Climate Change and Households' Risk-Taking[*]

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Abstract

This paper studies a novel channel through which climate risks affect households' choices of risky asset allocation: a stringent climate change regulation elevates labor income risk for households employed by high-emission industries which in turn discourages households' financial risk-taking. Using staggered adoptions of climate change action plans across states, we find that climate change action plans lead to a reduction in the share of risky assets by 15% for households in high-emission industries. We also find a reduction in risky asset holdings after the stringent EPA regulation. These results are stronger with experiences of climate change-related disasters. Our study implies an unintended consequence of climate regulations for wealth inequality by discouraging low-wealth households' financial risk-taking.

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1 Introduction

Climate change is undoubtedly a critical challenge of our time. It is important for financial economists to study risks posed by climate change and its impact on investors' behaviors and financial markets. In line with this, a recent group of research finds that environmental and climate risks are an important consideration in institutional investors' portfolio choices.[1] However, in contrast to extensive studies on the impact of climate risks on institutional investors' portfolio choices, little is known about how climate change influences households' investment decisions. Does climate change matter for households' financial risk-taking? If so, through which economic mechanism?

In this paper, we address these research questions by paying special attention to climate regulatory risks. Regulatory risks are regarded as the most important component of climate risks of the three components (physical, transitional, and regulatory) over the next five years (Stroebel and Wurgler, 2021), and it is widely believed that regulatory risks have already begun to materialize (Krüeger et al., 2020). Motivated by the growing importance of regulatory risks, we investigate a novel channel through which climate regulatory risks can affect households' financial investment: as high-emission industries are more likely to face climate change-related regulations which impose additional labor income risks on their employees, we expect that households in these industries significantly reduce their investment in risky assets.

To test this hypothesis, we rely on the micro-level longitudinal Survey of Income and Program Participation (SIPP, hereafter) data from 1984 to 2019. We exploit detailed infor-

[1] E.g., Bolton and Kacperczyk (2021); Krüeger et al. (2020); Starks et al. (2020); Cao et al. (2021b); Choi et al. (2022); Humphrey and Li (2021), among others.

mation on households' occupations and industries as well as the state of residence. After we match the classification of high-emission industries by the Intergovernmental Panel on Climate Change (IPCC, hereafter) with the SIPP households' occupation industry classification, we first examine the impact of climate change action plans led by state governments. As these plans were adopted in different years across states in the U.S., we rely on a staggered triple-differences empirical strategy to investigate how households employed by high-emission industries change their financial risk-taking behaviors after their residential states adopt climate change-related action plans. Our triple-differences setting allows us to fully control for state-level time-variation by analyzing the difference in risk-taking between households in high-emission industries and non-high-emission industries within states. We find a substantial impact of climate change action plans on these households: adoptions of climate change action plans lead to a statistically significant decrease in the share of risky assets by 15.0% for households in high-emission industries relative to those in non-high-emission industries, conditional on participation. This suggests that climate change regulatory risks play an important role in explaining the financial risk-taking behaviors of households in high-emission industries.

In addition to adoptions of action plans, we further exploit the time-variation and cross-sectional variation in the regulatory stringency across states as the second measure to capture climate regulatory risks. We apply the U.S. Environmental Protection Agency (EPA, hereafter) environmental stringency measure and study the relationship between the stringency measure and the high-emission industry employees' financial risk exposure. We find a consistent pattern that a more stringent climate regulation leads to a statistically significant reduction of investment in risky assets by the employees working in one of the high-emission sectors. A one-standard-deviation increase in the EPA measure is associated with a decrease in the share of risky assets by 2.75%, conditional on participation.

Previous studies show that personal experience with global warming could update households' beliefs about climate change (Choi et al. (2020a); Konisky et al. (2016); Borick and Rabe (2014); Joireman et al. (2010)). If households' residential state is hit by climate change-related natural disasters, local employees in the high-emission industries might become more concerned about regulatory risks. We indeed find that an increase in injuries and fatalities per capita due to climate change-related disasters is associated with an increase in EPA stringency in the future. As such, households in the high-emission industries who experienced climate change-related disasters would reduce their exposure to risky assets in the financial markets in anticipation of further environmental regulations. Our empirical results confirm this hypothesis: A one-standard-deviation increase in the number of injuries and fatalities (per capita) is significantly associated with a decrease in the share of risky assets by 1.50% (1.29%), respectively. Furthermore, we find that natural disaster experiences intensify the effect of regulatory risks on high-emission industry employees' investment choices – for both adoptions of action plans and EPA stringency, an increase in injuries and fatalities interacted with these measures for climate regulations are significantly associated with a decrease in the share of risky assets.

One way to hedge against climate change risks could be to switch to a non-high-emission industry that is not negatively affected by elevated climate change risk. We find that indeed households significantly switch to a non-high-emission industry after elevated climate change regulatory risks measured by adoptions of action plans, an increase in EPA, and climate change-related disasters. Those households who switch to a non-high-emission industry allocate a significantly higher proportion of wealth to risky assets than households who stay in a high-emission industry, further highlighting the importance of climate change regulatory risks for households' risky asset allocation choices.

We provide an additional set of evidence supporting our hypothesis that the income risk channel drives households in high-emission industries to reduce their financial risk exposure. First, our placebo test shows that adoptions of action plans and changes in the EPA stringency measure do not affect the financial risk-taking choices of households in non-high-emission industries. This strongly supports that it is the labor income risk channel that drives our result because the income uncertainty of those households in non-high-emission industries is supposed not to be affected by climate regulatory changes. Second, we find that adoptions of action plans do not lead to a lower labor income level for households in high-emission industries, ruling out the possibility that households reduce financial risk exposure due to the first-moment effect (changes in the level of labor income). Rather, we find that the cross-sectional income dispersion significantly increases after the adoption of action plans, supporting the effect on the risky asset allocation choices through the second-moment effect. Third, we also examine climate change-unrelated disasters such as volcanoes and earthquakes and find an insignificant impact of these events, which assures that the effect stems from concerns about climate change-related risks together with the fact that they work for a firm in a high-emission sector. Finally, one could be concerned that our results are driven by households in high-emission industries holding employers' stock which underperform after the adoption of climate change action plans. However, we find that the performance of stocks in high-emission industries is statistically indistinguishable from those in other industries.

An important implication of our findings is that climate regulations have unintended consequences for households. Climate regulations discourage financial risk-taking for households in high-emission industries. We show that households working for high-emission industries are less wealthy, young, and less educated. We also show that the effect of regulatory risks is stronger for low-income and low-wealth households. Given the demographics of households in high-emission industries and the fact that low-income and low-wealth households are the most affected by climate regulatory risks in terms of financial risk-taking, climate regulation reinforces wealth inequality at the societal level. This is because climate regulation discourages less wealthy households' financial risk-taking, resulting in ineffective wealth accumulation. This is not to say that the entire society is worse off from climate regulations. But, the implication of our paper stresses the importance of the implementation of climate regulations in a way that does not elevate labor income risks for employees in high-emission industries.

Related literature: Our study is linked to the existing literature and contributes to academic research on various fronts. Our paper adds to the emerging and increasingly important research field of climate finance that studies the impact of climate change on financial markets and how financial markets, in turn, affect our environment (see Hong et al. (2020) and Giglio et al. (2021) for the literature reviews).

Most of the existing literature on households' responses to climate and environmental change considers the impact of physical risks such as sea-level rise (e.g., Bernstein et al., 2019; Murfin and Spiegel, 2020; Baldauf et al., 2020; Ilhan, 2022), weather experience (e.g., Choi et al., 2020a; Zaval et al., 2014; Akerlof et al., 2013; Myers et al., 2013), flooding (e.g., Hu, 2021; Gallagher, 2014), and air pollution (e.g., Chang et al., 2018; Graff Zivin and

Neidell, 2012). Different from these studies, we examine the influence of climate regulatory risks on households and find a novel channel through which regulatory risks could affect the financial decisions of households in the high-emission industries. As the high-emission industries are most exposed to regulatory shocks related to climate change, employees in the relevant sectors face uninsured labor income risk due to potential regulations. As a result, climate regulatory risks shape households' investment decisions through the labor income risk channel.

Our work contributes to a growing literature on climate regulatory risks. The survey conducted by Stroebel and Wurgler (2021) finds that regulatory risks are regarded as the top climate risk to firms and investors over the next five years by financial professionals, financial economists in academics and public institutions, and regulators. In addition, Krüeger et al. (2020) survey institutional investors' perceptions about climate change-related risks. Institutional investors believe that these risks, in particular, regulatory risks have started to materialize. Different from the current studies which mainly focus on firms' actions regarding climate and environmental policy changes (e.g., Ramadorai and Zeni, 2021; Karpoff et al., 2005) as well as stock and bond market reactions (e.g., Seltzer et al. (2020); Ramelli et al. (2021)), our paper examines households' behaviors and echos the significance of regulatory risks not only for firms and institutional investors but also for households' financial decisions.

Our paper also contributes to the household portfolio choice literature, especially the research on the effect of uninsured "background" risks. Our focus in this paper is labor income risk, the primary uninsurable risk for households (e.g., Guiso et al., 1996; Angerer and Lam, 2009; Betermier et al., 2012; Palia et al., 2014; Fagereng et al., 2017; Catherine et al., 2020). Specifically, our paper identifies climate regulatory risk as a novel source of uninsured labor income risks which pose important job and income concerns for employees in high-carbon-emission industries. As a result, we provide novel empirical evidence that households reduce their financial risk exposure in response to an increase in climate regulatory risks, supporting the importance of uninsurable income risk for households' portfolio choices.

Our paper also contributes to the literature on how disaster experiences shape households' beliefs and risk attitudes and in turn affect their stock investment (e.g., Bharath and Cho, 2021; Malmendier and Nagel, 2011). Different from this line of literature, we compare portfolio adjustments of households in high-emission industries with those of households in non-high-emission industries within the same states following disaster experiences. This empirical strategy shuts down the direct effect of disaster experiences on households' risk preferences and risk-taking behaviors documented in the previous literature. Thus, our findings of the impact of natural disasters go beyond the existing literature by documenting that it is households in high-emission industries that adjust risk-taking behaviors more significantly after climate change-related natural disasters.

A closely related study by Ilhan (2022) documents that homeowners who are exposed to sea-level rise are less likely to take financial risks. Different from Ilhan (2022) who focuses on the homeownership channel, in our paper, we demonstrate that households' income risk channel affects households' portfolio choices in response to climate change-related regulatory risk. Ilhan (2022) finds that the adoption of state governments' climate change-related action plans alleviates homeowners' uncertainty about sea-level rise and increases homeowners' willingness to hold risky assets. In contrast, we show that the regulatory shock reduces the stock holdings of employees in high-emission industries because they become more concerned about their labor income risk. Finally, while the homeownership channel is important for wealthy households, we find that the novel labor income risk channel is more important for low-income and low-wealth households. Taken together, adoptions of climate change-related action plans encourage homeowners, who are relatively wealthy, to take more financial risk and discourage households in high-emission industries, who are relatively poor, from taking the financial risk.

The rest of the paper is organized as follows. We describe the datasets and variable constructions in Section 2. We discuss empirical strategies in Section 3. We then present our empirical results in Section 4. Section 5 concludes this paper.

2 Data

2.1 SIPP Data

We use the Survey of Income and Program Participation (SIPP) data by the U.S. Census Bureau to observe households' portfolio choices as well as the state of residence. The SIPP data provide a large sample of households' asset holdings and demographic information in a panel setting. There are two major benefits of the SIPP data for our study. First, as pointed out in Campbell (2017), it is crucial to have a panel setting to examine households' portfolio choices in association with labor income risk. This is because, without households' fixed effects that can control for households' time-invariant risk aversion, an endogeneity arises from the fact that households who are risk-tolerant could choose risky jobs and risky portfolios, leading to a positive correlation between labor income risk and portfolio choices. Given this potential endogeneity, the panel setting of the SIPP makes this data set particularly well-suited for our analysis. Second, SIPP collects households' asset-holding information every year, and thus, researchers can observe annual changes in portfolios, different from biannual changes in portfolios in the Panel Study of Income Dynamics (PSID) data. Moreover, up until the 2014 panel, there are observations every month. Therefore, we can have annual portfolio changes at a monthly frequency. With a quite high frequency of observation of households' portfolio changes, we can have a clearer identification to study the impact of a change in climate change-related regulatory or environment shocks on households' portfolio changes.

We use the data from August 1984 - December 2019 based on 1984, 1985, 1986, 1987, 1990, 1991, 1992, 1993, 1996, 2001, 2004, 2008, 2014, 2018, 2019, and 2020 panels. The SIPP surveys around 20,000 to 30,000 households over several waves - 8 to 12 waves - for 2 to 3 years. Each wave refers to four months of information. As is common in the literature, we do our analysis at the household level, assuming household members pool assets and make financial decisions together. Therefore, we aggregate individual data into households and use households' head demographic information. Our final sample of households is 353,482 household-year observations with 152,009 unique households.

