exposure to firms at the forefront of the potential green energy transition) generates divergent effects. Such differences may arise if exposure type shapes the information respondents seek out or update upon, or if belief formation is influenced by motivated reasoning. By including a $0 fantasy arm, we can test whether treatment effects arise merely from providing an opportunity to learn through our platform (or from increased salience of the stocks in our study), or whether real (albeit small) financial incentives are necessary to generate the treatment effects. Finally, assigning $50 or $100 to treated respondents allows us to test for income effects.

As part of our treatment, we invited all participants assigned to the trading condition to enroll in a six-week trading module. Participants were informed that they had been selected to participate in a study of investor behavior in which they would receive a financial portfolio,[9] and would complete weekly surveys in which they tracked and traded the assets in their portfolio.[10] Overall, 84% of treated respondents ($n = 2,030$) participated in at least one week of trading, and 81% ($n = 1,653$) of these participants actively engaged in five or six weeks of trading. For more information on the trading surveys, see Appendix B.3. Figure 1a provides a summary of the main treatments in our RCT.

Fourth, after three weeks of trading restricted to their initial assigned green or brown assets portfolios, all baseline survey respondents (including those in the control group) were invited to participate in an entirely separate, anonymously fielded midline survey.[11] In total, 3,424 baseline respondents completed the midline survey, corresponding to a 90% response rate.[12] Appendix B.2 provides further information about the midline survey, and Table A5 shows that attrition is not correlated with treatment assignment.

Fifth, after completing the midline survey, all treated respondents received unrestricted access to trade in both green and brown assets (four of each type) regardless of their initial treatment assignment. Figure 2a shows average portfolio compositions (in percent of green stocks) over time for both green and brown portfolios. Even when individuals were allowed to trade across portfolio types, there is some persistence in the type of portfolio to which participants were assigned.[13] In the fifth and sixth trading surveys, we introduced a randomized climate disclosure treatment within the treatment group, and gave financial disclosure information to all treated respondents. This treatment is controlled for in all regressions using endline surveys.

Sixth, at the end of the six-week trading period, we invited all study participants to complete an endline survey. We collected 3,592 responses, corresponding to a 94% response rate. Additional details on the

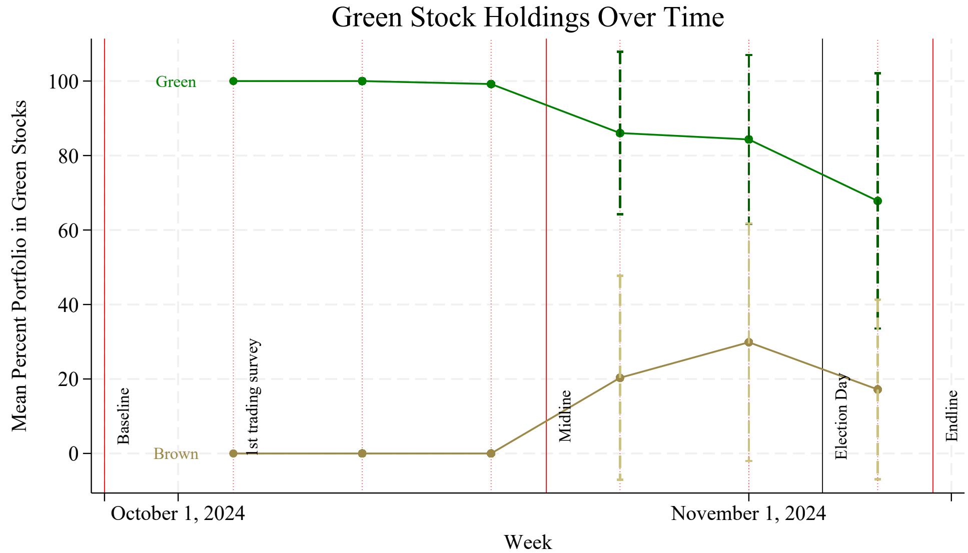
[9]More precisely, the portfolios were paid from the authors' research account in amounts that perfectly tracked the prices of the underlying assets, rather than actual asset ownership (through the implementation partner, Forthright). This was explained to participants in non-technical language.

[10]All surveys were rolled out on Fridays after market closure, and access to surveys was terminated on Monday before markets re-opened. To incentivize participation, we informed respondents that failing to complete a weekly trading survey would result in a 10% loss to the overall value of their portfolio. In addition, respondents received standard compensation from Forthright for each weekly trading survey they completed.

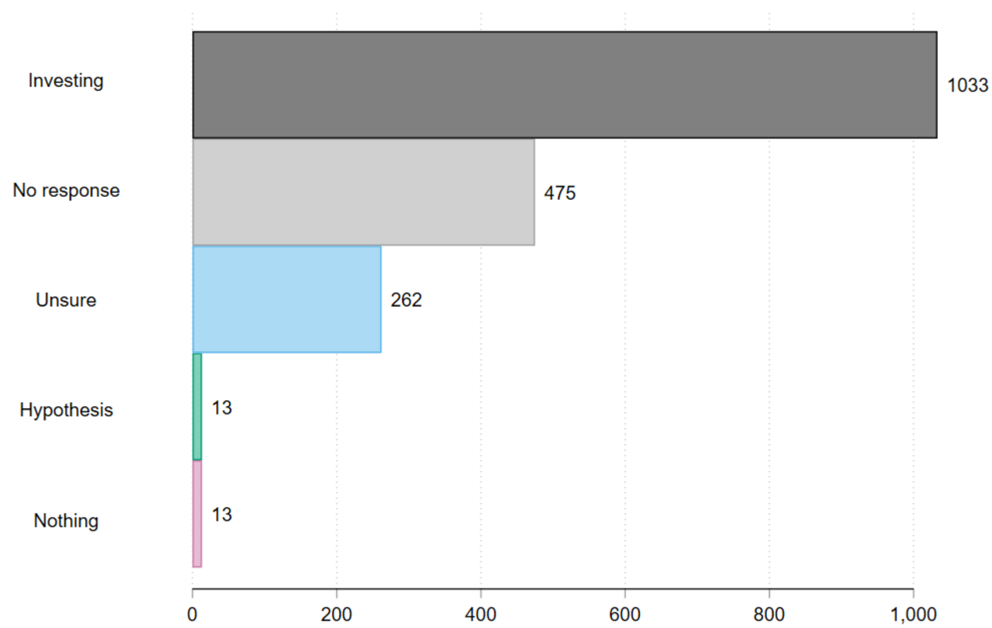
[11]The invitation to the midline survey did not mention the trading module, and a different visual layout was used to minimize the perceived connection between treatment and outcome measurement instruments.

[12]We concluded the midline survey on Thursday, October 24, 2024, allowing us to resume the trading surveys on Friday, October 25, 2024.

[13]This is consistent with the endowment effect found in other financial market studies, such as Anagol, Balasubramaniam and Ramadorai (2018).



(a) Composition of financial portfolios over time.



(b) What can researchers learn from this study?

Figure 2: **Description of financial assets and portfolio compositions against the RCT timeline, and respondent expectation regarding the purpose of the financial module.** Panel (a) reports the average composition of financial portfolios (+/- 1 SDs) over time among respondents initially assigned to hold either green or brown assets. Panel (b) reports responses to the question “What can the researchers learn from this study?” from participants in the financial market treatment group. Only the most common answers to this question are reported in this figure.

endline survey are provided in Appendix B.2 and Table A5 shows that attrition does not correlate with treatment assignment. Finally, we recontacted respondents for a long-term follow-up survey approximately eight months following our sixth trading survey. We successfully recontacted 2,959 participants, yielding a 78% response rate. As shown in Table A5, attrition at this stage is also independent of treatment conditions.

Figure 2b provides evidence that separating our trading modules from our other surveys minimized social desirability bias.[14] When asked what the research team might learn from the trading module, a majority of treated respondents believed the study concerned investing behavior. Only thirteen respondents (less than 0.5%) provided an answer that made any mention of the environment or climate change.[15] Together, these responses suggest that social desirability concerns are unlikely to be driving our results.

3 Empirical Strategy

Our main specification is the pre-registered regression in Equation 1:

$$y_i = \beta_1 \text{Financial Market Treatment} + \beta_2 \text{Disclosure} + \beta_3 X_i + \eta_i + e_i \tag{1}$$

In this specification, y_i represents a given outcome of interest for respondent i, measured in the post-treatment surveys. The coefficient β_1 captures the Intent-to-Treat (ITT) effect of exposure to financial markets and trading. In specifications using the endline and long-term follow-up outcomes, we control for respondents' climate disclosure status (Disclosure), as these surveys were administered after the disclosure treatment.[16] All specifications include LASSO-selected baseline covariates (X_i), and fixed effects accounting for randomization strata (η_i). Consistent with our pre-registered hypotheses, we report both one-tailed and two tailed p-values, with the former reported numerically in each table, and the latter by stars denoting conventional (two-sided) significance thresholds.

In addition to this primary specification, we also present results for the main outcomes separately by green and brown portfolio treatments, to examine potentially diverging effects by the type of assets respondents initially received. Furthermore, we present results separately for the real (pooling the $50 and $100 treatments) and fantasy ($0 real value) treatment arms to test whether salience (as opposed to financial stakes) is an important mechanism driving these effects.

[14]To create Figure 2b, we used ChatGPT4 to code open-ended respondents from our trading model, eliciting respondents' expectations regarding what researchers can learn from the trading module. To do so, we asked the model to read each open-ended response and create a series of binary indicators taking a value of 1 if a respondent explicitly mentioned: i) the authors' hypothesis, ii) investing behavior, iii) uncertainty regarding the objective of the study, or iv) explicit mention that the researchers can learn nothing from the study. To increase the precision of coding, we required the model to complement these variables with an explanation providing the rationale for coding decisions. Members of the research team reviewed the coding of variables to ensure their validity.

[15]Examples for open ended responses that are closest to identifying the purpose of are study, include: "*How we react to stock price changes. How we choose our stocks based on if they are good or bad for the environment.*" and "*Participants beliefs about the environmental impacts of these companies* ".

[16]The disclosure treatment gave a randomized subset of the treatment group information about their portfolio firms' emissions intensity and emissions, as well as the chance to read their climate disclosure reports in detail. All treated respondents additionally received financial information about their portfolio firms, such as profits. We are analyzing the impacts of climate disclosure on trading behavior in a companion paper.

4 Main Outcomes Overview

We survey respondents on a range of outcomes to estimate how the treatment impacts their understanding of anthropogenic contribution to climate change, their perceptions of the costs and benefits of mitigation policies, and their support for mitigation. To sidestep concerns regarding multiple comparisons, we aggregate these outcomes into an index that serves as our primary measure of support for climate action (*Climate Action Support Index*; *CASI*). *CASI* comprises nine sub-indices capturing respondents' climate beliefs, preferences, and behaviors. This structure allows us to identify which parts of the causal chain are impacted by exposure to, and trading in, financial markets. The most upstream subindex, titled the Climate Beliefs Index, measures the respondents' belief in the role of human agency — and anthropogenic emissions in particular— in having a significant impact on climate change, as well as their beliefs about the impacts of climate change on quality of life. However, these beliefs are arguably not sufficient for support of climate action, as individuals may still perceive mitigation as too costly relative to its benefits. More downstream and policy-relevant outcomes include willingness to donate to climate causes, support for mitigation policies, and intentions to undertake adaptation behaviors. In Figure 3, we report the pre-treatment distribution of all the sub-indices comprising our overall climate index. We present results by political party identification given extensive evidence that climate change beliefs and policy attitudes differ systematically across partisan groups (Chinn, Hart and Soroka, 2020; Falkenberg et al., 2022).

Our *Beliefs* index is based on four questions, eliciting respondents' agreement with statements regarding the causes and impacts of climate change (e.g., "Human activities are a significant cause of climate change"). The *Transition Benefits* and *Transition Projections/ Tradeoffs* indices elicit respondents' perceptions regarding the benefits and tradeoffs/ projected efficacy of the green transition using four-questions each. We measure respondents' policy preferences using two-item indices eliciting support for government and business action (*Government Action* and *Business Action*), as well as a single-item measure of the priorization of climate relative to other policies (ranging from 0-6; *Policy Priority*). To measure behaviors, we use three complementary outcomes: (i) a five-item index of self-reported engagement in pro-environmental behaviors (*Behavior*); (ii) a three-item decision index measuring how climate change influences respondents' investment and life decisions (*Decision*); and (iii) an incentivized willingness-to-pay measure capturing donations to a climate-related cause (*Donate to Climate*).[17] We construct all indices by averaging the z-scores of their components (Kling, Liebman and Katz, 2007).[18] We provide the full set of survey questions underlying these outcomes in Appendix Table A3, and discuss the measurement of each index in detail as we present the results.

Figure 3 yields two important insights. First, at baseline there is substantial variation in climate attitudes, preferences and behaviors. Second, in the U.S. context, and specifically in the run-up to the 2024 elections,

[17]The three-item life decisions index was not in our initial pre-registration and was added to the midline and endline survey after the research team posted their pre-analysis plan in response to feedback received on the design. Therefore, in Figure 3, we report the sub-index distribution among the control group at midline, and also report effects on the overall *CASI* without this index in Appendix Table A2.

[18]Z-scores are calculated by subtracting the control group mean and dividing by the control group standard deviation.

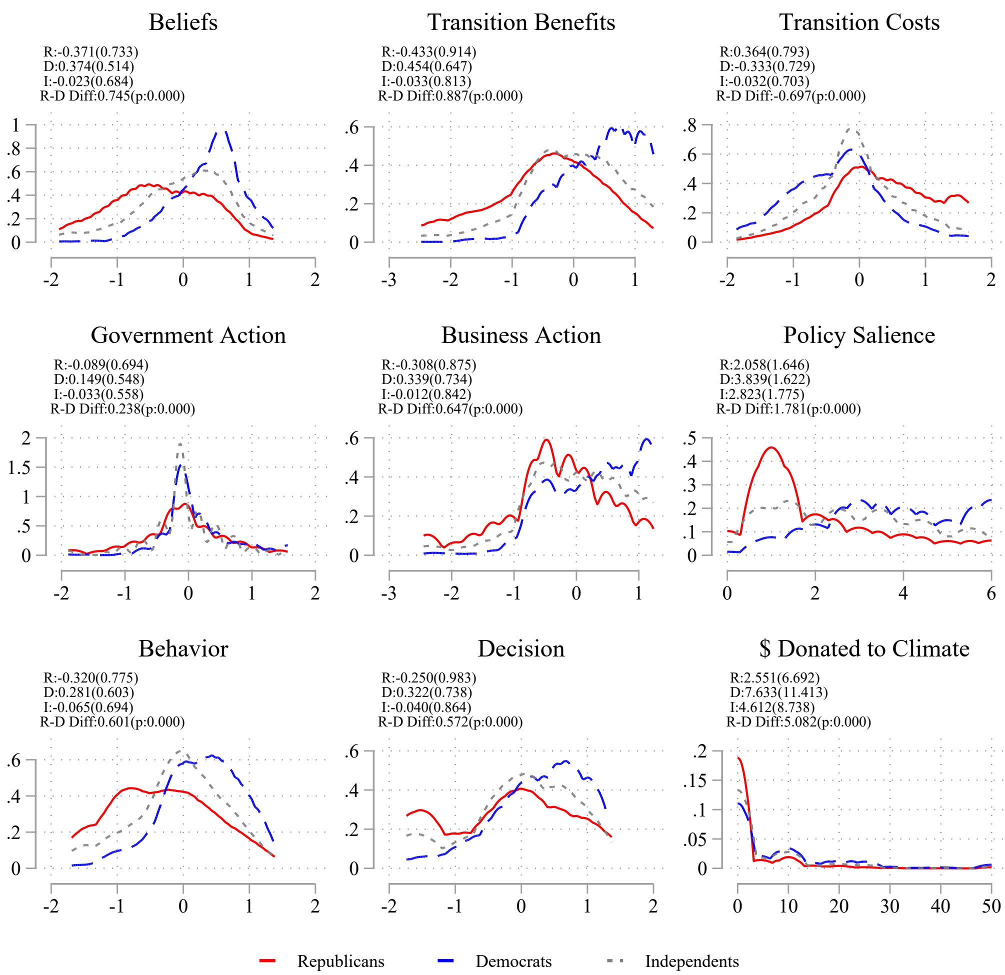


Figure 3: **Components of Climate Index at Baseline.** This figure reports the baseline distribution of all sub-indices comprising our general climate index. Please refer to Table 2 for more detailed information on the construction of these sub-indices. With the exception of the panel named *Decision* (measuring intentions to adapt and invest), all panels report baseline distributions for the full sample. Since the decisions index was not collected at baseline, we report the midline-distribution among the control group.

climate change is a highly polarized issue. Across all sub-indices, we observe pronounced differences in beliefs, preferences, and behaviors between Democratic and Republican respondents, consistent with prior evidence on polarization (Gustafson, 2025). For most sub-indices reported in Figure 3, the partisan gap is approximately equal to the pre-treatment standard deviation of the control group, with Independent respondents' beliefs typically lying between those of Democrats and Republicans.

5 Results

Table 1 presents results for the main outcome—the overall index aggregating all our primary outcome variables (*CASI*)—measured at both the midline (three-weeks after treatment assignment) and the endline survey (six weeks after treatment assignment, and three weeks after treated respondents were allowed to trade across green and brown portfolios). At midline (Column 1), respondents assigned to hold and trade portfolios in energy firms (green or brown) exhibit a 0.036 SD increase in the *CASI* ($p < 0.05$, one-tail test). The ITT estimate of trading at endline (Column 4) is larger and also more precisely estimated, 0.065 SDs ($p < 0.01$, one-sided). Thus, treatment effects increase between the midline and endline surveys, which we attribute to learning and explore further in the next section.[19]

Columns 2 and 5 of Table 1 show that treatment effects are largely driven by respondents assigned portfolios with real assets rather than fantasy portfolios. Coefficients for the fantasy arm are smaller in magnitude and not statistically different from zero. The fantasy treatment—implemented using $100 in notional dollars, and designed to provide respondents identical access to the trading platform, information, and salience of stock portfolios—yields positive but smaller treatment effects that are not statistically significant. In both our midline and endline surveys, the ITT estimates for real-asset portfolios are substantively larger and statistically different from those for fantasy portfolios ($p < 0.05$ in midline and $p < 0.10$ in endline, both one-tailed tests). At endline, respondents holding and trading fantasy portfolios exhibit a 0.035 SD increase in the *CASI* (p-value=0.103, one-tailed tests), while those trading real portfolios exhibit a 0.072 SD increase in *CASI* (p-value<0.01). These results suggest that providing respondents modest financial stakes significantly increases their beliefs and preferences related to climate action.

Turning to columns 3 and 6, we examine treatment effects by respondents' initial assignment to green vs. brown stock portfolios.[20] We find that exposure to either portfolio type has a positive, and for the most part, precisely estimated effect on the *CASI*. However, the ITT estimates associated with initial assignment to green portfolios are larger than those associated with initial assignment to brown portfolios. At endline, respondents assigned to either portfolio type report higher support for climate action relative to the control group, with effects that are larger in magnitude for those initially assigned green portfolios ($p < 0.10$, one-tailed test). As discussed in Section 2, we randomized respondents into green and brown portfolios to test whether the type of financial exposure—particularly differences in exposure to climate transition risk—shapes belief formation (e.g., if motivated reasoning is a mechanism at work in our setting). The

[19]The p-value on the Wald test testing for equality of coefficients for column 2 vs. column 5 is 0.11.

[20]Note that at endline, all respondents were permitted to trade in both green and brown assets. On average, respondents initially endowed with a green (brown) portfolio held nearly 40% brown assets (20% green assets).

