Essays in Climate Finance

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Introduction

The thesis consists of three chapters, which can be read independently. The common theme across all three chapters is how the current and expected effects of climate change influence the agents in the economy.

The first chapter addresses whether physical climate risks that are yet to materialize may influence household stock market participation behavior today. I identify physical climate risks emanating from sea level rise (SLR) risks as a prominent risk that households face due to the location of the homes that they own and occupy. I hypothesize that SLR risks constitute a source of uninsurable background risks for exposed households. The presence of such uninsurable background risks reduces the demand for other types of risks, such as financial risks, in models of portfolio choices. Using detailed location variation in SLR exposure and disaggregated geographic information on households in the United States, I document that SLR exposed households participate less in the stock market compared to their unexposed counterparts within the same neighborhood. I provide further empirical evidence that this observed effect is driven by long-run SLR risks as opposed to short-run flood risks and is elevated at times when households' attention to climate risks is amplified. Finally, I provide causal evidence of the effect of SLR risks on household portfolio allocation decisions by leveraging exogenous variation stemming from the adoption of state-led climate change adaptation plans that reduced households' perceived SLR risks. Additional tests give support to the interpretation that SLR risks constitute a source of uninsurable background risks for households and isolate this effect from alternative explanations, including changes in house prices, past flooding experiences, endogenous location choices, political beliefs, or differences in risk preferences.

The second chapter is joint work with Zacharias Sautner and Grigory Vilkov and examines whether investors price climate policy uncertainty in the options market. Specifically, we explore whether the cost of option protection against downside tail risks is higher for firms with more carbon-intense business models, as these firms will be most affected by policies that aim to curb emissions. Our analysis uses three option market measures for firms in the S&P500 to proxy for the cost of option protection for these firms. Our focal measure, *SlopeD*, identifies downside tail risk and reflects the steepness of the implied volatility slope (i.e., the slope of a function that relates left-tail implied volatility to moneyness measured by the option's delta). The other two measures are the model-free implied skewness (*MFIS*) proposed by Bakshi, Kapadia, and Madan (2003), which quantifies the asymmetry of the risk-neutral distribution, and the variance risk premium (*VRP*), which is computed as the difference between the risk-neutral expected and the realized variances. Focusing on options with 30-day maturity, we find evidence that climate policy uncertainty is priced in the options market. For example, the cost of option protected as measured by the implied volatility slope is on average higher for firms in more carbon-intense industries. In a next step, we show that the cost of option protection against downside tail risks are magnified at times when public attention to climate change spikes. Finally, we use the election of President Trump in 2016 as a shock that reduced climate policy uncertainty in the short term. Following President Trump's election, the cost of option protection goes down as the climate policy uncertainty is also lower since the Trump administration largely maintained that the prevailing climate policies would not become stricter.

The third chapter is joint work with Philipp Krueger, Zacharias Sautner, and Laura Starks and examines the role of institutional investors in improving their portfolio firms' climate disclosure practices. In this study, we provide evidence from a survey of institutional investors, and observational data relating corporate climate risk disclosures and institutional holdings. On the survey side, we find that institutional investors value and demand climate-related disclosures from their portfolio firms. Investors also find that current disclosure practices insufficient and imprecise and they perceive that markets are underpricing these climate risks when current disclosure practices are more lacking. In the analyses on observational data, we focus on what we call climate-conscious institutional ownership that plausibly reflect a stronger demand for climate risk reporting. On the climate risk disclosure side, we use a voluntary disclosure data set collected by the CDP. We consider three distinct variables that measure whether firms disclose their raw carbon emissions, whether they disclose soft information on the categories of climate risks they face (i.e., regulatory, physical, and other), and a climate disclosure score calculated based on the completeness of the answers of firms to CDP's surveys and how detailed the answers are. Based on these measures, we document that climate-conscious institutional ownership is positively associated with more and better-quality climate risk reporting. In further tests, we exploit demand and supply shocks to climate-related disclosures. We consider the adoption of the French Article 173 in 2016, which mandated that institutional investors must disclose the climate risk exposures of their portfolios, as a demand shock. In addition, we consider the U.K. mandatory emissions reporting law adopted in 2013, which mandated that listed U.K. firms must disclose their carbon emissions in annual reports, as a supply shock. Using these plausibly exogenous developments, we find that both influence and selection effects exist in equilibrium to explain the relationship between climate-conscious institutional ownership and increased corporate climate risk reporting. That is, institutional investors induce firms to provide more climate risk disclosures, but they also self-select into better disclosing firms to begin with.

Research Contributions

Sea Level Rise and Portfolio Choice

Emirhan Ilhan

Abstract

Many households face uninsurable background risks due to future sea level rise (SLR). Using detailed local variation in SLR exposure and disaggregated geographic information on households in the United States, I show that SLR exposed households participate less in the stock market compared to their unexposed counterparts within the same neighborhood. This effect is driven by long-run SLR risks as opposed to short-run flood risks and is elevated at times when attention to climate change is high. I provide causal evidence of the effect of SLR risks on household portfolio choices by exploiting plausibly exogenous variation stemming from the adoption of state-led climate change adaptation plans that reduced households' SLR risks. Additional tests isolate the effect of SLR exposure as a background risk from alternative explanations, including changes in house prices, past flooding experiences, endogenous location choices, political beliefs, or differences in risk preferences.

JEL Codes: G11, G51, Q54

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Scientists project that sea levels globally can rise by more than 6 feet by the turn of this century (Sweet et al., 2017; DeConto and Pollard, 2016) and the rate of sea level rise (SLR) currently tracks the worst-case scenario laid out by the Intergovernmental Panel on Climate Change (IPCC)'s Fifth Assessment Report (Slater, Hogg and Mottram, 2020). According to recent estimates, a 3 feet SLR scenario will leave 4.2 million people in the United States under water, whereas a 6 feet SLR scenario will inundate 13.1 million people (Hauer, Evans and Mishra, 2016). While permanent flooding of certain areas will take place with virtual certainty in a long enough horizon, there is significant uncertainty associated with its timing and costs. Coastal communities are also vulnerable to SLR risks emanating from aggravated chronic flooding and extreme weather events.

In this paper, I study how future SLR risks influence household portfolio choices. Owner-occupied housing comprises the largest asset class in most households' portfolios (Guiso and Sodini, 2013; Gomes, Haliassos and Ramadorai, 2021). The value of real estate is inextricably linked to the land it is built on and therefore, homeownership exposes many households to SLR risks. It is ex-ante ambiguous whether and how SLR risks may induce changes in households' portfolio allocation decisions. On one hand, SLR exposed households may be more willing to take financial risks if, for example, risk preferences drive both SLR exposures and investments in risky financial assets. On the other hand, because houses are illiquid and indivisible assets, homeowners find it costly to adjust their consumption of housing in response to economic shocks (Campbell, 2006). The long-run and undiversifiable nature of physical climate risks also limits individual investors' ability to insure against them (Engle et al., 2020).[1] Thus, SLR risks constitute a source of background risk for exposed households (i.e., a risk that cannot be avoided). In models of portfolio choices, the presence of background risks makes investors less willing to take other types of risks, such as

[1] Flood insurance is not mandatory in the United States and even homeowners at risk of flooding often do not own flood insurance (Kousky, 2018). The Federal Emergency Management Agency (FEMA) provides subsidized flood insurance to properties that they deem at risk based on outdated maps that do not take future SLR into account. These flood insurance policies are renewed annually, and rates are subject to change at renewal such that these policies likely provide little to no hedging benefits against long-term risks such as SLR risks. I discuss the inadequacy of flood insurance markets in the United States and low take-up rates in these markets in further detail in Section 1.

financial risks.[2] I provide evidence consistent with the implications of these models.

A key challenge in my analysis lies in creating a meaningful measure of SLR exposure at the household level. Traditional sources of household data are unsuitable to study the effects of local physical risks such as SLR risks, because they only provide information on the households' state of residence as the narrowest geographical region. I circumvent this issue by employing the restricted version of the Panel Study of Income Dynamics (PSID) data, which allows me to observe granular geographical location of households. To generate cross-sectional variation in households' exposure to SLR risks, I geocode households' locations and merge them with SLR maps from the National Oceanic and Atmospheric Administration (NOAA). I restrict attention to homeowner households (henceforth, households) who reside in the house they own. I estimate the effect of SLR exposure on household portfolio choices by comparing households with varying degrees of SLR exposure in the same zip code and year, after accounting for a battery of household financial, demographic, and geographic characteristics.[3]

I find strong evidence that SLR exposed households have a lower propensity to participate in the stock market and invest a smaller share of their financial wealth in equities, compared to unexposed households in the same neighborhood. These effects are economically sizable. A one-standard-deviation increase in SLR exposure decreases the propensity of stock market participation by 1.8 percentage points (pp), a 6% decrease since the sample mean of households' participation rate is 30%. The same one-standard-deviation increase in SLR exposure decreases the share of financial wealth invested in risky assets by 1.6 pp, which equals 9% of households' mean risky share. These effects are comparable in magnitude to those estimated by Fagereng, Guiso and Pistaferri (2018) for uninsurable labor income risk.[4] My analysis also yields strong evidence that SLR exposed households are more likely to exit from and less likely to enter

[2] A sufficient condition for a background risk effect to arise is a utility function that exhibits decreasing and (weakly) convex absolute risk aversion. Kimball (1993) and Gollier and Pratt (1996) discuss such classes of utility functions.
[3] I also indirectly control for differences in flood insurance purchase rates since the fixed effects I employ in this analysis would absorb all the variation in the publicly available FEMA flood insurance data. However, the location of properties cannot be identified in these data because of privacy protection.
[4] Uninsurable labor income risk is likely the most prominent source of background risk studied in the literature.

into the stock market compared to unexposed households in the same zip code.

To narrow the interpretation about whether these findings are driven by long-run inundation risks or short-run risks associated with more severe and more frequent extreme events, I employ data on storm surge exposure by using the National Storm Surge Hazard maps also provided by NOAA. I augment my baseline analysis with this measure of storm surge exposure. The coefficient estimates in these regressions that include both SLR exposure and storm surge exposure indicate that my findings are primarily attributable to long-run SLR risks.

In a next step, I examine how the presence of informational frictions and limited attention to SLR risks might reduce the extent to which SLR risks are taken into account by households. Indeed, some recent papers in the literature highlight the key role that attention to climate risks plays in determining housing prices (Bernstein, Gustafson and Lewis, 2019; Baldauf, Garlappi and Yannelis, 2020; Engle et al., 2020). I extend my baseline analysis by implementing two tests that leverage time-series variation in households' attention to climate risks and the salience of flood risks. First, I use the Wall Street Journal climate change index introduced by Engle et al. (2020) to proxy for attention to climate risks. Second, in a research design inspired by Baldauf, Garlappi and Yannelis (2020), I focus on the top ten costliest hurricanes in my sample period and consider households living in states unaffected by these hurricanes with the assumption that these households experience an increased salience of climate risks even though they did not bear direct costs due to these extreme weather events. In both of these tests, I find that the negative relationship between SLR exposure and stock market participation is amplified at times when attention to climate risks is elevated, consistent with the notion that informational frictions and limited attention are operative for my findings.

Finally, I provide causal evidence for the relationship between SLR exposure and disinvestment in risky financial assets. As of 2021, the federal government in the United States is yet to take action to address climate risks, making state level actions even more important. Since 2008, 17 states and D.C. have finalized state-led climate change adaptation plans with the goal of protecting residents against the impacts of climate change, including sea level rise.[5] These plans lead to plausibly exogenous decreases in the perception of SLR risks, since the adoption of such climate change adaptation plans reflects state governments' commitment towards mitigating SLR risks for residents and partially resolves the uncertainty in how these risks will be handled by the government. Exploiting this orthogonal source of variation, I test whether households' willingness to take financial risks increases following the adoption of climate adaptation plans. In a staggered diff-in-diff research design, I document that following the adoption of such adaptation plans, a one-standard-deviation increase in SLR exposure of households increases the propensity to participate in the stock market (the share of financial wealth invested in risky assets) by 3.9 (2.7) pp.

When interpreting the results, I emphasize the background risk role of SLR exposure as the underlying channel. However, there exist three potential alternative explanations that can generate the same patterns in the data. Through a series of auxiliary tests, I rule out these alternative explanations. First, one may be concerned that changes in house prices (instead of SLR risks) might crowd out stock holdings of SLR exposed households. I show that SLR exposure reduces household stock market participation even in regions that experienced high house price growth in the recent past, suggesting that second moment effects of SLR exposure matter for household portfolio choices. Relatedly, if SLR exposed houses experience flooding more frequently, the reduced stock market participation by SLR exposed households may be due to direct costs incurred from these flooding incidents. Consistent with the background risk effect of SLR exposure, I find that SLR exposure continues to crowd out stock holdings of exposed households compared to their unexposed counterparts even in regions that experienced no flooding events in the recent past.

Second, households endogenously choose whether to participate in the stock market and where they live. Self-selection based on wealth, for example, likely biases my results downwards as richer households are both more likely to live in SLR exposed houses and participate in the stock market. Nevertheless, I find that my results remain unchanged in a subsample of households who never moved in

[5] See https://www.georgetownclimate.org/adaptation/plans.html for more information.

the entire sample of 20 years (for whom backgrounds risks are also likely to be especially prevalent), indicating that household relocation decisions are unlikely to explain my results. Similarly, Bernstein et al. (2021) document that Republican households are more likely to own SLR exposed houses compared to Democratic households. If Republicans are also less likely to participate in the stock market, the differences in political beliefs may explain the relationship between SLR exposure of one's house and stock market participation. Mitigating this concern, I find no evidence that differences in political beliefs drive my results.

Third, there may be a concern that the observed patterns in the data can be accounted for by unobservables, such as differences in risk preferences. I note that self-selection based on risk preferences would likely bias my results downwards as risk tolerant households are both more likely to purchase SLR exposed houses and participate in the stock market. Supporting this line of argument, my results are robust to controlling for risk aversion at the household level computed from the 1996 survey of PSID, following the methodology of Kimball, Sahm and Shapiro (2009). Furthermore, if unobservables can explain the documented effect, we should again observe a negative relationship between SLR exposure and household stock market participation in a sample of renters. If not, we should see no relationship since SLR exposure should pose little to no threat on renters as rental markets are liquid and renters have no home equity. Thus, I conduct a placebo test in a sample of renters and find no evidence that SLR exposure has an effect on the stock market participation behavior of renters, confirming a homeownership channel.[6]

This paper contributes to two strands of literature. First, my analysis complements studies that investigate the effects of climate risks by providing, to the best of my knowledge, the first evidence on how household portfolio choices are influenced by forward-looking physical climate risks in the form of SLR

[6] In unreported results, I compare homeowners to renters in a research design akin to the difference-in-differences strategy employed by Schmalz, Sraer and Thesmar (2017) and also find that SLR exposure reduces homeowners' willingness to take financial risks compared to renters. However, there may be a concern that renters are not an appropriate control group for homeowners in this research design, because the balance sheets of homeowners and renters look inherently different. In contrast, the tests I employ throughout the paper do not have this issue as I compare homeowners to homeowners in my main tests and renters to renters in the placebo tests.

risks. I contribute to the prior work that examines how SLR risks affect house prices (Bernstein, Gustafson and Lewis, 2019; Murfin and Spiegel, 2020; Baldauf, Garlappi and Yannelis, 2020; Keys and Mulder, 2020) by documenting that the second moment effects of SLR exposure on household portfolio choices. My findings are also complementary to the body of work that investigates households' responses to immediate loss of household wealth due to natural disasters by documenting the effects of physical climate risks yet to materialize. Recent studies in this area focus on career choices (Cen, 2021), human capital accumulation (Billings, Gallagher and Ricketts, 2021), and mortgage decisions (Issler et al., 2019) while I focus on risky asset allocation. More broadly, my paper is related to studies that employ measures of SLR risks (Goldsmith-Pinkham et al., 2021; Giglio et al., 2021) and attention to climate risks (Engle et al., 2020; Choi, Gao and Jiang, 2020; Hu, 2020).

Second, I contribute to the large literature that analyzes the determinants of household portfolio choices by identifying a unique source of background risk, whose importance will likely rise going forward. Models of household portfolio choices in this literature argue that consumers who face background risks respond by reducing exposure to risks they can avoid (Kimball, 1993; Gollier and Pratt, 1996). I measure households' background risks due to SLR risks and provide supportive evidence for the predictions of these models in the data. Other empirical applications of these portfolio models focus on background risks such as uninsurable wage risk (Heaton and Lucas, 2000b; Angerer and Lam, 2009; Betermier et al., 2012; Fagereng, Gottlieb and Guiso, 2017) and human capital risk (Cocco, Gomes and Maenhout, 200S; Jansson and Karabulut, 2021), entrepreneurial risk (Heaton and Lucas, 2000a), health risk (Edwards, 2008), among others.

1. Background and Hypotheses

There are two primary physical channels through which SLR exposure can affect housing investments. First, there is the risk of slowly rising oceans that will eventually and permanently flood coastal areas. Second, sea level rise is predicted to exacerbate high tide flooding over time and reduce the time between such flood events (Hayhoe et al., 2018; Sweet et al., 2020). Increasing sea levels are also expected to make storm surge flooding (i.e, when the ocean levels rise temporarily due to a storm) and hurricanes more devastating (Marsooli et al., 2019; Knutson et al., 2020).

Either of these channels can adversely affect home values and thus, the housing wealth of households.[7] At the same time, both of these physical channels contain substantial uncertainty about their potential outcomes. While permanent inundation of certain areas will take place with virtual certainty in a long enough horizon, there is significant uncertainty associated with its timing. Case in point, scientists frequently update forecasts of sea level rise in light of new findings, especially due to new research on the melting patterns of Greenland and Antarctic ice sheets (Goelzer et al., 2020; Passeri et al., 2018; Reese et al., 2020). Extreme weather events are more idiosyncratic in nature and therefore, also characterized by high uncertainty in their expected costs, timing, and frequency. Moreover, the adaptation measures governments will need to take to mitigate the effects of sea level rise amplify this uncertainty, because they vary in scope, timing and costs.

The effects of sea level rise are especially relevant for households, because housing investments constitute the largest share of assets owned for most households (Campbell and Cocco, 2007; Chetty, Sándor and Szeidl, 2017) and almost seven out of every ten households are homeowners as of 2020 (U.S. Census Bureau, 2020). Houses are indivisible and illiquid assets and for most households, all real estate wealth is tied to the house they occupy, rendering housing wealth difficult and costly to transact as a response to wealth shocks (Guiso and Sodini, 2013). Hence, the literature exploring the relationship between housing investments and portfolio choices tends to treat housing as a source of background risk (Guiso and Sodini, 2013; Gomes, Haliassos and Ramadorai, 2021). Under fairly general conditions (i.e., a

[7] There exists mixed evidence in the literature about the pricing of SLR risks in housing markets. Bernstein, Gustafson and Lewis (2019) and Baldauf, Garlappi and Yannelis (2020) find that SLR risks are priced in local real estate markets using NOAA sea level rise data. Murfin and Spiegel (2020) draw attention to land subsidence and rebound as a contributing factor to sea level rise and find limited pricing effects. Keys and Mulder (2020) document a disconnect in coastal Florida real estate where home sale prices only very recently started declining due to sea level rise exposure, but home sale volumes in the SLR exposed communities have been declining for almost a decade.

utility function that exhibits decreasing and convex absolute risk aversion),[8] background risks make investors less willing to take other types of risks, such as investments in risky financial assets.

Combining the high degree of uncertainty about the costs and timing of the impacts of sea level rise and the illiquid nature of housing wealth, I posit that sea level rise is a source of background risk and arrive at my main hypothesis:

HYPOTHESIS 1. SLR exposed households are less likely to participate in the stock market and invest a smaller share of their financial wealth in risky assets compared to unexposed households.

Insofar as households are not aware of SLR risks, informational frictions and limited attention potentially pose constraints for households to consider these risks in their portfolio allocation decisions. Indeed, several papers in the literature emphasize the role of attention to climate change when evaluating how house prices are affected by SLR risks (Baldauf, Garlappi and Yannelis, 2020; Bernstein, Gustafson and Lewis, 2019), when calculating the appropriate discount rates for valuing investments in climate change abatement (Giglio et al., 2021), and when investigating the reasons behind low flood insurance take-up rates (Hu, 2020). These frictions should be, at least to some extent, alleviated at times when attention to climate change is elevated as households seek more information about SLR risks and consider these risks in their portfolio allocation decisions, leading to the following hypothesis:

HYPOTHESIS 2. The crowding out effect of SLR exposure on stock holdings of households is amplified at times when attention to climate change is elevated.

Local governments can implement various policies to mitigate the impacts of sea level rise. For example, reforming the flood insurance system such that affordable rates are available for all SLR exposed households and ensuring that coverage is broad would reduce SLR risks and provide protection for

[8] For examples of these types of utility functions being considered the reader is referred to the works of Kimball (1993) and Gollier and Pratt (1996).

households. Similarly, financing and building new levees and flood walls that can withstand strong hurricanes with the best scientific data available can guarantee the safety and financial well-being of the state residents.[9] States face different challenges due to sea level rise and thus, they need to follow different adaptation and mitigation paths. Whether, how, and when states will tackle these challenges and implement pro-climate policies is highly uncertain. As of 2020, 17 states and the District of Columbia have finalized state-led climate change adaptation plans as preparation against the adverse effects of climate change, including sea level rise. If households perceive the adoption of these plans as credible signals of state governments' commitments towards protecting the state residents, the adoption of these plans should resolve some uncertainty emanating from SLR risks. It follows that a reduction in the perceived background risk due to SLR risks should be reflected in increased stock market participation for SLR exposed households following the adoption of these state-led climate change adaptation plans, leading to the hypothesis:

HYPOTHESIS 3. The propensity to participate in the stock market and the share of financial wealth invested in risky assets increased for SLR exposed households compared to unexposed households, following the adoption of state-led climate change adaptation plans.

1.1 Flood Insurance and Disaster Assistance in the United States

In principle, insurance markets can alleviate SLR risks and thus, a discussion of flood insurance in the United States is warranted. A standard home insurance does not cover flooding damages in the United States and flood insurance is predominantly provided through the National Flood Insurance Program (NFIP) under FEMA. FEMA creates flood maps to designate areas exposed to different levels of flood risks to set

[9] Unlike common belief, Hurricane Katrina was not simply too big that it got through the flood defenses of New Orleans. In fact, Horne (2012) reported that the United States Army Corps of Engineers eventually conceded that the levees in New Orleans failed due to flawed engineering and poor maintenance even though Hurricane Katrina only sideswiped the city of New Orleans. The federal government announced nearly $15 billion to finance the construction of new flood protection improvements, but reports show that the new levees are already in need of replacement due to rising sea levels and sinking ground levels.

the flood insurance rates, which can be as expensive as a home insurance, if not more (Insurance Information Institute, 2021). Many of these maps have been shown to be outdated (National Research Council, 2009; Kousky, 2018), because they use data of poor quality and inappropriate methods and they do not take into account changed conditions or changing conditions due to climate change. For example, the designation procedure of high flood risk areas does not take into account predictions of sea level rise and the number of inundated buildings can increase by an estimated 60% in some areas after considering predicted sea level rise (Habete and Ferreira, 2017).

One of the most important frictions with the NFIP and the flood insurance policies it provides is that the take-up of flood insurance is only mandatory for properties purchased with a federally backed mortgage that lie in a high flood risk area, while being voluntary for all remaining properties. As such, many households in flood zones do not maintain flood insurances policies (Kunreuther et al., 2019) and take-up rates for flood insurance are incredibly low, even in areas at risk of flooding (Kousky et al., 2018). For example, less than 20% of houses flooded by Hurricane Sandy and an estimated 12% of houses flooded by the 2016 Baton Rouge flooding had flood insurance (Kousky, 2018). Even more importantly, the flood insurance policies are one-year contracts with rates that are subject to change at renewal. Rates are not fixed and can increase drastically over the years. Therefore, these contracts can provide little to no hedging benefits against long-term risks such as SLR risks, as the flood insurance price will rise when the insurance becomes relevant. Perhaps as a consequence, the median tenure NFIP policies is only 2-4 years (Michel-Kerjan, Lemoyne de Forges and Kunreuther, 2012). A further limitation of these flood insurance policies is that the coverage is only up to $250,000 minus deductibles. All things considered, flood insurance likely cannot effectively insure against SLR risks.

A potential explanation for the lack of high flood insurance take-up could be the expectation that the federal government acts swiftly to provide generous disaster assistance to flooding victims. Disaster assistance in the United States comes in two forms: federal disaster loans are low-interest loans that must be repaid and federal disaster grants are subject to a Presidential Disaster Declaration (which is not the case for flood insurance claims).[10] Survivors are required to register and be eligible for either of these types of federal aids. Federal disaster grants are around \$5,000 on average per household, whereas the average flood insurance claim payment in recent years was about \$69,000 (NFIP, 2020). Hence, federal disaster assistance is not a substitute for flood insurance, but a supplement.

2. Data Sources and Main Variables of Interest

2.1 Household Survey Data

Data on households' equity holdings, wealth, income, and demographics come from the Panel Study of Income Dynamics (PSID), a national survey of households widely in the United States used in the household finance literature.[11] The survey data were collected once a year until 1996 and once every two years since 1997. Before 1999, the survey question about stock holdings included stocks in pension accounts and individual retirement accounts (IRAs). Starting from 1999, the same question excludes any stock holdings in IRAs, with a separate question asking whether a household has any stocks in IRAs. I focus on households' stock holdings in brokerage accounts, mutual funds, and investment trusts outside of IRAs since investments in IRAs can be affected by default choices (Beshears et al., 2009). For this reason, I use all the waves from 1999 to 2017 to construct my sample.

The main proxy I use for household equity market participation, *Equity Participation*, is an indicator variable that is equal to one if a household holds any stocks in publicly held corporations, mutual funds, or investment trusts in a given year. I also provide results using an equity market participation measure that includes stock investments in IRAs. Furthermore, I extend my analysis using several alternative measures similar to the ones employed by Giannetti and Wang (2016) and Brunnermeier and

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[10] Husted and Nickerson (2014), Langabeer, DelliFraine and Alqusairi (2012), and Reeves (2011) study the probability and delays of Presidential Disaster Declarations and provide evidence that a state's electoral competitiveness, the party affiliation of the President and a state's Governor, and whether a disaster takes place in a reelection year are all determinants whether and how quickly federal disaster assistance may be available for survivors.

[11] The PSID started collecting information on a sample of roughly 5,000 households in 1968, about 3,000 were representative of the United States population as a whole (i.e., the core sample), and about 2,000 were low-income families (i.e., the Survey of Economic Opportunity (SEO) sample). Some recent examples of papers using PSID data include, but are not limited to: Blundell, Pistaferri and Saporta-Eksen (2016), Chen, Michaux and Roussanov (2020), Giannetti and Wang (2016), Barras and Betermier (2020).

Nagel (2008). First, I create a variable measuring the share of financial wealth invested in risky assets, *Risky Share*, which is equal to the net value of stocks held by a household divided by the financial wealth of the household (i.e., sum of cash, stocks, and bonds). Second, I consider changes in stock market participation using two variables that capture entry into and exit from the stock market. In particular, *Entry* is an indicator variable equal to one for households that did not participate in the previous wave of the survey but participate in the current round, and zero for households who did not participate in both the current wave as well as the previous wave. This variable is set to missing otherwise. Similarly, *Exit* is an indicator variable equal to one for households who participated in the previous wave of the survey but do not participate in the current round, and zero for participants in both the previous and current rounds of the survey. This variable is set to missing otherwise. I also extract a number of other household characteristics from PSID, which I summarize in Table 1.

2.2 Sea Level Rise Data

I obtain data on sea level rise from the National Oceanic and Atmospheric Administration (NOAA)'s SLR Viewer tool to construct the main variable of interest, the SLR exposure of a household. NOAA provides maps of projected sea level rise up to 10 feet above average high tides with 1-foot increments for the United States except Alaska. These inundation maps show the regions projected to be under water given a certain sea level rise by the end of 2100 and are agnostic about what the actual sea level rise will be at that time. Instead, these maps are meant to be used as a screening tool for the regions under a given risk scenario.

The ideal SLR exposure measure is an indicator variable equal to one if the coordinates of a household's address is within a certain sea level rise layer provided by NOAA, and zero if the coordinates are outside of this layer. Giglio et al. (2021), Bernstein, Gustafson and Lewis (2019), and Baldauf, Garlappi and Yannelis (2020) construct such a measure. As mentioned in the previous section, however, PSID does not provide the addresses of households, just a household's state of residence. Therefore, I use the restricted PSID geospatial data in which the most precise geospatial indicator is the Census Block[12] and construct the

[12] A Census Block is the smallest geographic unit used by the Census Bureau for tabulation of 100-percent data. Blocks are typically bounded by streets, roads or creeks. In cities a Census Block may correspond to a city block.

SLR exposure measure as the fraction of the area projected to be under water for a given level of SLR at the Census Block level.[13] By definition, this means that two households in the same Census Block have the same SLR exposure.

Figure 1 Panel A illustrates the raw 3 feet sea level rise map over the counties of Florida using NOAA's 3 feet SLR layer and Census county shapefiles based on political boundaries.[14] A careful reader will notice that these legal county boundaries do not correspond to physical county boundaries. As a result, the majority of Monroe County (i.e., the southernmost county in Florida) appears to be covered by water in a 3 feet SLR scenario even though a lot of the area within these legal Census boundaries is ocean water. To take the physical boundaries into account when creating the SLR exposure measure, I make use of the 0 feet SLR layer provided by NOAA. By definition, the intersection of the 0 feet SLR layer and the legal Census boundaries is the natural water area of a given Census area. I calculate the fraction of each Census area that are covered by the 3 feet SLR layer and 0 feet layer. The difference between these two values gives me the fraction of the land area that is projected to be under water for a 3 feet sea level rise projection, such that I end up with a continuous SLR exposure measure varying between zero and one. A heatmap of this final measure for the counties in Florida is presented in Figure 1, Panel B. Moreover, Figure 2 depicts the variation in this measure across the continental United States. The regions most at risk of being inundated are the East Coast and the Gulf Coast whereas the West Coast is relatively safe from rising sea levels.

2.2.1 Geographical Factors Influencing Sea Level Rise

The physical processes used to create NOAA SLR maps account for ground elevation, local and regional

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There were 11,155,486 Census Blocks in the United States and Puerto Rico in the 2010 Census. About 5,000,000 blocks were reported to have a population of zero while a block that is entirely occupied by an apartment complex might have several hundred inhabitants.

[13] There are other studies in the literature that use SLR measures based on fraction of land exposed. Keenan and Bradt (2020) construct a similar measure at the Census Tract level, and Goldsmith-Pinkham et al. (2021) construct the SLR exposure measure by dividing the number of properties exposed within a NOAA SLR layer by the total number of properties in a school district.

[14] I choose to illustrate this variable at the county level since a sea level rise map of all Census Blocks in any state is difficult to perceive in a figure. However, I provide a snapshot of all the Census Blocks in the vicinity of TIAA Bank Field Stadium in Jacksonville, Florida as an example in the Appendix Figure 1 for interested readers.

tidal variation as well as hydrological connectivity and current man-made hydraulic features (e.g., pipes, bridges, levees). One limitation of these SLR maps, however, is that they do not incorporate future changes in coastal geomorphology and assume that the present conditions will remain. To put it differently, this assumption states that ground levels do not rise or sink over time.

Murfin and Spiegel (2020) emphasize the importance of considering subsidence and land rebound and use an alternative measure based on historical trends in regional mean sea levels from 142 tidal stations around the United States. They define a relative sea level rise (RSLR) measure as the weighted average trend of the two nearest water stations by inverse distance.[15] I follow their methodology to recreate the vertical land motion (VLM) component of their measure and plot it in Figure 3. Panel A shows the VLM projections by the end of 2100 in feet based on historical trends at each tidal station location, where positive values indicate that land will rise and negative values indicate that land will sink. Areas in which land is expected to rise substantially compared to current elevation levels are located mainly on the coasts of Alaska. A few areas on the West Coast are also expected to be elevated slightly. Ground levels in most of the continental United States as well as Hawaii and Puerto Rico are expected subside due to erosion and land subsidence, with larger drops observable especially on the Gulf Coast. Panel B shows four histograms to better illustrate the magnitude of vertical land motion based on geography. Taken together, vertical land motion mostly amplifies the risk of inundation due to rising sea levels and only attenuates the risk of inundation in Alaska.[16] Nevertheless, I include VLM in my regressions as a control variable.

2.3 Other Geographical Variables

All else equal, houses that are closer to the coast are likely more exposed to sea level rise risk. At the same

[15] While this measure has the advantage of taking vertical land motion into account, it also has serious shortcomings. First, the RSLR measure assumes the sea level trends vary linearly between each pair of the 142 tidal stations which potentially introduces large measurement errors. Second, NOAA states that the effects of land subsidence and rebound are "sufficiently unknown that they may compound or offset each other in unpredictable ways, such that including only some processes may cause greater error than ignoring them". Finally, RSLR does not take into consideration hydrological connectivity and is inherently forecasting how much sea level rise will occur based on historical trends. These forecasts are likely to have large degrees of uncertainty as scientists update the end of century sea level rise projections in light of new research. For more information and assumptions made in the generation process of the SLR maps, the reader is referred to: https://coast.noaa.gov/data/digitalcoast/pdf/slr-faq.pdf

[16] Remember that NOAA SLR Viewer does not include SLR maps for Alaska and therefore, there are no households living in Alaska in the sample I use to conduct my analysis.

time, proximity to coasts is also an amenity as easy access to beaches is a favorable quality for residents. Similarly, high-altitude houses are not only better protected against SLR exposure, but also enjoy housing amenities such as improved views. To control for the potentially confounding effects of distance to coast and ground elevation, I construct two variables measuring these quantities for each Census Block. Block level elevation and distance-to-coast calculations are based on the centroid coordinates of each Census Block.

3. Effect of SLR Exposure on Household Portfolio Choices

3.1 Empirical Strategy

In my baseline empirical analysis, I investigate the relationship between sea level rise exposure and the dynamics of household stock market participation for homeowners. Formally, I estimate the following model:

$$Participation_{i,j,t} = \alpha + \beta \cdot Sea\ Level\ Rise\ Exposure_{i,j,t} + \gamma \cdot X_{i,j,t} + c_{j,t} + \epsilon_{i,j,t} \qquad (1)$$

for household *i* located in zip code *j* in time *t*. In this estimation, participation is *Equity Participation* (either excluding or including IRAs), *Risky Share*, *Entry*, or *Exit*. My explanatory variable of interest is SLR Exposure (3 ft), which measures the fraction of the Census Block in which the household *i* lives projected to be inundated under a 3 feet sea level rise scenario.[17] $c_{j,t}$ denotes zip code by year fixed effects and $X_{i,j,t}$ is a vector of control variables. Specifically, I control for age, marital status, race, educational attainment (i.e., having completed high school or college), family size (i.e., household head, household head's partner, and children), total income, net wealth, whether there is home insurance on the occupied house, elevation of the house in feet, distance to coast in km, and vertical land motion. The coefficient of interest is β, which relates the stock market participation behavior of households to SLR exposure of households. The null hypothesis is that $\beta = 0$, which would indicate that SLR exposure does not affect stock market participation. By contrast, if SLR exposure affects stock market participation, I should expect a negative

[17] The selection of the sea level rise scenario is informed by Goldsmith-Pinkham et al. (2021) who track the time-series evolution of SLR projections in the scientific literature. Appendix Figure 2 shows that the mean SLR forecasts have increased over time, reaching just above 3 feet in 2017. I also provide results for sea level rise exposures under 1 feet and 2 feet scenarios in Appendix Table 3.

estimate $\beta < 0$.

Many factors correlated with SLR exposure are also potentially correlated with household stock market participation, which makes identifying the coefficient β difficult. For instance, homes closer to the coast may be more likely to be inundated as a result of future sea level rise, but at the same time they enjoy amenities such as beach access. These amenities likely attract wealthier and older buyers who are also more likely to participate in the stock market and differ from other households in terms of the portion of their financial wealth invested in risky assets (Calvet and Sodini, 2014; Ameriks and Zeldes, 2004). Similarly, elevation serves as a hedge against rising water levels while also providing housing amenities such as improved views. Moreover, households endogenously choose the locations of their homes and the unobserved household characteristics may drive the decision to live in more SLR exposed locations and stock market participation simultaneously.

I mitigate the possibility that the estimated relationship between SLR exposure and the dynamics of household stock market participation is driven by omitted variables in several ways. First, I include in my estimations a large set of household demographic and financial characteristics as controls to absorb any variation that may determine both SLR exposure and household stock market participation behavior as well as geographic determinants such as vertical land motion (Murfin and Spiegel, 2020), distance-to-coast, and elevation. Second, I control for systematic differences across zip codes using zip code fixed effects (c_j) and for macroeconomic conditions using year fixed effects (c_t). In particular, my regressions use zip code by year fixed effects such that I compare households within the same zip code and same year. Therefore, the identifying variation comes from the households in the same neighborhood that differ in SLR exposure. Finally, I exploit various dimensions of cross-sectional heterogeneity to show my results are likely driven by the effects of sea level rise and not some other omitted factors.[18]

Since my specifications include a large number of fixed effects, I estimate all equations using

[18] The results to be presented from this point forward are robust only including zip code or year fixed effects as well as including fixed effects at the state level alone or its interactions with year fixed effects. The choice of zip code by year fixed effects represents a compromise between tightening identification and keeping enough statistical variation to exploit cross-sectional heterogeneity.

ordinary least squares even when they involve a limited dependent variable. All variables are weighted using PSID population weights throughout the analysis. I cluster standard errors at the household level, because a household's stock market participation is likely persistent over time. The results remain unchanged if I cluster standard errors by state or by year.

3.2 Baseline Results

Table 2 presents estimates of how sea level rise exposure relates to households' stock market participation dynamics. Specifically, I compare the stock market participation behavior of households in the same zip code in a given year, with varying degrees of SLR exposure.

First, I investigate the relationship between participation in the stock market and sea level rise exposure. Table 2 reports household level regressions on stock market participation measures. Column (1) shows that sea level rise exposure has a negative and statistically significant effect on the propensity to participate in the stock market for households. This effect is not only statistically significant, but also economically meaningful. The point estimate in column (1) suggests that a one-standard-deviation increase in 3 feet SLR exposure (4.6 pp) decreases the probability that an SLR exposed household participates in the stock market by 1.8 pp compared to an unexposed household living in the same zip code and year. Since approximately 30% of the households participate in the stock market, this implies a 6% decrease in the probability of household stock market participation. I also find a similar, albeit smaller in magnitude, effect when I include stock holdings in IRAs in the dependent variable as shown in column (2). The smaller size of the coefficient in column (2) may partially reflect the rigidity in the allocation of individual retirement accounts which are affected by default choices, rather than the risks to which a household is exposed (Giannetti and Wang, 2016).

Second, I examine the effect of SLR exposure on the risky share of households' financial wealth. Here, I define the dependent variable Risky Share as the value of stocks owned divided by the financial wealth (i.e., sum of stocks, bonds, and cash). The point estimate in column (3) implies that the proportion of equity investments in the households' financial wealth is decreasing in their SLR exposures. The economic magnitude of this estimate is also substantial. A one-standard-deviation change in 3 feet SLR exposure (4.6 pp) decreases the risky portfolio share by 1.6 pp, which equals 9% of households' mean risky portfolio share.

Third, I consider the effect of SLR exposure on the changes in stock market participation by focusing on Entry into and Exit from the stock market. As expected, SLR exposed households are more likely to exit from and less likely to enter into the stock market compared to unexposed households in the same zip code and year. A one-standard-deviation increase in the 3 feet SLR exposure increases (decreases) the probability that households exit from (enter into) the stock market by 5 (1) pp, which equals an 18% increase (9% decrease) in the probability of exiting from (entering into) the stock market compared to the mean exit (entry) rates in the sample.

Overall, the results in Table 2 are consistent with the notion that SLR exposure constitutes a background risk for SLR exposed households through homeownership, decreasing their demand for risky assets as reflected in reduced stock market participation and a smaller share of financial wealth invested in risky assets.

3.3 Long- and Short-run Risks to Households

SLR exposure creates both long- and short-run inundation risks for exposed households. In the long-run, slowly rising oceans will eventually and permanently flood exposed areas. On the other hand, scientists project that rising sea levels will cause more frequent and more severe extreme weather events, such as storm surge flooding, tropical storms, and hurricanes (Marsooli et al., 2019; Knutson et al., 2020). Importantly, both of these physical channels have substantial uncertainty about them and can trigger a background risk effect on the exposed households. While it is a virtual certainty that rising oceans will permanently inundate exposed areas, the timing of this phenomenon is highly uncertain, as reflected in frequently updated forecasts of sea level rise by climate scientists (e.g, see Appendix Figure 2 for the evolution of SLR projections throughout my sample period). Extreme weather events such as storm surge flooding and hurricanes also have inherent uncertainties in their expected costs, timing, and frequency.

The analysis conducted above remains agnostic as to whether the uncertainty emanating from long- or short-run inundation risks affects household stock market participation behavior. Even though the SLR maps provided by NOAA aim to illustrate areas exposed to long-run SLR risks in the form of permanent inundation, the implicit correlation between more frequent and more devastating extreme weather events and rising sea levels makes it difficult to disentangle whether long- or short-run SLR risks drive changes in household stock market participation.

To investigate the relative importance of long- versus short-run SLR risks on household stock market participation behavior, I make use of National Storm Surge Hazard Maps also provided by NOAA. These maps depict the storm surge flooding vulnerability in hurricane-prone coastal areas along the East and Gulf coasts. NOAA uses the so-called hydrodynamic Sea, Lake, and Overland Surges from Hurricanes (SLOSH) model to simulate storm surge from tropical cyclones and hurricanes. The SLOSH model simulates 100,000 hurricanes along the East and Gulf coasts to predict areas that are exposed to flooding due to storm surges. I use these storm surge maps that simulate Category 4 hurricanes and compute a Census Block level storm surge exposure to proxy for short-run SLR risks.[19]

Table 3 repeats my baseline analysis with the addition of this storm surge exposure measure.[20] The estimates in columns (1) through (4) for the SLR exposure remain similar to the estimates in the baseline results, both in terms of the coefficients and magnitudes, indicating that the long-run SLR risks induce households to be less likely to participate in the stock market and hold a smaller share of their financial wealth in risky assets. In column (5), the coefficient for the SLR exposure stays positive as in the baseline results and becomes insignificant with a t-stat of 1.58, potentially due to a loss in statistical power as the number of observations go from 1,166 to 485 after the inclusion of the storm surge exposure measure. On the other hand, the coefficients on Storm Surge Exposure are all insignificant for all outcome variables I

[19] Similar storm surge exposure measures are also used by Goldsmith-Pinkham et al. (2021) who use maps simulated using Category 3 hurricanes and Ouazad (2021) who uses maps simulated using Category 4 hurricanes. The results in regressions I present where the storm surge exposure measure is added as a covariate are not sensitive to the choice of these different maps. SLR exposure and storm surge exposure measures have a correlation of 0.78 at the county level, consistent with scientists' views on rising sea levels inducing more frequent and more severe extreme weather events. The correlation at the Census Block level is less than half that at 0.36 in the final matched sample of households.

[20] The number of observations drop slightly in Table 3, because NOAA only provides storm surge maps for the East and Gulf coasts. For this reason, observations for the storm surge exposure measure for households residing (mainly) on the West coast are coded missing.

consider. The main takeaway from Table 3 is that the background risk channel of SLR exposure appears to operative through exposure to long-run SLR risks to as opposed to short-run SLR risks.

3.4 Alternative Explanations and Robustness

The above results indicate that households perceive future SLR risks as an important source of background risk. As such, in the presence of SLR risks, SLR exposed households are less willing to take other types of independent risks (e.g., financial risks) compared to unexposed households living in the same neighborhood in the same year. This effect obtains after controlling for the households' wealth, income, demographic characteristics, and geographical characteristics of the houses in which households reside. Moreover, I use zip code by year fixed effects in my analysis, which capture local economic shocks that may affect household stock market participation behavior. It is possible, however, that there are confounding unobservable factors that affect both SLR exposure and household stock market participation. In what follows, I explore alternative explanations that might drive the findings discussed above.

3.4.1 House Price Changes and SLR Risks

When interpreting the results in Table 2, I highlight the background risk channel generated by SLR exposure as the underlying mechanism. Alternatively, one can argue that changes in the prices of SLR exposed houses leading to a decrease in household wealth could also generate the observed patterns in Table 2. Indeed, many models highlight the role of investment in housing as well as house price risk in explaining the demand for risky assets. For example, Cocco (2005) documents that both the level of housing wealth and house price risks crowd out stock holdings.

It is difficult to disentangle the mean effect of housing wealth from house price risks. Nevertheless, I address the concern above in several ways. First, all my regressions control for the net wealth and home value of households such that the identified relationship between SLR exposure and stock market participation behavior is conditional on the level of household net wealth and current home value. Second, I use zip code by year fixed effects in all specifications which capture local economic conditions including changes in regional house prices, alleviating the concern that changes in mean housing wealth is the primary driver off reduced stock market participation. Third, I use the Zillow Home Value Index data and calculate house price growths over the last 5 years in each zip code. I then split the sample by the median house price growth in each state-year and repeat my baseline analysis.[21]

The estimates for this analysis are presented in Table 4. Again, I find negative and statistically significant (and economically comparable) effects of SLR exposure on household stock market participation behavior in both subsamples. Crucially, even households living in regions that experienced high house price growth have reduced stock market participation and hold a smaller share of their financial wealth in risky assets in the presence of SLR exposure. Overall, these findings indicate that the negative effects of SLR exposure on household stock market participation behavior do not only run through their impact on first moment of housing wealth and second moment effects matter for portfolio choices.

3.4.2 The Role of Past Flooding Experiences

One may be concerned that households with high SLR exposure are also more likely to have experienced a flooding in the past. As a consequence, the observed effect of SLR exposure on household stock market participation behavior may be due to the direct costs of these past flooding incidents as opposed to the background risk channel I highlight. One way to test this hypothesis is to keep track of all flood-related incidents that affected a household's place of residence and examine if these households who have not experienced flooding incidents also exhibit the same stock market participation behavior associated with their SLR exposure.

I make use of the Presidential Disaster Declaration data provided by OpenFEMA to measure households' past flooding experiences.[22] This database includes disaster ID numbers, declaration dates, declared states and counties, and incident types. I restrict my attention to flood related categories, that is, "Tornado", "Flood", "Hurricane", "Severe Storm(s)", "Typhoon", "Coastal Storm". For any given year in my sample, I create an indicator variable that is equal to one if the county a household lives in experienced

[21] The results remain virtually unchanged when I split the sample by the median house price growth in each year in the entire United States or when I calculate house price growth rates using the house prices over last 3 years for each zip code.