We construct two measures of households' financial risk-taking as in the literature. The first measure is a continuous variable that measures the value of risky assets as a fraction of the total financial assets each household possesses. Risky assets include stocks and mutual funds. The total financial assets are risky assets plus checking, savings, and bonds. The second measure is a binary variable that indicates whether each household has any holdings in the stock market and mutual funds or not. Following the literature (e.g., Hong et al., 2004; Agarwal et al., 2018; Kozak and Sosyura, 2019), we do not consider stock investment indirectly through pension accounts or individual retirement accounts (IRAs/401K) given inactive trading behaviors in retirement accounts.

Table 1 presents household-level descriptive statistics for SIPP households. For comparison, Online Appendix Table A1 presents the descriptive statistics for households in the Survey of Consumer Finances (SCF) using the waves from 1984 to 2019. Panel A of Table 1 shows that 62.8% of household heads are male, and 89.2% of them are white. They are on average 51.83 years old. 56.1% of respondents have college degrees. 37.2% of respondents have high school degrees as the highest education. 53.4% of them are married and have 0.667 children on average. As well known in the literature, stockholders are more likely to be male, white, older, more educated, and more likely to be married (e.g., Campbell, 2006; Malloy et al., 2009). This is also the case in the SCF as shown in Online Appendix Table A1.

[Insert Table 1 here]

Panel B of Table 1 reports information about SIPP households' asset holdings. All dollar values are deflated using the CPI with 1982-1984=100. The share of stocks and mutual funds in the financial wealth is 14.6% on average. 27.3% of households own stocks and mutual funds directly. 42.7% of them own risky assets either directly or indirectly through retirement accounts. The average (median) value of savings and checking accounts is $9,931 ($2,325). As in Agarwal et al. (2018), total wealth in this paper is defined as the liquid asset plus illiquid asset (which is the sum of rental assets, business, and vehicles) minus debts against them. As is well-known literature, assets are highly positively skewed, reflecting severe wealth inequality. Also, stockholders are much wealthier than non-stockholders, and stockholders have higher labor income than non-stockholders. Table A1 shows the distribution of SCF households' characteristics which are highly similar to the SIPP, confirming that SIPP survey data is a nationally representative sample. For example, average college and high degrees are 56.1% and 37.2%, respectively in SIPP versus 54.7% and 39.0% in SCF. Also, all values of percentiles are the exactly same except for age in Panel A. Average participation rate with retirement accounts in SIPP is 42.7% versus 49.5% in SCF, suggesting that the SIPP is a nationally representative survey data set.

Comparing households in high-emission industries and those in non-high-emission industries, there are no significant differences in the share of risky assets, participation, and dollar value of stocks and mutual funds between the two groups, suggesting a similar level of financial risk-taking between the two groups. However, it is worth noting that the two groups differ in other demographic features. Households in high-emission industries are on average more likely to be male, white, younger, less educated, and less wealthy. Households in high-emission industries have on average a total wealth of $34,079 versus $50,865 for those in non-high-emission industries. The demographics of households in high-emission industries are consistent with previous studies showing that less-educated workers are predominant in manufacturing and construction sectors (e.g., Krause and Sawhill, 2017; Rose, 2017; Gould, 2019).

Given that significant differences in households' characteristics could affect the way households respond to an increase in climate regulatory risks, we control for these households' characteristics.

2.2 Climate Change Action Plans

To test whether households employed by high-emission industries change their portfolios in response to an increase in climate regulatory risks, we first exploit the time- and geographic variation in the introduction of State-led Climate Change Action Plans. State and local governments have introduced climate change action plans to mitigate the adverse effects of climate change. For example, Florida introduced an energy and climate change action plan on October 15, 2008. The plan contains 50 separate policy recommendations that will reduce harmful greenhouse gas emissions and provide a framework for climate change action strategies (Governor's Action Team on Energy & Climate Change, 2008). The introduction of the plan aimed to reduce gas emissions would lead to an increase in labor income risk for households employed by high-emission industries residing in Florida. We collect the entire list of climate change action plans available on the Georgetown Climate Center, part of Georgetown University Law Center.[2] Figure 1 displays the states that adopted climate change action plans and the adoption years. Notably, there is a considerable time and cross-sectional variation in the adoption of action plans across states, which we will exploit in a triple-differences setting.

[Insert Figure 1 here]

2.3 EPA Regulation Data

In addition to climate change action plans, we also use the EPA enforcement data, which is widely used in the literature (e.g., Seltzer et al., 2020; Cao et al., 2021a; Dasgupta et al., 2021). Specifically, we construct the regulatory stringency measure using the EPA enforce-

[2]https://www.georgetownclimate.org/adaptation/plans.html

ment data available in the Integrated Compliance Information System (ICIS) for Federal Civil Enforcement Case Data. We count the number of compliance and enforcement actions for the Clean Water Act (CWA), Clean Air Act (CAA), and Resource Conservation and Recovery Act (RCRA) which includes both informal enforcement actions (notifications of violation) and formal actions (fines and administrative orders) in a given state in a given year. Then, we scale the number of enforcement by the total number of facilities that are subject to EPA regulations in a given state in a given year as in Seltzer et al. (2020). We then merge the state-year regulatory stringency measure with households' state and year. Figure 2 plots a heatmap that visualizes the EPA stringency measure across states in 1999, 2009, and 2019. Note that the color scale is different each year and therefore, the color scale represents the relative stringency within a year. Overall, it is clear that there is a large cross-sectional and time variation in the EPA stringency. We exploit these variations and test whether households in a high-emission industry change their risk-taking behaviors after a change in EPA stringency.

[Insert Figure 2 here]

2.4 Natural Disaster Data

We use the Spatial Hazard Events and Losses Database for the United States (SHELDUS) to introduce natural disasters as exogenous shocks on households' perception of regulatory risks. The database provides information on the date, affected location at the county level, and direct losses caused by 18 types of natural hazards starting from 1960. This database has been widely used by recent empirical studies in economics and finance (e.g., Barrot and Sauvagnat, 2016; Bernile et al., 2017; Cortés and Strahan, 2017).

Among variables such as crop and property damage, counts and the length of events, injuries and fatalities, we use injuries and fatalities as our main measure of the intensity of natural disasters (e.g., Kahn, 2005; Kellenberg and Mobarak, 2008; Bernile et al., 2017). The rationale behind this choice is that these losses are arguably the most concern by the general public in the affected area. Therefore, we construct this combined measure as a reasonable proxy for the perception of the public on natural disasters.

To focus on the effect of climate change, we differentiate climate change-related disasters from other natural disasters. We first follow Correa et al. (2020) which classify earthquakes, tornadoes, and winter weather as climate change-unrelated disasters based on a recent report from the Intergovernmental Panel on Climate Change (IPCC) (Seneviratne et al., 2012). Following Thomas et al. (2013), we further add volcanoes to this group because they are geophysical disasters that are not climate change-related in the classification system of the Emergency Events Database (EM-DAT) from the Center for Research on the Epidemiology of Disasters (CRED). Therefore, all the remaining 14 natural disasters in the SHELDUS are considered climate change-related natural disasters in our analysis. We aggregate injuries and fatalities from all climate change-related natural disasters to the state-month level and match them with the household data.

2.5 High Carbon Emission Industries

In order to identify high-carbon emission industries, we rely on the definitions of high-emission industries by the Intergovernmental Panel on Climate Change (IPCC). The IPCC categorizes five sectors as major emission sources: 1) Energy; 2) Transport; 3) Buildings; 4) Industry (such as chemicals and metals); and 5) Agriculture, Forestry, and Other Land

Use. Choi et al. (2020b) match the IPCC subcategories with the industry classification by Fama and French (1997) which classify 4-digit SIC codes into 48 groups. We hand-match the high-emission Fama and French (1997) industries with the 3-digit industry classification for jobs in SIPP. The list of high-emission industries classified by IPCC is in Appendix A.

3 Empirical Strategy

3.1 Hypothesis Development

Climate change-related regulations impose more risks on high-emission industries through various economic channels. For example, the ability to grow their businesses could be limited for firms in high-emission industries due to environmental regulations (List et al., 2004; Greenstone et al., 2012; Dechezleprêtre and Sato, 2020). Moreover, the profitability of firms in high-emission industries could be hurt due to an increase in costs to follow new regulations (e.g., Ryan, 2012; Chan et al., 2013; Pasurka, 2020). Climate change-related regulations also could bring environmental issues to customers' attention that could turn into a decrease in sales (e.g., Kolk and Pinkse, 2008; Sullivan and Gouldson, 2017). Therefore, a higher regulatory risk poses a great risk to firms in high-emission industries, which could in turn lead to a higher perceived labor income risk for the employees in these industries. Thus, we conjecture that an increase in climate change-related regulatory risks would translate into elevated labor income risks faced by households working for environmentally high-emission industries.

Among many theoretical studies that examine optimal risky asset allocation under risky labor income, Campbell and Viceira (2002) derive the optimal share of the risky asset in financial wealth (α_t) using a simple setup of the power utility and lognormal distribution of labor income and risky asset as follows.

$$\alpha_t = \underbrace{\frac{1}{\rho}(\frac{\mu + \sigma_u^2/2}{\gamma\sigma_u^2})}_{Speculative\ demand} \underbrace{-\frac{1-\rho}{\rho}(\frac{\sigma_{yu}}{\sigma_u^2})}_{Hedging\ demand}, \tag{1}$$

where μ is the expected log excess returns on the risky asset. σ_u is the volatility of the log return on the risky asset. σ_{yu} is the covariance between labor income growth and risky asset returns. ρ is the steady state portion of financial wealth to total wealth that includes human capital. $0 < \rho = \frac{exp(r_p+w-y)}{1+exp(r_p+w-y)} < 1$ where r_p is the mean log return on wealth. w is the mean log of wealth and y is the mean log labor income ($= logE[Y] - \sigma_y^2/2$ where Y is labor income). Our key interest of parameter is σ_y^2 which may be elevated due to climate change risk for households working for environmentally high-emission industries. There are two cases that σ_y^2 and α_t are negatively related: (1) idiosyncratic income risk ($\sigma_{yu} = 0$); (2) non-zero correlation ($\sigma_{yu} \neq 0$).

First, for the case where labor income risk is idiosyncratic (i.e., $\sigma_{yu} = 0$), Campbell and Viceira (2002) derive a sufficient condition for the negative relation between income uncertainty and allocation to the risky asset: That is, $\gamma > (1/\rho) > 1$. Even though labor income risk is idiosyncratic, sufficiently conservative investors would lower her financial exposure following an elevated income uncertainty. This prediction is in line with Pratt and Zeckhauser (1987), Kimball (1993), and Eeckhoudt et al. (1996). Therefore, as long as households' risk aversion is sufficiently high, to the extent that labor income risks faced by households in high-emission industries are elevated, households' financial risk exposure will be reduced after a higher regulatory risk whether their labor income risk is correlated with returns of stocks that they hold.

Second, for the case where labor income risk is not idiosyncratic (i.e., $\sigma_{yu} \neq 0$), the link between the optimal share of the risky asset and labor income risk depends on the sign of the correlation between income growth and stock returns. When the correlation is positive, households optimally reduce their stock exposure in response to an increase in labor income to hedge against income risk and in turn smooth their consumption. If this is the case in the data, an elevated labor income risk for households in high-emission industries would lead to a decrease in the allocation to the stock market.

Past empirical evidence is consistent with the positive correlation between income growth and stock returns at the individual level. This is because households tend to hold local stocks (e.g., Grinblatt and Keloharju, 2001; Seasholes and Zhu, 2010; Gargano and Rossi, 2018) or their employers' stock (e.g., Benartzi, 2001; Mitchell and Utkus, 2002; Meulbroek, 2005). Since shocks to their employer firms' fundamentals affect both stock returns and labor income in the same direction, labor income and returns of stocks households own are likely positively correlated. Moreover, given this investment behavior of households, it is unlikely that households in high-emission industries purchase stocks that are negatively correlated with their labor income (e.g., green stocks).

3.2 Main Specification

To begin with, we estimate the impact of adoptions of state-level climate change action plans, as a measure of regulatory risk, on risky asset allocation choices of households in high-emission industries, we will test this hypothesis in the triple-differences setting as follows:

$$y_{i,s,t} = \alpha + \beta \cdot \text{Plan}_{s,t} \times \text{Job-Ind}_{i,t} + X'_{i,s,t}\Gamma + \theta_i + \gamma_{j,t} + \psi_{s,t} + \epsilon_{i,s,t}, \tag{2}$$

where $y_{i,s,t}$ is the share of risky assets in total financial wealth (*Share of Risky Assets*) for a household i living in a state s at time t or a dummy variable that takes one for stock market participation (*Participation*). As is common in the literature, when we examine changes in the share of risky assets, we condition on participation (intensive margin). This is because a decision to enter the stock market is not the same decision to change an allocation to risky assets as a stockholder (e.g., entry costs). *Plan*$_{s,t}$ is a dummy variable that takes one for state s at year t after a climate change action plan is adopted in its state, and zero otherwise. *Job-Ind*$_{i,t}$ is a dummy variable that takes one if a household i's job industry belongs to one of the high-emission industries by IPCC at year t. β is the coefficient of interest that captures the change in households' exposure to financial risk in response to adoptions of climate change action plans for households in high-emission industries relative to others. $X_{i,s,t}$ is the set of time-varying households' characteristics that are age, age squared, college dummy variable, high school dummy variable, log of one plus labor income, log of one plus total wealth, married dummy variable, and the number of children. θ_i denotes households' fixed effects. $\gamma_{j,t}$ denotes occupation industry-year-month fixed effects. $\psi_{s,t}$ denotes state-year-month fixed effects. Throughout our analysis, standard errors are double clustered by year-month and state.

