Human Capital Effects of Corporate Climate Exposure

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Abstract

This paper investigates how firms' climate change exposures affect their innovative employees. By analyzing climate exposures extracted from conference call transcripts using machine learning, I find that departure rates of inventors are higher for firms that are more exposed to physical climate shocks. After the departure of such high-skilled workers, firms' innovative productivity declines and subsequent patents become less valuable. Moreover, such a brain drain effect is more pronounced among inventors who are more concerned about climate change and when climate awareness is higher. Overall, the results indicate that corporate physical climate exposure has significant impacts on the mobility of talents across firms and the value of innovative human capital.

JEL Classifications: Q54; Q58; J22; J24

Keywords: climate change; human capital; innovation; brain drain; conference calls

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1 Introduction

Climate change is one major threat in the world, and it harms society in multiple ways. One of the most salient consequences of climate change is the amplification of natural hazards, which often cause significant damage. Climate-related risks in physical dimensions, such as floods and extreme temperatures, put the operations of many companies at risk. According to recent research by S&P Global, 92% of the largest firms around the world have at least one asset subject to "high risk" due to physical hazards caused by climate change by the 2050s.[1] The exposure to climate change could pose a variety of threats to companies, among which an important one is the potential loss of talented workers. According to a global survey of CEOs (PwC, 2022), 26% of managers are "very concerned" or "extremely concerned" that climate change could hurt the company's ability to attract and retain key talents.[2] Despite the concern, there have not been systematic investigations on how corporate physical climate change exposure affects firms' human capital. In this paper, I examine this crucial question.

It is challenging to study whether employees are more likely to move out of firms with higher exposure to climate-related physical shocks for two reasons. First, it is not easy to measure firm-level physical climate change exposure. This is because firms' exposure to physical climate shocks depends on various factors, including their locations and activities, business inventory, supply chain, continuity plans, and so on.[3] To overcome this challenge, I employ a firm-level physical climate exposure measure that is recently constructed by Sautner, van Lent, Vilkov, and Zhang (2022). This measure is extracted using a machine learning algorithm from transcripts of corporate earnings conference calls. Essentially, it captures the relative frequency of bigrams related to physical climate shocks in communications between managers and other participants during earnings conference calls. These conversations could potentially cover many aspects affecting firms' climate change exposure; thus, the transcripts-based exposure measure can be viewed as a composite proxy.[4]

[1] Please click here for more details.

[2] This portion is comparable to the percentage (28%) of managers who are "very concerned" or "extremely concerned" about the damage brought by climate change to the firm's ability to raise capital.

[3] This feature is discussed in a report issued by the European Bank for Reconstruction and Development. Please click here for details.

[4] Table IA.1 in the Internet Appendix provides examples of earnings conference call transcripts that mention physical climate shocks such as heavy snow and hurricanes. As illustrated in these examples, conversations in conference calls could discuss physical climate shocks related to both firms' headquarters and their establishments, which may be located in different areas. In addition, a company's earnings conference calls may discuss physical

The second obstacle to exploring the human capital effects of corporate climate exposure is that detailed information on individuals' employment is not readily available.[5] In this paper, I take advantage of the patent filings provided by the United States Patent and Trademark Office (USPTO), which contains a mapping between the inventor(s) of each patent and the company that the patent is initially assigned to. The dataset enables me to track inventors' employment history and identify the departure of innovative workers from their former employers. Another significant advantage of the USPTO data is that it allows me to examine the mobility of inventors, who are employees with critical human capital as they are major contributors to innovation and technological advancement (e.g., Akcigit, Baslandze, and Stantcheva, 2016). Innovative inventors are also shown to be a powerful driver of productivity, firm performance, firm value, and economic growth (e.g., Hirshleifer, Hsu, and Li, 2013; Kogan, Papanikolaou, Seru, and Stoffman, 2017). Moreover, it is costly for firms to replace inventors (Belo, Li, Lin, and Zhao, 2017), making their departure a significant concern for investors and managers. It is, therefore, meaningful to understand whether and how inventors are influenced by corporate climate exposure.

Tracking the mobility of inventors who have worked for U.S. public firms from 2002 to 2019, I find that departure rates of innovative workers are significantly higher for firms that are more exposed to physical climate-related shocks. Results from inventor-level regressions show that a one-standard-deviation increase in firm-level physical climate exposure leads to an increase in the likelihood of inventor departure that corresponds to 4.2%–11.2% of the mean departure rate. After departure, the inventors are more likely to move to firms with lower physical climate exposure compared to their original employers. The positive impact of physical climate exposure on inventors' departure is also confirmed in a firm-level regression. Further analyses suggest that this finding is robust to alternative measures of corporate physical climate exposure, including the number of climate-related disasters experienced by a firm. These results provide robust evidence that there exists a significant brain drain effect of corporate physical climate exposure.

I conduct several heterogeneity tests to explore mechanisms underlying the brain drain effect. One

threats not only to the firm but also to its business partners.

[5] Only a few studies employ proprietary employee-employer matched data from the U.S. Census Bureau, social media websites, or other platforms (Graham, Kim, Li, and Qiu, 2013; Jeffers, 2019; Fedyk and Hodson, 2020; Agrawal, Hacamo, and Hu, 2021).

potential reason why inventors tend to leave companies that are exposed to physical climate-related shocks is that they believe such exposure would be detrimental to their employers and, therefore, to them personally. If this explanation works, one may expect that corporate climate exposure exerts a larger impact on the departure rate among workers who are more concerned about climate change and in periods when individuals' climate awareness is higher. Indeed, I find supporting evidence for this conjecture in a set of tests. First, I show that the effect of physical climate exposure is more pronounced among inventors who are likely to have greater concerns about climate change. The high-concern inventors refer to those residing in a Democratic county or in a county where a higher portion of locals believe climate change will largely harm them personally. Second, I find a stronger result in periods of higher public climate awareness, that is, in more recent years and in periods when more locals are using Google to search for information about climate change.

Heightened financing costs faced by high-climate-exposure firms (e.g., Acharya, Johnson, Sundaresan, and Tomunen, 2022) is another potential driver for the higher departure rate of inventors. On the one hand, higher financing costs may force high-exposure firms to discharge some inventors due to, for example, a cut in research and development investment. On the other hand, inventors may choose to leave high-climate-exposure firms if they believe that the increased cost of financing will bring the firm into trouble. To test whether the financing channel helps explain my baseline finding, I exploit variations in firms' reliance on external financing and financial constraints. Using a firm-level index of external financing needs, an accounting-based financial constraint index, and a text-based financial constraint index, I find that the brain drain effect of climate exposure does not vary significantly with the levels of firms' external financing dependence and financial constraints. The results suggest that inventors' departure from high-climate-exposure firms is unlikely driven by the financing channel.

Unlike other common firm characteristics, the firm-level physical climate exposure measure tends to be exogenous to corporate decisions since physical climate shocks are mostly unpredictable in nature.[6] However, one may argue that the unobserved heterogeneity in managerial quality could potentially bias my results. In particular, climate exposure may be higher in firms operated by low-quality managers due to their lack of skills to prepare for and/or deal with physical climate shocks.

[6] Consistent with this view, I find that the physical climate exposure measure is uncorrelated with a wide range of past firm characteristics such as firm size, profitability, sales growth, investment, tangibility, research and development expenses, financial leverage, and cash holdings (Table IA.3 in the Internet Appendix).

At the same time, it is possible that inventors tend to leave firms with low-quality management. To mitigate this concern, I incorporate firm-by-CEO fixed effects. I find that the brain drain effect of corporate climate exposure holds in this specification, indicating that my previous findings are unlikely driven by heterogeneity in managerial quality.

Next, I analyze whether inventors departing from high-climate-exposure firms move within a state or to another state. The results show that both the likelihood of changing jobs within a state and that of moving out of the original state increase if an inventor is working for a firm with higher exposure to physical climate-related shocks. The analysis of inventors' geographical reallocation indicates that firm-level physical climate exposure affects talent mobility not only between firms but also across regions. The evidence provides insight into regional flows of human capital, which is of particular interest for local policymakers.

I then provide evidence that firm-level physical climate exposure could affect corporate innovative productivity. First, I focus on a subsample of superstar inventors who are among the best innovators in their particular fields. Specifically, superstar inventors refer to those who rank at the top quintile in their technology field based on the number of patents they hold, the number of citations they receive, and the value of their patents. I find that firms with higher physical climate exposure are likely to lose the best inventors. The results imply an adverse impact of climate exposure on firms' innovative productivity. Second, I directly test how a firm's number of patents per year, patent citations per year, and economic value per patent change after the company experiences inventor departures. With a matched sample, I show that compared with similar firms not losing inventors, firms' innovative productivity and economic value of subsequent patents decline significantly after inventor departures.

Finally, I examine whether a high degree of employee satisfaction helps firms to retain inventors. To conduct this analysis, I assess employees' satisfaction using their reviews on employers from Glassdoor.com, a website for employees to post reviews. I find that in firms with higher employee satisfaction, the likelihood of inventor departure is less affected by corporate physical climate exposure. In other words, treating employees better helps firms with high climate exposure retain talented innovative workers.

This paper makes several contributions to the literature. First, it contributes to the growing literature on the effects of firms' climate change exposures. It is shown that firms more exposed to sea-level rise risk face higher costs of loan financing (e.g., Jiang, Li, and Qian, 2020) and are more likely to diversify geographically through M&As (Bai, Chu, Shen, and Wan, 2021). Acharya, Johnson, Sundaresan, and Tomunen (2022) document that firms' exposure to heat stress is priced in sub-investment grade corporate bonds and equities. Pankratz and Schiller (2021) find that supplier firms' exposure to heatwaves and floods disrupts supply-chain relations. The paper is the first study, to my best knowledge, to examine the human capital effects of corporate climate exposure. The brain drain effect of firm-level physical climate exposure is new to the literature and improves our understanding of the consequences of corporate climate change exposure.

Second, my paper adds to the literature on the mobility and productivity of skilled labor, and in particular, innovative workers. Prior research suggests that the mobility of inventors is related to local lending relations (Hombert and Matray, 2017) or public resources (Cornaggia, Hund, Pisciotta, and Ye, 2022). Bernstein, McQuade, and Townsend (2021) document that household wealth shocks arising from price changes in the local housing market affect inventors' productivity and mobility. Fich, Harford, and Tran (2022) find that waivers of duty of loyalty increase the rate of inventor departure and reduce inventors' productivity. My paper shows that inventors tend to depart from firms with higher climate change exposure and that corporate innovative productivity is adversely affected.

The remainder of the paper proceeds as follows. Section 2 reviews the related literature. Section 3 describes variable constructions and data sources. Section 4 presents the effects of corporate physical climate exposure on inventor departure rates. Section 5 analyzes the impacts on corporate innovative productivity. Section 6 examines the role of employee satisfaction in inventor retention. Finally, Section 7 concludes.

2 Related Literature

2.1 Impacts of Climate Change Exposure

Firms' exposure to physical climate change risks could affect not only corporate decisions but also asset prices. The corporate finance literature has documented how firms' exposure to various climate-related shocks affect corporate innovative strategies, mergers and acquisitions, and supply-chain relations. In particular, Li, Lin, and Lin (2022) show that firms in countries with higher climate vulnerability produce fewer patents and collaborate more with firms from other countries in the innovation process. Bai, Chu, Shen, and Wan (2021) find that U.S. firms located in coastal areas tend to acquire targets that are less exposed to sea-level rise risk. Moreover, Pankratz and Schiller (2021) document that customer firms are more likely to terminate the supply-chain relation if suppliers are more exposed to physical climate risks.[7]

On the asset pricing side, Acharya, Johnson, Sundaresan, and Tomunen (2022) document that physical climate change exposure is priced in equities and sub-investment grade corporate bonds. In addition, higher exposure to physical climate-related risks leads to higher bank loan spreads (Jiang, Li, and Qian, 2020; Javadi and Masum, 2021; Huang, Kerstein, Wang, and Wu, 2022). Other studies in the finance literature have studied the direct effects of climate shocks on firm profitability (e.g., Pankratz, Bauer, and Derwall, 2019; Addoum, Ng, and Ortiz-Bobea, 2021) and stock returns (Kumar, Xin, and Zhang, 2019).[8]

2.2 Mobility and Productivity of Skilled Labor

The input of labor, especially labor with high skills, is crucial to the success of a company. It is also recognized that talented employees contribute substantially to the value of their employers (e.g. Belo, Li, Lin, and Zhao, 2017; Liu and Ni, 2021; Shen, 2021). Therefore, firms are eager to attract and retain skilled workers, and finance scholars have recently paid much attention to the drivers of skilled labor mobility. For instance, Tate and Yang (2015) establish the relationship between corporate diversification and workers' mobility across industries. In particular, employees from diversified companies are more likely than other workers to move to industries where their original employer operates. Baghai, Silva, Thell, and Vig (2021) examine how skilled employees respond to firms' financial conditions. They document that workers with high cognitive and noncognitive skills are likely to leave quit jobs when their employers are in serious financial difficulty. In addition, the

[7] Barrot and Sauvagnat (2016) and Seetharam (2018) also examine the propagation of natural disasters along input-output linkages.

[8] Other studies have examined the effects of climate shocks on real estate prices (e.g., Baldauf, Garlappi, and Yannelis, 2020; Murfin and Spiegel, 2020; Giglio, Maggiori, Rao, Stroebel, and Weber, 2021), the aggregate economy (e.g., Dell, Jones, and Olken, 2012; Diffenbaugh and Burke, 2019; Cruz and Rossi-Hansberg, 2021) and global trade (e.g., Dingel, Meng, and Hsiang, 2019; Gu and Hale, 2022).

migration of corporate executives and other skilled employees is affected by regional factors such as local housing prices and air conditions (e.g., Brown and Matsa, 2020; Levine, Lin, and Wang, 2020; Kong, Liu, and Zhang, 2021; Xue, Zhang, and Zhao, 2021).

More closely related to this paper, a growing literature investigates the mobility of inventors. In a cross-country setting, Akcigit, Baslandze, and Stantcheva (2016) demonstrate that the international migration of superstar inventors is influenced by the difference in top tax rates across countries. Hombert and Matray (2017) document that young and productive inventors in the U.S. tend to move out of regions where firms' lending relationship is hurt. Cornaggia, Hund, Pisciotta, and Ye (2022) show that inventors in the U.S. are likely to migrate away from counties where fewer public resources are available. Moreover, inventors are known to consider firm characteristics when moving across firms. For example, inventors are more likely to leave a firm after it goes public (Bernstein, 2015), more likely to join firms with better top management (Chemmanur, Kong, Krishnan, and Yu, 2019), and less likely to leave firms that take more social responsibilities (Rice and Schiller, 2022).

3 Data and Variables

This paper combines data from various sources. This section introduces these datasets and describes how I construct variables used for the analysis. Detailed descriptions for variable constructions are also listed in Table A.1 in the Appendix. It also presents summary statistics of main variables.

3.1 Firm-level Climate Change Exposure

In this paper, I employ the measures of firm-level physical climate change exposure developed by Sautner, van Lent, Vilkov, and Zhang (2022).[9] The measures are constructed based on the transcripts of firms' quarterly earnings conference calls. Following the promulgation of Regulation Fair Disclosure by the U.S. Securities and Exchange Commission (SEC) in 2000, corporate conference calls have become an essential means for firms to relay information to market participants (Bushee, Matsumoto, and Miller, 2004). A typical earnings conference call starts with corporate managers' comments on the firm's recent performance, which is followed by a question-and-answer (Q&A)

[9] I thank the authors for making the data publicly available at https://osf.io/fd6jq/.

session. In the Q&A session, managers respond to questions raised by other call participants (e.g., equity analysts and investors). Comments from top management and discussions between managers and other participants usually contain rich information about various risks faced by the firm, among which are risks related to climate change. Table IA.1 in the Internet Appendix provides examples of earnings conference call transcripts that mention physical climate shocks.

Sautner, van Lent, Vilkov, and Zhang (2022) extract the climate-related information from earnings conference call transcripts based on a computational linguistics algorithm that identifies bigrams associated with climate change.[10] Specifically, they start with a short list of climate-related bigrams that are used as the input for the algorithm. Then, the machine-learning algorithm searches for keywords that are relevant to climate change and generates the final list of bigrams. The physical climate change exposure measure refers to the frequency of physical climate bigrams in a transcript, scaled by the total number of bigrams.[11] The annual firm-level physical climate change exposure measure is the average of quarterly exposure measures for a firm in a given year.