[22] The Presidential Disaster Declaration data is available at https://www.fema.gov/openfema-data-page/disaster-declarations-summaries-v2.

a flooding event in the last two years, and zero otherwise.[23] Based on this variable, I repeat my baseline analysis in sample splits for regions that did not experience any flooding events in the recent past and regions that did experience flooding events in the recent past.

Table 5 reports the results based on the sample splits described above. Columns (1) and (2) show that SLR exposed households who did not experience floods in the last two years still have a lower propensity to participate in the stock market and hold a lower share of their financial wealth in risky assets, compared to unexposed households in the same neighborhood who also did not experience floods in the near past. This suggests that even if past flooding experiences reduce household stock market participation, they are unlikely to be the only cause for SLR exposed households. In columns (3) and (4), I repeat the same analysis for households who experienced flooding incidents in the last two years and I find very comparable results.

Lastly, columns (5) and (6) show the estimates where I pool these observations and use an indicator variable capturing whether a household's county experienced flooding events in the near past or not. The interaction of this indicator variable with SLR exposure is statistically insignificant in both regressions where the outcome variable is equity participation and risky share. These estimates suggest that past flooding experiences are unlikely to be the driving force between SLR exposure and household stock market participation behavior.

3.4.3 Endogenous Choice of Housing Location

As alluded to in prior discussion, households choose where they live endogenously and there might a concern that this is the driving mechanism behind the effect of SLR exposure on household stock market participation. Unobservable factors influencing the location choice may also be correlated with the stock market participation behavior of households in the stock market. For example, if a household moves to a location with a different SLR exposure for a reason that may also affect its stock market participation, my estimates would be biased.

[23] The results remain unchanged when I construct this variable for any number of years between one and five.

To mitigate the concern that housing relocation may drive my findings, I consider households who have never moved across the entire sample period of twenty years. I construct an indicator variable I dub *Nevermover* that equals one if a household has never moved out of the Census Block in which they live during the sample period. By construction, these households bought their homes twenty years or longer ago (in times when SLR risks were arguably much less salient and for reasons likely unrelated to SLR) and their cost of moving was sufficiently high that they resided in the same location for the entire sample period. As such, *Nevermovers* can be thought of a group of households for whom the background risks emanating from SLR exposure are likely to be the most prevalent.

Table 6 presents the results of regressions described above. Columns (1) through (4) show regressions where I interact SLR exposure with the nevermover dummy, which compare households who never moved during the sample period to households who moved with varying degrees of SLR exposure. Columns (5) through (8) show estimates from regressions where the sample is restricted to nevermovers. In all columns, the point estimates stay negative and statistically significant, obtaining slightly larger values in magnitude than the baseline specification, with the exception of the coefficient of *Exit* in column (4). In unreported results, I restrict the sample to only movers in the sample period and estimate statistically zero coefficients for all outcome variables. Taken together, I find no evidence that endogenous choice of housing location drives the effect of SLR exposure on household stock market participation.

3.4.4 Differences in Political Beliefs

In the recent years, one of the defining features of the public discourse in the United States on climate change has been its partisan nature. For example, Republican President Donald Trump announced his intentions to withdraw the United States from the Paris Climate Agreement in 2017 and his administration eventually gave a formal notice of withdrawal in 2019. Following the 2020 Presidential Election in the United States, Democratic President Joe Biden signed an executive order to rejoin the agreement in 2021.

This divide on climate-related topics along the partisan lines is also present in the general public. According to a 2020 Pew Research Center survey that asked registered voters in the United States about top policy priorities, 11% of Trump supporters thought of climate change as a top priority compared to 68%

of Biden supporters (the widest gap for any topic in the survey).[24] Relatedly, recent work by Bernstein et al. (2021) show that this climate change partisanship is reflected in residential choice as SLR exposed houses are more likely to be owned by Republicans and less likely to be owned by Democrats. If political affiliation is also a driver of household stock market participation, then it might constitute an omitted variable which threaten the validity of the results presented in this paper.

To mitigate this concern and get a better understanding of whether differences in political beliefs drive the effect of SLR exposure on household stock market participation behavior, I use a data set containing county-level returns for presidential elections from the MIT Election Lab. More specifically, I count only the votes for the Republican or the Democratic presidential candidate in a given election and compute the share of votes cast for the Republican candidate in a given year using the most recent presidential election in a given year in my sample. I then construct indicator variables identifying households who live in "Republican" counties and ones who live in "Democratic" counties based on either the state median or the national median in a year.

Table 7 presents the results of these sample splits. In all specifications, the coefficients on the interaction term of high Republican share indicator with SLR exposure are statistically insignificant, while the estimates on SLR exposure stay negative and statistically significant. In unreported results where I split the sample based on the Republican share variable, I continue to find negative and statistically significant effects of SLR exposure on equity participation and the share of financial wealth invested in risky assets in both subsamples. Taken together, differences in political beliefs do not appear to be the driving force behind the relationship between SLR exposure and household stock market participation behavior.

3.4.5 Differences in Risk Preferences

Risk preferences play a key role in models of financial decisions. Their role is essential in understanding the demand for insurance, the choice of mortgage type, the frequency of stock trading as well as willingness to buy risky assets. In particular, the interaction of household risk preferences with the choice of location

[24] For a discussion of the results of this survey, see https://www.pewresearch.org/politics/2020/08/13/important-issues-in-the-2020-election/.

to live in and with the stock market participation behavior poses a threat for identification in my analysis. One may be concerned that households' risk tolerance may be an omitted variable that is correlated both with households' SLR exposure and stock market participation.

I address this concern in various ways. First, I control for the 1999 risky share of financial wealth as a proxy for the initial risk aversion of households. Assuming risk aversion to be fixed over the sample period, this variable should capture the risk preferences of households accurately.[25] Second, I exploit the 1996 wave of PSID to infer the risk aversion of households. 1996 PSID survey asked respondents a series of questions about their willingness to take jobs with different prospects. All choices were 50-50 chance to either double their current income or cut income by different fractions. Based on these questions, it is possible to divide households into six buckets in terms of their risk preferences. To control for risk aversion, I use fixed effects based on these categories. The underlying assumption behind this specification is that households do not move between different categories after 1996. Third, Kimball, Sahm and Shapiro (2009) compute risk aversion coefficients for these six risk aversion categories from the 1996 wave of PSID assuming CRRA utility. I include these risk aversion coefficients as additional controls in my regressions. Finally, I remove the waves in the 2007-2009 financial crisis as experiences through these years may have affected the risk preferences of households (Malmendier and Nagel, 2011).

The results are presented in Table 8. In all specifications, results remain statistically significant, indicating that risk preferences of households do not drive the effect between SLR exposure and household stock market participation. In fact, the estimates increase in magnitude in all specifications apart from the exclusion of the financial crisis period.

3.4.6 The Role of Proximity to Coast

[25] Another way to control for individual risk preferences would be to include household fixed effects in my analysis. As I already employ zip code by year fixed effects, however, the inclusion of household fixed effects would subsume all variation that is remaining, making statistical estimation impossible. Moreover, the SLR exposure measure I use is time-invariant since it is constructed from the NOAA SLR maps that are simply a snapshot in time. Thus, an analysis that incorporates household fixed effects only would forego variation coming from households who have never moved, but rely on variation from households who moved from locations exposed to SLR risks to locations that are unexposed or vice versa. Therefore, the inclusion of household fixed effects in my setting is not feasible as it severely restricts the statistical variation available.

My sample consists of all households surveyed by PSID between 1999 and 2017, who are the descendants of a representative sample of families first surveyed in 1968. As a result, the respondents are distributed all over the United States, including land-locked states and states far away from the shore. Sea level rise, on the other hand, is most relevant for households living in coastal areas and living close to other bodies of water. By virtue of this fact, studies in the literature investigating the effects of sea level rise have focused on certain geographies. Bernstein, Gustafson and Lewis (2019) consider properties 0.25 miles away or closer to the coast to study whether SLR exposure is priced in the residential real estate prices. Baldauf, Garlappi and Yannelis (2020) and Murfin and Spiegel (2020) use a 50 km and a 30 km restriction from the coast, respectively, to answer the same question. Goldsmith-Pinkham et al. (2021) study the pricing of municipal bonds as it relates to SLR exposure and restrict their sample to watershed counties.[26]

To ensure that the results are driven by households for whom SLR exposure is most relevant, I repeat my analysis after imposing sample restrictions based on distance to coast and watershed counties. In particular, I restrict the sample to households who live 50 km away or closer to the coast,[27] or households who live in watershed counties. Table 9 presents the point estimates for these regressions. The results continue to be statistically significant with the same signs as the baseline results. If anything, the coefficients increase in magnitude as one would expect.

4. Homeownership Channel: Placebo Test on Renters

Housing serves a dual role for homeowners: as a consumption good and as a portfolio asset (Cocco, 2005; Yao and Zhang, 2005). At the event of flooding, a homeowner therefore loses claims to future dividends related to consumption dimension of housing and also faces a negative shock to the asset value. Because housing markets are illiquid, homeowners bear the full brunt of sea level rise risks due to the absence of an efficient flood insurance market in the United States. On the other hand, rental markets allow investors to

[26] According to NOAA, coastal watershed counties can be thought of as "the population that most directly affects the coast". For a more detailed definition, please see https://coast.noaa.gov/htdata/SocioEconomic/NDAA_CoastalCountyDefinitions.pdf.

[27] 27The results are not sensitive to this choice. For example, unreported results show qualitatively the same results when this cutoff is chosen as any value in [10, 20, 30, 40, 60, 70, 80, 90, 100] km.

separate the consumption and investment dimensions of housing. Renters derive utility from consumption of housing services, but do not have a housing component in their portfolios. Moreover, the liquid nature of rental markets allows renters to face smaller costs in the event of negative shocks to their housing consumption. Overall, SLR exposure poses little to no threat to renters as opposed to homeowners.

Exploiting this stark difference between homeowners and renters in terms of exposure to SLR risks allows me to test whether SLR exposure indeed affects household stock market participation through a homeownership channel. In particular, I conduct a placebo test in a sample of only renter households and compare renters in the same zip code and year with varying degrees of SLR exposure. This placebo test also helps mitigating the possibility that the effect of SLR exposure on household stock market participation is due to unobservable differences between SLR exposed and unexposed households.

Formally, I restrict the sample to renter households only and estimate the following empirical model similar to equation 1:

$$Participation_{i,j,t} = \alpha + \beta \cdot Sea\ Level\ Rise\ Exposure_{i,j,t} + \gamma \cdot X_{i,j,t} + c_{j,t} + \epsilon_{i,j,t}$$

for household *i* located in zip code *j* in time *t*. The outcome and independent variables are the same as in equation 1. $X_{i,j,t}$ is a vector of control variables and $c_{j,t}$ denotes zip code by year fixed effects. Since the sample only consists of renter households, I do not control for house value and whether the household *i* has home insurance, but instead the rent paid by the household.

4.1 Results: Homeowners vs. Renters

Table 10 presents both the results for homeowners and renters separately. For ease of comparison, odd-numbered columns report the same the estimates as in Table 2 and even-numbered columns report the estimates for the sample that includes renter households only. Column (8) does not report any coefficients, because the number of renter households within the same zip code and year does not exceed one and therefore, I am unable to identify the regression model.[28]

The point estimates in Table 10 indicate that homeowners with SLR exposure are less likely to

[28] In unreported results, I find statistically insignificant estimates for SLR Exposure (3 ft) when I replace zip code by year fixed effects with zip code and year fixed effects with only 423 observations.

participate in the stock market, hold a smaller share of their financial wealth in stock, are less likely to enter into and more likely to exit from the stock market. On the other hand, regressions in the renters sample show negative, but statistically insignificant coefficients. These findings indicate that the effect of SLR effect on household stock market participation operates through the homeownership channel, as SLR exposed renters do not behave statistically differently than unexposed renters when it comes to stock market participation.

5. The Role of Attention to Climate Change

Several papers in the literature emphasize the role of attention to climate change and salience of flood risk in determining house prices and household flood insurance decisions. For example, Baldauf, Garlappi and Yannelis (2020) focus on transaction prices of houses and show that SLR exposed houses trade at a discount when the salience of flood risk is high. Hu (2020) provides evidence that the low salience of flood risk might lead to inattention and thus, to low insurance take-up rates. In this section, I leverage time-series variation in two different empirical strategies to examine the role of attention to climate change.

5.1 Attention to Climate Change: Wall Street Journal Climate Change Index

Engle et al. (2020) construct a climate change news index based on climate news coverage in The Wall Street Journal (WSJ) and show that this index can be used to build climate change hedge portfolios. The WSJ Climate Change News Index implicitly assumes that the number of climate change discussions increases at times when climate risk is high. This WSJ index is available for the entire duration of my sample and publicly made available by the authors. A potential shortcoming of this measure for the analysis in this paper is that the measure might run the risk of inaccurately capturing positive climate news as elevated attention to climate risks. Moreover, if the typical household is not a part of WSJ's audience, the WSJ index might not perfectly correlate with households' attention to climate change. Nevertheless, I use the WSJ Climate Change News Index to proxy for aggregate attention to climate change.

Table 11 reports the results of regressions including interactions between SLR exposure and a high attention indicator variable based on the WSJ Climate Change News Index. The interaction coefficients in all columns are negative and statistically significant (with the exception of the coefficient in column (4) with a t-stat of 1.44), indicating that at times of high attention to climate change, the background risk effect of SLR exposure is higher on household stock market participation behavior. The magnitudes of the interaction coefficients are even larger for a subsample of people living 50 km or closer to a coast and households who have never moved during the sample period, likely due to increased levels of background risks. All in all, SLR exposed households appear to have a lower propensity to participate in the stock market and hold a smaller share of their financial wealth in risky assets at times when attention to climate change is elevated.

5.2 Salience of Flood Risk: Major Past Hurricanes

The second empirical strategy I employ assumes that the occurrence of devastating natural disasters such as hurricanes increases the salience of flood risks. Similar to the strategy employed by Baldauf, Garlappi and Yannelis (2020), I identify the top ten costliest hurricanes (listed in Appendix Table 5) over my sample period, the year in which they occurred, and the states they hit. I focus on states *unaffected* by these events in the time period following these events, because households' stock market participation behavior in the hurricane affected states might change due to costs directly incurred. Therefore, the identifying variation in this empirical strategy comes from households living in states unaffected by these hurricanes, but for whom the salience of flood risks will be higher due to major hurricanes that recently took place. I create an indicator variable $Hurricane_{s,t}$ equal to one in an unaffected state *s* in time period *t* if there was a major hurricane taking place in period $t-1$. If the effect of SLR exposure on household stock market participation is at least partially operative through the salience of flood risks, then I expect a negative and statistically significant coefficient for an interaction of SLR Exposure and $Hurricane_{s,t}$.

Table 12 reports the results of this test. Similar to the results above, the interaction coefficients in all columns are negative and significant (with the exception of the coefficient in column (4) with a t-stat of 1.18). The salience effect of major hurricanes is especially large for households living close to the coast in unaffected states and households who never moved during the sample period. Overall, these results provide supportive evidence that the salience of flood risks exacerbates the effects of SLR risks for households.

6. State-Led Climate Change Adaptation Plans

The costs associated with the disastrous effects of sea level rise, in the form of inundation of large areas and increased extreme weather events both in intensity and frequency, will take a significant toll on the economy. Governments will need to assume this burden and spend large amounts of money on emergency response, insurance payouts, and to rebuild flooded infrastructure. If governments fail to plan for these impacts, valuable public investment and significant private investment may literally fall into the sea.

Governments have powerful tools to counteract the negative impacts of sea level rise and reasons to begin planning and adapting now.[29] However, the regulatory environment on climate change in the United States at the federal level has been stagnant until the Paris Agreement in 2015. The election of President Trump and his withdrawal from the Paris Agreement further showed the reluctance of the federal government to enact regulations to meet future climate challenges. The lack of political will at the federal level for prevention against the future impacts of climate change makes state level actions more important and relevant for residents.

As of 2020, 17 states and the District of Columbia have finalized state-led climate change adaptation plans as preparation for the negative effects of climate change. Florida, Maryland, and Virginia are the first three states adopting climate change adaptation plans, all in 2008, whereas North Carolina has been the latest state adopting such a plan in June 2, 2020.[30] State-led climate change adaptation plans (SCCAPs) vary in their scopes, goals, and strategies, but they share the common goal of combating the adverse effects of climate change, including the adverse effects of future sea level rise. I discuss the content

[29] These tools include, but are not limited to: zoning regulations to impose restrictions on development in at-risk zones, building code regulations to promote resilient design for new constructions against coastal flooding, establishing setbacks and buffers from the coast, creating soft- and hard-armoring permits to facilitate coastal protection for existing development or critical infrastructure, acquiring vulnerable properties to be demolished and restored or conserved as open space, public parks, or for natural resources, requirements for sellers of real estate to disclose information about a property's SLR vulnerabilities, and tax incentives to encourage preferred development patterns. For detailed discussion of tools governments can employ to prepare for the impacts of sea level rise, see Grannis (2011).

[30] Of all the 18 states (including D.C.) with finalized plans, 16 are in my sample period of 1999-2017. Since NOAA does not provide SLR data for Alaska, I am able to make use of 15 state-led climate change adaptation plans in my analysis. For more information in the timing and content of state-led climate change adaptation plans, the reader is referred to Ray and Grannis (2015).

of these plans in further detail as they relate to sea level rise in the Internet Appendix Part B.

6.1 Empirical Strategy: Staggered Difference-in-Differences

Although I consider a myriad of alternative explanations that may drive the relationship between SLR exposure and household portfolio decisions in the above analyses, the concern that unobservables drive this relationship might still remain. To alleviate the worry that endogeneity may be biasing my estimations, I exploit the exogenous variation that the adoption of state-led climate change adaptation plans generate.

Similar to the Paris Agreement signaling the commitment of countries worldwide to curb CO_2 emissions, SCCAPs signal the state governments' commitment to protect the state residents and the environment. If households are aware of the adoption of SCCAPs and view them as credible signals, then the perception of background risks SLR entails for households should be significantly reduced.[31] Put differently, one should observe that SLR exposed households increase stock market participation and the risky share of their financial wealth following the adoption of SCCAPs, reflecting the reduced riskiness of their background risks due to future sea level rise. On the other hand, if households do not see SCCAPs as credible signals of commitment, then there should be either no change in their stock market participation behavior or even a reduction in their willingness to take financial risks as the announcement of SCCAPs make SLR risks more salient.

To formally test this hypothesis, I restrict attention to homeowner households and I carry out a staggered diff-in-diff analysis and estimate the following model in equation 2:

$$Participation_{i,j,t} = \alpha + \beta_1 \cdot Sea\ Level\ Rise\ Exposure_{i,j,t} + \beta_2 \cdot Post\ SCCAP_{j,t} + \beta_3 \cdot Sea\ Level\ Rise\ Exposure_{i,j,t} \times Post\ SCCAP_{j,t} + \gamma \cdot X_{i,j,t} + c_{j,t} + \epsilon_{i,j,t} \quad (2)$$

for household *i* located in zip code *j* in time *t*. The outcome and independent variables are the same as in

[31] Indeed, there is reason to think this may be the case by looking at news in the mainstream media. For example, Mayor Michael Bloomberg announced that $20 billion would be spent over the next decade to address the threat of rising sea levels and powerful storm surges by building an extensive network of flood walls and levees to protect New York City (NY Times, 2013). Miami Beach is pursuing a $500 million program of infrastructure upgrades to reduce flooding as a part of their adaptation plan, with an additional $400 million for projects to prevent flooding and mitigate sea level rise (Wall Street Journal, 2018). The voters in San Francisco approved a $425 million bond to start fortifying a sea wall along the bayfront road, the Embarcadero, and the San Francisco airport, which sits on tidal marshlands, is getting a $587 million makeover to raise its sea wall (NY Times, 2020).

equation 1. $X_{i,j,t}$ is a vector of control variables and $c_{j,t}$ denotes zip code by year fixed effects. $Post\ SCCAP_{j,t}$ is an indicator variable equal to one for zip code j in the year and all years after a climate adaptation plan is adopted in its state, and zero otherwise.[32] The coefficient of interest is β_3 in this model.

My analysis up until this point employs a time-invariant SLR measure according to 3 feet SLR projections. Because the model in equation 2 focuses on the changes in the relationship between SLR exposure and household portfolio decisions over time, I create a time varying SLR exposure measure based on the evolution of sea level rise projections by following the procedure described in Goldsmith-Pinkham et al. (2021). Appendix Figure 2 plots the mean SLR projections for each year from 2001 to 2017 as well as the 1st and 99th percentile bounds. There is a clear upward trend in the SLR projections over time, especially in the upper bound. While the average SLR projection is just below 1 foot in the scientific literature in 2001, the average SLR projection triples that amount by 2017 to above 3 feet. The upper bound of SLR projections in 2017 is well over 5 feet. Since NOAA provides SLR layers with 1 foot increments, I compute a time varying SLR exposure measure in two steps. First, I determine the level of 99th percentile SLR projection in a given year. Second, I assign the SLR exposure values to each household based on the NOAA SLR layer that is just above the aforementioned level is determined. For example, the 99th percentile value of SLR projection in 2017 is between 5 feet and 6 feet in Appendix Figure 2. Hence, I use the 6 feet SLR layer to compute the SLR exposure of households in 2017.

6.1.1 Timing of Adoption and Parallel Trends

The causal interpretation of the coefficient β_3 in equation 2 depends on two crucial assumptions. Namely, these are the lack of contaminating events around the time of the shocks and the existence of parallel pre-trends in the outcome variables. Both of these assumptions are inherently untestable. Nevertheless, a discussion of whether they are likely to be satisfied is beneficial.

First, I focus on the possibility of contaminating events around the adoption of SCCAPs. The timing with which these climate adaptation plans are adopted depends on the expected benefits and political costs

[32] The estimates of this model are not sensitive to creating an indicator variable equal to zero in the year of adoption.

associated with enacting recommended policies in these plans to mitigate the effects of climate change. The states with more at-risk properties likely stand to gain more from adaptation plans. Moreover, political costs of adopting climate adaptation plans are likely lower in states where the levels of belief and worry about climate change are higher. Figure 4 provides a depiction of when and where climate adaptation plans have been adopted in the United States. A quick look at this figure shows that climate adaptation plans are mostly eventually adopted in coastal states, with notable exceptions of Louisiana, Texas, and New Jersey. In fact, a one-to-one comparison with Figure 2 reveals that all SCCAP adopting states have at least some level of sea level rise risk, apart from the land-locked state of Colorado. Hence, it seems implausible that whether to adopt an adaptation plan and the timing of adoption are driven mainly by the magnitude of sea level rise exposure of each state.

There is also little evidence that there is geographical clustering in terms of the timing. Neighboring states do not necessarily follow each other in terms of adoption nor is there a clear pattern that plans are adopted along the political party lines. There are early adopter states that are typically Republican (e.g., Alaska) as well as Democratic (e.g., California). There are also states that typically vote for either party that have not adopted climate adaptation plans so far (e.g., Texas and New Jersey) even though they face significant sea level rise risk. Moreover, the staggered structure of equation 2 makes it difficult for contaminating events to threaten the validity of my analysis as it is difficult to think of contaminating events that are staggered both in time and geographic dimensions in the same way SCCAPs are.

Second, I examine the parallel trends assumption which is key for any diff-in-diff estimator. That is, in the absence of treatment, the average change in the outcome variable would have been the same for both treated and untreated groups. To shed light on the validity of this assumption, I follow Roberts and Whited (2013) and perform a paired sample t-test of the difference in average growth rates across the two groups.[33] For this purpose, I create an indicator variable, reflecting a treated household, equal to one if a household's time varying SLR exposure is in the top quartile in a state-year, and zero otherwise. Next, I

[33] A similar test is also performed by Lemmon and Roberts (2010).

compute the growth in *Equity Participation* and *Risky Share* and report the p-value of the difference-in-means test and the *p*-value of the two-sample Wilcoxon test in Appendix Table 4. The former tests the hypothesis that mean values of the two groups are the same, whereas the latter tests the hypothesis that the two groups are taken from populations with the same median. The *p*-values for both tests are statistically insignificant for each outcome variable and hence, the treatment and control groups appear to satisfy the parallel trends assumption.

6.2 Results

Table 13 presents the estimates on how the effect of SLR exposure on household stock market participation behavior changes following the adoption of state-led climate change adaptation plans in a sample of households. Similar to my baseline analysis, I populate these estimations with zip code by year fixed effects such that the interaction coefficient between SLR exposure and SCCAP dummy estimates the incremental change in the effect of SLR exposure following the adoption of SCCAPs.

I start by exploring the effect of SLR exposure following the adoption of SCCAPs on the propensity to participate in the stock market. Column (1) presents a negative and statistically significant coefficient on SLR exposure, consistent with the baseline results in Table 2. The interaction term that identifies the effect of SLR exposure on participation behavior following the adoption of climate adaptation plans is positive and statistically significant. This finding supports the notion that households see climate adaptation plans as local governments' commitment towards protect state residents against the adverse impacts of sea level rise. The economical magnitude is also substantial as one-standard-deviation increase in the time varying SLR exposure (6.2 pp) increases the probability that an SLR exposed households participates in the stock market by 3.9 pp in states after the adoption of climate adaptation plans.

Next, I examine the effect of SLR exposure on households' share of financial wealth invested in risky assets. If climate adaptation plans are seen as public safety nets, then SLR exposed households in adopting states should be more willing to take financial risks following adoptions, as reflected in higher proportion of financial wealth invested in risk assets. The positive and statistically significant interaction coefficient in column (5) is supporting evidence that indeed, households' willingness to take financial risks rises after the adoption of climate adaptation plans. The coefficient on SLR exposure is negative and statistically significant, mirroring the estimates in Table 2. Based on the interaction coefficient in column (5), one-standard-deviation increase in time varying SLR exposure (6.2 pp) increases the risky share of financial wealth by 2.7 pp after climate adaptation plans are adopted.

I perform several additional tests to address different concerns with the analysis above. In columns (2) and (6), I allow for time-varying coefficients on my control variables in the pre- and post-periods by adding an interaction term with Post SCCAP for each control variable. Moreover, households' experiences through the 2007-2009 may have confounding effects for my estimates. In columns (3) and (7), I remove observations from the waves in the 2007-2009 financial crisis to ensure the financial crisis period does not constitute a contaminating event. Goodman-Bacon (2018) emphasizes that in diff-in-diff models with variation in treatment timing, untreated observations may influence estimates drastically. This might be of particular concern in my regressions as all households living in land-locked states have both zero SLR exposure and none of the land-locked states adopt a climate adaptation plan (with the exception of Colorado). These households may not be appropriate control groups for households living in SLR exposed states. Thus, I restrict my sample to all households living either in states with SLR exposure and SCCAP adopting states in columns (4) and (8). The coefficients stay positive and statistically significant with similar magnitudes in all these specifications, giving confidence in the robustness of the staggered diff-in-diff analysis.

Overall, the results show that the adoption of state-led climate adaptation plans were effective in alleviating the background risk emanating from SLR exposure for exposed households. Following the adoption these climate adaptation plans, SLR exposed households in the adopting states increase stock market participation and the share of financial wealth invested in risky assets compared unexposed households in the same zip code.

6.3 Placebo Test on Renters

In order to provide additional checks on the internal validity of my estimates, I repeat my analysis after restricting the sample to renters only. If the effect I identify in the analysis above on households' stock market participation is driven by unobservables correlated with SLR exposure or contaminating events, then similar increases in the stock market participation of renters following state-led climate change adaptation plans can be expected. If the identified effect is indeed due to SLR exposure, however, I expect to observe no change in the stock market participation behavior of SLR exposed renters compared to unexposed renters in states following the adoption of climate adaptation plans since renters should not be subject to background risk.

Table 14 presents the estimates on a sample of renters. The coefficients of interaction terms in all columns are negative and statistically insignificant, consistent with the notion that renters are not subject to background risk due to SLR exposure and the adoption of climate adaptation plans do not affect renter households' stock market participation behavior.

7. Conclusion

I provide the first evidence that sea level rise risks constitute a source of uninsurable background risk for households. Consequently, SLR exposed households are less likely to participate in the stock market and hold a smaller proportion of their financial wealth in risky financial assets. One-standard-deviation increase in SLR exposure reduces the propensity to participate in the stock market by 1.8 pp and the share of financial wealth invested in equities by 1.6 pp. These numbers correspond to 6% and 9% decreases compared to the mean stock market participation and mean risky share, respectively. The effect mainly stems from long-run SLR risks as opposed to short-run risks and alternatives explanations including endogenous relocation decisions, differences in risk preferences, past flooding experiences, or differences in political beliefs are unable to account for this effect. Placebo tests based on renter households show statistically insignificant results, which highlights the role of homeownership for sea level rise exposure. Exploiting time-series variation in the attention to climate risks, I also document that the crowding effect of SLR risks on household stock holdings is amplified at times when attention to climate change is elevated.

Local governments have an important role to play in mitigating these risks for households. To test whether the households' perceptions of background risks can be mitigated by state governments, I exploit a plausibly exogenous source of variation in the form of state-led climate adaptation plans. Climate adaptation plans aim to protect residents of the adopting state from the adverse effects of climate change and therefore, provide a public safety net for households exposed to sea level rise. A staggered diff-in-diff analysis around the adoption dates of climate adaptation plans shows that households see these plans as credible signals of state governments' commitment towards protecting citizens. As such, sea level rise exposed households' willingness to take financial risks increases after the adoption of these plans, as reflected in the propensity to participate in the stock market and share of financial wealth in risky assets.

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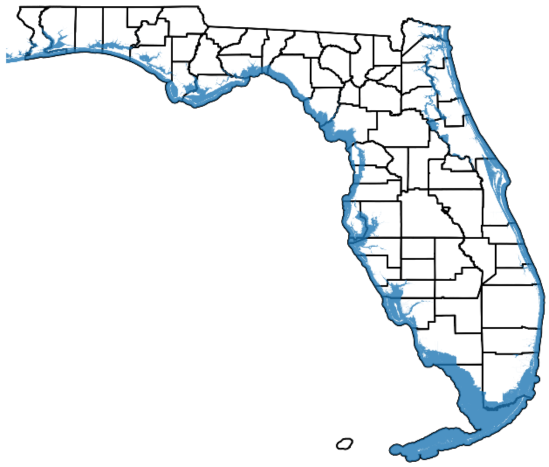
Figure 1. 3 feet sea level rise in counties in Florida

This figure illustrates the regions at risk of being under water in a 3 feet sea level rise scenario by the year 2100. Panel A shows the 3 feet sea level rise projection map provided by NOAA and Panel B shows the heatmap of sea level rise risk exposure in each county, after removing the existent bodies of water in each county.

Panel A



Panel B

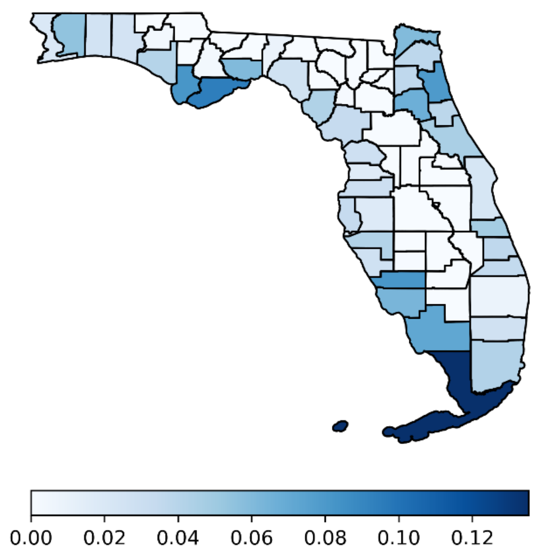


Figure 2. Sea level rise exposure of counties in the United States

This figure illustrates the sea level rise exposure of counties in the continental United States under a 3 feet sea level rise scenario by the end of 2100. The values indicate the fraction of land area of each county that is at risk of being under water if sea level rise by 3 feet globally. The plotted state lines follow political boundaries and not physical boundaries.

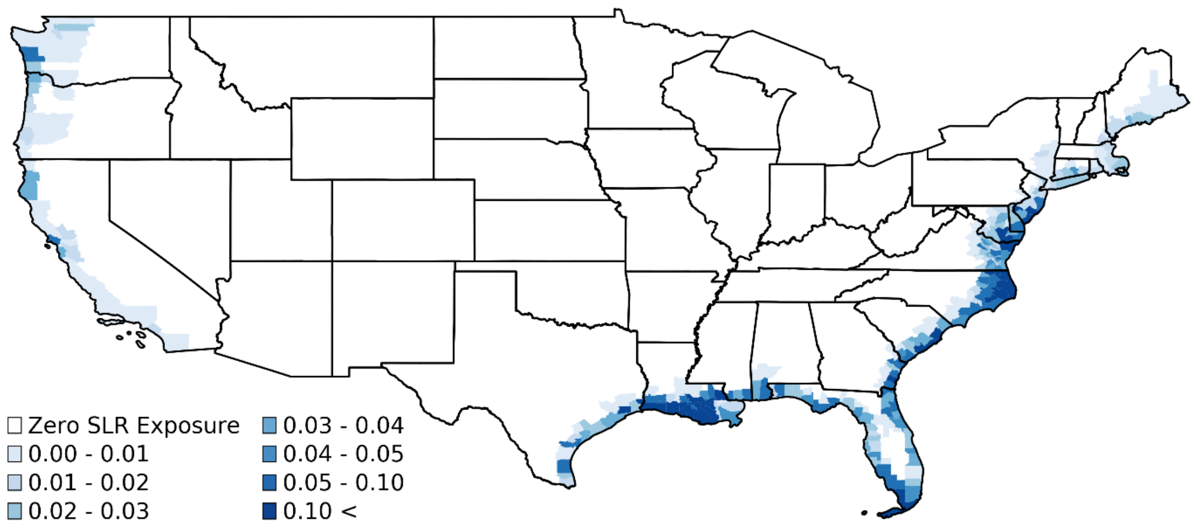
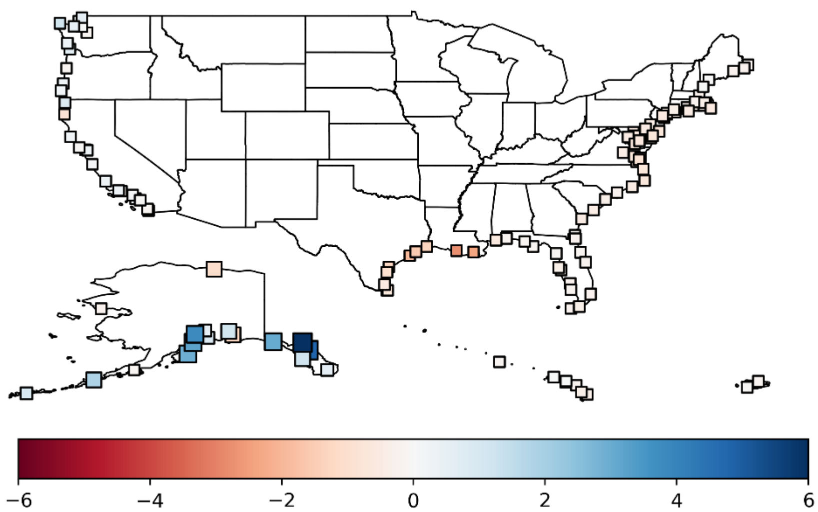


Figure 3. Vertical land motion in the United States

This figure illustrates the projected vertical land motion (VLM) around the United States. The VLM values are reversed such that positive values indicate that land is rising and negative values indicate that land is sinking. The values in the color bar indicate levels of VLM between -6 feet and +6 feet. Panel A illustrates the projected vertical land motion at the tidal station locations. Panel B shows the distribution of projected vertical land motion based in the continental United States and Puerto Rico (PR), Alaska, and Hawaii.

Panel A



Panel B

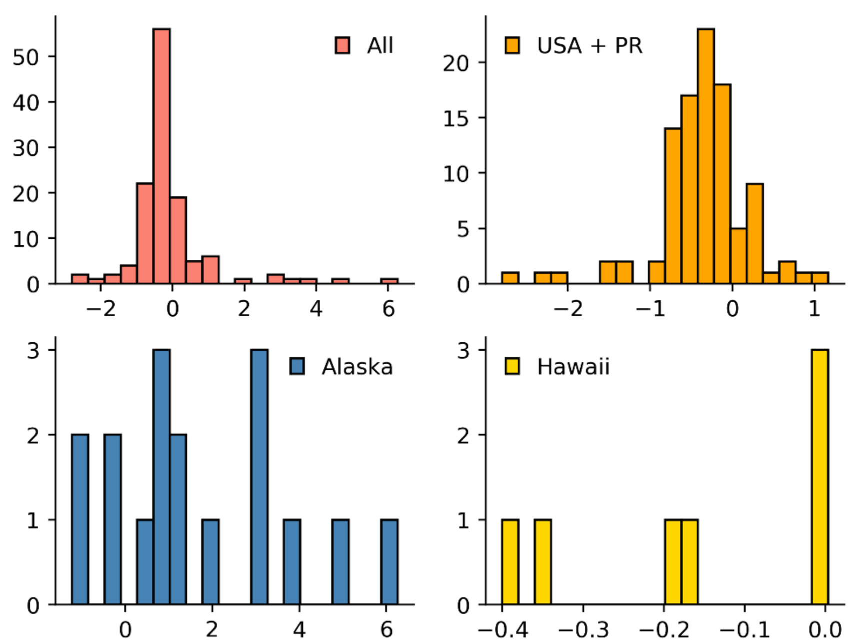


Figure 4. State-led Climate Change Adaptation Plans: Geographical Distribution Over Time

This figure illustrates when and where state-led climate change adaptation plans have been finalized across the United States between 1999 and 2017 (i.e., the sample period considered in this paper). Notably, Rhode Island (plan finalized in 2018) and North Carolina (plan finalized in 2020) have finalized such plans after 2017 and thus, excluded from this figure.

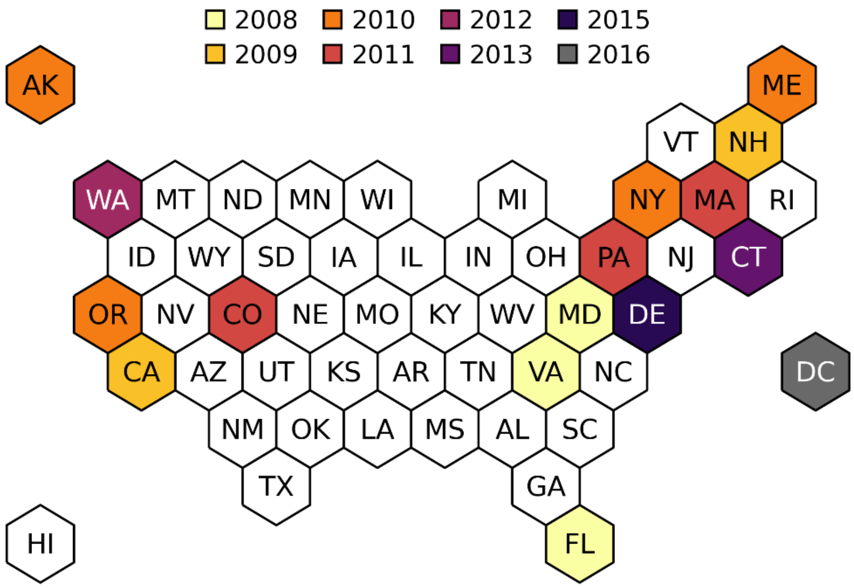


Table 1. Summary statistics

Sample:	Full			Homeowners			Renters		
	Mean	**STD**	**Obs.**	**Mean**	**STD**	**Obs.**	**Mean**	**STD**	**Obs.**
Stock Market Participation:									
Equity Participation	0.22	0.41	75,527	0.29	0.45	44,021	0.09	0.29	31,506
Equity Participation (incl. IRAs)	0.38	0.49	75,437	0.50	0.50	43,967	0.17	0.37	31,470
Risky Share	0.14	0.30	49,255	0.18	0.32	32,514	0.06	0.21	16,741
Entry	0.08	0.27	50,210	0.11	0.31	28,378	0.03	0.18	21,832
Exit	0.30	0.46	10,280	0.29	0.45	8,872	0.39	0.49	1,408
Sea Level Rise:									
SLR Exposure (1 ft)	0.001	0.018	75,856	0.001	0.017	44,276	0.001	0.019	31,580
SLR Exposure (2 ft)	0.002	0.031	75,856	0.003	0.031	44,276	0.002	0.031	31,580
SLR Exposure (3 ft)	0.004	0.048	75,856	0.004	0.046	44,276	0.004	0.052	31,580
Storm Surge Exposure	0.128	0.319	35,740	0.120	0.308	20,456	0.143	0.337	15,284
Demographics and Education:									
Age	51.00	17.60	75,856	54.97	15.99	44,276	43.42	18.06	31,580
Married	0.49	0.50	75,847	0.63	0.48	44,273	0.22	0.41	31,574
Divorced	0.20	0.40	75,847	0.16	0.37	44,273	0.27	0.44	31,574
Male	0.70	0.46	75,856	0.76	0.43	44,276	0.57	0.50	31,580
Non-White	0.28	0.45	75,856	0.22	0.41	44,276	0.40	0.49	31,580
Family Size	2.32	1.39	75,856	2.47	1.35	44,276	2.03	1.41	31,580
College Education	0.31	0.46	73,387	0.35	0.48	42,889	0.23	0.42	30,498
High School Education	0.53	0.50	73,387	0.52	0.50	42,889	0.55	0.50	30,498
Wealth and Income:									
Total Income	61,858	92,250	75,856	75,483	106,478	44,276	35,840	45,603	31,580
Wealth, excl. home equity	182,472	979,994	62,173	272,252	1,210,977	34,801	27,360	219,297	27,372
House Value	128,021	208,710	74,332	197,057	231,184	42,753			31,579
Home Insurance	0.60	0.49	69,523	0.96	0.19	37,943			31,580
Stocks	38,321	281,620	73,835	55,292	342,988	42,586	6,925	82,953	31,249
Bonds	8,135	77,842	73,611	10,835	89,171	42,628	3,072	49,730	30,983
Cash	23,501	101,673	70,902	32,213	121,280	40,846	7,378	42,980	30,056
Financial Wealth	70,650	345,552	68,072	100,393	419,411	38,716	17,243	116,282	29,356
Geographical Variables:									
Elevation (ft)	820	1,103	75,856	860	1,127	44,276	744	1,051	31,580
Distance-to-Coast (km)	267	317	75,856	277	321	44,276	248	308	31,580
Vertical Land Motion	0.49	0.50	75,856	0.50	0.50	44,276	0.47	0.51	31,580

Table 2. Sea level rise and stock market participation

This table reports estimates of how sea level rise exposure relates to households' stock market behavior. The sample includes only homeowner households from 1999 to 2017 PSID waves. Controls include *Age*, *Age Squared*, *Married*, *Divorced, Male, Non-White, Family Size, Log(Total Income), Ihs(Wealth) excluding home equity, College Education, High School Education, Log(House Value), Home Insurance, Elevation x 1000, Distance-to-Coast x 1000, Vertical Land Motion.* All variables are defined in Appendix Table 1 and are weighted using PSID population weights. Parameter estimates are obtained by OLS. All regressions include a constant term and fixed effects indicated in the table, whose coefficients I do not report. t-statistics, based on standard errors clustered by household, are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Dependent variable:	Equity Participation	Equity Participation (incl. IRAs)	Risky Share	Entry	Exit
	(1)	(2)	(3)	(4)	(5)
SLR Exposure (3 ft)	-0.392***	-0.265*	-0.353***	-0.224**	1.133**
	(-3.59)	(-1.92)	(-4.78)	(-2.49)	(2.20)
Controls	Yes	Yes	Yes	Yes	Yes
Zip Code x Year FEs	Yes	Yes	Yes	Yes	Yes
Obs.	14,173	14,168	11,012	8,532	1,166
Adj. R^2	0.36	0.41	0.32	0.20	0.17

Table 3. Sea level rise and stock market participation: Long- vs. short-run SLR risks

This table reports estimates of how sea level rise exposure and storm surge exposure relate to households' stock market behavior. The sample includes only homeowner households from 1999 to 2017 PSID waves. Controls include *Age, Age Squared, Married, Divorced, Male, Non-White, Family Size, Log(Total Income), Ihs(Wealth) excluding home equity, College Education, High School Education, Log(House Value), Home Insurance, Elevation x 1000, Distance-to-Coast x 1000, Vertical Land Motion*. All variables are defined in Appendix Table 1 and are weighted using PSID population weights. Parameter estimates are obtained by OLS. All regressions include a constant term and fixed effects indicated in the table, whose coefficients I do not report. t-statistics, based on standard errors clustered by household, are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Dependent variable:	Equity Participation	Equity Participation (incl. IRAs)	Risky Share	Entry	Exit
	(1)	(2)	(3)	(4)	(5)
SLR Exposure (3ft)	-0.391***	-0.245*	-0.366***	-0.259***	0.796
	(-3.50)	(-1.78)	(-4.61)	(-3.04)	(1.58)
Storm Surge Exposure	0.020	0.067	0.010	0.145	-0.049
	(0.13)	(0.89)	(0.07)	(1.41)	(-0.10)
Controls	Yes	Yes	Yes	Yes	Yes
Zip Code x Year FEs	Yes	Yes	Yes	Yes	Yes
Obs.	6,585	6,583	4,685	4,088	485
Adj. R^2	0.43	0.51	0.35	0.31	0.25

Table 4. Sea level rise and stock market participation: House price growth

This table reports estimates of how sea level rise exposure relates to households' stock market behavior in areas that experienced high house price growth and low house price growth. The sample includes only homeowner households from 1999 to 2017 PSID waves. The sample is split based on the house price growth in each zip code over the last five years for any given year. The high house price growth sample includes the zip codes that experienced growths higher than the median in a state and the low house price growth sample includes the remaining zip codes. Controls include *Age, Age Squared, Married, Divorced, Male, Non-White, Family Size, Log(Total Income), Ihs(Wealth) excluding home equity, College Education, High School Education, Log(House Value), Home Insurance, Elevation x 1000, Distance-to-Coast x 1000, Vertical Land Motion*. All variables are defined in Appendix Table 1 and are weighted using PSID population weights. Parameter estimates are obtained by OLS. All regressions include a constant term and fixed effects indicated in the table, whose coefficients I do not report. t-statistics, based on standard errors clustered by household, are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Dependent variable:	Equity Participation		Risky Share	
	High House Price Growth	Low House Price Growth	High House Price Growth	Low House Price Growth
	(1)	(2)	(3)	(4)
SLR Exposure (3 ft)	-0.297**	-0.548***	-0.324***	-0.376***
	(-2.32)	(-4.75)	(-3.57)	(-3.54)
Controls	Yes	Yes	Yes	Yes
Zip Code x Year FEs	Yes	Yes	Yes	Yes
Obs.	8,883	5,290	6,854	4,158
Adj. R^2	0.37	0.34	0.33	0.29