Table 1: Effect of Treatment on Climate Action Support Index

Climate Action Support Index	Midline			Endline		
	(1)	(2)	(3)	(4)	(5)	(6)
Pooled Treatment	0.039**			0.065***		
	(0.017)			(0.019)		
Real Assets		0.046***			0.072***	
		(0.017)			(0.020)	
Real Green			0.059***			0.089***
			(0.021)			(0.022)
Real Brown			0.033			0.057**
			(0.021)			(0.023)
Fantasy Assets		-0.002	-0.001		0.035	0.035
		(0.025)	(0.025)		(0.028)	(0.028)
Observations	3420	3420	3420	3587	3587	3587
p (Pooled Treatment > 0)	0.010			0.000		
p (Real Assets > 0)		0.004			0.000	
p (Real Assets > Fantasy Assets)		0.024			0.064	
p (Real Green > Real Brown)			0.139			0.074

Note: This table reports OLS estimates of the effect of financial market exposure on the *Climate Action Support Index (CASI)*. The index aggregates nine sub-indices capturing climate beliefs, preferences, and behaviors. *Pooled Treatment* compares all participants assigned to financial market exposure (real and fantasy portfolios, n=2,406, with n representing the number of participants assigned treatment at baseline) versus control (n=1,400). *Real Assets* pools participants assigned \$50 or \$100 real-value portfolios (n=1,907), while *Fantasy Assets* includes those assigned \$100 fantasy portfolios (n=499). *Real Green* and *Real Brown* separately estimate effects for participants initially assigned real green energy stocks (n=953) versus real brown energy stocks (n=954). All regressions control for post-double selection (p-ds) LASSO-selected baseline covariates and include block fixed effects accounting for randomization strata (stratified by party identification, geographic region, climate policy prioritization, and prior trading experience). Endline regressions (columns 4-6) additionally control for climate disclosure treatment status. Robust standard errors in parentheses. Stars denote two-tailed p-values: *** $p<0.01$, ** $p<0.05$, * $p<0.10$. One-tailed p-values for directional hypotheses reported in bottom rows.

finding that both portfolio types generate positive effects runs counter to motivated beliefs acting as the primary mechanism, as such reasoning would predict negative effects for respondents exposed to brown assets.

Overall, these results indicate that exposure to financial markets and opportunities to trade in energy assets increases support for climate action, with the impacts driven by participation in portfolios with real assets. Next, we unpack which components of the causal chain—from beliefs about anthropogenic climate change to policy preferences—are most affected by financial exposure.

Table 2 reports treatment effects on our sub-indices, each capturing a different dimension of the causal chain. We begin by examining whether the treatment affects beliefs about both human agency in causing climate change and its impacts on the quality of life, arguably important pre-conditions for the reciprocal beliefs that human agency on climate mitigation can also be effective and worthwhile. These beliefs are measured using an index constructed from four Likert-scale questions assessing agreement with the following statements: "Human activities are a significant cause of climate change," "Climate change will have a serious impact on the quality of life of people in the U.S. during my lifetime," "Extreme weather events such as floods, fires, and hurricanes are made more likely due to climate change," and "Climate change is not a serious issue" (reverse-coded).

Table 2: Real Asset Treatment Effect on Components of Climate Action Support Index

Midline				
Outcome	Real Asset Treatment	SE	p $(\lvert\beta\rvert > 0)$	N
Overall Climate Action Support Index	0.046***	0.017	0.004	3420
Beliefs About Human Agency and Tradeoffs				
Climate Beliefs Index	0.026	0.022	0.127	3420
Transition Benefits Beliefs	0.033	0.020	0.052	3392
Transition Projections/Tradeoffs	−0.054**	0.027	0.023	3392
Policy Preferences				
Support for Government Action	−0.003	0.032	0.541	3387
Support for Business Action	0.041	0.027	0.064	3387
Climate Policy Priority	0.028	0.026	0.136	3322
Pro-Climate Personal Decisions and Behaviors				
Donate to Climate Cause (Yes/No)	0.050*	0.029	0.043	3384
Daily Decisions	0.004	0.022	0.420	3386
Investment and Life Decisions	0.044	0.028	0.057	3394
Endline				
Overall Climate Action Support Index	0.072***	0.020	0.000	3587
Beliefs About Human Agency and Tradeoffs				
Climate Beliefs Index	0.044*	0.025	0.041	3587
Transition Benefits Beliefs	0.056**	0.023	0.009	3559
Transition Projections/Tradeoffs	0.005	0.030	0.567	3559
Policy Preferences				
Support for Government Action	0.122***	0.036	0.000	3557
Support for Business Action	0.064**	0.029	0.014	3557
Climate Policy Priority	−0.012	0.030	0.656	3527
Pro-Climate Personal Decisions and Behaviors				
Donate to Climate Cause (Yes/No)	0.067**	0.034	0.025	3556
Daily Decisions	0.028	0.025	0.135	3556
Investment and Life Decisions	0.083***	0.032	0.004	3567

Note: This table reports OLS estimates of the real asset treatment effect on the *Climate Action Support Index (CASI)* and its nine component sub-indices. The *Real Asset Treatment* compares participants assigned real-value portfolios ($50 or $100) to control. All regressions control for post-double selection (p-ds) LASSO-selected baseline covariates and include block fixed effects accounting for randomization strata (stratified by party identification, geographic region, climate policy prioritization, and prior trading experience), and for fantasy portfolio assignment. Endline regressions additionally control for climate disclosure treatment. Robust standard errors reported. Stars denote two-tailed significance: *** p<0.01, ** p<0.05, * p<0.10. One-tailed p-values reported in column 4.

At midline, the treatment increases this beliefs index by 0.026 SDs (p-value=0.13, one sided). At endline, the effect rises to 0.044 SDs (p-value$<$ 0.05, one-sided), indicating a precisely estimated increase in beliefs about the role of human actions in causing climate change six-weeks after treatment. While beliefs about anthropogenic climate change and its consequences do not necessarily translate directly into support for mitigation, they represent a necessary input for increasing support for climate policy and intentions to adapt.

Next, we examine whether the treatment also affects beliefs about the potential benefits of the green transition. We measure these beliefs using an index constructed from four Likert-scale questions assessing agreement with the following statements: "Renewable energy industries, including those based on wind, solar, etc., will create many well-paying jobs for Americans," "Renewable energy industries have the potential to be a central cause of economic growth in the U.S.," "Investing in renewable energy is an important way to fight climate change," and "On balance, the transition to renewable energy like solar from fossil fuels, coal and gas will be beneficial for the U.S. economy in the next 10 years." Table 2 shows that this transition-benefits beliefs index increased by 0.032 SDs at midline (p-value<0.10, one-sided) and by 0.056 SDs at endline (p-value<0.01, one-sided).

We also measure beliefs about the potential tradeoffs and projected efficacy of the green transitions using an index based on agreement with the following statements: "Renewable energy will threaten many coal, oil, and gas jobs in America," "Renewable energy will take up land that could be used for more productive economic causes," "Renewable energy will not be able to efficiently meet the needs of the American economy in the next 10 years," and "Renewable energy will not be able to efficiently meet the needs of the American economy in the next 20 years." In contrast to the transition-benefits index, this trade-offs index decreases by 0.054 SDs at midline (p-value<0.05, one-sided), indicating increased optimism about the projected efficacy of the green transition and reasonableness of the tradeoffs involved, but is close to zero at endline, just following the U.S. election. As a result, beliefs about transition tradeoffs do not contribute meaningfully to the overall index effect observed endline.

In sum, treated respondents are more likely to believe in the role of human agency in causing climate change and to perceive the benefits of the green transition more positively. However, particularly after the elections, they are not more or less likely to perceive the projected efficacy and trade-offs of the transition as favorable. Next, we test whether these belief changes translate into increased support for mitigation action by the government and the private sector, as well as greater willingness to take personal responsibility in adaptation and mitigation, including a revealed-preference willingness-to-pay measure of donations to a well-regarded climate and environmental policy focused nonprofit, the Environmental Defense Fund.

Mitigation could rely on government action (e.g., mandatory climate risk disclosure), or private-sector actions (e.g., voluntarily disclosing climate risk or investing in lower-emissions technologies). We measure support for government mitigation using an index constructed from two Likert-scale questions assessing agreement with the following statements: "The U.S. government should do more to reduce greenhouse gas emissions," and "The U.S. government should only contribute to climate mitigation if other countries like China and India do the same." The latter statement captures whether respondents view mitigation as worthwhile only under global coordination rather than as a unilateral policy, a common theme in debates over climate policy.

We measure support for private-sector mitigation analogously using an index based on agreement with the following two statements: "U.S. companies should do more to reduce greenhouse gas emissions," and "U.S. companies should contribute to climate mitigation if companies in other countries, such as China and India, do the same." Finally, we assess broader policy priorities using a ranking task in which respondents order climate change, immigration, the economy, healthcare, the military, social services and an "other" category; the precise wording is listed in Table A3.

Table 2 shows that support for government action increases by 0.122 SDs at endline (p-value< 0.01, one-sided), although it is not statistically different from zero at midline. Support for private-sector action also increases, though the magnitude is smaller at endline than the support for government action (0.064 SDs, p-value< 0.05, one-sided). This index exhibits positive but less precisely estimated effects at midline, with an estimated increase of 0.041 SDs, (p-value< 0.10, one-tailed).

The climate as a policy priority measure shows a positive effect at midline of approximately 0.027 SDs (p-value=0.14), but also no detectable effect at endline, indicating that it does not contribute to the larger endline treatment effect observed in the overall index. Taken together, these results suggest that exposure to financial markets and opportunities to trade energy sector stocks increases support for mitigation action by both the government and private sector, with relatively stronger support for action by the state. We next examine whether these treatment effects extend to intentions to undertake personal responsibility for addressing climate change, including an incentive-compatible willingness-to-pay measure.

Our revealed preference measure asked respondents to indicate how they would allocate a potential $50 prize between keeping the funds for themselves and donating to nonprofits focused on issues such as political polarization, veterans' welfare, and environmental protection. To ensure incentive compatibility, respondents were informed that one participant would be randomly selected and their chosen allocation would be implemented in full, including the amount retained personally. Table 2 shows that exposure to financial markets increases the likelihood of donating to the climate-related nonprofit by 0.05 SDs at midline and by 0.067 SDs at endline (p-value< 0.05, one-sided for both), indicating increased support for climate action when real financial stakes are involved.

We also measure personal responsibility for addressing climate change through self-reported intentions related to both daily behaviors and longer-run decisions. The daily decisions index comprises five statements, capturing respondents' stated likelihood of engaging in actions such as signing a climate petition, joining an environmental group, using transport other than personal vehicles, using reusable bags, and reducing meat consumption. The longer-run investments and life decisions index comprises three questions eliciting the extent to which climate-related considerations influence respondents' decisions about where to live, where to work, and in which companies to invest.

Exposure to financial markets does not affect respondents' stated intentions to engage in pro-environmental behaviors in their daily lives at midline, and endline effects are positive but imprecisely estimated (an increase of 0.028 SDs, one-tailed p-value of 0.13). In contrast, we find strong evidence at endline that treated respondents are more likely to consider climate-related concerns when making important longer-run decisions. The endline ITT estimate for the investment and life-decision index is large and precisely estimated, at 0.083 SDs. The effects at midline are also positive, though smaller (0.045 SDs, and significant at the 10% level using one-sided p-values). We discuss the treatment effects on disaggregated outcomes underlying the indices in Section C.1.

In sum, we find that our primary treatment—exposure to, and opportunities to trade in, financial markets—increases beliefs about human agency in causing climate change and leads to more positive perceptions of the benefits of the green transition. These beliefs translate into greater support for mitigation action by both the government and private sector, as well as willingness to account for climate-related considerations in life decisions, and willingness to donate to a climate cause when faced with a probabilistic choice involving real financial stakes.

More generally, our analyses thus far allow us to rule out several potential mechanisms. First, the relatively small and imprecisely estimated effects of fantasy assets reported in Table 1 suggest that our primary effects are not merely driven by rising salience in response to treatment. Indeed, it appears that for exposure to generate meaningful impacts for policy support, salience of financial assets is insufficient, and respondents must have a positive financial stake in the market to incur learning-related costs. Second, the positive and precisely estimated effects of assignment to both green and brown assets reported in Table 1 suggests that our effects are not driven by motivated beliefs. Motivated beliefs could potentially explain preference change among respondents receiving exposure to green assets. However, the substantial effects we identify among respondents endowed with brown portfolios suggest that motivated beliefs are an unlikely mechanism in our case. Third, the relative similarity in effect magnitude among respondents endowed with portfolios with varying values (presented in Table A10) suggests that our primary mechanism is not purely income effects, that could shape attitudes and preferences. In the next section, we leverage a range of unique design features and secondary outcomes to consider which mechanisms drive our main effects.

5.1 Learning Mechanisms

Our primary treatment—financial exposure—was designed to motivate participants to learn about financial markets, and in particular about energy-sector firms whose cash flows and stock prices are directly affected by climate policy. We hypothesize that such learning could potentially shape beliefs about climate change, and, in turn, increase support for mitigation action as well as intentions to adapt personally to climate change. In this section, we provide evidence consistent with a learning mechanism. Specifically, we show that our primary treatment increases consumption of financial news while reducing reliance on partisan and social media sources, and leads to greater objective knowledge of firms' emissions, more favorable and informed assessments of firms' broader environmental impact, and increased financial confidence.

5.1.1 Media Consumption

We measure media consumption by asking respondents to report where they had obtained news during the previous week, allowing them to select from a list of platforms (including cable news, local news, major newspapers, financial news and social media) or to enter additional sources. Using this measure, we analyze changes in respondents' media diets at both midline and endline. We present these results in Table 3. In

Table 3: Real Asset Treatment Effect on Media Consumption

Outcome	Real Asset Treatment	SE	$p\ (\lvert\beta\rvert = 0)$	N
Midline				
Major TV Networks (ABC, NBC,CBS)	−0.020	0.030	0.493	3420
Major Newspapers (NYT, USA Today, Washington Post)	−0.025	0.027	0.339	3420
Local News	0.033	0.035	0.345	3420
Financial News (WSJ, Yahoo Finance, Financial Times, Other)	0.088***	0.030	0.003	3420
Fox News	−0.045	0.027	0.101	3420
Social Media	−0.030	0.032	0.359	3420
Endline				
Major TV Networks (ABC, NBC,CBS)	−0.037	0.035	0.283	3587
Major Newspapers (NYT, USA Today, Washington Post)	−0.031	0.030	0.302	3587
Local News	0.033	0.040	0.401	3587
Financial News (WSJ, Yahoo Finance, Financial Times, Other)	0.102***	0.035	0.004	3587
Fox News	−0.080**	0.032	0.011	3587
Social Media	−0.139***	0.037	0.000	3587

Note: This table reports OLS estimates of the real asset treatment effect on standardized media consumption outcomes. The *Real Asset Treatment* compares participants assigned real-value portfolios ($50 or $100) to fantasy treatment (not shown) against the control (not trading). Outcomes are z-scored standardized measures based on responses to the question "Where did you get your news from this week (select all that apply)?" measured at midline and endline. All regressions control for post-double selection (p-ds) LASSO-selected baseline covariates and block fixed effects accounting for randomization strata (stratified by party identification, geographic region, climate policy prioritization, and prior trading experience), and fantasy portfolio assignment. Endline regressions additionally control for climate disclosure treatment. Robust standard errors reported. Stars denote two-tailed significance: *** p<0.01, ** p<0.05, * p<0.1. Two-sided p-values reported in column 4.

line with our prior that treated respondents would be incentivized to seek information regarding the risks and returns associated with their portfolios, we find strong evidence that exposure to financial markets leads participants to change their media consumption. Specifically, exposure to financial markets increases consumption of financial news by 0.088 SDs at midline, and by 0.102 SDs at endline (p-value<0.001 for both). At endline, treated respondents are also significantly less likely to consume news via social media (0.139 SDs, p-value <0.001), which is is more likely to feature polarized content (Braghieri et al., 2024). We additionally observe reductions in consumption of Fox News (0.080 SDs, p-value <0.005), and smaller, less precisely estimated declines in consumption of major TV networks and major newspapers (0.037 SDs and 0.031 SDs, respectively) at both midline and endline.

Taken together, these results indicate that exposure to financial markets motivates treated respondents to shift their media diets away from polarized sources (e.g., social media) towards outlets that provide information relevant to financial markets (e.g. WSJ and Yahoo Finance). We next examine whether this shift in information consumption translates into measurable learning, by testing for changes in objective knowledge and subjective assessments of portfolio firms' environmental impacts.

5.1.2 Knowledge and Perception of Environmental Impacts of Energy Assets Allocated in the Treatment

To further evaluate our learning mechanism, we elicit both objective and subjective assessments of the environmental impacts of assets included in the treatment. We measure objective knowledge by testing respondents' knowledge of firms' greenhouse gas (GHG) emissions. Specifically, respondents were asked to estimate each company's annual CO_2-equivalent emissions by order of magnitude (e.g. "thousands of tons," "millions of tons," and so on).[21] Table 4 shows that respondents assigned to treatment are more likely to correctly identify firms' emission levels by 0.160 SDs relative to the control group. This effect is larger for those respondents allocated real assets, at 0.185 SDs (p-value < 0.01, one-sided), than those allocated fantasy assets, whose estimated effect is 0.054 SDs. We can reject equality of real- and fantasy-asset treatment effects, consistent with the larger impacts in overall support for climate action observed for the real-assets group in Table 1. Both real green and real brown asset arms exhibit increases in emissions knowledge. While the point estimate is larger for respondents initially assigned green assets, we cannot reject the null hypothesis that the treatment for the two real-asset arms are equal.

Complementing the findings in Table 4, Table 5 shows that the treatment also affects respondents' subjective evaluations of firms' environmental impacts. Respondents were asked to rate the environmental impact of each company included in the intervention on a seven-point scale ranging from "extremely negative" to "extremely positive." We standardize these responses to create an index of perceptions of firms' climate impact. Table 5 shows that treated respondents were more likely to rate green assets as having a positive environmental impact and brown assets as having a negative environmental impact. The estimated effects are symmetric in magnitude, with perceptions increasing by 0.106 SD for green firms and reducing by 0.111 SD for brown firms (one-tailed p-values < 0.10 for both). These effects are not mechanical, as respondents evaluated the environmental impact of each firm (green and brown) separately.[22]

5.1.3 Financial Knowledge and Confidence

In this section, we test whether exposure to the treatment also increases respondents' general financial knowledge and confidence. We hypothesize that exposure to financial markets and opportunities to trade encourages individuals to learn about investing, which includes factors that affect the value of their assets. While such learning includes climate-related knowledge when participants are endowed with energy-sector assets, the treatment should also promote broader learning about financial markets and investing. To examine whether the treatment leads to such generalized learning, we follow Jha and Shayo (2025) and Lusardi and Mitchell (2014), constructing a financial confidence index that combines respondents' willingness to invest in the future, their risk taking preferences, and answers to the *Big Three* financial literacy test questions. We

[21] This question was embedded in the endline survey for non-compliers and control group participants, and in the final trading survey for compliers. For the precise wording of this question, see B.2.

[22] This question was embedded in the final trading survey for compliers, and in the endline survey for non-compliers (those who did not answer the trading surveys). For the precise wording of this question, see B.2.