Moreover, we also use the state-level EPA regulatory stringency measure as an alternative measure to capture a change in climate change regulatory risks as follows.

$$y_{i,s,t} = \alpha + \beta \cdot \text{Stringency}_{s,t-1} \times \text{Job-Ind}_{i,t} + X'_{i,s,t}\mathit{\Gamma} + \theta_i + \gamma_{j,t} + \psi_{s,t} + \epsilon_{i,s,t}, \tag{3}$$

where *Stringency*$_{s,t}$ is the EPA stringency measure computed as the ratio of the number of compliance and enforcement actions to the total number of facilities in a state s and year

t. We take one year lag on the EPA measure to examine the impact of the EPA stringency in a previous year on portfolio changes.

In addition, when climate change-related natural disasters intensify the concerns about climate change, people would be more likely to perceive regulatory risks as a critical threat to high-emission industries. We, hence, expect a stronger impact of regulatory risks on portfolio choices by local employees in the high-emission industries after climate change-related natural disasters hit the residential states. We develop our empirical test for this hypothesis. We first directly test whether a past disaster experience affects portfolio choices of households in high-emission industries in anticipation of regulatory risks following disasters as follows:

$$y_{i,s,t} = \alpha + \beta \cdot \text{Disaster}_{s,t-1} \times \text{Job-Ind}_i + X'_{i,s,t}\Gamma + \theta_i + \gamma_{j,t} + \psi_{s,t} + \epsilon_{i,s,t} \tag{4}$$

We use two measures for the disaster experience, *Disaster*$_{s,t}$: (1) the number of injuries and fatalities caused by a disaster, *inj-fat*$_{s,t}$ and (2) the number of injuries and fatalities per capita, which is scaled by county population, *inj-fat-per*$_{s,t}$. Next, we examine whether the impact of regulatory risks on portfolio choices is stronger with disaster experiences. To this end, we interact the disaster variables with the difference-in-differences term for either action plans or the EPA measure as follows.

$$y_{i,s,t} = \alpha + \beta \cdot \text{Disaster}_{s,t-1} \times \text{Plan}_{s,t} \times \text{Job-Ind}_{i,t} + X'_{i,s,t}\Gamma + \theta_i + \gamma_{j,t} + \psi_{s,t} + \epsilon_{i,s,t} \tag{5}$$

$$y_{i,s,t} = \alpha + \beta \cdot \text{Disaster}_{s,t-1} \times \text{Stringency}_{s,t-1} \times \text{Job-Ind}_{i,t} + X'_{i,s,t}\Gamma + \theta_i + \gamma_{j,t} + \psi_{s,t} + \epsilon_{i,s,t} \tag{6}$$

3.3 Identification Strategy

Our key identifying assumption is that households in high-emission industries (treatment group) in a state would have changed their financial risk exposure in the same way as households in non-high-emission industries (control group) in the same state without the adoption of climate change action plans or changes in environmental regulations. One potential concern is households in high-emission industries have different characteristics that are correlated with households' portfolio choices. For example, as shown before, households in high-emission industries are more likely to be white, male, married, younger, less educated, and have more kids, which could affect the way households in high-emission industries change their financial risk exposure after the adoption of action plans.

We mitigate this concern in several ways. First, we directly control for a wide set of household characteristics that can affect households' choices of financial risk-taking. Therefore, even though household characteristics could be significantly different between the two groups, these differences are controlled for. Second, we examine whether the two groups have significantly different exposure to financial risk before the adoption of climate change action plans. We show that there is no significant difference in the level of the share of risky assets and participation between the two groups before the adoption of climate change action plans. Further, we confirm that there is no discernible dynamic pattern of the difference in the extent of risk exposure before the adoption, implying that the parallel pre-trend assumption is supported.

Moreover, throughout our analysis, we control for state-year-month fixed effects and occupation industry-year-month fixed effects to fully absorb any time-varying state-level and industry-level omitted factors that could be correlated with households' portfolio choices. For example, in studying the impact of natural disasters on households' financial risk-taking behaviors, our empirical setting allows us to rule out the effect of time-varying risk aversion led by disasters, by examining households in high-emission industries and others within the same states after controlling for state-year-month fixed effects. In the same way, state-year-month fixed effects fully control for any state-level time-varying economic and political environments that could be correlated with portfolio choices of households in states. Finally, household fixed effects control for any time-invariant household-level factors such as time-invariant risk aversions. As raised in Campbell (2017), this would address the endogeneity problem that could result in a spurious positive link between a high labor income risk and a positive asset holding without controlling for risk aversion in a cross-sectional setting.

4 Empirical Results

4.1 Climate Change Action Plans

4.1.1 Do climate change action plans affect portfolio choices?

We first examine whether households in high-emission industries reduce their exposure to financial risk after the adoption of climate change action plans in a state where households reside. Table 2 presents the triple-difference regression results. Column (1) presents the result for the share of risky assets in total financial wealth (*Share of Risky Assets*), conditional on participation (intensive margin). Column (2) presents the result for a binary decision to be a stockholder or non-stockholder (extensive margin). Since the first year of the adoption of a climate change action plan is 2004, we restrict our attention to samples from the year 2001 to 2019.[3] Column (1) shows that conditional on participation, households employed by one of the high-emission industries indeed reduce the share of risky assets in total financial wealth after the adoption of climate change action plans, consistent with our hypothesis. An adoption, on average, leads to a decrease in the share of risky assets by 6.9 percentage points for households in high-emission industries relative to others. Given the average share of risky assets is 45.98% conditional on participation, the decrease in the share of risky assets of 6.9 percentage points translates into an economically significant decrease by 15.0% (=0.069/0.4598) evaluated at the mean. Also, the effect is statistically significant at the 5% significance level. Column (2) shows that stock market participation, on average, decreases by 2.6 percentage points or 8.92% (=0.026/0.2916) for households in high-emission industries relative to others. Although the sign of the coefficient is consistent with the effect of climate change action plans on the share of risky assets, and the coefficient is economically significant, the effect on participation is not statistically significant. This implies that a reduction in financial risk exposure is pronounced for existing stockholders reducing the exposure instead of exiting the stock market completely. Given this finding, we focus on the risky asset allocation choices of households conditional on participation (intensive margin) throughout our remaining analyses.

[Insert Table 2 here]

4.1.2 Placebo tests

If the above finding is indeed due to the income risk channel, the adoption of climate action plans should not increase the income risk of households employed by non-high-

[3] Estimating the same regression equation using the full sample from 1984 produces virtually identical results since there was no adoption before 2001 and also due to state-time-fixed effects.

emission industries. Therefore, the effect of climate action plans on the risk-taking of households in the entire state would be insignificant or much milder than those of households in a high-emission industry. To conduct a placebo test, we relax state-year-month fixed effects and run the following difference-in-differences regression. In this specification, we test whether households in states that adopted action plans adjust their financial risk exposure relative to other states that did not adopt plans.

$$y_{i,s,t} = \alpha + \beta \cdot \text{Plan}_{s,t} + X'_{i,s,t}\Gamma + Z'_{s,t}\delta + \theta_i + \gamma_{j,t} + \psi_s + \epsilon_{i,s,t}, \tag{7}$$

where $Z_{s,t}$ is a set of the state-level control variables, which includes state-level GDP growth, income growth, a dummy variable that takes one for a Democratic governor, and the fraction of Democrats in a state's legislature (both House of Representatives and Senate). These state-level time-varying controls are necessary for this setting without state-year-month fixed effects.

Columns (3) and (4) of Table 2 present the result. Although the signs on the difference-in-differences term are negative for both risk exposure measures, the magnitude is negligible and statistically insignificant. This finding suggests that households on average do not adjust their portfolios of risky assets. Therefore, our placebo tests support that our findings are not spurious, and it is likely the income risk channel that drives the effect of climate action plans on the risk-taking behaviors of households in a high-emission industry.

4.1.3 Dynamic effects

Figure 3 plots the dynamic effect of the adoption of climate change action plans on the risk-taking behaviors of households in a high-emission industry by displaying the coefficients on triple-differences dummy variables. For both the share of risky assets and participation measures, there are no significant differences between the treatment and the control group before the adoption, suggesting that the parallel pre-trend assumption is supported. Also, for both outcome measures, households in high-emission industries have always lower financial risk exposure than households in non-high-emission industries after the adoption of climate change action plans, which is not the case before adoptions. In terms of statistical significance, the share of risky assets is always significant at the 10% level after the adoption. Participation is significant 5 years after the adoption. Overall, our analysis of the dynamic effect of the adoption of climate change action plans shows that there is no notable dynamic pattern before adoptions, and also adoptions have a long-lasting effect on risk-taking behaviors of households in high-emission industries at the intensive margin.

[Insert Figure 3 here]

4.1.4 Is the result driven by the first-moment effect?

It might be possible that households in high-emission industries reduce their financial risk exposure due to a decrease in the expected level of labor income (first-moment effect) instead of elevated perceived labor income risk (second-moment effect). Since no data shows the perception of households about the first and second moment of labor income, we instead rely on the cross-sectional distribution of labor income changes after the adoption of action plans. Specifically, we examine whether and how the cross-sectional dispersion and level of labor income change after the adoption of action plans.

Table 3 reports the regression results that show changes in the distribution of labor income for households in high-emission industries relative to others after the adoption of action plans. The dependent variable in Columns (1) and (2) is the standard deviation of labor income for each state, each time, and the industry group normalized by the mean. The dependent variable in Columns (3) and (4) is the level of labor income. Columns (1) and (2) show that the cross-sectional dispersion of labor income among high-emission industries becomes significantly higher than the dispersion among non-high-emission industries after the adoption of action plans. This result is more statistically significant among stockholders. In contrast, Columns (3) and (4) show that there is no significant difference in the level of labor income between households in high-emission industries and others after the adoption of climate change action plans. Taken together, our set of evidence suggests that it is likely not the first-moment effect, but the second-moment effect that drives the reduction in financial risk exposure.

[Insert Table 3 here]

4.1.5 Discussion

To the best of our knowledge, Ilhan (2022) is the only study that examines the effect of climate change on households' portfolio choices. He finds that homeowners who are exposed to sea-level rise take more financial risk after the adoption of climate change action plans. This is because these plans to mitigate climate change risk could lead to a decrease in the perception of sea level risk. Different from Ilhan (2022), our study provides a novel economic channel through which climate change affects portfolio choices. While homeowners exposed to sea-level risk take more risk after the adoption of plans, we show that households employed by high-emission industries take less risk after adoptions due to elevated labor income risk. Ilhan (2022) shows that homeowners are older, more educated, and wealthier than non-homeowners. We show in Table 1 that households employed by high-emission industries are younger, less educated, and less wealthy. Given that demographics of homeowners are opposite to households employed by high-emission industries, Ilhan (2022) and our findings together imply that adoptions of climate change action plans have unintended consequences: while these plans induce wealthy homeowners to take more financial risk, they discourage less wealthy, young, and uneducated households from taking a financial risk, leading to an ineffective wealthy accumulation.

4.2 EPA Environmental Stringency Measure

In this subsection, we use the state-level EPA environmental stringency as an alternative measure to capture climate change regulatory risks. In contrast with our dummy measure for the adoption of action plans, this EPA measure introduces more variations by estimating the level of stringency of environmental regulations across states and over years. To study how climate change regulatory risks are linked to risk-taking behaviors, we use the EPA stringency measure and repeat our previous analysis. Table 4 presents the result. Column (1) shows that households in a high-emission industry reduce their financial risk exposure relative to others after an increase in EPA stringency. This result is consistent with a reduction in financial risk-taking after the adoption of climate action plans. In terms of magnitude, a one-standard-deviation increase in the EPA stringency measure previous year is associated with a decrease in the share of risky assets next year by 1.21 percentage points, or 2.75% evaluated at the mean for households in high-emission industries relative to others.

To ensure that this result is not spurious, as before, we examine whether the EPA stringency is associated with entire households within states regardless of their industries of occupation. Column (2) shows that there is no significant relationship between the EPA stringency and risk-taking behaviors of all households that include those who work in a non-high-emission industry. This result suggests that an increase in EPA stringency is not associated with the entire households in the state. Rather, an environmental regulatory change matters only for households employed by high-emission industries. This result further supports that it is likely labor income concerns that drive the reduction in risk-taking after an elevated climate regulatory risk.

