In the Mood for Creativity: Weather-induced Mood, Inventor Productivity, and Firm Value*

Yangyang Chen[a], Po-Hsuan Hsu[b], Edward J. Podolski[c], Madhu Veeraraghavan[d]

[a] *School of Accounting and Finance, The Hong Kong Polytechnic University, Hong Kong*
[b] *Faculty of Business and Economics, The University of Hong Kong, Hong Kong*
[c] *Department of Finance, Deakin University, Australia*
[d] *Finance and Strategy Area, TA PAI Management Institute, India*

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Abstract

Does the external environment have the potential to affect economic outcomes? In this paper, we investigate this question by examining the effect of sunshine-induced mood on inventors' productivity and the value implication of such an effect. Our main finding is that inventors exposed to more sunshine create patents with higher market value, with this effect being most pronounced for inventors working alone. We also show that inventors exposed to more sunshine generate more patents, patents which receive more forward citations, patents that are based on newer technologies and outside knowledge, and patents that are more likely to be "hits" than "flops". In sum, our results suggest that sunshine induced inventor mood positively influences productivity via its effect on inventor optimism and creativity. We find no support for alternate behavioral and economic channels explaining the relation between sunshine exposure and inventor productivity.

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"When the sun is shining, I can do anything; no mountain is too high, no trouble too difficult to overcome."

Wilma Rudolph

1. Introduction

Human beings are unavoidably subject to emotions induced by the external environment. Does the external environment have the potential to affect economic outcomes, however, is less clear? In this paper, we investigate this question by examining the influence of sunshine exposure on inventor productivity. At first pass this question appears farfetched, but there are good reasons to believe that the external environment can indeed influence real economic outcomes. For instance, prior research in the asset pricing literature lends support for this proposition, by showing that stock returns are positively related to the level of sunshine that investors are exposed to (see, e.g., Saunders, 1993; Kamstra, Kramer, and Levi, 2003; Hirshleifer and Shumway, 2003; Goetzmann and Zhu, 2005; Goetzmann, Kim, Kumar, and Wang, 2015).[1] Furthermore, deHann, Masden, and Piotrowski (2017) show that equity analysts exposed to unpleasant weather are slower or less likely to respond to an earnings announcement, while Cortes, Duchin, and Sosyura (2016) find that weather-induced mood influences credit approval rates by lower-level finance officers.

Creative ideas are necessary for innovation, and a strong competitive advantage is conferred on organizations that are adept at eliciting creativity from their employees (Kanter, 1988; Audia and Goncalo, 2007). However, factors which, influence inventor productivity are not well established in the literature. Although prior research shows that monetary incentives play a role in motivating inventor productivity (Manso, 2011; Chang, Fu, Low, and Zhang, 2015), these extrinsic incentives have a number of limitations. First, since a valuable invention has to be novel and non-obvious, contracting is bound to be incomplete. More significantly, survey evidence suggests that inventors are motivated more by intrinsic rewards than by extrinsic rewards (Sauermann and Cohen, 2010), with studies finding that extrinsic motivations, such as pay-for-performance, crowd out intrinsic motivation (Kohn, 1993; Frey and Jegen, 2001; Benabou and Tirole, 2003). Highlighting the point that non-monetary factors are a more significant determinant of inventor motivation and productivity than monetary incentives, Lam (2011) finds that scientists are primarily motivated by reputation and career rewards. Paruchuri, Nerkar, and Hambrick (2006) and Kapoor and Lim (2007) highlight the mental and emotional

[1] We concentrate on the aspect of weather that is directly related to sunshine since this has been widely studied in the psychology, economics and finance literature. We do not consider other dimensions of weather, such as temperature, wind, humidity etc.

dimension to inventor productivity by showing that social disruptions associated with acquisitions result in reduced inventor productivity. This line of research suggests that subtle factors influencing inventors' mental states can have significant effects on inventor productivity.

We address the question of how subtle emotional factors influence inventor productivity by examining the effect of sunshine exposure on inventor patent output. Patent output includes patent value, patent volume, forward citations, information set used by new patents, and indicators capturing whether the patents are "hits" or "flops". We specifically concentrate on the effects of sunshine exposure on inventor productivity, since this setting offers us a plausibly exogenous variation in inventor mood. This approach is motivated by evidence from both psychology and neurobiology literature, which establishes a robust relation between sunshine and mood (e.g., Cunningham, 1979; Schwartz and Clore, 1983; Parrott and Sabini, 1990; Lambert et al., 2002; Spindelegger et al., 2012). Consistent with this intuition, sunshine exposure has been extensively used in the economics and finance literature as an exogenous mood-priming construct (Kamstra et al., 2003; Hirshleifer and Shumway, 2003; Cortes et al., 2016; deHaan et al., 2017).