Table 5. Sea level rise and stock market participation: The effect of past flooding incidents

This table reports estimates of how sea level rise exposure relates to households' stock market behavior and the role of past flooding incidents for this relationship. The sample includes only homeowner households from 1999 to 2017 PSID waves. No Recent Disasters is an indicator variable equal to one if there were no flooding related incident in a household's county of residence over the last two years, and zero otherwise. Controls include *Age*, *Age Squared*, *Married*, *Divorced*, *Male*, *Non-White*, *Family Size*, *Log(Total Income)*, *Ihs(Wealth) excluding home equity*, *College Education*, *High School Education*, *Log(House Value)*, *Home Insurance*, *Elevation x 1000*, *Distance-to-Coast x 1000*, *Vertical Land Motion*. All variables are defined in Appendix Table 1 and are weighted using PSID population weights. Parameter estimates are obtained by OLS. All regressions include a constant term and fixed effects indicated in the table, whose coefficients I do not report. t-statistics, based on standard errors clustered by household, are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Experienced Floods in the Last 2 Years?	No		Yes		Full	
Dependent variable:	Equity Participation	Risky Share	Equity Participation	Risky Share	Equity Participation	Risky Share
	(1)	(2)	(3)	(4)	(5)	(6)
SLR Exposure (3 ft)	-0.391**	-0.333***	-0.405***	-0.390***	-0.394**	-0.351***
	(-2.57)	(-3.16)	(-3.65)	(-4.18)	(-2.55)	(-3.23)
SLR Exposure (3 ft) x No Recent Disasters					0.009	-0.005
					(0.05)	(-0.03)
No Recent Disasters					-0.136	-0.083
					(-1.49)	(-1.24)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code x Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	6,911	5,424	7,208	5,543	14,173	11,012
Adj. R^2	0.35	0.29	0.37	0.34	0.36	0.32

Table 6. Sea level rise and stock market participation: Nevermovers

This table reports estimates of how sea level rise exposure relates to households' stock market behavior and compares households who never moved during the sample period to households who did move. The sample includes only homeowner households from 1999 to 2017 PSID waves. A nevermover household is defined as a household who has never moved out of the Census Block in which they live during the sample period. Controls *include Age, Age Squared, Married, Divorced, Male, Non-White, Family Size, Log(Total Income), Ihs(Wealth) excluding home equity, College Education, High School Education, Log(House Value), Home Insurance, Elevation x 1000, Distance-to-Coast x 1000, Vertical Land Motion*. All variables are defined in Appendix Table 1 and are weighted using PSID population weights. Parameter estimates are obtained by OLS. All regressions include a constant term and fixed effects indicated in the table, whose coefficients I do not report. t-statistics, based on standard errors clustered by household, are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Sample:	Full			
Dependent variable:	Equity Participation	Risky Share	Entry	Exit
	(1)	(2)	(3)	(4)
Nevermover x SLR Exposure (3 ft)	-0.589***	-0.379**	-0.237***	0.333
	(-4.10)	(-2.36)	(-2.63)	(0.33)
SLR Exposure (3ft)	0.003	-0.041	-0.053	0.893
	(0.03)	(-0.32)	(-0.92)	(0.81)
Nevermover	0.019	0.000	0.008	0.013
	(1.21)	(0.01)	(0.85)	(0.30)
Controls	Yes	Yes	Yes	Yes
Zip Code x Year FEs	Yes	Yes	Yes	Yes
Obs.	14,173	11,012	8,532	1,166
Adj. R^2	0.36	0.32	0.20	0.17

Sample:	Only Nevermovers			
Dependent variable:	Equity Participation	Risky Share	Entry	Exit
	(5)	(6)	(7)	(8)
SLR Exposure (3 ft)	-0.436***	-0.314***	-0.281*	1.529***
	(-3.83)	(-2.64)	(-1.68)	(3.47)
Controls	Yes	Yes	Yes	Yes
Zip Code x Year FEs	Yes	Yes	Yes	Yes
Obs.	4,692	3,575	2,586	339
Adj. R^2	0.30	0.29	0.14	0.02

Table 7. Sea level rise and stock market participation: Differences in political beliefs

This table reports estimates of how sea level rise exposure relates to households' stock market behavior as well as to a measure of political party affiliation. The sample includes only homeowner households from 1999 to 2017 PSID waves. *High RepShare* is an indicator variable equal to one if the share of voters who voted for the Republican candidate in the last presidential election is higher than the state median in a county-year, and zero otherwise. *High RepShare All* is an indicator variable equal to one if the share of voters who voted for the Republican candidate in the last presidential election is higher than the national median in a county-year, and zero otherwise. Controls include *Age, Age Squared, Married, Divorced, Male, Non-White, Family Size, Log(Total Income), Ihs(Wealth) excluding home equity, College Education, High School Education, Log(House Value), Home Insurance, Elevation x 1000, Distance-to-Coast x 1000, Vertical Land Motion*. All variables are defined in Appendix Table 1 and are weighted using PSID population weights. Parameter estimates are obtained by OLS. All regressions include a constant term and fixed effects indicated in the table, whose coefficients I do not report. t-statistics, based on standard errors clustered by household, are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Dependent variable:	Equity Participation			Risky Share		
Sample:	Full	Full	Distance-to-coast ≤ 50 km	Full	Full	Distance-to-coast ≤ 50 km
	(1)	(2)	(3)	(4)	(5)	(6)
SLR Exposure (3 ft) x High RepShare	-0.009		-0.095	0.082		0.021
	(-0.44)		(-0.31)	(0.65)		(0.11)
SLR Exposure (3 ft) x High RepShare All		-0.153			0.069	
		(-0.67)			(0.53)	
SLR Exposure (3 ft)	-0.341*	-0.312*	-0.477**	-0.400***	-0.390***	-0.488***
	(-1.86)	(-1.66)	(-2.15)	(-5.86)	(-5.48)	(-4.83)
High RepShare	-0.098		0.415	0.014		0.313
	(-0.44)		(1.06)	(0.29)		(1.07)
High RepShare All		-0.087			-0.060	
		(-1.58)			(-1.56)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code x Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	14,169	14,169	2,972	11,008	11,008	2,327
Adj. R^2	0.36	0.36	0.35	0.32	0.32	0.31

Table 8. Sea level rise and stock market participation: Risk preferences

This table reports estimates of how sea level rise exposure relates to households' stock market behavior and controls additionally for different measures of household risk aversion. The sample includes only homeowner households from 1999 to 2017 PSID waves. The sample includes all respondents in the PSID. Columns (1) and (5) additionally control for a household's Risky Share in 1999. Columns (2) and (6) additionally control for risk aversion fixed effects, based on the categories extracted from the 1996 wave of the PSID and categories defined in Kimball, Sahm and Shapiro (2009). Columns (3) and (7) additionally control for the risk aversion coefficients based on Kimball, Sahm and Shapiro (2009)'s coefficient estimations on the 1996 wave of the PSID. Columns (4) and (8) exclude the waves 2007 and 2009. Controls include *Age*, *Age Squared*, *Married*, *Divorced*, *Male*, *Non-White*, *Family Size*, *Log(Total Income)*, *Ihs(Wealth) excluding home equity*, *College Education*, *High School Education*, *Log(House Value) Home Insurance*, *Elevation x 1000*, *Distance-to-Coast x 1000*, *Vertical Land Motion*. All variables are defined in Appendix Table 1. Parameter estimates are obtained by OLS. All regressions include a constant term and fixed effects indicated in the table, whose coefficients I do not report. t-statistics, based on standard errors clustered by household, are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Dependent variable:	Equity Participation			
	Risky Share 1999 incl.	Risk Aversion FEs	Risk Aversion (Kimball, Sahm and Shapiro, 2009)	2007-2009 excl.
	(1)	(2)	(3)	(4)
SLR Exposure (3 ft)	-0.683**	-0.562**	-0.564**	-0.288***
	(-2.06)	(-2.24)	(-2.30)	(-2.88)
Controls	Yes	Yes	Yes	Yes
Zip Code x Year FEs	Yes	Yes	Yes	Yes
Obs.	6,191	4,993	4,993	11,515
Adj. R^2	0.42	0.32	0.32	0.37

Dependent variable:	Risky Share			
	Risky Share 1999 incl.	Risk Aversion FEs	Risk Aversion (Kimball, Sahm and Shapiro, 2009)	2007-2009 excl.
	(5)	(6)	(7)	(8)
SLR Exposure (3 ft)	-0.625**	-0.442*	-0.446*	-0.283***
	(-2.47)	(-1.83)	(-1.86)	(-4.27)
Controls	Yes	Yes	Yes	Yes
Zip Code x Year FEs	Yes	Yes	Yes	Yes
Obs.	5,509	4,030	4,030	8,908
Adj. R^2	0.47	0.28	0.28	0.32

Table 9. Sea level rise and stock market participation: Effect of distance-to-coast

This table reports estimates of how sea level rise exposure relates to households' stock market behavior for subsamples with respect to proximity to coast. The sample includes only homeowner households from 1999 to 2017 PSID waves, but is restricted to households that are 50 km or closer to the coast and households living in watershed counties, as indicated. Controls include *Age, Age Squared, Married, Divorced, Male, Non-White, Family Size, Log(Total Income), Ihs(Wealth) excluding home equity, College Education, High School Education, Log(House Value), Home Insurance, Elevation x 1000, Distance-to-Coast x 1000, Vertical Land Motion*. All variables are defined in Appendix Table 1 and are weighted using PSID population weights. Parameter estimates are obtained by OLS. All regressions include a constant term and fixed effects indicated in the table, whose coefficients I do not report. t-statistics, based on standard errors clustered by household, are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Sample:	Distance-to-coast ≤ 50 km			
Dependent variable:	Equity Participation	Risky Share	Entry	Exit
	(1)	(2)	(3)	(4)
SLR Exposure (3 ft)	-0.523***	-0.474***	-0.298**	1.492***
	(-3.20)	(-4.20)	(-2.09)	(3.32)
Controls	Yes	Yes	Yes	Yes
Zip Code x Year FEs	Yes	Yes	Yes	Yes
Obs.	2,972	2,327	1,475	361
Adj. R^2	0.35	0.31	0.30	0.08

Sample:	Only Watershed Counties			
Dependent variable:	Equity Participation	Risky Share	Entry	Exit
	(5)	(6)	(7)	(8)
SLR Exposure (3 ft)	-0.332***	-0.294***	-0.191*	1.110**
	(-2.92)	(-3.43)	(-1.89)	(2.47)
Controls	Yes	Yes	Yes	Yes
Zip Code x Year FEs	Yes	Yes	Yes	Yes
Obs.	6,041	4,492	3,440	554
Adj. R^2	0.38	0.32	0.27	0.13

Table 10. Sea level rise and stock market participation: Placebo test on renters

This table reports estimates of how sea level rise exposure relates to households' stock market behavior. The sample includes all households from 1999 to 2017 PSID waves. Odd-numbered columns include only homeowner households and even-numbered columns only include renter households in the sample. Controls include *Age, Age Squared, Married, Divorced, Male, Non-White, Family Size, Log(Total Income), Ihs(Wealth) excluding home equity, College Education, High School Education, Log(House Value), Home Insurance, Elevation x 1000, Distance-to-Coast x 1000, Vertical Land Motion*. In Columns (2), (4), (6), and (8), Log(House Value) and Home Insurance are replaced by Rent. All variables are defined in Appendix Table 1 and are weighted using PSID population weights. Parameter estimates are obtained by OLS. All regressions include a constant term and fixed effects indicated in the table, whose coefficients I do not report. t-statistics, based on standard errors clustered by household, are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Dependent variable:	Equity Participation		Risky Share	
Sample:	Homeowners	Renters	Homeowners	Renters
	(1)	(2)	(3)	(4)
SLR Exposure (3ft)	-0.392***	-0.102	-0.353**	-0.168
	(-3.59)	(-1.52)	(-4.78)	(-1.23)
Controls	Yes	Yes	Yes	Yes
Zip Code x Year FEs	Yes	Yes	Yes	Yes
Obs.	14,173	13,389	11,012	5,074
Adj. R^2	0.36	0.48	0.32	0.34

Dependent variable:	Entry		Exit	
Sample:	Homeowners	Renters	Homeowners	Renters
	(5)	(6)	(7)	(8)
SLR Exposure (3ft)	-0.224**	-0.073	1.133**	
	(-2.49)	(-1.04)	(2.20)	
Controls	Yes	Yes	Yes	
Zip Code x Year FEs	Yes	Yes	Yes	
Obs.	8,532	9,108	1,166	
Adj. R^2	0.20	0.46	0.17	

Table 11. Sea level rise and stock market participation: Attention to climate change proxied by the WSJ index

This table reports estimates of how sea level rise exposure relates to households' stock market behavior at times when attention to climate change is elevated. The sample includes only homeowner households from 1999 to 2017 PSID waves. High Attention is an indicator variable equal to one if the WSJ Climate Change News Index constructed by Engle et al. (2020) is larger than its time-series median over the previous year, and zero otherwise. Controls include *Age, Age Squared, Married, Divorced, Male, Non-White, Family Size, Log(Total Income), Ihs(Wealth) excluding home equity*, *College Education*, *High School Education*, *Log(House Value), Home Insurance, Elevation x 1000, Distance-to-Coast x 1000, Vertical Land Motion*. All variables are defined in Appendix Table 1 and are weighted using PSID population weights. Parameter estimates are obtained by OLS. All regressions include a constant term and fixed effects indicated in the table, whose coefficients I do not report. t-statistics, based on standard errors clustered by household, are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Dependent variable:	Equity Participation			Risky Share		
Sample:	Full	Distance-to-coast ≤ 50 km	Only Nevermovers	Full	Distance-to-coast ≤ 50 km	Only Nevermovers
	(1)	(2)	(3)	(4)	(5)	(6)
SLR Exposure (3 ft) x High Attention	-0.435*	-0.587**	-0.542**	-0.228	-0.378**	-0.358***
	(-1.80)	(-2.22)	(-2.05)	(-1.44)	(-2.32)	(-3.45)
SLR Exposure (3 ft)	-0.219*	-0.316*	-0.192**	-0.262***	-0.337***	-0.160
	(-1.77)	(-1.79)	(-2.26)	(-3.18)	(-2.63)	(-1.53)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code x Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	14,173	2,972	4,692	11,012	3,227	3,575
Adj. R^2	0.36	0.36	0.30	0.32	0.31	0.29

Table 12. Sea level rise and stock market participation: Attention to climate change proxied by major hurricanes

This table reports estimates of how sea level rise exposure relates to households' stock market behavior at times when the salience of flood risks is elevated. The sample includes only homeowner households from 1999 to 2017 PSID waves. $Hurricane_{st}$ is an indicator variable equal to one in an unaffected state s in time period t if there was a major hurricane taking place in period $t+1$. Controls include *Age*, *Age Squared*, *Married*, *Divorced*, *Male*, *Non-White*, *Family Size*, *Log(Total Income)*, *Ihs(Wealth) excluding home equity*, *College Education*, *High School Education*, *Log(House Value)*, *Home Insurance*, *Elevation x 1000*, *Distance-to-Coast x 1000*, *Vertical Land Motion*. All variables are defined in Appendix Table 1 and are weighted using PSID population weights. Parameter estimates are obtained by OLS. All regressions include a constant term and fixed effects indicated in the table, whose coefficients I do not report. t-statistics, based on standard errors clustered by household, are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Dependent variable:	Equity Participation			Risky Share		
Sample:	Full	Distance-to-coast ≤ 50 km	Only Nevermovers	Full	Distance-to-coast ≤ 50 km	Only Nevermovers
	(1)	(2)	(3)	(4)	(5)	(6)
SLR Exposure (3 ft) x $Hurricane_{st}$	-0.444**	-0.571**	-0.582**	-0.146	-0.235*	-0.318***
	(-2.03)	(-2.35)	(-2.15)	(-1.18)	(-1.78)	(-2.72)
SLR Exposure (3 ft)	-0.238**	-0.344**	-0.219**	-0.298***	-0.394***	-0.203**
	(-2.05)	(-1.99)	(-3.31)	(-3.31)	(-2.89)	(-1.99)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code x Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	14,173	2,972	4,692	11,012	2,327	3,575
Adj. R^2	0.36	0.36	0.30	0.32	0.31	0.29

Table 13. Sea level rise and stock market participation: State-led climate change adaptation plans

This table reports estimates of how sea level rise exposure relates to households' stock market behavior around the adoption of state-led climate change adaptation plans. The sample includes all homeowner households from 1999 to 2017 PSID waves. Controls include *Age, Age Squared, Married, Divorced, Male, Non-White, Family Size, Log(Total Income), Ihs(Wealth) excluding home equity, College Education, High School Education, Log(House Value), Home Insurance, Elevation x 1000, Distance-to-Coast x 1000, Vertical Land Motion*. All variables are defined in Appendix Table 1 and are weighted using PSID population weights. Parameter estimates are obtained by OLS. All regressions include a constant term and fixed effects indicated in the table, whose coefficients I do not report. t-statistics, based on standard errors clustered by household, are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Dependent variable:	Equity Participation			
Sample:	Full	Full	Exclude 2007 & 2009	Drop Untreated
	(1)	(2)	(3)	(4)
SLR Exposure x Post SCCAP	0.633***	0.561**	0.628****	0.521**
	(2.78)	(2.32)	(2.88)	(2.07)
SLR Exposure	-0.293***	-0.296***	-0.221***	-0.215
	(-3.63)	(-3.66)	(-2.92)	(-1.50)
Controls	Yes	Yes	Yes	Yes
Zip Code x Year FEs	Yes	Yes	Yes	Yes
Controls x Post SCCAP	No	Yes	No	No
Obs.	14,173	14,173	11,515	7,941
Adj. R^2	0.36	0.36	0.37	0.39

Dependent variable:	Risky Share			
Sample:	Full	Full	Exclude 2007 & 2009	Drop Untreated
	(5)	(6)	(7)	(8)
SLR Exposure x Post SCCAP	0.431***	0.346**	0.409**	0.416***
	(3.19)	(2.22)	(3.04)	(2.82)
SLR Exposure	-0.266***	-0.262***	-0.213***	-0.289***
	(-4.83)	(-4.77)	(-4.20)	(-4.12)
Controls	Yes	Yes	Yes	Yes
Zip Code x Year FEs	Yes	Yes	Yes	Yes
Controls x Post SCCAP	No	Yes	No	No
Obs.	11,012	11,012	8,908	5,906
Adj. R^2	0.32	0.32	0.32	0.33

Table 14. Sea level rise and stock market participation: Placebo test on renters around state-led climate change adaptation plans

This table reports estimates of how sea level rise exposure relates to households' stock market behavior around the adoption of state-led climate change adaptation plans. The sample includes all renter households from 1999 to 2017 PSID waves. Controls include *Age, Age Squared, Married, Divorced, Male, Non-White, Family Size, Log(Total Income), Ihs(Wealth) excluding home equity, College Education, High School Education, Log(House Value), Home Insurance, Elevation x 1000, Distance-to-Coast x 1000, Vertical Land Motion*. All variables are defined in Appendix Table 1 and are weighted using PSID population weights. Parameter estimates are obtained by OLS. All regressions include a constant term and fixed effects indicated in the table, whose coefficients I do not report. t-statistics, based on standard errors clustered by household, are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Dependent variable:	Equity Participation			
Sample:	Full	Full	Exclude 2007 & 2009	Drop Untreated
	(1)	(2)	(3)	(4)
SLR Exposure x Post SCCAP	-0.019	-0.029	-0.020	-0.057
	(-0.26)	(-0.37)	(-0.25)	(-0.70)
SLR Exposure	-0.003	-0.005	-0.011	0.021
	(-0.10)	(-0.19)	(-0.32)	(0.59)
Controls	Yes	Yes	Yes	Yes
Zip Code x Year FEs	Yes	Yes	Yes	Yes
Controls x Post SCCAP	No	Yes	No	No
Obs.	13,819	13,819	11,215	8,481
Adj. R^2	0.49	0.49	0.48	0.53

Dependent variable:	Risky Share			
Sample:	Full	Full	Exclude 2007 & 2009	Drop Untreated
	(5)	(6)	(7)	(8)
SLR Exposure x Post SCCAP	-0.196	-0.177	-0.203	-0.193
	(-0.79)	(-0.74)	(-0.82)	(-0.77)
SLR Exposure	-0.001	-0.001	0.0004	0.002
	(-0.01)	(-0.27)	(0.01)	(0.03)
Controls	Yes	Yes	Yes	Yes
Zip Code x Year FEs	Yes	Yes	Yes	Yes
Controls x Post SCCAP	No	Yes	No	No
Obs.	5,227	5,227	4,286	3,174
Adj. R^2	0.37	0.38	0.38	0.40

Appendix

for

Sea Level Rise and Portfolio Choice

Emirhan Ilhan

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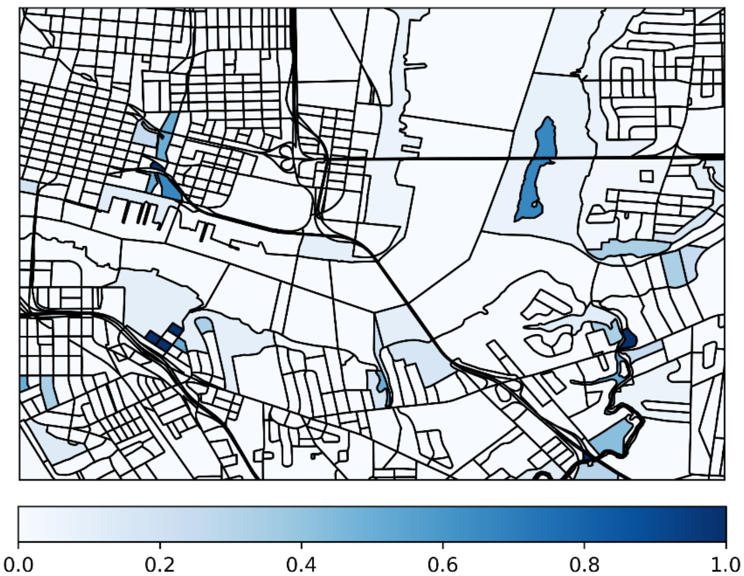
& Management

Appendix Part A: Additional Tables

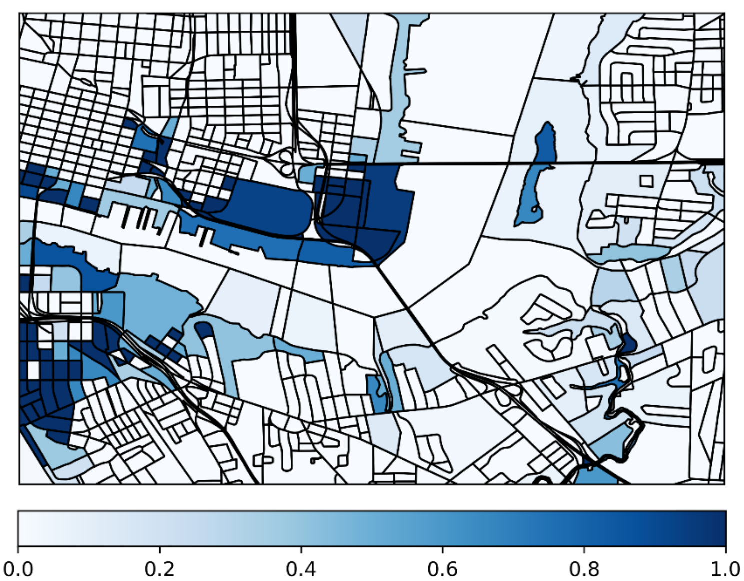
Appendix Figure 1. 3 feet and 6 feet SLR risk exposures of census blocks around the TIAA Bank Field Stadium

This figure illustrates the Census Blocks exposed to 3 feet and 6 feet SLR around the TIAA Bank Field Stadium, home of the Jacksonville Jaguars NFL team. Panel A shows the exposure of Census Blocks under a 6 feet sea level rise scenario and Panel B shows the exposure of Census Blocks under a 3 feet sea level rise scenario.

Panel A

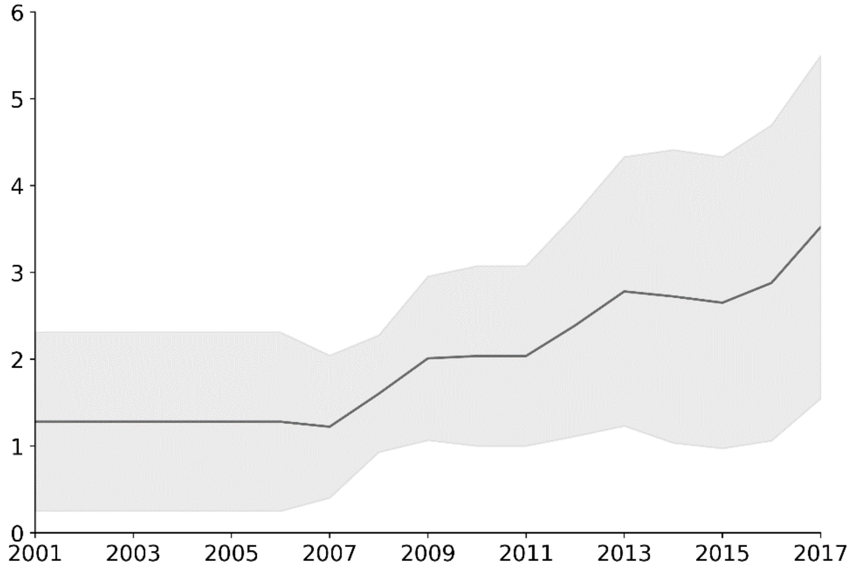


Panel B



Appendix Figure 2. Evolution of sea level rise projections over time

This figure reports the evolution of sea level rise projections over time. The black line is the mean of sea level rise forecasts across major scientific studies from 2001 and 2017. The upper bound is the 99th percentile and the lower bound is the 1st percentile. For details on how this time-series was created, the reader is referred to Goldsmith-Pinkham et al. (2021).



Appendix Table 1. Variable Definitions

Variable	Definition	Data Source
Stock Market Participation Variables		
Equity Participation	An indicator variable equal to one if the household holds any shares in publicly held corporations, mutual funds, or investment trusts in a given year.	PSID
Equity Participation (IRA)	An indicator variable equal to one if the household holds any shares in publicly held corporations, mutual funds, or investment trusts in a given year, including holdings in pensions or individual retirement accounts.	PSID
Risky Share	The value of stocks held by the household divided by the financial wealth (stocks, cash, and bonds) of the household.	PSID
Entry	An indicator variable equal to one if a household did not participate in the stock market in the prior survey year but does in the current survey year. This variable is defined only for households that did not participate in the stock market in the prior survey year.	PSID
Exit	An indicator variable equal to one if a household participated in the stock market in the prior survey year but not in the current survey year. This variable is defined only for households that participated in the stock market in the prior survey year.	PSID
Income, Wealth, and Other Demographic Variables		
Age	The age of the household head in years.	PSID
Age Squared	The square of the age of the household head.	PSID
Married	An indicator variable equal to one if the household head is married.	PSID
Divorced	An indicator variable equal to one if the household head is divorced.	PSID
Male	An indicator variable equal to one if the household head is male.	PSID
Non-White	An indicator variable equal to one if the household head's race is different than white.	PSID
Family Size	The number of family members in a given year.	PSID
Log(Total Income)	The natural logarithm of the total family income in 2017 dollars.	PSID
Ihs(Wealth, excl. Home Equity)	Inverse hyperbolic sine of the family net wealth, excluding home equity, in 2017 dollars. I use the asinh function instead of natural logarithm, because there are many observations with negative values. asinh provides a way of renormalizing the data without dropping negative values.	PSID
College Education	An indicator variable equal to one if the household head has at least 16 years of education.	PSID
High School Education	An indicator variable equal to one if the household head has between 12 and 6 years of education.	PSID
Log(House Value)	The natural logarithm of the house value in 2017 dollars if the household owns the house they reside in.	PSID
Home Insurance	An indicator variable equal to one if the household has home insurance, zero otherwise.	PSID
Nevermover	An indicator variable equal to one if the household does not relocate to a new house in the sample period 1999-2017.	PSID
Owner	An indicator variable equal to one if the household is the owner of the house they reside in.	PSID
Risk Aversion (Kimball et al. 2009)	Risk aversion coefficient as computed by Kimball, Sahm and Shapiro (2009). This variable is created by using the series of questions in the 1996 wave of the PSID survey about different gambles. For more information, the reader is referred to Kimball, Sahm and Shapiro (2009).	PSID, Kimball, Sahm and Shapiro (2009)

Geographical Variables		
SLR Exposure (1 ft)	Sea level rise (SLR) exposure of the household under the 1 ft sea level rise scenario computed at the Census Block level. For a given Census Block, SLR exposure (1 ft) is computed as the area covered by the 1 ft SLR layer minus the area covered by the 0 ft SLR layer.	NOAA
SLR Exposure (2 ft)	Sea level rise (SLR) exposure of the household under the 2 ft sea level rise scenario computed at the Census Block level. For a given Census Block, SLR exposure (2 ft) is computed as the area covered by the 2 ft SLR layer minus the area covered by the 0 ft SLR layer.	NOAA
SLR Exposure (3 ft)	Sea level rise (SLR) exposure of the household under the 3 ft sea level rise scenario computed at the Census Block level. For a given Census Block, SLR exposure (3 ft) is computed as the area covered by the 3 ft SLR layer minus the area covered by the 0 ft SLR layer.	NOAA
Post SCAP	An indicator variable equal to one for years after a State Climate Change Adaptation Plan is finalized in a state, zero otherwise.	Georgetown Climate Center
Elevation (ft)	Ground elevation in feet of the centroid of the Census Block in which the household resides.	USGS
Distance-to-coast (km)	The distance to closest coastline of the Census Block in which a household resides in kilometers. I compute the length of the line that connects the centroid of the Census Block to the coastline perpendicularly.	Self-constructed
Vertical Land Motion	The vertical land motion component of the relative sea level rise variable defined in Murfin and Spiegel (2020). The variable is based on historical trends from 142 tidal stations. For each Census Block, vertical land motion is defined as the weighted average ground level change of the two nearest tide gauges, where weighting is done by inverse distance.	NOAA

Appendix Table 2. Sea level rise and stock market participation: Expanded table with control variables

This is an expanded version of Table 2. The coefficients of control variables are suppressed in Table 2, but are explicitly displayed in this table.

Dependent variable:	Equity Participation		Equity Participation (incl. IRAs)		Risky Share		Entry		Exit	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
SLR Exposure (3 ft)	-0.392***	-0.469***	-0.265*	-0.337**	-0.353***	-0.389***	-0.224**	-0.316***	1.133**	1.147**
	(-3.59)	(-3.93)	(-1.92)	(-1.98)	(-4.78)	(-5.04)	(-2.49)	(-3.01)	(2.20)	(2.29)
Age	-0.003	-0.004	0.006**	0.006*	-0.003	-0.003	-0.002	-0.002	-0.016*	-0.019*
	(-1.13)	(-1.20)	(2.13)	(1.94)	(-1.45)	(-1.40)	(-1.06)	(-1.08)	(-1.68)	(-1.96)
Age Squared	0.000*	0.000*	-0.000	-0.000	0.000**	0.000**	0.000	0.000	0.000	0.000*
	(1.81)	(1.81)	(-1.22)	(-1.22)	(2.08)	(2.02)	(1.24)	(1.19)	(1.57)	(1.82)
Married (1/0)	-0.009	-0.006	0.043	0.055	-0.033	-0.031	0.012	0.022	0.190**	0.190**
	(-0.34)	(-0.18)	(1.40)	(1.51)	(-1.44)	(-1.24)	(0.73)	(1.07)	(2.32)	(2.23)
Divorced (1/0)	-0.049*	-0.046	-0.007	-0.004	-0.044*	-0.037	-0.010	-0.008	0.270***	0.256***
	(-1.94)	(-1.52)	(-0.25)	(-0.11)	(-1.96)	(-1.53)	(-0.64)	(-0.37)	(3.21)	(2.99)
Male (1/0)	0.009	0.016	-0.008	-0.015	0.028	0.034	-0.015	-0.019	-0.057	-0.077
	(0.35)	(0.52)	(-0.27)	(-0.45)	(1.20)	(1.34)	(-0.99)	(-0.99)	(-0.71)	(-0.94)
Non-White (1/0)	-0.075***	-0.052*	-0.080**	-0.052	-0.050***	-0.035*	-0.036**	-0.036*	0.034	-0.019
	(-3.18)	(-1.94)	(-2.56)	(-1.44)	(-2.81)	(-1.75)	(-2.28)	(-1.95)	(0.38)	(-0.19)
Family Size	-0.015***	-0.018***	-0.030***	-0.036***	-0.009*	-0.009*	-0.010***	-0.014***	-0.025	-0.030
	(-2.91)	(-2.81)	(-4.65)	(-4.57)	(-1.88)	(-1.77)	(-2.93)	(-3.04)	(-1.20)	(-1.38)
Log(Total Income)	0.047***	0.042***	0.078***	0.077***	0.029***	0.025**	0.018**	0.015	-0.034	-0.026
	(4.33)	(3.39)	(6.56)	(5.62)	(3.20)	(2.54)	(2.37)	(1.60)	(-0.94)	(-0.70)
Ihs(Wealth excl. Home Equity)	0.009***	0.010***	0.017***	0.019***	0.006***	0.006***	0.003***	0.004***	-0.018***	-0.020***
	(11.58)	(10.77)	(17.86)	(16.80)	(9.19)	(8.76)	(6.07)	(5.46)	(-3.42)	(-3.51)
College Education (1/0)	0.200***	0.214***	0.205***	0.204***	0.108***	0.110***	0.055***	0.062***	-0.297**	-0.334***
	(6.61)	(6.14)	(6.73)	(5.79)	(4.21)	(3.92)	(2.88)	(2.66)	(-2.54)	(-2.84)
High School Education (1/0)	0.057***	0.067***	0.061**	0.066**	0.041**	0.042*	0.009	0.010	-0.086	-0.113
	(2.73)	(2.64)	(2.50)	(2.26)	(2.04)	(1.89)	(0.80)	(0.69)	(-0.74)	(-0.98)
Log(House Value)	0.034***	0.040***	0.039***	0.046***	0.033***	0.036***	0.020***	0.027***	0.097**	0.115**
	(3.53)	(3.53)	(3.39)	(3.45)	(3.78)	(3.79)	(3.10)	(3.38)	(2.09)	(2.44)
Home Insurance (1/0)	-0.025	-0.022	0.030	0.038	0.021	0.033	-0.010	-0.009	-0.308	-0.362
	(-0.99)	(-0.69)	(0.88)	(0.89)	(0.81)	(1.12)	(-0.53)	(-0.37)	(-1.23)	(-1.38)
Elevation (ft) / 1000	0.067	0.061	0.011	-0.005	0.031	0.028	0.004	-0.006	-0.179	-0.190
	(1.21)	(1.08)	(0.19)	(-0.08)	(0.65)	(0.58)	(0.08)	(-0.11)	(-1.42)	(-1.49)
Distance-to-coast (km) / 1000	0.090	0.531	3.178	3.748	-0.289	-0.113	0.499	0.586	8.972	9.733
	(0.05)	(0.28)	(1.46)	(1.54)	(-0.22)	(-0.08)	(0.49)	(0.49)	(1.34)	(1.41)
Vertical Land Motion (ft)	0.382**	0.396**	0.012	0.007	0.238**	0.227**	0.255**	0.284**	-1.049***	-1.032***
	(2.49)	(2.27)	(0.05)	(0.03)	(2.21)	(2.03)	(2.11)	(1.97)	(-3.33)	(-3.17)
Zip Code x Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample:	Full	SRC	Full	SRC	Full	SRC	Full	SRC	Full	SRC
Obs.	14,173	9,573	14,168	9,569	11,012	8,385	8,532	5,096	1,166	1,073
Adj. R^2	0.36	0.33	0.41	0.36	0.32	0.30	0.20	0.16	0.17	0.17

Appendix Table 3. Sea level rise and stock market participation: 1 foot and 2 feet sea level rise scenarios

This table reports estimates of how sea level rise exposure relates to households' stock market behavior. The sample includes only homeowner households from 1999 to 2017 PSID waves. Full sample includes all respondents in the PSID and SRC sample includes only the respondents in the main PSID sample, as indicated in the table. Controls include *Age, Age Squared, Married, Divorced, Male, Non-White, Family Size, Log(Total Income), Ihs(Wealth) excluding home equity, College Education, High School Education, Log(House Value), Home Insurance, Elevation x 1000, Distance-to-Coast x 1000, Vertical Land Motion*. All variables are defined in Appendix Table 1. Parameter estimates are obtained by OLS. All regressions include a constant term and fixed effects indicated in the table, whose coefficients I do not report. t-statistics, based on standard errors clustered by household, are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Dependent variable:	Equity Participation		Equity Participation (incl. IRAs)		Risky Share		Entry		Exit	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
SLR Exposure (1 ft)	-0.838*	-1.183*	-0.578	-0.881	-0.722*	-0.878*	-0.368	-0.722	0.930	1.026
	(-1.74)	(-1.81)	(-1.43)	(-1.53)	(-1.84)	(-1.83)	(-0.99)	(-1.18)	(0.85)	(0.93)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code x Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample:	Full	SRC	Full	SRC	Full	SRC	Full	SRC	Full	SRC
Obs.	14,173	9,573	14,168	9,569	11,012	8,385	8,532	5,096	1,166	1,073
Adj. R^2	0.36	0.32	0.41	0.36	0.32	0.30	0.20	0.16	0.17	0.16

Dependent variable:	Equity Participation		Equity Participation (incl. IRAs)		Risky Share		Entry		Exit	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
SLR Exposure (2 ft)	-0.433**	-0.515**	-0.239	-0.316	-0.495***	-0.553***	-0.300**	-0.454***	0.833	0.864*
	(-2.18)	(-2.24)	(-1.19)	(-1.28)	(-3.93)	(-4.17)	(-2.01)	(-2.60)	(1.56)	(1.65)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip Code x Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample:	Full	SRC	Full	SRC	Full	SRC	Full	SRC	Full	SRC
Obs.	14,173	9,573	14,168	9,569	11,012	8,385	8,532	5,096	1,166	1,073
Adj. R^2	0.36	0.33	0.41	0.36	0.32	0.30	0.20	0.16	0.17	0.16

Appendix Table 4. State-led climate change adaptation plans: Parallel trends

This table compares the growth rates in Equity Participation and Risky Share between the treatment and control group in the period before state-led climate change adaptation plans are adopted. The treatment group consists of households who are in the top quartile in terms of sea level rise exposure in a state-year and the control group consists of all other households. I present the p-value of a difference-in-means test, which tests the hypothesis that mean values of the two groups are the same. I also present the Wilcoxon p-value of the two-sample Wilcoxon test, which tests the hypothesis that the two groups are taken from populations with the same median.

	Mean Growth High SLR Exposure (Treated)	Mean Growth Low SLR Exposure (Control)	Difference	*p*-value	Wilcoxon *p*-value
Equity Participation Growth	-0.045	-0.005	-0.04	0.28	0.28
Risky Share Growth	-0.0076	-0.0047	-0.0029	0.9285	0.26

Appendix Table 5. Sea level rise and stock market participation: List of top ten costliest hurricanes in the United States

This table reports the top ten costliest hurricanes in the United States in the sample period 1999-2017, when these hurricanes took place, and which states they have hit.

Name	Year	Affected States
Charley	2004	FL, GA, SC, NC
Ivan	2004	AL, FL, LA, TX
Frances	2004	FL
Katrina	2005	LA, MS, AL, FL
Wilma	2005	FL
Rita	2005	LA, TX
Ike	2008	TX, LA
Irene	2011	SC, NC, GA, VA, MD, PA, DE, NJ, NY, CT, RI, MA, ME
Sandy	2012	SC, NC, GA, VA, MD, PA, DE, NJ, NY, CT, RI, MA, ME
Matthew	2016	FL

Appendix Part B: State-led climate change adaptation plans: Risks, costs, and adaptation strategies

Governments' responses to climate change typically include mitigation and adaptation strategies. Mitigation strategies are related to acts that are aimed at combating climate change directly. In particular, policies that aim to reduce greenhouse gas emissions such as carbon taxes and cap-and-trade schemes fall into this category. While policies towards mitigation are often at the forefront of climate change discussions, the realization of proposed mitigation policies in the United States has been limited.

Adaptation strategies aim at making each state more resilient and prepared towards the adverse effects of climate change. As such, there is substantial heterogeneity in what adaptation strategies include depending on the geographic challenges of each state. For instance, California mainly suffers from wildfires, drought, and water scarcity whereas Louisiana is much more affected sea level rise, hurricanes, and severe storms. It is not, therefore, surprising to also see significant heterogeneity in the timing of adoptions of such plans and how states plan to tackle issues relevant for them.

Figure 4 shows the geographic distribution and timing of state-led climate change adaptation plans across the United States. All states who finalized such adaptation plans are coastal, with the exception of Colorado, New Hampshire, and Pennsylvania.[34] Nevertheless, the adaptation plans of all of these states emphasize the significant risks they face due to sea level rise. These risks take the form of inundation of densely populated areas, increased severity and frequency of hurricanes and storm surges, salt water intrusion into groundwater caused by flooding rivers leading to water scarcity.

Costs associated with the risks of sea level rise in most states with plans are also economically sizable. Massachusetts' plan emphasizes less than a foot of sea level rise by 2050 could damage assets worth an estimated $463 billion just in Boston. The plan cites the estimated costs of evacuation

[34] As a land-locked state, Colorado mainly faces the risk of water scarcity and wildfires due to climate change. New Hampshire and Pennsylvania both cite increased flooding and severe storms as significant risks they face due to climate change even though both of these states have limited coastlines. However, the settlement pattern in New Hampshire has taken place largely around rivers and lakes with floodplains. Pennsylvania's adaptation plan further cites salt water intrusion in the Delaware River as a significant risk due to sea level rise.

alone in the Northeast region from sea level rise and storms during a single event to be between $2 billion and $6.5 billion. Florida's plan points out that barrier islands, which already host extensive development of high value oceanfront real estate, are at significant risk from sea level rise and the costs incurred due to beach erosion are $600 million per year and rising. California's plans suggest that out of state's $4 trillion real estate assets, $2.5 trillion is at risk from extreme weather events, sea level rise, and wildfires with a projected cost up to $3.9 billion per year over this century.

Consider the case of Florida for an illustration of the process that leads to a climate change adaptation plan. On July 12-13, 2007, Florida Governor Charlie Crist hosted "Serve to Preserve: A Florida Summit on Global Climate Change" in Miami, gathering leaders of business, government, and science together. At the conclusion of the summit, Governor Crist signed an executive order and established the Florida Governor's Action Team on Energy and Climate Change. The executive order directed that the team devise an Action Plan including strategies to reduce greenhouse gas emissions and, in a second-phase, long-term strategies for reducing climate impacts to society, public health, the economy, and the environment. The final Energy and Climate Change Action Plan ("Action Plan") was submitted to the Governor on October 15, 2008. The Action Plan provides 50 separate policy recommendations covering topics like a Florida cap-and-trade scheme, government policy and coordination, adaptation strategies related to such as transportation and land use, infrastructure, coastal resources, extreme climate events and emergency response and many more.

Despite the heterogeneity in state adaptation plans, there are many common strategies proposed by all states. Promoting resilient design in new residential development and infrastructure and discouraging projects in areas that cannot be adequately protected from flooding or erosion are common in most adaptation plans. These strategies also include incorporation of new building design criteria and codes for resisting future loads that may result in sea level rise related hazards. All plans also emphasize the importance of scientific data collection, analysis, and risk assessment to guide their decision making and policy making efforts. Many plans demonstrate ambition towards reforming the local and national insurance markets such that insurance rates reflect risks from climate change and be affordable, with policies particularly discouraging high risk development along the coasts.

Carbon Tail Risk

Emirhan Ilhan   Zacharias Sautner   Grigory Vilkov

Abstract

Strong regulatory actions are needed to combat climate change, but climate policy uncertainty makes it difficult for investors to quantify the impact of future climate regulation. We show that such uncertainty is priced in the option market. The cost of option protection against downside tail risks is larger for firms with more carbon-intense business models. For carbon-intense firms, the cost of protection against downside tail risk is magnified at times when the public's attention to climate change spikes, and it decreased after the election of climate change skeptic President Trump.

JEL Codes: G13, G32, Q54

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Scientists broadly agree that strong regulatory actions are needed to avoid the potentially catastrophic consequences of climate change.[35] Climate change is mostly caused by the combustion of fossil fuels, so any regulation will have to aim at significantly curbing firms' carbon emissions. However, whether, how, and when regulatory climate policies will be implemented is highly uncertain. Regulation to limit carbon emissions could be enforced via carbon taxes, cap-and-trade schemes, or emission limits, all of which have different impacts on firms. Even in the case of carbon taxes, it is highly uncertain what the price for carbon emissions should be (it ranges between \$15 and \$360 per ton of CO_2, depending on the model) (*Financial Times* 2019). Climate policy uncertainty is further amplified because of fundamental uncertainty about how strongly emissions have to be reduced to limit global warming (see Barnett, Brock, and Hansen 2020).

Climate policy uncertainty has heterogeneous effects across firms in the economy. Uncertainty is likely to be most relevant for carbon-intense firms, as such firms will be most affected by policies that aim at curbing emissions. For such firms, regulation that limits carbon emissions can lead to stranded assets or a large increase in the cost of doing business (Litterman 2016). Carbon-intense firms may also experience financing constraints if banks reduce funding because of climate-related capital requirements. Yet the extent to which carbon-intense firms will be affected by regulation is highly uncertain. This uncertainty makes it difficult for investors to quantify the impact that future climate regulation will have on firms in terms of large drops in stock prices or general increases in volatility.

In this paper, we test whether climate policy uncertainty is priced in the option market.[36] Specifically, we explore whether the cost of option protection against downside tail risks is larger for firms with more carbon-intense business models. We also explore whether the cost of option protection against increases in return volatility (variance risk) is larger for more carbon-intense firms. Our analysis builds on prior work documenting that political or regulatory uncertainty is priced in the option market.

[35] The Intergovernmental Panel on Climate Change (IPCC 2018) summarizes the current scientific consensus about climate change. The IPCC is the United Nations' intergovernmental body for providing scientific evidence related to climate change.

[36] In this paper, the term "priced" means that option prices reflect that certain stocks are riskier than others, rather than that the market compensates investors for taking a certain risk by offering an expected return. Likewise, "uncertainty" is not to be understood strictly in the Knightian sense of the word. This wording follows the meaning used in the related literature (Pastor and Veronesi 2013; Kelly, Pastor, and Veronesi 2016).