Although the EPA stringency provides consistent findings with adoptions of climate change action plans, these two measures capture different aspects of climate change-related regulations. While action plans are a forward-looking measure for future possible regulations, the EPA stringency reflects current implementations of environmental and climate policies. Our results suggest that both uncertainties about future regulations and concerns over regulatory enforcement would elevate perceived labor income risks for households employed by high-emission industries which negatively affects their financial investment. We also perform quadruple-differences regressions by interacting these two measures. Online Appendix Table A2 shows that their interactions are statistically significant. This finding suggests that the adoption of action plans and the EPA stringency reinforce each other in influencing the risk-taking of households' in a high-emission industry.

[Insert Table 4 here]

4.3 Natural Disasters

Few studies have linked natural disasters with households' risk-taking behaviors. Bharath and Cho (2021) show that after a natural disaster shock, households become more risk-averse and less likely to participate in risky asset markets. In this subsection, we go a step further and study whether households in high-emission industries adjust their financial risk-taking behaviors relative to other households within the same states after climate change-related natural disasters. By comparing two different groups within the same states, we can rule out the possibility that a higher risk aversion of households or income shocks caused by disasters drives our results.

Then, through which economic channel, could natural disasters be linked to the risk-taking of households in high-emission industries? Past studies show that personal experiences of global warming could affect households' beliefs about climate change (Choi et al. (2020a); Konisky et al. (2016); Borick and Rabe (2014); Joireman et al. (2010)). As such, experiences of climate change-related natural disasters can lead to the expectation that there will be more stringent environmental regulations that could elevate the perceived labor income risk of those households in high-emission industries. Through this income risk channel, households in high-emission industries could reduce financial risk exposure in response to climate change-related natural disasters.

4.3.1 Do natural disasters affect risk-taking?

Table 5 shows that households in high-emission industries reduce their allocation to risky assets after climate change-related natural disasters. Moreover, the result is robust to both the number of injuries & fatalities and the number of injuries & fatalities per capita. In terms of the magnitude, a one-standard-deviation increase in the number of injuries & fatalities (per capita) is associated with a decrease in the share of risky assets by 1.50% (1.29%) next year for households in high-emission industries relative to those in non-high-emission industries, evaluated at the mean. The magnitudes for natural disasters are smaller than those for action plans and EPA stringency. This result is intuitive in the sense that natural disasters are indirectly linked to an increase in the labor income risk of households in high-emission industries. That is, households react to natural disasters in anticipation of more stringent regulations in the future while action plans and EPA stringency are direct changes in regulations.

We emphasize that our results are not affected by the impact of a higher risk aversion led by disaster experiences (e.g., Bharath and Cho, 2021). This is because our regression is a triple-difference setting where we compare the risk-taking of households in high-emission industries with others within the same states. Therefore, both the treatment and control groups have the same disaster experiences and thus the impact of a higher risk aversion led by disaster experiences does not affect our results.

In sum, our findings of the impact of natural disasters go beyond Bharath and Cho (2021) by emphasizing that it is households in high-emission industries that adjust risk-taking behaviors more significantly after climate change-related natural disasters. More importantly, we provide further evidence that households in high-emission industries reduce financial risk exposure after disasters related to climate regulatory risks.

[Insert Table 5 here]

If households in high-emission industries, who experienced disasters, change their financial risk exposure due to elevated labor income concerns, these households should not respond to natural disasters that are not related to climate change. Therefore, to examine whether our findings are driven by another economic channel instead of the income risk channel, we test the risk-taking behaviors of households in high-emission industries following climate change-unrelated natural disasters which are volcanoes, tornadoes, earthquakes, and winter weather. To this end, we repeat the same analysis as above by replacing the type of natural disaster in constructing the number of injuries & fatalities measures. Online Appendix Table A3 shows no significant relationship between the risk-taking of households in high-emission industries and climate change-unrelated disasters. This indicates that the risk-taking of households in high-emission industries is only affected by climate change-*related* disasters, but not by climate change-*unrelated* disasters. Therefore, this result supports that the link between climate change-related disasters and risk-taking behaviors is likely driven by the possibility that climate change-related disasters lead to a more stringent environmental regulation, which raises income risk.

4.3.2 Do natural disasters intensify the impact of regulatory risks?

Our empirical evidence with climate change-related natural disasters shows that households in high-emission industries lower their financial risk exposure relative to others after disaster experiences. We further examine whether climate change-related natural disasters intensify the concerns about climate and lead to portfolio changes when there is an environmental regulation change. To this end, we first interact disaster measures with the action plan triple-differences dummy variable (Plan$_{s,t}\times$ Job-Ind$_{i,t}$) to examine whether the presence of disasters after the adoption of action plans further affects households' risk-taking behaviors. Panel A of Table A4 shows that an increase in injuries & fatalities per capita caused by climate change-related disasters intensifies the impact of the adoption of action plans on changes in the share of risky assets. Evaluated at the mean of injuries and fatalities (per capita), an adoption of action plans leads to 1.33 (5.03) percentage points or a 2.89% (10.95%) decrease in the share of risky assets at the mean. Panel B of Table A4 reports the result for EPA stringency interacted with disaster measures. It shows that climate change-related disaster experiences together with EPA stringency lead to a reduction in exposure to financial risk. This result is robust to both disaster measures: *inj-fat* and *inj-fat-per*.

Overall, these findings suggest that climate change-related disasters impact changes in households' portfolio choices through changes in environmental regulations by intensifying the impact of regulatory risks.

4.4 Are Results Driven by Holding Own Company Stocks?

One concern is that our results are due in part to households in high-emission industries owning employers' stock which underperformed after the adoption of climate change action plans. This is a valid concern since past studies find a pattern of households owning significant amounts of their employers' stock (e.g., Benartzi, 2001; Mitchell and Utkus, 2002; Meulbroek, 2005). Although industry $\times$ time fixed effects alleviate this concern in part, this concern still may impact our results to the extent that households' own companies are local companies whose returns are unlikely captured by industry $\times$ time fixed effects.

To address this concern, we examine stock returns of firms that belong to high-emission industries in a state that adopted firms in a panel setting (Pukthuanthong et al., 2019; Martin and Wagner, 2019; Harvey and Liu, 2021; Hasler and Martineau, 2022). Specifically, we run a triple difference regression to examine the difference in stock returns between firms in high-emission industries and others within the same states. We use headquarters information to identify stocks affected by state-level climate change action plans.

Table 6 shows that although firms in high-emission industries underperform other stocks, the magnitude is negligible. Column (1) shows that stocks affected by action plans underperform only by 4 basis points. Moreover, this difference is statistically indistinguishable from zero (t-stat = -0.28). This is the case after controlling for three factors or five factors (Fama and French, 2015), as shown in Columns (2) and (3). This result indicates that firms in high-emission industries do not experience significantly negative stock returns relative to other stocks in the same states, following the adoption of a climate change action plan. Therefore, our evidence of a reduction of financial risk exposure after adoptions is more likely driven by a rebalancing of households in high-emission industries instead of significant declines in stock prices of high-emission industries that households own.

[Insert Table 6 here]

4.5 Do Households Hedge Against Climate Regulatory Risk by Switching to A Non-high-emission Industry?

One way to hedge against climate regulatory risks could be to switch to a non-high-emission industry that is not negatively affected by elevated climate regulatory risk. Moreover, if the labor income risk channel is the major economic force behind our findings, we would observe a higher level of risk-taking among households who switch to a non-high-emission industry compared to households who stay in a high-emission industry. In this subsection, we test this hypothesis. To this end, we first examine whether households in a high-emission industry tend to switch to a non-high-emission industry after elevated climate change risks, measured by action plans, EPA stringency, or climate change-related disasters before examining risk-taking behaviors. Specifically, a dummy variable that is set to be one for a household that switches to a non-high-emission industry at time t from a high-emission industry at time $t-1$ is regressed on the same set of variables as above to examine financial risk-taking behaviors. Table 7 shows that households in a high-emission industry significantly switch to a non-high-emission industry after elevated climate change risk. This result is always significant at the 1% significance level and robust to all of the climate change risk measures that we consider – the adoption of an action plan, EPA stringency, and climate change-related natural disasters. This finding implies that households in a high-emission industry are concerned about elevated climate change risk in choosing the industry of their occupation.

[Insert Table 7 here]

Having empirically documented the significant tendency to switch to a non-high-emission industry from a high-emission industry after an elevated climate change risk, we examine the financial risk-taking behaviors of those who switch. In this analysis, out of households in a high-emission industry at time $t-1$, we examine households that switch to a non-high-emission industry at time t from a high-emission industry (switchers), compared to households that stay in a high-emission industry (non-switchers). Table 8 shows that while there is no significant difference in the degree of financial risk-taking between switchers and non-switchers after the adoption of an action plan or an increase in EPA stringency, switchers allocate a significantly higher proportion of financial wealth to risky assets than non-switchers after climate change-related disasters, as shown in Columns (3) and (4).

This finding suggests that households belonging to a high-emission industry are an important consideration for financial risk-taking behaviors after elevated climate change risk, supporting the incomer risk channel. Moreover, we show that households indeed hedge against climate change risks by switching to a non-high-emission industry which enables households to take a higher level of financial risks compared to those who stay in a high-emission industry.

[Insert Table 8 here]

4.6 Heterogeneous Effects

In this subsection, we examine the heterogeneous effects of climate change risks on households' financial risk-taking choices. If our key results are driven by the labor income channel, we expect a stronger effect of climate change risks on risk-taking behaviors for low-income or low-wealth households because they have less ability to hedge against elevated income risk than others. To test this hypothesis, we interact our triple-differences terms (Plan$_{s,t}\times$Job-Ind$_{i,t}$) with low-income and low-wealth dummy variables that take one for households whose income or wealth level is less than the median.

Panels A and B of Table 9 reports the heterogeneous effect results with low-income and low-wealth households, respectively. Columns (1) and (2) of Panel A show that when there is an adoption of a climate change action plan or a change in EPA stringency, low-income households do not have statistically different risk-taking behaviors than others at the intensive margin. However, Columns (3) and (4) of Panel A show that low-income households in a high-emission industry react to climate change-related natural disasters more sensitively than the other households in a high-emission industry.

Panel B shows that along with the income level, the wealth level is an important household characteristic in explaining the heterogeneous effects of climate change risk on risky asset allocation choices. Low-wealth households in a high-emission industry allocate a less proportion of financial wealth to risky assets than the others in a high-emission industry after an increase in EPA stringency or climate change-related natural disaster events.

In sum, we find that among households in high-emission industries, low-income and low-wealth households more sensitively reduce their financial risk exposure in response to a higher climate change risk. This finding further suggests that income risk is the channel through which households in high-emission industries react to elevated climate change risks because those households are more subject to labor income uncertainty relative to high-income and wealthy households who can hedge against income shocks driven by climate change risks. Moreover, in the sense that low-income and low-wealth households are the most affected by climate regulatory risks in terms of financial risk-taking, our findings suggest that climate regulations play a role in reinforcing wealth inequality.

[Insert Table 9 here]

5 Conclusion

In this paper, we examine whether an increase in climate change regulatory risks can affect households' financial risk-taking through the labor income risk channel. To this end, we exploit the state-level measures for climate change regulatory risks as well as micro-level household data where we observe portfolio holdings and job industries of households. We find that households employed by one of the high-emission industries reduce their exposure to financial risk in response to an increase in regulatory policy risks. The effect is robust to both climate change action plans and the EPA stringency measure. We also find that households significantly switch to a non-high-emission industry after elevated climate change regulatory risks. Those households who switch to a non-high-emission industry allocate a significantly higher proportion of wealth to risky assets than households who stay in a high-emission industry.

Overall, we document a novel economic channel through which climate change risks affect households' risk-taking behaviors. In doing so, our study echoes the importance of climate change regulatory risks. Previous studies document various channels through which how climate change regulatory risks affect firms, but we document the impact on the household side and portfolio choices in particular.

An important implication of our findings is that climate regulations have unintended consequences for households in high-emission industries. Households working for high-emission industries are less wealthy, young, and less educated. Moreover, low-income and low-wealth households are the most affected by climate regulatory risks in terms of financial risk-taking. Therefore, climate regulation plays a role in reinforcing wealth inequality at the societal level by discouraging less wealthy households' financial risk-taking, resulting in ineffective wealth accumulation. We do not argue that society is worse off from climate regulations, but our findings imply that it is important to implement climate regulations in a way not to elevate labor income risks for employees in high-emission industries.