Our main findings reveal that average annual sunshine around an inventor's residential location is positively associated with patent value, patent volume and forward citations. In addition, sunshine exposure results in new patents relying less on local knowledge and old technologies, being more likely to be "hits" rather than "flops", and being more closely related to the inventors area of expertise. At a practical level, our findings should be of interest to managers interested in maximizing inventor productivity. The results presented in this paper clearly highlight the significant role that inventor's state of mind plays in their creative process. Recognizing this fact should allow executives and middle-managers to oversee their human capital more productively.

Our paper is related to several strands of the academic literature. Our first contribution is to the growing literature that identifies mood as a channel through which weather affects economic activities (Saunders, 1993; Hirshleifer and Shumway, 2003; Goetzmann and Zhu, 2005; Goetzmann et al., 2015; deHaan et al., 2017). Second, our results based on inventor data, offer large-scale, micro-level evidence for the role of mood in innovative outcomes. While prior studies in psychology have provided experimental evidence for the positive effect of good weather on creativity through improving mood (Isen, 1999; Schwartz and Clore, 1983, 2003), we provide the first large-scale evidence to support this claim by using inventors' local weather conditions and patenting activities. Finally, prior research has examined the effects of behavioral traits, including optimism, overconfidence, and risk-taking, on innovation, but mainly from the perspective of top-managers, board of directors, and shareholders (Galasso and Simcoe, 2011; Hirshleifer, Low, and Teoh, 2012; Tian and Wang, 2014; Ederer and Manso, 2013; Balsmeier, Fleming, and Manso, 2017).[2] We are the first to document the effect that workplace mood has on corporate innovation.

2. A Simple Model

Following prior research, we derive a simple model that justifies the channel through which sunshine/weather influences inventors' productivity. We first model firm *j*'s patent output PV (measured as patent value in our empirical analysis) in a Cobb-Douglas form in year t+1 as a function of inventors' efforts and other factors:

$$PV_{j,t+1} = aM_{g,t}^{\alpha_M} K_{j,t}^{\alpha_K} A_{g,t}^{\alpha_A} B_{j,t}^{\alpha_B} (L_{i,t} H_{i,t} N_{i,t})^{\alpha_L} exp(\lambda_j + \delta_t + \mu_g)\, \varepsilon_{j,t+1}, \quad (1)$$

where a denotes the process of patenting. $M_{g,t}$ denotes the local market demand for location g in year t and α_M is the sensitivity for local market demand (page 260 of Kortum and Lerner 1998). $K_{j,t}$ denotes knowledge capital in firm j in year t and α_K is the sensitivity parameter (page 42 of Ahuja, Lampert, and Tandon, 2008; page 262 of Kortum and Lerner 1998). $A_{g,t}$ denotes local spillovers of location g and α_A is the sensitivity parameter. $B_{j,t}$ denotes investments (including R&D capital and physical capital, as innovation requires equipment and tangible assets) (Griliches 1979, 1987) and α_B is the sensitivity parameter. We solve firm *i*'s optimization problem in year t to decide $B_{j,t}$. $H_{i,t}$ denotes inventor quality (Griliches 1979), which can be related to health and efficiency. $N_{i,t}$ reflects the number of inventors. For simplicity, we assume that there is only one representative inventor *i*, and let $N_{i,t}$ be team-work. The component $exp(\lambda_j + \delta_t + \mu_g)$ accommodates all fixed effects, following Griliches (1981), Cockburn and Griliches (1988), and Hall (1993 and 2000). λ_j denotes firm fixed effects, δ_t denotes time fixed effects, and μ_g denotes location fixed effects. Lastly, $\varepsilon_{j,t+1}$ denotes the random noise with unit mean and is orthogonal to all other terms.

We use a two-period horizon: inventor *i* chooses to work in year *t* and consumes all income in year *t*+1 and maximizes the sum of current leisure and expected future consumption from the bonus from the firm:[3]

[2] Some exceptions are Acharya, Baghai, and Subramanian (2014), Chang et al. (2015), Bradley, Kim, and Tian (2017), and Chen, Chen, Hsu, and Podolski (2016). These papers examine how risk-taking incentives and compensation plans provided to non-executive employees positively influence a firm's innovative success.