In addition to the physical climate exposure measure extracted from earnings conference calls, I construct an alternative measure that represents the number of climate-related natural hazards experienced by a firm. To construct this disaster-based measure, I combine data from the Spatial Hazard Events and Losses Database for the United States (SHELDUS) and Data Axle (formerly Infogroup). SHELDUS is a county-level hazard data set for the U.S. and covers various natural hazards. It provides both the date of a hazard and affected locations. Data Axle offers information on the geographic locations of firms' establishments and estimated sales from each location.

3.2 Inventor Mobility and Productivity

I obtain data on patents filed to the United States Patent and Trademark Office (USPTO) from the website of PatentsView. The dataset contains information regarding the company to which each patent is initially assigned as well as individual inventors associated with it. USPTO assigns

[10] Li, Shan, Tang, and Yao (2021) and Hu, Li, and Yu (2022) adopt similar methodologies to construct measures of firms' climate change exposure.

[11] Table IA.2 in the Internet Appendix displays the initial bigrams used to search for physical climate change bigrams and the most frequent bigrams in the final list that are related to physical climate change shocks.

each inventor a unique identifier based on the "discriminative hierarchical coreference" method.[12] This dataset allows me to track each inventor's career path and identify their movement across firms. To measure inventor mobility, I construct a sample at the inventor firm-year level. Inventors who appear only in one year are excluded. If an inventor is associated with patents assigned to more than one employer in a single year, I assume that the inventor is employed by the firm with which he or she shares a geographical location.[13] Figure 1 illustrates the geographical distribution of inventors in the U.S. A darker color indicates that a larger number of inventors are working in the county. The graph shows that there is a large variation in terms of inventors' location, although the number of inventors is substantially higher in some regions such as San Jose-Sunnyvale-Santa Clara, CA and New York-Northern New Jersey-Long Island, NY-NJ-PA.[14]

[Insert Figure 1 Here]

I use an indicator variable for inventor departure, *Inventor Depature*, as the main variable of interest. Following Rice and Schiller (2022), the departure indicator for inventor i in year t takes one if the inventor files a patent application in year $t+1$ that is initially assigned to a firm different from his or her previous employer, and zero otherwise. The inventor data is matched to the firm-level climate exposure and firm fundamentals using the patent-permno link from Kogan, Papanikolaou, Seru, and Stoffman (2017) and the permno-gvkey link from the CRSP/Compustat Merged (CCM) database.

The USPTO data also allows me to measure innovative productivity both at the inventor level and at the firm level. The number of patents that are associated with each inventor and firm is calculated based on the patent-inventor and patent-assignee links provided by USPTO. In addition, USPTO offers information on patent citations. To capture the economic value of each patent granted to U.S. public firms, I use the approach proposed by Kogan, Papanikolaou, Seru, and Stoffman (2017). The patent value is measured by the stock market response to news about patents.

[12] This inventor disambiguation method identifies individual inventors using information about the inventor name, inventors' employers, technology class of patents, and inventors' co-authors. More details about it are available in https://s3.amazonaws.com/data.patentsview.org/documents/UMassInventorDisambiguation.pdf.

[13] If there is no assignee sharing the same location as the inventor, I choose the assignee listed in the previous application or the subsequent application. Inventors who have simultaneously filed patent applications for multiple firms in two consecutive filing years or more are excluded.

[14] My main conclusion holds after excluding inventors from California, the state with the highest number of inventors (Table IA.6 in the Internet Appendix).

3.3 Other Variables

I obtain firms' financial information from Compustat. Data on climate concerns of the U.S. population is from the Yale Climate Opinion Survey. The county-level voting preferences in elections are from MIT Election Lab. Google Trends provides the regional search volumes for climate change over time. The text-based financial constraint index is provided by Hoberg and Maksimovic (2015). Information on corporate CEOs is obtained from Execucomp. In addition, I collect data on employees' reviews for firms from Glassdoor.

3.4 Summary Statistics

Table 1 provides summary statistics for the final sample during the period between 2002 and 2019.[15] Panel A reports descriptive statistics for inventor characteristics. The average departure rate of inventors is 6.3%. The majority (around 90%) of inventors are male. Inventors have an average of 0.83 new patents and 7.40 cumulative patents (i.e. patents since the start of their career as an inventor) per year. An average inventor receives approximately 71 cumulative citations. These innovative workers generate significant economic value. Based on Kogan, Papanikolaou, Seru, and Stoffman (2017)'s measure of patent value, the average value of patents filed by inventors is $17.91 million.

[Insert Table 1 Here]

Panel B shows summary statistics for firm-level variables. In the sample, seven inventors change jobs on average per year. The measure of corporate physical climate exposure is multiplied by 100 for the sake of exposition. On average, firms are 25 years old and have total assets of $6.46 billion. The expenditure on research and development (R&D) is around 10% of their total assets. In addition, the average book-to-market ratio is 0.58, and the return on assets has an average of 5.3%. Debt accounts for 19.9% of their assets. These firms hold 27.6% of their assets as cash.

[15] The sample starts from 2002 due to the availability of the corporate climate exposure measure.

4 Physical Climate Exposure and Inventor Departure

This section investigates how corporate physical climate exposure affects the departure rate of inventors. First, I present results from linear regressions of the indicator for inventor departure on firms' exposure to physical climate-related shocks. Then, I explore mechanisms underlying the effect of corporate climate exposure on inventors' departure. Next, I examine regional reallocations of departing inventors. Finally, I provide evidence obtained from alternative specifications and measures.

4.1 Baseline Results

I start by analyzing the univariate relation between corporate physical climate exposure and the departure rate of inventors. This relation is graphically illustrated in Figure 2. The bars represent the average rate of inventor departure in each group of firms with different levels of physical climate exposure. It shows that as firms' exposure to physical climate shocks increases, the average rate of inventor departure increases monotonically. The evidence indicates that inventors are more likely to change employers if the original employer is more exposed to physical climate shocks.

[Insert Figure 2 Here]

I then estimate the effects of physical climate exposure on inventors' departure rate in multivariate regressions. In particular, I estimate a regression model using inventor-firm-year level observations. The regression is specified as follows:

$$\begin{aligned} Inventor\ Departure_{i,j,t} &= \alpha + \beta Physical\ Climate\ Exposure_{j,t-1} + \mathbf{X}_{i,t-1}\boldsymbol{\gamma}_1 \\ &+ \mathbf{X}_{j,t-1}\boldsymbol{\gamma}_2 + \delta_j + \delta_{c,t} + \epsilon_{i,j,t}, \end{aligned} \tag{1}$$

where i indexes an inventor, j indexes a firm that employs an inventor, t indexes year, and c indexes the county in which an inventor works. The dependent variable, $Inventor\ Departure_{i,j,t}$, is an indicator that is equal to one if inventor i leaves firm j in year t, and zero otherwise. $Physical\ Climate\ Exposure_{j,t-1}$ refers to the physical climate exposure of firm j in year $t-1$, which is measured by the relative frequency of bigrams capturing climate-related physical shocks in conference call transcripts. The coefficient, β, is of my interest and captures the effects of corporate physical climate change exposure on inventor departure rates.

Following prior literature on innovations, the regression incorporates a set of inventor-level and firm-level characteristics that may affect inventors' decisions to change their employer, as represented by $\mathbf{X}_{i,t-1}$ and $\mathbf{X}_{j,t-1}$, respectively. Inventor characteristics are a male indicator for the inventor (*Male*) and the logarithm of one plus the inventor's cumulative number of patents (*log(1 + Cumulative Patents)*). Firm-level control variables include firm size (*Size*), logarithm of firm age (*log(Firm Age)*), book-to-market ratio (*B/M*), research and development expenses (*R&D*), return on assets (*ROA*), book leverage (*Leverage*), and cash holdings (*Cash*). Firm size is the logarithm of total assets; firm age refers to the number of years since a firm's first appearance in Compustat; book-to-market ratio is the ratio of book value of total assets to divided by the sum of market value of equity and the difference between total assets and total common equity; R&D is research and development expenses scaled by total assets; book leverage is calculated as total book debt divided by total assets; and cash holdings are Cash and short-term investments scaled by total assets. δ_j and $\delta_{c,t}$ denote firm fixed effects and inventor-county-by-year fixed effects, respectively. Standard errors are clustered at the firm level.[16]

[Insert Table 2 Here]

Table 2 reports the regression results from Equation (1). Column (1) shows that the departure rate of inventors is higher for firms with higher physical climate exposure. The regression incorporates year fixed effects and firm fixed effects. Year fixed effects absorb common trends and shocks associated with inventor mobility, such as the financial crisis. Firm fixed effects control for time-invariant cross-firm heterogeneity in innovative workers' propensity to change their employer. In Column (2), I include both individual- and firm-level characteristics that may affect inventor departure. The result again shows a positive effect of corporate physical climate exposure on inventors' departure rate.

Column (3) further includes county-by-year fixed effects, where the county is defined according to an inventor's geographical location disclosed in the patent applications. This model specification accounts for county-specific time-varying factors such as local economic conditions and housing market conditions in the local area. I find that the estimated coefficient on *Physical Climate Exposure* remains positive (0.349) and statistically significant (t = 4.65). This indicates that

[16] The results are robust to alternative clustering (Table IA.4 in the Internet Appendix).

a one-standard-deviation increase in physical climate exposure leads to a 0.26% increase in the inventor departure rate, which corresponds to 4.2% of the average likelihood of inventor departure (6.3%). Overall, the results from baseline regressions suggest that the departure rate of inventors is significantly higher for firms that are more exposed to physical climate-related shocks.[17]

One caveat of the data on patent filings is that it does not provide the exact dates of inventor departures. To mitigate concerns about the measurement error in inventors' departure, I redo the analysis using subsamples of inventors who file patent applications in most years during their career. Table IA.11 in the Internet Appendix shows that my main conclusion holds in the alternative samples. In the sample of inventors who file patent applications every year, a one-standard-deviation increase in corporate physical climate exposure leads to an increase in the likelihood of inventor departure that corresponds to 11.2% of the mean departure rate.

I have documented that, with everything else being equal, inventors are more likely to depart from firms with higher exposure to physical climate shocks. One question that follows is whether the departing inventors move to a firm with lower physical climate exposure compared to their original employers. To answer this question, I compare the level of physical climate exposure of departing inventors' new employer with that of their original employer. Figure 3 demonstrates the histogram of the differences in physical climate exposures of departing inventors' new and original employers. It shows that the change in employer's climate exposure is mostly negative, suggesting that the departing inventors are more likely to move from a high-climate-exposure firm to a firm with lower physical climate exposure. The evidence corroborates my previous finding and further strengthens the argument that corporate physical climate exposure drives the departure rates of innovative workers.

[Insert Figure 3 Here]

4.2 Mechanisms

To understand the underlying mechanisms behind the positive effect of corporate physical climate exposure on inventor departure rates, I conduct cross-sectional heterogeneity tests in this section.

[17] In a robustness test, I find that the result is not driven by individuals working in a few large firms. In particular, the positive effect of corporate physical climate exposure on inventors' departure rate exists in firms with different sizes of inventor team (Table IA.7 in the Internet Appendix).

First, I examine how the baseline effect varies with inventors' climate awareness and the extent to which they are concerned about climate-related issues. In addition, I test whether the effect of physical climate exposure is stronger among firms that are more financially constrained.

4.2.1 Climate Change Concerns and Awareness

One plausible reason inventors tend to move out of companies more exposed to physical climate-related shocks could be that they believe such a high degree of climate exposure is detrimental to their employers and, therefore, to themselves. If this is true, we should expect the baseline effect to be stronger among inventors who are more concerned about the negative effects brought by climate change. To test this conjecture, I employ the variation in beliefs about climate change across inventors.

I first use the data from the Yale Climate Opinion Survey to measure inventors' level of concerns about climate change issues. This survey asks respondents about their opinions on climate-related questions and provides rich information about people's climate change beliefs, risk perceptions, and policy preferences at the state and local levels. In my analysis, I focus on answers to the survey question: "Do you think global warming will harm them personally a moderate amount/a great deal?" In particular, inventors' degree of concerns about climate change is measured by the percentage of respondents who answered "Yes" to the question above in their residential county.[18] Figure 4 plots the mean percentage of positive responses over time in each U.S. county. It shows that there is a large cross-county variation in locals' opinions about the harmfulness of climate change. For example, around two-thirds of the respondents in Bronx County, New York, think that global warming will largely harm them personally, while less than one-third of the respondents in Bland County, Virginia, believe the same.

[Insert Figure 4 Here]

With the survey-based measure, I estimate the following regression model:

[18] The answers to this particular survey question is available in 2014, 2016, 2018, 2019, 2020. For each county, I calculate the time-series average of positive responses over different survey years and use the mean percentage as the proxy.

$$Inventor\ Departure_{i,j,t} = \alpha + \beta_1 Physical\ Climate\ Exposure_{j,t-1} \times High\ Concerns_c$$
$$+ \beta_2 Physical\ Climate\ Exposure_{j,t-1} + \mathbf{X}_{i,t-1}\boldsymbol{\gamma}_1 + \mathbf{X}_{j,t-1}\boldsymbol{\gamma}_2 + \delta_j + \delta_{c,t} + \epsilon_{i,j,t}, \quad (2)$$

where *High Concerns* is a dummy variable that equals one if the proportion of the local residents in inventors' county who believe that global warming will harm them personally a moderate amount or a great deal is above the sample median, and zero otherwise. Other variables are defined the same as in Equation (1). The coefficient on the interaction term, β_1, is of interest. If inventors' climate concerns drive their departure from companies with high physical climate exposure, β_1 is expected to be positive.

The estimation result is presented in Column (1) of Table 3. It shows that the estimated coefficient on *Physical Climate Exposure* × *High Concerns* is 0.244 with a t-statistic of 2.54. The coefficient estimate for *Physical Climate Exposure* is positive (0.124) but statistically insignificant ($t = 1.05$). The evidence suggests that the effect of physical climate exposure on inventor departure rates is concentrated among individuals who are more concerned about climate change. This finding is consistent with the view that employees move away from high-exposure companies to avoid the potential negative impacts of climate change.

[Insert Table 3 Here]

As an alternative measure for inventors' climate concerns, I rely on the fact that Democrats are much more concerned about climate-related issues than Republicans and use an indicator for whether an inventor resides in a more Democratic-leaning county.[19] The county-level Democratic vote shares in presidential elections between 2000 and 2016 are obtained from MIT Election Lab. In any given year, the *Democratic* dummy is set to one if an inventor is located in a county from which a democratic candidate got the highest vote share in the most recent presidential election, and zero otherwise.

I reestimate Equation (2) with *High Concerns* replaced by *Democratic*. Column (2) in Table 3 reports the results. I find that the coefficient on *Physical Climate Exposure* × *Democratic* is estimated

[19] According to a survey of U.S. adults conducted by Pew Research Center in 2020, 78% (21%) of Democrats (Republicans) regard dealing with climate change as a top priority. Please click here for more details.

to be 0.417 ($t = 3.17$). The evidence suggests that the departure rate of an inventor is more strongly influenced by the employer's physical climate exposure if the inventor works in a Democratic-leaning county. The result is again consistent with the conjecture that corporate climate exposure affects the inventor departure rate through individuals' concerns about the adverse impacts of climate change.

Next, I turn to time-series heterogeneity in public awareness of climate change issues. If individuals' climate concerns help explain the baseline finding, one would expect that the positive effect of physical climate exposure on inventor departure rates is more pronounced during periods with greater climate change awareness. In general, public attention to climate change is growing over time, especially in recent years, potentially due to the increased frequency of extreme weather (Choi, Gao, and Jiang, 2020) and several attention-grabbing climate-related events such as the Paris Agreement (Bolton and Kacperczyk, 2021). Therefore, I compare the effects of corporate physical climate exposure during the first and second half of the sample period. Specifically, I rerun the regression in Equation (2) and replace *High Concerns* with $Post2010$, which is a dummy variable set to one in years after 2010, and zero otherwise. As shown in Column (3) of Table 3, the coefficient estimate on *Physical Climate Exposure* is positive (0.121) but statistically insignificant. The coefficient on the interaction term, however, is positive (0.306) and significantly different from zero at the 1% level ($t = 3.11$). The result suggests that the brain drain effect of physical climate exposure is concentrated in more recent years.