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Table 1. **Descriptive Statistics**

This table provides descriptive statistics for all households, non-stockholders versus stockholders, and households employed by non-high-emission and high-emission industries. The list of high-emission industries classified by IPCC is in Appendix A. Stockholders are identified based on their direct investment in either stocks or mutual funds, excluding investment through retirement accounts. All dollar-valued variables are deflated by the CPI with 1982-1984=100. The variables *Male*, *White*, and *Married* are indicators for male, white, and married household heads, respectively. *Age* is the age of households' heads. *College* and *High* are indicators for household heads whose highest education level is college or above and high school, respectively. *Number of children* is the number of children for each household. *Share of Risky Assets* is the percentage of the value of stocks and mutual funds in the value of total financial wealth, where total financial wealth is savings, checking, bonds, stocks, and mutual funds. *Participation* is an indicator for a positive stock holding, excluding retirement. *Rental value* is the value of a rental property. *Business value* is the value of equity in a business. *Vehicle* is the value of vehicles minus the value of debts against vehicles. *4-month labor income* is the sum of households' labor income for 4 months. *Total wealth* is total financial wealth plus business value plus vehicle. *t*-stat denotes *t*-statistics, based on Heteroskedasticity-consistent (HC3) standard errors, of whether the two samples (households in non-high-emission vs high-emission industries) have equal means where ***,**, and * indicate significance at 1%, 5%, and 10%, respectively. p1, p10, p50, p90, and p99 denote the value of 1, 10, 50, 90, and 99th percentile, respectively.

	Mean						p1	p10	p50	p90	p99
	Total	Non-holders	Holders	Non-high-emission	High-emission	*t*-stat					
Panel A: Demographics											
Male	0.628	0.616	0.661	0.572	0.853	158.0***	0	0	1	1	1
White	0.892	0.876	0.935	0.891	0.898	4.9***	0	0	1	1	1
Age	51.831	51.389	53.007	53.920	43.330	-177.0***	23	31	50	76	85
College	0.561	0.500	0.721	0.571	0.519	-21.9***	0	0	1	1	1
High	0.372	0.415	0.257	0.356	0.436	33.5***	0	0	0	1	1
Married	0.534	0.506	0.607	0.514	0.616	42.7***	0	0	1	1	1
Number of children	0.667	0.683	0.624	0.592	0.970	69.9***	0	0	0	2	4
Panel B: Asset holding											
Share of Risky Assets	0.146	0.000	0.536	0.147	0.146	-0.9	0	0	0	1	1
Participation	0.273	0.000	1.000	0.273	0.272	-0.6	0	0	0	1	1
Participation with retirement	0.427	0.211	1.000	0.424	0.440	6.9***	0	0	0	1	1
Savings and Checking	9,931.1	7,788.1	15,635.9	10,709.6	6,763.4	-55.6***	0	105	2,325	30,539	86,111
Stocks and mutual funds	15,824.7	0.000	57,952.1	16,139.7	14,542.7	-0.6	0	0	0	18,576	241,981
Bonds	3,556.6	1,674.2	8,567.9	3,994.3	1,775.9	-30.9***	0	0	0	3,136	90,498
Rental value	8,480.0	5,653.3	16,005.2	9,128.1	5,843.2	-16.3***	0	0	0	0	212,993
Business value	7,494.7	6,165.0	11,034.4	8,609.3	2,959.4	-30.5***	0	0	0	462	206,992
Vehicle	2,266.2	1,885.7	3,279.0	2,283.7	2,194.9	-5.1***	-2,415	0	0	7,396	18,519
4 month labor income	7,780.2	6,847.9	10,262.1	6,919.8	11,281.0	125.6***	0	0	6,096	17,738	36,519
Total wealth	47,553.3	23,166.4	112,474.5	50,864.8	34,079.4	-6.3***	14	452	8,723	106,703	529,959

Table 2. **The Effect of Action Plans on Risk-Taking Behaviors**

This table shows the effect of climate change action plans on risk-taking behaviors. *Share of Risky Assets* is the percentage of the value of stocks and mutual funds in the value of total financial wealth, where total financial wealth is savings, checking, bonds, stocks, and mutual funds. *Participation* is an indicator for a positive stock holding, excluding retirement. *Plan*$_{s,t}$ is an indicator taking one for years after a state adopted a climate change action plan. *Job-Ind*$_{i,t}$ is an indicator taking one for a household i at time t employed by one of the high-emission industries. The list of high-emission industries classified by IPCC is in Appendix A. Household controls are age, age squared, college dummy variable, high school dummy variable, log of one plus labor income, log of one plus net worth, married dummy variable, and the number of children. State controls, which are used in Columns (3) and (4), are state-level GDP growth, income growth, a dummy variable that takes on for a Democratic governor, and the fraction of Democrats in a state's legislature (both House of Representatives and Senate). Standard errors are clustered by time and state. t-statistics are in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Dep. Var	Share of Risky Assets	Participation	Share of Risky Assets	Participation
Plan$_{s,t}$×Job-Ind$_{i,t}$	-0.069**	-0.026		
	(-2.14)	(-1.32)		
Plan$_{s,t}$			-0.005	-0.013
			(-0.26)	(-0.85)
Adj. R^2	0.277	0.712	0.289	0.713
Observations	46,015	137,076	45,322	135,185
Household controls	Yes	Yes	Yes	Yes
Household Fixed effects	Yes	Yes	Yes	Yes
State × Year-month Fixed effects	Yes	Yes	No	No
Job-Ind × Year-month Fixed effects	Yes	Yes	Yes	Yes
State controls	No	No	Yes	Yes
State Fixed effects	No	No	Yes	Yes

Table 3. **The Effect of Action Plans on Distribution of Labor Income**

This table shows the effect of climate change action plans on the distribution of labor income. The dependent variable in Columns (1) and (2) is the standard deviation of labor income for each state, each time, and the high-emission industry group versus the non-high-emission industry group normalized by the mean. The dependent variable in Columns (3) and (4) is the level of labor income where labor income is the log of one plus 4-month labor income. *Plan*$_{s,t}$ is an indicator taking one for years after a state adopted a climate change action plan. *Job-Ind*$_{i,t}$ is an indicator taking one for a household i at time t employed by one of the high-emission industries. The list of high-emission industries classified by IPCC is in Appendix A. Household controls are age, age squared, college dummy variable, high school dummy variable, log of one plus labor income (only for Columns (1) and (2)), log of one plus net worth, married dummy variable, and the number of children. Standard errors are clustered by time and state. t-statistics are in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Dep. Var	Cross-sectional dispersion		log labor	
	Full sample	Share of Risky Assets > 0	Full sample	Share of Risky Assets > 0
Plan$_{s,t}$×Job-Ind$_{i,t}$	0.037*	0.025**	0.098	0.038
	(1.98)	(2.11)	(0.83)	(0.20)
Adj. R^2	0.994	0.995	0.884	0.890
Observations	188,035	47,991	188,035	47,991
Household controls	Yes	Yes	Yes	Yes
Household Fixed effects	Yes	Yes	Yes	Yes
State × Year-month Fixed effects	Yes	Yes	Yes	Yes
Job-Ind × Year-month Fixed effects	Yes	Yes	Yes	Yes

Table 4. **The Effect of EPA Stringency on Risk-Taking Behaviors**

This table shows the effect of EPA stringency on risk-taking behaviors. The dependent variable is *Share of Risky Assets*, the percentage of the value of stocks and mutual funds in the value of total financial wealth, where total financial wealth is savings, checking, bonds, stocks, and mutual funds. *Stringency*$_{s,t-1}$ is the EPA stringency measure a year ago computed as the ratio of the number of compliance and enforcement actions to the total number of facilities. *Job-Ind*$_{i,t}$ is an indicator taking one for a household i at time t employed by one of the high-emission industries. The list of high-emission industries classified by IPCC is in Appendix A. Household controls are age, age squared, college dummy variable, high school dummy variable, log of one plus labor income, log of one plus net worth, married dummy variable, and the number of children. State controls are state-level GDP growth, income growth, a dummy variable that takes on for a Democratic governor, and the fraction of Democrats in a state's legislature (both House of Representatives and Senate). Standard errors are clustered by time and state. t-statistics are in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Dep. Var	Share of Risky Assets	
Stringency$_{s,t-1}$×Job-Ind$_i$	-16.508**	
	(-2.35)	
Stringency$_{s,t-1}$		-3.072
		(-0.87)
Adj. R^2	0.323	0.334
Observations	99,959	99,055
Household controls	Yes	Yes
Household Fixed effects	Yes	Yes
State × Year-month Fixed effects	Yes	No
Job-Ind × Year-month Fixed effects	Yes	Yes
State controls	No	Yes
State Fixed effects	No	Yes

Table 5. **The Effect of Climate Change-Related Disasters on Risk-Taking Behaviors**

This table shows the effect of climate change-related disasters on risk-taking behaviors. Climate change-related disasters are all types of disasters in SHELDUS data except for volcanoes, tornadoes, earthquakes, and winter weather. The dependent variable is *Share of Risky Assets*, the percentage of the value of stocks and mutual funds in the value of total financial wealth, where total financial wealth is savings, checking, bonds, stocks, and mutual funds. *inj-fat*$_{s,t-1}$ is the number of injuries and fatalities in a state s and year $t-1$, and *inj-fat-per*$_{s,t-1}$ is the number of injuries and fatalities per capita in a state s and year $t-1$. *Job-Ind*$_{i,t}$ is an indicator taking one for a household i at time t employed by one of the high-emission industries. The list of high-emission industries classified by IPCC is in Appendix A. Household controls are age, age squared, college dummy variable, high school dummy variable, log of one plus labor income, log of one plus net worth, married dummy variable, and the number of children. Standard errors are clustered by time and state. t-statistics are in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Dep. Var	Share of Risky Assets	
inj-fat$_{s,t-1}\times$ Job-Ind$_{i,t}$	-1.9×10^{-4}***	
	(-6.68)	
inj-fat-per$_{s,t-1}\times$ Job-Ind$_{i,t}$		-6.309***
		(-5.21)
Adj. R^2	0.326	0.326
Observations	113,924	113,924
Household controls	Yes	Yes
Household Fixed effects	Yes	Yes
State $\times$ Year-month Fixed effects	Yes	Yes
Job-Ind $\times$ Year-month Fixed effects	Yes	Yes

Table 6. **The Effect of Climate Change Action Plans on Stock Returns**

This table shows the effect of climate change action plans on stock returns at the individual stock level. Specifically, we estimate:

$$R_{i,t} = a + b_1 \text{Plan}_{s,t} \times \text{Ind}_i + b_2[\hat{\beta}^{Mkt}_{i,t-1} Mkt_t] + b_3[\hat{\beta}^{SMB}_{i,t-1} SMB_t] + b_4[\hat{\beta}^{HML}_{i,t-1} HML_t] + b_5[\hat{\beta}^{RMW}_{i,t-1} RMW_t] + b_6[\hat{\beta}^{CMA}_{i,t-1} CMA_t] + \gamma_i + \psi_{s,t} + \theta_{ind,t} + \epsilon_{i,t},$$

where *Plan*$_{s,t}$ is an indicator taking one following adoptions for firms headquartered in a state that adopted climate change action plans. *Ind*$_i$ is an indicator taking one for a firm i that belongs to one of the high-emission industries. The list of high-emission industries classified by IPCC is in Appendix A. Each factor loading $\hat{\beta}^F_i$ is estimated using the 36 months prior to month t for each stock i. *MKT*, *SMB*, *HML*, *RMW*, and *CMA* denote the five factors from Fama and French (2015). Sample stocks are all stocks listed in NYSE/AMEX/NASDAQ from January 2000 to June 2022, using the CRSP/Compustat Merged Database. Standard errors are clustered by time and state. t-statistics are in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
Dep. Var		Stock Returns	
Plan$_{s,t}\times$Ind$_i$	-3.91 $\times 10^{-4}$	-2.87 $\times 10^{-4}$	-3.49 $\times 10^{-4}$
	(-0.28)	(-0.20)	(-0.24)
$\hat{\beta}^{MKT}_{i,t-1} MKT_t$		0.058***	0.064***
		(4.15)	(3.91)
$\hat{\beta}^{SMB}_{i,t-1} SMB_t$		0.027***	0.031**
		(2.69)	(2.04)
$\hat{\beta}^{HML}_{i,t-1} HML_t$		0.026***	0.048***
		(3.11)	(3.96)
$\hat{\beta}^{RMW}_{i,t-1} RMW_t$			0.063***
			(4.82)
$\hat{\beta}^{CMA}_{i,t-1} CMA_t$			0.014
			(1.12)
Intercept	0.010***	0.011***	0.011***
	(68.95)	(57.21)	(55.26)
Adj. R^2	0.146	0.165	0.166
Observations	1,195,410	1,148,312	1,148,312
Firm Fixed effects	Yes	Yes	Yes
State $\times$ Year-month Fixed effects	Yes	Yes	Yes
SIC Industry $\times$ Year-month Fixed effects	Yes	Yes	Yes

Table 7. **The Effect of Climate Change Risk on Switching to Non-high-emission industry**