[3] This utility function is based on the log utility function (Long and Plosser 1983; Hansen 1985), $U_{i,t} = w_{g,t} ln(1 - L_{i,t}) + \rho_{g,t}\, ln(Consumption_{i,t})$, for simplicity in subsequent model derivation.

$w_{g,t} ln(1 - L_{i,t}) + \rho_{g,t}\, E_{i,t}[ln(ePV_{j,t+1})]$, (2)

in which inventor *i*'s working time is $L_{i,t}$ in year *t*, which ranges between 0 and 1, and $1 - L_{i,t}$ is leisure time, also ranging between 0 and 1. Let $w_{g,t}$ denote the utility from leisure, which is assumed to be positive as the utility from leisure increases with sunshine. So, when the weather is good, the utility from leisure $1 - L_{i,t}$ is higher. On the other hand, an inventor expects to receive a bonus from firm *j* in year *t*+1, which is proportional (*e*) to his output of patent value $PV_{j,t+1}$.[4] Let $\rho_{g,t}$ represent the inventor's optimism and is higher when the inventor is more positive about future outcome. It can be positively affected by sunshine (i.e., increase with $w_{g,t}$) as well.

We then solve the optimal working time through the inventor optimization problem, which is

$$\max_{L_{i,t}}\{w_{g,t} ln(1 - L_{i,t}) + \rho_{g,t}\, E_{i,t}[ln(ePV_{j,t+1})]\}$$

$$= \max_{L_{i,t}}\{w_{g,t} ln(1 - L_{i,t}) + \beta E_t[\rho_{g,t}\, ln(eaM_{g,t}^{\alpha_M} K_{j,t}^{\alpha_K} A_{g,t}^{\alpha_A} B_{j,t}^{\alpha_B} (L_{i,t}H_{i,t}N_{i,t})^{\alpha_L} \exp(\cdot)\varepsilon_{j,t+1})]\}, \quad (3)$$

where β is the subjective discount factor for intertemporal substitution. The first order condition of Equation (3) is $0 = -\frac{w_{g,t}}{(1-L_{i,t})} + \frac{\beta\rho_{g,t}\alpha_L}{L_{i,t}}$, which implies that $L_{i,t} = \frac{\beta\rho_{g,t}\alpha_L}{w_{g,t}+\beta\rho_{g,t}\alpha_L}$. The optimal working hours increase with the sensitivity of patent output to labor α_L, increase with inventor's optimism $\rho_{g,t}$, and decrease with the sensitivity of utility to leisure $w_{g,t}$.

In year *t*, the firm *j* decides the investment $B_{j,t}$ to maximizes the patent value in year *t+1*:[5]

$$\max_{B_{j,t}}\{-B_{j,t} + \beta E_t[PV_{j,t+1}]\}. \quad (4)$$

The first order condition of Equation (4) is

$0 = -1 + \beta\alpha_B(aM_{g,t}^{\alpha_M} K_{j,t}^{\alpha_K} A_{g,t}^{\alpha_A} B_{j,t}^{\alpha_B - 1} (L_{i,t}H_{i,t}N_{i,t})^{\alpha_L} \exp(\cdot))$, which implies that

$B_{j,t} = [\beta\alpha_B aM_{g,t}^{\alpha_M} K_{j,t}^{\alpha_K} A_{g,t}^{\alpha_A} (L_{i,t}H_{i,t}N_{i,t})^{\alpha_L} \exp(\cdot)]^{1/(\alpha_B - 1)}$. The relation between $B_{j,t}$ and $w_{g,t}$ will be discussed further in the later context.

By inputting the solved inventor efforts $L_{i,t}$ and corporate investment $B_{j,t}$ into the patent value in Equation (2), we have the following decomposition of patent value:

[4] We assume that there is no fixed wage and the inventor only gets stocks or stock options. Considering fixed wage in our model will not alter our model implications in general.