In order to take into account the possibility that people in different geographical locations may be concerned about climate change at different times, I conduct another test that employs a location-specific definition for high-awareness periods. To be specific, I identify periods with high climate change awareness for each state using data provided by Google Trends. *High SVI* is defined as a dummy variable that takes one in a given state and year if the state-wide Google search index for "climate change" in that year is above the time-series median value of the index in the state, and zero otherwise. Consistent with the result above, I find that the coefficient on *Physical Climate Exposure* $\times$ *High SVI* is significantly positive. The evidence shows that physical climate exposure has a more pronounced effect on inventor departure rates when local people pay more attention to climate change problems. Overall, the results in this section are consistent with the idea that inventors' concerns about the adverse effects of climate change motivate them to move away from employers with higher exposure to physical climate-related shocks.

4.2.2 Financing Costs

Prior literature (e.g., Jiang, Li, and Qian, 2020; Acharya, Johnson, Sundaresan, and Tomunen, 2022; Huang, Kerstein, Wang, and Wu, 2022) shows that companies with higher exposure to physical climate risks face higher costs of external financing. Heightened financing costs may explain the effect of corporate physical climate exposure on the departure rate of inventors. On the one hand, higher financing costs may force high-exposure firms to discharge some inventors due to, for example, a cut in research and development investment. On the other hand, inventors may choose to depart from firms that are more exposed to physical climate-related shocks if they believe that their high-exposure employer will suffer from the heightened financing costs. If this mechanism explains the brain drain effect of climate exposure, one would expect such an effect to be more pronounced among firms for which external financing is more important. To test this conjecture, I investigate whether the relation between physical climate exposure and the inventor departure rate is stronger among firms facing higher external financing needs or firms that are more financially constrained. This analysis is conducted by estimating the following regression model:

$$\begin{aligned} &Inventor\ Departure_{i,j,t} = \alpha + \beta_1 Physical\ Climate\ Exposure_{j,t-1} \times Constrained_{j,t-1} \\ &+ \beta_2 Constrained_{j,t-1} + \beta_3 Physical\ Climate\ Exposure_{j,t-1} + \mathbf{X}_{i,t-1}\boldsymbol{\gamma}_1 + \mathbf{X}_{j,t-1}\boldsymbol{\gamma}_2 \\ &+ \delta_j + \delta_{c,t} + \epsilon_{i,j,t}, \end{aligned} \tag{3}$$

where $Constrained_{j,t-1}$ is an indicator for firms with high external financing needs or high financial constraints. Other variables are defined the same as in Equation (1). The coefficient of interest, β_1, is expected to be positive if the financing channel drives the effect of physical climate exposure on the inventor departure rate.

I follow Demirgüç-Kunt and Maksimovic (1998) to measure firms' external financing needs. It is calculated as the net growth rate of sales times total assets minus gross sales growth rate times retained earnings, scaled by total assets. The *Constrained* indicator is equal to one if a firm's external financing needs are above the sample median in a given year, and zero otherwise. Column (1) in Table 4 reports the estimation result. It shows that the coefficient on corporate physical climate exposure is positive (0.345) and significant at the 1% level ($t = 4.39$). This result indicates that firms with low external financing needs are more likely to lose inventors if they are more exposed to physical climate-related shocks. Moreover, the coefficient on the interaction term is not statistically distinguishable from zero, suggesting that the brain drain effect of physical climate exposure does not depend on firms' level of external financing needs. The evidence does not support the financing channel.

[Insert Table 4 Here]

Next, I continue with two measures of financial constraints to test the financing channel. The first measure is proposed by Whited and Wu (2006) and is constructed using firms' accounting data, while the second measure is extracted from 10-K reports by Hoberg and Maksimovic (2015) using textual analysis. Similar to the analysis with external financing needs, I set the financially-constrained indicator, *Constrained*, to be one if a firm's financial constraint index is higher than the sample median in a given year. I estimate Equation (3) with the two financial constraint measures and report the results in Columns (2) and (3) of Table 4. It turns out that the coefficient on the interaction term, Physical Climate Exposure $\times$ *Constrained*, is not statistically significant, regardless of whether the financial constraint index is accounting-based or text-based. The evidence is again inconsistent with the financing channel. To sum up, the results in this subsection show that the impacts of corporate physical climate exposure on the inventor departure rate are unlikely driven by heightened financing costs faced by high-exposure firms.

4.3 Geographical Reallocation

In this section, I investigate the geographical reallocation effects of inventors by analyzing whether inventors affected by high corporate physical climate exposure move within a state or across states. This analysis aims to provide insights regarding regional flows of human capital and will be of interest to local policymakers. For this test, I estimate a regression model specified as follows:

$$Y_{i,j,t} = \alpha + \beta Physical\ Climate\ Exposure_{j,t-1} + \mathbf{X}_{i,t-1}\boldsymbol{\gamma}_1 + \mathbf{X}_{j,t-1}\boldsymbol{\gamma}_2 + \delta_j + \delta_{c,t} + \epsilon_{i,j,t}, \qquad (4)$$

where $Y_{i,j,t}$ can be either $Within\text{–}state\ Move_{i,j,t}$ or $Out\text{–}of\text{–}state\ Move_{i,j,t}$. *Within-state Move* (*Out-of-state Move*) is a dummy variable that takes one if an inventor moves to a new employer located in the same state as (a different state than) the original employer. Employer location refers to the place where the inventor works and is obtained from the location information in patent applications filed by the inventor.

[Insert Table 5 Here]

Table 5 reports the results from Equation (4). In Column (1), the dependent variable is the indicator for within-state moves. It shows that the coefficient on corporate physical climate exposure is positive and significant, indicating that the likelihood of shifting to a new within-state employer is higher when an inventor is working for a company with higher exposure to physical climate-related shocks. Column (2) shows that after incorporating individual-level and firm-level characteristics, the positive effect of firm-level physical climate exposure on inventors' within-state mobility rate remains significant.

Columns (3) and (4) present results from regressions of the indicator for out-of-state moves. I find that the coefficients on physical climate exposure are significantly positive, suggesting that inventors are also more likely to move out of state if their employer has higher exposure to climate change. In addition, the coefficients on physical climate exposure are almost half of those obtained from the regressions of mobility within a state. The smaller magnitude of cross-state moves may be attributed to the fact that inventors tend to face higher costs when relocating from one state to another. These costs may be incurred by various factors such as differences in local regulations and the potential damage to social connections.

4.4 Alternative Specifications and Measures

This section presents results from alternative model specifications and measures. First, I control for unobserved heterogeneity in managerial quality. Second, I replace the climate exposure measure extracted from earnings conference calls with an alternative measure based on firms' experience with climate-related natural hazards. Third, I employ a climate exposure measure that accounts for the typical frequency of terms appearing in conference call transcripts. Fourth, I estimate firm-level regressions to demonstrate the effect of firms' physical climate exposure on their human capital more directly. Finally, I estimate the effect of corporate abnormal climate exposure on inventors' departure rate.[20]

4.4.1 Heterogeneity in Managerial Quality

One may argue that a firm's degree of physical climate exposure could be correlated with the managerial quality of the firm. Specifically, low-quality managers may not be active in preparing for and dealing with physical shocks related to climate change. On the other hand, it is possible that inventors would like to avoid firms operated by low-quality managers. If this is true, my previous findings could be biased. In order to mitigate this concern, I augment my baseline specifications with firm-by-CEO fixed effects. In the extended estimations, I essentially compare the departure rate of inventors who are working in the same firm and monitored by the same CEO. To the extent that CEOs lead the decision-making process in a company, incorporating firm-by-CEO fixed effects absorbs unobserved heterogeneity in managerial quality and thus resolves the issue.

[Insert Table 6 Here]

Table 6 reports estimation results from regressions incorporating firm-by-CEO fixed effects. I find that the coefficients on corporate physical climate exposure remain positive and statistically significant. The evidence implies that my baseline results are unlikely to be driven by heterogeneity in managerial quality. The effects of corporate physical climate exposure become stronger after controlling for heterogeneity in managerial quality. According to Column (3), a one-standard-deviation increase in corporate physical climate exposure leads to an increase of 0.36% in the likelihood of inventor departure, which corresponds to 5.8% of the mean departure rate. This result suggests that the heterogeneity in managerial quality appears to bias previously estimated effects downward, if any bias exists.

[20] The Internet Appendix reports results from additional specifications. My baseline findings are robust to excluding firms of which the corporate physical exposure measure is always equal to zero during the sample period (Table IA.6 in the Internet Appendix). The results are similar after controlling for other dimensions of corporate climate change exposures, such as opportunity climate change exposure and regulatory climate change exposure (Table IA.12 in the Internet Appendix). I find that opportunity climate exposure and regulatory climate exposure do not affect the departure rate of inventors. This may be due to employees' vaguer understanding of opportunities and regulatory shocks associated with climate change than they do with physical climate shocks. In addition, when distinguishing the sentiment towards physical climate exposure, I find that the effect of physical climate exposure on inventors' departure rate is mainly concentrated in situations when sentiment towards climate exposure is likely to be negative (Table IA.8 in the Internet Appendix).

4.4.2 Disaster-based Climate Exposure Measure

The physical climate exposure measure extracted from conference calls has various advantages. For example, it can capture firm-level variations in climate exposures. This feature is important because exposure to physical climate-related shocks depends heavily on firm-specific characteristics such as the nature of the firm's operations, locations of the firm's headquarter and establishments, and the firm's supply-chain relations. Conversations between managers and analysts during earnings conference calls could potentially cover many of these aspects; thus, the transcripts-based exposure measure may be regarded as a composite proxy. These communications may even contain soft information that is related to climate exposure but cannot be observed from other sources. However, one caveat of this measure is that it only captures climate risks perceived by conference call participants. As an attempt to overcome this shortage, I redo the baseline analysis with a more objective exposure measure that is constructed based on the number of climate-related natural disasters experienced by the firm.

The disaster-based measure, *Climate Disasters*, is calculated as the sales-weighted number of climate-related natural hazards that occurred in counties where a firm's establishments are located.[21] The information for the construction is from SHELDUS and Data Axle. I estimate the regression specified in Equation (1) with *Physical Climate Exposure* replaced by *Climate Disasters*. The results are reported in Table 7. Column (1) shows that the coefficient on *Climate Disasters* is positive (0.013) and statistically significant at the 1% level (t = 3.11). The result suggests that departure rates of inventors are higher for firms that experienced more climate-related natural hazards, consistent with the finding obtained from the transcript-based exposure measure. A one-standard-deviation increase in the alternative exposure measure is associated with an increase in the departure likelihood corresponding to 3% of the average departure rate. In addition, the regression yields similar results after controlling for individual- and firm-level characteristics as well as county-specific time-varying factors (Columns (2) and (3)).[22]

[Insert Table 7 Here]

[21] Climate-related natural hazards include avalanches, coastal storms, droughts, flooding, hails, heatwaves, hurricanes/tropical storms, landslides, lightning, severe storms/thunderstorms, tornados, wildfires, winds, and winter weather.

[22] The results are similar if the climate disasters that happened in inventors' counties are excluded.

4.4.3 Adjustment for Common Terms

In the baseline regressions, I use a climate change exposure measure that equally weighs all bigrams related to physical climate change shocks. This proxy does not account for the importance or typical frequency of individual bigrams. Intuitively, terms that are frequently mentioned in most transcripts are less informative about the content of a particular conference call and thus deserve a lower weight. As a robustness check, I consider an alternative climate exposure measure that assigns lower weights to common bigrams appearing in more transcripts. The adjustment is made to reflect the representativeness of a bigram for climate-related discussions.

The alternative measure is constructed with the "term frequency-inverse document frequency" (TFIDF) approach. Specifically, the TFIDF-adjusted measure is calculated as $\frac{1}{B_{j,q}} \sum_{b}^{B_{j,q}} \left(1 \left[b \in \mathbb{C} \right] \times \log \left(\frac{N_{\mathbb{T}}}{f_{b,\mathbb{T}}} \right) \right)$, where $B_{j,q}$ is the total number of bigrams in the earnings call transcript of firm j in quarter q; $1 \left[b \in \mathbb{C} \right]$ is an indicator for bigram b is in the set of bigrams related to physical climate-related shocks; $N_{\mathbb{T}}$ refers to the number of conference call transcripts; and $f_{b,\mathbb{T}}$ is the number of transcripts in which bigram b appears. By construction, more common terms receive lower weights since given $N_{\mathbb{T}}$, $\log \left(\frac{N_{\mathbb{T}}}{f_{b,\mathbb{T}}} \right)$ decreases as $f_{b,\mathbb{T}}$ increases (i.e., bigram b appear in more transcripts). Table IA.5 reports results from baseline regressions with the TFIDF-adjusted physical climate exposure as the independent variable. Consistent with my baseline findings, coefficient estimates on *Physical Climate Exposure*^{TFIDF} are all positive and statistically significant at the 1% level. According to Column (3), a one-standard-deviation (0.059) increase in the alternative measure is associated with a 0.27% increase in inventors' departure rate, which is similar to the economic magnitude obtained from the unadjusted measure.

4.4.4 Firm-level Regressions

The evidence from inventor-level analysis suggests that with all else being equal, firms with higher physical climate exposure are likely to lose more inventors. In order to test this implication, I estimate firm-level regressions. Specifically, the logarithm of one plus the number of departing inventors in a firm and year is regressed on firm-level physical climate exposure. The regressions control for firm characteristics incorporated in Equation (1) and include both year and firm fixed effects. The results from firm-level regressions are reported in Table IA.9 in the Internet Appendix. I find that higher physical climate exposure is associated with a larger number of departing inventors, which is consistent with results from the inventor-level analysis. In addition, Cohn, Liu, and Wardlaw (2022) suggest that OLS regressions of the log of 1 plus the outcome may produce biased estimates. To address this concern, I follow their suggestion and estimate fixed-effects Poisson models where the dependent variable is the total number of inventors who leave a firm in a given year. It turns out that the positive effect of corporate physical climate exposure on the loss of innovative workers holds in Poisson models.

4.4.5 Abnormal Climate Exposure

In addition to the level of corporate climate exposure, the abnormal change in firms' climate exposure may affect the departure rate of innovative workers. It is possible that inventors who work in low-exposure firms would like to change jobs after their firm experiences a relatively large increase in exposure to physical climate shocks. To test this conjecture, I construct an abnormal climate exposure measure and estimate its effect on inventors' departure rate. A firm's abnormal physical climate exposure is calculated as its physical climate exposure in a given year minus the average of its physical climate exposure over the past three years. The regression results are reported in Table IA.10 in the Internet Appendix. I find that the coefficients on the abnormal climate exposure measure are positive and significant, indicating that departure rates of inventors are higher for firms with abnormally high exposure to physical climate shocks. The evidence is consistent with my baseline finding.

5 Corporate Innovative Productivity

I now turn to the effects on corporate innovative productivity. First, I test whether the most productive inventors are affected by corporate physical climate exposure. Second, I examine changes in the number of new patents, the number of citations for new patents, and the value of new patents after inventors' departure.

5.1 Departure of Superstar Inventors

As shown in Table 1 Panel A, the standard deviations of the number of patents, patent citations, and patent value are large relative to their mean values. The evidence suggests that there is a wide variation in inventors' productivity and the value of patents they produce. Presumably, the importance of workers to their employers increases with their productivity. Therefore, it is crucial to understand how firm-level exposure to physical climate-related shocks affects the departure rates of the most productive inventors. To answer this question, I focus on the subsample of "superstar" inventors who are the most productive and who produce the most valuable patents.

[Insert Table 8 Here]

I first measure inventors' innovative productivity by the quantity of patents they have been granted. In particular, I identify productive inventors by comparing their average cumulative number of patents per year, which is calculated as the cumulative number of patents for an inventor scaled by the number of years since they start their career as an inventor. The "superstar" inventors refer to those with the productivity measure in the top quintile within a given technology class and year. The technology class for an inventor is defined as the modal cooperative patent classification section code of all previous patents the inventor has filed.

Column (1) in Table 8 reports the estimation results from Equation (1) with the subsample of "superstar" inventors. I find that the estimated coefficient on corporate physical climate exposure is positive and statistically significant at the 1% level. The result shows that departure rates of the most productive inventors are higher in high-exposure firms than in low-exposure firms. The brain drain effect among top inventors further highlights the significance of corporate physical climate exposure in determining firms' innovative human capital.