Table 4: Effect of Treatment on Total Correct Emissions Answers (Endline)

Correct Emissions	(1)	(2)	(3)
Pooled Treatment	0.160***		
	(0.045)		
Real Assets		0.185***	
		(0.046)	
Real Green			0.215***
			(0.054)
Real Brown			0.155***
			(0.053)
Fantasy Assets		0.054	0.053
		(0.068)	(0.068)
Observations	3276	3276	3276
p (Pooled Treatment > 0)	0.000		
p (Real Assets > 0)		0.000	
p (Real Assets > Fantasy Assets)		0.018	
p (Real Green > Real Brown)			0.141

Note: This table reports OLS estimates of the effect of trading treatment on standardized emissions knowledge outcomes measured at endline. Outcomes are z-scored indices of correct answers to the question: "In your opinion, how many tons of CO2 equivalent annual greenhouse gas do each of these companies produce?" with answers given in order of magnitude. *Pooled Treatment* compares all participants assigned financial market exposure (real and fantasy portfolios, n=2,406, with n representing the number of participants assigned treatment at baseline) versus control (n=1,400). *Real Assets* pools participants assigned \$50 or \$100 real-value portfolios (n=1,907), while *Fantasy Assets* includes those assigned \$100 fantasy portfolios (n=499). *Real Green* and *Real Brown* separately estimate effects for participants initially assigned real green energy stocks (n=953) versus real brown energy stocks (n=954). All regressions control for post-double selection (p-ds) LASSO-selected baseline covariates and block fixed effects accounting for randomization strata (stratified by party identification, geographic region, climate policy prioritization, and prior trading experience). Endline regressions additionally control for climate disclosure treatment status. Robust standard errors in parentheses. Stars denote two-tailed p-values: *** p<0.01, ** p<0.05, * p<0.10. One-tailed p-values for directional hypotheses reported in bottom rows.

Table 5: Effect on Perception of Climate Impact (Endline)

Perception of Climate Impact	Green Firms			Brown Firms		
	(1)	(2)	(3)	(4)	(5)	(6)
Pooled Treatment	0.106**			-0.111***		
	(0.043)			(0.039)		
Real Assets		0.124***			-0.087**	
		(0.045)			(0.041)	
Real Green			0.130**			-0.042
			(0.052)			(0.047)
Real Brown			0.111**			-0.123***
			(0.052)			(0.046)
Fantasy Assets		0.034	0.030		-0.209***	-0.205***
		(0.064)	(0.063)		(0.054)	(0.053)
Observations	3290	3290	3290	3291	3291	3291
p (| Pooled Treatment | $>$ 0)	0.007			0.002		
p (| Real Assets | $>$ 0)		0.003			0.016	
p (Real Assets $>$ Fantasy Assets)		0.061			0.006	
p (Real Green $>$ Real Brown)			0.364			0.042

Note: This table reports OLS estimates of the trading treatment on standardized z-score indices created from respondents' answers on a 1-7 scale to the question: "How impactful are each of these companies on the environment." Columns (1)-(3) show effects on perceived environmental impact of green firms; columns (4)-(6) show effects on perceived impact of brown firms. *Pooled Treatment* compares all participants assigned financial market exposure (real and fantasy portfolios, n=2,406, with n representing the number of participants assigned treatment at baseline) versus control (n=1,400). *Real Assets* pools participants assigned $50 or $100 real-value portfolios (n=1,907), while *Fantasy Assets* includes those assigned $100 fantasy portfolios (n=499). *Real Green* and *Real Brown* separately estimate effects for participants initially assigned real green energy stocks (n=953) versus real brown energy stocks (n=954). All regressions control for post-double selection (p-ds) LASSO-selected baseline covariates and block fixed effects accounting for randomization strata (stratified by party identification, geographic region, climate policy prioritization, and prior trading experience). Endline regressions additionally control for climate disclosure treatment status. Robust standard errors in parentheses. Stars denote two-tailed p-values: *** p<0.01, ** p<0.05, * p<0.10. One-tailed p-values for directional hypotheses reported in bottom rows. For pooled and real asset treatment, direction of hypothesis is that treatment will increase magnitude of perception of green firms (positive) and decrease perception of brown firms (negative).

Table 6: Effect of Treatment on Financial Confidence Index

Financial Confidence Index	Midline			Endline		
	(1)	(2)	(3)	(4)	(5)	(6)
Pooled Treatment	-0.015			0.067**		
	(0.030)			(0.032)		
Real Assets		-0.004			0.088***	
		(0.031)			(0.033)	
Real Green			-0.050			0.073*
			(0.038)			(0.038)
Real Brown			0.039			0.095**
			(0.037)			(0.038)
Fantasy Assets		-0.090*	-0.089*		-0.013	-0.016
		(0.047)	(0.047)		(0.046)	(0.046)
Observations	3420	3420	3420	3587	3587	3587
p (Pooled Treatment > 0)	0.692			0.019		
p (Real Assets > 0)		0.552			0.004	
p (Real Assets > Fantasy Assets)		0.030			0.007	
p (Real Green > Real Brown)			0.982			0.718

Note: This table reports OLS estimates of the trading treatment on a general index of financial confidence measured at midline and endline. The financial confidence index is a z-score index constructed from the following standardized components: the willingness of participants to invest in the future, their own assessment of risk, and total (out of 3) basic financial literacy questions they answered correctly. *Pooled Treatment* compares all participants assigned financial market exposure (real and fantasy portfolios, n=2,406, with n representing the number of participants assigned treatment at baseline) versus control (n=1,400). *Real Assets* pools participants assigned $50 or $100 real-value portfolios (n=1,907), while *Fantasy Assets* includes those assigned $100 fantasy portfolios (n=499). *Real Green* and *Real Brown* separately estimate effects for participants initially assigned real green energy stocks (n=953) versus real brown energy stocks (n=954). All regressions control for post-double selection (p-ds) LASSO-selected baseline covariates and block fixed effects accounting for randomization strata (stratified by party identification, geographic region, climate policy prioritization, and prior trading experience). Midline regressions (columns 1-3) control for fantasy portfolio assignment; endline regressions (columns 4-6) additionally control for climate disclosure treatment status. Robust standard errors in parentheses. Stars denote two-tailed p-values: *** p<0.01, ** p<0.05, * p<0.10. One-tailed p-values for directional hypotheses reported in bottom rows.

present our primary treatment effects on financial confidence in Table 6.

The financial confidence index does not significantly differ from the control group at midline. By endline, however, as respondents gain more experience trading in financial markets, the treatment effect becomes larger, amounting to an overall increase of 0.067 SDs (one-tailed p-value < 0.05). Consistent with our earlier findings, this effect is driven by respondents allocated with real assets: the estimated effect for the real-asset treatment arm is 0.088 SDs (one-sided p-value < 0.01), which is significantly larger than the estimate for the fantasy-asset arm (point estimate of -0.013 SD, not statistically different from zero). Importantly, treatment effects are similar for respondents endowed with green and brown portfolios alike (0.073 SDs for the real green arm and 0.095 SDs for the real brown arm), and we cannot reject the equality of these coefficients. We interpret these findings as evidence that, in addition to acquiring climate-specific knowledge, treated respondents also gain broader financial knowledge and confidence.

Taken together, these additional analyses suggest that exposure to financial markets catalyzes a learning process by motivating changes in media consumption that increases both climate-related and broader financial knowledge. These results underscore how exposure to financial markets, and specifically assets in the energy sector, facilitates non-paternalistic learning. Rather than informing citizens of optimal climate policies, our intervention encourages them to seek out information independently, acquire credible knowledge, and form their own informed policy preferences. Our evidence emphasizes that this process can effectively increase support for climate mitigation action as well as intentions to adapt.

6 Long Term Effects

Thus far, we find that exposure to financial assets in the energy sector (both green and brown) incentivizes learning, which in turn increases investors' beliefs in anthropogenic climate change, support for climate mitigation, and intentions to adapt. A natural question is whether these effects persist in the long-run, even after respondents are divested from their assets. Ex-ante, persistence is ambiguous for several reasons. On the one hand, respondents may have paid attention to climate mitigation benefits primarily while holding the assets, such that divestment reduces incentives to continue learning, or knowledge acquired during trading may decay over time. In this case, treatment effects would be expected to fade. On the other hand, once acquired, this knowledge may durably shift beliefs and preferences, or respondents may retain what they learned, leading effects to persist even after divestment.

To investigate the persistence of these effects, we administered a final follow-up survey between June 2 and June 18, 2025, approximately seven months following the final trading survey (and more than eight months post-treatment assignment), conducted on November 8, 2024.[23] We successfully recontacted 2,959 study participants, corresponding to a 78% response rate. As shown in Table A5, there is no differential attrition by treatment. Outcome measures in the follow-up survey mirror those used in the midline and endline surveys.

Table 7 presents long-term treatment effects on the primary climate index. We find that eight months post-treatment, when respondents have long since divested from their assets, treatment effects for those allocated real assets remain positive, albeit smaller in magnitude and more imprecisely estimated.[24] Exposure to financial markets increases pro-climate preferences measured by the overall index by 0.038 SDs ($p < 0.05$, one-tailed test). Several components of the index exhibit more persistent effects. In particular, treated respondents continues to hold more positive beliefs about the benefits of the green transition, with an estimated effect of 0.036 SDs (one-tailed p-value$<$ 0.10), and show increased support for government-led mitigation action, with an effect of 0.087 SDs (one-tailed p-value$<$ 0.05). Other sub-indices show positive but smaller effects and less precisely estimated effects, including the likelihood that climate considerations influence longer-run life decisions (0.047 SDs, one-tailed p-value $<$ 0.10) and willingness to donate to a climate-related cause (0.050 SDs, one-tailed p-value$<$ 0.10).

Overall, these results indicate that the positive effects of financial market exposure on support for climate action attenuate over time but remain directionally positive, indicating that exposure to financial markets can

[23] Appendix B.2 provides details on the implementation of this survey.
[24] We present pooled treatment effect estimates in Table A21.

Table 7: Real Asset Treatment Effect on Components of Climate Action Support Index Eight Months Post-Treatment

Outcome	Real Asset Treatment	SE	p ($\|\beta\| > 0$)	N
Overall Climate Action Support Index	0.038*	0.023	0.048	2934
Beliefs About Human Agency and Tradeoffs				
Climate Beliefs Index	0.010	0.031	0.375	2934
Transition Benefits Beliefs	0.036	0.028	0.098	2922
Transition Costs Beliefs	−0.033	0.035	0.173	2922
Policy Preferences				
Support for Government Action	0.087**	0.042	0.019	2914
Support for Business Action	0.001	0.034	0.490	2914
Climate Policy Salience	−0.047	0.033	0.920	2892
Pro-Climate Personal Decisions and Behaviors				
Daily Decisions	0.023	0.028	0.208	2911
Donate to Climate Cause (Yes/No)	0.050	0.038	0.093	2910
Investment and Life Decisions	0.047	0.035	0.092	2931

Note: This table reports OLS estimates of the real asset treatment effect on the *Climate Action Support Index (CASI)* and its nine component sub-indices measured eight months post-treatment. The *Real Asset Treatment* compares participants assigned real-value portfolios ($50 or $100) to control. All regressions control for post-double selection (p-ds) LASSO-selected baseline covariates and block fixed effects accounting for randomization strata (stratified by party identification, geographic region, climate policy prioritization, and prior trading experience), as well as climate disclosure treatment status and fantasy portfolio assignment. Robust standard errors reported. Stars denote two-tailed significance: *** p<0.01, ** p<0.05, * p<0.10. One-tailed p-values reported in column 4.

durably shape climate policy preferences, albeit with partial decay. More generally, our long term positive estimates are especially notable, given that most interventions and information treatments in the existing literature on building mitigation support focus on immediate impacts, rendering questions of durability mostly unexplored. Thus, we cannot benchmark the magnitude of our long-term estimates against those of other information treatments. But it is worth nothing that both our shorter-run and long-term effects are similar in magnitude to the immediate effects found in a multi-arm replication of top-cited climate-related information interventions (Voelkel et al., 2026).

Complementing our main long-term estimates reported in Table 7, we also report long-run treatment effects on the main mechanisms-related outcomes in the Appendix. Table A23 shows that treated respondents remain more likely to correctly identify the GHG emissions of firms included in the treatment, with an effect of 0.109 SDs for the real assets arm (one-tailed p-value <0.01). This effect is smaller in magnitude than the corresponding estimate at endline, six weeks post-treatment inception. Table A24 shows that treated respondents continue to hold more positive perceptions of the environmental impact of green firms (an effect driven by respondents allocated real assets), while perceptions of brown firms are no longer statistically different from those of the control group. Table A25 shows that financial confidence remains persistently higher for respondents in the real-assets arm (effect of 0.066 SDs, one sided p-value < 0.05). Finally, Table A22 presents long-run effects on media consumption, and shows no statistically significant differences relative to the control group. This pattern suggests that respondents adjusted their media diets primarily while they held financial stakes in the assets, and that these changes in information consumption do not persist once ownership ends.

7 Additional Analyses and Robustness Checks

In this section, we present additional analyses, as well as show robustness of the main result to alternative specifications.

First, we present an additional piece of evidence in support of the learning mechanism. In Table 8 we consider treatment effects by pre-treatment support for climate action. To do so, we divided our sample into sub-samples of respondents reporting lower than (above) median values on the overall climate index. These results show that treatment effects are driven by individuals with lower baseline support for climate action. Indeed, although measured with some degree of uncertainty, estimates for the below median subsample more than four times larger at midline, about 1.6 times larger at endline, and almost five times larger eight months post-treatment. This is consistent with learning and belief updating as the primary mechanism, in line with the changes in media consumption and knowledge we document earlier. We also present this heterogeneity analysis using a double interaction specification in Tables A8-A9, and find consistent results. Thus, the treatment broadens support for mitigation action, by inducing greater support among individuals with lower ex-ante support for climate action.

Furthermore, as mentioned earlier, in Table A5 we examine whether patterns of attrition in our three post-treatment surveys correlate with treatment status. To do so, we follow our main empirical specification. We regress a measure of post-treatment attrition over a treatment indicator, and include block fixed effects and LASSO selected covariates. We find no consistent evidence that any of our treatments influence attrition measured.

In our main analyses, we employ LASSO for covariate selection (Belloni, Chernozhukov and Hansen, 2013), considering all baseline survey measures as potential covariates. In Table A6 we report our main specification, based on a limited set of potential covariates to be selected for covariate adjustment. These potential covariates include: all pre-treatment sub-indices that create our primary climate support index, as well as age, race, gender, trading experience, education, and party ID. Like in our main specification, all regressions include block fixed effects. Our results remain very similar to the main specification.

As noted in Section 3, in our main endline specification we account for our secondary disclosure treatment. In Table A7, we report additional analyses that adjust for disclosures at midline prior to their roll-out, as well as at endline following their roll-out. Across all models reported in Table A7, our primary estimates remain similar, and the effects of disclosures are mostly small and imprecisely estimated.

Finally, in Tables A8-A9, we further examine (pre-specified) treatment effect heterogeneity. We focus on a range of theoretically motivated pre-treatment covariates, including baseline support for mitigation, party identification, past trading experience, risk tolerance, exposure to FEMA hurricane aid, exposure to negative impacts of the green transition, polarization, and stock price performance (for initial stocks exogenously endowed to respondents). For the most part (with baseline climate preferences being the exception), we do

Table 8: Examining Effects

Wave	Real Asset Treatment	SE	p $(\|\beta\| > 0)$	N	Control Mean
Below Median					
Midline	0.078***	0.026	0.002	1688	-0.730
Endline	0.086***	0.030	0.002	1791	-0.702
FollowUp	0.068*	0.035	0.027	1465	-0.703
Above Median					
Midline	0.018	0.025	0.231	1711	0.682
Endline	0.055**	0.028	0.024	1775	0.690
FollowUp	0.014	0.031	0.325	1442	0.695

Note: This table reports OLS estimates of the effect of real asset treatment on the standardized *Climate Action Support Index (CASI)* separately for participants above and below the median pre treatment climate preferences across different waves of the study. The *Real Asset Treatment* compares participants assigned real-value portfolios to control. See the heterogeneous treatment effects table (A8 and A9) for further information. All regressions control for post-double selection (p-ds) LASSO-selected baseline covariates and block fixed effects accounting for randomization strata (stratified by party identification, geographic region, climate policy prioritization, and prior trading experience). Each subsample has its own LASSO-selected controls. Midline regressions control for fantasy portfolio assignment; endline and follow-up regressions additionally control for climate disclosure treatment status. Robust standard errors reported. P-values are one-sided in the direction of the estimated coefficient. Stars denote two-tailed significance: *** p<0.01, ** p<0.05, * p<0.10.

not find strong and consistent treatment effect heterogeneity along these pre-specified covariates.[25]

8 Conclusion

Effective climate mitigation policies have the potential to save millions of lives (Carleton et al., 2022), yet achieving meaningful climate action requires broad-based political support (Gazmararian, Mildenberger and Tingley, 2025). Such support is increasingly undermined by the uneven short-term costs of mitigation policies (Stokes, 2016; Gaikwad, Genovese and Tingley, 2022) and growing polarization over climate change (Chinn, Hart and Soroka, 2020; Falkenberg et al., 2022; Bosetti et al., 2025). We show that durable support for climate mitigation can be fostered through exposure to financial markets—specifically, to energy-sector stocks whose cash flows and stock prices are directly affected by climate policy.

Such exposure induces respondents to shift their news consumption away from outlets with polarized news, particularly social media, toward financial news outlets. They acquire greater knowledge about financial markets and the firms in which they are invested, and develop more informed views of those firms' environmental risks and impacts. Together, these changes translate into increased and persistent support for climate mitigation. More broadly, while financial markets are sometimes construed as zero-sum, tailored exposure to investment opportunities can enable individuals to learn about, participate in, and benefit from investment, diversification, and broadly-shared gains, including those associated with the green transition. These mechanisms are likely to be increasingly salient as the recent democratization of finance—advances in financial technology—continues to lower barriers to participation in financial markets.

[25] While our pilot survey (Appendix A) established that survey respondents distinguish between green and brown assets, especially in terms of their environmental impacts, we do not have pre-treatment measures of companies expected environmental impact or climate exposure. Thus we cannot estimate heterogeneity based on these measures.

These results have several policy implications. First, they highlight the potential of financial innovations as instruments for learning and building policy support on complex issues. Identifying engaging ways to increase citizens' awareness of their stakes in financial markets (e.g., via passive investment vehicles such as pension plans) may encourage learning about financial markets with positive downstream effects on climate-related preferences and behaviors.

As the same time, direct and indirect exposure to financial markets remains limited in many contexts worldwide. One promising way to expand such exposure is to complement existing cash transfer programs—often implemented in communities vulnerable to climate shocks or to the uneven distributional consequences of the green transition—with financial instruments. Combining direct transfers with tailored financial portfolios could allow recipients to diversify against climate-related risks while directly benefiting from the economic opportunities created by the transition. Finally, financial literacy interventions that improve individuals' ability to assess risks and returns of different financial assets may further shape policy preferences by clarifying the economic trade-offs associated with climate mitigation. Such interventions could therefore help reduce polarization around climate policies that are otherwise perceived as costly or contentious.

These findings also raise several other avenues for further research. First, future work should examine whether even longer-term exposure to financial markets, or exposure through larger investment portfolios, produces similar or divergent effects. We expect these more intensive forms of exposure to strengthen incentives for learning, potentially amplifying the effects we document above. Second, future work should examine whether the effects of exposure to financial markets on climate-related knowledge translates into downstream adaptive behaviors, including investment in insurance or other protective measures to mitigate the consequences of weather shocks. Finally, extending our individual-level estimates, one may consider the extent to which informational effects of exposure to financial markets diffuse along social ties to network peers. These and related questions remain open for future work, and would speak to understanding the broader reach of market-based interventions to increase support for climate action.

References

Allcott, Hunt. 2011. "Social norms and energy conservation." *Journal of public Economics* 95(9-10):1082–1095.

Anagol, Santosh, Vimal Balasubramaniam and Tarun Ramadorai. 2018. "Endowment effects in the field: Evidence from India's IPO lotteries." *The Review of Economic Studies* 85(4):1971–2004.

Anderson, Anders and David T Robinson. 2019. "Climate fears and the demand for green investment." *Swedish House of Finance Research Paper* (19-14).