This table shows the effect of climate change risk measured by action plans, EPA stringency, or climate change-related disasters on households' choice of switching to a non-high-emission industry from a high-emission industry. The dependent variable is a dummy variable set to be one for a household that switches to a non-high-emission industry at time t from a high-emission industry at time $t-1$. *Plan*$_{s,t}$ is an indicator taking one for years after a state adopted a climate change action plan. *Stringency*$_{s,t-1}$ is the EPA stringency measure a year ago computed as the ratio of the number of compliance and enforcement actions to the total number of facilities. Climate change-related disasters are all types of disasters in SHELDUS data except for volcanoes, tornadoes, earthquakes, and winter weather. *inj-fat*$_{s,t-1}$ is the number of injuries and fatalities in a state s and year $t-1$, and *inj-fat-per*$_{s,t-1}$ is the number of injuries and fatalities per capita in a state s and year $t-1$. *Job-Ind*$_{i,t}$ is an indicator taking one for a household i at time t employed by one of the high-emission industries. The list of high-emission industries classified by IPCC is in Appendix A. Household controls are age, age squared, college dummy variable, high school dummy variable, log of one plus labor income, log of one plus net worth, married dummy variable, and the number of children. Standard errors are clustered by time and state. t-statistics are in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Dep. Var	Switch to non-high-emission industry			
Plan$_{s,t}$×Job-Ind$_{i,t-1}$	0.363***			
	(3.75)			
Stringency$_{s,t-1}$×Job-Ind$_{i,t-1}$		119.608***		
		(3.68)		
inj-fat$_{s,t-1}$×Job-Ind$_{i,t-1}$			2.8×10^{-4}***	
			(2.89)	
inj-fat-per$_{s,t-1}$×Job-Ind$_{i,t-1}$				9.721***
				(4.91)
Adj. R^2	0.498	0.504	0.512	0.512
Observations	188,035	393,797	461,057	461,057
Household controls	Yes	Yes	Yes	Yes
Household Fixed effects	Yes	Yes	Yes	Yes
State × Year-month Fixed effects	Yes	Yes	Yes	Yes
Job-Ind × Year-month Fixed effects	Yes	Yes	Yes	Yes

Table 8. **Risk-Taking Behaviors of households who switched to Non-high-emission industry**

This table shows the effect of climate change risk measured by action plans, EPA stringency, or climate change-related disasters on risk-taking behaviors of households who switch to a non-high-emission industry from a high-emission industry relative to households who stay in a high-emission industry. The dependent variable is *Share of Risky Assets*, the percentage of the value of stocks and mutual funds in the value of total financial wealth, where total financial wealth is savings, checking, bonds, stocks, and mutual funds. *Plan*$_{s,t}$ is an indicator taking one for years after a state adopted a climate change action plan. *Stringency*$_{s,t-1}$ is the EPA stringency measure a year ago computed as the ratio of the number of compliance and enforcement actions to the total number of facilities. Climate change-related disasters are all types of disasters in SHELDUS data except for volcanoes, tornadoes, earthquakes, and winter weather. *inj-fat*$_{s,t-1}$ is the number of injuries and fatalities in a state s and year $t-1$, and *inj-fat-per*$_{s,t-1}$ is the number of injuries and fatalities per capita in a state s and year $t-1$. *Job-Ind*$_{i,t}$ is an indicator taking one for a household i at time t employed by one of the high-emission industries. The list of high-emission industries classified by IPCC is in Appendix A. Household controls are age, age squared, college dummy variable, high school dummy variable, log of one plus labor income, log of one plus net worth, married dummy variable, and the number of children. Standard errors are clustered by time and state. t-statistics are in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Dep. Var	Share of Risky Assets			
Plan$_{s,t}$×Job-Ind$_{i,t-1}$	-0.039			
	(-0.99)			
Plan$_{s,t}$×Job-Ind$_{i,t-1}$× Switch$_{i,t}$	0.064			
	(1.13)			
Stringency$_{s,t-1}$×Job-Ind$_{i,t-1}$		-28.036***		
		(-3.73)		
Stringency$_{s,t-1}$×Job-Ind$_{i,t-1}$× Switch$_{i,t}$		-3.076		
		(-0.23)		
inj-fat$_{s,t-1}$×Job-Ind$_{i,t-1}$			-1.8×10^{-4}***	
			(-6.58)	
inj-fat$_{s,t-1}$×Job-Ind$_{i,t-1}$× Switch$_{i,t}$			1.9×10^{-4}**	
			(2.13)	
inj-fat-per$_{s,t-1}$×Job-Ind$_{i,t-1}$				-5.971***
				(-4.95)
inj-fat-per$_{s,t-1}$×Job-Ind$_{i,t-1}$× Switch$_{i,t}$				6.573***
				(3.99)
Adj. R^2	0.277	0.323	0.326	0.326
Observations	46,015	99,959	113,924	113,924
Household controls	Yes	Yes	Yes	Yes
Household Fixed effects	Yes	Yes	Yes	Yes
State × Year-month Fixed effects	Yes	Yes	Yes	Yes
Job-Ind × Year-month Fixed effects	Yes	Yes	Yes	Yes

Table 9. **Heterogeneous effect on Risk-Taking Behaviors**

This table shows the heterogeneous effect of climate change risk measured by action plans, EPA stringency, or climate change-related disasters on risk-taking behaviors, depending on households' income level (Panel A) and wealth level (Panel B). *lower income* is a dummy variable taking one for households whose labor income is lower than the median level. *lower wealth* is a dummy variable taking one for households whose total wealth is lower than the median level. The dependent variable is *Share of Risky Assets*, the percentage of the value of stocks and mutual funds in the value of total financial wealth, where total financial wealth is savings, checking, bonds, stocks, and mutual funds. $Plan_{s,t}$ is an indicator taking one for years after a state adopted a climate change action plan. $Stringency_{s,t-1}$ is the EPA stringency measure a year ago computed as the ratio of the number of compliance and enforcement actions to the total number of facilities. Climate change-related disasters are all types of disasters in SHELDUS data except for volcanoes, tornadoes, earthquakes, and winter weather. $inj\text{-}fat_{s,t-1}$ is the number of injuries and fatalities in a state s and year $t-1$, and $inj\text{-}fat\text{-}per_{s,t-1}$ is the number of injuries and fatalities per capita in a state s and year $t-1$. $Job\text{-}Ind_{i,t}$ is an indicator taking one for a household i at time t employed by one of the high-emission industries. The list of high-emission industries classified by IPCC is in Appendix A. Household controls are age, age squared, college dummy variable, high school dummy variable, log of one plus labor income, log of one plus net worth, married dummy variable, and the number of children. Standard errors are clustered by time and state. t-statistics are in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Dep. Var	Share of Risky Assets			
Panel A: Low income (income =< median level)				
$\text{Plan}_{s,t}\times\text{Job-Ind}_{i,t}$	-0.071**			
	(-2.16)			
$\text{Plan}_{s,t}\times\text{Job-Ind}_{i,t}\times$ low $\text{income}_{i,t}$	0.017			
	(0.13)			
$\text{Stringency}_{s,t-1}\times\text{Job-Ind}_{i,t}$		-15.290**		
		(-2.06)		
$\text{Stringency}_{s,t-1}\times\text{Job-Ind}_{i,t}\times$ low $\text{income}_{i,t}$		-12.927		
		(-0.64)		
$\text{inj-fat}_{s,t-1}\times\text{Job-Ind}_{i,t}$			-1.6×10^{-4}***	
			(-6.48)	
$\text{inj-fat}_{s,t-1}\times\text{Job-Ind}_{i,t}\times$ low $\text{income}_{i,t}$			-8.9×10^{-4}***	
			(-3.50)	
$\text{inj-fat-per}_{s,t-1}\times\text{Job-Ind}_{i,t}$				-5.510***
				(-5.46)
$\text{inj-fat-per}_{s,t-1}\times\text{Job-Ind}_{i,t}\times$ low $\text{income}_{i,t}$				-23.454**
				(-2.50)
Adj. R^2	0.277	0.323	0.326	0.326
Observations	46,015	99,959	113,924	113,924
Household controls	Yes	Yes	Yes	Yes
Household Fixed effects	Yes	Yes	Yes	Yes
State × Year-month Fixed effects	Yes	Yes	Yes	Yes
Job-Ind × Year-month Fixed effects	Yes	Yes	Yes	Yes

Table 9. Heterogeneous effect on Risk-Taking Behaviors (Cont'd)

	(1)	(2)	(3)	(4)
Dep. Var		Share of Risky Assets		
	Panel B: Low wealth (wealth $=<$ median level)			
Plan$_{s,t}$ $\times$Job-Ind$_{i,t}$	-0.072**			
	(-2.34)			
Plan$_{s,t}$ $\times$Job-Ind$_{i,t}$$\times$ low wealth$_{i,t}$	0.025			
	(0.96)			
Stringency$_{s,t-1}$$\times$Job-Ind$_{i,t}$		-14.278*		
		(-1.94)		
Stringency$_{s,t-1}$$\times$Job-Ind$_{i,t}$$\times$ low wealth$_{i,t}$		-23.529*		
		(-1.81)		
inj-fat$_{s,t-1}$$\times$Job-Ind$_{i,t}$			-1.5$\times 10^{-4}$**	
			(-4.13)	
inj-fat$_{s,t-1}$$\times$Job-Ind$_{i,t}$$\times$ low wealth$_{i,t}$			-4.8$\times 10^{-4}$***	
			(-3.61)	
inj-fat-per$_{s,t-1}$$\times$Job-Ind$_{i,t}$				-5.379***
				(-3.82)
inj-fat-per$_{s,t-1}$$\times$Job-Ind$_{i,t}$$\times$ low wealth$_{i,t}$				-12.975**
				(-2.23)
Adj. R^2	0.277	0.323	0.326	0.326
Observations	46,015	99,959	113,924	113,924
Household controls	Yes	Yes	Yes	Yes
Household Fixed effects	Yes	Yes	Yes	Yes
State $\times$ Year-month Fixed effects	Yes	Yes	Yes	Yes
Job-Ind $\times$ Year-month Fixed effects	Yes	Yes	Yes	Yes

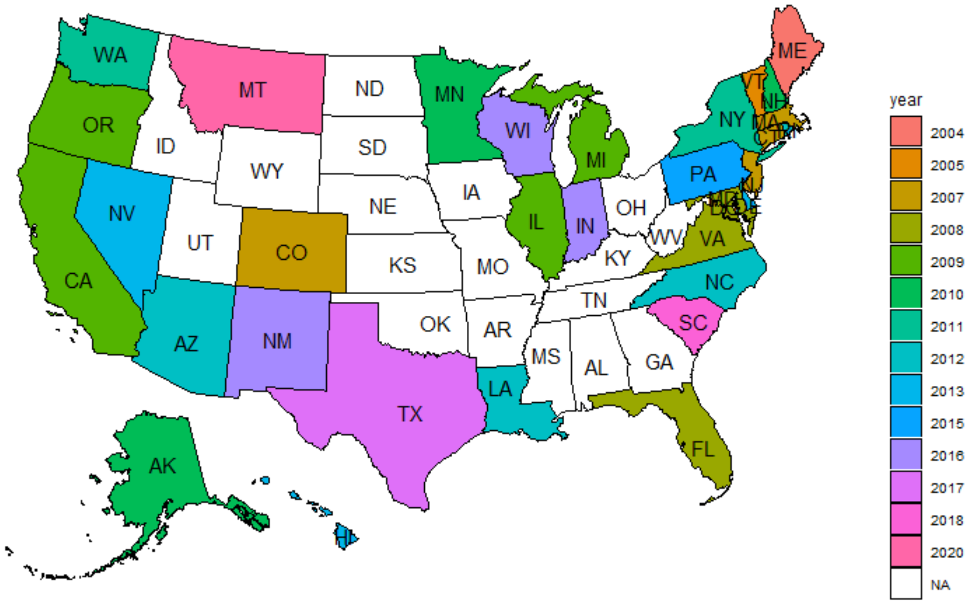
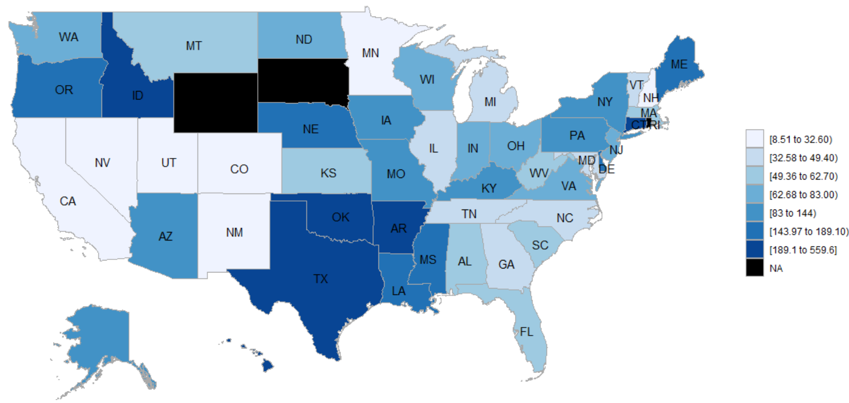


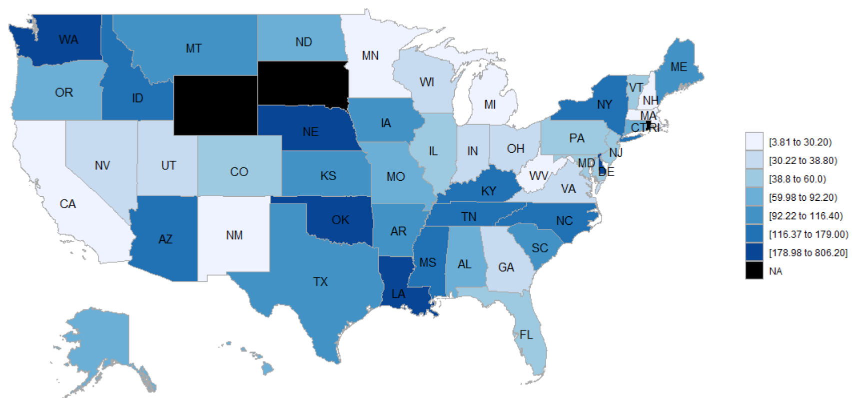
Figure 1. **States that adopted Action Plans**

This figure displays the states that adopted adaption plans and the years of the adoption. The list of climate change action plans is available at the Georgetown Climate Center, part of Georgetown University Law Center.