Next, I consider the quality of inventors to measure their productive productivity. I use two proxies of inventor quality: the number of citations and the economic value associated with the patents filed by an inventor. Specifically, the patent citation measure is calculated as the cumulative number of citations for patents filed by an inventor scaled by the number of years since they start their career as an inventor. And the patent value measure refers to the average Kogan, Papanikolaou, Seru, and Stoffman (2017) value of patents granted to an inventor. Using these two measures, I identify "superstar" inventors in the same way as described above and reestimate Equation (1) with these top inventors. The results are presented in Columns (2) and (3) in Table 8. The coefficients on *Physical Climate Exposure* are estimated to be 0.483 ($t = 4.02$) and 0.348 ($t = 3.70$), respectively. The results again show that high-quality inventors are more likely to move away from firms with higher exposure to physical climate-related shocks.

5.2 Corporate Innovative Productivity after Inventor Departures

In this subsection, I examine the consequences of inventor departures by examining how firms' innovative productivity changes after the departure of inventors. To do so, I compare the innovative productivity of firms that experience inventor departures to comparable control firms without inventor departures before and after inventor departures. In the first step, I identify firms with inventor departures (i.e., treated firm) in any given year. The departure of inventors in a given firm and year is regarded as an event (departures of multiple inventors from one firm in the same year are treated as a single event). To avoid confounding effects, I drop events in which the treated firm experiences another inventor departure within three years before or three years after the event. Then, I identify matched control firms that are comparable to the treated firms. In each event, control firms refer to companies that do not experience any inventor departure in the [-3, +3] event window. Firms are matched using the propensity score matching approach based on firm size, the logarithm of one plus firm age, book-to-market ratio, research and development expenses, return-on-assets, book leverage, cash holdings, the logarithm of one plus the number of patents filed in the year before the event, and industry. The nearest-neighbor matching is used where a treated firm is matched with up to three control firms.

With the matched sample, I estimate the effect of inventor departure on firms' subsequent innovative productivity using a regression model specified as follows:

$$\begin{aligned} Y_{j,h,t} = {} & \alpha + \beta_1 \mathit{Departed\ Firm}_{j,h} \times \mathit{Post\ Departure}_{h,t} + \beta_2 \mathit{Departed\ Firm}_{j,h} \\ & + \beta_3 \mathit{Post\ Departure}_{h,t} + \mathbf{X}_{i,t-1}\boldsymbol{\gamma}_1 + \mathbf{X}_{j,t-1}\boldsymbol{\gamma}_2 + \delta_j + \delta_t + \epsilon_{j,h,t}, \end{aligned} \tag{5}$$

where $Y_{j,h,t}$ is a measure of the innovative productivity of firm j in year t; h denotes an event of inventor departure in a given firm and year; $\mathit{Departed\ Firm}_{j,h}$ is a dummy variable that equals one if firm j experiences inventor departures (i.e., treated firm) in event h, and zero otherwise; $Post\ Departure_{h,t}$ is a dummy variable that equals one if year t belongs to the post-event periods in event h, and zero otherwise; $\mathbf{X}_{i,t-1}$ and $\mathbf{X}_{j,t-1}$ include inventor-level and firm-level characteristics, respectively; δ_j and δ_t denote firm fixed effects and year fixed effects, respectively. The estimations include observations during the period from three years before to three years after the event. The coefficient on the interaction term, β_1, is of interest. It captures how the innovative productivity of treated firms changes after the inventors' departure compared to the matched control firms.

[Insert Table 9 Here]

I use three measures of firms' innovative productivity. They include the logarithm of one plus the number of patents filed by a firm in a year, the logarithm of one plus the number of citations (during five years after patent issue) for patents filed by a firm in a year, and the logarithm of one plus the average economic value of patents filed by a firm in a year. Table 9 reports the results. In Column (1), the independent variable is the patent-number-based measure of corporate innovative productivity. I find that the coefficient on *Departed Firm* $\times$ *Post Departure* is negative and statistically significant. The result suggests that compared to firms without inventor departure, firms that experience inventor departures file fewer patent applications after the loss of inventors. I obtain similar results using the citation-based measure (Column (2)). Column (3) shows that following the inventor departure, the average economic value of patents filed by a treated firm is significantly lower than that of patents from a control firm. Overall, the evidence in Table 9 indicates that after inventors leave a firm, both the firm's innovative productivity and the value of patents produced by the firm decline significantly.

6 Employee Satisfaction and Inventor Retention

In this section, I examine whether better employee treatment helps firms to retain inventors and mitigate the brain drain effect of corporate physical climate exposure. To assess employee treatment of firms, I collect ratings posted by employees on Glassdoor.com. This website, which was launched in 2008, allows individuals to post reviews anonymously for their employers. Existing studies (e.g., Green, Huang, Wen, and Zhou, 2019) show that employee reviews on Glassdoor indeed reflect workers' opinions about their employers and contain value-relevant information. Employees rate their firm on various aspects such as compensation, work/life balance, and corporate culture. In my analysis, I use the overall rating that can be regarded as a composite measure of employee satisfaction. The overall rating has a scale from zero to five, with a higher rating indicating a greater level of satisfaction.

I estimate the following regression to examine whether employee satisfaction influences the effect of corporate physical climate exposure on inventor departure rate:

$$
\begin{aligned}
&Inventor\ Departure_{i,j,t} = \alpha + \beta_1 Physical\ Climate\ Exposure_{j,t-1} \times Employee\ Ratings_{j,t-1} \\
&+ \beta_2 Physical\ Climate\ Exposure_{j,t-1} + \beta_3 Employee\ Ratings_{j,t-1} + \mathbf{X}_{i,t-1}\boldsymbol{\gamma}_1 + \mathbf{X}_{j,t-1}\boldsymbol{\gamma}_2 \\
&+ \delta_j + \delta_{c,t} + \epsilon_{i,j,t},
\end{aligned}
\tag{6}
$$

where $Employee\ Ratings_{j,t-1}$ is the average value of the overall ratings for firm j posted by its employees in year $t-1$; other variables are defined the same as in Equation (1). The coefficient of interest is β_1.

[Insert Table 10 Here]

Table 10 presents the results. Column (1) shows that the coefficient on *Physical Climate Exposure* is positive (1.557) and statistically significant. More importantly, the coefficient estimate on *Physical Climate Exposure* × *Employee Ratings* is negative (-0.383) and significant. The result suggests that in a company that treats its employees well, the inventor departure rate is less likely to be influenced by corporate physical climate exposure. In other words, higher employee satisfaction mitigates the brain drain effect of firms' exposure to climate-related physical shocks. Moreover, the mitigation effect holds in alternative regression specifications (Columns (2) and (3)). Overall, the results show that better employee treatment helps retain innovative workers.

7 Conclusions

This paper investigates the effects of firms' physical climate change exposure on their key human capital, that is, innovative workers. Combing a firm-level climate exposure measure extracted from earnings conference call transcripts with inventors' employment history provided in patent filings, I find that departure rates of inventors are significantly higher for firms that are more exposed to physical climate-related shocks. The findings are confirmed in both individual-level regressions and firm-level regressions. The effect is also robust to an alternative measure based on firms' experience of climate disasters. I further show that such a brain drain effect is likely due to inventors' belief that such climate risk exposure would be detrimental to their employers and, therefore, themselves. In addition, I find that firms' innovative productivity and the economic value of subsequent patents decline significantly following inventor departures. The result highlights the adverse effects of climate risk exposure on the firms, especially the value of innovative human capital. Finally, I provide evidence that greater employee satisfaction helps high-climate-exposure firms retain inventors.

This paper has important implications for not only firms but also local governments. Given the significant brain drain effect of corporate physical climate exposure, firms should attach enough attention to the evolvement of its physical climate exposure and take prompt measures to deal with the adverse effects on innovative human capital, such as improving employee benefits. On the other hand, governments should pay close attention to local firms' physical climate exposure because some inventors affected by high corporate climate exposure will move out of the original state. The loss of talents due to corporate climate exposure can be detrimental to the local economy.

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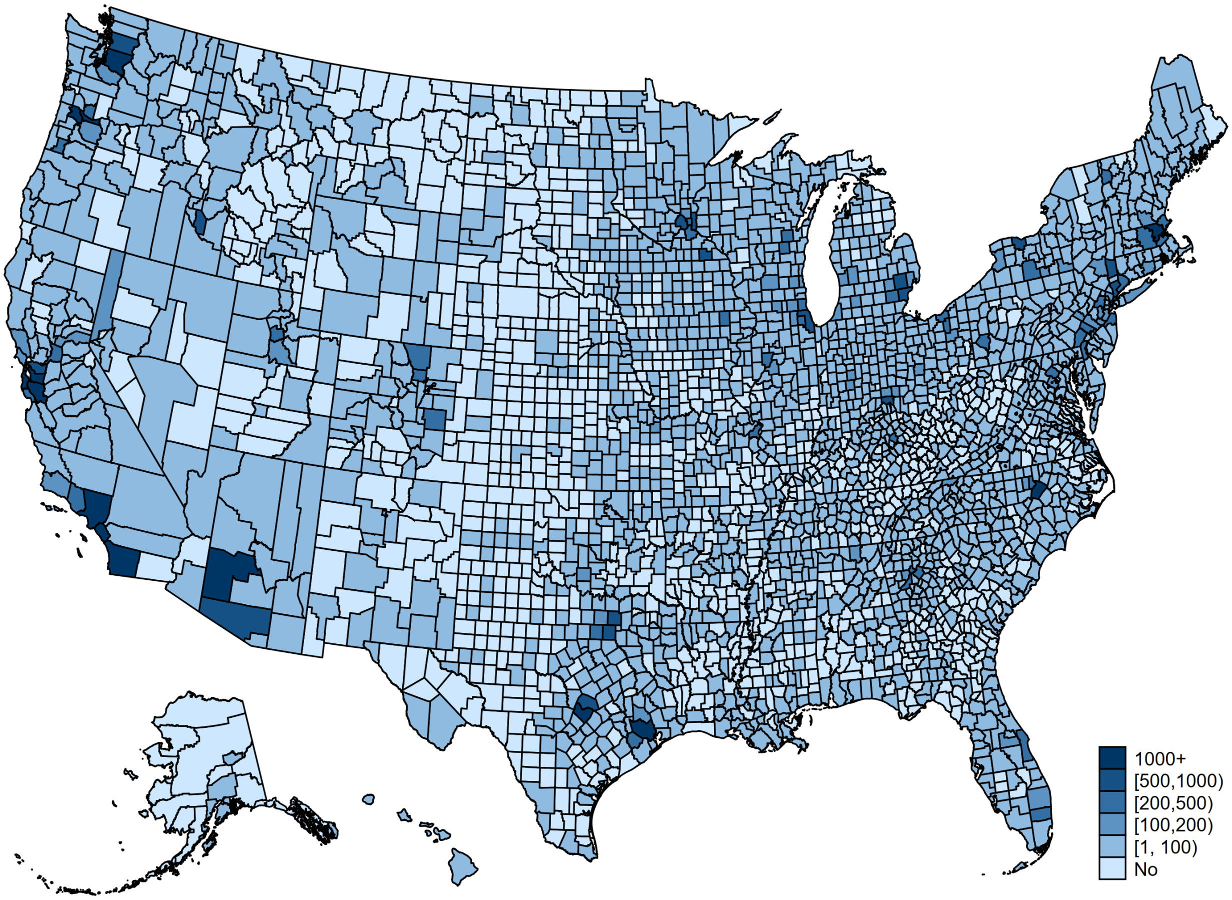

Figure 1 Geographical Distribution of Inventors

This figure plots the number of inventors in each U.S. county. Darker color indicates a higher number. Inventor location information is from USPTO. The sample period is from 2002 to 2019.

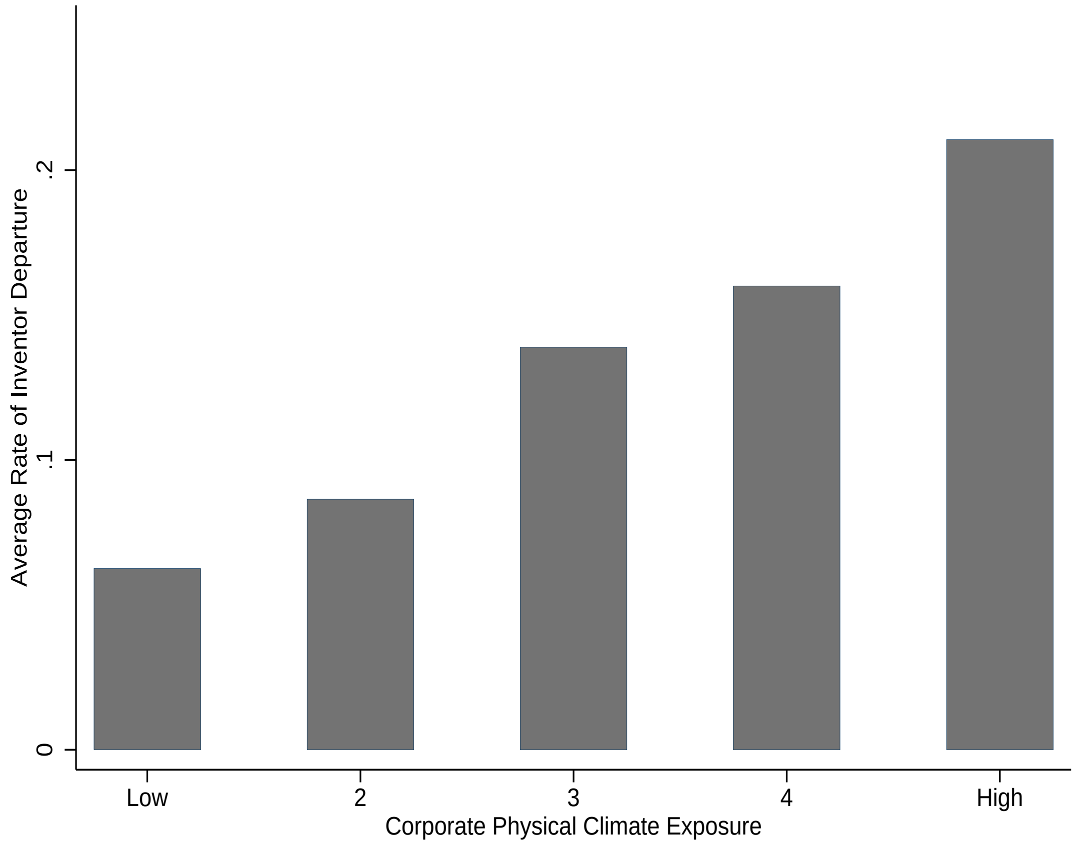

Figure 2 Corporate Physical Climate Exposure and Inventor Departure Rate

This figure plots the relation between corporate physical climate exposure and inventors' departure rate. The bars represent the average rate of inventor departure in each group. The first (Low) group contains firms with physical climate exposure below 0.1. The second group contains firms with physical climate exposure between 0.1 and 0.15. The third group contains firms with physical climate exposure between 0.15 and 0.2. The fourth group contains firms with physical climate exposure between 0.2 and 0.3. The fifth (High) group contains firms with physical climate exposure above 0.3. The sample period is from 2002 to 2019.