Arias, Sabrina B and Christopher W Blair. 2024. "In the eye of the storm: Hurricanes, climate migration, and climate attitudes." *American Political Science Review* 118(4):1593–1613.

Baccini, Leonardo and Lucas Leemann. 2021. "Do natural disasters help the environment? How voters respond and what that means." *Political Science Research and Methods* 9(3):468–484.

Belloni, Alexandre, Victor Chernozhukov and Christian Hansen. 2013. "Inference on Treatment Effects after Selection among High-Dimensional Controls†." *The Review of Economic Studies* 81(2):608–650.

Bernstein, Asaf, Matthew T Gustafson and Ryan Lewis. 2019. "Disaster on the horizon: The price effect of sea level rise." *Journal of financial economics* 134(2):253–272.

Bolsen, Toby and James N Druckman. 2018. "Do partisanship and politicization undermine the impact of a scientific consensus message about climate change?" *Group Processes & Intergroup Relations* 21(3):389–402.

Bosetti, Valentina, Italo Colantone, Catherine E. de Vries and Giorgio Musto. 2025. Green backlash and right-wing populism. Working Paper Series 26 Bocconi Milan: .

Braghieri, Luca, Sarah Eichmeyer, R Levy, MM Mobius, J Steinhardt and R Zhong. 2024. "Article level slant and polarization of news consumption on social media." *Available at SSRN* 4932600.

Briere, Marie and Stefano Ramelli. 2020. *Personal values, responsible investing and stock allocation*. Netspar, Network for Studies on Pensions, Aging and Retirement.

Broockman, David E, Elizabeth Rhodes, Alexander W Bartik, Karina Dotson, Sarah Miller, Patrick K Krause and Eva Vivalt. 2024. The Causal Effects of Income on Political Attitudes and Behavior: A Randomized Field Experiment. Technical report National Bureau of Economic Research.

Buccione, Giulia. 2023. Religious messaging and adaptation to water scarcity: Evidence from Jordan. Technical report Working paper.

Bucher-Koenen, Tabea, Bennet Janssen, Caroline Knebel and Panagiota Tzamourani. 2023. "Financial literacy, stock market participation, and financial wellbeing in Germany." *Journal of Financial Literacy and Wellbeing* 1(3):486–513.

Burke, Marshall, Solomon M Hsiang and Edward Miguel. 2015. "Global non-linear effect of temperature on economic production." *Nature* 527(7577):235–239.

Carleton, Tamma, Amir Jina, Michael Delgado, Michael Greenstone, Trevor Houser, Solomon Hsiang, Andrew Hultgren, Robert E Kopp, Kelly E McCusker, Ishan Nath et al. 2022. "Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits." *The Quarterly Journal of Economics* 137(4):2037–2105.

Chinn, Sedona, P Sol Hart and Stuart Soroka. 2020. "Politicization and polarization in climate change news content, 1985-2017." *Science Communication* 42(1):112–129.

Coglianese, John, Todd Gerarden and James Stock. 2020. "The Effects of Fuel Prices, Environmental Regulations and Other Factors on US Coal Production, 2008-2016." *Energy Journal* 40(1):55–82.

Dechezleprêtre, Antoine, Adrien Fabre, Tobias Kruse, Bluebery Planterose, Ana Sanchez Chico and Stefanie Stantcheva. 2025. "Fighting Climate Change: International Attitudes toward Climate Policies." *American Economic Review* 115(4):1258–1300.

Drews, Stefan and Jeroen CJM Van den Bergh. 2016. "What explains public support for climate policies? A review of empirical and experimental studies." *Climate policy* 16(7):855–876.

Energy Policy Institute. 2024. 2024 Poll: Americans' Views on Climate Change and Policy in 12 Charts. Technical report University of Chicago, Energy Policy Institute.

Falkenberg, Max, Alessandro Galeazzi, Maddalena Torricelli, Niccolò Di Marco, Francesca Larosa, Madalina Sas, Amin Mekacher, Warren Pearce, Fabiana Zollo, Walter Quattrociocchi et al. 2022. "Growing polarization around climate change on social media." *Nature Climate Change* 12(12):1114–1121.

Feinberg, Matthew and Robb Willer. 2011. "Apocalypse soon? Dire messages reduce belief in global warming by contradicting just-world beliefs." *Psychological science* 22(1):34–38.

Feinberg, Matthew and Robb Willer. 2013. "The moral roots of environmental attitudes." *Psychological science* 24(1):56–62.

Ferraro, Paul J and Michael K Price. 2013. "Using nonpecuniary strategies to influence behavior: Evidence from a large-scale field experiment." *Review of Economics and Statistics* 95(1):64–73.

Gaikwad, Nikhar, Federica Genovese and Dustin Tingley. 2022. "Creating climate coalitions: mass preferences for compensating vulnerability in the world's two largest democracies." *American Political Science Review* 116(4):1165–1183.

Gazmararian, Alexander F. 2025. “Sources of Partisan Change: Evidence from the Shale Gas Shock in American Coal Country.” *The Journal of Politics* 87(2):601–615.

Gazmararian, Alexander F and Dustin Tingley. 2023. *Uncertain futures: How to unlock the climate impasse*. Cambridge University Press.

Gazmararian, Alexander F, Matto Mildenberger and Dustin Tingley. 2025. “Public opinion foundations of the clean energy transition.” *Environmental Politics* pp. 1–23.

Golman, Russell, David Hagmann and George Loewenstein. 2017. “Information avoidance.” *Journal of economic literature* 55(1):96–135.

Gosnell, Greer K, John A List and Robert D Metcalfe. 2020. “The impact of management practices on employee productivity: A field experiment with airline captains.” *Journal of Political Economy* 128(4):1195–1233.

Gustafson, Abel. 2025. “Yale program on climate change communication.” *Journal of Applied Communication Research* 53(1):73–75.

Hazlett, Chad and Matto Mildenberger. 2020. “Wildfire exposure increases pro-environment voting within democratic but not republican areas.” *American Political Science Review* 114(4):1359–1365.

Hilbig, Hanno and Sascha Riaz. 2024. “Natural disasters and green party support.” *The Journal of Politics* 86(1):241–256.

Hornsey, Matthew J, Emily A Harris, Paul G Bain and Kelly S Fielding. 2016. “Meta-analyses of the determinants and outcomes of belief in climate change.” *Nature climate change* 6(6):622–626.

Hsiang, Solomon, Robert Kopp, Amir Jina, James Rising, Michael Delgado, Shashank Mohan, D. J. Rasmussen, Robert Muir-Wood, Paul Wilson, Michael Oppenheimer, Kate Larsen and Trevor Houser. 2017. “Estimating economic damage from climate change in the United States.” *Science* 356(6345):1362–1369.

IPCC. 2022. “Sixth Assessment Report: Impacts, Adaptation and Vulnerability.”. Working Group II Contribution to the Sixth Assessment Report.

Ito, Koichiro, Takanori Ida and Makoto Tanaka. 2018. “Moral suasion and economic incentives: Field experimental evidence from energy demand.” *American Economic Journal: Economic Policy* 10(1):240–267.

Jessoe, Katrina and David Rapson. 2014. “Knowledge is (less) power: Experimental evidence from residential energy use.” *American Economic Review* 104(4):1417–1438.

Jha, Saumitra. 2025. “Resisting Populism through Financial Market Exposure: Experimental Evidence from Brexit.” *Stanford GSB Research Paper 4266* .

Jha, Saumitra and Moses Shayo. 2019. "Valuing peace: the effects of financial market exposure on votes and political attitudes." *Econometrica* 87(5):1561–1588.

Jha, Saumitra and Moses Shayo. 2025. "Trading Stocks Builds Financial Confidence and Compresses the Gender Gap." *Economic Journal* 135(655):235–263.

Jha, Saumitra, Moses Shayo and Chagai M Weiss. 2025. "Financial market exposure increases generalized trust." *Journal of Public Economics* 242:105303.

Jones, Charlotte, Donald W Hine and Anthony DG Marks. 2017. "The future is now: Reducing psychological distance to increase public engagement with climate change." *Risk Analysis* 37(2):331–341.

Keohane, Robert O and David G Victor. 2016. "Cooperation and discord in global climate policy." *Nature Climate Change* 6(6):570–575.

Kling, Jeffrey R, Jeffrey B Liebman and Lawrence F Katz. 2007. "Experimental analysis of neighborhood effects." *Econometrica* 75(1):83–119.

Knittel, Christopher R and Samuel Stolper. 2019. Using machine learning to target treatment: The case of household energy use. Technical report National Bureau of Economic Research.

Loy, Laura S and Alexa Spence. 2020. "Reducing, and bridging, the psychological distance of climate change." *Journal of Environmental Psychology* 67:101388.

Lusardi, Annamaria and Olivia S. Mitchell. 2014. "The Economic Importance of Financial Literacy: Theory and Evidence." *Journal of Economic Literature* 52(1):5–44.

Margalit, Yotam and Moses Shayo. 2021. "How markets shape values and political preferences: A field experiment." *American Journal of Political Science* 65(2):473–492.

Meeuwis, Maarten, Jonathan A Parker, Antoinette Schoar and Duncan Simester. 2022. "Belief disagreement and portfolio choice." *The Journal of Finance* 77(6):3191–3247.

Mildenberger, Matto, Alexander Sahn, Chris Miljanich, Michelle A Hummel, Mark Lubell and Jennifer R Marlon. 2024. "Unintended consequences of using maps to communicate sea-level rise." *Nature Sustainability* 7(8):1018–1026.

Ranney, Michael Andrew and Dav Clark. 2016. "Climate change conceptual change: Scientific information can transform attitudes." *Topics in cognitive science* 8(1):49–75.

Rivera, Eduardo, Enrique Seira and Saumitra Jha. 2025. "Apex Corruption Erodes Democratic Values." *Stanford University Graduate School of Business Research Paper* 4166.

Stokes, Leah C. 2016. "Electoral backlash against climate policy: A natural experiment on retrospective voting and local resistance to public policy." *American Journal of Political Science* 60(4):958–974.

Sunstein, Cass R, Sebastian Bobadilla-Suarez, Stephanie C Lazzaro and Tali Sharot. 2016. "How people update beliefs about climate change: Good news and bad news." *Cornell L. Rev.* 102:1431.

Vlasceanu, Madalina, Kimberly C Doell, Joseph B Bak-Coleman, Boryana Todorova, Michael M Berkebile-Weinberg, Samantha J Grayson, Yash Patel, Danielle Goldwert, Yifei Pei, Alek Chakroff et al. 2024. "Addressing climate change with behavioral science: A global intervention tournament in 63 countries." *Science advances* 10(6):eadj5778.

Voelkel, Jan G, Ashwini Ashokkumar, Adina T Abeles, Jarret T Crawford, Kylie Fuller, Chrystal Redekopp, Renata Bongiorno, Troy H Campbell, Ullrich KH Ecker, Matthew Feinberg et al. 2026. "A registered report megastudy on the persuasiveness of the most-cited climate messages." *Nature Climate Change* pp. 1–12.

Zhou, Jack. 2016. "Boomerangs versus javelins: How polarization constrains communication on climate change." *Environmental politics* 25(5):788–811.

Seeing Green: The Effects of Financial Exposure on Climate Beliefs and Political Attitudes

Supplementary Information

A Asset Evaluation Pilot Survey

We selected our renewable energy and fossil fuel assets to be stocks with high market capitalization, but clearly different in terms of their expected climate impact. To ensure our selection aligned with survey respondents' perceptions and evaluations of our selected financial assets, before rolling out our experiment we ran a brief pilot survey with 102 respondents using the same survey provider (Forthright/Bovitz). Our primary goal was to ensure that respondents clearly differentiate between renewable energy and fossil fuel assets in terms of their environmental impact.

Our survey provided respondents a one-sentence description of each financial asset (the same as in the main experiment, listed in Table A4), and asked respondents to assess the environmental impact of the asset on a 1-7 scale (ranging from extremely negative to extremely positive). Figure A1 clearly demonstrates that all renewable energy assets have a higher rating, compared to fossil fuel assets. Indeed, the highest rated fossil fuel asset (DRLL, which is an ETF), received an average score that is more than a full point lower than the lowest ranking renewable energy asset. Thus, respondents are able to distinguish the relative impact of green vs. brown firms easily, which allows us to interpret impacts of being allocated green vs. brown portfolios as being allocated assets in different phases of the green transition.

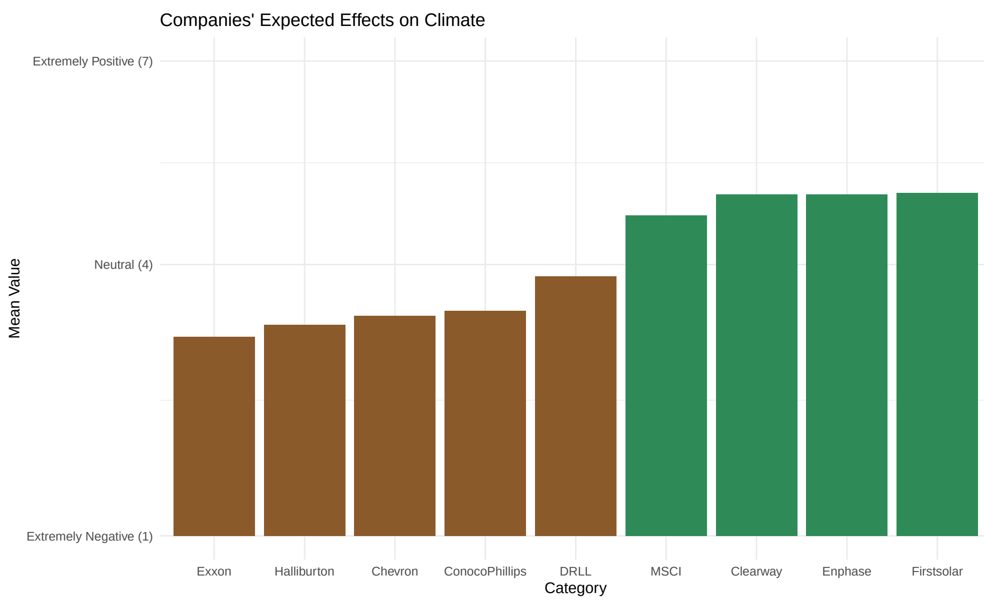


Figure A1: Perceived Environmental Impact

B The RCT: Additional Information

In this section, we provide further information regarding the surveys and trading platform employed in our RCT.

B.1 Baseline Survey

To recruit participants for our study, we contracted Forthright Inc. to onboard a sample of 3,806 U.S.-based survey respondents to participate in a longitudinal survey on economic, social, and climate-related issues. Our baseline survey was fielded between September 27 and October 2, 2024. As noted in the main text, we over-sampled respondents from states that are exposed to climate risks due to energy transitions and extreme weather events. Specifically, we increased the representation of respondents from the following states by 1.5 times relative to their population share: Alabama, Georgia, Kentucky, Mississippi, North Carolina, South Carolina, Ohio, Pennsylvania, Tennessee, West Virginia, Arizona, and Louisiana. Despite their climate-related vulnerabilities, we did not over-sample respondents from California, Florida, and Texas, given their large population relative to other states. Figure A2 reports the distribution of respondents relative to population size across U.S. states.

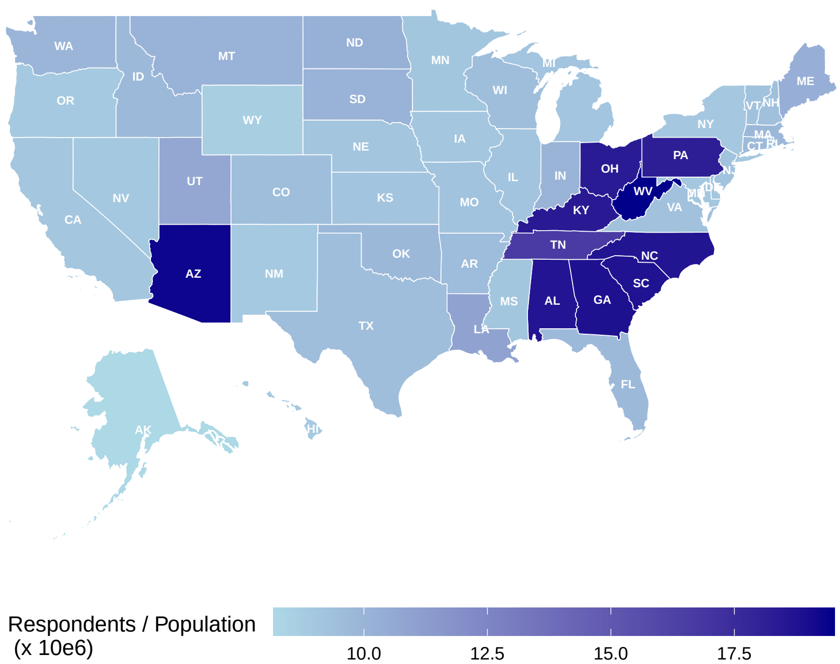


Figure A2: **Respondents distribution across states.**

At baseline, we collected data detailing respondents' demographic characteristics, political identity and preferences, climate-related beliefs, preferences and behaviors, and financial literacy. We report descriptive statistics from our baseline survey in Table A1.