Notably, Kelly, Pastor, and Veronesi (2016, KPV hereafter) show that options which provide insurance against tail and variance risks are more expensive when general political uncertainty is higher. The benefit of using options-based measures is that these measures reflect forward-looking expectations of subjective or perceived risk.

Pastor and Veronesi (2013, PV hereafter) provide a theoretical framework that helps us explain why political uncertainty about climate regulation ("climate policy uncertainty") may affect asset prices. In their model, the government decides whether to change its current policy. Potential new policies are heterogeneous ex ante; that is, agents expect different policies to affect firms in unique ways and with varying degrees of uncertainty. The government decides on adopting a new policy based on investors' welfare and political costs. A new policy is more likely to be adopted if its positive impact on firms' profitability is higher and if the political costs associated with it are lower. While investors can only start learning about policy impacts when a new policy is adopted, "political signals" allow them to learn about political costs before the adoption of a new policy. Asset prices are affected by shocks that originate from learning about the political costs of the new policies: as new shocks occur, investors change their beliefs about expected future policies. PV show that political uncertainty leads investors to demand compensation for political events (debates, negotiations, or elections) as such events affect beliefs about future policies. Hence, investors' expectations about future policy changes affect asset prices. A cross-sectional implication of PV's model is that the cost of protection against downside tail and variance risks associated with climate policy events depends on the sensitivity of firms to potential climate regulation.

Our analysis uses three option market measures for firms in the S&P 500 as well as for the economic sectors of the index. Our focal measure, *SlopeD*, originates from KPV and identifies downside tail risk. The measure reflects the steepness of the implied volatility slope, and it is created as the slope of a function that relates left-tail implied volatility to moneyness (with moneyness being measured by the option's delta). The measure is on average positive, because far out-of-the money (OTM) puts are typically more expensive (in terms of implied volatilities) than puts that are less OTM. An increase in *SlopeD* indicates that deeper OTM puts become more expensive, which reflects a relatively higher cost of protection against downside tail risks. *SlopeD* measures the properties of the risk-neutral probability distribution implied by option prices, and, hence, takes into account both the physical distribution of a stock's returns and an adjustment for the risk premium associated with the stock's risk.[37]

Our other two measures provide complimentary information from the option market. The model-free implied skewness (*MFIS*) quantifies the asymmetry of the risk-neutral distribution (Bakshi, Kapadia, and Madan 2003). By being the third central moment of the distribution normalized by the risk-neutral variance (raised to the power of 3/2), *MFIS* reflects the expensiveness of protection against left tail events *relative* to the cost of exposure to right tail events. The variance risk premium (*VRP*) allows us to evaluate the cost of protection against general variance risk, and it is computed as the difference between the risk-neutral expected and the realized variances (Carr and Wu 2009; Bollerslev, Tauchen, and Zhou 2009).

We focus on measures constructed from options with 30 days to maturity. Short-term options are traded more frequently and with lower effective transaction costs compared to long-term derivatives. Hence, their prices adjust faster to investors' flow of information as well as to changes in perceived uncertainty and risks.[38] Further, we aim to identify the cost of protection against large price drops, and such tail events have the most pronounced pricing effects for short-term options (Cont and Tankov 2004).

Our data on carbon emissions are collected by means of a survey by CDP, formerly known as the Carbon Disclosure Project. We focus on Scope 1 emissions, which originate from the combustion of fossil fuels or from releases during manufacturing. We scale carbon emissions by firms' equity market values to obtain a measure of carbon intensity. We perform this scaling as the impact of the costs of future climate regulation should be considered relative to market values; for a given amount of emissions, firms with high equity market values are likely to suffer less from regulation than firms with

[37] We follow the literature in using risk-neutral quantities as risk measure proxies. The benefit of option-implied variables compared to equivalents under the physical probability measure is their forward-looking character, while the cost includes a potential bias stemming from the risk premium effect (for discussions of related issues, see, e.g., Chang, Christoffersen, and Jacobs 2013; Cremers, Halling, and Weinbaum 2015; DeMiguel et al. 2013).
[38] For example, Muravyev and Pearson (2020) document that investors trade options on S&P 500 constituents with time to maturity less than 3 months 30% more often (in terms of stock-days) than options with maturities between 3 and 12 months. The bid-ask spreads, adjusted for execution timing based on a high-frequency trade analysis, are on average about 50% higher for longer-term options than for shorter-term ones.

low market values. Our main measure is a firm's industry carbon intensity, that is, Scope 1 emissions of all reporting firms in the industry divided by the market value of all reporting firms in the industry. We use this measure as carbon intensities are primarily driven by industry characteristics (as we will show). Recent evidence also indicates that industry characteristics drive the effect of Scope 1 intensities on returns and investor screening (Bolton and Kacperczyk 2020).[39] We use a selection model as firms disclose emissions voluntarily to CDP.

We find strong evidence that climate policy uncertainty is priced in the option market. A one-standard-deviation increase in a firm's log industry carbon intensity increases the implied volatility slope (*SlopeD*) by 0.014, or by 10% of the variable's standard deviation. We confirm our finding for sector exchange-traded fund (ETF) options: the cost of option protection against downside tail risks is higher for the more carbon-intense sectors of the S&P 500. These results are highly robust. For example, they are unaffected if we drop oil and gas firms (our regressions already control for oil betas), and we continue to find effects for option maturities of up to one year. Overall, our estimates suggest that options written on carbon-intense firms are relatively more expensive, especially for the far-left tail region, as they provide protection against downside tail risks associated with climate policy uncertainty.

Evidence for the two other measures is more mixed, but it complements the picture presented by *SlopeD*. While we find some effects for *MFIS* at the sector level, we cannot detect corresponding effects at the firm level. These weaker results reflect that *MFIS*, different from *SlopeD*, does not directly capture left tail risk. Instead, it measures distribution asymmetry by comparing left and right tail risk, with the latter, as we show, also being higher for carbon-intense firms. For *VRP*, we find effects at the firm level, but not at the sector level. Hence, our results for all three measures combined indicate that higher climate policy uncertainty increases at the firm level the likelihood of left and right tail events, and it has some effect on firm-level uncertainty as measured by *VRP*. On the sector level, however, where firm-specific risks are partially diversified away,[40] we observe that the effect is more systematic and concentrated in the left tail.

[39] Bolton and Kacperczyk (2020) explain their finding with Gennaioli and Shleifer's (2010) local thinking hypothesis, whereby investors use a coarse categorization of firms within a given industry when evaluating carbon risks.

[40] Full diversification is unlikely for sectors with a low number of constituents and for sectors with a skewed

In a next step, we investigate whether the effect of carbon intensities on downside tail risk is amplified at times when public attention to climate change is high. Our assumption is that high public attention to global warming increases the probability that pro-climate policies are adopted.[41] Importantly, as the probability of a policy change rises, so does uncertainty about which specific new policies will be selected and what their *impact* on firm profitability will be. While this implies more certainty that a regulatory change occurs, pro-climate policies are characterized by large uncertainties in terms of their impact on firm profitability as such policies represent larger deviations from current practices. The cost of option protection against downside tail risk should therefore be magnified at times when public attention to climate change spikes. To obtain proxies for attention to climate change, we use the negative climate change news index developed by Engle et al. (2020) as well as Google search volume data for the topic "climate change." While we find that the effect of carbon intensities on *SlopeD* is aggravated when there is more negative climate change news, we cannot detect a corresponding effect for Google search data.[42]

Finally, we use the election of President Trump in 2016 as a shock that reduced climate policy uncertainty in the short term. Advantages of the election are that its outcome was unexpected to the market and that it featured two candidates with opposing views on climate regulation. While President Trump signaled in his campaigns that prevailing climate policies would not become stricter, Hillary Clinton, to the contrary, promised pro-climate policies. Hence, President Trump's election meant little change in the status quo of U.S. climate regulation, whereas Clinton's election would have implied the opposite if she were elected.[43] The cost of insurance against downside tail risks associated with climate

distribution of value weights.

[41] In the PV model, the probability of the adoption of new policies increases (a) when the impact of the current policy is harmful to firm profitability and (b) when political costs associated with new policies are low. We are agnostic about which of these components drives our assumption. Public attention on climate change is often increased after natural disasters and climate summits or political events related to climate change. The former likely reveals inadequacy of current climate policies and, thereby, their harmful impact, whereas the latter likely reduces political costs of adopting pro-climate policies.

[42] An explanation for the difference in results may be that the Engle et al. (2020) index captures downside aspects associated with climate change more directly, as it focuses on negative news.

[43] No or little change in the status quo under President Trump was likely, especially when compared to Clinton's plans, even though he campaigned on withdrawing from the Paris Agreement. However, as the Paris Agreement did not have any in-built enforcement mechanisms and U.S. climate regulation had been lenient prior to his election, the expected uncertainty of the set of potential new policies under a regime of President Trump should still be lower than that under a Clinton regime.

policy uncertainty should therefore have declined after President Trump's election, especially for carbon-intense firms. Supporting this prediction, *SlopeD* for highly carbon-intense firms decreased by 0.025 after President Trump's election, relative to less carbon-intense firms, a decline equal to 12% of the variable's standard deviation during the event window. We find similar effects for sector options.

Our findings contribute to two strands of literature. The first strand documents that regulatory or political uncertainty affects asset prices. As mentioned, KPV is most closely related to us as they show that options are more expensive if they provide protection against risks associated with political events. Consistent with their model, PV find that stocks are more volatile and command a higher risk premium when political uncertainty is higher, measured using the Baker, Bloom, and Davis (2016) index. Similar evidence is provided by Brogaard and Detzel (2015). Brogaard et al. (2020) find that higher global political uncertainty is associated with lower equity returns and higher volatilities around the world. Related evidence from the healthcare market comes from Koijen, Philipson, and Uhlig (2016), who show theoretically and empirically that political uncertainty related to medical approval regulation and reimbursement policies affects the profit risk of healthcare firms. As a result, healthcare firms need to compensate investors with a risk premium. Using data on U.S. healthcare firms, they document a 4%–6% annual medical innovation premium, which reflects investor uncertainty about healthcare regulation.

Only a few papers in finance study climate policy uncertainty. Barnett (2019) shows that climate policies that restrict oil use can generate a run on oil, whereby oil firms accelerate extraction. This leads to a decrease in the oil price and the value of oil firms. He also shows that firms with high climate policy risk benefited from President Trump's election. Similarly, Ramelli et al. (2020) show that stock prices of carbon-intensive firms positively reacted to President Trump's election. Delis, de Greiff, and Ongena (2019) find that climate policy uncertainty started to be priced into syndicated loans, especially among fossil fuel firms. Engle et al. (2020) develop a dynamic strategy that hedges news about climate change, and Barnett, Brock, and Hansen (2020) provide a decision theory framework to address how climate uncertainty affects asset prices.

The second strand examines the effects of climate change on asset prices. Hong, Li, and Xu (2019) find that stock prices of food companies do not fully reflect climate risks. Bolton and Kacperczyk

(2020) document that firms with higher carbon intensities earn a carbon premium. This finding is similar to Hsu, Li, and Tsou (2020), who find that firms that generate many toxic chemical emissions earn higher returns. Görgen et al. (2020) create a carbon factor to capture firms' sensitivity to the transition to a low-carbon economy. Matsumura, Prakash, and Vera-Munoz (2014) find that higher emissions are associated with lower firm values. Similarly, Berkman, Jona, and Soderstrom (2019) use a firm-specific climate risk measure that they find is negatively related to firm value. Using aggregate market outcomes, De Haas and Popov (2019) show that more equity-funded markets have lower per capita emissions, as stock markets seem to reallocate investment toward more carbon-efficient sectors. Bansal, Kiku, and Ochoa (2017) show that equity portfolios have negative exposure to long-run temperature fluctuations, and Daniel, Litterman, and Wagner (2016) calibrate the price of climate risk. Giglio et al. (2019) study long-term discount rates to evaluate climate change mitigation policies. Although most of these studies concentrate on underlying price effects and risk premiums, we analyze whether the cost of protection against climate policy uncertainty is priced in the option market.

1. Hypotheses Development

Our hypothesis development is guided by PV, who provide a framework to explain why political uncertainty affects asset prices. Asset prices in their model are affected by political shocks, which are due to investors learning about the political costs associated with new policies. As these costs are uncertain, investors are unable to predict which policies will be chosen, and investors change their beliefs once political shocks arise. Hsu, Li, and Tsou (2020) build on PV to analyze how firms with toxic emissions are affected by political uncertainty. In their model, the government learns about the welfare costs of toxic emissions and decides between strong and weak regulatory regimes. Strong regulation has a more negative effect on the profitability of emission-intense firms, and, as a result, these firms face larger risks.

Our hypotheses are related to these papers because global warming generates large climate policy uncertainty for carbon-intense firms. (We consider climate policy uncertainty to be a specific form of political uncertainty.) As global warming is primarily caused by the combustion of fossil fuels, regulation must be aimed at significantly reducing carbon emissions. Importantly, it remains highly uncertain whether, how, and when such regulation would be implemented. How firm profitability would be affected by any new policies is also highly unclear. Climate policy uncertainty matters most for carbon-intense firms, as these firms are the most directly affected by policy instruments that curb emissions, such as emission limits, cap-and-trade schemes, or carbon taxes. These instruments would likely reduce future cash flows of carbon-intense firms and may depress their valuations as a result.

In summary, climate policy uncertainty makes it difficult for investors to quantify the impact of future climate regulation on carbon-intense firms, in terms of both large stock price drops and general increases in return volatility. Hence, the cost of option protection against downside tail and variance risks associated with climate policy uncertainty should be larger for such firms:

HYPOTHESIS 1: The cost of option protection against downside tail and variance risks associated with climate policy uncertainty is higher at carbon-intense firms.

High public attention to global warming, which may be the result of climate-related natural disasters or political summits on climate change, should make new pro-climate policies and their adoption more likely. New pro-climate regulations can take many different forms with varying levels of severity (as modelled in PV), and this heterogeneity generates policy uncertainty.[44] As the probability of a policy change rises, so does the political uncertainty about *which* new policies will be adopted and their impact on firm profitability. The cost of protection against downside tail risks associated with climate policy uncertainty therefore should be magnified at such times. This leads to the following hypothesis:

HYPOTHESIS 2: The cost of option protection against downside tail risks associated with climate policy uncertainty increases at times when public attention to climate change is higher.

[44] Pastor and Veronesi (2012) formally model impact uncertainty. Pastor and Veronesi (2012) differs from PV's model in a way that has implications for our hypotheses. Pastor and Veronesi (2012) assume that prior beliefs about the impacts of potential policies are identical. In contrast, PV allow the impacts and uncertainties to vary across potential policies. It is these a priori heterogeneous beliefs about potential policies in PV that induce an endogenous increase in political uncertainty as the probability of a policy change rises. In a limiting case in which the probability of policy change goes to zero, there is no political uncertainty since the status quo is sure to remain.

Finally, we exploit President Trump's election in 2016 as a shock that reduced climate policy uncertainty in the short term. The advantage of the 2016 presidential election is that it featured two candidates with opposing views on climate change. While Hillary Clinton supported new pro-climate policies, President Trump signaled that prevailing climate policies were likely to stay. He dubbed climate change "a hoax" and tweeted that "the concept of global warming was created by and for the Chinese in order to make U.S. manufacturing non-competitive" (Trump 2012). His stance can be interpreted as a desire to keep the lenient status quo intact, whereas Clinton's position was more radical with a desire to make forward progress in pro-climate regulation. Therefore, the set of climate policies likely to be adopted under President Trump should have a lower variance compared to that under Clinton. Hence, his unexpected election should have reduced uncertainty about which climate policies will be adopted after Election Day.[45] This should reduce the cost of insurance against downside tail risks associated with climate policy uncertainty at carbon-intense firms. This leads to the following hypothesis:

HYPOTHESIS 3: The cost of option protection against downside tail risks associated with climate policy uncertainty declined after the election of President Trump in 2016 at carbon-intense firms.

2. Data

2.1 Carbon emissions

2.1.1 Data source

We collect data on carbon emissions from CDP, formerly known as the Carbon Disclosure Project. The data are collected by CDP on behalf of institutional investors representing over $87tr in assets under management in 2018.[46] Firms submit their data to CDP at the end of June, covering emissions

[45] An advantage to the analysis of President Trump's election is that his victory was largely unexpected by the market. On Election Day morning, online gambling company Betfair put the probability of a victory by President Trump at 17% (Wagner, Zeckhauser, and Ziegler 2018). President Trump also lost the popular vote by almost 3 million votes.
[46] CDP data are reliable. First, many CDP signatories are influential investors in the surveyed firms, so false reporting could have major ramifications. Second, many institutions consider CDP data to be so trustworthy that they use them for their own risk management (Krueger, Sautner, and Starks 2020), and leading ESG data providers use them for rating models (e.g., MSCI ESG Research, Bloomberg, or Sustainalytics).

of the prior calendar year (the deadline was changed to mid-August for 2018 submissions). CDP then releases these data by the end of October. We examine emissions generated between 2009 and 2016. We focus on S&P 500 firms because CDP primarily covers these firms for its U.S. survey. Figure 1 shows that participation in the CDP survey among S&P 500 firms has increased over time, in terms of the number of reporting firms (Figure 1, panel A) and as a fraction of the S&P 500 market capitalization (Figure 1, panel B).

The data include information on three types of emissions. Scope 1 emissions are direct emissions, which originate from the combustion of fossil fuels or from releases during manufacturing. Scope 2 emissions are indirect emissions from the consumption of electricity or steam, and Scope 3 emissions are emissions that occur in the value chain of a firm (both upstream and downstream). CDP translates all greenhouse gases into carbon dioxide (CO_2) equivalents. We focus on Scope 1 emissions because they are directly owned and controlled by firms. (We find no effects for Scope 2 emissions and do not use Scope 3 emissions, because they are not controlled by firms.) Table 1 shows that Scope 1 emissions are highly skewed. While the average S&P 500 firm that reports emissions data produces almost 5 million tons of carbon, the median firm emits only about 118,000 tons.

2.1.2 Variable measurement

We scale firms' Scope 1 emissions by their end-of-year equity market values to obtain a measure of carbon intensity. We divide emissions by equity values because new regulation is likely to be implemented via cap-and-trade mechanisms or carbon taxes, which implies that the amount to be paid by a firm should be considered relative to its market value. Specifically, the stock price of a firm with a large market value is likely to be affected less by, for example, a carbon tax, compared to a firm with the same emissions but a low market value. We show that results are robust if we scale emissions by total assets instead.

We employ a firm's *industry* carbon intensity as the main measure in our regressions. First, Table 2 shows that high carbon intensities cluster within a few industries (and sectors) and are highly skewed. Figure 2 confirms this pattern across the sample.[47] Second, Table 3, panel A, documents that firms' carbon intensities are primarily driven by industry characteristics. The panel explains in columns 1 and 2 a firm's carbon intensity, *log(Scope 1/MV firm)*. While column 1 uses a firm's industry carbon intensity, *log(Scope 1/MV industry)*, as the only explanatory variables, column 2 adds firm characteristics and year fixed effects. In column 1, the adjusted R^2 of the regression is .920, which demonstrates that firm-level variation in carbon intensity is largely subsumed by industry-level variation. In column 2, the adjusted R^2 increases only slightly, which indicates that firm characteristics play only a modest role in explaining firm-level carbon intensities. Columns 3 and 4 estimate the same regressions from columns 1 and 2 but rely on unscaled instead of scaled emissions. We report these two regressions to ensure that our results are not affected by the use of market values on both sides of the equations. Reassuringly, the regressions confirm the pattern that is documented in the first two columns. Third, Bolton and Kacperczyk (2020) show that the effects of Scope 1 intensities on returns and exclusionary screening by investors are driven by industry characteristics.

Therefore, our variable of interest is *Scope 1/MV industry*, defined as total Scope 1 carbon emissions (in metric tons of CO_2) of all reporting firms in the industry divided by the total market capitalization of all reporting firms in the industry (in millions $). The measure is calculated at the SIC4 level because emissions can vary substantially within the SIC2 level (Internet Appendix Table 2).

2.2 Option market measures

2.2.1 Data source

We use option market measures to identify the effects of climate policy uncertainty. Option prices subsume expectations about investment opportunities (Vanden 2008), and option-based variables work well in predicting future assets price dynamics (e.g., Christoffersen, Jacobs, and Chang 2013). Most importantly, options-based measures reflect expectations about all possible future events, even the rarest ones. We use options data from the Surface File of Ivy DB OptionMetrics. For sectors, we use options on State Street Global Advisors' ETFs (SPDR ETFs) as the underlying. The Surface File contains daily

[47] Internet Appendix Table 1 shows that unscaled emissions are similarly skewed. In fact, the top-20 emitting firms alone generate about 60% of all carbon emissions in the S&P 500, and 29% come from just five firms.

Black-Scholes implied volatilities for standard maturities and delta points (for absolute deltas from 0.2 to 0.8, with 0.05 delta increments). The implied volatilities are created from closing options prices through inter- and extrapolation in the time and delta dimensions. Although these implied volatilities do not correspond to traded option contracts and form a standardized volatility surface, they reflect the consensus expectations of market participants priced into the options. We select OTM calls and puts with absolute deltas smaller than 0.5. Return and market capitalization data are from CRSP.[48]

We process the surface data to make them less discrete in the moneyness (defined as strike over spot) dimension. For each underlying, maturity, and day, we interpolate the observed implied volatilities as a function of moneyness within the available data range using monotonic cubic splines (piecewise cubic Hermite interpolating polynomials). We then fill in the implied volatilities beyond the observed moneyness bounds with the volatilities on the bounds. For OTM puts, we use the leftmost available data point (corresponding to a Black-Scholes delta of -0.2), and for OTM calls, we use the rightmost available data point (corresponding to a delta of 0.2). In this way, we produce 1,001 data points over the moneyness range from 1/3 to 3 (corresponding to equally spaced points from a log-moneyness of -log 3 to log 3). Each of these data points contains an implied volatility for a particular moneyness level and, hence, for an option delta level.

2.2.2 Variable measurement

2.2.2.1 Primary measure: Implied volatility slope.

The implied volatility slope (*SlopeD*), borrowed from KPV, is a function relating the left-tail implied volatility to moneyness, measured using the Black-Scholes delta. Specifically, *SlopeD* is the slope coefficient from regressing implied volatilities of OTM puts (deltas between -0.5 and -0.1) on the corresponding deltas and a constant. Because far OTM puts (with smaller absolute deltas) are typically more expensive, *SlopeD* usually takes positive values. A more positive value of *SlopeD* indicates that deeper OTM puts are relatively more expensive, suggesting a relatively higher cost of protection against

[48] We obtain the composition of the S&P 500 and its sectors from Compustat and merge these data with data from CRSP through the CCM linking table using GVKEY and IID to link to PERMNO, following the second-best method from Dobelman, Kang, and Park (2014). We match CRSP data with options data through the historical CUSIP link, provided by Ivy DB OptionMetrics.

downside tail risks. Because *SlopeD* is defined as a regression slope, it measures relative expensiveness and does not depend on the average level of the implied volatility. This feature allows us to compare the measure across firms with different levels of general risk. *SlopeD* is our preferred measure as it most directly captures the relative cost of protection against downside tail risk. Intuitively, it quantifies the cost of protection against extreme downside tail events relative to the cost of protection for less extreme downside events. We derive our results from options with 1-month maturities and provide results for maturities of up to 12 months for robustness. (Internet Appendix B illustrates the information content of this and the two other measures.)

2.2.2.2 Additional measures: Model-free implied skewness and variance risk premium.

MFIS is constructed following Bakshi, Kapadia, and Madan (2003, BKM hereafter) and quantifies the asymmetry of the risk-neutral distribution. It is computed using the standard formula for the skewness coefficient, that is, as the third central moment of the risk-neutral distribution, normalized by the risk-neutral variance (raised to the power of 3/2). By being normalized, *MFIS* also provides information about the expensiveness of protection against left tail events, though now relative to right tail events. As changes in the distribution asymmetry are driven by the probability mass in the downside relative to the upside region, *MFIS* is affected by both tails. In terms of interpretation, more negative values of *MFIS* indicate a relocation of probability mass under the risk-neutral measure (i.e., after adjusting for preferences toward risk) from the right to the left tail. Like in BKM, *MFIS* at time t for period τ is given by

$$\mathrm{MFIS}(t,\tau)=\frac{e^{r\tau}W(t,\tau) - 3\mu(t,\tau)e^{r\tau}V(t,\tau) + 2\mu(t,\tau)^3}{[e^{r\tau}V(t,\tau) - \mu(t,\tau)^2]^{3/2}} ,$$

where $V(t,\tau)$ and $W(t,\tau)$ are prices of variance and cubic contracts, respectively; r is the prevailing risk-free rate; and $\mu(t,\tau)$ is the risk-neutral expectation of the underlying log return over the period τ. All unknown ingredients (variance, cubic contracts, and expected log return) in the formula are computed by integration of some functions of options prices over the continuum of strikes for a given maturity (see BKM for details). We approximate these integrals with finite sums using the interpolated volatility surface (see above). As *MFIS* captures the distribution of the probability mass in the left versus the right tail of the risk-neutral distribution, it can be interpreted as the cost of protection against left tail events relative to the cost of gaining positive realizations on the left tail.

VRP is computed as the difference between the risk-neutral expected and the realized variance (Carr and Wu 2009; Bollerslev, Tauchen, and Zhou 2009). As a proxy for the risk-neutral expected variance, we use the model-free implied variance ($MFIV_{t,t+M}$) computed on day t for maturity M following Britten-Jones and Neuberger (2000) by again approximating the respective integrals with finite sums using the interpolated volatility surface observed on day t for maturity M. The realized variance ($RV_{t,t+M}$) is computed from daily log returns over a future window from t to $t+M$, that is, with a length corresponding to the maturity of the options used for the risk-neutral variance. The variance risk premium ($VRP_{t,t+M}$) for maturity M is computed in the ex post version on each day t as $MFIV_{t,t+M}$-$RV_{t,t+M}$, and expressed in annual terms.[49]

VRP captures the cost of protection against general uncertainty-related volatility changes in down and up directions, whereas our other measures capture the relative cost of protection against left tail risk (relative to "normal" risks, *SlopeD*, or relative to the right tail, *MFIS*).

3. Empirical Model

3.1 Selection model and truncation rule

We estimate a selection model to mitigate the concern that our estimates are biased because firms voluntarily disclose their carbon emissions to CDP. The need for a selection model arises because firms only disclose their emissions if the (unobservable) net benefit of disclosing is positive. As a result, we only observe the emissions generated by firm i during year t if the firm discloses this information to CDP (i.e., if $CDP\ disclosure_{i,t} = 1$). In all other cases, data on carbon emissions is missing (i.e., if $CDP\ disclosure_{i,t} = 0$). We therefore jointly estimate the following model:

$$OMM_{i,m,t+1} = \beta_0 + \beta_1 Log(Scope\ 1/MV\ industry)_{i,t} + \boldsymbol{x_{i,t}\beta} + u_{i,m,t+1}, \qquad (1)$$

[49] We follow KPV to compute the ex post *VRP* as opposed to an ex ante *VRP* (which is used by, e.g., Bollerslev, Tauchen, and Zhou 2009). The reason for selecting the ex post version is that, by construction, it reflects all the information flow from the observation date to the option maturity and can capture the reaction of traders to particular events, while the ex ante version is based only on expectations formed before and on the observation date, which implies that it can miss important information. We thank a referee for pointing out this potential problem. Note that our results are robust to using either version of *VRP*.

$$CDP\ disclosure_{i,t} = \gamma_0 + \gamma_1 Industry\ CDP\ disclosure_{i,t} + \boldsymbol{x_{i,t}\gamma} + v_{i,t}, \quad (2)$$

whereby Equation (1) constitutes the outcome equation and Equation (2) the selection equation. As explained, Equation (1) is only observed if $CDP\ disclosure_{i,t} = 1$. We relate a firm's carbon intensity in year t to option market measures ($OMM_{i,m,t+1}$) in year t+1 as emissions of year t are only made public by CDP in year $t+1$ (at the end of October). Consequently, information about emissions generated in year t is only available to investors in the 12-month period starting from November of year t+1. For our sample period, this implies that we estimate the effect of emissions generated between 2009 and 2016 on option market variables measured between November 2010 and December 2017. Note that we employ a firm-level selection model even though carbon intensities are at the industry level. The reason is that, for some industries, no firms within the S&P 500 disclose any emissions data. This makes industry carbon intensities unobserved for some firms and may bias ordinary least squares (OLS) estimates.

We estimate our model using full-information maximum likelihood (FIML) with the assumptions that $(u_{i,m,t+1}, v_{i,t})$ is bivariate normal with zero means and nonzero variances; $u_{i,m,t+1}$ is uncorrelated over m within a given firm-year; and $Cov(u_{i,m,t+1}, v_{i,t})$ is nonzero. Joint normality of the error terms is more restrictive than the assumptions required by the Heckman (1979) two-step procedure. However, the FIML estimator has the advantage that it is more efficient (Wooldridge 2010) and that it produces standard errors that can be used directly. Our setting differs from a standard selection model in that Equations (1) and (2) operate at different observation levels. While the decision to disclose carbon emissions is at the firm-year level (i.e., (i,t)), the option market measures are the firm-month-year level (i.e., (i,m,$t+1$)). Internet Appendix C discusses how this affects the FIML estimator. A similar FIML model with data from different observation levels is also estimated in Brav et al. (2019).

3.2 Outcome equation: Option market variables and carbon intensities

For firm i in month m and year $t+1$, each option market measure is calculated as the average across daily values. We estimate regressions at the firm-month level to increase power, to exploit that the options measures are available throughout the year, and because emissions are relatively persistent within the firm-year. Importantly, some of our tests also explore how the effect of emissions varies when climate attention fluctuates *within* the year (monthly).

Scope 1/MV industry$_{i,t}$ is the Scope 1 industry carbon intensity of firm *i* during year *t*. We use (one plus) the variable's natural logarithm because emission intensities are highly skewed. Results are unaffected by within-year changes in equity market values (the denominator of the emissions variable) as we scale emissions by end-of-year market capitalizations.

We control for firm characteristics that prior work identified as determinants of firm risk, notably *log(Assets)*, *Dividends/net income*, *Debt/assets*, *EBIT/assets*, *CapEx/assets*, *Book-to-market*, *Returns*, *CAPM beta*, and *Volatility* (unless we explain the *VRP*). We also control for *Institutional ownership, Oil beta,* and a time trend. Control variables are measured at year *t*.

3.3 Selection equation: CDP disclosure decision

CDP disclosure$_{i,t}$ equals one if firm *i* discloses data to CDP on the carbon emissions released during year *t*, and zero otherwise. Equation (2) includes the same control variables as the outcome regression, but additionally controls for the disclosure level in firm *i*'s industry in year *t* (*Industry CDP disclosure*$_{i,t}$). We include this variable to capture the effects of peer pressure on the decision to disclose emissions. As more firms within an industry disclose their emissions, nondisclosers likely feel greater pressure to disclose their CO_2 footprints too. Like with Matsumura, Prakash, and Vera-Munoz (2014), for our purposes, this variable constitutes the excluded instrument in Equation (2), so it is omitted in Equation (1). Internet Appendix D discusses potential violations of the exclusion restriction.

Table 3, panel B, reports the selection regression. The estimates show that the propensity for a firm to report emissions significantly increases if other firms in the same industry disclose their data as well. In column 5, a one-standard-deviation shock in *Industry CDP disclosure* (0.32) increases the probability to disclose emissions by 30%, a large number relative to the unconditional mean of 51%. The estimates in Table 3, panel B, confirm the importance of accounting for selection bias. Firms that disclose emissions are larger, have lower leverage, higher earnings, lower book-to-market ratios, higher betas, and lower volatility.

4. Empirical Results

4.1 Carbon intensity and downward option protection: Cross-sectional results

4.1.1 Firm- and sector-level evidence: Main results

Table 4, panel A, tests Hypothesis 1 and reports firm-level regressions of the effects of *log(Scope 1/MV industry)* on option market measures. Column 1 shows that a firm's industry carbon intensity has a positive and significant effect on *SlopeD*. A one-standard-deviation increase in a firm's log industry carbon intensity (2.28) increases *SlopeD* by 0.014, which equals 10% of the variable's standard deviation. In comparison, a one-standard-deviation decrease in a firm's profitability (*EBIT/assets*) increases *SlopeD* by 0.013 or 10% of the variable's standard deviation. *SlopeD* is generally lower for firms that are larger, that are more profitable, invest less, and have lower volatility. It is higher for firms with higher leverage and with higher book-to-market ratios.

Column 2 shows that we cannot detect that a higher carbon intensity is associated with a more negatively skewed risk-neutral distribution of a firm's stock return (*MFIS*). The weaker results for *MFIS* may reflect that this measure does not directly capture left tail risk. Instead, *MFIS* captures the cost of protection against left tail events relative to right tail events. In fact, Internet Appendix Table 3 shows that carbon-intense firms also have higher right tail risk (as reflected in the negative coefficient on *SlopeU*), which may explain why we do not find effects for *MFIS*. In column 3, we find that carbon-intense firms exhibit a higher variance risk premium (*VRP*): a one-standard-deviation increase in log industry emissions increases the *VRP* by 0.002, or 3% of the standard deviation.

If industry characteristics largely capture investors' perceptions of firms' carbon intensities, then we should be able to also identify effects at the sector level. We next use option measures directly derived from S&P 500 sector ETF options. To calculate a sector's carbon intensity, *Scope 1/MV sector*, we aggregate emissions of all CDP-disclosing S&P 500 firms in a sector and divide them by the respective firms' equity market values. To do this, we first identify the sectors to which each disclosing firm belongs. As sector weights vary with stock market performance, we then construct monthly sector weights (averages of daily weights) for each firm. Subsequently, we multiply these weights by the emissions of each sector constituent, using only disclosing firms. We use the resultant weighted average emissions as a proxy for sector-level emissions.[50] A similar procedure is used to compute the equity market values of each sector, using again only disclosing firms. Our sample includes 9 of the 11 sectors of the S&P 500. Sector intensities are largest in the Utilities and Energy sector, as displayed in Table 2, panel B.

Table 4, panel B, documents in column 1 that sector carbon intensities remain positively and statistically related to *SlopeD*. A one-standard-deviation increase in a sector's log carbon intensity (2.35) increases *SlopeD* by 0.09, almost 1.4 times the risk variable's standard deviation. Results are again weaker for the other two measures. While we now find a weakly significant effect for *MFIS* in column 2, the effect for *VRP* in column 3 is insignificant with a *t*-stat of 1.46.

Taken together, the results indicate that higher climate policy uncertainty increases the firm-level likelihood of left and right tail events, and it has some effect on firm-level *VRP*. On the sector level, where firm-specific risks are diversified away, we observe an effect that is more systematic and concentrated in the left tail. (One other reason sector-level results may differ from those at the firm level is that sector carbon intensities are noisier as we do not have carbon emissions for all firms in a given sector; this may introduce measurement error.)

4.1.2 Firm versus industry carbon intensities: Relative importance

The firm-level analysis raises the question of whether firms with carbon intensities that are lower (higher) than those of their industry peers exhibit less (more) downside tail risk once we account for industry effects. To this end, Table 5 evaluates the relative importance of firm- versus industry-level carbon intensities. As a starting point, column 1 documents that firm-level carbon intensities, *log(Scope 1/MV firm)*, are also positively and significantly related to *SlopeD*. The economic magnitudes of the effects are also similar. Nevertheless, to what extent this finding reflects firm, rather than industry, effects is unclear. We therefore evaluate in the next two columns whether there is information in firm-level carbon intensities *beyond* what is captured in industry-level variation. We first estimate a regression in which we calculate for each firm-year the part of firm-level carbon intensities that is

[50] The sector-level analysis does not allow us to estimate a selection model. However, bias from selective disclosure could be plausibly less of a concern in this analysis, as there are only a few S&P 500 sectors.

unexplained by industry-level intensities. By construction, the estimated regression residual is positive (negative) for firm-years where firm-level carbon intensities are above (below) those of the industry peers. Columns 2 and 3 of Table 5 replace *log(Scope 1/MV firm)* with this regression residual. The estimates show that firm-level *residual* carbon intensities are unrelated to *SlopeD*, when we both do and do not control for industry-level emissions. Importantly, *log(Scope 1/MV industry)* remains positively and significantly related to *SlopeD*, even after accounting for the firm-level residual. This confirms that the market's perception of a firm's exposure to climate policy uncertainty is driven by its industry affiliation.

4.1.3 Firm- and sector-level evidence: Robustness

Internet Appendix Tables 4 and 5 address different concerns with our analysis. Internet Appendix Table 4, panel A, shows that our firm-level results for *SlopeD* are highly robust. In column 1, results are unchanged if we scale emissions by total assets instead of equity values. In column 2, results are unaffected when we estimate a regression at the firm-year level using annual values of *SlopeD*. Column 3 shows that results are similar for OLS regressions. In column 4, the magnitude of the effects increases with firm fixed effects. In column 5, results hold after dropping oil and gas firms, indicating that results are not driven by the decline in oil prices between 2014 and 2016. In columns 6 to 8, we continue to find effects if we calculate *SlopeD* from options with 3- to 12-month maturities. Column 9 shows that Scope 2 intensities are unrelated to *SlopeD.* In panel B, we continue to find mostly insignificant effects for *MFIS* when using 30-day options (the point estimates for most specifications remain negative). Interestingly, we do however observe significant coefficients for longer maturities. Thus, the cost of left tail protection relative to right tail gains seems to be growing with an option's horizon. Short-term options instead seem to be used mostly to take firm-specific (volatility) bets in both directions. In panel C, the firm-level results for *VRP* remain largely robust.

Internet Appendix Table 5, panel A, shows that the sector results for *SlopeD* remain highly robust. Apart from scaling by assets and using annual values, the robustness tests include a variety of alternative fixed effects as well as option maturities of up to one year. Panel B confirms the sector-level evidence for *MFIS* from the main analysis: the point estimates are negative in almost all cases, though highly significant coefficients appear rarely. In panel C, results continue to be mostly insignificant for *VRP*, as in the main analysis.

Our emissions data from CDP are only available for the years between 2009 and 2016, but options data exist for much longer. To analyze results for the more distant past, we use a prediction model and backfill *Scope 1/MV firm* for the years 1995 to 2008. Using predicted carbon intensities, we observe a statistically insignificant effect of carbon intensities on *SlopeD* (see Internet Appendix Table 6). This suggests that climate policy uncertainty was priced to a lower extent in the more distant past, assuming that our prediction model delivers reasonable emission estimates.

4.2 Carbon intensity, downward option protection, and attention to climate change

To test Hypothesis 2, we allow the effect of carbon intensities to vary with two proxies for public attention to climate change. To create the first proxy, we use an index developed by Engle et al. (2020) which captures the share of news articles in outlays, such as *Wall Street Journal*, *The New York Times*, or *Yahoo News*, that are about "climate change" and have been assigned to a "negative sentiment" category. We capture the time-series effects of climate attention by creating *Negative climate change news high*, which equals one if the Engle et al. (2020) index is above the median, and zero otherwise.

To create the second proxy, we use Google's search volume index (SVI) for the search topic "climate change." The index takes values between 0 and 100, with 100 corresponding to the month with the highest number of searches on climate change topics during our sample period. We use U.S. search data and calculate for each month an average value for the search topic from daily data. We then create the dummy variable *Climate change SVI high*, which equals one if the search index is above the median, and zero otherwise. Search activity on Google plausibly proxies for attention by investors, as shown by Da, Engelberg, and Gao (2011). Choi, Gao, and Jiang (2020) show that search volume on climate change topics surges when investors experience abnormally high temperatures.

The regressions in Table 6 then interact each of these two variables with *log(Scope 1/MV industry)*. Column 1 provides the results for the Engle et al. (2020) index, and column 2 those for Google's SVI. The estimates in column 1 show that *log(Scope 1/MV industry)* has a positive and significant effect on *SlopeD* during low-attention times (i.e., when *Negative climate change news high* is zero). Importantly, the coefficient estimate on the interaction term, which is positive (0.002) and significant (*t*-stat of 1.67), reveals that the effect of carbon intensities on *SlopeD* increases by 40% during high-attention times. During such times, the total effect of *log(Scope 1/MV industry)* on *SlopeD* equals 0.007 (=0.002+0.005), which is also statistically significant. In column 2, using Google's SVI as the proxy for attention, we continue to find a positive effect of *log(Scope 1/MV industry)* on *SlopeD* during periods of low and high climate change attention. However, the interaction term that reflects the difference between these two states of the world is statistically insignificant (though it has the predicted positive sign). Overall, the results in Table 6 therefore provide only weak evidence in support of Hypothesis 2.

4.3 Effect of the 2016 election of President Trump: Event study results

To test Hypothesis 3, we use President Trump's election in 2016 as an event that reduced climate policy uncertainty in the short term. President Trump's election was unexpected and, unlike his opponent Hillary Clinton, his positions on climate policies were mostly about preserving the status quo, which was characterized by a lack of strict climate regulation. His election on November 9, 2016, therefore, should have lowered the cost of option protection for carbon-intense firms. To quantify the effect of President Trump's election, we estimate a difference-in-differences (DiD) model, using daily option data around Election Day 2016. We estimate the following model for firm *i* at day *t*:

$$\begin{aligned} OMM_{i,t} = \gamma_0 + \gamma_1 Post\ Trump\ election_t \text{ x } Scope\ 1/MV\ industry\ high_i \qquad (3) \\ + \gamma_2\ Scope\ 1/MV\ industry\ high_i + \gamma_3 Post\ Trump\ election_t \\ + \boldsymbol{x_{i,t-1}\gamma} + \epsilon_{i,t} \end{aligned}$$

In this regression, *Post-Trump election* equals one for all firm-day observations after Election Day on November 9, 2016, and zero for all firm-day observations before. To identify treatment firms for which climate policy uncertainty likely declined the most after President Trump's election, we create *Scope 1/MV industry high*, which equals one for the ten industries with the highest carbon intensities, and zero otherwise (see Table 2, panel A). We use *SlopeD* as the proxy for *OMM* and employ a relatively wide event window of [-250; +250] days as daily option measures for single names tend to be noisy and driven by idiosyncratic effects. For robustness, we exclude in some tests the [-50; +50] days around Election Day.[51] We report results with different sets of fixed effects.

Our test relies on the sharp climate policy differences between President Trump and Hillary Clinton. Other policy differences may confound our results if they are correlated with the treatment status. Two such important differences are tax and healthcare policies. With respect to tax policies, Clinton supported an increase in taxes on high-income earners, whereas President Trump campaigned on large corporate tax cuts.[52] To ensure that expected tax changes do not contaminate our results, we control for firms' effective tax rates (interacted with the post-election dummy). With respect to healthcare policies, President Trump campaigned on repealing Obamacare, whereas Clinton did not announce any plans to do so. To verify that results are not driven by an increase in *SlopeD* among healthcare firms (which have low emissions and are part of the control group), we exclude such firms in a robustness test.

Table 7 shows that γ_1 in Equation (3), the DiD estimator, is negative and statistically significant across all specifications. This indicates that the cost of downward protection at highly carbon-intense firms significantly decreased after President Trump's election, relative to less carbon-intense firms. In economic terms, column 1 implies that *SlopeD* of firms in carbon-intense industries decreased by 0.025 after the election, relative to firms in industries with low carbon intensities. This decline equals 12% of the variable's standard deviation during the event window. Results are similar in Columns 2 to 4, which add different sets of fixed effects to the model. The point estimate of the DiD effect is largest in Column 5, in which we exclude the narrow window directly surrounding the election. Results are unaffected if we drop healthcare firms in column 6. The estimates further indicate that tail risk generally declined after President Trump's election (negative coefficients on *Post-Trump election*), which may reflect that policies are more business friendly under a Republican government.

We perform several further robustness tests. Internet Appendix Table 7 shows that *SlopeD* exhibits parallel trends for high- and low-emission firms prior to the election. Internet Appendix Table

[51] We want to exclude potentially confounding effects related to the generally higher uncertainty around elections, which are reflected in options spanning those days (see KPV).

[52] Wagner, Zeckhauser, and Ziegler (2018) find that firms with high effective tax rates and large deferred tax liabilities benefitted from President Trump's election.

8, panel A, shows that results are similar for longer and shorter event windows. However, the statistical significance gets weaker once we move to a shorter window. Internet Appendix Table 8, panel B, verifies that our results do not reflect a seasonal pattern in early November. To this end, we generate a series of placebo dates with the same day and month as the election date, but from all other sample years. These seven pseudo-DiD estimators are all statistically insignificant. Internet Appendix Table 8, panel C, uses regressions at the sector level. At the sector level, we are able to use a shorter event window of [-100, +100] days as daily sector options are less noisy. To identify treatment sectors, we create *Scope 1/MV sector high*, which equals one for the two sectors with the highest sector carbon intensities (Utilities and Energy), and zero otherwise (see Table 2, panel B). The results are consistent with those in Table 7: *SlopeD* of the highly carbon-intense sectors decreased after President Trump's election, relative to less carbon-intense sectors.[53]

5. Conclusion

Strong regulatory actions are needed to avoid the potentially catastrophic consequences of climate change. As climate change is mostly caused by the combustion of fossil fuels, new regulation will have to aim at significantly curbing firms' carbon emissions. Whether, how, and when regulatory climate policies will be implemented is highly uncertain, and firms with carbon-intense business models will be most affected by this uncertainty.

We show that climate policy uncertainty is priced in the option market. Specifically, the cost of option protection against downside tail risk is larger for more carbon-intense firms. A one-standard-deviation increase in a firm's log industry carbon intensity increases the implied volatility slope, which captures protection against downside tail risk, by 10% of the variable's standard deviation. We confirm our results using sector options. The cost of downward option protection is magnified when public

[53] The noninteracted effect of *Scope 1/MV sector high* is negative, which is surprising, though it is only weakly significant (while *Scope 1/MV industry high* has the expected positive direct effect in Table 7). A reason for the differences may be that the number of observations (sectors) we are identifying the effects off is smaller at the sector level (two vs. seven sectors). Moreover, sector intensities may be noisier, since not all sector constituents disclose their emissions.

attention to climate change spikes. Moreover, it significantly decreased at highly carbon-intense firms after President Trump's election in 2016, relative to other firms.

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Figure 1. CDP disclosure over time

This figure reports how disclosure of carbon emissions to CDP by S&P 500 firms has evolved over time. Panel A reports the number of S&P 500 firms disclosing (blue) and not disclosing (white) the carbon emissions generated in a given year as a fraction of the number of firms in the S&P 500. Panel B reports the market capitalization of firms disclosing (blue) and not disclosing (white) the carbon emissions generated in a given year as a fraction of the total market capitalization of the S&P 500.