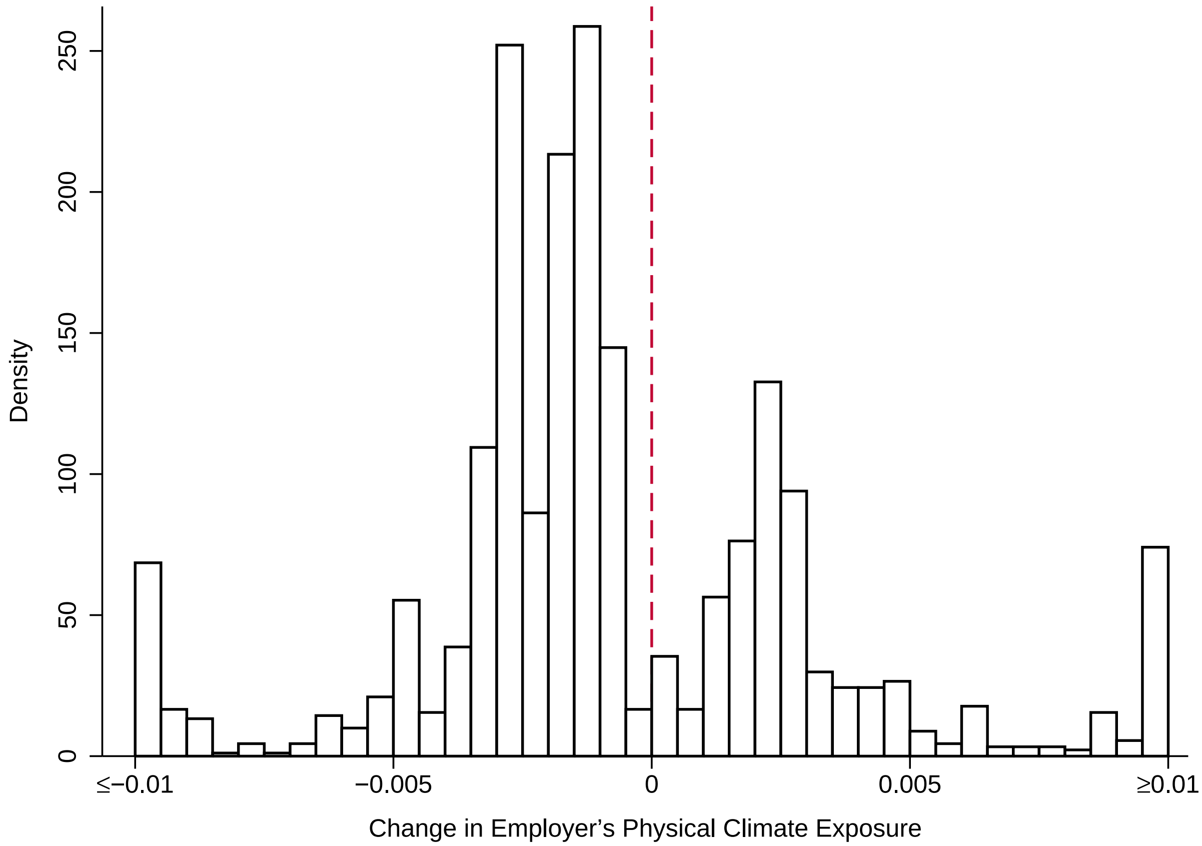

Figure 3 Histogram of the Difference in Physical Climate Exposures: New Versus Original Employers

The histogram illustrates the distribution of the difference in physical climate exposures of the departing inventors' new versus original employers. Firms' physical climate exposure is measured by the relative frequency of bigrams capturing climate-related physical shocks in conference call transcripts. The sample period is from 2002 to 2019.

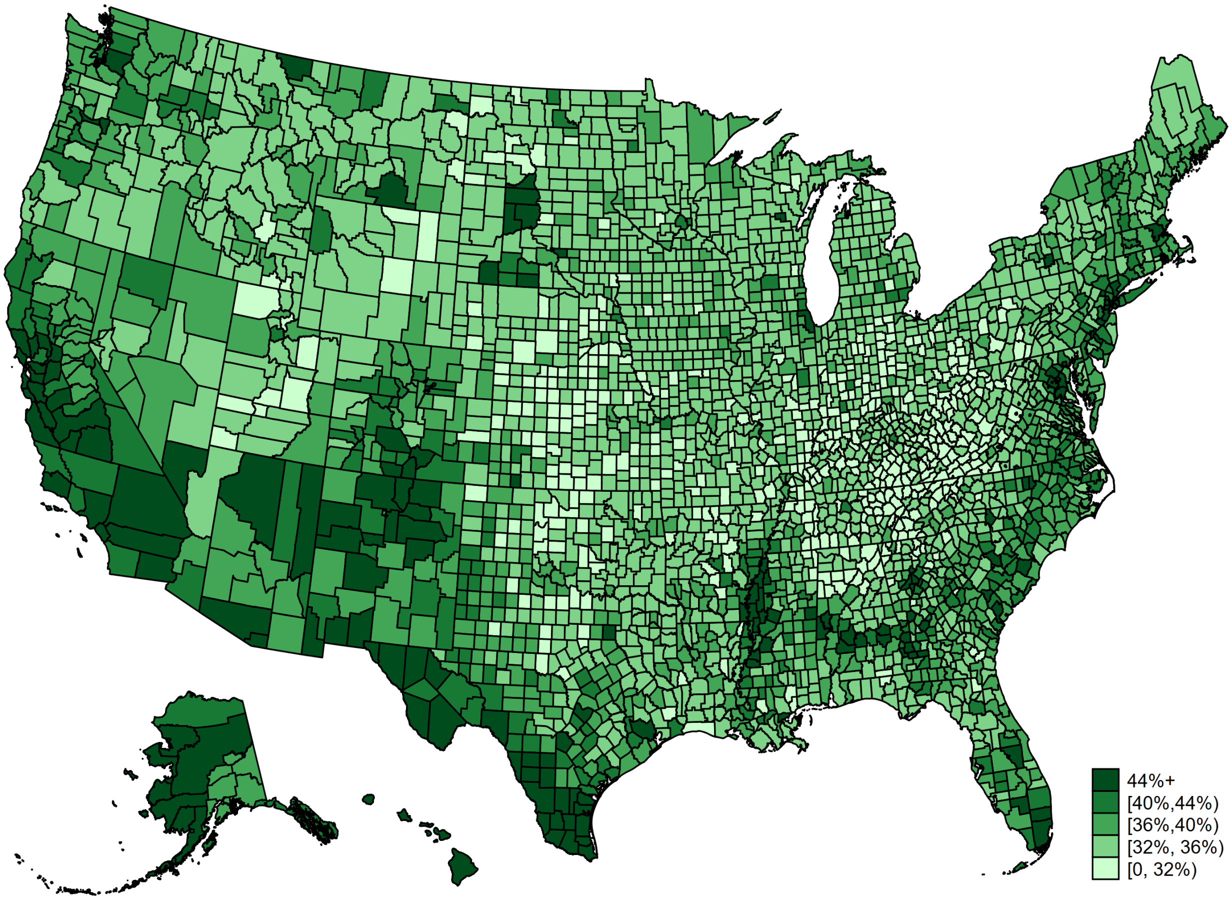

Figure 4 Percentage of Locals Who Believe Global Warming Largely Harm Them Personally

This figure illustrates opinions towards climate change of local residents across U.S. counties. It plots the percentage of local adults who believe that global warming will harm them personally a moderate amount or a great deal. Darker color indicates a higher proportion. The information is from Yale Climate Opinion Survey.

Table 1 Summary Statistics

This table reports summary statistics for inventor and firm characteristics used in the analysis. Panel A summarizes inventor-level variables. *Inventor Departure* is an indicator for inventors' departure from the original employer. *Male* is an indicator for male inventors. *Patents Per Year* is the number of granted patents in a year for an inventor. *Cumulative Patents* is the cumulative number of previously granted patents for an inventor. *Cumulative Citations* is the cumulative number of citations for patents granted to an inventor. *Patent Value* is the economic value of patents calculated in Kogan et al. (2017). Panel B summarizes firm-level variables. *# Departing Inventors* is the total number of inventors who leave the firm. *Physical Climate Exposure* is firm-level physical climate exposure is measured by the relative frequency of bigrams capturing climate-related physical shocks in conference call transcripts. *Total Assets* is the book value of assets. *Firm Age* is the number of years since a firm's first appearance in Compustat. *B/M* is book-to-market ratio. *R&D* is research and development expenses scaled by total assets. *ROA* is return-on-assets. *Leverage* is the total book leverage ratio. *Cash* is cash holdings. The sample period is from 2002 to 2019.

Panel A: Inventor Characteristics

	Mean	S.D.	Q1	Median	Q3
Inventor Departure	0.063	0.242	0.000	0.000	0.000
Male	0.885	0.319	1.000	1.000	1.000
Patents Per Year	0.829	1.021	0.250	0.500	1.000
Cumulative Patents	7.403	10.213	2.000	4.000	9.000
Cumulative Citations	71.088	162.549	1.000	10.000	58.000
Patent Value ($Million)	17.905	26.944	4.538	9.200	18.472

Panel B: Firm Characteristics

	Mean	S.D.	Q1	Median	Q3
# Departing Inventors	6.974	29.621	0.000	1.000	4.000
Physical Climate Exposure	0.001	0.010	0.000	0.000	0.000
Total Assets ($Billion)	6.463	17.998	0.180	0.719	3.369
Firm Age	24.913	17.149	12.000	19.000	33.000
B/M	0.582	0.279	0.366	0.558	0.766
R&D	0.098	0.140	0.009	0.049	0.124
ROA	0.053	0.261	-0.068	0.032	0.076
Leverage	0.199	0.210	0.004	0.158	0.312
Cash	0.276	0.248	0.072	0.196	0.430

Table 2 Corporate Climate Exposure and Inventor Departure: Baseline Results

This table estimates the effect of corporate physical climate change exposure on the departure rate of inventors. The regression model is specified as follows:

$$Inventor\ Departure_{i,j,t} = \alpha + \beta Physical\ Climate\ Exposure_{j,t-1} + \mathbf{X}_{i,t-1}\boldsymbol{\gamma}_1 + \mathbf{X}_{j,t-1}\boldsymbol{\gamma}_2 + \delta_j + \delta_{c,t} + \epsilon_{i,j,t},$$

where $Inventor\ Departure_{i,j,t}$ is an indicator variable that equals one if inventor i leaves firm j in year t; $Physical\ Climate\ Exposure_{j,t-1}$ is the physical climate exposure of firm j in year $t-1$; $\mathbf{X}_{i,t-1}$ and $\mathbf{X}_{j,t-1}$ include inventor-level and firm-level characteristics respectively; δ_j and $\delta_{c,t}$ denote firm fixed effects and inventor-county-by-year fixed effects, respectively. Firms' physical climate exposure is measured by the relative frequency of bigrams capturing climate-related physical shocks in conference call transcripts. Control variables include a male indicator, logarithm of one plus inventors' cumulative number of patents, firm size, logarithm of firm age, book-to-market ratio, research and development expenses, return on assets, book leverage, and cash holdings. Detailed variable definitions are provided in Table A.1 in the Appendix. Firm and year fixed effects are included in Columns (1) and (2); firm and inventor-county-by-year fixed effects are included in Column (3). The sample period is from 2002 to 2019. t-statistics based on standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Inventor Departure		
	(1)	(2)	(3)
Physical Climate Exposure	0.214***	0.267***	0.349***
	(4.62)	(5.82)	(4.65)
Male		0.008***	0.009***
		(8.08)	(8.42)
log(1 + Cumulative Patents)		-0.002**	-0.001*
		(-2.16)	(-1.89)
Size		-0.012***	-0.012***
		(-4.50)	(-4.89)
log(Firm Age)		0.058***	0.064***
		(5.91)	(6.31)
B/M		0.017**	0.020***
		(2.41)	(2.87)
R&D		-0.040*	-0.033
		(-1.89)	(-1.62)
ROA		-0.000	0.001
		(-0.00)	(0.16)
Leverage		-0.000	-0.001
		(-0.05)	(-0.15)
Cash		-0.008	-0.008
		(-1.01)	(-0.90)
Year FE	Yes	Yes	No
Firm FE	Yes	Yes	Yes
County × Year FE	No	No	Yes
Obs	1,440,736	1,440,736	1,440,736
Adjusted R^2	0.019	0.020	0.025

Table 3 Climate Exposure and Inventor Departure: Climate Concerns and Awareness

This table shows how inventors' concerns and awareness about climate change affect the relation between corporate physical climate change exposure and the departure rate of inventors. The regression model is specified as follows:

$$Inventor\ Departure_{i,j,t} = \alpha + \beta_1 Physical\ Climate\ Exposure_{j,t-1} \times Z + \beta_2 Physical\ Climate\ Exposure_{j,t-1} + \mathbf{X}_{i,t-1}\gamma_1 + \mathbf{X}_{j,t-1}\gamma_2 + \delta_j + \delta_{c,t} + \epsilon_{i,j,t},$$

where Z is a dummy variable that indicates high climate concerns or awareness; other variables are defined the same as in Table 2. In Columns (1) to (4), Z represents *High Concerns*, *Democratic*, *Post2010*, and *High SVI*, respectively. *High Concerns* is based on the Yale Climate Opinion Survey and takes one if the proportion of the local residents in inventors' county who believe that global warming will harm them personally a moderate amount or a great deal is above the sample median, and zero otherwise. *Democratic* takes one in a year if the inventor resides in a county from which a democratic candidate got the highest vote share in the most recent presidential election, and zero otherwise. *Post2010* takes one in years after 2010, and zero otherwise. *High SVI* takes one in a given state and year if the state-wide Google search index for "climate change" in that year is above the time-series median value of the index in the state, and zero otherwise. Firm and inventor-county-by-year fixed effects are included in the regressions. The sample period is from 2002 to 2019, except for Column (4) where the Google search data is available after 2004. t-statistics based on standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Inventor Departure			
	Climate Concerns		Climate Awareness	
	Yale Survey (1)	Party Affiliation (2)	Earlier/Recent Periods (3)	Google Search (4)
Physical Climate Exposure × High Concerns	0.244**			
	(2.54)			
Physical Climate Exposure × Democratic		0.417***		
		(3.17)		
Physical Climate Exposure × Post2010			0.306***	
			(3.11)	
Physical Climate Exposure × High SVI				0.212***
				(2.72)
Physical Climate Exposure	0.124	0.149**	0.121	0.224***
	(1.05)	(2.38)	(1.29)	(3.20)
Male	0.009***	0.009***	0.009***	0.008***
	(8.42)	(8.44)	(8.42)	(7.44)
log(1 + Cumulative Patents)	-0.001*	-0.001*	-0.001*	-0.002***
	(-1.90)	(-1.91)	(-1.90)	(-2.67)
Size	-0.012***	-0.012***	-0.012***	-0.012***
	(-4.90)	(-4.90)	(-4.91)	(-4.59)
log(Firm Age)	0.064***	0.064***	0.064***	0.072***
	(6.31)	(6.29)	(6.34)	(6.37)
B/M	0.020***	0.019***	0.020***	0.020**
	(2.87)	(2.86)	(2.92)	(2.52)
R&D	-0.033	-0.033	-0.033	-0.038*
	(-1.62)	(-1.64)	(-1.63)	(-1.68)
ROA	0.001	0.001	0.001	-0.003
	(0.16)	(0.15)	(0.17)	(-0.38)
Leverage	-0.001	-0.001	-0.001	-0.004
	(-0.16)	(-0.16)	(-0.15)	(-0.51)
Cash	-0.008	-0.008	-0.008	-0.005
	(-0.91)	(-0.88)	(-0.94)	(-0.53)
Firm FE	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes
Obs	1,440,736	1,440,736	1,440,736	1,278,017
Adjusted R^2	0.025	0.025	0.025	0.026

Table 4 Corporate Climate Exposure and Inventor Departure: Financial Constraints

This table shows how firms' financial constraints affect the relation between corporate physical climate change exposure and the departure rate of inventors. The regression model is specified as follows:

$$\begin{aligned} Inventor\ Departure_{i,j,t} = {} & \alpha + \beta_1 Physical\ Climate\ Exposure_{j,t-1} \times Constrained_{j,t-1} + \beta_2 Constrained_{j,t-1} \\ & + \beta_3 Physical\ Climate\ Exposure_{j,t-1} + \mathbf{X}_{i,t-1}\boldsymbol{\gamma}_1 + \mathbf{X}_{j,t-1}\boldsymbol{\gamma}_2 + \delta_j + \delta_{c,t} + \epsilon_{i,j,t}, \end{aligned}$$

where $Constrained_{j,t-1}$ is an indicator for financially-constrained firms; other variables are defined the same as in Table 2. In Columns (1) to (3), financial constraints are measured by firms' external financing needs calculated as in Demirgüç-Kunt and Maksimovic (1998), accounting-based financial constraint index proposed by Whited and Wu (2006), and text-based financial constraint index proposed by Hoberg and Maksimovic (2015), respectively. Financially-constrained firms refer to those with financial constraint measures above the sample median in a given year. Firm and inventor-county-by-year fixed effects are included in the regressions. The sample period is from 2002 to 2019, except for Column (3) where the Hoberg-Maksimovic index is not available after 2015. t-statistics based on standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Inventor Departure		
	External Financing Needs	Whited-Wu	Hoberg-Maksimovic
	(1)	(2)	(3)
Physical Climate Exposure × Constrained	0.072	-0.126	-0.206
	(0.36)	(-0.53)	(-1.11)
Physical Climate Exposure	0.345***	0.358***	0.327***
	(4.39)	(4.70)	(6.18)
Constrained	0.002	0.001	-0.000
	(1.06)	(0.38)	(-0.06)
Male	0.009***	0.009***	0.008***
	(8.36)	(8.36)	(8.01)
log(1 + Cumulative Patents)	-0.001*	-0.001*	0.001
	(-1.92)	(-1.92)	(1.37)
Size	-0.012***	-0.012***	-0.012***
	(-4.79)	(-4.67)	(-4.41)
log(Firm Age)	0.064***	0.064***	0.036***
	(6.29)	(6.27)	(2.91)
B/M	0.019***	0.019***	0.018***
	(2.82)	(2.79)	(3.68)
R&D	-0.033	-0.032	-0.006
	(-1.60)	(-1.55)	(-0.29)
ROA	0.002	0.002	0.010*
	(0.28)	(0.36)	(1.65)
Leverage	-0.002	-0.001	-0.000
	(-0.23)	(-0.10)	(-0.02)
Cash	-0.007	-0.008	-0.016*
	(-0.86)	(-0.90)	(-1.76)
Firm FE	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes
Obs	1,439,099	1,439,247	686,893
Adjusted R^2	0.025	0.025	0.023