Panel A: EPA in 1999



Panel B: EPA in 2009



Panel C: EPA in 2019

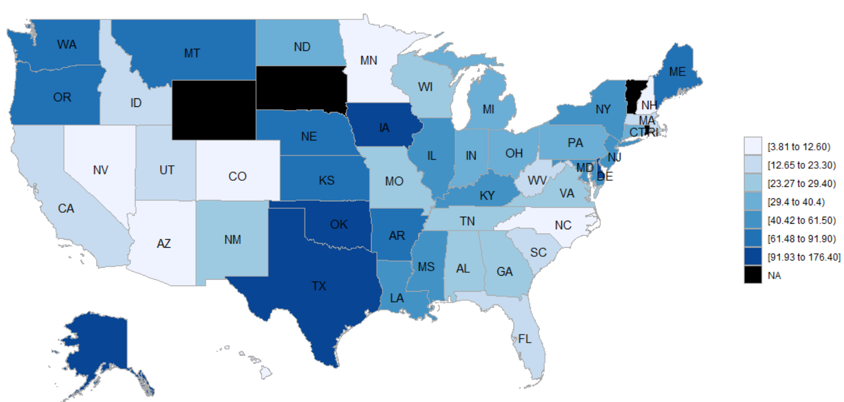


Figure 2. **EPA stringency**

This heatmap visualizes the EPA stringency measure across states in 1999, 2009, and 2019. The EPA stringency measure for a state in a year is computed as the ratio of the number of compliance and enforcement actions to the total number of facilities. For ease of readability, we multiply the EPA stringency by 10^5.

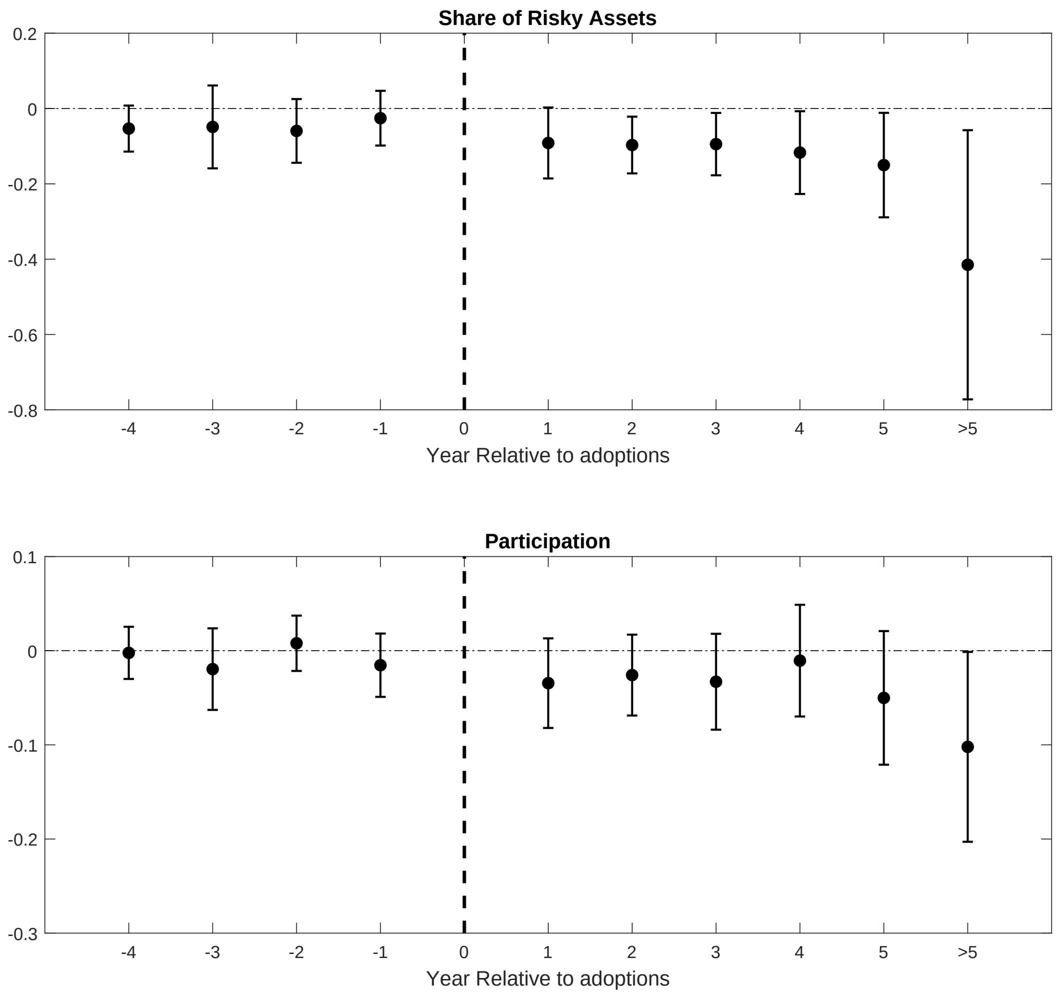


Figure 3. **Dynamic effects of State-level Action Plans**

This figure shows the dynamic effect of adoptions of climate change action plans on financial risk exposure around adoptions for households in high-emission industries relative to those in non-high-emission industries. We plot point estimates as well as a 90% confidence interval using standard errors clustered at the state and year-month levels. The specification is the same as that in Equation (2), except that the triple-differences term is replaced by time-indicators interacted with the high-emission industry dummy variable where time-indicators take one for 4, 3, 2, and 1-year before adoptions as well as the year of adoption or 1, 2, 3, 4, 5 years after and longer than 5 years after adoptions.

Online Appendix to "Climate Change and Households' Risk-Taking"

September 27, 2024

Table A1. **SCF, Descriptive Statistics**

This table provides descriptive statistics for all households, non-stockholders versus stockholders. Stockholders are separated based on their direct investment in either stocks or mutual funds, excluding investment through retirement accounts. The variables *Male*, *White*, and *Married* are indicators for male, white, and married household heads, respectively. *Age* is the age of the household's head. *College* and *High* are indicators for household heads whose highest education level is college or above and high school, respectively. *Number of children* is the number of children for each household. *Share of Risky Assets* is the percentage of the value of stocks and mutual funds in the value of total financial wealth, where total financial wealth is savings, checking, bonds, stocks, and mutual funds. *Participation* is an indicator for a positive stock holding, excluding retirement. p1, p10, p50, p90, and p99 denote the value of 1, 10, 50, 90, and 99th percentile.

	Mean			p1	p10	p50	p90	p99
	Total	Non-holders	Holders					
Panel A: Demographics								
Male	0.723	0.698	0.843	0.000	0.000	1.000	1.000	1.000
White	0.728	0.698	0.878	0.000	0.000	1.000	1.000	1.000
Age	49.882	49.355	52.465	21.000	28.000	48.000	75.000	88.000
College	0.547	0.499	0.782	0.000	0.000	1.000	1.000	1.000
High	0.390	0.427	0.206	0.000	0.000	0.000	1.000	1.000
Married	0.579	0.552	0.712	0.000	0.000	1.000	1.000	1.000
Number of children	0.815	0.835	0.721	0.000	0.000	0.000	2.000	4.000
Panel B: Asset holding								
Share of Risky Assets	0.094	0.000	0.495	0.000	0.000	0.000	0.449	0.986
Participation	0.170	0.000	1.000	0.000	0.000	0.000	1.000	1.000
Participation with retirement	0.495	0.392	1.000	0.000	0.000	0.000	1.000	1.000

Table A2. **The Effect of Action Plans and EPA Stringency on Risk-Taking Behaviors**

This table shows the effect of action plans and EPA stringency on risk-taking behaviors. The dependent variable is *Share of Risky Assets*, the percentage of the value of stocks and mutual funds in the value of total financial wealth, where total financial wealth is savings, checking, bonds, stocks, and mutual funds. *Plan*$_{s,t}$ is an indicator taking one for years after a state adopted a climate change action plan. *Stringency*$_{s,t-1}$ is the EPA stringency measure a year ago computed as the ratio of the number of compliance and enforcement actions to the total number of facilities. Job-Ind$_{i,t}$ is an indicator taking one for a household i employed by one of the high-emission industries. The list of high-emission industries classified by IPCC is in Appendix A. Household controls are age, age squared, college dummy variable, high school dummy variable, log of one plus labor income, log of one plus net worth, married dummy variable, and the number of children. State controls are state-level GDP growth, income growth, a dummy variable that takes on for a Democratic governor, and the fraction of Democrats in a state's legislature (both House of Representatives and Senate). Standard errors are clustered by time and state. t-statistics are in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var	Share of Risky Assets
Plan$_{s,t}\times$ Stringency$_{s,t-1}\times$Job-Ind$_{i,t}$	-58.911**
	(-2.44)
Adj. R^2	0.276
Observations	45,570
Household controls	Yes
Household Fixed effects	Yes
State $\times$ Year-month Fixed effects	Yes
Job-Ind $\times$ Year-month Fixed effects	Yes

Table A3. **The Effect of Climate Change-Unrelated Disasters on Risk-Taking Behaviors**

This table shows the effect of climate change-unrelated disasters on risk-taking behaviors. Climate change-unrelated disasters are volcanoes, tornadoes, earthquakes, and winter weather. The dependent variable is *Share of Risky Assets*, the percentage of the value of stocks and mutual funds in the value of total financial wealth, where total financial wealth is savings, checking, bonds, stocks, and mutual funds. inj-fat$_{s,t-1}$ is the number of injuries and fatalities in a state s and year $t-1$, and inj-fat-per$_{s,t-1}$ is the number of injuries and fatalities per capita in a state s and year $t-1$, which is scaled by county population. Job-Ind$_{i,t}$ is an indicator taking one for a household i employed by one of the high-emission industries. The list of high-emission industries classified by IPCC is in Appendix A. Household controls are age, age squared, college dummy variable, high school dummy variable, log of one plus labor income, log of one plus net worth, married dummy variable, and the number of children. Standard errors are clustered by time and state. t-statistics are in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Dep. Var	Share of Risky Assets	
inj-fat$_{s,t-1}\times$ Job-Ind$_{i,t}$	0.9×10^{-4}	
	(0.68)	
inj-fat-per$_{s,t-1}\times$ Job-Ind$_{i,t}$		7.822
		(1.62)
Adj. R^2	0.326	0.326
Observations	113,924	113,924
Household controls	Yes	Yes
Household Fixed effects	Yes	Yes
State $\times$ Year-month Fixed effects	Yes	Yes
Job-Ind $\times$ Year-month Fixed effects	Yes	Yes

Table A4. **The Effect of Disasters and Regulatory risks on Risk-Taking Behaviors**

This table shows the effect of climate change-related disasters together with either action plans (Panel A) or EPA stringency (Panel B) on risk-taking behaviors. Climate change-related disasters are all types of disasters in SHELDUS data except for volcanoes, tornadoes, earthquakes, and winter weather. The dependent variable is *Share of Risky Assets*, the percentage of the value of stocks and mutual funds in the value of total financial wealth, where total financial wealth is savings, checking, bonds, stocks, and mutual funds. inj-fat$_{s,t-1}$ is the number of injuries and fatalities in a state s and year $t-1$, and inj-fat-per$_{s,t-1}$ is the number of injuries and fatalities per capita in a state s and year $t-1$, which is scaled by county population. *Plan*$_{s,t}$ is an indicator taking one for years after a state adopted a climate change action plan. *Stringency*$_{s,t-1}$ is the EPA stringency measure in a state s and year $t-1$, computed as the ratio of the number of compliance and enforcement actions to the total number of facilities. Job-Ind$_{i,t}$ is an indicator taking one for a household i employed by one of the high-emission industries. The list of high-emission industries classified by IPCC is in Appendix A. Household controls are age, age squared, college dummy variable, high school dummy variable, log of one plus labor income, log of one plus net worth, married dummy variable, and the number of children. Standard errors are clustered by time and state. t-statistics are in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Dep. Var	Share of Risky Assets	
	Panel A: Action plans	
inj-fat$_{s,t-1}\times$ Plan$_{s,t}\times$ Job-Ind$_{i,t}$	-0.002	
	(-1.07)	
inj-fat-per$_{s,t-1}\times$ Plan$_{s,t}\times$ Job-Ind$_{i,t}$		-6.3$\times10^2$**
		(-2.39)
Adj. R^2	0.276	0.276
Observations	45,607	45,607
	Panel B: EPA Stringency	
inj-fat$_{s,t-1}\times$ Stringency$_{s,t-1}\times$ Job-Ind$_{i,t}$	-0.076***	
	(-4.95)	
inj-fat-per$_{s,t-1}\times$ Stringency$_{s,t-1}\times$ Job-Ind$_{i,t}$		-2.4$\times10^3$***
		(-4.78)
Adj. R^2	0.323	0.323
Observations	99,959	99,959
Household controls	Yes	Yes
Household Fixed effects	Yes	Yes
State $\times$ Year-month Fixed effects	Yes	Yes
Job-Ind $\times$ Year-month Fixed effects	Yes	Yes

A List of high-emission Fama and French (1997) industries

This is a list of high-emission Fama and French (1997) classifications according to the IPCC classification. Choi et al. (2020b) match the IPCC subcategories with the industry classification by Fama and French (1997).