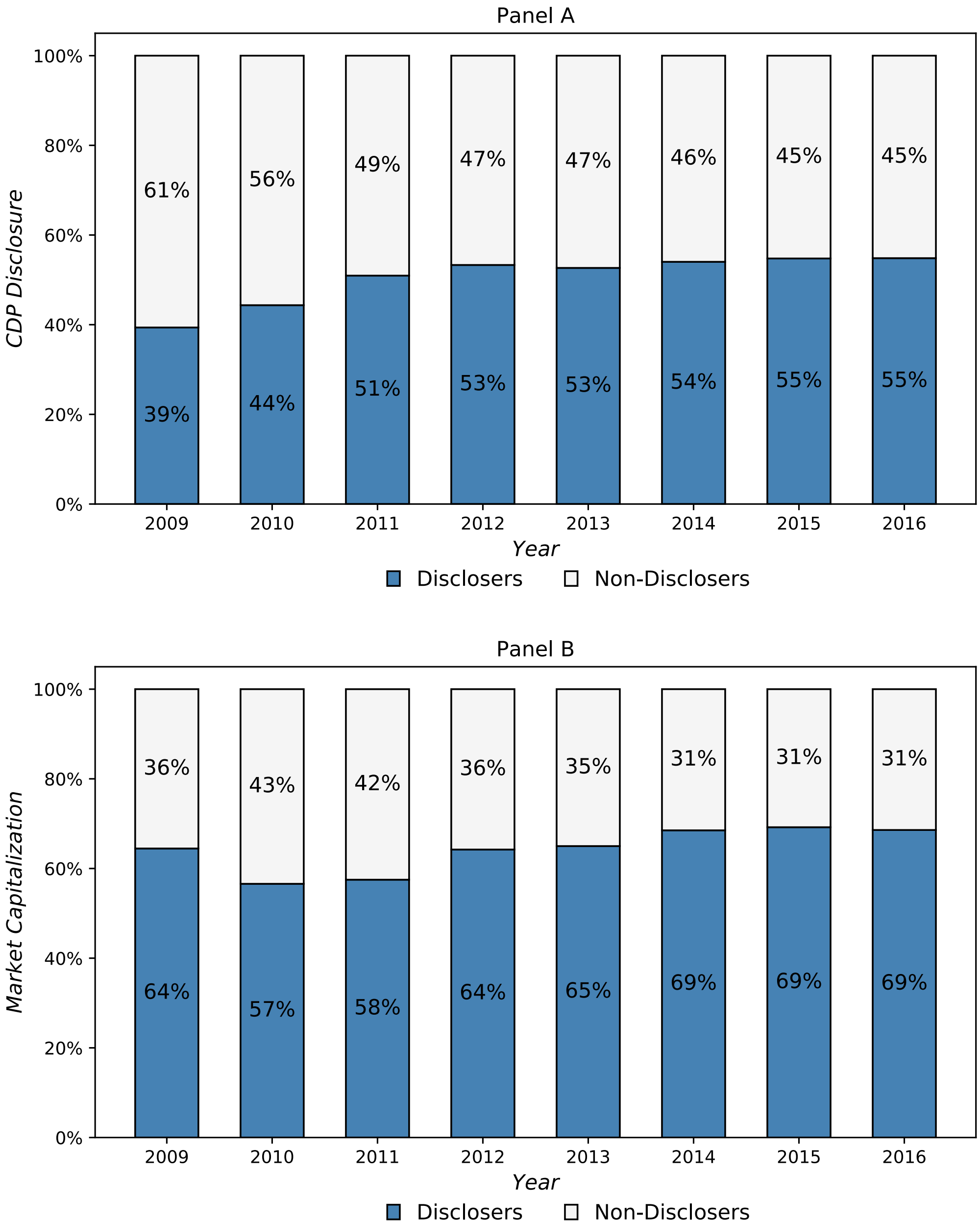

Figure 2. Distribution of carbon intensities across S&P 500 firms

This figure reports a histogram of *log(Scope 1/MV firm)*. *Scope 1/MV firm* are a firm's Scope 1 carbon emissions (in metric tons of CO_2) divided by the firm's equity market value (in millions $). The sample includes S&P 500 firms with data on carbon emissions disclosed to CDP. The sample covers emissions generated between 2009 and 2016.

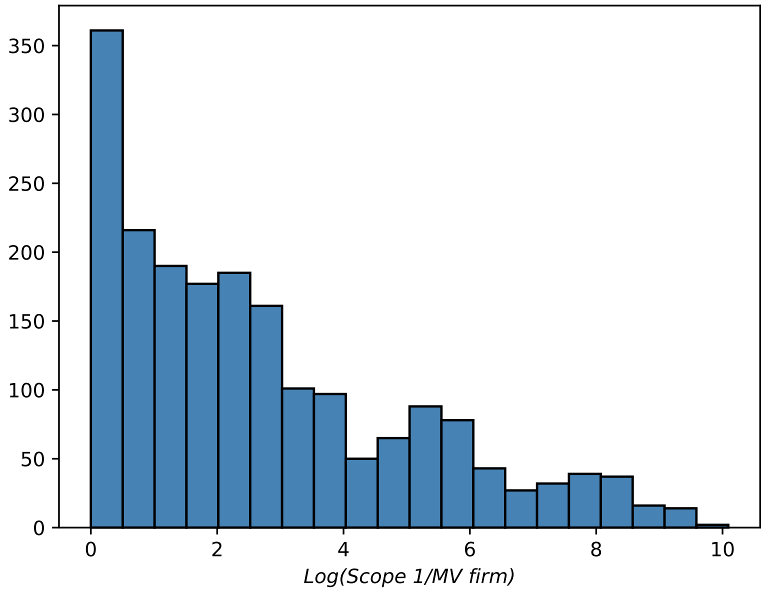

Table 1. Summary statistics

Summary statistics are reported at the firm-year level. The sample includes all firms in the S&P 500 with data on carbon emissions disclosed to CDP. Table A.1 defines all variables in detail. The sample period covers emissions generated during the years 2009 to 2016 and option market measures from 2010 to 2017.

Variable	Mean	STD	25th	Median	75th	Obs.
Scope 1 firm	4,957,597	15,853,469	16,829	117,715	1,078,551	1,963
Scope 1/MV firm	313.82	1,131.91	1.15	6.76	54.46	1,815
Scope 1/MV industry	261.85	757.36	1.61	6.43	48.64	1,903
Scope 2/MV firm	38.20	69.56	5.02	12.70	36.36	1,763
Industry CDP disclosure	0.710	0.238	0.500	0.667	1.000	1,963
SlopeD	0.176	0.136	0.100	0.135	0.207	1,959
MFIS	-0.415	0.271	-0.564	-0.429	-0.284	1,959
VRP	-0.002	0.087	-0.011	0.005	0.021	1,959
Institutional ownership	0.793	0.130	0.711	0.811	0.883	1,916
log(Assets)	10.12	1.33	9.12	9.95	10.88	1,963
Dividends/Net income	0.395	0.516	0.165	0.331	0.522	1,949
Debt/assets	0.263	0.157	0.149	0.246	0.362	1,960
EBIT/assets	0.104	0.072	0.053	0.095	0.143	1,963
CapEx/assets	0.039	0.038	0.013	0.028	0.055	1,959
Book-to-market	0.407	0.286	0.202	0.343	0.562	1,815
Returns	0.171	0.270	0.008	0.149	0.307	1,963
CAPM beta	1.065	0.531	0.671	1.021	1.390	1,963
Volatility	0.066	0.028	0.046	0.058	0.079	1,963
Oil beta	-0.018	0.169	-0.115	-0.034	0.057	1,963

Table 2. Firms' carbon intensities by industry and sector

Panel A reports firms' Scope 1 carbon intensities for the top-10 industries. Statistics are reported at the firm-year level across different SIC2 industries. *Scope 1/MV firm* are a firm's Scope 1 carbon emissions (in metric tons of CO_2) divided by a firm's equity market value (in millions $). We rank industries by the average carbon intensity of firms in an industry. The sample includes all firms in the S&P 500 with data on carbon emissions disclosed to CDP. The sample period covers emissions generated during the years 2009 to 2016. Not all firms are included in our sample across all years, which explains why the number of observations in some industries falls below eight. Panel B reports Scope 1 carbon intensities of the economic sectors of the S&P 500. Statistics are reported at the sector-year level. *Scope 1/MV sector* is a sector's Scope 1 carbon emissions (in metric tons of CO_2) divided by a sector's equity market value (in millions $). We rank sectors by the average sector carbon intensity. The sample includes 9 of the 11 sectors of the S&P 500. The sample period covers emissions generated during the years 2009 to 2016.

A. Ranking of top-10 industries by Scope 1/MV firm

Rank	Industry name	SIC2	Mean	STD	25th	Median	75th	Obs.
1	Primary metal industries	33	12,029	549	11,642	12,029	12,417	2
2	Electric, gas, & sanitary services	49	3,216	3,584	630	2,329	4,119	153
3	Stone, clay, & glass products	32	1,100	356	798	1,022	1,378	5
4	Transportation by air	45	1,091	759	479	937	1,436	26
5	Water transportation	44	334	67	281	314	407	6
6	Petroleum & coal products	29	322	46	285	330	353	16
7	Oil & gas extraction	13	232	151	133	200	306	69
8	Railroad transportation	40	200	50	157	209	244	23
9	Paper & allied products	26	189	244	44	64	421	35
10	Auto repair, services, & parking	75	188	36	163	171	225	7

B. Ranking of S&P 500 sectors by Scope 1/MV sector

Rank	Sector	SPDR ETF	Mean	STD	25th	Median	75th	Obs.
1	Utilities	XLU	2,396	572	1,880	2,602	2,883	8
2	Energy	XLE	324	45	290	314	355	8
3	Materials	XLB	292	59	280	304	327	8
4	Industrials	XLI	54	5	51	53	57	8
5	Consumer staples	XLP	19	3	16	19	21	8
6	Consumer discretionary	XLY	16	12	8	11	21	8
7	Healthcare	XLV	4	2	3	4	6	8
8	Technology	XLK	1.2	0.7	0.6	1.1	1.8	8
9	Financials	XLF	0.8	0.3	0.5	0.8	1.0	8

Table 3. Determinants of carbon intensities, carbon emissions and carbon disclosure to CDP

Regressions in panel A are estimated at the firm-year level. *Scope 1/MV firm* are a firm's Scope 1 carbon emissions (in metric tons of CO_2) divided by the firm's equity market value (in millions $). *Scope 1/MV industry* is the Scope 1 carbon intensity of all firms in the same industry (SIC4) and year. It is defined as total Scope 1 carbon emissions (metric tons of CO_2) of all reporting firms in the industry divided by the total market capitalization of all reporting firms in the industry (in millions $). *Scope 1 firm* are a firm's Scope 1 carbon emissions (in metric tons of CO_2) (unscaled). *Scope 1 industry* are the Scope 1 carbon emissions (in metric tons of CO_2) of all firms in the same industry (SIC4) and year (unscaled). The sample includes all firms in the S&P 500 with data on carbon emissions disclosed to CDP. The sample period covers emissions generated during the years 2009 to 2016. Regressions in panel B are estimated at the firm-year level. *CDP disclosure* equals one for a given firm-year if a firm discloses data on the carbon emissions released during the year, and zero otherwise. *Industry CDP disclosure* is the fraction of firms in the same SIC4 industry and year that discloses data on the carbon emissions released during the year. The sample includes all firms in the S&P 500. The sample period is the same as in the first panel. Table A.1 defines all variables in detail. *t*-statistics, based on standard errors clustered by industry (SIC4) and year, are in parentheses. *p< .1; **p< .05; ***p< .01.

	A. Determinants of carbon intensities or carbon emissions				*B. Disclosure decision*
Dependent variable:	*log(Scope 1/MV firm)*		*log(Scope 1 firm)*		*CDP disclosure*
	(1)	(2)	(3)	(4)	(5)
log(Scope 1/MV industry)	0.969***	0.940***			
	(180.20)	(87.06)			
log(Scope 1 industry)			1.015***	0.927***	
			(148.91)	(50.36)	
Industry CDP disclosure					0.926***
					(113.84)
log(Assets)		0.015		0.342***	0.076***
		(0.89)		(8.77)	(11.69)
Dividends/net income		0.056*		0.125**	0.019
		(1.78)		(2.44)	(1.35)
Debt/assets		0.561***		1.123***	-0.067*
		(3.80)		(4.19)	(-1.75)
EBIT/assets		0.073		2.334***	0.202**
		(0.23)		(3.85)	(1.99)
CapEx/assets		1.807**		5.812***	-0.121
		(2.27)		(3.98)	(-0.88)
Book-to-market		0.365***		0.142	-0.104***
		(3.82)		(0.93)	(-2.85)
Returns		0.013		0.059	-0.051*
		(0.16)		(0.33)	(-1.89)
Institutional ownership		0.212		0.022	-0.084
		(1.26)		(0.09)	(-1.35)
CAPM beta		0.093***		0.168**	0.042***
		(2.98)		(2.57)	(3.16)
Volatility		-2.444***		-8.362***	-0.530*
		(-3.05)		(-4.45)	(-1.70)
Oil beta		-0.096		-0.341*	0.041
		(-1.13)		(-1.86)	(1.23)
Time trend		-0.006		-0.029	-0.006**
		(-0.70)		(-1.37)	(-1.97)
Model	OLS	OLS	OLS	OLS	OLS
Year fixed effects	No	Yes	No	Yes	Yes
Level	Firm	Firm	Firm	Firm	Firm
Frequency	Annual	Annual	Annual	Annual	Annual
Obs.	1,815	1,772	1,963	1,772	3,206
Adj. R^2	0.92	0.92	0.83	0.85	0.46

Table 4. Carbon intensities and option market variables: Main results

Regressions in panel A are estimated at the firm-month level. *SlopeD* measures the steepness of the function that relates implied volatility to moneyness (measured by an option's Black-Scholes delta) for OTM put options with 30 days maturity. *MFIS* is a measure of the model-free implied skewness. *VRP* is a measure of the variance risk premium. *Scope 1/MV industry* is the Scope 1 carbon intensity of all firms in the same industry (SIC4) and year. It is defined as total Scope 1 carbon emissions (metric tons of CO_2) of all reporting firms in the industry divided by the total market capitalization of all reporting firms in the industry (in millions $). The sample includes all firms in the S&P 500 with data on carbon emissions disclosed to CDP. We estimate the effect of emissions generated between 2009 and 2016 on option market variables measured between November 2010 and December 2017. *t*-statistics, based on standard errors clustered by industry (SIC4) and year, are in parentheses. Regressions in panel B are at the sector-month level. The option variables are calculated for S&P 500 sector options. *Scope 1/MV sector* is the Scope 1 carbon intensity of a sector. It is defined as a sector's Scope 1 carbon emissions (in metric tons of CO_2) divided by a sector's equity market value (in millions $). The sample includes 9 of the 11 sectors of the S&P 500. The sample period is the same as in the first panel. *t*-statistics, based on standard errors clustered by sector and year, are in parentheses. Table A.1 defines all variables in detail. n/a, not applicable. **p*< .1; ***p*< .05; ****p*< .01.

A. Firm-level regressions			
Dependent variable:	*SlopeD*	*MFIS*	*VRP*
	(1)	(2)	(3)
log(Scope 1/MV industry)	0.006***	-0.002	0.001***
	(3.85)	(-0.70)	(3.79)
log(Assets)	-0.029***	-0.043***	-0.005***
	(-9.22)	(-8.04)	(-7.10)
Dividends/net income	0.009	-0.014	-0.000
	(1.54)	(-1.26)	(-0.00)
Debt/assets	0.038**	0.062**	0.003
	(2.28)	(2.00)	(0.71)
EBIT/assets	-0.187***	-0.078	-0.018
	(-4.59)	(-1.02)	(-1.60)
CapEx/assets	-0.374***	0.216*	-0.060**
	(-5.13)	(1.75)	(-2.35)
Book-to-market	0.077***	0.122***	0.016***
	(8.10)	(5.21)	(4.30)
Returns	-0.018**	-0.054***	-0.010*
	(-2.13)	(-2.95)	(-1.93)
Institutional ownership	-0.045*	-0.085	-0.008
	(-1.75)	(-1.59)	(-1.20)
CAPM beta	0.010	-0.033***	-0.001
	(1.42)	(-3.18)	(-0.44)
Volatility	-0.687***	1.926***	
	(-6.48)	(8.27)	
Oil beta	-0.008	-0.003	-0.020***
	(-0.50)	(-0.10)	(-2.73)
Time trend	-0.000	0.033***	-0.001*
	(-0.29)	(9.93)	(-1.67)
Model	Heckman	Heckman	Heckman
Year-by-quarter fixed effects	Yes	Yes	Yes
Level	Firm	Firm	Firm
Frequency	Monthly	Monthly	Monthly
Obs.	18,664	18,664	18,664
Adj. R^2	n/a	n/a	n/a

Table 4 (continued)

B. Sector-level regressions			
Dependent variable:	*SlopeD*	*MFIS*	*VRP*
	(1)	(2)	(3)
log(Scope 1/MV sector)	0.037***	-0.067*	0.003
	(2.80)	(-1.92)	(1.46)
Model	OLS	OLS	OLS
Sector fixed effects	Yes	Yes	Yes
Level	Sector	Sector	Sector
Frequency	Monthly	Monthly	Monthly
Obs.	774	774	774
Adj. R^2	0.14	0.37	0.01

Table 5. Firm versus industry carbon intensities: Relative importance

Regressions are estimated at the firm-month level. *SlopeD* measures the steepness of the function that relates implied volatility to moneyness (measured by an option's Black-Scholes delta) for OTM put options with 30 days maturity. *Scope 1/MV firm* are a firm's Scope 1 carbon emissions (in metric tons of CO_2) divided by the firm's equity market value (in millions $). *Scope 1/MV industry* is the Scope 1 carbon intensity of all firms in the same industry (SIC4) and year. It is defined as total Scope 1 carbon emissions (metric tons of CO_2) of all reporting firms in the industry divided by the total market capitalization of all reporting firms in the industry (in millions $). *Residual log(Scope 1 MV/firm)* is the residual of an OLS regression with *log(Scope 1/MV firm)* as the dependent variable and *log(Scope 1/MV industry)* as the independent variable. The regressions in the table control for *log(Assets), Dividends/net income, Debt/assets, EBIT/assets, CapEx/assets, Book-to-market, Returns, Institutional ownership, CAPM beta, Volatility, Oil beta,* and a time trend (not reported). The sample includes all firms in the S&P 500 with data on carbon emissions disclosed to CDP. We estimate the effect of emissions generated between 2009 and 2016 on option market variables measured between November 2010 and December 2017. *t*-statistics, based on standard errors clustered by industry (SIC4) and year, are in parentheses. Table A.1 defines all variables in detail. n/a, not applicable. *$p< .1$; **$p< .05$; ***$p< .01$

Dependent variable:	*SlopeD*	*SlopeD*	*SlopeD*
	(1)	(2)	(3)
log(Scope 1/MV firm)	0.006***		
	(3.39)		
Residual log(Scope 1/MV firm)		0.003	0.005
		(0.81)	(1.06)
log(Scope 1/MV industry)			0.006***
			(3.76)
Model	Heckman	Heckman	Heckman
Controls	Yes	Yes	Yes
Year-by-quarter fixed effects	Yes	Yes	Yes
Level	Firm	Firm	Firm
Frequency	Monthly	Monthly	Monthly
Obs.	18,664	18,664	18,664
Adj. R^2	n/a	n/a	n/a

Table 6. Carbon intensities and option market variables: Effects of public attention to climate change

Regressions are estimated at the firm-month level. *SlopeD* measures the steepness of the function that relates implied volatility to moneyness (measured by an option's Black-Scholes delta) for OTM put options with 30 days maturity. In column 1, we measure attention to climate change using *Negative climate change news high,* which is a dummy variable based the CH Negative Climate Change News Index developed in Engle et al. (2020) (as in their paper, we use monthly averaged AR(1) innovation of the index). *Negative climate change news high* equals one if the index is above the median, and zero otherwise. In column 2, we measure attention to climate change using monthly values of Google's SVI for the search topic "climate change." SVI is a relative index and takes values between 0 and 100. The highest number of searches in a month takes the value of 100 and values for other months are relative to this number. *Climate change SVI high* equals one if Google's SVI is above the median, and zero otherwise. *Scope 1/MV industry* is the Scope 1 carbon intensity of all firms in the same industry (SIC4) and year. It is defined as total Scope 1 carbon emissions (metric tons of CO_2) of all reporting firms in the industry divided by the total market capitalization of all reporting firms in the industry (in millions $). The regressions control for *log(Assets), Dividends/net income, Debt/assets, EBIT/assets, CapEx/assets, Book-to-market, Returns, Institutional ownership, CAPM beta, Volatility, Oil beta,* and a time trend (not reported). The sample includes all firms in the S&P 500 with data on carbon emissions disclosed to CDP. We estimate the effect of emissions generated between 2009 and 2016 on option market variables measured between November 2010 and December 2017. *t*-statistics, based on standard errors clustered by industry (SIC4) and year, are in parentheses. Table A.1 defines all variables in detail. n/a, not applicable. **p*< .1; ***p*< .05; ****p*< .01.

Dependent variable:	*SlopeD*	*SlopeD*
	(1)	(2)
log(Scope 1/MV industry) x Negative climate change news high	0.002*	
	(1.67)	
log(Scope 1/MV industry) x Climate change SVI high		0.001
		(0.45)
log(Scope 1/MV industry)	0.005***	0.006***
	(3.47)	(3.61)
Negative climate change news high	-0.003	
	(-0.82)	
Climate change SVI high		-0.005
		(-1.01)
Estimated slope if *Negative climate change news high* = 1	0.007***	
Estimated slope if *Climate change SVI high* = 1		0.007***
Model	Heckman	Heckman
Controls	Yes	Yes
Year-by-quarter fixed effects	Yes	Yes
Level	Firm	Firm
Frequency	Monthly	Monthly
Obs.	18,664	18,664
Adj. R^2	n/a	n/a

Table 7. Effect of the election of President Trump in 2016 on option market variables

Regressions are estimated at the firm-day level. We report results from difference-in-differences regressions around the date of President Trump's election on November 9, 2016. *SlopeD* measures the steepness of the function that relates implied volatility to moneyness (measured by an option's Black-Scholes delta) for OTM put options with 30 days maturity. *Post-Trump election* equals one for all days after President Trump's election, and zero for all days before the election. *Scope 1/MV industry high* equals one for firms that operate in the top-10 industries based on *Scope 1/MV industry*, and zero otherwise (see Table 2, panel A). The regressions control for *Effective tax rate*, *Effective tax rate x Post-Trump election*, *log(Assets)*, *Dividends/net income*, *Debt/assets*, *EBIT/assets*, *CapEx/assets*, *Book-to-market*, *Returns*, *Institutional ownership*, *CAPM beta*, *Volatility*, and *Oil beta* (not reported). The sample includes all firms in the S&P 500 with data on carbon emissions disclosed to CDP. Column 6 excludes firms in the healthcare industry (SIC4 codes 2834, 3841, 6324, 3826, 3842, 2836, 5122, 3845, 8062, 8071, 5912, 2835, 3851, 3844, 3843, and 5047). *t*-statistics, based on standard errors double clustered by firm and day, are in parentheses. Table A.1 defines all variables in detail. **p*< .1; ***p*< .05; ****p*< .01.

Dependent variable:	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*
Event window:	[-250; +250]	[-250; +250]	[-250; +250]	[-250; +250]	[-250; +250], excl. [-50; +50]	[-250; +250], excl. [-50; +50], excl. Healthcare
	(1)	(2)	(3)	(4)	(5)	(6)
Post-Trump election x Scope 1/MV industry high	-0.025**	-0.029**	-0.025***	-0.020**	-0.037***	-0.035**
	(-2.18)	(-2.43)	(-2.88)	(-2.20)	(-2.63)	(-2.45)
Scope 1/MV industry high	0.041*	0.043*			0.046*	0.043*
	(1.67)	(1.77)			(1.88)	(1.72)
Post-Trump election	-0.025***			-0.022***	-0.036***	-0.041***
	(-4.63)			(-4.33)	(-5.97)	(-6.13)
Model	DiD	DiD	DiD	DiD	DiD	DiD
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Day fixed effects	No	Yes	Yes	No	No	No
Firm fixed effects	No	No	Yes	No	No	No
Industry fixed effects	No	No	No	Yes	No	Yes
Level	Firm	Firm	Firm	Firm	Firm	Firm
Frequency	Daily	Daily	Daily	Daily	Daily	Daily
Obs.	200,897	200,897	200,897	200,897	159,041	139,635
Adj. R^2	0.06	0.09	0.29	0.18	0.06	0.06

Appendix

for

Carbon Tail Risk

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Appendix Part A: Additional Tables

Appendix Table 1. Firms' carbon emissions by industry

This table reports firms' Scope 1 carbon emissions (unscaled) by industry. We report figures for the top-20 industries, ranked by the average carbon emissions of firms in an industry. *Scope 1 firm* are a firm's Scope 1 carbon emission (in metric tons of CO_2) (unscaled). Statistics are reported at the firm-year level across different SIC2 industries. The sample includes all firms in the S&P 500 with data on carbon emissions disclosed to CDP. The sample period covers emission generated during the years 2009 to 2016. Not all firms are included in our sample across all years, which explains why the number of observations in some industries falls below eight.

				Top-20 industries by Scope 1 firm				
Rank	Industry name	SIC2	Mean	STD	25th	Median	75th	Obs.
1	Petroleum refining & related industries	29	93,403,464	35,699,673	59,279,610	90,068,022	130,000,000	16
2	Primary metal industries	33	43,544,068	1,151,571	42,729,784	43,544,068	44,358,352	2
3	Electric, gas & sanitary services	49	38,065,211	36,047,530	10,112,329	21,708,938	57,000,000	153
4	Transportation by air	45	21,698,358	10,249,014	13,838,695	17,866,753	31,436,892	26
5	Water transportation	44	10,506,412	269,392	10,319,475	10,402,394	10,700,267	6
6	Oil & gas extraction	13	9,799,780	12,297,789	2,856,000	6,065,844	10,450,000	69
7	Motor freight transportation & warehousing	42	8,812,352	5,323,841	1,681,697	11,715,635	12,000,000	11
8	Railroad transportation	40	7,273,642	3,018,934	5,088,315	5,300,099	11,207,344	23
9	Stone, clay, glass, & concrete products	32	4,548,400	471,826	4,529,000	4,703,000	4,805,000	5
10	Paper & allied products	26	3,829,735	3,425,980	222,174	2,611,787	5,669,920	35
11	Metal mining	10	3,715,079	1,730,674	1,590,000	4,110,000	5,358,795	23
12	Nonclassifiable establishments	99	3,065,286	1,393,459	1,970,000	2,598,089	3,988,622	14
13	Chemicals & allied products	28	1,851,756	3,601,290	80,111	324,302	1,176,667	204
14	General merchandise stores	53	1,741,086	2,555,653	104,949	429,980	785,682	33
15	Textile mill products	22	1,602,088		1,602,088	1,602,088	1,602,088	1
16	Food & kindred products	20	1,311,414	3,109,622	127,354	380,118	855,363	133
17	Food stores	54	1,275,677	862,879	374,782	1,619,322	2,010,936	14
18	Lumber & wood products, except furniture	24	865,568	718,040	39,879	1,390,232	1,434,076	11
19	Transportation equipment	37	715,987	726,745	127,564	579,000	955,785	57
20	Rubber & miscellaneous plastic products	30	620,643	607,242	174,981	236,137	1,234,311	20

Appendix Table 2. Carbon intensities within SIC2 industries

This table illustrates variation in Scope 1 carbon intensities within SIC2 industries. Statistics are reported at the firm-year level for sample firms that operate in the two-digit SIC code "49" (Electric, Gas, & Sanitary Services). *Scope 1/MV firm* are a firm's Scope 1 carbon emissions (in metric tons of CO_2) divided by a firm's equity market value (in million $). The sample includes S&P 500 firms in the specific industry with data on carbon emissions disclosed to CDP. The sample period covers emissions generated during the years 2009 to 2016. Not all firms are included in our sample across all years, which explains why the number of observations in some cases falls below eight.

Scope 1/MV firm			
Industry name	SIC	Mean	Obs.
Electric services	4911	4,609	49
Natural gas transmission & distribution	4923	371	4
Electric & other services combined	4931	2,393	72
Gas & other services combined	4932	2,707	7
Water supply	4941	5	2
Refuse systems	4953	1,026	12
Cogeneration services & small power producers	4991	8,751	7
All	Total	3,216	153

Appendix Table 3. Carbon intensities and option market variables: Right-tail risk

The regression in panel A is at the firm-month level. *SlopeU* measures the steepness of the function that relates implied volatility to moneyness (measured by an option's Black-Scholes delta) for OTM call options with 30 days maturity. *Scope 1/MV industry* is the Scope 1 carbon intensity of all firms in the same industry (SIC4) and year. It is defined as total Scope 1 carbon emissions (metric tons of CO_2) of all reporting firms in the industry divided by the total market capitalization of all reporting firms in the industry (in million $). The regressions control for *log(Assets), Dividends/net income, Debt/assets, EBIT/assets, CapEx/assets, Book-to-market, Returns, Institutional ownership, CAPM beta, Volatility, Oil beta,* and a time trend (not reported). The sample includes all firms in the S&P 500 with data on carbon emissions disclosed to CDP. We estimate the effect of emissions generated between 2009 and 2016 on option market variables measured between November 2010 and December 2017. *t*-statistics, based on standard errors clustered by industry (SIC4) and year, are in parentheses. The regression in panel B is at the sector-month level. The option variables are calculated for S&P 500 sector options. *Scope 1/MV sector* is the Scope 1 carbon intensity of a sector. It is defined as a sector's Scope 1 carbon emissions (in metric tons of CO_2) scaled by a sector's equity market value (in million $). The sample includes nine of the eleven sectors of the S&P 500. The sample period is the same as in the first panel. *t*-statistics, based on standard errors clustered by sector and year, are in parentheses. Table A.1 defines all variables in detail. *p< .1; **p< .05; ***p< .01.

A. Firm-level regression	
Dependent variable:	*SlopeU*
	(1)
log(Scope 1/MV industry)	-0.006***
	(-3.83)
Model	Heckman
Controls	Yes
Year-by-quarter fixed effects	Yes
Level	Firm
Frequency	Monthly
Obs.	18,664
adj. R^2	n/a

B. Sector-level regression	
Dependent variable:	*SlopeU*
	(1)
log(Scope 1/MV sector)	0.024
	(1.34)
Model	OLS
Sector fixed effects	Yes
Level	Sector
Frequency	Monthly
Obs.	774
Adj. R^2	0.14

Appendix Table 4. Carbon intensities and option market variables: Robustness checks for firm-level regressions

Regressions are at the firm-month or firm-year level (indicated accordingly). Each panel reports in each column the results of a different regression. Panel A to C differ in the dependent variable that is used. In panel A, *SlopeD* measures the steepness of the function that relates implied volatility to moneyness (measured by an option's Black-Scholes delta) for OTM put options with 30 days maturity (or longer, indicated accordingly). In panel B, *MFIS* is a measure of the model-free implied skewness. In panel C, *VRP* is a measure of the variance risk premium. *Scope 1/assets industry* is the Scope 1 carbon intensity of all firms in the same industry (SIC4) and year. It is defined as total Scope 1 carbon emissions (metric tons of CO_2) of all reporting firms in the industry divided by the total assets of all reporting firms in the industry (in million $). *Scope 1/MV industry* is the Scope 1 carbon intensity of all firms in the same industry (SIC4) and year. It is defined as total Scope 1 carbon emissions (metric tons of CO_2) of all reporting firms in the industry divided by the total market capitalization of all reporting firms in the industry (in million $). *Scope 2/MV industry* is defined accordingly, but for Scope 2 carbon emissions. The regressions control for *log(Assets), Dividends/net income, Debt/assets, EBIT/assets, CapEx/assets, Book-to-market, Returns, Institutional ownership, CAPM beta, Volatility* (not in panel C), *Oil beta*, and a time trend (not reported). The sample includes all firms in the S&P 500 with data on carbon emissions disclosed to CDP. We estimate the effect of emissions generated between 2009 and 2016 on option market variables measured between November 2010 and December 2017. *t*-statistics, based on standard errors clustered by industry (SIC4) and year, are in parentheses. Table A.1 defines all variables in detail. *p< .1; **p< .05; ***p< .01.

	Scale by assets	Yearly average of *SlopeD*	OLS	Firm fixed effects	Exclude oil, gas, coal (SIC 29; 13)	91 days options	182 days options	365 days options	Scope 2
Panel A. Robustness checks for SlopeD									
Dependent variable:	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log(Scope 1/Assets industry)	0.006***								
	(3.43)								
log(Scope 1/MV industry)		0.006***	0.006***	0.019***	0.006***	0.003***	0.002***	0.002***	
		(3.76)	(3.63)	(5.85)	(3.60)	(3.64)	(3.41)	(3.28)	
log(Scope 2/MV industry)									0.002
									(1.00)
Panel B. Robustness checks for MFIS									
Dependent variable:	*MFIS*	*MFIS*	*MFIS*	*MFIS*	*MFIS*	*MFIS*	*MFIS*	*MFIS*	*MFIS*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log(Scope 1/Assets industry)	-0.003								
	(-0.97)								
log(Scope 1/MV industry)		-0.004	-0.001	0.007	-0.002	-0.006***	-0.006***	-0.005**	
		(-1.34)	(-0.48)	(0.52)	(-0.76)	(-2.79)	(-2.83)	(-2.39)	
log(Scope 2/MV industry)									0.000
									(0.02)
Panel C. Robustness checks for VRP									
Dependent variable:	*VRP*	*VRP*	*VRP*	*VRP*	*VRP*	*VRP*	*VRP*	*VRP*	*VRP*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log(Scope 1/Assets industry)	0.001***								
	(3.82)								
log(Scope 1/MV industry)		0.002***	0.001***	0.001	0.001***	0.001**	0.001**	0.001***	
		(4.12)	(3.60)	(0.19)	(3.27)	(2.12)	(2.02)	(2.78)	
log(Scope 2/MV industry)									0.000
									(0.36)
Model	Heckman	Heckman	OLS	Heckman	Heckman	Heckman	Heckman	Heckman	Heckman
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	No	Yes	No	No	No	No	No
Level	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
Frequency	Monthly	Annual	Monthly	Monthly	Monthly	Monthly	Monthly	Monthly	Monthly
Obs.	18,664	1,771	18,664	18,664	17,744	18,663	18,663	18,663	18,190

Appendix Table 5. Carbon intensities and option market variables: Robustness checks for sector-level regressions

Regressions are at the sector-month or sector-year level (indicated accordingly). Each panel reports in each column the results of a different regression. Panel A to C differ in the dependent variable that is used. In panel A, *SlopeD* measures the steepness of the function that relates implied volatility to moneyness (measured by an option's Black-Scholes delta) for OTM sector put options with 30 days maturity (or longer, indicated accordingly). In panel B, *MFIS* is a measure of the model-free implied skewness. In panel C, *VRP* is a measure of the variance risk premium. *Scope 1/assets sector* the Scope 1 carbon intensity of a sector. It is defined as a sector's Scope 1 emissions (in metric tons of CO_2) divided by a sector's total assets (in million \$). *Scope 1/MV sector* is the Scope 1 carbon intensity of a sector. It is defined as a sector's Scope 1 carbon emissions (in metric tons of CO_2) divided by a sector's equity market value (in million \$). *Scope 2/MV sector* is defined accordingly, but for Scope 2 carbon emissions. The sample includes nine of the eleven sectors of S&P 500. We estimate the effect of emissions generated between 2009 and 2016 on option market variables measured between November 2010 and December 2017. *t*-statistics, based on standard errors clustered by sector and year, are in parentheses. Table A.1 defines all variables in detail. *p< .1; **p< .05; ***p< .01.

A. Robustness Checks for SlopeD								
	Scale by assets	Yearly average of *SlopeD*	Sector-by-quarter fixed effects	Year-by-quarter fixed effects	91 days options	182 days options	365 days options	Scope 2
Dependent variable:	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(Scope 1/assets sector)	0.045**							
	(2.42)							
log(Scope 1/MV sector)		0.052***	0.039***	0.024*	0.047***	0.046***	0.051***	
		(3.96)	(2.83)	(1.85)	(4.34)	(3.84)	(3.95)	
log(Scope 2/MV sector)								-0.001
								(-0.08)
B. Robustness checks for MFIS								
Dependent variable:	*MFIS*	*MFIS*	*MFIS*	*MFIS*	*MFIS*	*MFIS*	*MFIS*	*MFIS*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(Scope 1/assets sector)	-0.093**							
	(-2.38)							
log(Scope 1/MV sector)		-0.076**	-0.065*	0.093*	-0.044	-0.055	-0.147***	
		(-2.14)	(-1.83)	(1.88)	(-1.14)	(-1.39)	(-3.26)	
log(Scope 2/MV sector)								-0.018
								(-0.46)
C. Robustness checks for VRP								
Dependent variable:	*VRP*	*VRP*	*VRP*	*VRP*	*VRP*	*VRP*	*VRP*	*VRP*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(Scope 1/assets sector)	0.004							
	(1.26)							
log(Scope 1/MV sector)		0.003	0.004	0.004*	0.006	0.008	0.011*	
		(1.38)	(1.56)	(1.73)	(1.38)	(1.43)	(1.69)	
log(Scope 2/MV sector)								0.000
								(0.04)
Model	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Sector fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-by-quarter fixed effects	No	No	Yes	No	No	No	No	No
Year-by-quarter fixed effects	No	No	No	Yes	No	No	No	No
Level	Sector	Sector	Sector	Sector	Sector	Sector	Sector	Sector
Frequency	Monthly	Annual	Monthly	Monthly	Monthly	Monthly	Monthly	Monthly
Obs.	774	72	774	774	774	774	774	774

Appendix Table 6. Predicted carbon intensities and option market variables

The regression is at the firm-month level. *SlopeD* measures the steepness of the function that relates implied volatility to moneyness (measured by an option's Black-Scholes delta) for OTM put options with 30 days maturity. *Scope 1/MV industry* is the Scope 1 carbon intensity of all firms in the same industry (SIC4) and year. It is defined as total Scope 1 carbon emissions (metric tons of CO_2) of all reporting firms in the industry divided by the total market capitalization of all reporting firms in the industry (in million $). The sample includes all firms in the S&P 500 with *predicted* carbon emissions for the period 1995 to 2008. Emissions are backfilled based on a prediction model using emissions data from the years 2009 to 2016. The prediction model is similar to the regression in Column (4) of Table 3, panel A, except that we use industry dummies instead of industry carbon intensities. We estimate the effect of emissions generated between 1995 and 2008 on option market variables measured between November 1996 and December 2008. *t*-statistics, based on standard errors clustered by industry (SIC4) and year, are in parentheses. Table A.1 defines all variables in detail. *p< .1; **p< .05; ***p< .01.

Dependent variable:	*SlopeD*
	(1)
log(Scope 1/MV industry)	-0.000
	(-0.35)
log(Assets)	-0.010***
	(-4.41)
Dividends/net income	0.007
	(1.04)
Debt/assets	0.080***
	(4.53)
EBIT/assets	-0.055
	(-1.13)
CapEx/assets	-0.001
	(-0.02)
Book-to-market	0.037***
	(2.76)
Institutional ownership	-0.077***
	(-4.08)
CAPM beta	-0.008
	(-1.46)
Volatility	0.056
	(0.46)
Oil beta	-0.023*
	(-1.88)
Time trend	0.004***
	(3.39)
Model	OLS
Year-by-quarter fixed effects	Yes
Level	Firm
Frequency	Monthly
Obs.	11,916
Adj. *R*-sq.	0.12

Internet Appendix Table 7. President Trump's election: Test of parallel trends

This table compares mean daily growth rates for *SlopeD* between the treatment and control group during the [-1,000;-250] window prior to election of President Trump on November 9, 2016. The analysis follows Lemmon and Roberts (2010). The treatment group consists of high-carbon-emission firms, which are firms that operate in in the top-10 industries based on *Scope 1/MV industry* (see Table 2, panel B). The control groups consist of low-carbon-emission sectors. We present the *p*-value of a difference-in-means test, which tests the hypothesis that mean values of the two groups are the same. We also present the Wilcoxon *p*-value of the two-sample Wilcoxon test, which tests the hypothesis that the two groups are taken from populations with the same median.

	Treatment firm	Control firm	Difference	*p*-value	Wilcoxon *p*-value
SlopeD Growth (x100)	0.0041	0.0090	-0.005	.9455	.3001

Appendix Table 8. Effect of the election of President Trump in 2016: Robustness

Regressions in panel A are at the firm-day level. We report results from difference-in-differences regressions around the date of the election on November 9, 2016. *SlopeD* measures the steepness of the function that relates implied volatility to moneyness (measured by an option's Black-Scholes delta) for OTM put options with 30 days maturity. *Post Trump election* equals one for all days after President Trump's election, and zero for all days before the election. *Scope 1/MV industry high* equals one for firms that operate in the top-10 industries based on *Scope 1/MV industry*, and zero otherwise (see Table 2, panel A). The sample includes all firms in the S&P 500 with data on carbon emissions disclosed to CDP. *t*-statistics, based on standard errors double clustered by firm and day, are in parentheses. Regressions in panel B are at the firm-day level. We report results from different placebo difference-in-differences regressions around the date of November 9 of placebo years between 2010 and 2017. *t*-statistics, based on standard errors double clustered by firm and day, are in parentheses. The regressions in panel C are at the sector-day level. *Scope 1/MV sector high* equals for the two sector with the highest mean values of *Scope 1/MV sector* (Utilities and Energy), and zero otherwise. The sample includes nine of the eleven sectors of the S&P 500. *t*-statistics, based on standard errors double clustered by sector and day, are in parentheses. Table A.1 defines all variables in detail. *p< .1; **p< .05; ***p< .01.