Table A1: Balance by Treatment

	(1) Control Mean	(2) Pooled Treatment		(3) Real		(4) Fantasy		(5) Green		(6) Brown		(7) $50 Portfolio		(8) $100 Portfolio	
	[SD]	Diff.	P-value	Diff.	P-value	Diff.	P-value	Diff.	P-value	Diff.	P-value	Diff.	P-value	Diff.	P-value
Age	46.193	0.807	0.127	0.592	0.286	1.659	0.048	0.990	0.110	0.630	0.314	0.520	0.440	0.608	0.354
	[15.919]	(0.529)		(0.554)		(0.839)		(0.620)		(0.625)		(0.673)		(0.656)	
Female	0.520	-0.013	0.441	-0.012	0.481	-0.016	0.548	-0.018	0.345	-0.008	0.687	-0.020	0.325	-0.005	0.826
	[0.500]	(0.016)		(0.017)		(0.026)		(0.019)		(0.019)		(0.021)		(0.021)	
Race: white	0.746	0.034	0.015	0.028	0.056	0.055	0.008	0.042	0.009	0.025	0.125	0.010	0.568	0.044	0.009
	[0.435]	(0.014)		(0.014)		(0.021)		(0.016)		(0.016)		(0.018)		(0.017)	
Not White	0.254	-0.034	0.015	-0.028	0.056	-0.055	0.008	-0.042	0.009	-0.025	0.125	-0.010	0.568	-0.044	0.009
	[0.435]	(0.014)		(0.014)		(0.021)		(0.016)		(0.016)		(0.018)		(0.017)	
Northeast	0.171	-0.000	0.993	-0.001	0.944	0.003	0.880	0.001	0.923	-0.002	0.909	-0.005	0.767	0.003	0.867
	[0.377]	(0.013)		(0.013)		(0.020)		(0.015)		(0.015)		(0.016)		(0.016)	
Midwest	0.198	-0.001	0.946	-0.002	0.896	0.002	0.905	-0.004	0.821	0.002	0.914	-0.005	0.767	0.001	0.948
	[0.399]	(0.013)		(0.014)		(0.021)		(0.016)		(0.016)		(0.017)		(0.017)	
South	0.421	-0.001	0.962	-0.000	0.982	-0.002	0.935	-0.002	0.916	0.001	0.979	0.009	0.671	-0.009	0.649
	[0.494]	(0.017)		(0.017)		(0.026)		(0.019)		(0.019)		(0.021)		(0.020)	
West	0.209	0.002	0.895	0.003	0.826	-0.003	0.873	0.004	0.795	-0.001	0.975	0.001	0.964	0.006	0.742
	[0.407]	(0.014)		(0.014)		(0.021)		(0.016)		(0.016)		(0.017)		(0.017)	
Not Affected by Hurricanes	0.576	0.012	0.453	0.012	0.492	0.019	0.466	-0.002	0.906	0.027	0.163	0.008	0.710	0.014	0.491
	[0.494]	(0.016)		(0.017)		(0.026)		(0.019)		(0.019)		(0.021)		(0.020)	
College Degree	0.486	0.008	0.612	0.007	0.664	0.010	0.691	-0.014	0.448	0.031	0.095	0.026	0.195	-0.009	0.637
	[0.500]	(0.016)		(0.017)		(0.025)		(0.019)		(0.019)		(0.020)		(0.020)	
Income $	69092	302	0.853	-621	0.715	3699	0.154	-611	0.747	1286	0.503	293	0.888	-1299	0.517
	[51615]	(1632)		(1704)		(2594)		(1894)		(1919)		(2071)		(2004)	
Democrat	0.333	0.001	0.971	0.001	0.932	-0.002	0.919	0.001	0.975	0.001	0.974	-0.001	0.950	0.004	0.839
	[0.471]	(0.015)		(0.016)		(0.024)		(0.018)		(0.018)		(0.019)		(0.019)	
Republican	0.365	-0.005	0.764	-0.005	0.768	-0.004	0.862	-0.004	0.845	-0.006	0.749	-0.016	0.432	0.005	0.795
	[0.482]	(0.016)		(0.017)		(0.024)		(0.018)		(0.018)		(0.020)		(0.020)	
Independent	0.274	-0.000	0.980	-0.002	0.917	0.004	0.850	-0.001	0.938	0.001	0.972	0.010	0.600	-0.012	0.500
	[0.446]	(0.015)		(0.016)		(0.023)		(0.018)		(0.018)		(0.019)		(0.018)	
Climate Priority	0.225	0.001	0.922	0.001	0.924	0.001	0.950	0.001	0.970	0.002	0.895	0.011	0.523	-0.008	0.643
	[0.418]	(0.014)		(0.014)		(0.021)		(0.016)		(0.016)		(0.017)		(0.017)	
Trading Experience	0.519	0.003	0.841	0.003	0.857	0.004	0.876	0.005	0.810	0.002	0.917	0.011	0.616	-0.004	0.852
	[0.500]	(0.017)		(0.018)		(0.026)		(0.020)		(0.020)		(0.021)		(0.021)	
Financial Literacy	1.856	-0.018	0.547	-0.029	0.374	0.014	0.768	-0.039	0.273	0.004	0.902	0.022	0.566	-0.071	0.064
	[0.961]	(0.031)		(0.032)		(0.047)		(0.036)		(0.036)		(0.039)		(0.038)	
Trading Experience (6 mo.)	0.306	0.011	0.479	0.011	0.502	0.011	0.645	0.007	0.690	0.015	0.420	0.013	0.492	0.009	0.654
	[0.461]	(0.016)		(0.016)		(0.024)		(0.018)		(0.018)		(0.020)		(0.019)	
Risk Propensity	55.651	-2.927	0.000	-2.466	0.002	-4.821	0.000	-2.953	0.001	-2.924	0.001	-1.380	0.164	-3.358	0.000

Continued on next page

Table A1 continued

	(1) Control Mean	(2) Pooled Treatment		(3) Real		(4) Fantasy		(5) Green		(6) Brown		(7) $50 Portfolio		(8) $100 Portfolio	
	[SD]	Diff.	P-value	Diff.	P-value	Diff.	P-value	Diff.	P-value	Diff.	P-value	Diff.	P-value	Diff.	P-value
	[23.536]	(0.777)		(0.812)		(1.204)		(0.898)		(0.917)		(0.991)		(0.943)	
Major TV	0.521	0.008	0.634	0.014	0.439	-0.017	0.517	0.031	0.118	-0.015	0.432	0.021	0.320	0.008	0.690
	[0.500]	(0.017)		(0.017)		(0.026)		(0.020)		(0.019)		(0.021)		(0.021)	
Major Newspapers	0.164	-0.016	0.075	-0.019	0.048	-0.008	0.562	-0.016	0.119	-0.016	0.128	-0.020	0.070	-0.016	0.141
	[0.283]	(0.009)		(0.009)		(0.014)		(0.011)		(0.011)		(0.011)		(0.011)	
Local News	0.156	0.009	0.488	0.004	0.769	0.027	0.172	0.007	0.639	0.010	0.488	-0.015	0.319	0.021	0.190
	[0.363]	(0.012)		(0.013)		(0.020)		(0.014)		(0.015)		(0.015)		(0.016)	
Financial News	0.096	-0.013	0.015	-0.013	0.021	-0.014	0.083	-0.013	0.049	-0.014	0.026	-0.010	0.163	-0.016	0.014
	[0.172]	(0.005)		(0.006)		(0.008)		(0.006)		(0.006)		(0.007)		(0.007)	
Fox News	0.344	0.003	0.863	0.003	0.846	-0.002	0.942	0.001	0.934	0.003	0.852	0.000	0.991	0.007	0.705
	[0.475]	(0.015)		(0.016)		(0.024)		(0.018)		(0.018)		(0.019)		(0.019)	
Social Media	0.543	-0.038	0.024	-0.029	0.094	-0.069	0.008	-0.054	0.005	-0.022	0.269	-0.035	0.095	-0.024	0.245
	[0.498]	(0.017)		(0.018)		(0.026)		(0.020)		(0.020)		(0.021)		(0.021)	
Climate Action Support Index (Pap)	-0.000	-0.021	0.257	-0.017	0.390	-0.037	0.213	-0.026	0.225	-0.016	0.470	-0.013	0.586	-0.018	0.410
	[0.687]	(0.018)		(0.019)		(0.030)		(0.022)		(0.022)		(0.024)		(0.022)	
Beliefs	0.000	-0.024	0.253	-0.018	0.417	-0.045	0.185	-0.026	0.291	-0.022	0.363	-0.022	0.402	-0.012	0.637
	[0.721]	(0.021)		(0.022)		(0.034)		(0.025)		(0.025)		(0.027)		(0.026)	
Transition Benefits	0.000	-0.028	0.280	-0.029	0.289	-0.023	0.565	-0.038	0.210	-0.017	0.571	-0.049	0.140	-0.008	0.797
	[0.869]	(0.026)		(0.027)		(0.041)		(0.031)		(0.031)		(0.033)		(0.032)	
Transition Costs	0.000	0.015	0.549	0.022	0.388	-0.016	0.674	0.041	0.157	-0.012	0.679	0.021	0.509	0.023	0.452
	[0.787]	(0.025)		(0.026)		(0.038)		(0.029)		(0.029)		(0.031)		(0.030)	
Government Action	0.000	0.010	0.604	0.023	0.276	-0.037	0.253	0.020	0.394	0.000	0.989	0.042	0.106	0.004	0.863
	[0.621]	(0.020)		(0.021)		(0.033)		(0.024)		(0.023)		(0.026)		(0.024)	
Business Action	-0.000	-0.005	0.856	-0.005	0.852	-0.003	0.948	-0.001	0.967	-0.009	0.773	0.009	0.783	-0.018	0.584
	[0.845]	(0.027)		(0.028)		(0.042)		(0.031)		(0.032)		(0.035)		(0.033)	
Policy Salience	2.869	0.028	0.428	0.045	0.228	-0.034	0.531	0.044	0.287	0.012	0.770	0.027	0.549	0.063	0.152
	[1.851]	(0.035)		(0.037)		(0.054)		(0.041)		(0.041)		(0.045)		(0.044)	
Decision	0.360	-0.020	0.180	-0.015	0.345	-0.043	0.074	-0.017	0.352	-0.025	0.157	-0.013	0.502	-0.015	0.411
	[0.480]	(0.015)		(0.016)		(0.024)		(0.018)		(0.018)		(0.019)		(0.019)	
Donation	0.000	-0.067	0.003	-0.066	0.005	-0.074	0.033	-0.076	0.004	-0.060	0.023	-0.069	0.017	-0.062	0.025
	[0.732]	(0.022)		(0.024)		(0.035)		(0.026)		(0.026)		(0.029)		(0.028)	
Joint balance F-tests	1.40*	0.080			1.16	0.192			1.06	0.363			1.12	0.216	

Note: This table reports balance tests across treatment groups for baseline characteristics measured in the pre-treatment survey. Standard deviations in brackets in Column 1. Each entry in Columns 2-15 is derived from a separate OLS regression where the dependent variable is the baseline covariate and the explanatory variable is an indicator for the respective treatment assignment. *Pooled Treatment* compares all participants assigned financial market exposure (real and fantasy portfolios, n=2,406, with n representing the number of participants assigned treatment at baseline) versus control (n=1,400). *Real* compares participants assigned real-value portfolios ($50 or $100, n=1,907) to control. *Fantasy* compares participants assigned fantasy portfolios ($100, n=499) to control. *Green* and *Brown* compare participants assigned green energy stocks (n=953) versus brown energy stocks (n=954) to control, respectively. *$50 Portfolio* and *$100 Portfolio* compare participants assigned $50 real portfolios (n=954) and $100 real portfolios (n=953) to control, respectively. All regressions include randomization strata controls (party identification, geographic region, climate policy prioritization, and prior trading experience). When the outcome variable is itself a strata control, that control is excluded from the regression. Joint F-tests report overall balance across all covariates listed, excluding indicators for independents and western region to avoid multicollinearity with political party and region variables. Robust standard errors in parentheses. Stars denote two-tailed significance: *** p<0.01, ** p<0.05, * p<0.10.

Table A2: Effect of Treatment on Climate Action Support Index (PAP)

Climate Action Support Index (PAP)	Midline			Endline		
	(1)	(2)	(3)	(4)	(5)	(6)
Pooled Treatment	0.027			0.051***		
	(0.017)			(0.019)		
Real Assets		0.032*			0.056***	
		(0.018)			(0.020)	
Real Green			0.052**			0.068***
			(0.022)			(0.022)
Real Brown			0.013			0.044*
			(0.021)			(0.023)
Fantasy Assets		0.003	0.004		0.029	0.027
		(0.026)	(0.026)		(0.029)	(0.029)
Observations	3420	3420	3420	3587	3587	3587
p (Pooled Treatment $>$ 0)	0.059			0.004		
p (Real Assets $>$ 0)		0.036			0.002	
p (Real Assets $>$ Fantasy Assets)		0.117			0.138	
p (Real Green $>$ Real Brown)			0.047			0.148

Note: This table reports OLS estimates of the effect treatments on the *Climate Action Support Index (CASI)*specified in the pre-analysis plan. The index aggregates eight sub-indices capturing climate beliefs, preferences, and behaviors. *Pooled Treatment* compares all participants assigned to financial market exposure (real and fantasy portfolios, n=2,406, with n representing the number of participants assigned treatment at baseline) versus control (n=1,400). *Real Assets* pools participants assigned $50 or $100 real-value portfolios (n=1,907), while *Fantasy Assets* includes those assigned $100 fantasy portfolios (n=499). *Real Green* and *Real Brown* separately estimate effects for participants initially assigned real green energy stocks (n=953) versus real brown energy stocks (n=954). All regressions control for post-double selection (p-ds) LASSO-selected baseline covariates and include block fixed effects accounting for randomization strata (stratified by party identification, geographic region, climate policy prioritization, and prior trading experience). Endline regressions (columns 4-6) additionally control for climate disclosure treatment status. Robust standard errors in parentheses. Stars denote two-tailed p-values: *** p<0.01, ** p<0.05, * p<0.10. One-tailed p-values for directional hypotheses reported in bottom rows.

B.2 Post Treatment Surveys

On October 21, 2024, following three weeks of trading, all baseline survey respondents were invited to participate in a seemingly unrelated midline survey eliciting social, political, and climate-related outcomes. Our invitation to the midline survey did not mention the trading module, and we adopted a different visual layout for this survey to minimize respondents' ability to link between our treatment and outcome measurement tools. With the exception of several measures, our midline survey was similar to the baseline survey. Over a period of four days, 3,424 baseline respondents participated in our midline survey, a 90% response rate.[26]

After completing the sixth and final trading survey, we invited all baseline survey respondents to participate in our endline survey. We began fielding the endline survey on November 7 and terminated data collection on November 27. After collecting endline data, all treated respondents received the true and most recent value of their financial portfolio. A total of 3,592 participated in our endline survey, amounting to a 94% response rate. Importantly, as we show in Appendix A5, treatment status does not correlate with

[26]We concluded the midline survey on Thursday, October 24, 2024, allowing us to resume the trading surveys on Friday, October 25, 2024.

midline or endline attrition.

In Table A3 we describe the surveys items used to construct our index outcomes, which are then used to construct an overall climate action index. Each index is constructed by averaging the z-scores of its components (Kling, Liebman and Katz, 2007). We then standardize and average these outcomes to create an overall climate index.

Table A3: Primary Outcomes

Outcome	Measurement
Climate Beliefs	Please indicate how much you agree or disagree with each of the following statements: 1. Climate change will have a serious impact on the quality of life of people in the U.S. during my lifetime 2. Human activities are a significant cause of climate change 3. Extreme weather events such as floods, fires, and hurricanes are made more likely due to climate change 4. Climate change is not a serious issue
Transition Benefits	Please indicate how much you agree or disagree with each of the following statements: 1. Renewable energy industries, including those based on wind, solar, etc., will create many well-paying jobs for Americans 2. Renewable energy industries have the potential to be a central cause of economic growth in the U.S. 3. Investing in renewable energy is an important way to fight climate change 4. On balance, the transition to renewable energy solar from fossil fuels like coal and gas will be beneficial for the U.S. economy in the next 10 years
Transition Costs	Please indicate how much you agree or disagree with each of the following statements: 1. Renewable energy will threaten many coal, oil, and gas jobs in America 2. Renewable energy will take up land that could be used for more productive economic causes 3. Renewable energy will not be able to efficiently meet the needs of the American economy in the next 10 years 4. Renewable energy will not be able to efficiently meet the needs of the American economy in the next 20 years
Support Government Action	Please indicate how much you agree or disagree with each of the following statements: 1. The U.S. government should do more to reduce greenhouse gas emissions 2. The U.S. government should only contribute to climate mitigation if other countries like China and India do the same
Support Business Action	Please indicate how much you agree or disagree with each of the following statements: 1. U.S. companies should do more to reduce greenhouse gas emissions 2. U.S. companies should contribute to climate mitigation if companies in other countries, such as China and India, do the same
Climate Decision	How likely are factors relating to climate change to influence your decisions on: 1. Where to live 2. Where to take a job 3. In which company to invest
Climate Policy Priority	Rate the following policy priorities: 1. Addressing climate change 2. Addressing immigration 3. Strengthening economy 4. Improving healthcare 5. Strengthening military 6. Improving social services 7. Other (please specify)
Pro Climate Behaviors	How likely are you to : 1. Sign climate petition 2. Join environmental group 3. Use other transport instead of personal vehicle 4. Attempt to use reusable bags 5. Reduce meat consumption
Donations	Did respondent donate a portion of potential$50 reward to the Environmental Defense Fund

Note: Unless otherwise noted, all survey outcomes measure preferences using a seven-point Likert scale. Climate decision index was not collected at baseline. Full survey wording is available in Appendix ap:surveyword.

B.3 The Financial Market Treatment

B.3.1 Primary Treatment and Sub-Treatments

After completing the baseline survey, we assigned 2,406 baseline survey respondents to participate in a six-week trading module. The remaining 1,400 survey respondents who participated in our baseline survey were assigned to a control condition, and were only contacted for participation in the midline and endline survey. After assigning respondents to a primary treatment or control condition, we further assigned treated respondents' to three additional sub-treatments determining the type of assets in their portfolio, the value of their portfolio, and whether they receive climate-related disclosures in the second half of the trading period.

As indicated in Figure 1a in the main text, treated respondents received initial exposure to either green or brown asset. We also provided a one-line description of the assets, which is included in Table A4 - note that the one-line description was the only information we gave them about the firm (in addition to the stock price, and did not label a stock as green or brown). The green assets in our study included Clearway Energy Inc. (CWEN, an energy infrastructure investor), Enphase (ENPH, an energy technology company focused on solar solutions), First Solar Inc. (FSLR, a solar technology company), and Invesco Solar ETF (TAN, an exchange-traded fund investing in companies in the solar energy industry). Brown assets in our study included ConocoPhillips (COP, a company engaged in hydrocarbon exploration and production), Exxon Mobil Corporation (XOM, a carbon and gas company), Halliburton (HAL, an oil service company), and Strive U.S. Energy ETF (DRLL, an exchange-traded fund that investing in the general U.S. energy industry). Each initial portfolio included three of the above assets based on a respondent's assignment to green or brown energy exposure.

We further randomized the initial value of portfolios, amounting to either \$50, \$100, or \$100 fantasy. In both the green and brown asset conditions, 80% of participants were assigned to either \$50 or \$100 portfolios (in equal proportions), and remaining 20% we assigned to \$100 fantasy condition. Finally, we assigned 1,206 treated respondents to receive financial and climate-related disclosures starting on the fifth week of trading. The remaining 1,200 treated respondents received only financial disclosures at that time.

B.3.2 The Trading Platform

On Friday, October 4, 2025, after block randomizing respondents into their various conditions, we invited all participants assigned to the trading condition to enroll in our six-week trading module. At the start of the module, participants were told that they were selected to participate in a study on investor behavior in which they would have an opportunity to learn about, hold, and trade financial assets. Participants were further informed that if they opt-in to the study, they would receive a financial portfolio,[27] and be invited to participate in weekly surveys where they would receive an update on the value of their financial portfolio, and have an opportunity to trade the assets in their portfolio.[28] To incentivize participation, we informed respondents that failing to complete a weekly trading survey would result in a 10% loss to the overall value of their portfolio.[29] Out of the 2,406 baseline survey respondents assigned to treatment 2,030 participated in at least one week of trading. In addition, 81% (1,653) of active participants completed five or six trading surveys suggesting that compliance with our treatment was especially high.

[27] The portfolios were paid from the authors' research account through the implementation partner, and this was explained to participants in non-technical language.

[28] All surveys were rolled out on Fridays after market closure and access to surveys was terminated on Monday before markets re-opened.

[29] In addition, respondents received standard compensation from Forthright for each weekly trading survey they completed.