Table 5 Corporate Climate Exposure and Geographical Reallocation of Inventors

This table estimates the effect of corporate physical climate change exposure on the departure rate of inventors. The regression model is specified as follows:

$$Y_{i,j,t} = \alpha + \beta Physical\ Climate\ Exposure_{j,t-1} + \mathbf{X}_{i,t-1}\gamma_1 + \mathbf{X}_{j,t-1}\gamma_2 + \delta_j + \delta_{c,t} + \epsilon_{i,j,t},$$

where $Y_{i,j,t}$ can be either $Within\text{–}state\ Move_{i,j,t}$ or $Out\text{–}of\text{–}state\ Move_{i,j,t}$; $Within\text{–}state\ Move_{i,j,t}$ (Columns (1) and (2)) is an indicator variable that equals one if inventor i moves from firm j in year t to a new employer located in the same state as the original employer; $Out\text{–}of\text{–}state\ Move_{i,j,t}$ (Columns (3) and (4)) is an indicator variable that equals one if inventor i moves from firm j in year t to a new employer located in a different state than the original employer; $Physical\ Climate\ Exposure_{j,t-1}$ is the physical climate exposure of firm j in year $t-1$; $\mathbf{X}_{i,t-1}$ and $\mathbf{X}_{j,t-1}$ include inventor-level and firm-level characteristics respectively; δ_j and $\delta_{c,t}$ denote firm fixed effects and inventor-county-by-year fixed effects, respectively. Firms' physical climate exposure is measured by the relative frequency of bigrams capturing climate-related physical shocks in conference call transcripts. Control variables include a male indicator, logarithm of one plus inventors' cumulative number of patents, firm size, logarithm of firm age, book-to-market ratio, research and development expenses, return on assets, book leverage, and cash holdings. Detailed variable definitions are provided in Table A.1 in the Appendix. Firm and year fixed effects are included in Columns (1) and (3); firm and inventor-county-by-year fixed effects are included in Columns (2) and (4). The sample period is from 2002 to 2019. t-statistics based on standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Within-state Move		Out-of-state Move	
	(1)	(2)	(3)	(4)
Physical Climate Exposure	0.135***	0.221***	0.079**	0.128***
	(4.09)	(3.24)	(2.49)	(5.33)
Male		0.004***		0.004***
		(8.67)		(4.67)
log(1 + Cumulative Patents)		0.003***		-0.004***
		(6.75)		(-10.41)
Size		-0.006***		-0.006***
		(-3.36)		(-3.62)
log(Firm Age)		0.049***		0.015***
		(5.81)		(4.53)
B/M		0.018***		0.001
		(3.21)		(0.69)
R&D		-0.022		-0.012
		(-1.30)		(-1.10)
ROA		0.001		0.000
		(0.16)		(0.09)
Leverage		-0.002		0.001
		(-0.38)		(0.45)
Cash		-0.006		-0.002
		(-0.82)		(-0.54)
Year FE	Yes	No	Yes	No
Firm FE	Yes	Yes	Yes	Yes
County × Year FE	No	Yes	No	Yes
Obs	1,440,736	1,440,736	1,440,736	1,440,736
Adjusted R^2	0.021	0.027	0.005	0.010

Table 6 Climate Exposure and Inventor Departure: Heterogeneity in Managerial Quality

This table estimates the effect of corporate physical climate change exposure on the departure rate of inventors after controlling for the heterogeneity in managerial quality. The regression model is specified in a manner similar to that in Table 2 except that the estimations incorporate firm-by-CEO fixed effects. Firms' physical climate exposure is measured by the relative frequency of bigrams capturing climate-related physical shocks in conference call transcripts. Control variables include a male indicator, logarithm of one plus inventors' cumulative number of patents, firm size, logarithm of firm age, book-to-market ratio, research and development expenses, return on assets, book leverage, and cash holdings. Detailed variable definitions are provided in Table A.1 in the Appendix. Firm-by-CEO and year fixed effects are included in Columns (1) and (2); firm-by-CEO and inventor-county-by-year fixed effects are included in Column (3). The sample period is from 2002 to 2019. *t*-statistics based on standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Inventor Departure		
	(1)	(2)	(3)
Physical Climate Exposure	0.371***	0.407***	0.481***
	(4.90)	(4.54)	(4.03)
Male		0.009***	0.009***
		(8.18)	(8.78)
log(1 + Cumulative Patents)		-0.002***	-0.002***
		(-2.86)	(-2.66)
Size		-0.004*	-0.006**
		(-1.69)	(-2.26)
log(Firm Age)		0.036***	0.035***
		(3.11)	(3.24)
B/M		0.007	0.008
		(0.99)	(1.26)
R&D		-0.035	-0.037
		(-1.45)	(-1.47)
ROA		0.010	0.010
		(1.61)	(1.57)
Leverage		0.026***	0.024***
		(3.93)	(3.54)
Cash		-0.010	-0.012
		(-1.28)	(-1.37)
Year FE	Yes	Yes	No
County × Year FE	No	No	Yes
Firm × CEO FE	Yes	Yes	Yes
Obs	1,333,389	1,333,389	1,333,389
Adjusted R^2	0.020	0.020	0.025

Table 7 Corporate Climate Exposure and Inventor Departure: Climate Disasters

This table estimates the effect of corporate physical climate change exposure on the inventor departure rate using an alternative measure of physical climate exposure. The regression model is specified as follows:

$$Inventor\ Departure_{i,j,t} = \alpha + \beta Climate\ Disasters_{j,t-1} + \mathbf{X}_{i,t-1}\gamma_1 + \mathbf{X}_{j,t-1}\gamma_2 + \delta_j + \delta_{c,t} + \epsilon_{i,j,t},$$

where $Inventor\ Departure_{i,j,t}$ is an indicator variable that equals one if inventor i leaves firm j in year t; $Climate\ Disasters_{j,t-1}$ is the sales-weighted number of climate-related disasters that occurred in counties of firm j's establishments in year $t-1$; $\mathbf{X}_{i,t-1}$ and $\mathbf{X}_{j,t-1}$ include inventor-level and firm-level characteristics respectively; δ_j and $\delta_{c,t}$ denote firm fixed effects and inventor-county-by-year fixed effects, respectively. The dependent variable is scaled to represent the weekly average number of climate-related hazards. Control variables include a male indicator, logarithm of one plus inventors' cumulative number of patents, firm size, logarithm of firm age, book-to-market ratio, research and development expenses, return on assets, book leverage, and cash holdings. Detailed variable definitions are provided in Table A.1 in the Appendix. Firm and year fixed effects are included in Columns (1) and (2); firm and inventor-county-by-year fixed effects are included in Column (3). The sample period is from 2002 to 2019. t-statistics based on standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Inventor Departure		
	(1)	(2)	(3)
Climate Disasters	0.013***	0.014***	0.013***
	(3.11)	(3.41)	(3.45)
Male		0.009***	0.009***
		(7.67)	(8.10)
log(1 + Cumulative Patents)		-0.003***	-0.002***
		(-3.34)	(-3.16)
Size		-0.012***	-0.012***
		(-3.92)	(-4.00)
log(Firm Age)		0.050***	0.056***
		(4.75)	(4.72)
B/M		0.010	0.011*
		(1.40)	(1.85)
R&D		-0.109***	-0.099**
		(-2.75)	(-2.56)
ROA		-0.012	-0.008
		(-1.61)	(-0.96)
Leverage		0.002	0.002
		(0.31)	(0.32)
Cash		-0.007	-0.007
		(-0.83)	(-0.70)
Year FE	Yes	Yes	No
Firm FE	Yes	Yes	Yes
County × Year FE	No	No	Yes
Obs	1,236,860	1,236,860	1,236,860
Adjusted R^2	0.015	0.016	0.021

Table 8 Corporate Climate Exposure and Inventor Departure: Superstar Inventors

This table estimates the effect of corporate physical climate change exposure on the departure rate of superstar inventors. The regression model is specified as follows:

$$Inventor\ Departure_{i,j,t} = \alpha + \beta Physical\ Climate\ Exposure_{j,t-1} + \mathbf{X}_{i,t-1}\boldsymbol{\gamma}_1 + \mathbf{X}_{j,t-1}\boldsymbol{\gamma}_2 + \delta_j + \delta_{c,t} + \epsilon_{i,j,t},$$

where $Inventor\ Departure_{i,j,t}$ is an indicator variable that equals one if inventor i leaves firm j in year t; $Physical\ Climate\ Exposure_{j,t-1}$ is the physical climate exposure of firm j in year $t-1$; $\mathbf{X}_{i,t-1}$ and $\mathbf{X}_{j,t-1}$ include inventor-level and firm-level characteristics respectively; δ_j and $\delta_{c,t}$ denote firm fixed effects and inventor-county-by-year fixed effects, respectively. The sample in Columns (1) to (3) contains inventors whose average cumulative number of patents per year, average cumulative number of patent citations per year, and average Kogan et al. (2017) value of patents granted is in the top quintile within a given technology class and year, respectively. The technology class for an inventor refers to the modal cooperative patent classification section code of all patents the inventor has filed up to year $t-1$. Firms' physical climate exposure is measured by the relative frequency of bigrams capturing climate-related physical shocks in conference call transcripts. Control variables include a male indicator, logarithm of one plus inventors' cumulative number of patents, firm size, logarithm of firm age, book-to-market ratio, research and development expenses, return on assets, book leverage, and cash holdings. Detailed variable definitions are provided in Table A.1 in the Appendix. Firm and inventor-county-by-year fixed effects are included in Column (3). The sample period is from 2002 to 2019. t-statistics based on standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Inventor Departure		
	Top Patent Number (1)	Top Patent Citations (2)	Top Patent Value (3)
Physical Climate Exposure	0.275***	0.483***	0.348***
	(2.88)	(4.02)	(3.70)
Male	0.005***	0.007***	0.010***
	(4.35)	(3.51)	(4.69)
log(1 + Cumulative Patents)	0.003***	-0.014***	-0.016***
	(4.34)	(-15.06)	(-14.67)
Size	-0.002	-0.018***	-0.019***
	(-0.75)	(-5.05)	(-3.21)
log(Firm Age)	0.031***	0.072***	0.061***
	(3.07)	(5.15)	(3.30)
B/M	0.014**	0.015*	0.020
	(2.26)	(1.65)	(1.31)
R&D	0.006	-0.029	-0.168***
	(0.28)	(-0.84)	(-2.85)
ROA	0.004	-0.002	-0.019
	(0.48)	(-0.23)	(-1.33)
Leverage	0.003	0.017	0.008
	(0.32)	(1.63)	(0.51)
Cash	-0.012	0.001	0.018
	(-1.44)	(0.08)	(1.25)
Firm FE	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes
Obs	230,627	290,067	168,944
Adjusted R^2	0.030	0.035	0.032

Table 9 Inventor Departure and Corporate Innovative Productivity

This table estimates the effect of inventor departure on firms' subsequent innovative productivity. The regression model is specified as follows:

$$\begin{aligned} Y_{j,h,t} &= \alpha + \beta_1 Departed\ Firm_{j,h} \times Post\ Departure_{h,t} + \beta_2 Departed\ Firm_{j,h} + \beta_3 Post\ Departure_{h,t} \\ &+ \mathbf{X}_{i,t-1}\boldsymbol{\gamma}_1 + \mathbf{X}_{j,t-1}\boldsymbol{\gamma}_2 + \delta_j + \delta_t + \epsilon_{j,h,t}, \end{aligned}$$

where $Y_{j,h,t}$ is a measure of the innovative productivity of firm j in year t; h denotes an event of inventor departure in a given firm and year (departures of multiple inventors from one firm in the same year are treated as a single event); $Departed\ Firm_{j,h}$ is a dummy variable that equals one if firm j experiences inventor departure (i.e., treated firm) in event h, and zero otherwise; $Post\ Departure_{h,t}$ is a dummy variable that equals one if year t belongs to the post-event periods in event h, and zero otherwise; $\mathbf{X}_{i,t-1}$ and $\mathbf{X}_{j,t-1}$ include inventor-level and firm-level characteristics, respectively; δ_j and δ_t denote firm fixed effects and year fixed effects, respectively. Treated firms that experience another inventor departure within three years before or three years after the event year are dropped. In each event, control firms refer to companies that do not experience any inventor departure in the [-3, +3] event window. Firms are matched using the propensity score matching approach based on firm size, logarithm of one plus firm age, book-to-market ratio, research and development expenses, return-on-assets, book leverage, cash holdings, logarithm of one plus the number of patents filed in the year before the event, and industry. The nearest-neighbor matching is used where a treated firm is matched with up to three control firms. The estimations include observations during the period from three years before to three years after the event. In Columns (1) to (3), the dependent variable is the logarithm of one plus the number of patents filed by a firm in a year, the logarithm of one plus the number of citations (during five years after patent issue) for patents filed by a firm in a year, and the logarithm of one plus the average economic value of patents filed by a firm in a year. Control variables are defined as in the baseline regressions. Detailed variable definitions are provided in Table A.1 in the Appendix. Firm and year fixed effects are included in these regressions. The sample period is from 2002 to 2019. t-statistics based on standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	log(1+Number of Patent)	log(1+Citations of Patent)	log(1+Value of Patent)
	(1)	(2)	(3)
Departed Firm × Post Departure	-0.112***	-0.081**	-0.099***
	(-4.10)	(-2.09)	(-3.09)
Departed Firm	-0.032	-0.016	-0.008
	(-1.16)	(-0.42)	(-0.26)
Post Departure	0.075	0.076	0.068
	(1.07)	(1.33)	(1.00)
Size	0.084***	0.036	0.062***
	(3.95)	(1.15)	(2.65)
log(Firm Age)	-0.125	-0.191*	-0.005
	(-1.36)	(-1.79)	(-0.06)
B/M	-0.139***	-0.227***	-0.185***
	(-3.19)	(-3.07)	(-4.49)
R&D	0.100	0.004	0.079
	(1.11)	(0.04)	(1.05)
ROA	0.017	0.024	-0.011
	(0.50)	(0.52)	(-0.37)
Leverage	-0.119**	-0.196**	-0.088
	(-2.52)	(-2.52)	(-1.51)
Cash	0.047	-0.080	-0.017
	(0.65)	(-0.61)	(-0.29)
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Obs	11,956	11,956	11,956
Adjusted R^2	0.441	0.317	0.396