A. Alternative event windows				
Dependent variable:	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*
Event window:	[-300; +300]	[-300; +300], excl. [-50; +50]	[-200; +200]	[-200; +200], excl. [-50; +50]
	(1)	(2)	(3)	(4)
Post-Trump election x Scope 1/MV industry high	-0.028**	-0.037***	-0.018	-0.029**
	(-2.53)	(-2.95)	(-1.61)	(-2.13)
Scope 1/MV industry high	0.043*	0.047**	0.037	0.043
	(1.83)	(2.03)	(1.46)	(1.63)
Post-Trump election	-0.026***	-0.036***	-0.018***	-0.030***
	(-4.98)	(-6.10)	(-3.11)	(-4.41)
Model	DiD	DiD	DiD	DiD
Controls	Yes	Yes	Yes	Yes
Sector fixed effects	No	No	No	No
Day fixed effects	No	No	No	No
Industry fixed effects	No	No	No	No
Level	Firm	Firm	Firm	Firm
Frequency	Daily	Daily	Daily	Daily
Obs.	234,613	192,757	162,080	120,224
Adj. R^2	0.06	0.06	0.06	0.06

B. Placebo event windows							
Dependent variable:	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*
Placebo year	*2010*	*2011*	*2012*	*2013*	*2014*	*2015*	*2017*
Event window:	[-250; +250]	[-250; +250]	[-250; +250]	[-250; +250]	[-250; +250]	[-250; +250]	[-250; +250]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post-November 9 x Scope 1/MV industry high	0.007	0.010	0.005	0.010	-0.001	-0.010	0.006
	(0.75)	(0.81)	(0.53)	(0.76)	(-0.04)	(-0.70)	(0.54)
Scope 1/MV industry high	0.020**	0.025	0.030**	0.037**	0.040*	0.049**	0.014
	(2.15)	(1.58)	(1.97)	(2.07)	(1.68)	(2.29)	(0.75)
Post-November 9	0.016***	0.002	-0.043***	0.013*	0.049***	0.021***	-0.001
	(3.10)	(0.31)	(-7.06)	(1.96)	(8.33)	(4.14)	(-0.08)
Model	DiD	DiD	DiD	DiD	DiD	DiD	DiD
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day fixed effects	No	No	No	No	No	No	No
Firm fixed effects	No	No	No	No	No	No	No
Industry fixed effects	No	No	No	No	No	No	No
Level	Firm	Firm	Firm	Firm	Firm	Firm	Firm
Frequency	Daily	Daily	Daily	Daily	Daily	Daily	Daily
Obs.	170,436	186,032	187,810	190,812	193,358	195,199	113,581
Adj. R^2	0.03	0.04	0.08	0.09	0.11	0.07	0.04

Appendix Table 8 (continued)

C. Sector-level regressions					
Dependent variable:	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*	*SlopeD*
Event window:	[-100; +100]	[-100; +100]	[-100; +100]	[-100; +100]	[-100; +100], excl. [-50; +50]
	(1)	(2)	(3)	(4)	(5)
Post-Trump election x Scope 1/MV sector high	-0.025**	-0.025***	-0.024**	-0.024**	-0.033**
	(-3.26)	(-3.56)	(-2.72)	(-2.88)	(-2.46)
Scope 1/MV sector high	-0.070*	-0.069*			-0.057*
	(-2.10)	(-2.10)			(-2.16)
Post-Trump election	0.002		0.002		0.003
	(0.30)		(0.22)		(0.29)
Model	DiD	DiD	DiD	DiD	DiD
Day fixed effects	No	Yes	No	Yes	No
Sector fixed effects	No	No	Yes	Yes	No
Level	Sector	Sector	Sector	Sector	Sector
Frequency	Daily	Daily	Daily	Daily	Daily
Obs.	1,790	1,790	1,790	1,790	882
Adj. R^2	0.05	0.04	0.33	0.36	0.06

Appendix Table 9. Variable definitions

Variable	Definition	Source
SlopeD	Steepness of the function that relates implied volatility to moneyness (measured by an option's Black-Scholes delta) for OTM put options with a 30-day maturity. It is constructed as the slope coefficient from regressing implied volatilities of OTM puts (deltas between -0.5 and -0.1) on the corresponding deltas and a constant. Because far OTM puts (with smaller absolute deltas) are typically more expensive, the variable usually takes positive values. We also construct similar measures using 91-, 182-, and 365-day maturities. To construct the variable, we follow Kelly, Pastor, and Veronesi (2016). The variable is constructed at the monthly level (average of daily values) or the daily level (indicated accordingly).	OptionMetrics
MFIS	Model-free implied skewness for options with a 30-day maturity. It is computed as the third central moment of the risk-neutral distribution, normalized by the risk-neutral variance (raised to the power of 3/2). To construct the variable, we follow Bakshi, Kapadia, and Madan (2003). The variable is constructed at the monthly level (average of daily values).	OptionMetrics
VRP	Ex post variance risk premium for options with a 30-day maturity. It is computed for each day *t* as the difference between the risk-neutral expected variance for the period from *t* to *t*+30 calendar days and the realized variance measured from daily log returns for the same period [*t*, *t*+30] (Carr and Wu 2009; Bollerslev, Tauchen, and Zhou 2009). As a proxy for the risk-neutral variance, we use the model-free implied variance computed like in Britten-Jones and Neuberger (2000). The variable is constructed at the monthly level (average of daily values).	OptionMetrics
Scope 1/MV industry	Annual Scope 1 carbon intensity of all carbon-disclosing firms in the same industry (SIC4) and year. It is computed as total Scope 1 carbon emissions (metric tons of CO_2) of all reporting firms in the industry divided by the total market capitalization of all reporting firms in the industry (in millions $).	CDP, Compustat
Scope 1/MV industry high	Dummy variable that equals one for firms that operate in the top-10 industries based on *Scope 1/MV industry*, and zero otherwise. The industries are listed in Table 2, panel A.	
Scope 1/MV firm	Annual Scope 1 carbon intensity of the firm itself. It is computed as a firm's total Scope 1 carbon emissions (metric tons of CO_2) divided by the firm's equity market value (in millions $) at the end of the year.	CDP, Compustat
Scope 1/MV sector	Annual Scope 1 carbon intensity of a sector. It is computed as a sector's total Scope 1 carbon emissions (in metric tons of CO_2) divided by a sector's equity market value (in millions $) at the end of the year.	CDP, Compustat
Scope 1/MV sector high	Dummy variable that equals one for the two sectors in the S&P 500 with the highest mean values of *Scope 1/MV sector*, and zero otherwise. The sectors are listed in Table 2, panel B.	CDP, Compustat
Scope 2/MV industry	Defined as *Scope 1/MV industry* but for Scope 2 carbon emissions instead of Scope 1 carbon emissions.	CDP, Compustat
CDP disclosure	Dummy variable that equals one for a given firm-year if a firm discloses to CDP data on the carbon emissions released during the year, and zero otherwise.	CDP
Industry CDP disclosure	Fraction of firms in the same SIC4 industry and year that discloses data to CDP on the carbon emissions released during the year.	CDP
Negative climate change news high	Dummy variable that equals one if the CH Negative Climate Change News Index is above the median, and zero otherwise. CH Negative Climate Change News Index is developed in Engle et al. (2020) and captures the share of all news articles that are about "climate change" and have been assigned to a "negative sentiment" category. As in their paper, we use monthly averaged AR(1) innovation of the index.	Engle et al. 2020
Climate change SVI high	Dummy variable that equals one if Google's search volume index (SVI) for the search topic "climate change is above the median, and zero otherwise. We use monthly values of the index during our sample period. The index is a relative index and takes values between 0 and 100. The highest number of	Google Trends

	searches in a month takes the value of 100, and values for other months are relative to this number.	
Assets	Total assets (Compustat data item AT) at the end of the year. Winsorized at the 1% level.	Compustat
Dividends/ net income	Dividends (Compustat data item DVT) at the end of the year divided by net income at the end of the year (Compustat data item NI). Winsorized at the 1% level.	Compustat
Debt/assets	Sum of the book value of long-term debt (Compustat data item DLTT) and the book value of current liabilities (DLC) at the end of the year divided by total assets at the end of the year (Compustat data item AT). Winsorized at the 1% level.	Compustat
EBIT/assets	Earnings before interest and taxes (Compustat data item EBIT) at the end of the year divided by total assets at the end of the year (Compustat data item AT). Winsorized at the 1% level.	Compustat
CapEx/assets	Capital expenditures at the end of the year (Compustat data item CAPX) divided by total assets at the end of the year (Compustat data item AT). Winsorized at the 1% level.	Compustat
Book-to-market	Difference between common equity (Compustat data item CEQ) and preferred stock capital (PSTK) at the end of the year divided by the equity market value (MKVALT) at the end of the year. Winsorized at the 1% level.	Compustat, CRSP
Returns	Stock price at the end of the year (Compustat data item PRCC_F) divided by the stock price at the end of the previous year, minus 1. Winsorized at the 1% level.	CRSP
Institutional ownership	Fraction of outstanding shares owned by institutional investors at the end of the year. Winsorized at the 1% level.	Thomson-Reuters
CAPM beta	Sensitivity of monthly stock returns to monthly S&P 500 returns. The variable is computed for each month with a rolling window of 60 months. For each firm *i*, the variable corresponds to the β_1 coefficient in the regression $Returns_{it} = constant + \beta_1 Market\ Returns_t$. We use averaged values over the year. Winsorized at the 1% level.	Kenneth French's data library
Oil beta	Sensitivity of monthly stock returns to monthly WTI oil returns after controlling for monthly market returns. The variable is computed for each month with a rolling window of 60 months. For each firm *i*, the variable corresponds to the β_2 coefficient in the regression $Returns_{it} = Constant + \beta_1 Market\ returns_t + \beta_2 Oil\ returns_t$. We use averaged values over the year. Winsorized at the 1% level.	U.S. Energy Information Administration, Kenneth French's data library
Volatility	Standard deviation of monthly stock returns, computed for each month with a rolling window of 12 months. We use averaged values over the year. Winsorized at the 1% level.	CRSP
Time trend	Linearly increasing variable that takes different integer values for each year in the sample, starting with zero.	Self-constructed
Effective tax rate	Cash taxes paid (Compustat data item TXPD) divided by current year pretax income (Compustat data items PI). Pretax income is adjusted for special items (Compustat data items SPI).	Compustat
Post-Trump election	Dummy variable that equals one for all days after President Trump’s election on November 9, 2016, and zero for all days before the election.	Self-constructed

Appendix Part B: Illustration and Relationship of Option Market Measures:

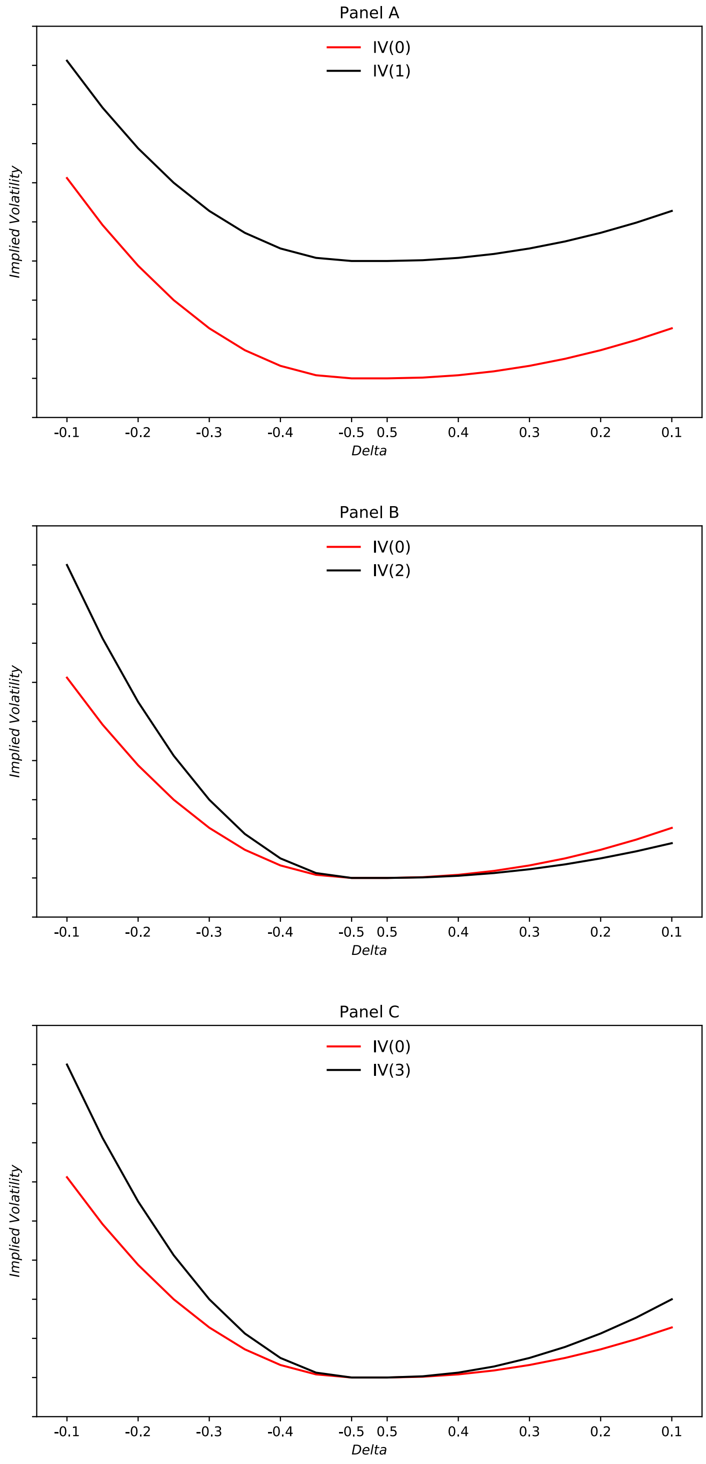
This internet appendix illustrates the information content of the three option market measures. The panels below depict volatility smiles for four different hypothetical firms, with the x-axis reporting option deltas. Options with deltas to the left of -0.5 are OTM puts (deeper OTM as we move to the left), while options to the right of 0.5 are OTM calls (deeper OTM as we move to the right). All three panels contain the implied volatility smile IV(0) for benchmark firm (firm 0). We then display in each panel a smile for a different firm (firm 1, 2, and 3), each representing a particular deviation of the volatility smile from IV(0). Panel A illustrates a parallel upward shift from IV(0) to IV(1), that is, all options are more expensive (in volatility terms). In panel B, deep OTM puts are relatively more expensive, and deep OTM calls are relatively less expensive, leading to a shift from IV(0) to get IV(2). Panel C displays the same left-tail transformation as in panel B, but additionally makes OTM puts and OTM calls more expensive the further away they are from the ATM level. This leads to a shift from IV(0) to IV(3).

What are the implications of these changes in IV smiles for our measures? In panel A, *SlopeD* remains unchanged because the shift from IV(0) to IV(1) is parallel. *MFIS* also remains unaffected as the symmetry properties of the risk-neutral probability distribution are unchanged. The effect on *VRP* is unclear: while the model-free variance based on IV(1) is higher than the one based on IV(0), the *VRP* difference depends on the realized variances for both firms. Thus, if the realized variance for firm 1 is much higher than the one for firm 0, it can overcompensate the difference in the model-free implied variances, and make *VRP* for firm 1 smaller than that for firm 0.

Turning to panel B, one can see that *SlopeD* for IV(2) is steeper than for IV(0), indicating a higher cost of downside protection (note that, as the x-axis gets larger once we move to the left, the regression slope from regressing implied volatility on delta is positive). *MFIS* is also more negative for IV(2) compared to IV(0), because downside protection gets more expensive, while it is now cheaper to get upside potential. The effect on *VRP* is again unclear: though one can expect that the expected risk-neutral variance increases (due to the fact that, computationally, OTM puts have a stronger effect on the model-free implied variance), the *VRP* difference again reveals the price of uncertainty about the realized variance, and it cannot be determined from option prices alone.

In panel C, IV(3) will have the same value as IV(2) for *SlopeD*, because the measure is based on OTM puts only. Hence, whether *SlopeD* becomes larger relative to IV(0) does not depend on the OTM call pricing. *MFIS* can change either way, depending on both the put and call price changes. However, even if it gets more negative by moving from IV(0) to IV(3), the effect is smaller than in panel B, where it moves from IV(0) to IV(2). The reason is that both OTM option types are getting more expensive and, thus, the probability mass is relocated from the central region to the tail region on both sides. The effect for *VRP* effect is again unclear. As in panel A, we can assert that the risk-neutral variance gets higher by moving from IV(0) to IV(3). The final change in *VRP* will depend on the realized counterparts.

Thus, *SlopeD* quantifies the expensiveness of protection against extreme price drops relative to cost of protection for less extreme (downside) events. Somewhat differently, *MFIS* captures the expensiveness of left-tail protection relative to the right tail, that is, the cost of protection against losses relative to the cost of gaining positive realizations. *VRP* rather captures price of uncertainty about the variance, that is, it quantifies how much investors are willing to pay for hedging the risk of (mostly) increasing variance, which is typically generated by tail-risk realizations or increasing uncertainty about the future prospects of a firm.



Appendix Part C: Full-Information Maximum Likelihood Estimator

In this appendix, we derive the Full-Information Maximum Likelihood (FIML) for our empirical model. The derivations build on Wooldridge (2010). Our basic model set-up is as follows:

$$OMM_{i,m,t+1} = \beta_1\, Scope\ 1_{i,t} + \boldsymbol{x_{i,t}\beta} + u_{i,m,t+1} \quad \text{(A1)}$$

$$CDP\ disclosure_{i,t} = 1\left[\boldsymbol{z_{i,t}\gamma} + v_{i,t} > 0\right] \quad \text{(A2)}$$

The sample selection nature of our estimation arises as the emissions generated by firm *i* in year *t*, $Scope\ 1_{i,t}$, are only observed when $CDP\ disclosure_{i,t} = 1$.[54] Our derivation differs from the standard case as the outcome and selection equations are estimated at different levels. Notably, while the option market variable $OMM_{i,m,t+1}$ in Equation (A1) is measured at the firm-month-year level (i.e., (*i,m,t+1*)), the decision to disclose carbon emissions $CDP\ disclosure_{i,t}$ in Equation (A2) is at the firm-year level (i.e., (*i,t*)). As a result, our empirical model merges observations of the (*i,t*)-level into the (*i,m,t+1*)-level. The approach of estimating a FIML selection model with data from different observation levels is similar to the estimation problem in Brav et al. (2019).

To derive the log likelihood function, we make the following assumptions:

(1) $\boldsymbol{x_{i,t}}$ is a strict subset of $\boldsymbol{z_{i,t}}$ and there exists at least one variable in $\boldsymbol{z_{i,t}}$ that is excluded from $\boldsymbol{x_{i,t}}$.
(2) $(u_{i,m,t+1}, v_{i,t})$ is bivariate normal with zero means, $\mathrm{Var}(u_{i,m,t+1}) = \sigma^2$, and $\mathrm{Var}(v_{i,t}) = \alpha^2 < 1$.[55]
(3) $(u_{i,m,t+1}, v_{i,t})$ is independent of $\boldsymbol{z_{i,t}}$ and $u_{i,m,t+1}$ is uncorrelated over m within a given firm-year.
(4) $\mathrm{Cov}(u_{i,m,t+1}, v_{i,t}) = \sigma_{12}$, so that the correlation coefficient $\rho = \sigma_{12}/\sigma\alpha$.

Under these assumptions, FIML estimation can be used to estimate Equations (A1) and (A2). For brevity, let us the denote the disclosure decision of firm i in year t with $s_{i,t}$. Because emissions are only observed when $s_{i,t} = 1$, we first use the density $f(OMM_{i,m,t+1}|s_{i,t}, \boldsymbol{z_{i,t}})$ when $s_{i,t} = 1$. To find $f(OMM_{i,m,t+1}|s_{i,t}, \boldsymbol{z_{i,t}})$ at $s_{i,t} = 1$, we use Bayes' rule and write:

$$f(OMM_{i,m,t+1}|s_{i,t}, \boldsymbol{z_{i,t}}) = \frac{f(s_{i,t}|OMM_{i,m,t+1}, \boldsymbol{z}_{i,t})f(OMM_{i,m,t+1}|\boldsymbol{z_{i,t}})}{f(s_{i,t}|\boldsymbol{z_{i,t}})}$$

Therefore,

$$f(OMM_{i,m,t+1}|s_{i,t} = 1, \boldsymbol{z_{i,t}}) = \frac{P(s_{i,t} = 1|OMM_{i,m,t+1}, \boldsymbol{z_{i,t}})f(OMM_{i,m,t+1}|\boldsymbol{z_{i,t}})}{P(s_{i,t} = 1|\boldsymbol{z_{i,t}})}$$

Because we consider the case when emissions are observed (i.e., $s_{i,t} = 1$), the denominator equals $P(s_{i,t} = 1|\boldsymbol{z_{i,t}}) = 1$, and the right-hand side in the expression reduces to only the numerator. Note that $OMM_{i,m,t+1}|\boldsymbol{z_{i,t}} \sim N(\beta_1 Scope1_{i,t} + \boldsymbol{x_{i,t}\beta}, \sigma^2)$ and furthermore that:[56]

[54] For brevity, we use $Scope\ 1_{i,t}$ in Equation (A1) while our actual estimation uses $Log(Scope\ 1/MV\ industry)_{i,t}$. In Equation (A2), $\boldsymbol{z_{i,t}}$ includes $Industry\ CDP\ disclosure_{i,t}$ and $\boldsymbol{x}_{i,t}$.
[55] A typical assumption in the standard FIML model for the error term v is to assume that it follows the standard normal distribution (Wooldridge 2010). However, our procedure to merge observations of the (*i,t*)-level into the (*i,m,t+1*)-level implies that the same values are replicated twelve times. In the actual estimations, this should reduce the variance of the error term v. Therefore, this reduction is reflected in the additional assumption that $\mathrm{Var}(v_{it}) = \alpha^2 < 1$.
[56] For two jointly normal variables $X \sim N(0, \sigma_X^2)$ and $Y \sim N(0, \sigma_Y^2)$, conditional expectation of X given Y can be written as $E(X|Y) = E(X) + \rho\sigma_x/\sigma_y[Y - E(Y)]$. Moreover, the estimation error $\tilde{X}$ has a normal distribution $\tilde{X} \sim N(0, \sigma_{\tilde{X}}^2)$ where $\sigma_{\tilde{X}}^2 = (1 - \rho^2)\sigma_X^2$ with $Corr(X, Y) = \rho$.

$$s_{i,t} = 1\left[\boldsymbol{z_{i,t}\gamma} + \frac{\sigma_{12}}{\sigma\alpha}\frac{\alpha}{\sigma}\left(OMM_{i,m,t+1} - \beta_1 Scope1_{i,t} - \boldsymbol{x_{i,t}\beta}\right) + e_{i,t} > 0\right],$$

where $e_{i,t}$ is independent of $(\boldsymbol{z_{i,t}}, OMM_{i,m,t+1})$ and $e_{i,t} \sim N(0, (1-\rho^2)\alpha^2)$ (this follows from standard conditional distribution results for joint normal random variables). Therefore,

$$P\left(s_{i,t} = 1 \middle| OMM_{i,m,t+1}, \boldsymbol{x_{i,t}}\right) = \Phi\left\{\frac{\boldsymbol{z_{i,t}\gamma} + \sigma_{12}\sigma^{-2}\left(OMM_{i,m,t+1} - \beta_1 Scope\ 1_{i,t} - \boldsymbol{x_{i,t}\beta}\right)}{\sqrt{Var(e_{i,t})}}\right\} \tag{A3}$$

For the case where emissions are not observed (i.e., $s_{it} = 0$), we can write the following term:

$$\left(1 - s_{i,t}\right)\log\left(1 - \Phi\left(\boldsymbol{z_{i,t}\gamma}\right)\right)$$

and for the case where emissions are observed (i.e., $s_{it} = 1$):

$$s_{i,t}\left(\log\Phi\left\{\frac{\boldsymbol{z_{i,t}\gamma} + \sigma_{12}\sigma^{-2}\left(OMM_{i,m,t+1} - \beta_1 Scope\ 1_{i,t} - \boldsymbol{x_{i,t}\beta}\right)}{\sqrt{Var(e_{i,t})}}\right\} + \log\left(\phi\left[\left(OMM_{i,m,t+1} - \beta_1 Scope\ 1_{i,t} - \boldsymbol{x_{i,t}\beta}\right)/\sigma\right]\right) - \log(\sigma)\right)$$

Noting $\rho = \frac{Cov(u_{i,m,t+1}, v_{i,t})}{\sqrt{Var(u_{i,m,t+1})Var(v_{i,t})}} = \frac{\sigma_{12}}{\sigma\alpha}$ and putting all of these ingredients together, we get:

$$\begin{aligned} l_{i,m,t+1} = {} & \left(1 - s_{i,t}\right)\log\left[1 - \Phi\left(\boldsymbol{z_{i,t}\gamma}\right)\right] \\ & + s_{i,t}\log\Phi\left\{\frac{\boldsymbol{z_{i,t}\gamma} + \rho\alpha/\sigma\left(OMM_{i,m,t+1} - \beta_1 Scope\ 1_{i,t} - \boldsymbol{x_{i,t}\beta}\right)}{\sqrt{1-\rho^2}\cdot\alpha}\right\} \\ & + s_{i,t}\log\left(\phi\left[\left(OMM_{i,mt,+1} - \beta_1 Scope1_{i,t} - \boldsymbol{x_{i,t}\beta}\right)/\sigma\right]\right) - s_{i,t}\log(\sigma) \end{aligned} \tag{A4}$$

where $\Phi(\cdot)$ and $\phi(\cdot)$ refer to the standard normal cumulative distribution function (CDF) and the probability density function (PDF), respectively. The log likelihood is obtained by summing $l_{i,m,t+1}$ across all observations.

Appendix Part D: Discussion of the Exclusion Restriction

Our analysis assumes that *Industry CDP disclosure* does not directly affect our option market measures. A concern could be that, if emissions data are widely disclosed at the industry level, disclosure may make aggregate emissions and their effects for climate change more salient. As a result, a high level of disclosure by an industry may increase the likelihood of future regulatory changes, and such regulation may target those industries that most disclosed. Highly carbon-intense firms could be affected more strongly by such regulation, and this could increase the cost of downside option protection at these firms. This channel could violate the exclusion restriction, as it implies a direct effect of industry disclosure on the option market measures.

We perform several tests to mitigate this concern. First, we exploit monthly time-series changes in public climate attention as an additional layer of variation to identify the effects of carbon intensities. The benefit of this analysis is that it allows us to study how the cost of option protection shifts *within the year* as climate attention varies, holding fixed firms' industry carbon intensities. Importantly, climate attention is largely unrelated to contemporaneous industry disclosure rates (ρ<10%), and disclosure rates do not vary within the year. Therefore, the sensitivity of the option measures to changes in climate attention should be unaffected by a potentially confounding direct effect of *Industry CDP disclosure*. Second, Lennox, Francis, and Wang (2012) point out that multicollinearity issues can arise in a selection model if a weak exclusion restriction is imposed. Thus, we verify, using variance inflation factors, that our outcome equation does not suffer from such problems. Third, we report OLS regressions for robustness, which are unaffected by a potential violation of the exclusion restriction. This also follows Lennox, Francis, and Wang (2012), who recommend testing for robustness using alternative model specifications. Fourth, we continue to find significant effects of carbon intensities if we examine an alternative instrument (unreported) that exploits that firms that generate more foreign earnings have a higher propensity to report to CDP (Stanny and Ely 2008). At the same time, the fraction of foreign income is unlikely to have a direct effect on the cost of option protection against climate policy uncertainty. The economic effects in the outcome equation are somewhat smaller with this instrument. The reason is that information on foreign income is missing for most utilities. However, these firms belong to the most carbon-intense firms and excluding them biases effects downwards. Fifth, we use President Trump's election as an exogenous shock to climate policy uncertainty to mitigate concerns about the exclusion restriction.

Climate Risk Disclosure and Institutional Investors

Emirhan Ilhan Philipp Krueger Zacharias Sautner Laura T. Starks

Abstract

Employing disclosure theory, we develop hypotheses regarding the preferences of institutional investors with respect to firms' climate risk disclosures. Through a survey and empirical tests, we test these hypotheses and provide systematic evidence suggesting that institutional investors value and demand climate risk disclosures, and that influence and selection effects explain the equilibrium relations between institutional ownership and disclosure. We establish evidence on the influence and selection effects of the climate risk disclosures by examining the French Article 173 and the UK mandatory carbon disclosure regulation.

JEL Codes: G11, G3, Q54

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Financial market efficiency relies on timely and accurate information regarding firms' risk exposures. However, many believe that investors lack sufficient information on an increasingly important and pertinent risk, climate risk. High-quality information on firms' climate risk exposures is critical for informed investment decisions as well as the appropriate pricing of these risks and their related opportunities (Litterman 2016; Krueger, Sautner, and Starks 2020). Moreover, with climate change increasingly considered to be a danger to the financial system, sound disclosure on climate risks is essential for regulatory efforts to protect financial stability, as pointed out by regulators in the UK, US and EU.[57]

Because of the perceived shortcomings in climate risk disclosures, initiatives have developed to encourage or mandate improved reporting on these risks. These initiatives, such as the Task Force on Climate-related Financial Disclosures (TCFD), investor letters to CEOs (Blackrock 2021), or government-mandated disclosures as already occurring in New Zealand, the UK or France and recently called for by the G7, reflect a belief that climate risk information is valuable and necessary for investment decision-making.[58]

However, the fact that many firms still do not provide the disclosures voluntarily suggests there exist counterbalancing considerations. As pointed out in reviews by Goldstein and Yang (2017) for financial information, and Christensen, Hail, and Leuz (2021) for non-financial information, although disclosure may have benefits, for example by increasing stock liquidity, reducing a firm's cost of capital, or making the pricing of risks more efficient, disclosure may also impose unwarranted costs on a firm. For example, in the climate context, disclosure on climate risks could reveal proprietary information about a firm's future strategy and current operations. Further, Bond and Goldstein (2015) show theoretically that if firm managers rely on market prices to learn, there may exist a cost to divulging too much information that can affect the prices.[59] In a climate context, however, given the

[57] See Carney (2015), Davidson (2021), or European Central Bank and European Systemic Risk Board (2021).
[58] See Carbis Bay G7 Summit Communiqué (2021).
[59] The authors' setting is with governments as the decision maker, but the authors point out that their results would also apply to firm management and boards of directors.

uncertainties surrounding the effects of climate change and the expected governmental responses, corporate managers may rely more than in other circumstances on learning from market prices. Moreover, Goldstein et al. (2021) show that mandated disclosure of non-pecuniary information may affect the pricing of financial information.

Consistent with these diverging perspectives on climate reporting and its benefits and costs, little systematic evidence exists regarding the extent to which institutional investors actually attribute value to firms' climate risk disclosures. Institutional investors have the potential to play a pivotal role in climate finance – their pressure is considered to be the most powerful financial mechanism to reduce firms' climate risk exposures according to the investors and academics surveyed by Stroebel and Wurgler (2021). This pressure is likely to extend also to climate-related disclosures.

In this paper, we employ concepts from theories of corporate disclosure to develop hypotheses regarding the preferences of institutional investors with respect to climate risk disclosures. Our hypotheses take into account that climate reporting differs from financial reporting. Employing climate risk disclosure data from CDP (formerly called the Carbon Disclosure Project) for an international sample, we examine the relation between disclosure measures and holdings of institutional investors. We also employ shocks to the firms' and investors' climate-related regulatory and operating environments to more closely examine disclosure-related influence and selection effects of the institutional investors.

We preview these empirical tests with insights from a survey of institutional investors regarding their opinions about climate disclosure. The survey serves the purpose of validating key hypotheses tested in the data and of adding insights difficult to research through archival methods. Our global respondent group consists of important decision makers at some of the world's largest investors: about one-third of the 439 respondents works at the executive level and 11% work for institutions with more than $100bn in assets under management.

The respondents share a strong belief that climate risk disclosure is important: 79% believe climate risk reporting to be at least as important as financial reporting, with almost one-third considering it to be more important. At the same time, the respondents state that the current disclosures are uninformative and imprecise. Investors from countries with high environmental norms, very large (and arguably universal) investors, and investors that incorporate climate risks when investing because of legal obligations or fiduciary duties attach a greater importance to climate risk reporting. Such investors also show a stronger demand for climate risk reporting and a higher willingness to engage firms to demand such disclosures. Investors who believe that reporting is lacking judge there to be more climate-related overvaluation in equity markets. Better disclosure may in turn contribute to the more efficient pricing of climate risks. Assuming the disclosure is related to financial effects of climate risk, this implication is consistent with academic theory and practitioners' views.[60]

Constituting the core of our paper, we use the holdings and disclosure data to test a series of hypotheses linking institutional ownership to climate risk reporting in an international sample. Instead of considering broadly-defined institutional ownership, we partition institutional ownership and predict effects for specific groups of institutional owners that would plausibly reflect a stronger demand for more meaningful climate disclosure.

Our first measure captures ownership from countries where institutional investors are expected to follow stewardship codes designed to promote corporate sustainability. In order to follow these codes, these institutions need more information from their portfolio firms and they should in turn have a higher propensity to demand climate risk disclosure. The second measure we employ takes into consideration that the demand for climate reporting should be based in part on whether the investors are located in countries with norms to be more climate-conscious (Dyck et al. 2019). Finally, the third measure identifies disclosure demand by universal owners, who by virtue of their broad ownership across many firms face externalities in their holdings. These investors can benefit if climate risk disclosure mandates pressure firms to reduce carbon emissions, i.e., reducing the externalities they face. We label these three measures of institutional investor ownership as "climate-conscious." Given the theoretical literature that suggests that voluntary climate disclosure can have unwarranted costs to firms and that our survey indicates institutional investors value such information, we expect that higher ownership by the climate-conscious groups of investors would be associated with a greater tendency for the firm to voluntarily

[60] See Goldstein and Yang (2017) or the statement by Michael Bloomberg, Chair of the TCFD, that *"increasing transparency makes markets more efficient, and economies more stable and resilient."* (https://www.fsb-tcfd.org/). If the disclosure is related to non-pecuniary information regarding climate risk, Goldstein et al. (2021) show that these statements about the relation between transparency and market efficiency may not hold.

disclose climate risks.

We use several measures to capture climate risk disclosures. First, we identify whether firms disclose their Scope 1 carbon emissions to CDP. Scope 1 emissions derive from sources directly owned or controlled by firms, and thus, serve as a proxy for regulatory climate risks (Ilhan, Vilkov, and Sautner 2021; Bolton and Kacperczyk 2021a). Second, we use a measure of disclosure on broadly-defined climate risks developed by Flammer, Toffel, and Viswanathan (2021). This measure is based on whether firms identify and disclose information on three climate-related risks to CDP: regulatory, physical, and other risks. Third, to capture the overall quality of a firm's CDP climate risk disclosures, we employ a score that measures the completeness of a firm's CDP survey responses.

All of these CDP-based measures of climate disclosure are positively and significantly associated with each of our three measures of climate-conscious ownership. Universal ownership most strongly predicts disclosures (always at the 1% significance level), but we also find meaningful associations between disclosure and the other measures of the presence of climate-conscious owners. In terms of magnitudes, a one-standard deviation increase in universal ownership implies an increase in the Scope 1 disclosure rate by 6 percentage points (pp), or 23% of the variable's mean. In addition, a one-standard deviation increase in ownership from high-norms country investors comes with an increase in the disclosure measure by Flammer, Toffel, and Viswanathan (2021) by 0.06 or 12% of the variable's mean.

We complement these findings by documenting that climate risk reporting depends on costs and benefits of producing such disclosures (Goldstein and Yang 2017; Christensen, Hail, and Leuz 2021). While the disclosure costs should be considered by firms and their investors, that is, in the supply and demand of the information, some disclosure benefits are not fully internalized by firms and accrue only for (some) investors. We consider these tests as mostly descriptive as they are based on rough proxies.

Climate risk disclosures are associated with proprietary costs if they reveal confidential information about a firm's strategy to competitors (Verrechia 1983). We examine the role of proprietary disclosure costs by exploiting that such costs are larger when firms operate in more competitive environments (Verrecchia 1990). An externality benefit of climate reporting is that it can increase firms' accountability regarding climate change, which has been shown to reduce their climate externalities on society (Tomar 2021; Downar et al. 2021; Jouvenot and Krueger 2021). Hence, the disclosure demand should be smaller for firms facing more competition, and larger for firms in high-emission industries. Our evidence is consistent with the disclosure demand being affected by these costs and benefits. The effect of climate-conscious ownership on disclosure is moderated among firms with high proprietary costs, and it is magnified among firms in high-emission industries.[61]

The estimated relationships could exist for two non-mutually exclusive reasons. Climate-conscious institutions may actively engage firms to demand that they voluntarily produce such information (influence effect), or climate-conscious institutions could have a propensity to invest in firms that already provide such disclosures (selection effect). We explore two settings to understand whether the relationship between climate-conscious ownership and climate reporting originates from either of these types of effects.

We start by exploiting a new regulation in France, Article 173, which requires French institutional investors to disclose the climate risks of their portfolio assets. As a result of the rule, firms owned by many French institutions should experience a plausibly exogenous shock to the demand for climate risk disclosures. Indeed, we demonstrate for firms owned by many French institutions that their disclosures improve in response to Article 173.

This setting supports an interpretation whereby institutions influence firms to improve their reporting. To evaluate selection effects, we consider a shock to the supply of climate-related information in the UK. In 2013, the country passed a law requiring listed firms to disclose carbon emissions in their annual reports. Apart from making emissions public, the law made these data more comparable by mandating standardized disclosures. We find that climate-conscious institutions significantly increased investments in previously non-disclosing firms mandated by the law to increase their climate disclosures.

Overall, we conclude that climate risk disclosures are the results of investors actively demanding

[61] In unreported tests, the effects of climate-conscious ownership is magnified among large firms. This result is consistent with an interpretation whereby larger firms find it less costly to produce the climate-related information and thus face stronger disclosure demand by climate-conscious investors. The reason is that climate disclosure costs, which originate from the collection, compilation, and reporting of the information, likely have a significant fixed cost component, and smaller firms may lack the structures or processes to efficiently produce the required climate risk data (Christensen, Hail, and Leuz 2021). We interpret these findings with due caution as firm size is a rough proxy for information production costs (e.g., firm size is related to many also reflect reputational benefits from disclosure).

more information, but also that these disclosures lead to increased investments by institutions that value such disclosures. An understanding of the equilibrium level of climate reporting in turn requires the consideration of influence and selection effects.

Our paper contributes several novel findings to the literature on voluntary disclosure (Bond and Goldstein 2015; Jayaraman and Wu 2019, 2020), and specifically to the literature on non-financial reporting, of which climate risks are the most important current component (Leuz and Wysocki 2016, Goldstein and Yang 2017, and Christensen, Hail, and Leuz 2021 review the disclosure literature). Most closely related to our work is Flammer, Toffel, and Viswanathan (2021) who find that activism by long-term institutional investors increases their portfolio firms' climate risk disclosures to CDP. While our work is complementary to that of Flammer, Toffel, and Viswanathan (2021), it is also fundamentally different as we examine investor heterogeneity across the climate-conscious investor dimension; we consider the role of influence and selection effects in three unique settings; we validate our insights with a survey instrument; and we provide global evidence.

We also contribute to the broader literature on climate disclosure. Matsumura, Prakash, and Vera-Muñoz (2014) conclude that markets discount firms that do not disclose emissions through CDP, although Griffin, Lont, and Sun (2017) suggest that the differences may not arise from CDP disclosure. Bolton and Kacperczyk (2021b) find that Scope 1 disclosures lead to lower returns and divestments by institutional investors (which they argue is due to exclusionary screening based on *disclosed* emissions). Matsumura, Prakash, and Vera-Muñoz (2021) analyze 10-K climate disclosures and find that disclosers have lower costs of equity, Kölbel et al. (2021) show that 10-K climate disclosure affects CDS spreads, and Berkman, Jona, and Soderstrom (2021) find that a 10-K measure of climate risk negatively correlates with firm value. Our paper is also related to Solomon et al. (2011) who interview investors revealing that they use private channels of discourse with firms to compensate for the inadequacies of climate reporting, and Ramadorai and Zeni (2021) and Bolton and Kacperczyk (2021c) who use CDP data to infer firms' emission abatement plans or net-zero commitments. Focusing on the oil and gas industry, Eccles and Krzus (2019) examine the extent to which firms disclose information in line with the TCFD recommendations. Climate effects of institutional owners are explored in Azar et al. (2021) who find that Big-3 ownership is associated with emission reductions, and in Kundu and Ruenzi (2021) who show that firms that experience increases in climate-conscious ownership reduce emissions in the longer run.

In terms of our specific settings, we relate to Krueger (2015) who shows beneficial valuation effects resulting from the UK carbon disclosure regulation, Jouvenot and Krueger (2021) who use the same setting to document emission reductions for UK firms relative to non-UK control firms, and Bolton and Kacperczyk (2021b) who find that the UK reform reduced stock-level uncertainty. Mésonnier and Nguyen (2021) show that Article 173 reduced the financing of fossil fuel firms by institutions subject to the new law.

1. Conceptual Framework

Our empirical analysis links institutional ownership to climate risk reporting, taking into account that climate reporting differs from financial reporting (Christensen, Hail, and Leuz 2021). Notably, climate-related reporting targets a wider audience, is multidimensional, is difficult to measure in monetary terms, is hard to compare and standardize, can have costs for firms, but is also argued to have externality benefits beyond a firm. These aspects affect the demand for such information more for some institutional investors. Thus, instead of considering broadly-defined institutional ownership, we develop measures that plausibly reflect a stronger demand for climate risk reporting by certain types of investors (Dasgupta, Fos, and Sautner 2021 highlight the importance of addressing such heterogeneity).

The first measure captures institutional ownership from countries with stewardship codes that develop principles for institutional investors with regard to their portfolio firms. Stewardship codes relate to the oversight role of institutions to create long-term value for their clients or beneficiaries, and they aim to promote corporate sustainability. Investors subject to stewardship codes should consequently have a higher propensity to demand climate risk disclosure from portfolio firms. [62]

The second measure captures disclosure demand due to environmental norms in an institutional investor's home country. In Williamson's (2000) framework for institutional influences in economic

[62] While stewardship codes do not formally require compliance with their principles, institutions that do not comply with them need to explain publicly why they did not follow a specific recommendation of the code. Compliance is therefore usually high. Shiraishi et al. (2019) provide international evidence demonstrating that stewardship codes are effective by enhancing the monitoring activities of institutional investors.

activity, the most fundamental are social norms and cultural influences. Similarly, Guiso, Sapienza, and Zingales (2006) discuss the link between economic and culture outcomes, which they define as "*those customary beliefs and values that ethnic, religious, and social groups transmit fairly unchanged from generation to generation*." Further, Dyck et al. (2019) show that investors from countries with high environmental norms actively improve firms' ESG policies. Thus, we expect that demand for climate reporting is based in part on whether investors are from countries with more climate-conscious norms.

The third measure captures ownership by universal owners, building on the idea that the benefits of climate risk disclosure are not reaped equally across investors.[63] Specifically, climate reporting can enhance the accountability of firms, which in turn can cause the firms to reduce their emissions and the corresponding negative externalities on other firms or society more generally (Christensen, Hail, and Leuz 2021). These benefits likely matter most for universal owners as they are long-term investors owning large parts of the economy and thus subject to climate externalities. Consequently, firms with greater ownership by universal owners would be expected to experience stronger demand for climate risk disclosure.

For the sake of brevity, we label these three groupings of institutional investors as "climate-conscious" investors.

As pointed out by Goldstein and Yang (2017) for disclosure in general, and Christensen, Hail, and Leuz (2021) for CSR disclosure, the demand and supply of climate risk disclosure depends on these costs and benefits.[64] While the disclosure costs should be considered by firms and their investors, that is, in their supply and demand of the information, some of the disclosure benefits are not fully internalized by firms and accrue only for (some) investors.

A cost arises because climate risk disclosure could reveal proprietary information about a firm's strategy to its competitors. This issue has been pointed out consistently by firms and other observers.

[63] As defined by Hawley and Williams (2000), a universal owner is a large institutional investor with three attributes: owning a broad cross-section of the economy, holding shares for the long term and not trading often, making them exposed to firms' externalities.
[64] We consider climate-specific costs and benefits, but climate disclosure may have other more general costs and benefits. On the benefit side, it may improve liquidity, lower the costs of capital, improve risk sharing, or facilitate monitoring. On the cost side, it may crowd out information acquisition, reduce risk sharing, or increase return volatility.

For example, Google reportedly would not reveal its carbon footprint because of trade secrecy and similarly, a group of oil and gas firms that were trying to abide by the TCFD recommendations maintain that contractual, practical or legal reasons could prohibit them or limit their scope for revealing disaggregated information about climate risks (WBSCD 2018). Moreover, Griffin and Jaffe (2018) point out that these costs of disclosure can be significant – that disclosing such confidential information, which would be available to rivals, *"could be particularly burdensome."* These costs can be particularly high for detailed disclosures. Appendix A1 provides further anecdotal evidence on these costs.[65]

To explore the role of proprietary disclosure costs, we build on evidence that product market competition is pivotal for the magnitude of such costs, and that competition reduces the propensity to make proprietary disclosures (Verrecchia 1990). Proprietary costs should in turn be higher for firms operating in more competitive markets, and the demand for disclosure by climate-conscious institutions should then be smaller.

There can also exist climate-specific disclosure benefits. A benefit for some investors is that the disclosure could increase pressure on firms to reduce the reported carbon emissions, which has been shown to lead to a reduction in the negative externalities generated on other firms and the environment more generally (Tomar 2021; Downar et al. 2021; Jouvenot and Krueger 2021). This externality benefit implies that the disclosure demand by climate-conscious institutions should be larger for firms in high-emission industries.

2. Climate Risk Disclosures and Institutional Investors: Survey Evidence

In this section, we preview the analysis using disclosure and ownership data with insights from a survey to corroborate our hypotheses and to provide results that cannot be obtained from the archival data. Surveys are increasingly used in the ESG literature (McCahery, Sautner, and Starks 2016; Krueger, Sautner, and Starks 2020; Amel-Zadeh and Serafeim 2018).

2.1 Survey Design

Our survey was developed through an iterative process and distributed through four channels, yielding

[65] Climate risk disclosure is also costly because of the need to develop new processes and structures to collect, compile, and report the relevant information (see Appendix A2 for anecdotal evidence).

a total of 439 responses. Appendix B1 provides details on the design and delivery. Table 1, panel A, reports summary statistics of the survey-based variables that we employ in our tests.[66] Definitions are provided in the Data Appendix. We are confident that in the vast majority of cases we have only one observation per institution as for 87% of the observations, key identifying characteristics do not coincide.

We assess the role of non-response bias by comparing key characteristics of the responding investors to those of the institutional investors in the FactSet population.[67] Although our respondents may be biased toward investors with a high ESG awareness (given the high median ESG share of 30% and that such investors may be more disposed to participate in our survey), responses of such investors are particularly important, because they are more likely to shape future climate disclosure policies through engagement, industry initiatives, or lobbying with regulators. Moreover, given that 27% of investors manage more than $50bn, they have the clout to be effective in their efforts. Appendix B2 discusses concerns over non-response and acquiescence bias in detail.

2.2 Investors' Views on Climate Risk Disclosures

In light of the potential benefits and costs of climate reporting, the importance that institutional investors attribute to this reporting is ambiguous. To evaluate the ambiguity, we asked the survey participants to indicate how important they consider the reporting on firms' climate risks relative to the reporting on financial information. Figure 1 shows that 79% of respondents believe that climate risk disclosure is at least as important as financial disclosure, with almost one-third considering it to be more important.

The fact that climate risk disclosures are considered important for the majority of the respondents raises the question of how they perceive the quality of the current disclosure practices. Table 2, panel A, shows a widespread view that existing disclosures are uninformative. Many respondents believe that management discussions on climate risks (68% agree or strongly agree) and quantitative information

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[66] Appendix Table 1 documents that about one-third of respondents hold executive-level positions in their institutions. Eleven percent are employed by institutions with assets of more than $100bn.

[67] This approach follows Karolyi, Kim, and Liao (2019). Appendix Figure 1 shows that pension funds and banks are overrepresented in our sample, while mutual funds and asset managers are underrepresented. Our respondents are more likely to work for institutions in North America and Europe.

on these risks (67% agree or strongly agree) are imprecise. This suggests that the current voluntary reporting regime does not enable fully informed climate-related investment decisions (this could be a reason why climate risks are difficult to price in equity markets, an issue we address below). Indirectly, the responses further imply that many firms do not consider the net benefits of climate risk reporting to be sufficiently high, as they would otherwise reveal such information voluntarily and with better quality. At the same time, many investors value such information, as indicated by their responses, believing that the benefits outweigh the costs at a typical firm.

The diverging perspectives between firms and their investors raise the question of whether mandatory and standardized reporting is needed. In general, the rationale for mandatory disclosure regulation requires the existence of externalities or market-wide cost savings that regulations can mitigate (Shleifer 2005). A firm's contribution to climate change is such an externality. Further, standardization would make it less costly for investors to acquire and interpret information relevant to evaluating a firm's climate risks. Mandatory disclosure could also provide commitment and credibility for firms' climate disclosures, especially if the standards are specific and well enforced (Christensen, Hail, and Leuz 2021).

Indeed, Table 2, panel A documents that many investors believe that standardized and mandatory climate risk reporting is necessary (73% agree or strongly agree). However, a significant challenge for changing the current reporting environment seems to be that standardized disclosure tools and guidelines are not yet widely available (61% agree or strongly agree), and that those that exist are uninformative (64% agree or strongly agree). These views are consistent with recent initiatives that provide explicit disclosure tools and guidelines. Notably, part of the TCFD recommendations center on how climate risks are reflected in metrics and targets. These recommendations are currently voluntary, but they could eventually constitute the basis for mandatory disclosures in many countries.

As a result of current disclosure shortcomings, some investors have developed initiatives beyond the TCFD to improve access to climate risk data (e.g., Climate Action 100+). Consistent with such initiatives, Table 2, panel A, shows that many respondents hold the belief that investors should put pressure on firms to disclose more on their climate risks (74% agree or strongly agree). In addition, in Table 2, panel B, 59% of investors engage or plan to engage firms to report according to the TCFD recommendations. These responses strongly indicate that many investors have a demand for climate risk disclosure, as hypothesized in Section 1. We will provide evidence that this demand leads to more disclosure by firms.

Finally, we surveyed the investors' opinions regarding reporting climate risks for their own portfolios (as required by the French Article 173). In Table 2, panel B, our respondents indicate support for this approach with 60% stating that they (plan to) disclose their portfolio carbon footprints. Guided by these responses and the resultant need for data, we test below whether Article 173 increased disclosures of firms owned by many French institutions.

Overall, our responses support key elements of our hypotheses by indicating a strong demand for climate risk disclosure by institutional investors, and by suggesting that many investors are willing to actively engage firms to increase such disclosure.

2.3 Explaining Investors' Views on the Climate Risk Disclosures

As explained, we expect that views on climate risk disclosure are based in part on whether investors are subject to stewardship codes in their home countries, are located in countries where norms make them more climate-conscious or are universal investors.

In the survey analysis, we proxy for whether an institution is subject to stewardship codes (or similar rules) based on a question in which the respondents were asked whether their institutions have to incorporate climate risks in the investment process because of legal obligations or fiduciary duties. *Fiduciary duty institution* equals one if a respondent strongly agrees to this statement, and zero otherwise. To quantify country norms, we follow Dyck et al. (2019) and use the Yale University's Environmental Performance Index (EPI) to measure environmental awareness across countries. The variable *HQ country norms* takes larger values for investors from countries with a stronger common belief in the importance of environmental issues (EPI value is greater than or equal to the median in a year). Finally, we define a *Very large institution* to be equal to one for responses from an institution with more than $100bn in assets under management, and zero otherwise. Very large investors tend to be universal owners whose broad-ranging ownership, as argued in Section 1, makes them more susceptible to the externalities engendered by climate change. We thus expect them to be more interested in climate risk disclosures and demand that firms produce them.