Table A4: One-Line Stock Description Provided to Treatment Groups (Real and Fantasy)

Company	Description	Type
Exxon	Exxon Mobil Corporation is an international energy and petrochemical company. Its primary businesses include exploration for and production of crude oil and natural gas, and it is one of the largest producers of crude oil in the U.S.	Brown
Halliburton	Halliburton Company is a provider of products and services to the energy industry, including for oil drilling.	Brown
ConocoPhillips	ConocoPhillips is a multinational corporation engaged in hydrocarbon exploration and production. It is one of the largest producers of crude oil in the U.S.	Brown
DRLL	Strive U.S. Energy ETF (DRLL) is a passively managed exchange-traded fund (ETF) that seeks to provide exposure to large- and mid-capitalization corporations in the U.S energy sector, including oil, coal, and natural gas companies. The top three companies included in the fund include Exxon-Mobil (XOM: 22.5%), Chevron (CVX: 20.7%) and Phillips 66 (PSX: 4.5%).	Brown
First Solar	First Solar, Inc. is a solar technology company and global provider of photovoltaic cells (PV) solar energy solutions.	Green
Clearway Energy	Clearway Energy, Inc. is a renewable energy company. The Company invests in energy infrastructures and focuses on investments in clean energy across North America.	Green
Enphase Energy	Enphase Energy, Inc. brings a high-technology, networked approach to solar generation plus energy storage, by leveraging its design across power electronics, semiconductors and cloud-based software technologies.	Green
TAN	Invesco Solar ETF Index (TAN) is an exchange-traded index fund (ETF) comprised of a number of companies in the solar energy industry. The top three companies included in the fund include FirstSolar (FSLR: 10.50%), Enphase Energy (ENPH: 9.83%) and NEXTracker inc (NXT:6.8%).	Green

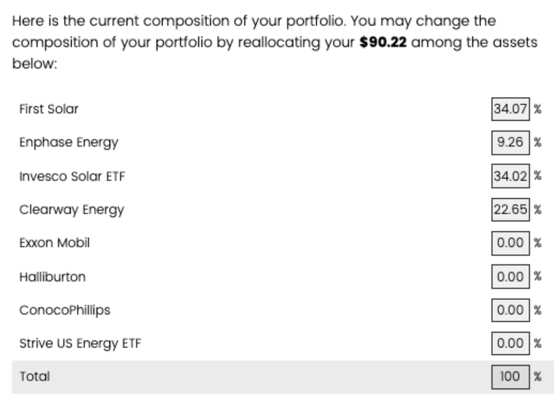
Each trading survey started off by eliciting participants' media consumption patterns, knowledge about the performance of their assets and the potential factors influencing performance, and expectations regarding the future performance of their assets. After responding to these questions, respondents received an update about the current price of their assets and the value of their overall portfolio (Figure A3a). They then received information about all companies available for trading in the module and were invited to sell and buy assets in light of this information (Figure A3b). After registering a trade or hold decision, respondents received an updated overview of their portfolio. The survey concluded by providing information about what the respondent may expect in the following week. Thus, in weeks 1-5 we reminded respondents that they will be invited to another trading survey. In week 6, we informed respondents that there are no more trading surveys to complete and that they will soon receive the full value of their portfolio).

Your portfolio status: Last week, the value of your portfolio was **$87.60**. The current value of your portfolio at the end of the trading week is **$90.22**. The value of your portfolio **increased by $2.62** over the past week.

Here is a table that summarizes your portfolio (*scroll to the right to see more details*):

Name	Price change (%)	Last week's stock value (Friday 4pm ET)	This week's stock value (Friday 4pm)	Number of shares owned	Total value
First Solar	2.2% ↑	200.55	204.94	0.15	30.74
Enphase Energy	-8.8% ↓	91.64	83.54	0.10	8.35
Invesco Solar ETF	6.8% ↑	37.32	39.86	0.77	30.69
Clearway Energy	1.3% ↑	27.25	27.61	0.74	20.43

(a) Portfolio Overview



Here is the current composition of your portfolio. You may change the composition of your portfolio by reallocating your **$90.22** among the assets below:

First Solar	34.07	%
Enphase Energy	9.26	%
Invesco Solar ETF	34.02	%
Clearway Energy	22.65	%
Exxon Mobil	0.00	%
Halliburton	0.00	%
ConocoPhillips	0.00	%
Strive US Energy ETF	0.00	%
Total	100	%

(b) Trading Window

Figure A3: **Description of online trading platform.** This figure presents the main elements of our trading platform that inform respondents about the assets in their financial portfolio and provide the opportunity to trade assets.

C Additional Tables and Analyses

Table A5: Effect of Treatment on Survey Completion Dummy

Completed Survey (Dummy)	Midline			Endline			Follow Up		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pooled Treatment	0.003			0.002			0.001		
	(0.010)			(0.010)			(0.017)		
Real Assets		-0.000			0.002			-0.000	
		(0.010)			(0.011)			(0.017)	
Real Green			-0.006			0.002			-0.010
			(0.012)			(0.012)			(0.020)
Real Brown			0.005			0.003			0.009
			(0.012)			(0.012)			(0.020)
Fantasy Assets		0.014	0.016		0.010	0.014		0.006	0.009
		(0.014)	(0.014)		(0.014)	(0.014)		(0.023)	(0.023)
Observations	3806	3806	3806	3806	3806	3806	3806	3806	3806
Control Mean	0.886	0.886	0.886	0.919	0.919	0.919	0.749	0.749	0.749
SD	0.318	0.318	0.318	0.272	0.272	0.272	0.434	0.434	0.434
p (Pooled Treatment > 0)	0.370			0.411			0.487		
p (Real Assets > 0)		0.514			0.420			0.507	
p (Real Assets > Fantasy Assets)		0.862			0.754			0.626	
p (Real Green > Real Brown)			0.797			0.528			0.833

Note: This table reports OLS estimates of treatment effects on survey completion rates across three survey waves. The dependent variable is a binary indicator equal to 1 if the participant completed the survey and 0 otherwise. Column (1) shows the effect of the pooled treatment (real and fantasy portfolios, n=2,406, with n representing the number of participants assigned treatment at baseline) vs. control (n=1,400) on midline survey completion. Column (2) compares real asset treatment (n=1,907)and fantasy assets (n=499) vs. control. Column (3) further disaggregates real assets into real green (green energy assets, n=953) and real brown (fossil fuel assets, n=954), comparing both to control alongside fantasy assets. Columns (4)-(6) repeat this structure for endline survey completion, and columns (7)-(9) for follow-up survey completion. All regressions control for covariates and include block fixed effects accounting for randomization strata (stratified by party identification, geographic region, climate policy prioritization, and prior trading experience); endline and follow-up surveys further control for climate disclosure treatment. One-sided *p*-values test directional hypotheses. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A6: Effect of Treatment on Climate Index (Supervised Lasso)

Climate Action Support Index	Midline			Endline			Follow Up		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pooled Treatment	0.036**			0.059***			0.025		
	(0.017)			(0.016)			(0.019)		
Real Assets		0.046***			0.067***			0.028	
		(0.017)			(0.017)			(0.020)	
Real Green			0.059***			0.083***			0.014
			(0.021)			(0.020)			(0.023)
Real Brown			0.033			0.051**			0.042*
			(0.021)			(0.020)			(0.024)
Fantasy Assets		-0.002	-0.001		0.031	0.030		0.012	0.012
		(0.025)	(0.025)		(0.025)	(0.025)		(0.028)	(0.028)
Observations	3414	3414	3414	3580	3580	3580	2924	2924	2924
p (Pooled Treatment > 0)	0.015			0.000			0.091		
p (Real Assets > 0)		0.004			0.000			0.078	
p (Real Assets > Fantasy Assets)		0.024			0.069			0.276	
p (Real Green > Real Brown)			0.139			0.074			0.864

Note: This table reports OLS estimates of treatment effects on the *Climate Action Support Index (CASI)* across three survey waves. The dependent variable is a standardized index aggregating nine measures of climate attitudes and support for climate policies. Columns (1)-(3) present results for the midline survey, columns (4)-(6) for the endline survey, and columns (7)-(9) for the long-run follow-up survey. Within each survey wave, column 1 shows the effect of financial market exposure (real and fantasy portfolios, n=2,406, with n representing the number of participants assigned treatment at baseline) vs. control (n=1,400). Column 2 compares real asset treatment (n=1,907) and fantasy assets (n=499) vs. control. Column 3 further disaggregates real assets into real green (n=953) and real brown (n=954), comparing both to control alongside fantasy assets. All regressions include block fixed effects accounting for randomization strata. Covariates are selected via post-double-selection (p-ds) LASSO covariates and include block fixed effects accounting for randomization strata (stratified by party identification, geographic region, climate policy prioritization, and prior trading experience). The supervised lasso control set limits the lasso inputs to political party affiliation, experience trading, age, race, education level, and pre-treatment responses to the questions that later constitute the climate action support index. One-sided *p*-values test pre-registered directional hypotheses. Robust standard errors in parentheses. Stars report two-sided p-values *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A7: Effect of Treatment on Climate Index (Including Disclosure)

Climate Action Support Index	Midline			Endline		
	(1)	(2)	(3)	(4)	(5)	(6)
Pooled Treatment	0.037*			0.065***		
	(0.020)			(0.019)		
Real Assets		0.054**			0.065***	
		(0.021)			(0.020)	
Real Green			0.074***			0.081***
			(0.028)			(0.025)
Real Brown			0.035			0.050*
			(0.027)			(0.026)
Fantasy Assets		-0.035	-0.034		0.063*	0.061*
		(0.036)	(0.036)		(0.036)	(0.037)
Pooled Treatment X Climate Disclosure	-0.001			-0.007		
	(0.021)			(0.020)		
Real Assets X Climate Disclosure		-0.015			0.007	
		(0.024)			(0.022)	
Fantasy Assets X Climate Disclosure		0.062	0.061		-0.058	-0.056
		(0.043)	(0.043)		(0.044)	(0.044)
Real Green X Climate Disclosure			-0.031			0.008
			(0.035)			(0.032)
Real Brown X Climate Disclosure			-0.001			0.003
			(0.032)			(0.031)
Observations	3414	3414	3414	3580	3580	3580
One Sided p-values						
Real Assets > 0		0.006			0.001	
Real Assets > Fantasy Assets		0.010			0.472	
Real Green > Real Brown			0.118			0.163

Note: This table reports OLS estimates of the effect of financial market exposure on the *Climate Action Support Index (CASI)*, including interactions with climate disclosure treatment. The index aggregates nine sub-indices measuring climate beliefs, preferences, and behaviors. *Pooled Treatment* compares all participants assigned to financial market exposure (real and fantasy portfolios, n=2,406, with n representing the number of participants assigned treatment at baseline) versus control (n=1,400). *Real Assets* pools participants assigned \$50 or \$100 real-value portfolios (n=1,907), while *Fantasy Assets* includes those assigned \$100 fantasy portfolios (n=499). *Real Green* and *Real Brown* separately estimate effects for participants initially assigned real green energy stocks (n=953) versus real brown energy stocks (n=954), relative to control. *Climate Disclosure* indicates assignment to receive climate-related information about portfolio assets. Interaction terms test whether disclosure moderates treatment effects. All regressions control for post-double selection (p-ds) LASSO-selected baseline covariates and include block fixed effects accounting for randomization strata (stratified by party identification, geographic region, climate policy prioritization, and prior trading experience). Robust standard errors in parentheses. Stars denote two-tailed p-values: *** p<0.01, ** p<0.05, * p<0.10. One-tailed p-values for directional hypotheses reported in bottom rows.

Table A8: Heterogeneous Treatment Effects of Real Asset Treatment

Climate Action Support Index	Above Median Baseline Climate (1)	Republican (2)	Democrat (3)	Independent (4)	Trading Experience (5)	Risk Tolerance (6)	FEMA Hurricane Aid (7)	Stock Price Performance (8)	Negatively Affected by Green Transition (9)	Partisans (10)	Polarization (11)
Panel A. Midline											
Real Asset Treatment	0.076***	0.064***	0.035	0.043**	0.065**	0.323	0.037**	0.040*	0.035*	0.061*	0.048
	(0.026)	(0.022)	(0.022)	(0.021)	(0.025)	(0.262)	(0.019)	(0.023)	(0.020)	(0.032)	(0.031)
Moderator Effect	0.016	0.015	0.066	0.054	0.029	-0.182	0.190**	0.050	0.104**	0.040	0.018
	(0.045)	(0.044)	(0.044)	(0.046)	(0.044)	(0.447)	(0.082)	(0.034)	(0.052)	(0.051)	(0.054)
Real Asset $\times$*Moderator*	-0.060	-0.048	0.030	0.012	-0.037	-0.505	0.153*	0.009	0.069	-0.022	-0.030
	(0.036)	(0.038)	(0.038)	(0.040)	(0.036)	(0.362)	(0.080)	(0.025)	(0.049)	(0.039)	(0.044)
Moderator Control Mean	0.505	0.365	0.333	0.274	0.519	55.651	0.076	0.000	0.179	0.698	0.508
Observations	3,420	3,420	3,420	3,420	3,420	3,420	3,420	3,420	3,420	3,420	2,397
Panel B. Endline											
Real Asset Treatment	0.105***	0.055**	0.079***	0.070***	0.095***	0.194	0.067***	0.066***	0.071***	0.068**	0.048
	(0.028)	(0.024)	(0.024)	(0.023)	(0.026)	(0.216)	(0.021)	(0.024)	(0.022)	(0.032)	(0.033)
Moderator Effect	0.026	0.089**	0.043	0.059	0.043	-0.434	0.068	0.069**	0.063	0.067	0.086
	(0.045)	(0.044)	(0.044)	(0.044)	(0.044)	(0.424)	(0.079)	(0.034)	(0.050)	(0.048)	(0.055)
Real Asset $\times$*Moderator*	-0.079**	0.035	-0.036	-0.011	-0.052	-0.628*	0.001	0.003	-0.008	-0.001	0.037
	(0.035)	(0.037)	(0.037)	(0.037)	(0.035)	(0.365)	(0.076)	(0.024)	(0.044)	(0.036)	(0.043)
Moderator Control Mean	0.505	0.365	0.333	0.274	0.519	55.651	0.076	0.000	0.179	0.698	0.508
Observations	3,587	3,587	3,587	3,587	3,587	3,587	3,587	3,587	3,587	3,587	2,500
Panel C. Follow-up											
Real Asset Treatment	0.067**	0.032	0.040	0.032	0.080**	0.097	0.028	0.058**	0.034	0.042	0.030
	(0.032)	(0.028)	(0.028)	(0.027)	(0.032)	(0.286)	(0.024)	(0.029)	(0.025)	(0.038)	(0.037)
Moderator Effect	0.004	0.040	0.022	0.040	-0.008	-0.349	0.176*	0.020	0.059	0.032	0.028
	(0.052)	(0.052)	(0.051)	(0.052)	(0.052)	(0.574)	(0.096)	(0.039)	(0.057)	(0.057)	(0.062)
Real Asset $\times$*Moderator*	-0.064	0.008	-0.018	0.008	-0.088**	-0.446	0.148	-0.038	0.025	-0.010	-0.002
	(0.041)	(0.044)	(0.043)	(0.044)	(0.041)	(0.497)	(0.093)	(0.027)	(0.051)	(0.043)	(0.049)
Moderator Control Mean	0.505	0.365	0.333	0.274	0.519	55.651	0.076	0.000	0.179	0.698	0.508
Observations	2,934	2,934	2,934	2,934	2,934	2,934	2,934	2,934	2,934	2,934	2,051

Note: This table reports OLS estimates of heterogeneous treatment effects of the Real Assets treatment (trading real climate-related financial assets) on the *Climate Action Support Index (CASI)* across three survey waves and eleven moderator variables. The dependent variable in all specifications is a standardized index aggregating nine measures of climate attitudes and support for climate policies. Each column represents a different moderator variable, and the table is organized into three panels corresponding to survey waves: Panel A reports effects at midline (immediately post-treatment), Panel B at endline (approximately 6 weeks post-treatment), and Panel C at follow-up (approximately 8 months post-treatment) Within each panel and column, Real Asset Treatment shows the treatment effect for participants with moderator = 0 (or below median for continuous moderators). Moderator Effect shows the treatment effect for participants with moderator = 1 (or above median), calculated as the sum of the main treatment effect and the interaction term. Real AssetXModerator shows the interaction coefficient, testing whether treatment effects differ across moderator levels. The eleven moderator variables are: (1) Above Median Baseline Climate: indicator for above-median pre-treatment climate concern index; (2) Republican: self-identified Republican party affiliation; (3) Democrat: self-identified Democratic party affiliation; (4) Independent: self-identified Independent or other party affiliation; (5) Trading Experience: prior experience trading stocks or other financial assets; (6) Risk Tolerance: categorical risk preference measure; (7) FEMA Hurricane Aid: indicator for receiving FEMA assistance following Hurricanes Helene or Milton; (8) Stock Price Performance: above-median portfolio value performance during the trading period constructed purely from exogenous returns on the initially assigned assets; (9) Negatively Affected by Green Transition: residing in states with high carbon footprints (Tier 1: Wyoming, Louisiana, Alaska; Tier 2: North Dakota, Montana, Idaho, Texas, Oklahoma, Kansas, Iowa, West Virginia, Indiana, Alabama, Mississippi), indicating greater exposure to economic disruption from climate transition; (10) Partisans: strong partisan identifier (pooling Democrats and Republicans); (11) Polarization: above-median affective polarization, measured as the difference between in-party and out-party thermometer ratings (excluding independent leaners). All regressions include block fixed effects accounting for randomization strata. All regressions control for post-double selection (p-ds) LASSO-selected baseline covariates and include block fixed effects accounting for randomization strata (stratified by party identification, geographic region, climate policy prioritization, and prior trading experience). Endline (Panel B) and Follow-up (Panel C) regressions additionally control for the climate disclosure treatment. Robust standard errors are reported throughout. Statistical significance: *** $p< 0.01$, ** $p<0.05$, * $p<0.10$.

Table A9: Heterogeneous Treatment Effects of Pooled Asset Treatment

Climate Action Support Index	Above Median Baseline Climate (1)	Republican (2)	Democrat (3)	Independent (4)	Trading Experience (5)	Risk Tolerance (6)	FEMA Hurricane Aid (7)	Stock Price Performance (8)	Negatively Affected by Green Transition (9)	Partisans (10)	Polarization (11)
Panel A. Midline											
Pooled Asset Treatment	0.059**	0.051**	0.028	0.031	0.047**	0.300	0.025	0.025	0.030	0.054*	0.030
	(0.024)	(0.021)	(0.021)	(0.020)	(0.024)	(0.264)	(0.018)	(0.022)	(0.019)	(0.030)	(0.030)
Moderator Effect	0.011	0.006	0.049	0.046	0.023	-0.167	0.175**	0.041	0.069	0.028	0.016
	(0.042)	(0.042)	(0.042)	(0.043)	(0.042)	(0.435)	(0.080)	(0.031)	(0.049)	(0.047)	(0.051)
Pooled Asset $\times$*Moderator*	-0.048	-0.045	0.021	0.016	-0.024	-0.467	0.150*	0.016	0.039	-0.026	-0.015
	(0.034)	(0.036)	(0.036)	(0.038)	(0.034)	(0.346)	(0.078)	(0.022)	(0.046)	(0.037)	(0.041)
Moderator Control Mean	0.505	0.365	0.333	0.274	0.519	55.651	0.076	0.000	0.179	0.698	0.508
Observations	3,420	3,420	3,420	3,420	3,420	3,420	3,420	3,420	3,420	3,420	2,397
Panel B. Endline											
Pooled Asset Treatment	0.098***	0.051**	0.071***	0.065***	0.087***	0.183	0.062***	0.055**	0.071***	0.059*	0.043
	(0.026)	(0.023)	(0.023)	(0.023)	(0.025)	(0.216)	(0.020)	(0.023)	(0.022)	(0.031)	(0.032)
Moderator Effect	0.021	0.080*	0.044	0.052	0.039	-0.447	0.064	0.064**	0.033	0.063	0.081
	(0.043)	(0.042)	(0.042)	(0.042)	(0.042)	(0.412)	(0.077)	(0.032)	(0.048)	(0.047)	(0.052)
Pooled Asset $\times$*Moderator*	-0.076**	0.029	-0.027	-0.014	-0.049	-0.630*	0.002	0.009	-0.037	0.004	0.038
	(0.034)	(0.035)	(0.035)	(0.036)	(0.033)	(0.351)	(0.074)	(0.021)	(0.043)	(0.035)	(0.041)
Moderator Control Mean	0.505	0.365	0.333	0.274	0.519	55.651	0.076	0.000	0.179	0.698	0.508
Observations	3,587	3,587	3,587	3,587	3,587	3,587	3,587	3,587	3,587	3,587	2,500
Panel C. Follow-up											
Pooled Asset Treatment	0.058*	0.032	0.034	0.033	0.077**	0.081	0.028	0.047*	0.027	0.033	0.030
	(0.031)	(0.027)	(0.027)	(0.026)	(0.030)	(0.275)	(0.023)	(0.027)	(0.025)	(0.036)	(0.036)
Moderator Effect	0.010	0.034	0.030	0.032	-0.009	-0.381	0.163*	0.022	0.075	0.032	0.025
	(0.049)	(0.049)	(0.048)	(0.049)	(0.049)	(0.539)	(0.094)	(0.036)	(0.054)	(0.054)	(0.059)
Pooled Asset $\times$*Moderator*	-0.048	0.002	-0.003	-0.001	-0.086**	-0.462	0.135	-0.025	0.048	-0.001	-0.005
	(0.039)	(0.042)	(0.040)	(0.042)	(0.039)	(0.464)	(0.091)	(0.024)	(0.048)	(0.041)	(0.047)
Moderator Control Mean	0.505	0.365	0.333	0.274	0.519	55.651	0.076	0.000	0.179	0.698	0.508
Observations	2,934	2,934	2,934	2,934	2,934	2,934	2,934	2,934	2,934	2,934	2,051