[5] We assume the interest rate to be zero and the stochastic discount factor (SDF) is one. This assumption is reasonable given that the SDF is exogenous and firm *j*'s patent value is orthogonal to the SDF.

$$PV_{j,t+1} = aM_{g,t}^{\alpha_M} K_{j,t}^{\alpha_K} A_{g,t}^{\alpha_A} \left[\beta \alpha_B a M_{g,t}^{\alpha_M} K_{j,t}^{\alpha_K} A_{g,t}^{\alpha_A} (\frac{\beta \rho_{g,t} \alpha_L}{w_{g,t} + \beta \rho_{g,t} \alpha_L} H_{i,t} N_{i,t})^{\alpha_L} \exp(\cdot) \right]^{\alpha_B/(\alpha_B - 1)}$$

$$(\frac{\beta \rho_{g,t} \alpha_L}{w_{g,t} + \beta \rho_{g,t} \alpha_L} \cdot H_{i,t} N_{i,t})^{\alpha_L} \exp(\cdot) \varepsilon_{j,t+1}, \quad (5)$$

which can be further log-linearized as following:

$$ln(PV_{j,t+1}) = ln(a) + [\alpha_B/(\alpha_B - 1)] ln(\beta \alpha_B a) + \alpha_M [1 + \alpha_B/(\alpha_B - 1)]\ ln(M_{g,t}) + \alpha_K [1 + \alpha_B/(\alpha_B - 1)]\ ln(K_{j,t}) + \alpha_A [1 + \alpha_B/(\alpha_B - 1)]\ ln(K_{g,t}) + \alpha_L [1 + \alpha_B/(\alpha_B - 1)]\ ln\left(\frac{\beta \rho_{g,t} \alpha_L}{w_{g,t} + \beta \rho_{g,t} \alpha_L}\right) + \alpha_L [1 + \alpha_B/(\alpha_B - 1)]\ ln(H_{i,t}) + \alpha_L [1 + \alpha_B/(\alpha_B - 1)]\ ln(N_{i,t}) + \lambda_j + \delta_t + \mu_g + ln(\varepsilon_{j,t+1}). \quad (6)$$

Equation (6) serves as the base for our empirical tests.

3. Hypothesis Development

To analyze the influence of sunshine exposure on patent output, we follow prior literature to design various factors in Equation (6) as functions of weather. Figure 1 illustrates the possible mechanisms through which sunshine exposure influences inventors' performance. Put simply, sunshine could impact corporate innovation through mood-related mechanisms and economic mechanisms. In what follows, we describe the two groups of mechanisms in detail and develop the testable hypotheses.

[Insert Figure 1 about here]

3.1. Mood-related Mechanisms

The influence of sunshine on mood has been well documented in the social psychology literature. Cunningham (1979) and Schwartz and Clore (1983) both conduct field experiments, showing that the amount of sunshine influences self-reported mood and can lead to misattribution of affective states for information. Parrott and Sabini (1990) show that exposure to clear and cloudy skies serves as an effective way of eliciting happy and sad moods. Sunshine has also been shown to improve the mood of clinically depressed individuals, including those suffering from seasonal (Rosenthal et al., 1984) and non-seasonal (Kripke, 1998) forms of clinical depression. The positive effect that sunshine has on mood has been documented across a range of behaviors and contexts, including tipping (Cunningham, 1979; Rind, 1996), life satisfaction (Schwartz and Clore, 1983), and responsiveness to persuasion (Clore et al., 1994).[6]

[6] Prior research in neurobiology suggests the mechanism for the relation between sunshine and mood. Lambert et al. (2002) and Spindelegger et al. (2012) show that higher serotonin transporter availability in healthy human

3.1.1. Inventor creativity and optimism

Sunshine exposure has the ability to change the mood of individual inventors, which may result in higher inventor creativity and optimism. Prior research shows that good mood is conducive to creative activities by promoting cognitive flexibility and remove cognitive constraints (e.g., Isen, Johnson, Mertz, and Robinson, 1985; To, Fisher, Ashkanasy, and Rowe, 2012). For instance, Isen et al. (1985) investigate the influence of mood on the uniqueness of word associations and show that good mood may facilitate creative problem solving, suggesting an impact of positive feelings on cognitive organization. Fredrickson (1998) and Isen (1999, 2000) propose that good mood increases the connectedness and breadth of cognitive elements, which make diverse cognitive elements more closely integrated. Instead, bad mood impacts individuals' creativity negatively by consuming attentional resources (Beal, Weiss, Barros, and MacDermid, 2005) and increasing individuals' rigidity as they respond to problems (Staw, Sandelands, and Dutton, 1981). Amabile, Barsade, Mueller, and Staw (2005) investigate how mood relates to creativity at work and document that positive mood enhances creativity in organizations. Since innovation requires path-breaking, critical thinking, and intellectual endeavors, creativity is a necessary condition for the success of innovation projects (Sauermann and Cohen, 2010).