Table 10 Employee Satisfaction and Inventor Retention

This table reports how employee satisfaction affects the relation between corporate physical climate change exposure and the departure rate of inventors. The regression model is specified as follows:

$$Inventor\ Departure_{i,j,t} = \alpha + \beta_1 Physical\ Climate\ Exposure_{j,t-1} \times Employee\ Ratings_{j,t-1}$$
$$+ \beta_2 Physical\ Climate\ Exposure_{j,t-1} + \beta_3 Employee\ Ratings_{j,t-1} + \mathbf{X}_{i,t-1}\gamma_1 + \mathbf{X}_{j,t-1}\gamma_2 + \delta_j + \delta_{c,t} + \epsilon_{i,j,t},$$

where $Inventor\ Departure_{i,j,t}$ is an indicator variable that equals one if inventor i leaves firm j in year t; $Employee\ Ratings_{j,t-1}$ is the average value of the overall ratings for firm j posted by its employees in year $t-1$. $Physical\ Climate\ Exposure_{j,t-1}$ is the physical climate exposure of firm j in year $t-1$; $\mathbf{X}_{i,t-1}$ and $\mathbf{X}_{j,t-1}$ include inventor-level and firm-level characteristics respectively; δ_j and $\delta_{c,t}$ denote firm fixed effects and inventor-county-by-year fixed effects, respectively. Firms' physical climate exposure is measured by the relative frequency of bigrams capturing climate-related physical shocks in conference call transcripts. Control variables include a male indicator, logarithm of one plus inventors' cumulative number of patents, firm size, logarithm of firm age, book-to-market ratio, research and development expenses, return on assets, book leverage, and cash holdings. Detailed variable definitions are provided in Table A.1 in the Appendix. Firm and year fixed effects are included in Columns (1) and (2); firm and inventor-county-by-year fixed effects are included in Column (3). The sample period is from 2008 to 2019 due to the availability of employee ratings. t-statistics based on standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Inventor Departure		
	(1)	(2)	(3)
Physical Climate Exposure × Employee Ratings	-0.383***	-0.335***	-0.352**
	(-2.69)	(-2.57)	(-2.44)
Physical Climate Exposure	1.557**	1.451**	1.650**
	(2.24)	(2.20)	(2.05)
Employee Ratings	-0.004**	-0.006***	-0.005**
	(-2.06)	(-3.06)	(-2.55)
Male		0.009***	0.009***
		(6.71)	(6.84)
log(1 + Cumulative Patents)		-0.003***	-0.003***
		(-4.01)	(-4.13)
Size		-0.011**	-0.010**
		(-2.57)	(-2.52)
log(Firm Age)		0.088***	0.095***
		(4.98)	(5.16)
B/M		0.007	0.010
		(0.68)	(1.04)
R&D		-0.099**	-0.097**
		(-2.18)	(-2.17)
ROA		-0.001	0.005
		(-0.06)	(0.41)
Leverage		-0.011	-0.008
		(-0.98)	(-0.80)
Cash		-0.006	-0.007
		(-0.47)	(-0.50)
Year FE	Yes	Yes	No
Firm FE	Yes	Yes	Yes
County × Year FE	No	No	Yes
Obs	819,907	819,907	819,907
Adjusted R^2	0.016	0.017	0.023

Appendix

Table A.1 Variable Definition

Variable	Definition	Source
Inventor Departure	A dummy variable that takes one if an inventor leaves their employer after a given year, and zero otherwise	USPTO
Physical Climate Exposure	Firm-level exposure to physical climate-related shocks, that is, the relative frequency of bigrams capturing climate-related physical shocks in conference call transcripts	Sautner et al. (2022)
Male	An indicator that takes one if an inventor is male, and zero otherwise	USPTO
$\log(1+\text{Cumulative Patents})$	The logarithm of one plus inventors' cumulative number of patents	USPTO
Size	The logarithm of total assets (Compustat item AT)	Compustat
log(Firm Age)	The logarithm of firm age, where firm age is the number of years since a firm's first appearance in Compustat	Compustat
B/M	Book-to-market ratio, calculated as the ratio of book value of total assets to divided by the sum of market value of equity (Compustat item CSHO×PRCC_F) and the difference between total assets and total common equity (Compustat item CEQ)	Compustat
R&D	Research and development expenses (Compustat item XRD) scaled by total assets	Compustat
ROA	Return-on-assets, calculated as the ratio of net income (Compustat item NI) to total assets	Compustat
Leverage	Book leverage ratio, calculated as total debt (Compustat item DLTT + DLC) divided by book value of total assets	Compustat
Cash	Cash and short-term investments (Compustat item CHE) scaled by total assets	Compustat
High Concerns	A dummy variable that takes one if the proportion of the local residents in inventors' county who believe that global warming will harm them personally a moderate amount or a great deal is above the sample median, and zero otherwise	Yale Climate Opinion Survey
Democratic	A dummy variable that takes one in a year if the inventor resides in a county from which a democratic candidate got the highest vote share in the most recent presidential election, and zero otherwise	MIT Election Lab
Post2010	A dummy variable that takes one in years after 2010, and zero otherwise	USPTO

Continued on the next page

Variable	Definition	Source
High SVI	A dummy variable that takes one in a given state and year if the state-wide Google search index for "climate change" in that year is above the time-series median value of the index in the state, and zero otherwise	Google Trends
External Financing Needs	External financing needs, which are defined as net growth rate of sales times total assets minus gross sales growth rate times retained earnings, scaled by total assets	Compustat
Whited-Wu Index	Financial constraint index proposed by Whited and Wu (2006)	Compustat
Hoberg-Maksimovic Index	Financial constraint index based on textual analysis of firms' 10-K reports	Hoberg and Maksimovic (2015)
Within-state Move	A dummy variable that takes one if an inventor moves to a new employer located in the same state as the original employer	USPTO
Out-of-state Move	A dummy variable that takes one if an inventor moves to a new employer located in a different state than the original employer	USPTO
Climate Disasters	Physical climate exposure based on climate-related natural hazards, calculated as the sales-weighted number of climate-related natural hazards that occurred in counties where a firm's establishments are located	SHELDUS and Data Axle (formerly Infogroup)
Employee Ratings	The average of the overall ratings for a firm from its employees in a given year	Glassdoor

Internet Appendix:
"Human Capital Effects of Corporate Climate Exposure"

- Table IA.1 provides examples of earnings conference call transcripts that discuss physical climate change risk.
- Table IA.2 reports the initial and top final bigrams that are related to physical climate change shocks in corporate earnings conference call transcripts.
- Table IA.3 presents the relation between corporate physical climate change exposure and lagged firm characteristics.
- Table IA.4 reports results from the baseline regression with standard errors clustered at alternative levels.
- Table IA.5 repeats the baseline regressions with a TFIDF-adjusted measure of corporate physical climate exposure. The alternative measure is constructed based on the term frequency-inverse document frequency (TFIDF) approach that assigns lower weights to bigrams appearing in more transcripts.
- Table IA.6 repeats the baseline regressions using alternative samples.
- Table IA.7 reports results from the baseline regression using subsamples of firms with different sizes.
- Table IA.8 estimates the effect of corporate physical climate change exposure on the departure rate of inventors by distinguishing different sentiment towards climate exposure.
- Table IA.9 reports results from firm-level regressions of the number of departing inventors on firms' physical climate change exposure.
- Table IA.10 estimates the effect of abnormal physical climate change exposure on the departure rate of inventors.
- Table IA.11 reports results from the baseline regression using the subsample of inventors who filed patent applications in most of their career years.

- Table IA.12 reports the effects of overall climate change exposure, opportunity climate change exposure, and regulatory climate change exposure on the departure rate of inventors.

Table IA.1 Examples of Climate-related Discussions in Earnings Conference Calls

And, of course, for those of you that are watching the weather channel, we are experiencing some ***severe and heavy snow*** *in western Oklahoma which undoubtedly will impact our processing plants and pipelines.*

— Q4 2012 ONEOK Inc. (February 26, 2013)

Heavy rain fall *in California combined with* ***colder weather*** *in our northern Midwest regions as compared to an unusually warm Q1 2016 was another significant factor in our margin decline.*

— Q1 2017 Forterra Inc. (May 15, 2017)

We obviously had ***extreme wet weather*** *from – and* ***flooding*** *in the Carolinas and Virginia from* ***Hurricane Florence****, and* ***Tropical Storm Gordon*** *caused record rain days in Dallas and San Antonio. We believe the* ***severe weather*** *negatively affected third quarter results with the loss of some 2.5 million tons of aggregates and related flooding costs. We estimate that the pretax loss due to weather to be approximately $27 million in the quarter.*

— Q3 2018 Vulcan Materials Co. (October 30, 2018)

To explain that further, we were hit with a perfect storm in Q3, and that perfect storm was multiple ***hurricanes****,* ***forest fire*** *out here. Those 2 distracted our utility partners that had to do tie-in enormously.*

— Q3 2018 Bloom Energy Corp. (November 05, 2018)

So you think about the ***extreme heat*** *in Europe, that did affect the packs in Europe. And so we see a delayed pack in Europe, probably a weaker pack in Europe than what we had originally expected.*

— Q2 2019 Silgan Holdings Inc. (July 24, 2019)

Table IA.2 Initial and Top Final Physical Climate Change Bigrams

This table reports the initial bigrams used to search for physical climate change bigrams and the fifteen most frequent bigrams in the final list of bigrams that are related to physical climate change shocks. The list is from Sautner, van Lent, Vilkov, and Zhang (2022).

No.	Initial Bigram	Top Final Bigram
1	coastal area	global warm
2	global warm	coastal area
3	snow ice	snow ice
4	forest land	friendly product
5	sea level	forest land
6	nickel metal	provide water
7	storm water	sea level
8	heavy snow	area florida
9	air water	nickel metal
10	natural hazard	supply water
11	sea water	natural hazard
12	warm climate	storm water
13	water discharge	air water
14	ice product	heavy snow
15		warm climate

Table IA.3 Physical Climate Exposure and Past Firm Characteristics

This table presents the relation between corporate physical climate change exposure and lagged firm characteristics. The regression model is specified as follows:

$$Physical\ Climate\ Exposure_{j,t} = \alpha + \mathbf{X}_{j,t-1}\gamma + \delta_j + \delta_t + \epsilon_{j,t},$$

where $Physical\ Climate\ Exposure_{j,t}$ is the physical climate exposure of firm j in year t; $\mathbf{X}_{j,t-1}$ represents firm characteristics; δ_j and δ_t denote firm fixed effects and year fixed effects, respectively. Firms' physical climate exposure is measured by the relative frequency of bigrams capturing climate-related physical shocks in conference call transcripts. The original value is multiplied by 10^4 for the sake of exposition. Firm characteristics include logarithm of total assets (*Size*), net income scaled by total assets (*ROA*), annual growth rate of sales (*Sales Growth*), capital expenditure scaled by total assets (*CAPX/Assets*), property, plant and equipment scaled by total assets (*Tangibility*), research and development expenses scaled by total assets (*R&D*), total book debt scaled by total assets (*Leverage*), and cash holdings scaled by total assets (*Cash*). Firm and year fixed effects are included in the regressions. The sample period is from 2002 to 2019. t-statistics based on standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Corporate Physical Exposure								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Size	-0.015								-0.013
	(-1.07)								(-0.85)
ROA		-0.007							0.005
		(-0.53)							(0.58)
Sales Growth			-0.000						0.001
			(-0.08)						(0.15)
CAPX/Assets				-0.157					-0.208
				(-0.69)					(-0.78)
Tangibility					0.043				0.052
					(0.62)				(0.62)
R&D						0.096			0.076
						(1.42)			(1.29)
Leverage							0.020		0.014
							(0.37)		(0.26)
Cash								-0.027	-0.025
								(-0.55)	(-0.42)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	40,537	40,537	40,537	40,537	40,537	40,537	40,537	40,537	40,537
Adjusted R^2	0.571	0.571	0.571	0.571	0.571	0.571	0.571	0.571	0.571

Table IA.4 Corporate Climate Exposure and Inventor Departure: Alternative Clustering

This table reestimates the baseline regressions in Table 2 with alternative ways to cluster standard errors. Firms' physical climate exposure is measured by the relative frequency of bigrams capturing climate-related physical shocks in conference call transcripts. Control variables include a male indicator, logarithm of one plus inventors' cumulative number of patents, firm size, logarithm of firm age, book-to-market ratio, research and development expenses, return on assets, book leverage, and cash holdings. Detailed variable definitions are provided in Table A.1 in the Appendix. Firm and inventor-county-by-year fixed effects are included in the regressions. The sample period is from 2002 to 2019. *t*-statistics based on standard errors clustered at alternative levels are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Inventor Departure			
	(1)	(2)	(3)	(4)
Physical Climate Exposure	0.349***	0.349***	0.349***	0.349***
	(4.15)	(3.94)	(3.41)	(3.39)
Male	0.009***	0.009***	0.009***	0.009***
	(7.95)	(4.48)	(7.81)	(4.49)
log(1 + Cumulative Patents)	-0.001	-0.001	-0.001*	-0.001*
	(-1.12)	(-1.17)	(-1.93)	(-1.93)
Size	-0.012***	-0.012***	-0.012***	-0.012***
	(-5.32)	(-3.27)	(-4.95)	(-3.19)
log(Firm Age)	0.064***	0.064***	0.064***	0.064***
	(5.26)	(4.07)	(6.13)	(4.49)
B/M	0.020**	0.020***	0.020***	0.020***
	(2.89)	(5.45)	(3.07)	(5.55)
R&D	-0.033	-0.033*	-0.033*	-0.033*
	(-1.74)	(-1.88)	(-1.78)	(-1.91)
ROA	0.001	0.001	0.001	0.001
	(0.19)	(0.18)	(0.17)	(0.17)
Leverage	-0.001	-0.001	-0.001	-0.001
	(-0.13)	(-0.17)	(-0.17)	(-0.31)
Cash	-0.008	-0.008	-0.008	-0.008
	(-0.92)	(-1.29)	(-1.00)	(-1.26)
Cluster	firm + year	industry + year	firm + county	industry + county
Firm FE	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes
Obs	1,440,736	1,440,736	1,440,736	1,440,736
Adjusted R^2	0.025	0.025	0.025	0.025

Table IA.5 TFIDF-Adjusted Climate Exposure Measure and Inventor Departure

This table reports the results from regressions of inventor departure rates on a TFIDF-adjusted climate change exposure. The regression model is specified as follows:

$$Inventor\ Departure_{i,j,t} = \alpha + \beta Physical\ Climate\ Exposure^{TFIDF}_{j,t-1} + \mathbf{X}_{i,t-1}\boldsymbol{\gamma}_1 + \mathbf{X}_{j,t-1}\boldsymbol{\gamma}_2 + \delta_j + \delta_{c,t} + \epsilon_{i,j,t},$$

where $Inventor\ Departure_{i,j,t}$ is an indicator variable that equals one if inventor i leaves firm j in year t; $Physical\ Climate\ Exposure^{TFIDF}_{j,t-1}$ is a TFIDF-adjusted physical climate exposure measure of firm j in year $t-1$ that accounts for typical frequencies of individual bigrams; $\mathbf{X}_{i,t-1}$ and $\mathbf{X}_{j,t-1}$ include inventor-level and firm-level characteristics respectively; δ_j and $\delta_{c,t}$ denote firm fixed effects and inventor-county-by-year fixed effects, respectively. The TFIDF-adjusted measure is constructed based on the term frequency-inverse document frequency (TFIDF) approach that assigns lower weights to bigrams appearing in more transcripts. Control variables include a male indicator, logarithm of one plus inventors' cumulative number of patents, firm size, logarithm of firm age, book-to-market ratio, research and development expenses, return on assets, book leverage, and cash holdings. Detailed variable definitions are provided in Table A.1 in the Appendix. Firm and year fixed effects are included in Columns (1) and (2); firm and inventor-county-by-year fixed effects are included in Column (3). The sample period is from 2002 to 2019. t-statistics based on standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Inventor Departure		
	(1)	(2)	(3)
Physical Climate Exposure$^{\mathrm{TFIDF}}$	0.028***	0.035***	0.046***
	(4.83)	(5.86)	(4.62)
Male		0.008***	0.009***
		(8.08)	(8.42)
log(1 + Cumulative Patents)		-0.002**	-0.001*
		(-2.16)	(-1.89)
Size		-0.012***	-0.012***
		(-4.50)	(-4.89)
log(Firm Age)		0.058***	0.064***
		(5.91)	(6.31)
B/M		0.017**	0.020***
		(2.41)	(2.87)
R&D		-0.040*	-0.033
		(-1.89)	(-1.62)
ROA		-0.000	0.001
		(-0.00)	(0.16)
Leverage		-0.000	-0.001
		(-0.05)	(-0.15)
Cash		-0.008	-0.008
		(-1.01)	(-0.90)
Year FE	Yes	Yes	No
Firm FE	Yes	Yes	Yes
County × Year FE	No	No	Yes
Obs	1,440,736	1,440,736	1,440,736
Adjusted R^2	0.019	0.020	0.025

Table IA.6 Corporate Climate Exposure and Inventor Departure: Alternative Samples