Note: This table reports OLS estimates of heterogeneous treatment effects of the Pooled Asset treatment (any trading experience, combining real and fantasy assets) on *Climate Action Support Index (CASI)* across three survey waves and eleven moderator variables. The dependent variable in all specifications is a standardized index aggregating nine measures of climate attitudes and support for climate policies. Each column represents a different moderator variable, and the table is organized into three panels corresponding to survey waves: Panel A reports effects at midline (immediately post-treatment), Panel B at endline (approximately 6 weeks post-treatment), and Panel C at follow-up (approximately 8 months post-treatment). Within each panel and column, Pooled Asset Treatment shows the treatment effect for participants with moderator = 0 (or below median for continuous moderators), representing the baseline treatment effect. Moderator Effect shows the treatment effect for participants with moderator = 1 (or above median), calculated as the sum of the main treatment effect and the interaction term. Pooled Asset X Moderator shows the interaction coefficient, testing whether treatment effects differ significantly across moderator levels. Standard errors are reported in parentheses below coefficient estimates. The eleven moderator variables examine heterogeneity across theoretically relevant dimensions: (1) Above Median Baseline Climate: indicator for above-median pre-treatment climate concern index, testing whether those already concerned respond differently; (2) Republican: self-identified Republican party affiliation; (3) Democrat: self-identified Democratic party affiliation; (4) Independent: self-identified Independent or other party affiliation; (5) Trading Experience: prior experience trading stocks or other financial assets before the experiment; (6) Risk Tolerance: categorical risk preference measure; (7) FEMA Hurricane Aid: indicator for receiving FEMA assistance following Hurricanes Helene or Milton in fall 2024, identifying participants with recent direct climate impact experience; (8) Stock Price Performance: above-median portfolio value performance during the six-week trading period constructed purely from exogenous returns on the initially assigned assets; (9) Negatively Affected by Green Transition: residing in states with high carbon footprints and fossil fuel dependence (Tier 1 highest exposure: Wyoming, Louisiana, Alaska; Tier 2 high exposure: North Dakota, Montana, Idaho, Texas, Oklahoma, Kansas, Iowa, West Virginia, Indiana, Alabama, Mississippi), indicating greater potential economic exposure to disruption from climate transition policies; (10) Partisans: strong partisan identifier (pooling Democrats and Republicans); (11) Polarization: above-median affective polarization, measured as the difference between in-party and out-party thermometer ratings (excluding independent leaners). All regressions include block fixed effects accounting for randomization strata based on baseline characteristics. All regressions control for post-double selection (p-ds) LASSO-selected baseline covariates and include block fixed effects accounting for randomization strata (stratified by party identification, geographic region, climate policy prioritization, and prior trading experience).Endline (Panel B) and Follow-up (Panel C) regressions additionally control for the climate disclosure treatment. Robust standard errors are used throughout to account for heteroskedasticity. Statistical significance: *** $p<0.01$, ** $p<0.05$, * $p<0.10$ based on two-sided tests.

Table A10: Effect of Portfolio Value on Climate Action Support Index

Climate Action Support Index	Midline (1)	Endline (2)	Follow Up (3)
\$50 Portfolio	0.048**	0.063***	0.047*
	(0.020)	(0.023)	(0.026)
\$100 Portfolio	0.041*	0.080***	0.029
	(0.022)	(0.023)	(0.026)
Fantasy Assets	-0.002	0.035	0.022
	(0.025)	(0.028)	(0.030)
Observations	3420	3587	2934
p (\$50 Portfolio > 0)	0.010	0.003	0.035
p (\$100 Portfolio > 0)	0.030	0.000	0.128
p (Fantasy Assets > 0)	0.533	0.106	0.230

Note: This table reports OLS estimates of the effect of financial market exposure on the *Climate Action Support Index (CASI)*, examining heterogeneity by initial portfolio value. The index aggregates nine sub-indices measuring climate beliefs, preferences, and behaviors. This table compares participants assigned \$50 real-value portfolios (n=953, with n representing the number of participants assigned treatment at baseline) versus \$100 real-value portfolios (n=954) versus participants assigned \$100 fantasy portfolios (n=499) versus control (n=1400). All regressions control for post-double selection (p-ds) LASSO-selected baseline covariates and include block fixed effects accounting for randomization strata (stratified by party identification, geographic region, climate policy prioritization, and prior trading experience). Endline (column 2) and Follow Up (column 3) regressions additionally control for climate disclosure treatment status. Robust standard errors in parentheses. Stars denote two-tailed p-values: *** p<0.01, ** p<0.05, * p<0.10. One-tailed p-values for directional hypotheses reported in bottom rows.

C.1 Effects on Disaggregated Outcomes

In this section, we report effects on the raw versions of each outcome which are inputs into the indices we create. The goal is to present evidence on which components of the sub-indices drive the impacts on beliefs and preferences caused by the treatment. Table A11 presents results on the four components of the beliefs index for the midline and endline survey. Real assets treatment increases the likelihood that individuals believe that climate change will have a serious impact on the quality of life in the U.S. during their lifetime in the endline survey, an effect size of 0.098 increase on a seven point scale with mean 3.91, so a 2.5% increase in the mean (one sided p-value <0.05). They are also more likely to disagree that climate change is not a serious issue, an effect size of 6.1% relative to mean (one-sided p-value of 0.11). Most coefficients show an increase in magnitude and point-estimates that are greater in the endline than the midline.

Table A12 presents results for components for the beliefs about business action, and Table A13 for components for the beliefs about government action. Each of these have two components - the first measures agreement with whether that stakeholder (business or government) should do more to reduce emissions, and the second a conditional statement asking them whether that stakeholder should do more to reduce emissions only if businesses or governments in other countries do so as well (i.e. they only support coordinated action). We see a larger jump in agreement with coordination action for businesses between the midline and endline, and a small increase for unilateral action in the government survey, though the coefficient is positive across specifications. For government action, both support and unilateral and coordination action increases significantly between midline and endline.

Table A14 presents results for how important respondents report climate to be when deciding adaptation decisions like where to live, as well as individual actions like where to take a job and invest. Of these, the largest and most precisely estimated treatment effects are for respondents taking climate into account when deciding which companies to invest in, which is intuitive given that the study was treatment was directly providing financial exposure to firms at different stages of the green transition (though all sub-components show positive effects). The point estimate for this variable is an increase of 0.185 in the midline (one-sided p-value < 0.01) on the scale and 0.307 in the endline (one-sided p-value < 0.01), an increase of 5.6% and 9.8% percent of the control mean, respectively. Table A15 presents results for the sub-components of the index measuring respondents' willingness to undertake individual mitigation actions such as use resuable bags as well as support community actions such as joining an environmental group or sign a petition. We do not find a precisely estimated treatment effect on this index, and consistent with this, the sub-components show noisy and smaller, albeit largely positive, treatment effects.

Tables A16 and A17 present results on the perceived benefits and costs of the green tranisition, respectively. The first sub-component of transition benefits- agreement with the statement that renewable energy will create well-paying jobs for Americans - increases by 0.067 (one-sided p-value < 0.05) and 0.113 (one-sided p-value < 0.01) on a 7-point scale in the midline and endline respectively, an increase of 1.63% and 2.8% relative to the control mean, respectively. This indicates that the treatment mitigates a key concern raised about the expansion of renewable energy, namely, with regard to job creation. The second sub-component, - agreement with the statement that renewable energy has the potential to cause economic growth in the U.S. - increases by 0.047 (one-sided p-value > 0.10) and 0.10 (one-sided p-value < 0.05) on a 7-point scale in the midline and endline respectively, an increase of 1.2% and 2.5% relative to the control mean, respectively. The other two sub-components, which measure beliefs about whether renewable energy investments are important to fight climate change as well as whether the energy transition will be beneficial for the U.S. economy in the next decade, show positive treatment effects, but are smaller in magnitude, and not statistically significant. Turning to perceived transition costs, we observe a reduction in these perceived costs (measured by the overall index) in the midline, but no impact on the endline. Three of the four sub-components show precisely estimated effects in the midline. Agreement with the statement that renewable energy will threaten fossil fuel jobs in the U.S. falls by 0.093 of the scale (one sided p-value < 0.05, 2.4 percent relative to the control mean), while agreement with the statement that renewable energy will take up land that could be used more productively falls 0.096 (one sided p-value < 0.05, 3.1 percent relative to the control mean). Agreement with the statement that renewable energy will not meet the needs of the U.S. economy in the next 20 years falls by 0.076 (one sided p-value < 0.10, 2.5 percent relative to the control mean). There is a much smaller and not statistically significant when this statement is asked for the next 10 years instead of 20, indicating the the increase in perceived ability of renewable energy to meet the needs of the U.S. economy is relatively long-term. Interestingly, there are no effects for this index in the endline, which is reflected in the sub-components, which are measured with significant noise. Next, we discuss the sub-components of the mechanisms indices.

Table A11: Real Asset Treatment Effect on Components of Beliefs Index, Full Sample

Outcome	Midline				Endline			
	Real Asset Treatment	$p\ (\lvert\beta\rvert > 0)$	N	Control Mean	Real Asset Treatment	$p\ (\lvert\beta\rvert > 0)$	N	Control Mean
Climate Beliefs Index: Beliefs on Climate Change	0.026 (0.022)	0.127	3420	0.001	0.044* (0.025)	0.041	3587	0.001
Will have serious impact U.S. quality of life in my lifetime	-0.001 (0.043)	0.507	3394	3.977	0.098** (0.046)	0.017	3571	3.913
Human activities are a significant cause	0.062 (0.042)	0.073	3394	4.153	0.060 (0.048)	0.107	3570	4.144
Extreme weather events are made more likely	0.033 (0.040)	0.210	3394	4.108	-0.011 (0.046)	0.597	3570	4.131
Climate change is not a serious issue (reverse coded)	0.046 (0.071)	0.259	3393	1.599	0.099 (0.081)	0.112	3566	1.631

Note: This table shows OLS coefficients of real asset treatment on the unstandardized outcomes in each row, with the exception of the first row, which presents results from the aggregated z-score index of the components. For the Climate Beliefs Index, participants were asked to rate their level of agreement with climate change statements on a continuous scale from 0-6 (0=Strongly Disagree, 1=Disagree, 2=Somewhat Disagree, 3=Neither agree nor disagree, 4=Somewhat agree, 5=Agree, 6=Strongly Agree). Specific questions asked: (1) “Climate change will have a serious impact on quality of life in the U.S. in my lifetime,” (2) “Human activities are a significant cause of climate change,” (3) “Extreme weather events are made more likely by climate change,” and (4) “Climate change is not a serious issue” (reverse coded). All regressions include post-double-selection (p-ds) LASSO covariates and block fixed effects, with LASSO variable selection performed on demographic controls (age, age squared, race/ethnicity, risk preferences, gender, education, income, financial literacy, vote intention, six-month trade exposure), strata controls (party identification, prior climate beliefs, experimental trade experience, region), and other controls (party identification strength, trade exposure status, baseline belief indices for climate beliefs/transition benefits/transition costs/government action/business action, baseline policy salience for climate, baseline climate donation, baseline behavior index, donation behavior). Robust standard errors in parentheses. One-sided p-values show p value in direction of hypothesis. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A12: Real Asset Treatment Effect on Components of Business Action Index, Full Sample

Outcome	Midline				Endline			
	Real Asset Treatment	p ($\lvert\beta\rvert > 0$)	N	Control Mean	Real Asset Treatment	p ($\lvert\beta\rvert > 0$)	N	Control Mean
Support Business Action Index: U.S. Companies Should	0.041 (0.027)	0.063	3387	0.000	0.064** (0.029)	0.014	3557	0.001
Do more to reduce greenhouse gas emissions	0.081** (0.039)	0.019	3387	4.250	0.057 (0.043)	0.092	3556	4.264
Contribute to climate mitigation if companies in other countries do	0.033 (0.056)	0.281	3387	3.760	0.133** (0.062)	0.017	3557	3.695

Note: This table shows OLS coefficients of real asset treatment on the unstandardized outcomes in each row, with the exception of the first row, which presents results from the aggregated z-score index of the components. For the Support Business Action Index, participants were asked to rate their support for business climate action on a continuous scale from 0-6 (0=Strongly Disagree, 1=Disagree, 2=Somewhat Disagree, 3=Neither agree nor disagree, 4=Somewhat agree, 5=Agree, 6=Strongly Agree). Specific questions asked participants to rate their agreement with: (1) "U.S. companies should do more to reduce greenhouse gas emissions" and (2) "U.S. companies should contribute to climate mitigation even if companies in other countries do not." All regressions include post-double-selection (p-ds) LASSO covariates and block fixed effects, with LASSO variable selection performed on demographic controls (age, age squared, race/ethnicity, risk preferences, gender, education, income, financial literacy, vote intention, six-month trade exposure), strata controls (party identification, prior climate beliefs, experimental trade experience, region), and other controls (party identification strength, trade exposure status, baseline belief indices for climate beliefs/transition benefits/transition costs/government action/business action, baseline policy salience for climate, baseline climate donation, baseline behavior index, donation behavior). Robust standard errors in parentheses. One-sided p-values show p value in direction of hypothesis. *** p<0.01, ** p<0.05, * p<0.10.

Table A13: Real Asset Treatment Effect on Components of Government Action Index, Full Sample

Outcome	Midline				Endline			
	Real Asset Treatment	p ($\lvert\beta\rvert > 0$)	N	Control Mean	Real Asset Treatment	p ($\lvert\beta\rvert > 0$)	N	Control Mean
Support Government Action Index: The U.S Government Should	-0.001 (0.032)	0.517	3387	-0.000	0.122*** (0.036)	0.000	3557	0.000
Do more to reduce greenhouse gas emissions	0.016 (0.039)	0.338	3387	4.120	0.120*** (0.042)	0.002	3557	4.052
Contribute to climate mitigation if other countries do	-0.037 (0.059)	0.733	3387	2.448	0.138** (0.067)	0.019	3557	2.388

Note: This table shows OLS coefficients of real asset treatment on the unstandardized outcomes in each row, with the exception of the first row, which presents results from the aggregated z-score index of the components. For the Support Government Action Index, participants were asked to rate their support for government climate action on a continuous scale from 0-6 (0=Strongly Disagree, 1=Disagree, 2=Somewhat Disagree, 3=Neither agree nor disagree, 4=Somewhat agree, 5=Agree, 6=Strongly Agree). Specific questions asked participants to rate their agreement with: (1) "The U.S. government should do more to reduce greenhouse gas emissions" and (2) "The U.S. government should contribute to climate mitigation even if other countries do not." All regressions include post-double-selection (p-ds) LASSO covariates and block fixed effects, with LASSO variable selection performed on demographic controls (age, age squared, race/ethnicity, risk preferences, gender, education, income, financial literacy, vote intention, six-month trade exposure), strata controls (party identification, prior climate beliefs, experimental trade experience, region), and other controls (party identification strength, trade exposure status, baseline belief indices for climate beliefs/transition benefits/transition costs/government action/business action, baseline policy salience for climate, baseline climate donation, baseline behavior index, donation behavior). Robust standard errors in parentheses. One-sided p-values show p value in direction of hypothesis. *** p<0.01, ** p<0.05, * p<0.10.

Table A14: Real Asset Treatment Effect on Components of Climate Decisions Index, Full Sample

Outcome	Midline				Endline			
	Real Asset Treatment	p ($\lvert\beta\rvert > 0$)	N	Control Mean	Real Asset Treatment	p ($\lvert\beta\rvert > 0$)	N	Control Mean
Climate Decision Index	0.045 (0.028)	0.052	3394	0.000	0.083*** (0.032)	0.004	3567	0.000
Where to live	0.041 (0.056)	0.237	3392	3.553	0.074 (0.065)	0.127	3567	3.406
Where to take a job	0.015 (0.059)	0.400	3390	3.251	0.087 (0.066)	0.095	3567	3.071
In which companies to invest	0.185*** (0.057)	0.001	3388	3.274	0.307*** (0.064)	0.000	3565	3.134

Note: This table shows OLS coefficients of real asset treatment on the unstandardized outcomes in each row, with the exception of the first row, which presents results from the aggregated z-score index of the components. For the Climate Decision Index, participants were asked to rate how likely climate change considerations would affect their decisions on a continuous scale from 0-6 (0=Extremely Unlikely, 1=Moderately unlikely, 2=Slightly Unlikely, 3=Neither likely nor unlikely, 4=Slightly likely, 5=Moderately likely, 6=Extremely likely). Specific questions asked participants to rate the likelihood that climate change would influence their decisions about: (1)Where to live, (2) Where to take a job, and (3)In which companies to invest. All regressions include post-double-selection (p-ds) LASSO covariates and block fixed effects, with LASSO variable selection performed on demographic controls (age, age squared, race/ethnicity, risk preferences, gender, education, income, financial literacy, vote intention, six-month trade exposure), strata controls (party identification, prior climate beliefs, experimental trade experience, region), and other controls (party identification strength, trade exposure status, baseline belief indices for climate beliefs/transition benefits/transition costs/government action/business action, baseline policy salience for climate, baseline climate donation, baseline behavior index, donation behavior). Robust standard errors in parentheses. One-sided p-values show p value in direction of hypothesis. *** p<0.01, ** p<0.05, * p<0.10.