Good mood also makes inventors more optimistic. Good mood impacts people by making similarly "valenced" (i.e., positive) thoughts and memories more accessible (Tversky and Kahneman, 1973; Isen, Shalker, Clark, and Karp, 1978). As a result, individuals in good mood rely more on positive cues and thus tend to be more optimistic. Optimism, in turn, entices individuals to take on more risks, as they underestimate the probability of negative outcomes. Seo, Barret, and Bartunek (2004) propose that good mood enhances the continuation of creative work because optimistic individuals tend to anticipate that their efforts will produce desirable outcomes. As such, inventors in good mood are more likely to allocate research efforts towards pursuing innovation, since they will overvalue the potential benefits stemming from exerting

subjects during sunny days and lower serotonin levels in winter. Serotonin is a neurotransmitter, which is associated with happiness and elevated emotional states. They also show that sunshine influences serotonin 1A receptor binding in limbic brain regions of healthy human subjects. When subjects are exposed to less sunlight, the human brain produces more of a hormone called melatonin, which is associated with depression, sleepiness, and fatigue. Melatonin is linked to light and dark in that when the sun sets earlier the brain produces melatonin, which makes a subject sleepy. Lieberman, Waldhauser, Garfield, Lynch, and Wurtman (1984) show that melatonin is secreted by the pineal organ during night and that it can be suppressed by intense light. They find that melatonin significantly decreases self-reported alertness and increases sleepiness. In short, they state that melatonin alters mood state similar to drugs with sedative-like properties.

effort. Bassi, Colacito, and Fulghieri (2013) investigate the link between weather, mood, and risk-taking behavior in financial decisions, and show that sunshine-induced optimism leads individuals to accept higher levels of risk. Since innovation projects involve high likelihood of failure (Holmstrom, 1989), optimism and risk-taking are necessary for the success of innovation projects (Galasso and Simcoe, 2011; Hirshleifer et al., 2012; Chen, Podolski, Rhee, and Veeraraghavan, 2014).

Based on the above discussion, we hypothesize that individual inventor creativity and optimism increase with sunshine exposure in the following manner.

$H_{i,t} = \exp(b_H w_{g,t})$ and b_H>0. (7)

The combination of Equations (6) and (7) leads to our first hypotheses:

HYPOTHESIS 1A: *Sunshine positively influences patent output by enhancing inventor creativity.*

HYPOTHESIS 1B: *Sunshine positively influences patent output by enhancing inventor optimism.*

3.1.2. Inventor teamwork

Prior literature argues that sunshine-induced good mood could increase inventors' propensity to engage in teamwork. Previous work in psychology characterizes mood by a bipolar construct "positive affect", which describes how animals and humans experience positive emotions and interact with others and with their surroundings (Clark and Watson, 1988; Watson, Wiese, Vaidya, and Tellegen, 1999). Numerous studies show that good mood facilitates social relationships and helping behavior (Harris and Smith, 1975; Cunningham, 1979; Bizman, Yinin, Ronco, and Schachar, 1980; Manucia, Baumann, and Cialdini, 1984; Carlson, Charlin, and Miller, 1988). For example, Cunningham (1979) shows that participants approached by an interviewer to participate in a survey are less reluctant to comply on sunnier days than on cloudier days. A rationale for these observations is that individuals who feel positive will tend to evaluate a given pro-social opportunity more favorably than will others, and therefore will more readily offer assistance (Clark and Isen, 1982; Isen et al., 1978). As a result, individuals with pro-social behavior are more willing to cooperate with each other and engage more in teamwork in their workplaces.

Teamwork is essential in the innovation process due to the complex nature of innovation projects (Dougherty, 1992; Van de Ven, 1986). Collaboration among team members provides opportunities for mutual learning and creation of new ideas (Tsai and Ghoshal, 1998; Tsai, 2001; West, Tjosvold and Smith, 2003). Kurtzberg and Amabile (2001), West (2004), and Pearsall, Ellis and Evans (2008) suggest that team creativity is important for both organizational success and innovation. Singh and Fleming (2010) document that collaboration in the form of team and/or organization affiliation enables careful and rigorous selection of the best ideas while also increasing the opportunities for novelty. They state that inventors affiliated with teams or organizations, or both, are less likely to create useless inventions and more likely to create breakthroughs. Chi, Chung and Tsai (2011) find that positive group affective tone creates an enjoyable team environment, which increases the team's willingness to engage in creative processes.