This table reestimates the baseline regressions in Table 2 using alternative samples. The sample in Column (1) excludes firms of which the corporate physical exposure measure is always equal to zero during the sample period. The sample in Column (2) excludes inventors located in California. The sample in Column (3) excludes firms in the most innovative industries, i.e., top five industries with the highest R&D intensity in each year. The industry-level R&D intensity is calculated as the sum of R&D expenditures of firms in the industry divided by the sum of total assets of firms in the industry (defined at the three-digit SIC codes level). Firms' physical climate exposure is measured by the relative frequency of bigrams capturing climate-related physical shocks in conference call transcripts. Control variables include a male indicator, logarithm of one plus inventors' cumulative number of patents, firm size, logarithm of firm age, book-to-market ratio, research and development expenses, return on assets, book leverage, and cash holdings. Detailed variable definitions are provided in Table A.1 in the Appendix. Firm and inventor-county-by-year fixed effects are included in the regressions. The sample period is from 2002 to 2019. *t*-statistics based on standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Inventor Departure		
	Exclude Always-Zero-Exposure Firms	Exclude California	Exclude Most Innovative Industries
	(1)	(2)	(3)
Physical Climate Exposure	0.386***	0.304***	0.759***
	(4.62)	(4.25)	(4.64)
Male	0.010***	0.009***	0.006***
	(8.35)	(7.57)	(3.20)
log(1 + Cumulative Patents)	-0.002	-0.002**	-0.002
	(-1.34)	(-2.00)	(-1.28)
Size	-0.015***	-0.013***	-0.013***
	(-3.42)	(-4.43)	(-3.59)
log(Firm Age)	0.066***	0.052***	0.120***
	(4.61)	(5.47)	(5.91)
B/M	0.006	0.014**	0.034***
	(0.69)	(2.25)	(3.56)
R&D	-0.048	-0.020	-0.008
	(-1.14)	(-0.93)	(-0.36)
ROA	0.012	0.005	0.015
	(1.10)	(0.84)	(1.54)
Leverage	0.008	-0.001	-0.002
	(0.78)	(-0.16)	(-0.15)
Cash	-0.015	-0.012	-0.019
	(-1.05)	(-1.62)	(-1.64)
Firm FE	Yes	Yes	Yes
County $\times$ Year FE	Yes	Yes	Yes
Obs	625,072	1,046,391	296,551
Adjusted R^2	0.027	0.027	0.032

Table IA.7 Corporate Climate Exposure and Inventor Departure: Firm Size

This table reestimates the baseline regressions in Table 2 in subsamples of firms with different sizes of inventor team. The sample in Column (1) includes firms with fewer than 500 inventors; the sample in Column (2) includes firms with more than 500 but fewer than 2,000 inventors; the sample in Column (3) includes firms with more than 2,000 inventors. Firms' physical climate exposure is measured by the relative frequency of bigrams capturing climate-related physical shocks in conference call transcripts. Control variables include a male indicator, logarithm of one plus inventors' cumulative number of patents, firm size, logarithm of firm age, book-to-market ratio, research and development expenses, return on assets, book leverage, and cash holdings. Detailed variable definitions are provided in Table A.1 in the Appendix. Firm and inventor-county-by-year fixed effects are included in the regressions. The sample period is from 2002 to 2019. *t*-statistics based on standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Inventor Departure		
# Inventors	0-500	500-2000	2000+
	(1)	(2)	(3)
Physical Climate Exposure	0.238**	0.725***	0.676***
	(2.16)	(4.01)	(3.36)
Male	0.010***	0.008***	0.008***
	(7.71)	(4.11)	(3.86)
log(1 + Cumulative Patents)	0.001**	-0.001	-0.004***
	(2.07)	(-0.92)	(-4.53)
Size	-0.012***	0.003	-0.006
	(-3.67)	(0.56)	(-1.26)
log(Firm Age)	0.043***	0.042	0.082**
	(4.43)	(1.62)	(2.35)
B/M	0.021***	0.017	-0.009
	(2.97)	(1.45)	(-0.90)
R&D	0.009	-0.063	-0.079
	(0.46)	(-0.74)	(-1.13)
ROA	0.012**	-0.014	-0.023
	(1.99)	(-0.86)	(-0.96)
Leverage	0.001	-0.014	0.010
	(0.17)	(-0.69)	(0.67)
Cash	-0.018**	-0.014	-0.005
	(-2.21)	(-1.09)	(-0.45)
Firm FE	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes
Obs	562,522	377,947	500,267
Adjusted R^2	0.032	0.024	0.025

Table IA.8 Corporate Climate Sentiment and Inventor Departure

This table estimates the effect of corporate physical climate change exposure on the departure rate of inventors by distinguishing different sentiment towards climate exposure. The regression model is specified as follows:

$$\begin{aligned} Inventor\ Departure_{i,j,t} &= \alpha + \beta_1 Physical\ Climate\ Exposure^{Neg}_{j,t-1} + \beta_2 Physical\ Climate\ Exposure^{Pos}_{j,t-1} \\ &+ \mathbf{X}_{i,t-1}\gamma_1 + \mathbf{X}_{j,t-1}\gamma_2 + \delta_j + \delta_{c,t} + \epsilon_{i,j,t}, \end{aligned}$$

where $Inventor\ Departure_{i,j,t}$ is an indicator variable that equals one if inventor i leaves firm j in year t; $Physical\ Climate\ Exposure^{Neg}_{j,t-1}$ ($Physical\ Climate\ Exposure^{Pos}_{j,t-1}$) is the negative (positive) sentiment towards firm-level climate change exposure of firm j in year $t-1$; $\mathbf{X}_{i,t-1}$ and $\mathbf{X}_{j,t-1}$ include inventor-level and firm-level characteristics respectively; δ_j and $\delta_{c,t}$ denote firm fixed effects and inventor-county-by-year fixed effects, respectively. Negative (positive) sentiment towards physical climate exposure is measured by the relative frequency with which bigrams capturing climate-related physical shocks appear in the same sentence together with negative (positive) tone words in conference call transcripts. Control variables include a male indicator, logarithm of one plus inventors' cumulative number of patents, firm size, logarithm of firm age, book-to-market ratio, research and development expenses, return on assets, book leverage, and cash holdings. Detailed variable definitions are provided in Table A.1 in the Appendix. Firm and inventor-county-by-year fixed effects are included in the regressions. The sample period is from 2002 to 2019. t-statistics based on standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Inventor Departure		
	(1)	(2)	(3)
Physical Climate Exposure$^{\text{Neg}}$	0.413***		0.339***
	(3.29)		(3.25)
Physical Climate Exposure$^{\text{Pos}}$		0.335	0.282
		(1.47)	(1.44)
Male	0.009***	0.009***	0.009***
	(8.42)	(8.43)	(8.42)
log(1 + Cumulative Patents)	-0.001*	-0.001*	-0.001*
	(-1.89)	(-1.89)	(-1.89)
Size	-0.012***	-0.012***	-0.012***
	(-4.86)	(-4.81)	(-4.86)
log(Firm Age)	0.063***	0.063***	0.063***
	(6.25)	(6.16)	(6.24)
B/M	0.019***	0.019***	0.019***
	(2.81)	(2.76)	(2.81)
R&D	-0.033	-0.032	-0.033
	(-1.59)	(-1.57)	(-1.60)
ROA	0.001	0.001	0.001
	(0.16)	(0.21)	(0.17)
Leverage	-0.002	-0.001	-0.001
	(-0.21)	(-0.18)	(-0.20)
Cash	-0.007	-0.007	-0.007
	(-0.87)	(-0.78)	(-0.86)
Firm FE	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes
Obs	1,440,736	1,440,736	1,440,736
Adjusted R^2	0.025	0.020	0.025

Table IA.9 Corporate Climate Exposure and Inventor Departure: Firm-level Regressions

This table reports the effect of corporate physical climate change exposure on the departure rate of inventors by estimating firm-level regressions. The regression model is specified as follows:

$$Y_{j,t} = \alpha + \beta Physical\ Climate\ Exposure_{j,t-1} + \mathbf{X}_{j,t-1}\boldsymbol{\gamma} + \delta_j + \delta_t + \epsilon_{j,t},$$

where $Y_{j,t}$ measures how many inventors leave firm j in year t; $Physical\ Climate\ Exposure_{j,t-1}$ is the physical climate exposure of firm j in year $t-1$; $\mathbf{X}_{j,t-1}$ include firm-level characteristics; δ_j and δ_t denote firm fixed effects and year fixed effects, respectively. Columns (1) and (2) estimate OLS regressions in which the outcome variable is the logarithm of one plus the total number of inventors who leave the firm in a given year. Columns (3) and (4) estimate fixed-effects Poisson models where the outcome variable is the total number of inventors who leave the firm in a given year. Firms' physical climate exposure is measured by the relative frequency of bigrams capturing climate-related physical shocks in conference call transcripts. Control variables include firm size, logarithm of firm age, book-to-market ratio, research and development expenses, return on assets, book leverage, and cash holdings. Detailed variable definitions are provided in Table A.1 in the Appendix. Firm and year fixed effects are included in the regressions. The sample period is from 2002 to 2019. t-statistics based on standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	log(1+# Departing Inventors)		# Departing Inventors	
	OLS	OLS	Poisson	Poisson
	(1)	(2)	(3)	(4)
Physical Climate Exposure	0.871**	0.855**	2.146***	2.541***
	(2.47)	(2.41)	(3.69)	(4.47)
Size		0.176***		0.439***
		(10.28)		(8.66)
log(Firm Age)		0.286***		0.449**
		(5.19)		(2.43)
B/M		0.039		0.102
		(1.30)		(1.26)
R&D		0.538***		1.844***
		(5.23)		(4.26)
ROA		-0.015		0.019
		(-0.43)		(0.29)
Leverage		-0.016		0.161
		(-0.39)		(1.32)
Cash		-0.000		-0.039
		(-0.01)		(-0.37)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Obs	18,295	18,295	18,295	18,295
Adjusted/Pseudo R^2	0.793	0.799	0.855	0.864

Table IA.10 Corporate Abnormal Climate Exposure and Inventor Departure

This table estimates the effect of abnormal physical climate change exposure on the departure rate of inventors. A firm's abnormal physical climate exposure is calculated as its physical climate exposure in a given year minus the average of its physical climate exposure over the past three years. Firms' physical climate exposure is measured by the relative frequency of bigrams capturing climate-related physical shocks in conference call transcripts. Control variables include a male indicator, logarithm of one plus inventors' cumulative number of patents, firm size, logarithm of firm age, book-to-market ratio, research and development expenses, return on assets, book leverage, and cash holdings. Detailed variable definitions are provided in Table A.1 in the Appendix. Firm and year fixed effects are included in Columns (1) and (2); firm and inventor-county-by-year fixed effects are included in Column (3). The sample period is from 2002 to 2019. *t*-statistics based on standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Inventor Departure		
	(1)	(2)	(3)
Abnormal Physical Climate Exposure	0.331***	0.358***	0.415***
	(3.72)	(3.34)	(3.09)
Male		0.008***	0.009***
		(7.68)	(7.99)
log(1 + Cumulative Patents)		-0.002**	-0.002**
		(-2.50)	(-2.24)
Size		-0.011***	-0.012***
		(-4.20)	(-4.75)
log(Firm Age)		0.060***	0.068***
		(5.50)	(5.92)
B/M		0.018**	0.022***
		(2.32)	(2.90)
R&D		-0.040*	-0.033
		(-1.73)	(-1.49)
ROA		0.002	0.003
		(0.30)	(0.55)
Leverage		-0.001	-0.001
		(-0.07)	(-0.17)
Cash		-0.005	-0.006
		(-0.71)	(-0.68)
Year FE	Yes	Yes	No
Firm FE	Yes	Yes	Yes
County $\times$ Year FE	No	No	Yes
Obs	1,389,551	1,389,551	1,389,551
Adjusted R^2	0.020	0.020	0.025

Table IA.11 Accuracy of Inventor Departure

This table estimates the effect of corporate physical climate change exposure on the inventor departure rate using inventors who file patent applications in most years during his/her career. The regression specification is the same as that in Table 2. The dependent variable is an indicator variable for inventor departure. Firms' physical climate exposure is measured by the relative frequency of bigrams capturing climate-related physical shocks in conference call transcripts. Control variables include a male indicator, logarithm of one plus inventors' cumulative number of patents, firm size, logarithm of firm age, book-to-market ratio, research and development expenses, return on assets, book leverage, and cash holdings. Detailed variable definitions are provided in Table A.1 in the Appendix. Columns (1) to (3) use the sample of inventors who filed patent applications in at least 50%, 75%, and 100% of their career years, respectively. Firm and inventor-county-by-year fixed effects are included in the regressions. The sample period is from 2002 to 2019. *t*-statistics based on standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Inventor Departure		
Minimum % of Career Years with Patent Filings	50%	75%	100%
	(1)	(2)	(3)
Physical Climate Exposure	0.374***	0.524***	0.697***
	(3.64)	(5.97)	(2.89)
Male	0.007***	0.005**	0.006**
	(6.05)	(2.04)	(2.27)
log(1 + Cumulative Patents)	-0.002***	-0.005***	-0.007***
	(-3.25)	(-7.80)	(-7.29)
Size	-0.004	-0.001	0.002
	(-1.17)	(-0.26)	(0.38)
log(Firm Age)	0.058***	0.046***	0.043**
	(4.64)	(3.03)	(2.29)
B/M	0.032***	0.030***	0.041***
	(3.68)	(3.02)	(3.14)
R&D	0.008	0.018	-0.013
	(0.28)	(0.49)	(-0.20)
ROA	0.006	0.007	-0.037**
	(0.74)	(0.61)	(-2.06)
Leverage	0.006	0.007	-0.006
	(0.67)	(0.58)	(-0.40)
Cash	-0.008	-0.010	-0.013
	(-0.89)	(-0.78)	(-0.71)
Firm FE	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes
Obs	673,761	232,022	70,381
Adjusted R^2	0.036	0.049	0.064

Table IA.12 Other Dimensions of Corporate Climate Exposure and Inventor Departure

This table estimates the effects of overall, opportunity, and regulatory climate change exposures on the departure rate of inventors. The regression models are specified the same as that in Table 2. The dependent variable is an indicator variable for inventor departure. Firms' physical climate exposure is measured by the relative frequency of bigrams capturing climate-related physical shocks in conference call transcripts. Firms' overall climate exposure is measured by the relative frequency of bigrams related to climate change in conference call transcripts. Firms' opportunity climate exposure is measured by the relative frequency of bigrams capturing opportunities related to climate change in conference call transcripts. Firms' regulatory climate exposure is measured by the relative frequency of bigrams capturing climate-related regulatory shocks in conference call transcripts. Control variables include a male indicator, logarithm of one plus inventors' cumulative number of patents, firm size, logarithm of firm age, book-to-market ratio, research and development expenses, return on assets, book leverage, and cash holdings. Detailed variable definitions are provided in Table A.1 in the Appendix. Firm and inventor-county-by-year fixed effects are included in the regressions. The sample period is from 2002 to 2019. *t*-statistics based on standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Inventor Departure			
	(1)	(2)	(3)	(4)
Physical Climate Exposure				0.367***
				(4.73)
Overall Climate Exposure	0.003			-0.013
	(0.34)			(-1.07)
Opportunity Climate Exposure		0.007		0.023
		(0.66)		(1.37)
Regulatory Climate Exposure			-0.006	-0.011
			(-0.11)	(-0.16)
Male	0.009***	0.009***	0.009***	0.009***
	(8.43)	(8.43)	(8.43)	(8.42)
log(1 + Cumulative Patents)	-0.001*	-0.001*	-0.001*	-0.001*
	(-1.88)	(-1.88)	(-1.88)	(-1.90)
Size	-0.012***	-0.012***	-0.012***	-0.012***
	(-4.79)	(-4.77)	(-4.79)	(-4.86)
log(Firm Age)	0.063***	0.063***	0.063***	0.064***
	(6.12)	(6.12)	(6.12)	(6.30)
B/M	0.019***	0.019***	0.019***	0.019***
	(2.74)	(2.73)	(2.73)	(2.87)
R&D	-0.031	-0.031	-0.032	-0.033
	(-1.53)	(-1.53)	(-1.54)	(-1.62)
ROA	0.001	0.001	0.001	0.001
	(0.20)	(0.20)	(0.20)	(0.13)
Leverage	-0.001	-0.001	-0.001	-0.001
	(-0.19)	(-0.20)	(-0.19)	(-0.19)
Cash	-0.006	-0.006	-0.006	-0.008
	(-0.74)	(-0.74)	(-0.76)	(-0.91)
Firm FE	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes
Obs	1,440,736	1,440,736	1,440,736	1,440,736
Adjusted R^2	0.019	0.020	0.019	0.025