Table A15: Real Asset Treatment Effect on Components of Climate Behaviors Index, Full Sample

Outcome	Midline				Endline			
	Real Asset Treatment	p ($\lvert\beta\rvert > 0$)	N	Control Mean	Real Asset Treatment	p ($\lvert\beta\rvert > 0$)	N	Control Mean
Climate Behaviors Index	0.005 (0.022)	0.418	3386	0.000	0.028 (0.025)	0.133	3556	-0.001
Sign a petition in support of protecting environment	-0.028 (0.049)	0.716	3386	3.664	0.055 (0.059)	0.174	3556	3.531
Join or renew membership in an environmental group	0.091* (0.051)	0.038	3386	2.391	0.040 (0.057)	0.240	3556	2.389
Choose to walk, bike or use public transport over driving	-0.057 (0.056)	0.844	3385	3.173	-0.018 (0.064)	0.608	3556	3.150
Attempt to use reusable bags at the grocery store	0.045 (0.047)	0.167	3386	4.438	0.102* (0.055)	0.031	3556	4.360
Consciously reduce meat consumption.	-0.019 (0.051)	0.646	3386	2.820	0.025 (0.060)	0.339	3556	2.754

Note: This table shows OLS coefficients of real asset treatment on the unstandardized outcomes in each row, with the exception of the first row, which presents results from the aggregated z-score index of the components. For the Climate Behaviors Index, participants were asked to rate how likely they would be to engage in climate-related behaviors on a continuous scale from 0-6 (0=Extremely Unlikely, 1=Moderately unlikely, 2=Slightly Unlikely, 3=Neither likely nor unlikely, 4=Slightly likely, 5=Moderately likely, 6=Extremely likely). Specific questions asked participants to rate their likelihood of: (1) Sign a petition in support of protecting the environment, (2) Join or renew membership in an environmental group, (3) Choose to walk, bike or use public transport over driving, (4) Attempt to use reusable bags at the grocery store, and (5) Consciously reduce meat consumption. All regressions include post-double-selection (p-ds) LASSO covariates and block fixed effects, with LASSO variable selection performed on demographic controls (age, age squared, race/ethnicity, risk preferences, gender, education, income, financial literacy, vote intention, six-month trade exposure), strata controls (party identification, prior climate beliefs, experimental trade experience, region), and other controls (party identification strength, trade exposure status, baseline belief indices for climate beliefs/transition benefits/transition costs/government action/business action, baseline policy salience for climate, baseline climate donation, baseline behavior index, donation behavior). Robust standard errors in parentheses. One-sided p-values show p value in direction of hypothesis. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A16: Real Asset Treatment Effect on Components of Transition Benefits Index, Full Sample

Outcome	Midline				Endline			
	Real Asset Treatment	p ($\lvert\beta\rvert > 0$)	N	Control Mean	Real Asset Treatment	p ($\lvert\beta\rvert > 0$)	N	Control Mean
Transition Benefits Index: Renewable Energy Will	0.032 (0.020)	0.055	3392	0.001	0.056** (0.023)	0.009	3559	0.000
Create well-paying jobs for Americans	0.067* (0.039)	0.041	3392	4.105	0.113** (0.044)	0.005	3559	4.075
Have potential to cause economic growth in the U.S.	0.047 (0.039)	0.116	3392	4.021	0.100** (0.045)	0.014	3559	3.943
Investments are an important way to fight climate change	0.030 (0.039)	0.218	3392	4.025	0.054 (0.044)	0.110	3559	3.976
The energy transition will be beneficial for U.S. economy (next 10 years)	0.030 (0.044)	0.249	3392	3.634	0.055 (0.054)	0.150	3555	3.577

Note: This table shows OLS coefficients of real asset treatment on the unstandardized outcomes in each row, with the exception of the first row, which presents results from the aggregated z-score index of the components. For the Transition Benefits Index, participants were asked to rate their level of agreement with statements about renewable energy benefits on a continuous scale from 0-6 (0=Strongly Disagree, 1=Disagree, 2=Somewhat Disagree, 3=Neither agree nor disagree, 4=Somewhat agree, 5=Agree, 6=Strongly Agree). Specific questions asked participants whether renewable energy will: (1) "Create well-paying jobs for Americans," (2) "Have potential to cause economic growth in the U.S.," (3) "Investments in renewable energy are an important way to fight climate change," and (4) "The energy transition will be beneficial for the U.S. economy over the next 10 years." All regressions include post-double-selection (p-ds) LASSO covariates and block fixed effects, with LASSO variable selection performed on demographic controls (age, age squared, race/ethnicity, risk preferences, gender, education, income, financial literacy, vote intention, six-month trade exposure), strata controls (party identification, prior climate beliefs, experimental trade experience, region), and other controls (party identification strength, trade exposure status, baseline belief indices for climate beliefs/transition benefits/transition costs/government action/business action, baseline policy salience for climate, baseline climate donation, baseline behavior index, donation behavior). Robust standard errors in parentheses. One-sided p-values show p value in direction of hypothesis. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A17: Real Asset Treatment Effect on Components of Transition Costs Index, Full Sample

Outcome	Midline				Endline			
	Real Asset Treatment	p ($\lvert\beta\rvert > 0$)	N	Control Mean	Real Asset Treatment	p ($\lvert\beta\rvert > 0$)	N	Control Mean
Transition Costs Index: Renewable Energy Will	-0.054** (0.027)	0.024	3392	0.000	0.005 (0.030)	0.567	3559	0.000
Threaten many fossil fuel jobs in America	-0.093* (0.052)	0.037	3391	3.829	-0.056 (0.060)	0.175	3559	3.685
Take up land that could be used more productively	-0.096* (0.051)	0.030	3392	3.064	0.036 (0.056)	0.739	3558	2.958
Not meet the needs of the American economy (next 10 years)	-0.013 (0.053)	0.406	3392	3.308	0.036 (0.060)	0.724	3558	3.362
Not meet the needs of the American economy (next 20 years)	-0.076 (0.054)	0.078	3392	3.014	0.043 (0.059)	0.769	3557	2.966

Note: This table shows OLS coefficients of real asset treatment on the unstandardized outcomes in each row, with the exception of the first row, which presents results from the aggregated z-score index of the components. For the Transition Costs Index, participants were asked to rate their level of agreement with statements about renewable energy costs on a continuous scale from 0-6 (0=Strongly Disagree, 1=Disagree, 2=Somewhat Disagree, 3=Neither agree nor disagree, 4=Somewhat agree, 5=Agree, 6=Strongly Agree). Specific questions asked participants whether renewable energy will: (1) "Threaten many fossil fuel jobs in America," (2) "Take up land that could be used more productively," (3) "Not meet the needs of the American economy over the next 10 years," and (4) "Not meet the needs of the American economy over the next 20 years." For this outcome, hypothesized effects are decreases (lower perceived costs), so one-sided p-values test whether treatment effects are negative. All regressions include post-double-selection (p-ds) LASSO covariates and block fixed effects, with LASSO variable selection performed on demographic controls (age, age squared, race/ethnicity, risk preferences, gender, education, income, financial literacy, vote intention, six-month trade exposure), strata controls (party identification, prior climate beliefs, experimental trade experience, region), and other controls (party identification strength, trade exposure status, baseline belief indices for climate beliefs/transition benefits/transition costs/government action/business action, baseline policy salience for climate, baseline climate donation, baseline behavior index, donation behavior). Robust standard errors in parentheses. One-sided p-values show p value in direction of hypothesis. *** p<0.01, ** p<0.05, * p<0.10.

Table A18, Table A19, and Table A20 presents results for sub-components of media consumption indices, including newspapers, financial media, and broader media consumption, respectively. We do not find any precisely estimated effects on newspaper consumption (Table A18). Treated respondents are 1.4 to 2.3 p.p. more likely to report consuming each of the three financial news sources (Wall Street Journal, Yahoo Finance, and Financial Times) in the midline survey, effect sizes that are between 14 and 46 percent relative to the mean. These effects are similar in magnitude in the endline survey, with the exception of Wall Street Journal, which is not different from zero. Finally, Table A20 shows impacts for broader media consumption. In the endline survey, treated respondents are less likely to report consuming social media by 4.3 p.p., an effect size of 7.4 percent relative to the control mean, though effects in the midline survey are smaller and not statistically significant. They are also less likely to report watching Fox News by 3.3 p.p. in the endline, a decrease of 9.3 percent relative to the control mean.

Table A18: Real Asset Treatment Effect on Newspapers Media Consumption, Full Sample

Outcome	Midline				Endline			
	Real Asset Treatment	$p\ (\lvert\beta\rvert = 0)$	Control Mean	N	Real Asset Treatment	$p\ (\lvert\beta\rvert = 0)$	Control Mean	N
Newspaper Index	-0.007	0.332	0.137	3420	-0.012*	0.064	0.129	3587
	(0.007)				(0.007)			
New York Times	-0.011	0.335	0.171	3420	-0.015	0.153	0.161	3587
	(0.011)				(0.010)			
USA Today	-0.000	0.986	0.115	3420	-0.014	0.158	0.115	3587
	(0.010)				(0.010)			
Washington Post	-0.012	0.240	0.127	3420	-0.010	0.281	0.112	3587
	(0.010)				(0.009)			

Note: This table shows OLS coefficients of real asset treatment on binary responses to the question "Where did you get your news from this week (select all that apply)?" p-values are two-sided. All regressions include post-double-selection (p-ds) LASSO covariates and block fixed effects, with LASSO variable selection performed on demographic controls (age, age squared, race/ethnicity, risk preferences, gender, education, income, financial literacy, vote intention), strata controls (party identification, prior climate beliefs, experimental trade experience, region), and other controls (party identification strength, trade exposure, baseline belief and behavior indices, donation behavior). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A19: Real Asset Treatment Effect on Financial Media Consumption, Full Sample

Outcome	Midline				Endline			
	Real Asset Treatment	p $(\|\beta\| = 0)$	Control Mean	N	Real Asset Treatment	p $(\|\beta\| = 0)$	Control Mean	N
Financial Media	0.012***	0.005	0.065	3420	0.013***	0.004	0.067	3587
	(0.004)				(0.004)			
Wall Street Journal	0.014	0.147	0.099	3420	-0.010	0.303	0.108	3587
	(0.010)				(0.009)			
Yahoo Finance	0.023***	0.009	0.068	3420	0.025***	0.003	0.075	3587
	(0.009)				(0.009)			
Financial Times	0.017***	0.008	0.037	3420	0.025***	0.000	0.034	3587
	(0.006)				(0.006)			

Note: This table shows OLS coefficients of real asset treatment on binary responses to the question "Where did you get your news from this week (select all that apply)?" p-values are two-sided. All regressions include post-double-selection (p-ds) LASSO covariates and block fixed effects, with LASSO variable selection performed on demographic controls (age, age squared, race/ethnicity, risk preferences, gender, education, income, financial literacy, vote intention), strata controls (party identification, prior climate beliefs, experimental trade experience, region), and other controls (party identification strength, trade exposure, baseline belief and behavior indices, donation behavior). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A20: Real Asset Treatment Effect on Broader Media Consumption, Full Sample

Outcome	Midline				Endline			
	Real Asset Treatment	p $(\|\beta\| = 0)$	Control Mean	N	Real Asset Treatment	p $(\|\beta\| = 0)$	Control Mean	N
PBS/NPR	0.002	0.807	0.120	3420	-0.002	0.837	0.123	3587
	(0.009)				(0.010)			
CNN	-0.016	0.200	0.297	3420	-0.013	0.290	0.286	3587
	(0.013)				(0.013)			
MSN	0.011	0.263	0.101	3420	0.021**	0.038	0.103	3587
	(0.010)				(0.010)			
New York Post	0.003	0.741	0.091	3420	-0.004	0.653	0.091	3587
	(0.009)				(0.009)			
Fox News	-0.022*	0.098	0.356	3420	-0.033**	0.010	0.355	3587
	(0.013)				(0.013)			
Social Media	-0.015	0.359	0.591	3420	-0.043***	0.006	0.582	3587
	(0.016)				(0.016)			

Note: This table shows OLS coefficients of real asset treatment on binary responses to the question "Where did you get your news from this week (select all that apply)?" p-values are two-sided. All regressions include post-double-selection (p-ds) LASSO covariates and block fixed effects, with LASSO variable selection performed on demographic controls (age, age squared, race/ethnicity, risk preferences, gender, education, income, financial literacy, vote intention), strata controls (party identification, prior climate beliefs, experimental trade experience, region), and other controls (party identification strength, trade exposure, baseline belief and behavior indices, donation behavior). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

C.2 Long-Term Effects: Additional Tables

Table A21: Effect of Treatment on Climate Action Support Index Eight Months Post-Treatment

Climate Action Support Index	(1)	(2)	(3)
Pooled Asset	0.035		
	(0.022)		
Real Asset		0.038*	
		(0.023)	
Real Green Asset			0.025
			(0.025)
Real Brown Asset			0.051**
			(0.026)
Fantasy Asset		0.023	0.024
		(0.030)	(0.030)
Observations	2924	2924	2924
p (Pooled Treatment $>$ 0)	0.052		
p (Real Assets $>$ 0)		0.045	
p (Real Assets $>$ Fantasy Assets)		0.289	
p (Real Green $>$ Real Brown)			0.854

Note: This table reports OLS estimates of the effect of financial market exposure on the *Climate Action Support Index (CASI)* taken in a follow up survey. The index aggregates nine sub-indices capturing climate beliefs, preferences, and behaviors. *Pooled Treatment* compares all participants assigned to financial market exposure (real and fantasy portfolios, n=2,406, with n representing the number of participants assigned treatment at baseline) versus control (n=1,400). *Real Assets* pools participants assigned 50 or $100 real-value portfolios (n=1,907), while *Fantasy Assets* includes those assigned $100 fantasy portfolios (n=499). Real Green and Real Brown separately estimate effects for participants initially assigned real green energy stocks (n=953) versus real brown energy stocks (n=954) All regressions control for post-double selection (p-ds) LASSO-selected baseline covariates and include block fixed effects accounting for randomization strata (stratified by party identification, geographic region, climate policy prioritization, and prior trading experience), and for climate disclosure treatment status. Robust standard errors in parentheses. Stars denote two-tailed p-values: *** p<0.01, ** p<0.05, * p<0.10. One-tailed p-values for directional hypotheses reported in bottom rows.

Table A22: Real Asset Treatment Effect on Media Consumption Eight Months Post-Treatment

Outcome	Real Asset Treatment	SE	$p\ (\lvert\beta\rvert = 0)$	N
Major TV Networks (ABC, NBC,CBS)	−0.018	0.039	0.651	2960
Major Newspapers (NYT, USA Today, Washington Post)	0.012	0.035	0.735	2960
Local News	−0.080*	0.042	0.055	2960
Financial News (WSJ, Yahoo Finance, Financial Times, Other)	0.056	0.038	0.136	2960
Fox News	0.021	0.036	0.564	2960
Social Media	0.038	0.042	0.364	2960

Note: This table reports OLS estimates of the real asset treatment effect on standardized media consumption outcomes. The *Real Asset Treatment* compares participants assigned real-value portfolios to fantasy treatment (not shown) and control group (participants who did not trade). Outcomes are z-scored standardized measures based on responses to the question "Where did you get your news from this week (select all that apply)?" measured eight months post treatment. All regressions control for post-double selection (p-ds) LASSO-selected baseline covariates and block fixed effects accounting for randomization strata (stratified by party identification, geographic region, climate policy prioritization, and prior trading experience). All regressions control for fantasy portfolio assignment, and climate disclosure treatment. Robust standard errors reported. Stars denote two-tailed significance: *** $p<0.01$, ** $p<0.05$, * $p<0.10$. Two-sided p-values reported in column 4.

Table A23: Effect of Treatment on Total Correct Emissions Answers (Eight Months Post-Treatment)

Correct Emissions	(1)	(2)	(3)
Pooled Treatment	0.105***		
	(0.040)		
Real Assets		0.109***	
		(0.042)	
Real Green			0.108**
			(0.050)
Real Brown			0.121**
			(0.051)
Fantasy Assets		0.088	0.092
		(0.063)	(0.063)
Observations	2860	2860	2860
p (Pooled Treatment > 0)	0.004		
p (Real Assets > 0)		0.005	
p (Real Assets > Fantasy Assets)		0.367	
p (Real Green > Real Brown)			0.593

Note: This table reports OLS estimates of the effect of the trading treatment on standardized emissions knowledge outcomes measured at eight months post-treatment. Outcomes are z-scored indices of correct answers to the question: "In your opinion, how many tons of CO2 equivalent annual greenhouse gas do each of these companies produce?" with answers given in order of magnitude. *Pooled Treatment* compares all participants assigned financial market exposure (real and fantasy portfolios, n=2,406, with n representing the number of participants assigned treatment at baseline) versus control (n=1,400). *Real Assets* pools participants assigned $50 or $100 real-value portfolios (n=1,907), while *Fantasy Assets* includes those assigned $100 fantasy portfolios (n=499). *Real Green* and *Real Brown* separately estimate effects for participants initially assigned real green energy stocks (n=953) versus real brown energy stocks (n=954). All regressions control for post-double selection (p-ds) LASSO-selected baseline covariates and block fixed effects accounting for randomization strata (stratified by party identification, geographic region, climate policy prioritization, and prior trading experience), and climate disclosure treatment status. Robust standard errors in parentheses. Stars denote two-tailed p-values: *** p<0.01, ** p<0.05, * p<0.10. One-tailed p-values for directional hypotheses reported in bottom rows.

Table A24: Effect on Perception of Climate Impact (Eight Months Post-Treatment)

Perception of Climate Impact	Green Firms			Brown Firms		
	(1)	(2)	(3)	(4)	(5)	(6)
Pooled Treatment	0.105**			0.036		
	(0.042)			(0.039)		
Real Assets		0.132***			0.045	
		(0.044)			(0.040)	
Real Green			0.115**			0.031
			(0.051)			(0.047)
Real Brown			0.141***			0.052
			(0.049)			(0.046)
Fantasy Assets		-0.004	-0.008		-0.002	-0.006
		(0.058)	(0.058)		(0.051)	(0.051)
Observations	2862	2862	2862	2863	2863	2863
p (Pooled Treatment $>$ 0)	0.007			0.177		
p (Real Assets $>$ 0)		0.001			0.130	
p (Real Assets $>$ Fantasy Assets)		0.004			0.148	
p (Real Green $>$ Real Brown)			0.710			0.674

Note: This table reports OLS estimates of the trading treatment on standardized z-score indices created from respondents' answers on a 1-7 scale to the question: "How impactful are each of these companies on the environment." Columns (1)-(3) show effects on perceived environmental impact of green firms; columns (4)-(6) show effects on perceived impact of brown firms. *Pooled Treatment* compares all participants assigned financial market exposure (real and fantasy portfolios, n=2,406, with n representing the number of participants assigned treatment at baseline) versus control (n=1,400). *Real Assets* pools participants assigned $50 or $100 real-value portfolios (n=1,907), while *Fantasy Assets* includes those assigned $100 fantasy portfolios (n=499). *Real Green* and *Real Brown* separately estimate effects for participants initially assigned real green energy stocks (n=953) versus real brown energy stocks (n=954). All regressions control for post-double selection (p-ds) LASSO-selected baseline covariates and block fixed effects accounting for randomization strata (stratified by party identification, geographic region, climate policy prioritization, and prior trading experience). Endline regressions additionally control for climate disclosure treatment status. Robust standard errors in parentheses. Stars denote two-tailed p-values: *** p<0.01, ** p<0.05, * p<0.10. One-tailed p-values for directional hypotheses reported in bottom rows.

Table A25: Effect of Treatment on Financial Confidence (Eight Months Post Treatment)

Financial Confidence Index	(1)	(2)	(3)
Pooled Treatment	0.049*		
	(0.028)		
Real Assets		0.066**	
		(0.029)	
Real Green			0.044
			(0.035)
Real Brown			0.085**
			(0.035)
Fantasy Assets		-0.011	-0.013
		(0.042)	(0.042)
Observations	2950	2950	2950
p (Pooled Treatment > 0)	0.042		
p (Real Assets > 0)		0.013	
p (Real Assets > Fantasy Assets)		0.028	
p (Real Green > Real Brown)			0.863

Note: This table reports OLS estimates of the trading treatment on a general index of financial confidence measured in a follow up suvey eight months post treatment. The financial confidence index is a z-score index constructed from the following standardized components: the willingness of participants to invest in the future, their own assessment of risk, and total (out of 3) basic financial literacy questions they answered correctly. *Pooled Treatment* compares all participants assigned financial market exposure (real and fantasy portfolios, n=2,406, with n representing the number of participants assigned treatment at baseline) versus control (n=1,400). *Real Assets* pools participants assigned $50 or $100 real-value portfolios (n=1,907), while *Fantasy Assets* includes those assigned $100 fantasy portfolios (n=499). *Real Green* and *Real Brown* separately estimate effects for participants initially assigned real green energy stocks (n=953) versus real brown energy stocks (n=954). All regressions control for post-double selection (p-ds) LASSO-selected baseline covariates and block fixed effects accounting for randomization strata (stratified by party identification, geographic region, climate policy prioritization, and prior trading experience). All regressions control for climate disclosure treatment status. Robust standard errors in parentheses. Stars denote two-tailed p-values: *** p<0.01, ** p<0.05, * p<0.10. One-tailed p-values for directional hypotheses reported in bottom rows.