Based on the above discussion, we hypothesize that inventor teamwork increases with sunshine exposure in the following manner.

$N_{i,t} = \exp(b_N w_{g,t})$ and $b_N > 0$. (8)

The combination of Equations (6) and (8) leads to our second hypothesis:

HYPOTHESIS 2: *Sunshine positively influences patent output by enhancing inventor team-working.*

3.1.3. Corporate Managers

Sunshine may improve the mood of managers, who have the decision power on innovation projects. As stated in Section 3.1.1, individuals in good mood tend to be more optimistic, which, in turn, entices their risk-taking behavior. Chhaochharia, Kin, Korniotis, and Kumar (2017) document that sunshine increases managers' level of optimism on economic perspective, which influences their hiring and investment decisions. Chen, Chen, Podolski, and Veeraraghavan (2017) also show that managers exposed to more sunshine are more likely to issue earnings forecasts and tend to make more optimistic earnings forecasts. As a result, managers in good mood may engage in more risky investments such as R&D projects. They may also take on more risks in the innovation process (e.g., select risky but high-potential projects). As innovative input, investments in R&D projects are essential. Risk-taking in the innovation process is also one of the key factors of firm innovative success (Galasso and Simcoe, 2011; Hirshleifer et al., 2012; Chen et al., 2014). Thus, sunshine could stimulate patent output through inducing managerial optimism.

Sunshine-induced managerial mood could also make managers engage more in pro-social and helping behaviors (Harris and Smith, 1975; Cunningham, 1979; Bizman, Yinin, Ronco, and Schachar, 1980; Manucia, Baumann, and Cialdini, 1984; Carlson, Charlin, and

Miller, 1988). As a consequence, managers may invest more in employee welfare (e.g., increase employee wages or other non-pecuniary benefits, improve employ work environment etc.). Increased employee treatment, in turn, stimulates corporate innovation through enhancing employee job security, proactive participation, and long-term commitment (Acharya et al., 2014; Chen et al., 2016).

Based on the above discussion, we argue that firm investments in innovation and patenting activities may increase with sunshine exposure in the following manner.

$$\frac{\partial B_{j,t}}{\partial w_{g,t}} > 0, \tag{9}$$

which leads to our third hypothesis:

HYPOTHESIS 3A: *Sunshine positively influences patent output by enhancing managerial optimism.*

HYPOTHESIS 3B: *Sunshine positively influences patent output by enhancing employee welfare.*

3.2. Economic Mechanisms

In this section we describe the non-mood related channels as we argue that sunshine could also impact corporate innovation through economic mechanisms. We describe them below.

3.2.1. Local knowledge capital and spillovers

The World Intellectual Property Organization data show that high-skilled employees such as inventors are highly mobile geographically, with a migration rate of about 8% (Miguelez and Fink, 2013). Previous work shows various factors that drive inventor mobility. For example, Miguelez and Moreno (2014) show that amenities and job opportunities are significant talent attractors. Moretti and Wilson (2014) and Akcigit, Baslandze, and Stantcheva (2016) suggest that inventors' location choices are significantly affected by local tax rates. It is likely that areas with sunny weather are regarded by inventors as more livable due to improved physical and mental health conditions associated with more sunshine exposure (e.g., Bart and Bourque, 1995; Molin et al., 1996; Young et al., 1997). As a result, inventors may be more willing to move to sunny areas, which lead to geographical knowledge clusters and knowledge spillovers among investors (Miguelez, 2013; Miguelez and Moreno, 2014). Breschi, Lenzi, Lissoni, and Vezzulli (2010) state that "[K]nowledge always travels along with people who master it. If those people move away from where they originally learnt, researched, and delivered their inventions, knowledge will diffuse in space". If there is greater local knowledge capital in sunny areas due to inventor migration, we expect inventors in these areas to be more innovative due to knowledge spillover and mutual learning.

Based on the above discussion, we argue that sunshine improves local knowledge capital and spillovers in the following manner.