We include several controls when relating these three variables to the respondents' views on climate risk disclosure. *Climate risk ranking* captures how the respondents rank climate risks relative to traditional investment risks.[68] *Climate risk financial materiality* ranges between one and five with larger values reflecting that climate risks are considered to be more financial materially (we average the responses to questions about the materiality of regulatory, physical, and technological risks). *ESG share of portfolio* is the fraction of assets under management that is subject to ESG principles. We control for an investor's horizon as longer-term investors may particularly value climate risk disclosure (Starks, Venkat, and Zhu 2020; Flammer, Toffel, and Viswanathan 2021). Finally, we account for fixed effects for the respondents' positions, the survey distribution channels, and investor types.

Table 3, panel A, reports the results. The dependent variable in column 1 is the perceived importance of climate risk disclosure (larger values indicate that climate risk reporting is relatively more important). The estimates show that more importance is placed on climate risk reporting by investors that incorporate climate risks in the investment process for legal/fiduciary reasons, by investors from countries with higher environmental norms, and by very large (potentially universal) investors. Beyond the ownership classifications, investors who consider climate risk to be more important and more financially material, also think climate reporting is more important. In the remaining tests, the fiduciary duty investors also believe that current quantitative information on climate risks is imprecise and that investors should demand better disclosure. Further, investors from high-norms countries are more likely to engage firms to demand reporting according to the TCFD recommendations and very large institutions are more likely to disclose their carbon footprints. Overall, Table 3, panel A, validate some key assumptions in our hypothesis development.

2.4 Investors' Views on Climate Risk Disclosure and Climate Risk Mispricing

An important role for climate risk disclosure is in correcting asset mispricing for climate risks, which evidence shows may be present in equity markets (Hong, Li, and Xu 2019). Daniel, Litterman, and Wagner (2018) develop a model in which uncertainty about the effect of emissions on temperature (and

[68] The variable ranges between one (climate risks are the least important risk) and six (most important risk).

on eventual damages from climate change) gradually resolves over time. A mechanism through which this uncertainty disappears is via climate risk disclosures. As firms evaluate climate risks and make their assessments public, equity prices converge towards their fair valuations through the harmonization and comparability benefits of disclosures (Jouvenot and Krueger 2021).

To measure beliefs about equity mispricing, in our survey we allow investors to indicate whether they think that equity valuations in sectors potentially most affected by climate change are overvalued or undervalued. We designate the responses for each sector as ranging from plus two (for valuations much too high) to minus two (for valuations much too low). We then create for each respondent *Climate risk underpricing*, which averages all positive mispricing scores across sectors (negative scores are set to zero). The variable hence captures the extent to which a respondent believes that climate-related overvaluation exists.[69]

In Table 3, panel B, we report regressions to explain perceptions about climate risk mispricing. The results show that perceptions of mispricing are higher for investors that attribute more importance to climate risks, who believe that management discussions or the available quantitative information about climate risks are imprecise, who more strongly agree that investors should demand climate risk disclosure, or who engage firms on either the TCFD recommendations or disclosing carbon footprints. Overall, the respondents' beliefs about the importance, quality, and demand for climate risk disclosure are associated with a perceived underpricing of climate risks. An implication is that better disclosure may contribute to a more efficient pricing of the risks. This insight is difficult to obtain from other types of data.

3. Climate Risk Disclosure and Institutional Ownership

In this section, we employ data on firms' climate disclosures and their institutional investor shareholdings to test predictions regarding institutional investors' preferences for disclosure.

3.1 Carbon-related Disclosure Data from CDP

[69] The average respondent believes that equity valuations in the average sector do not fully reflect the risks from climate change, as the mean of *Climate risk underpricing* exceeds zero (Table 1, panel A). As Appendix Figure 2 shows, the mean overvaluations are highest in the oil and automotive sector.

Our disclosure data derive from CDP, which conducts an annual survey of firms on behalf of institutional investors and other stakeholders. CDP requests that firms voluntarily produce the climate-related data. One complication arises because CDP does not reveal which firms they contact for participation in the survey, thus making it difficult to identify whether a missing observation is due to a firm's refusal to participate in the survey, or because a firm was not requested to participate. To remedy this issue, we follow the approach suggested in Krueger (2015), which builds on the idea that CDP typically requests information from the largest publicly listed firms in a country. Therefore, we create a sample of firms that CDP likely contacted based on their size relative to other firms in their countries. Appendix Figure 3 shows the sample country distribution of our "universe" of firms.

We use multiple complementary measures of climate risk disclosures from the CDP data over the 2010 to 2019 sample period: a measure of whether a firm discloses their carbon emissions, a measure of the types of climate risks the firm discloses, a CDP-assigned score regarding the completeness of the firm's disclosures, and two measures of the quality of the carbon disclosures (among CDP disclosers). Not all of these measures are available for every sample year because CDP added or deleted some questions over time. CDP also modified for some questions the response categories, making a reliable comparison across years difficult. We indicate for which years the respective variables are available.

CDP requests that firms report Scope 1, Scope 2, and Scope 3 emissions.[70] Our tests use *Scope 1 disclosure*, which is one if a firm discloses these emissions to CDP in a year, and zero otherwise. The variable is available for all sample years. Table 1, panel B, shows that Scope 1 emissions are disclosed in 26% of sample firm-years.

To capture disclosure on climate risks more broadly, we adopt a variable used by Flammer, Toffel, and Viswanathan (2021) which leverages the fact that CDP asks firms to disclose information on regulatory, physical, and other risks. *Climate risk disclosure* can take four values: zero if no information on the risks is disclosed; one if information on one risk type is disclosed; two if information

[70] Scope 1 emissions are direct emissions from owned or controlled sources of the disclosing firm. These emissions are distinct from Scope 2 and Scope 3 emissions, which are either indirect emissions from the generation of purchased energy (Scope 2), or all indirect emissions (except those included in Scope 2) that occur in the value chain (Scope 3). Firms that report on one emission type usually report on other emission types as well. In our sample, the correlation between Scope 1 and either Scope 2 or Scope 3 disclosures are above 96%, and we find similar results if we use either Scope 2 or Scope 3 as alternative emissions measures.

on two risk types is disclosed; and three if information on all three risk types is disclosed. We construct the measure from 2010 to 2016 (from 2017 onwards, the structure of the question changed), and we provide complementary tests for *Regulatory*, *Physical*, and *Other risk disclosure* (each variable equals one if information on the respective risk is disclosed, and zero otherwise). Table 1, panel B, shows that these three risks are disclosed in 17% to 19% of the firm-years. The mean of *Climate risk disclosure* is 0.5, and the correlation with *Scope 1 disclosure* is 70% (Appendix Table 2, panel A).

To capture the overall quality of climate disclosures, we use a score computed by CDP to measure the completeness of a firm's survey responses. CDP allocates points to each survey question depending on the amount of data requested, and the *Climate disclosure score* reflects the fraction of the answered questions (the score is multiplied by 100 and ranges from 0 to 100). The score is available from 2010 to 2015 as it was replaced in 2016 with a score that conflates disclosure quality with climate performance (e.g., in the revised score, lower reported emissions lead to higher scores). The average score across all firm-years is 16.

To disentangle the effects on climate reporting from a broader financial reporting preference, we control for the measure of financial disclosure quality proposed by Chen, Miao, and Shevlin (2015). As in their paper, we count the number of non-missing Compustat line items and scale the resultant count by the number of possible line items to capture the completeness of firms' reports.[71]

3.2 Institutional Ownership Data

We use FactSet data to create three institutional ownership variables.

Stewardship code IO is the fraction of a firm owned by institutional investors from countries with stewardship codes. To determine whether an institution's home country has a stewardship code in place, we use data from Katelouzou and Siems (2021) who document the staggered introduction of these codes across countries.

High-norms IO captures the fraction of ownership by institutions from countries with high environmental norms as suggested by Dyck et al. (2019). We again use the data from EPI and the same

[71] Our regressions use country fixed effects to control for the data source (Compustat NA or Global), but we add a *Compustat NA firm* dummy (not reported) as the sample contains four North American firms that are in Compustat Global (e.g., Royal Caribbean Group).

procedure as in Section 2.3.

Universal owner IO reflects the fractional ownership by universal owners. To identify such owners, we use FactSet to rank institutions based on the number of firms they own in a year, and classify investors as universal owners if they rank in the top 1%. Beyond the Big 3, universal owners include a number of institutions that are not primarily passive investors.

Table 1, panel B, shows that the three ownership variables vary between 9% and 15%, with considerable cross-sectional heterogeneity. Appendix Table 2, panel B, demonstrates that the measures, as would be expected, correlate positively, but the fact that correlations are between 60% and 74% reflects that they capture different aspects. We also create and control for three measures of the residual ownership by "non-climate-conscious" institutions.

3.3 Institutional Ownership and Climate Risk Disclosure

We analyze the CDP data by relating climate risk disclosure to climate-conscious institutional ownership. For firm *f* in country *c* and year *t*, the model is:

$$Climate\ disclosure_{f,c,t} = \alpha + \beta\, IO_{f,c,t} + \delta\, \boldsymbol{X}_{f,c,t} + \mu_f \text{ x } \theta_t + \gamma_c + \varepsilon_{f,t}, \quad (1)$$

where *Climate disclosure*$_{f,c,t}$ represents *Scope 1 disclosure*, *Climate risk disclosure,* or *Climate disclosure score* (Section 3.1), $IO_{f,c,t}$ denotes *Stewardship code IO*, *High-norms IO,* or *Universal owner IO* (Section 3.2), and $\boldsymbol{X}_{f,c,t}$ contains control variables. We control for the residual ownership measures, financial characteristics, and the quality of financial disclosures. As climate risks vary across sectors and time, we include industry fixed effects (μ_f) interacted with year fixed effects (θ_t). Unless indicated differently, we include country fixed effects (γ_c) to account for cross-country differences. Standard errors are clustered at the country level.

In Table 4, we report the results in columns 1 to 3 for *Scope 1 disclosure*, in columns 4 to 6 for *Climate risk disclosure*, and in columns 7 to 9 for *Climate disclosure score*. As explained earlier, the observations differ across regressions as the three variables are available for different years. We indicate the sample periods in the table.

We find strong and consistent evidence that climate-conscious ownership positively relates to the decision to disclose emissions, overall climate risk disclosure, and climate risk disclosure quality. In terms of statistical significance, *Universal owner IO* most strongly predicts disclosure (always at the 1% level). In column 1, a one-standard deviation increase in *Stewardship code IO* is associated with a 3pp increase in the propensity to disclose Scope 1 emissions, or 12% of the variable's unconditional mean. Across all specifications, large firms, firms with higher dividend payouts, and growth firms disclose more.

In Appendix Table 3, we examine the disclosure of the three components of climate risk separately. *Universal owner IO* predicts disclosure of all three risk components (i.e., regulatory, physical, and other risks), while the effects of *Stewardship code IO* and *High-norms IO* originate mostly from disclosure of regulatory climate risk. The weaker effects for physical and other risks may be due to an investor belief that such risks materialize later compared to regulatory risks (see Krueger, Sautner, and Starks 2020). The more immediate characteristics of regulatory risks may imply that disclosure about them is more important. The strong effects for *Universal owner IO* further indicate the importance of disclosure externalities, which matter the most for universal owners.

In In Appendix Table 4, we provide complementary tests using the text-based measures of climate risk disclosure in the 10-Ks of US sample firms from Matsumura, Prakash, and Vera-Muñoz (2021). We create a dummy variable that is one if at least one of eight climate-related keywords occurs in a 10-K, and zero otherwise (Appendix E contains details). We find no relationship between this variable and climate-conscious ownership. The lack of an effect may be explained with the less-structured, less-standardized, and more-greenwashed climate disclosures in 10-Ks. Investors may in turn prefer the structured and standardized CDP disclosures. (In unreported results, climate-conscious ownership remains positively and significantly related to carbon disclosures among US firms). This interpretation is consistent with our survey results in which the investors emphasized a lack of standardization and uninformative disclosures as problems of mandatory disclosure such as 10-Ks. In Appendix Table 2, panel A, the 10-K-based measures also correlate only weakly with the CDP measures.

3.4 Costs and Benefits of Climate Risk Disclosure

We next consider that the demand for climate risk reporting by climate-conscious institutions should depend on the costs and benefits of making these disclosures. For this purpose, we amend Equation (1) and allow the effects of the particular institutional ownership, $IO_{f,c,t}$, to vary across firms depending on the cost or benefit proxy:

$$Climate\ disclosure_{f,c,t} = \alpha + \beta_1\ IO_{f,c,t}\ x\ Z_{f,c,t} + \beta_2\ IO_{f,c,t} + \beta_3\ Z_{f,c,t} + \delta\ \boldsymbol{X}_{f,c,t} + \mu_f\ x\ \theta_t + \gamma_c + \varepsilon_{f,c,t}, \tag{2}$$

where $Climate\ disclosure_{f,c,t}$, and $IO_{f,c,t}$ are defined as above, and $Z_{f,c,t}$ is one of the two proxies for the cost or benefit of climate reporting, varying at the firm or industry level, respectively.

To test for the role of proprietary costs, we interact $IO_{f,c,t}$ with the Hoberg and Phillips (2016) firm-level, text-based HHI measure for whether a firm operates in a competitive environment. $High\text{-}competition\ firm_{f,c,t}$, is one if a firm operates in a competitive environment where the HHI is below the median in a year (this measure is only available for US firms). Since proprietary disclosure costs are expected to be higher for firms in more competitive markets, the demand for climate reporting by climate-conscious institutions should be smaller among such firms; this implies a negative estimate for the β_1 coefficient.

Further, the demand for climate disclosure by climate-conscious investors should be greater for firms in high-emitting industries. We test this effect by interacting $IO_{f,c,t}$ with $High\text{-}emission\ industry_f$, which equals one if a firm operates in one of the twenty industries with the highest Scope 1 emissions. In these regressions, we expect that β_1 is positive.

Table 5 reports the results. Panel A indicates that proprietary costs affect the disclosure demand as the coefficients on *High-competition firm x IO* are negative across all disclosure variables and for all climate-conscious ownership variables. In column 1, the positive effect of *Stewardship-code IO* on *Scope 1 disclosure* is reduced by half among firms in competitive environments.. Panel B also largely confirms a stronger disclosure demand for firms in high-emitting industries, with six of the nine specifications providing positive and significant estimates for β_1. Surprisingly, *Universal owner IO* only relates to *Climate risk disclosure*. Overall, Table 5 provides descriptive evidence that the climate reporting demand by climate-conscious institutions depends on the costs and benefits of the reporting.

4. Shocks to the Demand and Supply of Climate Risk Information

The positive relationship between climate-conscious ownership and climate risk disclosure that we have documented could exist for two *non-mutually exclusive* reasons, both of which may be relevant in practice. First, the relationship could exist because of influence effects. Climate-conscious institutions may actively engage firms to demand that they voluntarily produce climate risk information (e.g., through the submission of shareholder proposals calling for firms to share more information on their climate policies).[72] Engagement by institutional investors to demand disclosure can originate from several sources: the investors' beliefs that the disclosure will inform their investment decisions, including the possibility that it will reduce climate risks in the portfolios, the investors' needs to publish data in their own filing requirements, or the investors' own clients' or beneficiaries' desires for such disclosures.

A second explanation derives from selection effects, that is, climate-conscious institutions are likely to invest in firms that provide better disclosures because they believe such firms are less risky or because their clients and beneficiaries impose such a constraint. We exploit shocks to the demand and the supply of climate risk information in order to gauge whether one or both of them better explain the findings. The shocks we employ are changes in regulatory settings that allow us to directly speak to the influence and selection effects.

4.1 French Climate Risk Disclosure Article 173

Shortly before the Paris Agreement, on August 17, 2015, France passed the *Energy Transition for Green Growth Act*. As part of this law, Article 173 requires French institutional investors to disclose their climate risk exposures. Though, formally, the regulation is on a "comply or explain" basis, compliance among French institutions is high (86% in 2017/2018 according to Novethic 2018). In order to comply with Article 173, French institutional investors would need information on their portfolio holdings, increasing their demand for climate risk disclosures. Consequently, we hypothesize that firms held by many French institutions should have increased their climate risk disclosures after Article 173 went into

[72] In some cases, when the subsequent disclosure in response to these proposals has still been deemed inadequate, investors called for voting against the entire board. See "Exxon Shareholders Pressure Company on Climate Risks," *The Wall Street Journal*, May 31, 2017; "Occidental Shareholders Vote for Climate Proposal," *The Wall Street Journal*, May 31, 2017; and "Exxon Directors Face Shareholder Revolt Over Climate Change" *Bloomberg*, May 4, 2019.

effect in January 2016.

Although the demand effect should impact firms with large French institutional ownership around the world, a corollary prediction is that it should be particularly strong for firms headquartered in France. First, French investors would presumably exercise more pressure on local firms, possibly because of domestic reputational concerns (Krueger, Sautner, and Starks 2020). Second, Article 173 also mandates that French-listed firms disclose their climate risks, which at first glance implies an additional supply reporting shock for local firms. However, the law allows large discretion for French firms in how to comply with the mandate, suggesting that they could simply provide boilerplate disclosures and exploit the large ambiguity about how compliance is enforced. Thus, the French institutional investors may act as catalysts to improve disclosure even among French firms.[73] Consequently, we predict that the climate disclosures of firms owned by many French institutions increases in response to the Article 173 relative to those of other firms. French institutions may engage firms on their own or as lead investors in investor coalitions, as documented for PRI in Dimson, Karakaş, and Li (2021). The latter channel leverages the equity stakes of other investors and is, for example, used by Amundi, France's largest institutional investor (Amundi 2020).

To test our prediction, we estimate difference-in-differences regression (DiD) for firm f in country c and year t:

$$\begin{aligned}\textit{Climate disclosure}_{f,c,t} = \alpha + \beta_1\, \textit{Post Article 173}_t \times \textit{French IO}_{f,c,t} + \beta_2\, \textit{Post Article 173}_t \\ +\beta_3 \textit{French IO}_{f,c,t} + \delta \boldsymbol{X}_{f,c,t} + \mu_f \times \theta_t + \gamma_c + \varepsilon_{f,c,t},\end{aligned} \quad (3)$$

where $\textit{Climate disclosure}_{f,c,t}$ is *Scope 1 disclosure* or *Climate risk disclosure*. (*Climate risk disclosure* is available only for one year, and *Climate disclosure score* is unavailable, after Article 173.) $\textit{Post Article 173}_t$ equals one for 2016 and afterwards, and zero before. *French IO* denotes one of two measures of French institutional ownership: *French IO* is the percentage ownership by French institutions; and *High French IO* indicates whether French institutional ownership is above the sample median. Our coefficient of interest is β_1, which captures how the disclosure of firms with high French ownership changes from before to after Article 173. Some regressions include triple interactions to

[73] As the evidence for French firms is more difficult to interpret, we focus on non-French firms to provide evidence for influence effects.

examine effects among French firms.

Table 6, columns 1 and 5, shows that firms with higher French ownership (*French IO*) increase climate reporting more after Article 173 is introduced, compared to firms with lower French ownership. Effects get stronger in columns 2 and 7 if we consider the subsample of firms where French institutional ownership is at least 3%. Similarly, columns 3 and 5 continue to show effects in the full sample for *High French IO*. In column 3, *Scope 1 disclosure* increases by 4pp more at firms with high French ownership after Article 173, a large effect compared to the mean of 26%. In columns 4 and 8, effects are amplified among French firms as indicated by the significant triple interactions. However, *Post Article 173 x High French IO* remains positive and significant, so the overall effects are not confined to French firms only. Overall, Table 6 supports the notion that the shock to the demand for climate risk disclosure by French institutions due to Article 173 improved firm-level disclosures.

4.2 UK Mandatory Carbon Disclosure

We evaluate selection effects by exploiting a shock to the supply of climate risk information. In 2013, the UK passed a law requiring large, publicly listed UK firms to disclose carbon emissions in their annual reports (Krueger 2015; Jouvenot and Krueger 2021).[74] This mandate is intended to allow investors to incorporate climate risks into their analyses, and to better monitor whether the UK's carbon reduction objectives are being met. The regulation makes emissions available and more comparable, due to the standardized nature of the required disclosures. Hence, the regulation shocks the supply of climate information at previous non-disclosers, and it allows us to identify whether climate-conscious institutions increase investments in firms mandated to increase their disclosures. To test for the role of selection effects, we predict that climate-conscious institutional ownership in prior UK non-disclosers increases in response to the UK mandatory carbon disclosure requirement. We test this prediction using a triple DiD regression:

$$IO_{f,c,t} = \alpha + \beta_1\, \textit{Post UK carbon disclosure}_t \text{ x } \textit{UK firm}_{f,c,t} \text{ x } \textit{No voluntary carbon disclosure}_{f,c,t} + \beta_2\, \textit{Post UK carbon disclosure}_t \text{ x } \textit{No voluntary carbon disclosure}_{f,c,t} + \beta_3\, \textit{Post} \quad (5)$$

[74] Our sample contains only large listed firms. Through the *Streamlined Energy and Carbon Reporting* policy, the UK recently extended this mandatory disclosure requirements to all firms.

$$UK\ carbon\ disclosure_t \times UK\ firm_{f,c,t} + \beta_4\ UK\ firm_{f,c,t} \times No\ voluntary\ carbon\ disclosure_{f,c,t} + \delta$$

$$\boldsymbol{X}_{f,c,t} + \mu_f \times \theta_t + \gamma_c + \varepsilon_{f,c,t},$$

where $IO_{f,c,t}$ denotes one of the three climate-conscious ownership variables as well as the corresponding residual ownerships; *Post UK carbon disclosure* equals one for 2013 and afterwards, and zero otherwise; *No voluntary carbon disclosure* equals one if a firm did not disclose Scope 1 emissions to CDP before 2013, and zero otherwise; and *UK firm* is one if a firm is from the UK, and zero otherwise. The coefficient of interest is β_1, which reflects how institutional ownership changes due to the regulation at UK firms that did not disclose emissions prior to 2013, relative to UK firms that did disclose emissions.

Table 7, columns 1 to 3, document that climate-conscious ownership increases more strongly in UK firms forced to disclose emissions due the disclosure requirement, than in UK firms that already disclosed such information before the law was introduced. *Stewardship-code IO*, for example, increases by 1.8pp more at UK firms forced to comply, which compares with an average stewardship-code ownership in UK pre-reform non-compliers of 21% (regression coefficients are multiplied by 10 for presentation purposes). In columns 3 to 6, we find no such reactions for the residual ownership variables. In fact, non-universal ownership even decreases at firms prompted to comply with the regulation (the other estimates are positive but insignificant). Interestingly, the estimates for *Post UK carbon disclosure x No voluntary carbon disclosure* suggest that the residual owner types increase their holdings in non-disclosing firms outside of the UK.

Overall, the UK reform demonstrates that climate disclosure is not just the results of climate-conscious investors actively demanding more information, but that these investors also increase investments in firms that improve such disclosures.

5. Conclusion

High-quality information on firms' climate risks is a necessary component of informed investment decisions and of the correct market pricing of climate-related risks and opportunities. In this paper, we provide systematic international evidence from survey and portfolio holdings data on the preferences of institutional investors with respect to climate risk disclosures. We advance the literature by making two contributions.

First, we illustrate that institutional investors value and demand climate risk disclosures. In our survey, the respondents share a strong belief that climate disclosure is important, that their institutions have a strong investor demand for such disclosures, and that they actively engage portfolio firms to improve them. We corroborate these conclusions in our empirical tests using investor holdings, showing that ownership by institutions with a plausibly higher disclosure demand ("climate-conscious institutions") is positively associated with CDP-based measures of climate disclosure.

Second, we demonstrate that influence and selection effects explain the equilibrium relations between institutional ownership and disclosure. Climate risk disclosure of firms owned by many French institutions improves in response to Article 173, which provides a shock to the disclosure demand of French investors. The result support an interpretation whereby institutions influence firms to improve their reporting. We also document selection effects in that we find that climate-conscious institutions significantly increase investments in previously non-disclosing firms mandated by a UK law to disclose carbon emissions.

Institutional investors will remain important in ensuring informative, high-quality climate-related disclosures even if such disclosures become mandatory.

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Figure 1: Importance of Climate Risk Disclosure

This figure illustrates how important investors consider reporting by portfolio firms on climate risks compared to reporting on financial information (Question B1). Of the 439 individuals that participated in our survey, 416 responded to this question. The actual survey question is provided in Appendix B3.

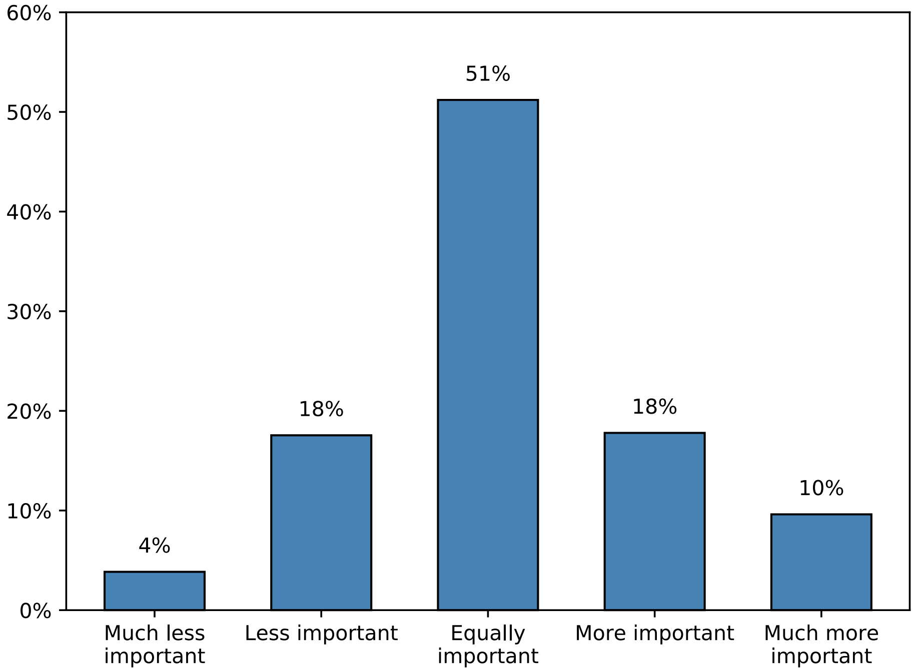

Table 1. Summary Statistics

This table provides summary statistics of the variables used in the survey (panel A) and climate disclosure and investor holdings (panel B) analysis. Observations in panel A are at the respondent level. Observations in panel B are at the firm-year level. Not all variables are available for all respondents and all firm-years.

Panel A. Survey Variables				
Variable	Mean	STD	Median	N
Importance of climate risk disclosure	3.12	0.94	3.00	416
Demand more disclosure	0.28			413
Quant. information imprecise	0.19			413
Management discussions imprecise	0.21			413
TCFD engagement	0.78			304
Carbon footprint disclosure	0.72			327
Climate risk underpricing	0.57	0.43	0.52	357
Climate risk ranking	2.95	1.64	3.00	386
Climate risk materiality	3.73	0.82	3.67	393
Fiduciary duty institution	0.27			415
HQ country norms	0.61	0.06	0.57	425
Very large institution	0.11			430
ESG share of portfolio	0.41	0.32	0.30	415
Medium-term horizon	0.77			432
Long-term horizon	0.18			432
Panel B. Climate-related Disclosure and Investor Holdings Variables				
Variable	Mean	STD	Median	N
Scope 1 disclosure	0.26			43,221
Scope 2 disclosure	0.25			43,221
Scope 3 disclosure	0.26			43,221
Climate risk disclosure	0.50	1.08	0.00	25,932
Regulatory risk disclosure	0.19			25,932
Physical risk disclosure	0.18			23,892
Other risk disclosure	0.17			23,892
Climate disclosure score	16.47	32.82	0.00	25,934
10-K Climate risk disclosure	0.70			3,962
Stewardship code IO	0.14	0.17	0.07	43,221
High-norms IO	0.09	0.11	0.05	43,221
Universal owner IO	0.14	0.14	0.09	37,740
Non-stewardship code IO	0.14	0.22	0.06	43,221
Low-norms IO	0.18	0.24	0.09	43,221
Non-universal owner IO	0.13	0.14	0.08	37,740
French IO	0.01	0.02	0.00	43,221
High French IO	0.50			43,221
Post Article 173	0.40			43,221
Post UK carbon disclosure	0.70			43,221
High-competition firm	0.50			4,739
High-emission industry	0.38			43,221
Log(Assets)	15.03	2.05	15.00	43,221
Dividends/net income	0.38	0.69	0.27	42,867
Debt/assets	0.45	0.20	0.45	36,164
EBIT/assets	0.07	0.10	0.06	42,317
CapEx/assets	0.04	0.05	0.03	42,967
Book-to-market ratio	0.72	0.57	0.58	43,174
Financial disclosure quality	0.68	0.09	0.71	31,323
Compustat NA firm	0.21	0.41	0.00	31,323

Table 2. Survey Responses on Climate Risk Disclosure

Panel A displays survey responses to questions on different aspects of climate risk disclosure practices currently in use (Question B3). Respondents were asked to indicate their agreement with different statements. Panel B reports survey responses to the question of whether the investors engage or plan to engage their portfolio firms to report according to the recommendations of the Task Force on Climate-related Financial Disclosures (TCFD) (Question E5), and whether the investors disclose or plan to disclose the carbon footprint of their portfolios (Question B2). The actual survey questions are provided in Appendix B3.

Panel A. Respondents' Views on Current Climate Risk Disclosure Practices

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
Management discussions on climate risk are not sufficiently precise	1%	9%	22%	47%	21%
Firm-level quantitative information on climate risk is not sufficiently precise	1%	7%	24%	48%	19%
Standardized and mandatory reporting on climate risk is necessary	2%	5%	20%	46%	27%
There should be more standardization across markets in climate-related financial disclosure	2%	7%	16%	48%	27%
Standardized disclosure tools and guidelines are currently not available	3%	12%	24%	40%	21%
Mandatory disclosure forms are not sufficiently informative regarding climate risk	3%	6%	28%	46%	18%
Investors should demand that portfolio firms disclose their exposure to climate risk	2%	6%	18%	46%	28%

Panel B. Respondents’ Views on TCFD and Carbon Footprint Disclosure (Percentages)

	No	Yes	Do not know
Do you engage (or plan to engage) portfolio companies to report according to the recommendations of the TCFD?	17%	59%	24%
Do you disclose (or plan to disclose) the overall carbon footprint of your portfolio?	24%	60%	16%

Table 3. Explaining Survey Responses on Climate Risk Disclosure

Panel A reports OLS regressions at the respondent level explaining investors' views on climate risk disclosure: (i) *Importance of climate risk disclosure* ranges between one and five, with one indicating that climate risk reporting is "much less important" and five indicating that it is "much more important" compared to reporting on financial information (Question B1); (ii) *Management discussions imprecise* equals one if a respondent indicates strong agreement that management discussions on climate risk are not sufficiently precise, and zero otherwise (Question B3); (iii) *Quantitative information imprecise* equals one if a respondent indicates strong agreement to the statement that firm-level quantitative information on climate risk is not sufficiently precise, and zero otherwise (Question B3); (iv) *Demand more disclosure* equals one if a respondent indicates strong agreement that investors should demand that portfolio firms disclose their exposure to climate risk, and zero otherwise (Question B3); (v) *TCFD engagement* equals one if a respondent engages or plans to engage portfolio firms to report according to the recommendations of the TCFD (Question E5), and zero otherwise; and (vi) *Carbon footprint disclosure* equals one if a respondent discloses or plans to disclose the overall carbon footprint of their portfolio, and zero otherwise (Question B2). Panel B reports OLS regressions at the respondent level explaining perceptions of climate-related overvaluations: *Climate risk underpricing* averages positive mispricing scores across several sectors most affected by climate change (negative scores are set to zero). The variable ranges between plus two (strong average overvaluation) and zero (no average overvaluation) (Question D1). We use the following independent variables in both panels: *Fiduciary duty institution; HQ country norms; Very large institution*; *Climate risk rating* (larger numbers reflect that climate risk is ranked as relatively more important compared to other investment risks); *Climate risk financial materiality* (larger numbers reflect greater perceived financial materiality); *ESG share of portfolio; Medium-term horizon; Long-term horizon.* Panel B additionally controls for the six dependent variables of panel A. Variable definitions are provided in the Data Appendix. Standard errors (in parentheses) are clustered at the respondent's country level. ***, **, * indicate significance levels of 1%, 5%, and 10%, respectively.

Panel A. Explaining Views on Climate Risk Disclosure

	Importance of climate risk disclosure	*Management discussions imprecise*	*Quantitative information imprecise*	*Demand disclosure*	*TCFD engagement*	*Carbon footprint disclosure*
	(1)	(2)	(3)	(4)	(5)	(6)
Fiduciary duty institution	0.19*	0.08	0.13*	0.16***	0.04	0.01
	(0.10)	(0.05)	(0.06)	(0.02)	(0.05)	(0.06)
HQ country norms	1.23**	0.24	-0.15	0.07	1.08***	0.22
	(0.52)	(0.37)	(0.26)	(0.24)	(0.18)	(0.34)
Very large institution	0.31**	0.02	0.11*	-0.02	0.04	0.18***
	(0.11)	(0.04)	(0.06)	(0.04)	(0.10)	(0.06)
Climate risk ranking	0.11***	0.02*	0.01	0.01	0.01	0.01
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Climate risk financial materiality	0.36***	0.07**	0.04	0.10***	0.02	0.05**
	(0.04)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
ESG share of portfolio	0.30	0.20***	0.14**	0.04	0.34**	0.23***
	(0.29)	(0.07)	(0.06)	(0.12)	(0.13)	(0.07)
Medium-term horizon	-0.05	0.07	0.01	-0.06	0.07	-0.02
	(0.19)	(0.08)	(0.08)	(0.13)	(0.09)	(0.10)
Long-term horizon	-0.12	0.11	0.06	-0.13	0.05	-0.09
	(0.26)	(0.10)	(0.09)	(0.12)	(0.07)	(0.10)
Respondent Position Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Distribution Channel Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Institutional Investor Type Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	363	363	363	363	277	306
Adj. R^2	0.21	0.10	0.09	0.14	0.07	0.03

Table 3 (continued)

Panel B. Climate Risk Disclosure and Climate Risk Mispricing						
	Climate risk underpricing					
	(1)	(2)	(3)	(4)	(5)	(6)
Importance of climate risk disclosure	0.09**					
	(0.03)					
Management discussions imprecise		0.21***				
		(0.07)				
Quantitative information imprecise			0.22**			
			(0.07)			
Demand more disclosure				0.20***		
				(0.05)		
TCFD engagement					0.10*	
					(0.06)	
Carbon footprint disclosure						0.15***
						(0.03)
Fiduciary duty institution	0.06	0.05	0.04	0.04	0.06	0.07
	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)
HQ country norms	-0.35**	-0.31*	-0.21	-0.25*	-0.36*	-0.18
	(0.14)	(0.18)	(0.12)	(0.14)	(0.19)	(0.30)
Very large institution	0.09	0.12	0.10	0.13	0.25	0.21
	(0.15)	(0.15)	(0.16)	(0.15)	(0.14)	(0.15)
Climate risk ranking	0.00	0.01	0.01	0.01	0.02	0.01
	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
Climate risk materiality	-0.02	-0.01	-0.00	-0.01	-0.03	-0.01
	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)
ESG share of portfolio	0.28***	0.28**	0.29***	0.30***	0.36***	0.33***
	(0.09)	(0.10)	(0.09)	(0.08)	(0.11)	(0.09)
Medium-term horizon	-0.04	-0.05	-0.04	-0.03	-0.12	-0.09
	(0.15)	(0.14)	(0.14)	(0.12)	(0.16)	(0.17)
Long-term horizon	-0.03	-0.06	-0.05	-0.01	-0.08	-0.06
	(0.13)	(0.12)	(0.12)	(0.11)	(0.14)	(0.16)
Respondent Position Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Distribution Channel Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Institutional Investor Type Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	335	335	335	335	262	282
Adj. R^2	0.07	0.07	0.07	0.07	0.07	0.08

Table 4. Climate Risk Disclosure and Institutional Investors

This table reports regressions at the firm-year level explaining firms' climate risk disclosures: *Scope 1 disclosure* equals one if a firm discloses Scope 1 carbon emissions to CDP in a year, and zero otherwise. *Climate risk disclosure* captures disclosure to CDP on up to three types of climate risks (regulatory, physical or other climate risks) in a year. It takes the value zero if a firm does not disclose climate risks to CDP in the year, one if it discloses information on one type of climate risk, two if it discloses information on two types of climate risk, and three if it discloses information on all three types of climate risk. *Climate disclosure score* measures how comprehensive climate risk disclosure to CDP is by counting the fraction of questions that were answered in the CDP survey in a year. The measure varies between 0 and 100, and higher numbers indicate better climate disclosure. We use the following key independent variables: (i) *Stewardship code IO* is the fraction of outstanding shares owned by institutional investors subject to stewardship codes in their home countries in a year; (ii) *High-norms IO* is the fraction of outstanding shares owned by institutional investors from high social norms countries in a year; (iii) *Universal owner IO* is the fraction of outstanding shares owned by institutional investors classified as universal owners in a year. Variable definitions are provided in the Data Appendix. Standard errors (in parentheses) are clustered at the country level. ***, **, * indicate significance levels of 1%, 5%, and 10%, respectively.

	Scope 1 disclosure			*Climate risk disclosure*			*Log(Climate disclosure score)*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Stewardship code IO	0.19**			0.57*			0.98*		
	(0.07)			(0.29)			(0.51)		
High-norms IO		0.24*			0.52*			0.72*	
		(0.12)			(0.29)			(0.42)	
Universal owner IO			0.45***			0.76***			1.51***
			(0.08)			(0.20)			(0.29)
Non-stewardship code IO	0.10			-0.02			-0.00		
	(0.08)			(0.37)			(0.57)		
Low-norms IO		0.09			0.11			0.27	
		(0.14)			(0.41)			(0.64)	
Non-universal owner IO			-0.09			-0.12			-0.38
			(0.11)			(0.30)			(0.50)
Log(Assets)	0.14***	0.14***	0.14***	0.31***	0.31***	0.31***	0.59***	0.59***	0.58***
	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
Dividends/net income	0.02***	0.02***	0.02***	0.05***	0.05***	0.06***	0.08***	0.08***	0.09***
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
				-	-	-	-	-	-
Debt/assets	-0.04	-0.04	-0.03	0.24***	0.24***	0.22***	0.49***	0.48***	0.44***
	(0.03)	(0.03)	(0.03)	(0.07)	(0.07)	(0.07)	(0.11)	(0.11)	(0.10)
EBIT/assets	-0.01	-0.01	-0.00	-0.16	-0.16	-0.12	-0.08	-0.08	-0.02
	(0.06)	(0.06)	(0.05)	(0.13)	(0.13)	(0.13)	(0.19)	(0.20)	(0.18)
CapEx/assets	0.03	0.03	0.05	0.12	0.14	0.21	-0.24	-0.21	-0.13
	(0.15)	(0.15)	(0.15)	(0.34)	(0.34)	(0.34)	(0.53)	(0.53)	(0.52)
	-	-	-	-	-	-	-	-	-
Book-to-market ratio	0.09***	0.09***	0.08***	0.19***	0.19***	0.18***	0.40***	0.39***	0.38***
	(0.01)	(0.01)	(0.01)	(0.04)	(0.04)	(0.04)	(0.06)	(0.06)	(0.06)
Financial disclosure quality	0.04	0.05	0.07	0.16	0.14	0.20	0.53***	0.50***	0.62***
	(0.04)	(0.04)	(0.05)	(0.12)	(0.13)	(0.14)	(0.17)	(0.17)	(0.18)
Sample		All Firms			All Firms			All Firms	
Years		2010-2019			2011-2016			2010-2015	
Industry x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	29,467	29,467	28,185	19,947	19,947	19,415	19,801	19,801	19,282
Adj. R^2	0.30	0.30	0.30	0.26	0.26	0.26	0.31	0.31	0.31

Table 5. Climate Risk Disclosure and Institutional Investors: Costs and Benefits of Disclosure

This table reports regressions at the firm-year level explaining how firms' climate risk disclosures vary with proxies of the costs and benefits of climate-related disclosure: *Scope 1 disclosure* equals one if a firm discloses Scope 1 carbon emissions to CDP in a year, and zero otherwise. *Climate risk disclosure* captures disclosure to CDP on up to three types of climate risks (regulatory, physical or other climate risks) in a year. It takes the value zero if a firm does not disclose climate risks to CDP in year, one if it discloses information on one type of climate risks, two if it discloses information on two types of climate risks, and three if it discloses information on all three types of climate risks. *Climate disclosure score* measures how comprehensive climate risk disclosure to CDP is by counting the fraction of questions that were answered in the CDP survey in a year. The measure varies between 0 and 100, and higher numbers indicate better climate disclosure. We use the following key independent variables: (i) *Stewardship code IO* is the fraction of outstanding shares owned by institutional investors subject to stewardship codes in their home countries in a year; (ii) *High-norms IO* is the fraction of outstanding shares owned by institutional investors from high social norm countries in a year; (iii) *Universal owner IO* is the fraction of outstanding shares owned by institutional investors classified as universal owners in a year. In panel A, *High-competition firm* equals one if a firm operates in a very competitive industry based on the text-based HHI measure by Hoberg and Phillips (2016), and zero otherwise. A firm operates in a very competitive industry if its HHI is below the sample median in a year. In panel B, *High-emission industry* equals one if a firm operates in an SIC2 industry that is in the top 20 across SIC2 industries based on Scope 1 emissions, and zero otherwise. Panel A contains only US firms as the competition measure is only available for such firms. *High-emission industry* in panel B is absorbed by the fixed effects. Variable definitions are provided in the Data Appendix. In panel A, standard errors (in parentheses) are clustered at the industry-year level. In panels B and C, standard errors (in parentheses) are clustered at the country level. ***, **, * indicate significance levels of 1%, 5%, and 10%, respectively.

Panel A. Proprietary Costs

	Scope 1 disclosure			*Climate risk disclosure*			*Log(Climate disclosure score)*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
High-competition firm	0.18**	0.19**	0.20**	0.74**	0.68**	0.65*	0.53	0.48	0.43
	(0.09)	(0.08)	(0.09)	(0.32)	(0.33)	(0.33)	(0.46)	(0.46)	(0.48)
High-competition firm x Stewardship code IO	-0.31***			-5.45***			-5.70**		
	(0.11)			(1.29)			(2.32)		
High-competition firm x High-norms IO		-1.09***			-3.42**			-6.14**	
		(0.39)			(1.48)			(2.44)	
High-competition firm x Universal owner IO			-0.49***			-1.05*			-1.75**
			(0.16)			(0.57)			(0.86)
Stewardship code IO	0.54***			5.96***			8.54***		
	(0.14)			(1.08)			(1.85)		
High-norms IO		1.71***			4.66***			7.20***	
		(0.30)			(1.14)			(1.82)	
Universal owner IO			0.76***			0.87*			2.83***
			(0.11)			(0.46)			(0.65)
Sample		US Firms			US Firms			US Firms	
Years		2010-2019			2011-2016			2010-2015	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	3,967	3,967	3,575	2,387	2,387	2,387	2,372	2,372	2,372
Adj. R^2	0.24	0.24	0.25	0.19	0.18	0.18	0.28	0.28	0.28

Panel B. Disclosure Externality Benefits

	Scope 1 disclosure			*Climate risk disclosure*			*Log(Climate disclosure score)*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
High-emission industry x Stewardship code IO	0.15***			0.43*			0.90***		
	(0.05)			(0.22)			(0.22)		
High-emission industry x High-norms IO		0.23***			0.54			1.05***	
		(0.08)			(0.36)			(0.34)	

High-emission industry x Universal owner IO			0.12			0.64**			0.59
			(0.11)			(0.24)			(0.43)
Stewardship code IO	0.12*			0.37			0.59		
	(0.06)			(0.22)			(0.46)		
High-norms IO		0.15			0.29			0.30	
		(0.10)			(0.20)			(0.36)	
Universal owner IO			0.39***			0.46***			1.20***
			(0.08)			(0.16)			(0.34)
Sample		All Firms			All Firms			All Firms	
Years		2010-2019			2011-2016			2010-2015	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	29,467	29,467	28,185	19,947	19,947	19,415	19,801	19,801	19,282
Adj. R^2	0.30	0.30	0.30	0.26	0.26	0.26	0.31	0.31	0.31

Table 6. Climate Risk Disclosure and Institutional Investors: Effects of French Article 173

This table reports regressions at the firm-year level explaining how firms' climate risk disclosures change after Article 173 is implemented in France in 2016: *Scope 1 disclosure* equals one if a firm discloses Scope 1 carbon emissions to CDP in a year, and zero otherwise. *Climate risk disclosure* captures disclosure to CDP on up to three types of climate risks (regulatory, physical or other climate risks) in a year. It takes the value zero if a firm does not disclose climate risks to CDP in year, one if it discloses information on one type of climate risks, two if it discloses information on two types of climate risks, and three if it discloses information on all three types of climate risks. We use the following key independent variables: *Post Article 173* equals one for the years of 2016 and afterwards, and zero otherwise; *French IO* is a continuous measure of institutional ownership by French institutions; *High French IO* equals one if the fraction of outstanding shares owned by French institutional investors is above the sample median, and zero otherwise; and *French firm* equals one if a firm is from France, and zero otherwise. Variable definitions are provided in the Data Appendix. Standard errors (in parentheses) are clustered at the country level. ***, **, * indicate significance levels of 1%, 5%, and 10%, respectively.