1 Agric Agriculture

- 0100-0199 Agric production - crops
- 0200-0299 Agric production - livestock
- 0910-0919 Commercial fishing
- 2048-2048 Prepared feeds for animals

2 Food Food Products

- 2000-2009 Food and kindred products
- 2010-2019 Meat products
- 2020-2029 Dairy products
- 2030-2039 Canned-preserved fruits-vegs
- 2040-2046 Flour and other grain mill products
- 2050-2059 Bakery products
- 2060-2063 Sugar and confectionery products
- 2070-2079 Fats and oils
- 2090-2092 Misc food preps
- 2095-2095 Roasted coffee
- 2098-2099 Misc food preparations

5 Smoke Tobacco Products

- 2100-2199 Tobacco products

9 Hshld Consumer Goods

- 2047-2047 Dog and cat food

12 MedEq Medical Equipment

- 3693-3693 X-ray, electromedical app

14 Chems Chemicals

- 2800-2809 Chemicals and allied products
- 2810-2819 Industrial inorganical chems
- 2820-2829 Plastic material & synthetic resin
- 2850-2859 Paints
- 2860-2869 Industrial organic chems
- 2870-2879 Agriculture chemicals
- 2890-2899 Misc chemical products

15 Rubbr Rubber and Plastic Products

- 3031-3031 Reclaimed rubber
- 3041-3041 Rubber & plastic hose and belting
- 3050-3053 Gaskets, hoses, etc
- 3060-3069 Fabricated rubber products
- 3070-3079 Misc rubber products
- 3080-3089 Misc plastic products
- 3090-3099 Misc rubber and plastic products

16 Txtls Textiles

- 2200-2269 Textile mill products
- 2270-2279 Floor covering mills
- 2280-2284 Yarn and thread mills
- 2290-2295 Misc textile goods
- 2297-2297 Nonwoven fabrics
- 2298-2298 Cordage and twine
- 2299-2299 Misc textile products
- 2393-2395 Textile bags, canvas products
- 2397-2399 Misc textile products

17 BldMt Construction Materials

- 0800-0899 Forestry
- 2400-2439 Lumber and wood products
- 2450-2459 Wood buildings-mobile homes
- 2490-2499 Misc wood products
- 2660-2661 Building paper and board mills
- 2950-2952 Paving & roofing materials
- 3200-3200 Stone, clay, glass, concrete etc
- 3210-3211 Flat glass
- 3240-3241 Cement hydraulic
- 3250-3259 Structural clay prods
- 3261-3261 Vitreous china plumbing fixtures
- 3264-3264 Porcelain electrical supply
- 3270-3275 Concrete gypsum & plaster
- 3280-3281 Cut stone and stone products
- 3290-3293 Abrasive and asbestos products
- 3295-3299 Non-metalic mineral products
- 3420-3429 Handtools and hardware
- 3430-3433 Heating equip & plumbing fix
- 3440-3441 Fabicated struct metal products
- 3442-3442 Metal doors, frames

- 3446-3446 Architectual or ornamental metal work
- 3448-3448 Pre-fab metal buildings
- 3449-3449 Misc structural metal work
- 3450-3451 Screw machine products
- 3452-3452 Bolts, nuts screws
- 3490-3499 Misc fabricated metal products
- 3996-3996 Hard surface floor cover

18 Cnstr Construction

- 1500-1511 Build construction - general contractors
- 1520-1529 Gen building contractors - residential
- 1530-1539 Operative builders
- 1540-1549 Gen building contractors - non-residential
- 1600-1699 Heavy Construction - not building contractors
- 1700-1799 Construction - special contractors

19 Steel Steel Works Etc

- 3300-3300 Primary metal industries
- 3310-3317 Blast furnaces & steel works
- 3320-3325 Iron & steel foundries
- 3330-3339 Prim smelt-refin nonfer metals
- 3340-3341 Secondary smelt-refin nonfer metals
- 3350-3357 Rolling & drawing nonferous metals
- 3360-3369 Non-ferrous foundries and casting
- 3370-3379 Steel works etc
- 3390-3399 Misc primary metal products

20 FabPr Fabricated Products

- 3400-3400 Fabricated metal, except machinery and trans eq
- 3443-3443 Fabricated plate work
- 3444-3444 Sheet metal work
- 3460-3469 Metal forgings and stampings
- 3470-3479 Coating and engraving

21 Mach Machinery

- 3510-3519 Engines & turbines
- 3520-3529 Farm and garden machinery
- 3530-3530 Constr, mining material handling machinery
- 3531-3531 Construction machinery
- 3532-3532 Mining machinery, except oil field
- 3533-3533 Oil field machinery

– 3534-3534 Elevators
– 3535-3535 Conveyors
– 3536-3536 Cranes, hoists
– 3538-3538 Machinery
– 3540-3549 Metalworking machinery
– 3550-3559 Special industry machinery
– 3560-3569 General industrial machinery
– 3580-3580 Refrig & service ind machines
– 3581-3581 Automatic vending machines
– 3582-3582 Commercial laundry and drycleaning machines
– 3585-3585 Air conditioning, heating, refrid eq
– 3586-3586 Measuring and dispensing pumps
– 3589-3589 Service industry machinery
– 3590-3599 Misc industrial and commercial equipment and mach

22 ElcEq Electrical Equipment

– 3600-3600 Elec mach eq & supply
– 3610-3613 Elec transmission
– 3620-3621 Electrical industrial appar
– 3623-3629 Electrical industrial appar
– 3640-3644 Electric lighting, wiring
– 3645-3645 Residential lighting fixtures
– 3646-3646 Commercial lighting
– 3648-3649 Lighting equipment
– 3660-3660 Communication equip
– 3690-3690 Miscellaneous electrical machinery and equip
– 3691-3692 Storage batteries
– 3699-3699 Electrical machinery and equip

23 Autos Automobiles and Trucks

– 2296-2296 Tire cord and fabric
– 2396-2396 Auto trim
– 3010-3011 Tires and inner tubes
– 3537-3537 Trucks, tractors, trailers
– 3647-3647 Vehicular lighting
– 3694-3694 Elec eq, internal combustion engines
– 3700-3700 Transportation equipment
– 3710-3710 Motor vehicles and motor vehicle equip
– 3711-3711 Motor vehicles & car bodies
– 3713-3713 Truck & bus bodies

- 3714-3714 Motor vehicle parts
- 3715-3715 Truck trailers
- 3716-3716 Motor homes
- 3792-3792 Travel trailers and campers
- 3790-3791 Misc trans equip
- 3799-3799 Misc trans equip

24 Aero Aircraft

- 3720-3720 Aircraft & parts
- 3721-3721 Aircraft
- 3723-3724 Aircraft engines, engine parts
- 3725-3725 Aircraft parts
- 3728-3729 Aircraft parts

25 Ships Shipbuilding, Railroad Equipment

- 3730-3731 Ship building and repair
- 3740-3743 Railroad Equipment

26 Guns Defense

- 3760-3769 Guided missiles and space vehicles
- 3795-3795 Tanks and tank components
- 3480-3489 Ordnance & accessories

27 Gold Precious Metals

- 1040-1049 Gold & silver ores
- 1000-1009 Metal mining
- 1010-1019 Iron ores
- 1020-1029 Copper ores
- 1030-1039 Lead and zinc ores
- 1050-1059 Bauxite and other aluminum ores
- 1060-1069 Ferroalloy ores
- 1070-1079 Mining
- 1080-1089 Mining services
- 1090-1099 Misc metal ores
- 1100-1119 Anthracite mining
- 1400-1499 Mining and quarrying non-metalic minerals

29 Coal Coal

- 1200-1299 Bituminous coal

30 Oil Petroleum and Natural Gas

- 1300-1300 Oil and gas extraction
- 1310-1319 Crude petroleum & natural gas

- 1320-1329 Natural gas liquids
- 1330-1339 Petroleum and natural gas
- 1370-1379 Petroleum and natural gas
- 1380-1380 Oil and gas field services
- 1381-1381 Drilling oil & gas wells
- 1382-1382 Oil-gas field exploration
- 1389-1389 Oil and gas field services
- 2900-2912 Petroleum refining
- 2990-2999 Misc petroleum products

31 Util Utilities

- 4900-4900 Electric, gas, sanitary services
- 4910-4911 Electric services
- 4920-4922 Natural gas transmission
- 4923-4923 Natural gas transmission-distr
- 4924-4925 Natural gas distribution
- 4930-4931 Electric and other services combined
- 4932-4932 Gas and other services combined
- 4939-4939 Combination utilities
- 4940-4942 Water supply

35 Comps Computers

- 3570-3579 Office computers
- 3680-3680 Computers
- 3681-3681 Computers - mini
- 3682-3682 Computers - mainframe
- 3683-3683 Computers - terminals
- 3684-3684 Computers - disk & tape drives
- 3685-3685 Computers - optical scanners
- 3686-3686 Computers - graphics
- 3687-3687 Computers - office automation systems
- 3688-3688 Computers - peripherals
- 3689-3689 Computers - equipment
- 3695-3695 Magnetic and optical recording media
- 7373-7373 Computer integrated systems design

36 Chips Electronic Equipment

- 3622-3622 Industrial controls
- 3661-3661 Telephone and telegraph apparatus
- 3662-3662 Communications equipment
- 3663-3663 Radio TV comm equip & apparatus

- 3664-3664 Search, navigation, guidance systems
- 3665-3665 Training equipment & simulators
- 3666-3666 Alarm & signaling products
- 3669-3669 Communication equipment
- 3670-3679 Electronic components
- 3810-3810 Search, detection, navigation, guidance
- 3812-3812 Search, detection, navigation, guidance

37 LabEq Measuring and Control Equipment

- 3811-3811 Engr lab and research equipment
- 3820-3820 Measuring and controlling equipment
- 3821-3821 Lab apparatus and furniture
- 3822-3822 Automatic controls - Envir and applic
- 3823-3823 Industrial measurement instru
- 3824-3824 Totalizing fluid meters
- 3825-3825 Elec meas & test instr
- 3826-3826 Lab analytical instruments
- 3827-3827 Optical instr and lenses
- 3829-3829 Meas and control devices
- 3830-3839 Optical instr and lenses

38 Paper Business Supplies

- 2600-2639 Paper and allied products
- 2670-2699 Paper and allied products

40 Trans Transportation

- 4000-4013 Railroads-line haul
- 4040-4049 Railway express service
- 4100-4100 Transit and passenger trans
- 4110-4119 Local passenger trans
- 4120-4121 Taxicabs
- 4130-4131 Intercity bus trans (Greyhound)
- 4140-4142 Bus charter
- 4150-4151 School buses
- 4170-4173 Motor vehicle terminals, service facilities
- 4190-4199 Misc transit and passenger transportation
- 4200-4200 Motor freight trans, warehousing
- 4210-4219 Trucking
- 4230-4231 Terminal facilities - motor freight
- 4240-4249 Transportation
- 4400-4499 Water transport

- 4500-4599 Air transportation
- 4600-4699 Pipelines, except natural gas
- 4700-4700 Transportation services
- 4710-4712 Freight forwarding
- 4720-4729 Travel agencies, etc
- 4730-4739 Arrange trans - freight and cargo
- 4740-4749 Rental of railroad cars
- 4780-4780 Misc services incidental to trans
- 4782-4782 Inspection and weighing services
- 4783-4783 Packing and crating
- 4784-4784 Fixed facilities for vehicles, not elsewhere classified
- 4785-4785 Motor vehicle inspection
- 4789-4789 Transportation services

46 RlEst Real Estate

- 6550-6553 Real estate developers

48 Other Almost Nothing

- 4950-4959 Sanitary services
- 4960-4961 Steam, air conditioning supplies
- 4970-4971 Irrigation systems
- 4990-4991 Cogeneration - SM power producer