$K_{j,t} = \exp(b_K w_{gt})$ and $b_K>0$, (11)

and

$A_{g,t} = \exp(b_A w_{gt})$ and $b_A>0$ (12)

The combination of Equations (6), (11), and (12) leads to our fifth hypothesis:

HYPOTHESIS 4A: *Sunshine positively influences patent output by enhancing local knowledge capital.*

HYPOTHESIS 4B: *Sunshine positively influences patent output by enhancing local spillovers.*

3.2.2. Local economy

Sunshine may affect the general population in the local area. Prior research suggests that people in good mood are likely to spend more money than in neutral mood (Golden and Zimmerman, 1986; Sherman and Smith, 1987; Spies, Hesse, and Loesch, 1997). Steele (1951) and Parsons (2001) document that bad weather makes shopping less attractive and thus have a negative impact on sales and store traffic. Murray et al. (2010) show that sunlight increases consumer spending through reducing negative affect. They suggest that retail stores could increase lighting levels on bad weather days to reduce negative feelings of consumers. Chhaochharia et al. (2017) show that when local individuals are more optimistic, their spending habits, labor productivity, and entrepreneurial or other risk-taking activities could be affected, which in turn has an impact on the local economic environment. They also show that recessions are weaker and expansions are stronger in states where individuals are more optimistic.

In general, these studies suggest that sunshine has a positive effect on local economic conditions, which, in turn, improves the profitability of local firms. Further, Coval and Moskowitz (1999) show that portfolio managers in the U.S. exhibit a strong preference for locally headquartered firms, particularly those with greater information uncertainty. Coval and Moskowitz (2001) further show that mutual fund managers bias their holdings toward local stocks and their funds exhibit greater local performance. One consequence of local bias is that it pushes stock prices of local firms up when there are relatively fewer firms per capital via an "only-game-in-town" effect (Hong, Kubik, and Stein, 2008). Since local investors is the major funding source of firms, improved local economic conditions could also increase the supply of equity financing, which makes it easier for local firms to fund their investments, especially risky R&D projects. As a result, improved local economic conditions associated with sunshine are expected to stimulate corporate innovation through increase firm investments in innovation.

Based on the above discussion, we argue that sunshine exposure impacts the local economic environment and stimulates innovation in the following manner. .

$M_{g,t} = \exp(b_M w_{g,t})$ and b_M>0.

(13)

The combination of Equations (6) and (13) leads to our sixth hypothesis:

HYPOTHESIS 5: *Sunshine positively influences patent output by enhancing local economy.*

3.2.3. Inventor health and working hours

There is evidence that sunshine improves workers' health conditions. Bart and Bourque (1995) review the medical literature and find that weather is closely related to health conditions of the general public. For example, increased exposure to sunlight is positively related to protection against coronary artery disease. In addition to physical health, sunshine is shown to be related to mental health as well. Molin et al. (1996) and Young et al. (1997) provide evidence that seasonal depression is related to hours of daylight. Rosenthal et al. (1984) and Kripke (1998) suggest that sunshine is closely related to the mood of clinically depressed individuals. As long as sunshine is able to improve workers' health conditions, it could reduce health-related worker absenteeism. More recently, Shi and Skuterud (2015) show a tendency for reported sickness absenteeism to increase with the recreational quality of the weather. They argue that employees misreport health to exploit weather conditions favorably for recreational activities. In addition to health-related absenteeism, sunshine could also affect worker absenteeism by reducing commuting time and effort. Smith (1977) illustrates that weather conditions can have a direct effect on worker absenteeism by making it more difficult to attend. Markham and Markham (2005) show that weather conditions (e.g., rainfall) are significantly associated with worker absence of work. If inventors are able to work longer in sunny days due to improved health conditions and ease of commuting, sunshine is expected to enhance labor productivity of inventors and thus corporate innovation.

Nevertheless, it is also likely that sunshine reduces working hours through changing individual utility function. As we have shown in the model, inventors may work less in good weather due to higher leisure value. Connolly (2008) and Zivin and Neidell (2014) find that individuals are less motivated for outdoor activities on bad weather days and hence spend more time at work. Connolly (2008) further shows that people shift on average 30 minutes from leisure to work on rainy days. Lee, Gino and Staats (2014) show that individuals are more productive on a bad weather day than on a good weather day. They argue that weather conditions influence cognition and focus in that more options or distractions decrease individuals' ability to complete tasks. As a consequence, sunshine may reduce the number of hours inventors work and hence decrease their productivity.