	Scope 1 disclosure				*Climate risk disclosure*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post Article 173 x French IO	0.89***	1.91***			1.96**	2.20*		
	(0.32)	(0.36)			(0.73)	(1.15)		
Post Article 173 x High French IO			0.04***	0.04**			0.13***	0.13***
			(0.01)	(0.02)			(0.04)	(0.04)
Post Article 173 x High French IO x French firm				0.07***				0.28***
				(0.02)				(0.07)
Post Article 173 x French firm				-0.08***				-0.27***
				(0.02)				(0.07)
High French IO x French firm				0.12***				0.33***
				(0.02)				(0.07)
French IO	1.30***	0.51**			3.72***	2.87***		
	(0.22)	(0.18)			(1.03)	(0.76)		
High French IO			0.04***	0.04***			0.06	0.05
			(0.01)	(0.01)			(0.04)	(0.04)
Log(Assets)	0.14***	0.17***	0.14***	0.14***	0.31***	0.39***	0.31***	0.31***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.05)	(0.03)	(0.03)
Dividends/net income	0.02***	0.00	0.02***	0.02***	0.05***	0.05	0.05***	0.05***
	(0.00)	(0.02)	(0.01)	(0.01)	(0.01)	(0.08)	(0.01)	(0.01)
Debt/assets	-0.04	-0.10	-0.03	-0.03	-0.24***	-0.41	-0.23***	-0.23***
	(0.03)	(0.11)	(0.03)	(0.03)	(0.07)	(0.48)	(0.07)	(0.07)
EBIT/assets	0.00	0.01	-0.01	-0.01	-0.14	-0.28	-0.14	-0.14
	(0.06)	(0.15)	(0.06)	(0.06)	(0.12)	(0.52)	(0.13)	(0.13)
CapEx/assets	0.04	-1.03***	0.02	0.02	0.16	-0.23	0.14	0.14
	(0.15)	(0.22)	(0.15)	(0.15)	(0.35)	(0.92)	(0.34)	(0.34)
Book-to-market ratio	-0.09***	-0.11***	-0.08***	-0.08***	-0.19***	-0.14	-0.19***	-0.19***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.09)	(0.04)	(0.04)
Financial disclosure quality	0.07	0.13	0.07*	0.07	0.18	0.22	0.20	0.20
	(0.04)	(0.13)	(0.04)	(0.04)	(0.14)	(0.87)	(0.14)	(0.14)
Sample	All Firms	French IO >3%	All Firms	All Firms	All Firms	French IO >3%	All Firms	All Firms
Years	2010-2019				2011-2016			
Industry x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	29,467	1,952	29,467	29,467	19,947	1,266	19,947	19,947
Adj. R^2	0.30	0.48	0.30	0.30	0.26	0.41	0.26	0.26

Table 7. Climate Risk Disclosure and Institutional Investors: Effects of UK Mandatory Carbon Disclosure

This table reports regressions at the firm-year level explaining how institutional ownership variables change after carbon disclosure is made mandatory in the UK in December 2017: (i) *Stewardship code IO* (*Non-stewardship code IO*) is the fraction of outstanding shares owned by institutional investors subject (not subject) to stewardship codes in their home countries in a year; (ii) *High-norms IO* (*Low-norms IO*) is the fraction of outstanding shares owned by institutional investors from high (low) social norm countries in a year; (iii) *Universal owner IO* (*Non-universal owner IO*) is the fraction of outstanding shares owned by institutional investors classified as universal owners (not universal owners) in a year. We use the following key independent variables: *Post UK carbon disclosure* equals one for the years of 2013 and afterwards, and zero otherwise; *No voluntary carbon disclosure* equals one if a firm did not disclose Scope 1 emissions to CDP in the years before 2013, and zero otherwise; *UK firm* equals one if a firm is from the UK, and zero otherwise. Variable definitions are provided in the Data Appendix. Standard errors (in parentheses) are clustered at the country level. We multiplied the dependent variables by 10, to scale the regression coefficients up by that factor. ***, **, * indicate significance levels of 1%, 5%, and 10%, respectively.

	Stewardship code IO	*High-norms IO*	*Universal owner IO*	*Non-stewardship code IO*	*Low-norms IO*	*Non-universal owner IO*
	(1)	(2)	(3)	(4)	(5)	(6)
Post UK carbon disclosure x UK firm x No vol. carbon disclosure	0.18**	0.12***	0.31***	0.18	0.24	-0.17**
	(0.09)	(0.04)	(0.07)	(0.11)	(0.17)	(0.08)
Post UK carbon disclosure x No voluntary carbon disclosure	-0.10	0.02	-0.01	0.18***	0.06	0.12***
	(0.06)	(0.02)	(0.05)	(0.05)	(0.07)	(0.02)
Post UK carbon disclosure x UK firm	-0.13	0.14***	-0.26**	0.08	-0.23	0.43***
	(0.17)	(0.05)	(0.10)	(0.09)	(0.15)	(0.05)
UK firm x No voluntary carbon disclosure	0.12	0.12**	-0.27**	-0.36	-0.37	0.14
	(0.11)	(0.05)	(0.13)	(0.22)	(0.28)	(0.16)
No voluntary carbon disclosure	0.15	-0.00	0.07	-0.13	0.02	-0.10
	(0.09)	(0.03)	(0.09)	(0.09)	(0.15)	(0.08)
Log(Assets)	0.10***	0.08***	0.16***	0.14**	0.15**	0.04
	(0.02)	(0.01)	(0.03)	(0.06)	(0.07)	(0.03)
Dividends/net income	0.02	0.01	-0.02	-0.07**	-0.05	-0.03
	(0.01)	(0.01)	(0.02)	(0.03)	(0.03)	(0.02)
Debt/assets	-0.01	-0.11**	-0.31***	-0.41***	-0.28*	-0.13
	(0.12)	(0.04)	(0.07)	(0.08)	(0.15)	(0.11)
EBIT/assets	0.64**	0.65***	0.57***	0.56***	0.53***	0.41***
	(0.23)	(0.21)	(0.13)	(0.16)	(0.17)	(0.14)
CapEx/assets	0.68***	0.43**	0.07	-0.19	-0.01	0.19
	(0.21)	(0.21)	(0.19)	(0.29)	(0.31)	(0.23)
Book-to-market ratio	-0.11***	-0.10***	-0.19***	-0.19***	-0.21***	-0.11***
	(0.02)	(0.02)	(0.04)	(0.04)	(0.04)	(0.02)
Financial disclosure quality	1.80**	0.44**	0.35***	-1.01	0.40*	0.46***
	(0.78)	(0.20)	(0.07)	(0.85)	(0.21)	(0.16)
Sample		All Firms			All Firms	
Years		2010-2019			2010-2019	
Industry x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	29,467	29,467	29,467	29,467	28,185	28,185
Adj. R^2	0.61	0.76	0.56	0.86	0.73	0.68

Appendix

for

Climate Risk Disclosure and Institutional Investors

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Appendix A: Anecdotal Evidence on Climate-related Disclosure Costs

Anecdotal evidence supports the argument that climate-related proprietary disclosure and information production costs are important for some firms.

A1. Proprietary Disclosure Costs

1. Feedback to New EU Guidelines on Climate-related Disclosures

For example, in response to a call for feedback to new EU guidelines on climate-related disclosures, *"several respondents point out the sensitivity and competitive nature of some the suggested disclosures and argue against the level of transparency that is recommended in the report."* Further, *"some respondents feared that detailed reporting on scenario analysis, in relation to financial impacts and strategy could result in the disclosure of competitive information"* (European Commission 2019).

2. Evidence from a Survey by the TCFD

In a TCFD survey, "*almost half of the respondents […] found disclosing scenario analysis assumptions difficult due to their inclusion of confidential business information*" (Financial Stability Board 2019).

A2. Information Production Costs

Feedback to SEC on Climate Disclosures

In response to a request for comments by the SEC on climate disclosure, respondents stated that "*Any new requirement for prescriptive, quantitative disclosures will result in significant direct and indirect costs to companies in the forms of data gathering and systems costs, legal expense, consulting expense, public relations expense, and litigation risk expense, among others"* (Society for Governance 2021). It was further stated that *"One large-cap company in the energy industry described its TCFD reporting process as involving 40 people from the company and six months of nearly full-time participation by 20 core team members. Employee hours spent on climate reporting for the two companies that provided data on this point ranged from 7,500 to 10,000 annually."*

Appendix B: Details on Survey Data

B1. Survey Methodology and Design

The survey we employed was developed through an iterative process as suggested by Krosnick and Presser (2010). Thus, we employed the feedback from academics and practitioners throughout the process with multiple versions of the survey presented for their feedback. We then had the survey reviewed by professional survey designer. The survey instrument is provided in Appendix B2. The original survey also contained questions on climate risk management and shareholder engagement, which are covered in Krueger, Sautner, and Starks (2020). More details of the iterative process that was used for developing the survey are provided in Krueger, Sautner, and Starks (2020).

Employing both an online and a paper version of the survey, we distributed the survey through four delivery channels, yielding a total of 439 responses. First, we personally distributed the paper version at four institutional investor conferences: The Sustainable Investment Conference in Frankfurt on November 9, 2017; the ICGN Paris Event on December 6-7, 2017; the Asset Management with Climate Risk Conference at Cass Business School in London on January 23, 2018; and the ICPM Conference in Toronto on June 10-12, 2018. We obtained a total of 72 responses from these four conferences.

Second, we distributed the online version to 1,018 individuals in senior functions at institutional investors. The online version was programmed so that response choices had random orderings. We identified these individuals using the help of a survey service provider that manages a global panel of more than 5m professionals. The panel contains detailed data on these individuals' job titles, employers, and their age to identify relevant subsamples. The service provider had several mechanisms in place to ensure the authenticity of the individuals. In March 2018, the provider emailed invitations to participate in the survey and we obtained 410 initial responses to these invitations. We then excluded 90 participants that took less than five minutes to complete the survey, and participants for which basic checks yielded logical inconsistencies in the responses (Meade and Craig 2012). This process left us with 320 responses of good quality. These respondents spent 15 minutes, on average, to complete the survey.

Third, in April 2018, we emailed invitations to participate in the survey to a list of institutional investors that cooperate with a major asset owner through CERES and IIGCC on climate risk topics. We obtained 28 responses through this channel. Fourth, we sent invitations to participate in the online survey to personal contacts at different institutional investors, yielding 19 additional responses.

We are confident that in the vast majority of cases we have only one observation per institution. The reason is that, for 87% of the observations, key identifying characteristics do not coincide. These characteristics are location, assets under management, institutional investor type, investor horizon, ESG share (+/–10% variation in the variable), equity share (+/–10%), and passive share (+/–10%). In the remaining cases we cannot exclude the possibility that respondents work for the same institution. However, the responses are sufficiently different among these respondents to discount that possibility with some degree of assurance.

B2. Non-Response and Acquiescence Bias

As in most surveys, there may be some concerns about the pool of respondents in our study. First, the sample of contacted individuals are not randomly distributed across the entire institutional investor universe and not all contacted individuals working at institutional investors responded to our survey. We assess the role of non-response bias by comparing key characteristics of the responding investors to those of the institutional investor in the FactSet population. As explained in the paper, IA Figure 1 shows that pension funds and banks are overrepresented in our sample, while mutual funds and asset managers are underrepresented. In terms of geography, our respondents are more likely to work for institutions in North America and Europe. Our respondents may be biased toward investors with a high ESG awareness (given the high median ESG share of 30%) as such investors may be more disposed to participate in our survey.

Second, concerns over untruthful or strategic responses may exist. For example, one might argue that investors not only have incentives to refrain from participating in our survey, but also that they may provide answers that make their institutions appear to be more climate-conscious. Based on our conversations with some of the respondents that were willing to share their identities, we believe that these issues are unlikely to affect our results in a systematic way. This is for several reasons. In our survey, we did not request the identities of our respondents (or those of their employers), we collected only limited information on their positions and institutions, and in the online survey we did not trace back IP addresses. The anonymity of our survey should hence minimize the incentives for untruthful or strategic responses, as the respondents cannot reap the potential benefits (e.g., reputational) of answering in a certain way. Further, a systematic pattern of strategic responses from our respondents to shift the distribution of their responses to appear more climate-conscious overall is also unlikely, since this would assume an implicit collaboration by our respondents. It is also unclear how respondents would benefit from such a practice since the readers of our analysis cannot infer the identities of their institutions. Finally, the respondents we spoke to stated that they would not spend the time on the survey if they intended to provide untruthful response.

Third, concerns about incorrect conclusions from the responses to our survey due to non-response bias or untruthful responses are moderated by our complementary tests that use investor holdings data. This observational analysis not only helps us in alleviating the limitations of our survey analysis, with the tests being built on the entire observable institutional investor universe, but they also allow us to test whether institutional investors "walk the climate-risk disclosure talk." We do this by designing tests that provide insights into the causal links between institutional ownership and climate-risk disclosure practices of their portfolio firms.

B3. Survey Instrument

Survey on Climate Risk

We are a team of professors from the University of Geneva, the Swiss Finance Institute, the University of Texas at Austin, and Frankfurt School of Finance & Management.

This survey seeks a better understanding of whether and how institutional investors incorporate **climate risk** when making investment decisions. The survey will take about **10 minutes**.

You can use this survey questionnaire or take the survey online at: [LINK]

We take the **confidentiality** of your responses very seriously. We **will not share your responses** with anyone, nor will individual firms or respondents be identified. Only aggregate data will be made public. We will not link the survey responses to any other data.

Thank you for participating in this survey. If you have any questions, please contact us.

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GENERAL INFORMATION

G1: How is the institution at which you work best described?

- □ Public pension fund
- □ Private pension fund
- □ Insurance company
- □ Hedge fund
- □ Mutual fund management company
- □ Private equity fund
- □ Asset manager (for pension funds, endowments, etc.)
- □ Endowment, charity
- □ Sovereign wealth fund
- □ Bank
- □ Other (please specify): ______________________________

G2: What is the typical holding period for investments in your portfolio, on average?

- □ Short (less than 6 months)
- □ Medium (6 months to 2 years)
- □ Long (2 years to 5 years)
- □ Very long (more than 5 years)

G3: What percentage of your portfolio is invested in fixed income versus equity securities?

___ % in fixed income

___ % in equities

G4: [NOT COVERED IN THIS PAPER]

G5: What percentage of your portfolio incorporates Environmental, Social and Governance (ESG) issues? ____ %

G6: What is the total size of assets under management for your institution?

- □ Less than $1 billion
- □ Between $1 billion and $20 billion
- □ Between $20 billion and $50 billion
- □ Between $50 billion and $100 billion
- □ More than $100 billion

G7: In which country are your institution's headquarters based?

____

G8: What is your position?

- □ Fund/Portfolio Manager
- □ Chief Executive Officer
- □ Investment Analyst/Strategist
- □ Executive/Managing Director

☐ Chief Investment Officer	☐ ESG/Responsible Investment Specialist
☐ CFO/COO/Chairman/Other Executive	☐ Other (please explain): ____________________

PART A: IMPORTANCE OF CLIMATE RISK

A1: Please rank the following six <u>risks</u> when making investments in portfolio firms from 1 to 6, where 1 is the most important to you and 6 the least important.

Financial risk (earnings, leverage, payout policy, etc.)	
Operating risk (changes in demand, input costs, etc.)	
Governance risk (board structure, executive pay, etc.)	
Social risk (labor standards, human rights, etc.)	
Climate risk	
Other environmental risk (pollution, recycling, etc.)	

A2: We have divided <u>climate risk</u> into *regulatory risks* (changes in regulation), *physical risks* (changes in the physical climate), and *technological risks* (climate-related technological disruption). Please rate the financial materiality of these risks.

	Not at all important	Slightly important	Important	Fairly important	Very important
Regulatory risks	☐	☐	☐	☐	☐
Physical risks	☐	☐	☐	☐	☐
Technological risks	☐	☐	☐	☐	☐

A3 [NOT COVERED IN THIS PAPER]

A4: To what extent do you agree with the following statements?

Incorporating climate risk …	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
• Is a legal obligation/fiduciary duty that we have to consider	☐	☐	☐	☐	☐
• [Other statements not used in this paper]	☐	☐	☐	☐	☐

A5 [NOT COVERED IN THIS PAPER]

PART B: DISCLOSURE ON CLIMATE RISK

B1: How important do you consider reporting by portfolio firms on climate risk compared to reporting on financial information?

Much less important	Less important	Equally important	More important	Much more important
◻	◻	◻	◻	◻

B2: Do you disclose (or plan to disclose) the overall carbon footprint of your portfolio?

◻ No ◻ Yes ◻ Do not know

B3: To what extent do you agree with the following statements regarding climate-risk disclosure by portfolio firms?

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
• Investors should demand that portfolio firms disclose their exposure to climate risk	◻	◻	◻	◻	◻
• Firm-level quantitative information on climate risk is not sufficiently precise	◻	◻	◻	◻	◻
• Management discussions on climate risk are not sufficiently precise	◻	◻	◻	◻	◻
• Standardized and mandatory reporting on climate risk is necessary	◻	◻	◻	◻	◻
• Mandatory disclosure forms are not sufficiently informative regarding climate risk	◻	◻	◻	◻	◻
• There should be more standardization across markets in climate-related financial disclosure	◻	◻	◻	◻	◻
• Standardized disclosure tools and guidelines are currently not available	◻	◻	◻	◻	◻

PART C: CLIMATE RISK MANAGEMENT & ENGAGEMENT

[NOT COVERED IN THIS PAPER]

PART D: PRICING OF CLIMATE RISK

D1: To what extent do equity valuations of firms in different industries reflect the risks and opportunities related to climate change?

Industry	Valuations much	Valuations somewhat	Valuations	Valuations somewhat	Valuations much

	too high	too high	more or less correct	too low	too low
Oil	□	□	□	□	□
Natural gas	□	□	□	□	□
Renewable energy	□	□	□	□	□
Nuclear energy	□	□	□	□	□
Electric utilities	□	□	□	□	□
Gas utilities	□	□	□	□	□
Water utilities	□	□	□	□	□
Coal mining	□	□	□	□	□
Raw materials (excluding coal)	□	□	□	□	□
Infrastructure	□	□	□	□	□
Chemicals	□	□	□	□	□
Automotive (traditional)	□	□	□	□	□
Automotive (electric)	□	□	□	□	□
Battery producers	□	□	□	□	□
Construction	□	□	□	□	□
Banking	□	□	□	□	□
Insurance	□	□	□	□	□
Agriculture	□	□	□	□	□
Forestry and paper	□	□	□	□	□
Information Technology	□	□	□	□	□
Telecommunications	□	□	□	□	□
Transportation	□	□	□	□	□
Coastal real estate	□	□	□	□	□

D2 to D4: [NOT COVERED IN THIS PAPER]

PART E: ADDITIONAL INFORMATION

E1 to E4: [NOT COVERED IN THIS PAPER]

E5: Do you engage (or plan to engage) portfolio companies to report according to the recommendations of the Task Force on Climate related Financial Disclosures (TCFD)?

◻ No ◻ Yes ◻ Do not know

Appendix C: Additional Tables

Appendix Table 1. Survey Respondent Characteristics

This table provides summary statistics on the characteristics of the 439 individuals that participated in our survey. As not all respondents provided information on all characteristics, we report the number of observations for different parts of the table. We report data on the distribution channel, position of the responding individuals (Question G8), type of institution they work for (Question G1), institution size (Question G6), investment horizon (Question G2), and geographic distribution (Question G7). Variable definitions are provided in the Data Appendix. The actual survey questions are provided in Appendix B3.

Distribution channels (N=439)	Percentage	Assets under management (N=430)	Percentage
Panel	73	Less than $1bn	19
Conferences	16	Between $1bn and $20bn	32
Asset owner	6	Between $20bn and $50bn	23
Personal	4	Between $50bn and $100bn	16
Respondent position (N=428)	Percentage	More than $100bn	11
Fund/Portfolio manager	21	Investor horizon (N=432)	Percentage
Executive/Managing director	18	Short (less than 6 months)	5
Investment analyst/strategist	16	Medium (6 months to 2 years)	38
CIO	11	Long (2 years to 5 years)	38
CEO	10	Very long (more than 5 years)	18
CFO/COO/Chairman/Other executive	10	Region (N=429)	Percentage
ESG/RI specialist	10	United States	32
Other	3	United Kingdom	17
Institutional investor type (N=439)	Percentage	Canada	12
Asset manager	23	Germany	11
Bank	22	Italy	7
Pension fund	17	Spain	5
Insurance company	15	The Netherlands	4
Mutual fund	8	France	3
Other institution	15	Others (<3%)	9

Appendix Table 2. Correlations

This table provides Spearman rank correlations of selected variables from the climate disclosure and investor holdings data. * indicates significance at the 5% level (or more). Variable definitions are provided in the Data Appendix

Panel A. Correlations of Climate Risk Disclosure Variables

		(1)	(2)	(3)	(4)	(5)
Scope 1 disclosure	(1)	1				
Climate risk disclosure	(2)	0.7038*	1			
Climate disclosure score	(3)	0.8130*	0.7043*	1		
10-K Climate risk disclosure (MPV)	(4)	0.1174*	0.1540*	0.0823*	1	
10-K Climate risk disclosure (KLRW)	(5)	0.0959*	0.1721*	0.0830*	0.2792*	1
High 10-K Climate risk disclosure (KLRW)	(6)	0.0329	0.1636*	0.0244	0.3910*	0.5835*

Panel B. Correlations of IO Variables

		(1)	(2)
Stewardship code IO	(1)	1	
High-norms IO	(2)	0.7240*	1
Universal owner IO	(3)	0.6792*	0.5927*

Appendix Table 3. Climate Risk Disclosure and Institutional Investors: Results by Risk Type Disclosure

This table reports regressions at the firm-year level explaining firms' climate risk disclosures: *Regulatory risk disclosure* captures disclosure to CDP on regulatory climate risks in a year. It equals one zero if a firm discloses regulatory climate risks to CDP in year, and zero otherwise. *Physical risk disclosure* and *Other risk disclosure* are defined accordingly, but for physical or other climate risks. We use the following key independent variables: (i) *Stewardship code IO* is the fraction of outstanding shares owned by institutional investors subject to stewardship codes in their home countries in a year; (ii) *High-norms IO* is the fraction of outstanding shares owned by institutional investors from high social norm countries in a year; (iii) *Universal owner IO* is the fraction of outstanding shares owned by institutional investors classified as universal owners in a year. Variable definitions are provided in the Data Appendix. Standard errors (in parentheses) are clustered at the country level. ***, **, * indicate significance levels of 1%, 5%, and 10%, respectively.

	Regulatory risk disclosure			*Physical risk disclosure*			*Other risk disclosure*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Stewardship code IO	0.23*			0.18			0.16		
	(0.12)			(0.11)			(0.10)		
High-norms IO		0.20*			0.16			0.13	
		(0.11)			(0.12)			(0.10)	
Universal owner IO			0.34***			0.25***			0.26***
			(0.08)			(0.08)			(0.07)
Non-stewardship code IO	0.01			-0.02			-0.02		
	(0.14)			(0.14)			(0.16)		
Low-norms IO		0.07			0.03			0.03	
		(0.16)			(0.15)			(0.17)	
Non-universal owner IO			-0.05			-0.05			-0.07
			(0.12)			(0.11)			(0.13)
Log(Assets)	0.13***	0.13***	0.13***	0.12***	0.12***	0.12***	0.11***	0.11***	0.11***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Dividends/net income	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
	-	-	-	-	-	-	-	-	-
Debt/assets	0.09***	0.09***	0.08***	0.09***	0.09***	0.08***	0.09***	0.09***	0.08***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
EBIT/assets	-0.07	-0.07	-0.06	-0.05	-0.05	-0.03	-0.06	-0.06	-0.05
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)
CapEx/assets	0.03	0.04	0.07	-0.01	-0.00	0.02	0.07	0.08	0.11
	(0.13)	(0.13)	(0.13)	(0.14)	(0.14)	(0.14)	(0.12)	(0.12)	(0.12)
	-	-	-	-	-	-	-	-	-
Book-to-market ratio	0.08***	0.08***	0.08***	0.08***	0.08***	0.08***	0.08***	0.08***	0.07***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Financial disclosure quality	0.08**	0.07*	0.10**	0.04	0.04	0.06	0.09*	0.09*	0.11**
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)
Sample		All Firms			All Firms			All Firms	
Years		2011-2016			2011-2016			2011-2016	
Industry x Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	18,247	18,247	17,716	18,247	18,247	17,716	18,247	18,247	17,716
Adj. R^2	0.30	0.30	0.30	0.28	0.28	0.28	0.27	0.27	0.27

Appendix Table 4. Climate Risk Disclosure in 10-K Annual Reports

This table reports regressions at the firm-year level explaining firms' 10-K climate risk disclosures: *10-K Climate risk disclosure* follows Matsumura, Prakash, and Vera-Muñoz (2021) and equals one if a 10-K contains the climate change words in a year, and zero otherwise. This variable is only available for US firms. We use the following key independent variables: (i) *Stewardship code IO* is the fraction of outstanding shares owned by institutional investors subject to stewardship codes in their home countries in a year; (ii) *High-norms IO* is the fraction of outstanding shares owned by institutional investors from high social norm countries in a year; (iii) *Universal owner IO* is the fraction of outstanding shares owned by institutional investors classified as universal owners in a year. Variable definitions are provided in the Data Appendix. Standard errors (in parentheses) are clustered at the industry-year level. ***, **, * indicate significance levels of 1%, 5%, and 10%, respectively.

	10-K Climate risk disclosure		
	(1)	(2)	(3)
Stewardship code IO	0.04		
	(0.16)		
High-norms IO		0.26	
		(0.28)	
Universal owner IO			-0.09
			(0.10)
Non-stewardship code IO	-0.15***		
	(0.06)		
Low-norms IO		-0.14***	
		(0.05)	
Non-universal owner IO			-0.12*
			(0.07)
Log(Assets)	0.04***	0.04***	0.05***
	(0.01)	(0.01)	(0.01)
Dividends/net income	0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)
Debt/assets	0.22***	0.22***	0.22***
	(0.05)	(0.05)	(0.05)
EBIT/assets	0.36***	0.35***	0.37***
	(0.09)	(0.09)	(0.09)
CapEx/assets	0.89***	0.88***	0.89***
	(0.20)	(0.20)	(0.20)
Book-to-market ratio	0.16***	0.16***	0.16***
	(0.03)	(0.03)	(0.03)
Financial disclosure quality	0.03	0.03	0.02
	(0.10)	(0.10)	(0.10)
Sample		US Firms	
Years		2010-2019	
Industry x Year Fixed Effects	Yes	Yes	Yes
Obs.	3,272	3,272	3,272
Adj. R^2	0.27	0.27	0.27

Appendix Table 5. Variable definitions

Panel A: Survey Analysis		
Variable	**Definition**	**Survey Question**
Importance of climate risk disclosure	Measures how important investors consider reporting by portfolio firms on climate risks compared to reporting on financial information. The variable ranges between one and five, with one indicating that climate risk reporting is "much less importance" and five indicating that it is "much more important".	Question B1
Demand more disclosure	Equals one if a respondent "strongly agrees" that investors should demand that portfolio firms disclose their exposure to climate risk, and zero otherwise. In the underlying questions, respondents were asked to indicate their agreement with the statements on a scale of one ("strongly disagree") through five ("strongly agree").	Question B3
Quant. information imprecise	Equals one if a respondent "strongly agrees" that firm-level quantitative information on climate risk is not sufficiently precise, and zero otherwise. In the underlying questions, respondents were asked to indicate their agreement with the statements on a scale of one ("strongly disagree") through five ("strongly agree").	Question B3
Management discussions imprecise	Equals one if a respondent "strongly agrees" that management discussions on climate risk are not sufficiently precise, and zero otherwise. In the underlying questions, respondents were asked to indicate their agreement with the statements on a scale of one ("strongly disagree") through five ("strongly agree").	Question B3
TCFD engagement	Equals one if a respondent engages or plans to engage portfolio companies to report according to the recommendations of the Task Force on Climate-related Financial Disclosures, and zero otherwise.	Question E5
Carbon footprint disclosure	Equals one if a respondent discloses or plans to disclose the overall carbon footprint of their portfolio, and zero otherwise.	Question B2
Climate risk underpricing	Averages positive mispricing scores (negative scores are set to zero). The variable ranges between plus two (strong average overvaluation) and zero (no average overvaluation).	Question D1
Climate risk ranking	Outcome of a ranking of the importance of climate risks relative to other investment risks. The variable ranges from one (if they are considered the least important risk) to six (if climate risks are considered the most important risk).	Question A1
Climate risk financial materiality	Averages the responses to three questions about the financial materiality of regulatory, physical, and technological climate risk. Each of these three variables can range between one (not at all important) and five (very important).	Question A2
Fiduciary duty institution	Equals one if a respondent strongly agrees to the statement that incorporating climate risks in the investment process "is a legal obligation/fiduciary duty that we have to consider," and zero otherwise.	Question A4
HQ country norms	Captures the importance of environmental issues in the country in which an institutional investor is headquartered. The data are from Dyck et al. (2019) who construct the variable based on the Environmental Performance Index obtained from the Yale Center for Environmental Law (Yale University) and the Center for International Earth Science Information Network (Columbia University) for 2004. Larger numbers reflect a stronger common belief in the importance of environmental issues.	Question G7
Very large institution	Equals one if the size of an institutional investor is more than $100bn, and zero otherwise.	Question G6
ESG share of portfolio	Percentage of the institution's portfolio that incorporates ESG issues.	Question G5
Medium-term horizon	Equals one if the indicated typical holding period of an institutional investor is between six months and two years, and zero otherwise.	Question G2
Long-term horizon	Equals one if the indicated holding period of an institutional investor is above two years, and zero otherwise.	Question G2

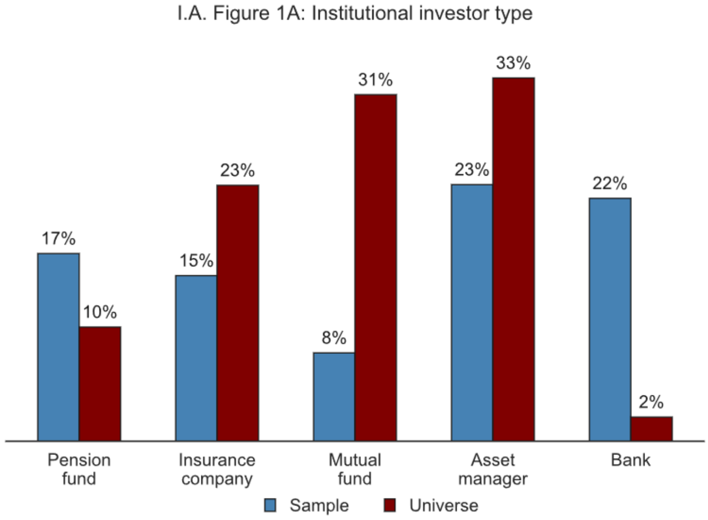
Panel B: Holdings and Disclosure Data Analysis		
Variable	**Definition**	**Source, Sample Years**
Scope 1 disclosure	Equals one if a firm discloses Scope 1 carbon emissions to CDP in a year, and zero otherwise.	CDP, 2010-2019
Climate risk disclosure	Follows the definition in Flammer, Toffel, and Viswanathan (2021) and captures disclosure to CDP on up to three types of climate risks (regulatory, physical or other climate risks) in a year. It takes the value zero if a firm does not disclose climate risks to CDP in year, one if it discloses information on one type of climate risks, two if it discloses information on two types of climate risks, and three if it discloses information on all three types of climate risks. This variable is available for the years 2011 to 2016 as CDP did not include this question in 2010 and changed the question design from 2017 onwards such that the responses are not comparable anymore for these years.	CDP, 2011-2016
Climate disclosure score	Measures how comprehensive climate risk disclosure to CDP is by counting the fraction of questions that were answered in the CDP survey in a year. This variable is only available between 2010 and 2015 as the score replaced by CDP in 2016 with an alternative measure that mixes disclosure and climate performance. The measures varies between 0 and 100 and higher numbers indicate better climate disclosure.	CDP, 2010-2015
10-K Climate risk disclosure	Follows Matsumura, Prakash, and Vera-Muñoz (2021) and equals one if a 10-K contains the climate change words “carbon”, “climate change”, “emissions”, “greenhouse”, “GHG”, “hurricanes”, “renewable energy”, and “extreme weather” appear in a year, and zero otherwise. Only available for US firms.	SEC EDGAR, 2010-2019, US firms
Stewardship code IO	Fraction of outstanding shares owned by institutional investors that are subject to stewardship codes in their home countries in a year. Winsorized at 1%.	FactSet, Katelouzou and Siems (2021), 2010-2019
High-norms IO	Fraction of outstanding shares owned by institutional investors from high-norms countries (as defined by Dyck et al. 2019) in a year. An institutional investor’s country is in the high-norms group if its Environmental Performance Index (EPI) is higher than the median in a year. Winsorized at 1%.	FactSet, 2010-2019
Universal owner IO	Fraction of outstanding shares owned by institutional investors that are classified as universal owners in a year. We classify as universal owners those institutional investors whose number of stocks in the portfolios is ranked in the top 1% across all institutions in a year. Winsorized at 1%.	FactSet, 2010-2019
Non-stewardship code IO	Fraction of outstanding shares owned by institutional investors that are not subject to stewardship codes in their home countries in a year. Winsorized at 1%.	FactSet, Katelouzou and Siems (2021), 2010-2019
Low-norms IO	Fraction of outstanding shares owned by institutional investors from low-norms countries (as defined by Dyck et al. 2019) in a year. An institutional investor’s country is in the low-norms group if its Environmental Performance Index (EPI) is lower than the median in a year. Winsorized at 1%.	FactSet, 2010-2019
Non-universal owner IO	Fraction of outstanding shares owned by institutional investors that are not classified as universal owners in a year. Winsorized at 1%.	FactSet, 2010-2019
High-competition firm	Equals one if a firm operates in a very competitive industry based on the text-based HHI measure developed by Hoberg and Phillips (2016), and zero otherwise. A firm operates in a very competitive industry if its HHI is below the sample median in a year. Only available for US firms.	Hoberg and Phillips (2016), 2010-

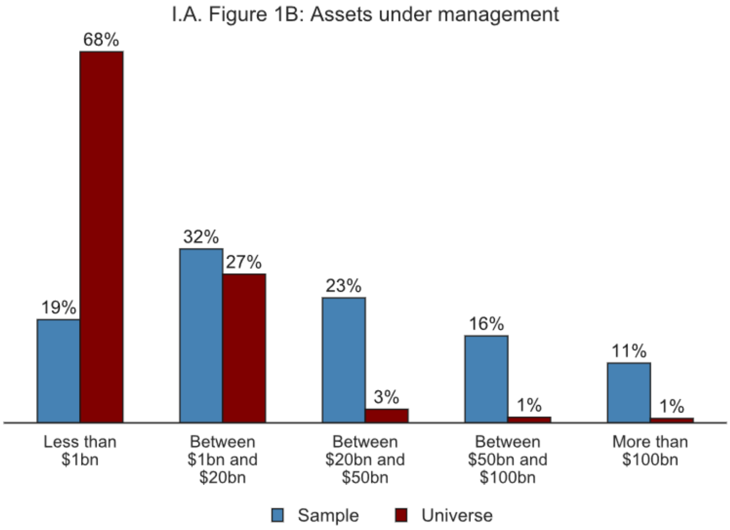
		2016, US firms
High-emission industry	Equals one if a firm operates in an SIC2 industry that is in the top 20 across SIC2 industries based on Scope 1 emissions, and zero otherwise.	Ilhan, Vilkov, and Sautner (2021), 2010-2019
Post Article 173	Equals one for the years of 2016 and afterwards, and zero otherwise.	Self-constructed,
French IO	Continuous measure of institutional ownership by French institutions.	FactSet, 2010-2019
High French IO	Equals one if the fraction of outstanding shares owned by French institutional investors is above the sample median, and zero otherwise.	FactSet, 2010-2019
French firm	Equals one if a firm is from France, and zero otherwise.	FactSet, 2010-2019
Post UK carbon disclosure	Equals one for the years of 2013 and afterwards, and zero otherwise.	Self-constructed
No voluntary carbon disclosure	Equals one if a firm did not disclose Scope 1 emissions to CDP in the years before 2013, and zero otherwise.	CDP, 2010-2019
UK firm	Equals one if a firm is from the UK, and zero otherwise.	Worldscope, 2010-2019
Assets	Total assets (Worldscope data item WC02999) at the end of the year. Winsorized at the 1% level. Winsorized at 1%.	Worldscope, 2010-2019
Dividends/net income	Dividends (Worldscope data item WC04551) at the end of the fiscal year, divided by net income/loss at the end of the year (Worldscope data item WC01706). Winsorized at the 1% level. Winsorized at 1%.	Worldscope, 2010-2019
Debt/assets	Sum of the book value of long-term debt (Worldscope data item WC03251) and the book value of current liabilities (WC03101) at the end of the year, divided by total assets at the end of the year (Worldscope data itemWC02999). Winsorized at 1%.	Worldscope, 2010-2019
EBIT/assets	Earnings before interest and taxes (Worldscope data item WC18191) at the end of the year, divided by total assets at the end of the year (Worldscope data item WC02999). Winsorized at 1%.	Worldscope, 2010-2019
CapEx/assets	Capital expenditures at the end of the year (Worldscope data item WC04601), divided by total assets at the end of the year (Worldscope data item WC02999). Winsorized at 1%.	Worldscope, 2010-2019
Book-to-market ratio	Difference between common equity (Worldscope data item WC03501) and preferred stock capital (WC03451) at the end of the year, divided by the equity market value (MV) at the end of the year. Winsorized at 1%.	Worldscope, 2010-2019
Financial disclosure quality	Follows Chen, Miao, and Shevlin (2015) and measures the overall financial disclosure quality of a firm in a year. The measure counts the number of non-missing data items in the income statement as reported in Compustat. The variable is scaled by the maximum number of data items in the income statement so that it ranged between 0 and 1. Winsorized at 1%.	Compustat NA and Compustat Global, 2010-2019
Compustat NA firm	Equals one if a firm is included in Compustat North America, and zero if it is included in Compustat Global.	Compustat NA and Compustat Global

Appendix D: Additional Figures

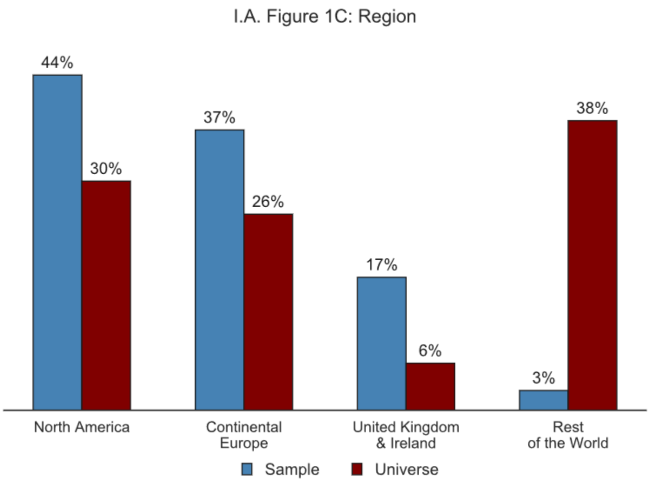
Appendix Figure 1. Comparison of sample characteristics with universe of institutional investors

These figures compare key characteristics of the institutional investors in our sample with those of the universe of institutional investors as defined by the FactSet Standard Entity database. In IA Figure 1A we use the FactSet item "entity_sub_type" to identify institutional investor types. Pension fund, Insurance and Mutual Fund correspond to "Pension fund manager", "Insurance Company", and "Mutual fund manager" entity structures, respectively. Bank corresponds to "Bank investment division" and "Investment banking". Asset manager includes "Fund of funds manager", "Fund of hedge funds manager", "Private banking/Wealth Management", "Real estate manager", "Family office" and "Investment Company entities". In IA Figure 1B assets under management measure the market value of a given fund portfolio. We use the Ownership (LionShares) - Unadjusted Fund Holdings Historical database to compute the market value of each fund portfolio. In IA Figure 1C we identify the geographic region of an institution by using FactSet item "ISO_country", which reports the country in which a security is domiciled. We do not use the fund country of incorporation since "ISO_country" better matches the location of the entity headquarters provided by the variable metro_area that reports the metropolitan area of the fund headquarters. Continental Europe includes Malta and Iceland. Our FactSet data covers the year 2015.



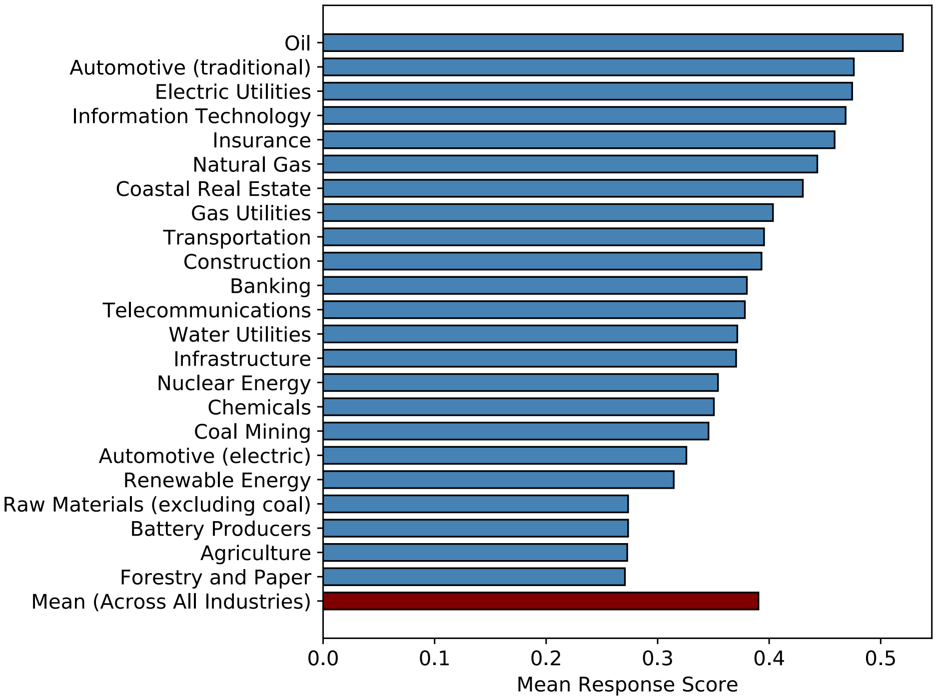


Appendix Figure 1 (continued)



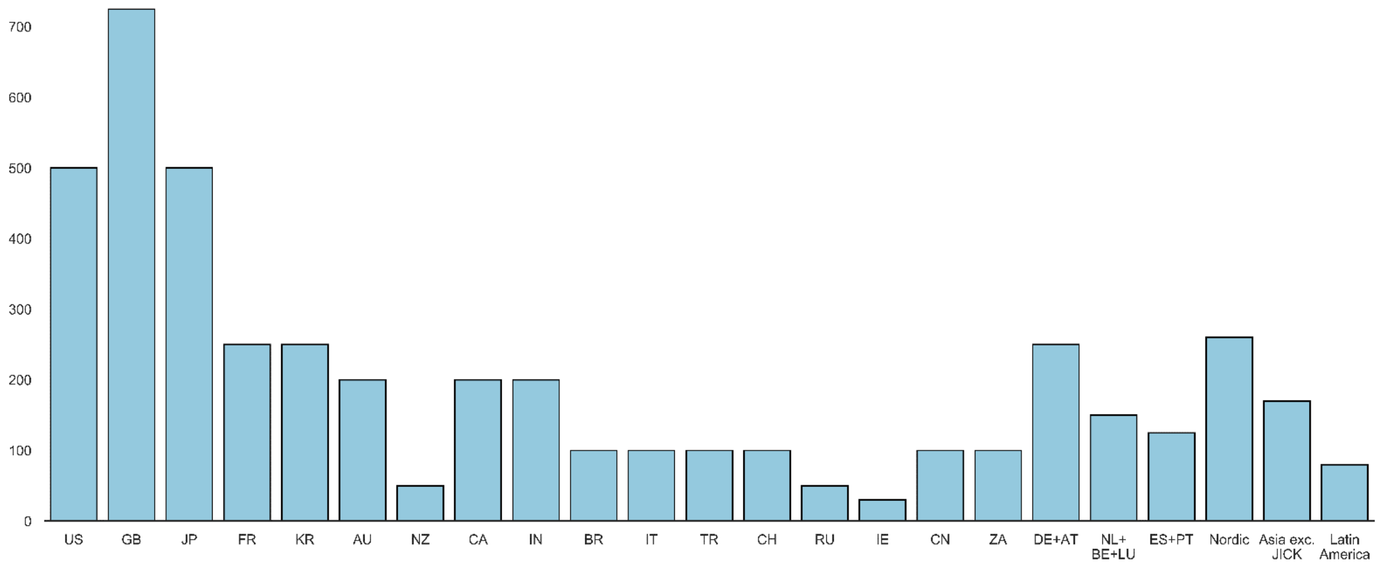
Appendix Figure 2. Climate Risk Underpricing

This figure reports investors' beliefs about whether current equity valuations in specified sectors correctly reflect the risks and opportunities related to climate change (Question D1). Responses for each sector could vary between plus two (valuations much too high) and minus two (valuations much too low). The figure reports the mean response scores per sector.



Appendix Figure 3. Distribution of Investor Holdings Sample across Countries

This figure shows the distribution of the investor holdings sample across countries. The sample construction follows Krueger (2015). In the figure, Nordic countries are Sweden, Denmark, Norway, Finland, and Iceland; Asia exc. JICK are Asia excluding Japan, India, China, and South Korea (i.e., Hong Kong, Singapore, Taiwan, Philippines, Pakistan, Indonesia, Malaysia, Thailand); and Latin America is Mexico, Chile, Colombia, Peru.



Appendix E: 10-K-Based Measure of Climate Risk Disclosure

To create the count-based measure of climate-related disclosures in 10-K we follow Matsumura, Prakash, and Vera-Muñoz (2021). The measures build on the 2010 interpretive guidance by the SEC, which states that firms are expected to disclose material climate risks in their 10-Ks (SEC 2010).

In a first step, we download a quarterly master index file, which contain links to all files disclosed to the SEC under https://www.sec.gov/Archives/edgar/full-index/. We then download all 10-K forms for our sample firms with a Python crawling algorithm. The resultant 10-K documents include the text in the annual 10-K reports, html code for formatting, as well as tables, exhibits and images. While a document does not have to be stripped-off of all unnecessary text structures such as html codes or tables for a word counting exercise, we nonetheless clean these documents to ensure our measure does not include any false positives. Since we are only interested in the text, we remove all Unicode characters such as &#146 or . We also remove digits, symbols, punctuation, and stop words. Finally, we replace multiple spaces with single space.

In a second step, we lemmatize each token (i.e., anything that is between two spaces, aka words). Lemmatization serve the purpose of standardizing the texts. For example, the string "emission" does not match to "emissions". But the lemmatized version of both "emission" and "emissions" is "emission". This process does a few other things apart from removing plurals and it is rather standard in word counting algorithms. Next, we make all strings in a text lowercase such that we do not have issues like "ghg" not matching "GHG" or "climate change" not matching "Climate change".

In a third step, we count how frequently climate change words of the dictionary by Matsumura, Prakash, and Vera-Muñoz (2021) appear in each 10-K. These words are "carbon", "climate change", "emissions", "greenhouse", "GHG", "hurricanes", "renewable energy", and "extreme weather." Note that before counting, we also lemmatize the dictionary and make all words lowercase. This only affects the string "emissions" and "hurricanes" which become singular, and the string "GHG" which becomes "ghg".

We create a dummy variable that is one if at least one of these eight climate-related keywords occurs in a 10-K, and zero otherwise.

Declaration of Authorship

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Emirhan Ilhan

March 30th, 2022