4. Data

To empirically examine our hypotheses, we collect and combine an extensive set of databases including the Harvard Business School (HBS) Patent Inventor database (Li et al., 2014) for inventor information, the patent database of Kogan et al. (2015) for patent value, the Integrated Surface Database (ISD) for weather information, the state mentioning data in 10-K form from Garcia and Norli (2012) for the geographic distribution of firms, the 2000 U.S. Census Data for the ethnic and gender distributions, the CRSP/Compustat database for financial and accounting information, the KLD Socrates database for employee treatment data, the immigration data from the Center for Demography and Ecology at the University of Wisconsin-Madison, personal income data from the Bureau of Economic Activity regional economic account files, the American Time Use Survey (ATUS) from the U.S. Census Bureau for time allocation, and the Center for Disease Control and Prevention for health indicators.

We obtain detailed patent inventor data from the HBS Patent Inventor database that contains every patent granted by the U.S. Patent and Trademark Office (USPTO) spanning the period 1976 to 2009, together with information on each patent inventor, including name, residential city, zip code, and state. We also use the HBS patent database to obtain corresponding citation data. We match patent inventors with each patent's owner company (assignee) using the patent data of Kogan et al. (2015). The data in Kogan et al. (2015) provides CRSP firm identifiers for each patent granted between 1926 and 2010.[7] After merging the inventor-level data with the assignee data, our sample period is limited to the years 1976 to 2010. The resulting data allows us to observe the identity of the inventor who invented a patent, where the inventor lives, and which U.S. public firm hires the inventor and owns the patent when the patent is granted. We aggregate the data to inventor-year for our empirical analysis.[8]

[7] The NBER Patent database is an alternative source of patent and citation data. However, this database is limited to the period 1976-2006.

[8] For each inventor, we create a time-series of observations ranging from the first to last year that the inventor appears in the database, and code inventor-years with no patent output as zero.

We use the application year (i.e., filing year) of patents as the time placer in our empirical tests as the application year should be closest to the time when the new technology occurs (Hall and Ziedonis, 2001). Given that there is an application-approval lag of two to three years (Hall and Ziedonis, 2001), we exclude the final three years (2008-2010) and hence our sample finishes at the end of 2007. The inventor level data is the primary dataset used in our baseline analysis. We discuss the specific variables used in this study, as well as any additional datasets in this section.

4.1. Sunshine Exposure Data

Following prior literature (e.g., Goetzmann et al., 2015; Chhaochharia et al., 2017), weather data is collected from the Integrated Surface Database (ISD), which is publicly available from the National Oceanic and Atmospheric Administration website (www.ncdx.noaa.gov/pub/data/noaa). We download data on sky cover readings for each weather station overlapping with our innovation sample, namely January 1990 to December 2014. For each weather station, we first calculate the average daily sky cover index (observed between 6am and midnight) and then compute an annual relative sunshine variable. The three hourly sky cover observations take a value from 1 to 5 (1=clear, 2=few, 3=scattered, 4=broken, and 5=overcast). Higher values of the index therefore indicate less sunshine. We identify each day as sunny if the daily average sky cover is either 2 or below.[9] We then aggregate the weather data to monthly intervals by summing the number of sunny days in each month. We construct an annual variable *sunshine*, which is the average number of sunny days per month for each weather station. Since the normal amount of sunshine differs between geographic locations, we construct a second sunshine exposure variable, where we deseasonalize the monthly data by deducting the average number of sunny days for a particular weather station in a particular month over the entire sample from the observation month. We then aggregate the deseasonalized monthly data to the annual level by taking the average relative number of sunny days for each weather station in each month over a year. We denote this variable *relative sunshine*.[10] We match each inventor to the weather stations within a 50-kilometer radius of

[9] Results are qualitatively identical when we define a "sunny day" as a day with a sky cover index equal to 1, or alternatively a day with a sky cover index of 3 or below.
[10] We also consider using the average unadjusted sunny days as an alternative measure for sunshine and obtain consistent results.

his/her residential location and calculate the average relative sunshine for these weather stations.[11]

To account for the fact that innovation is a long-term process, and sunshine exposure over a single year might not entirely capture the time period during which inventions are generated, we also construct *sunshine* and *relative sunshine* variables over two and three yearly periods for robustness. In additional tests, we relate sunshine conditions around the firm's headquarters with firm corporate policies. We obtain data from Garcia and Norli (2012) on the geographic dispersion of a firm's business operations. Garcia and Norli (2012) rely on state name counts in annual reports filed with the SEC on Form 10-K, which allows us to construct business operation weighted measures of firm sunshine.

4.2.1. Patent Output

We are interested in examining whether inventor-level sunshine exposure is value relevant for the firm, and therefore employ a number of measures of economic importance of patents developed by each inventor in a given year. As a primary measure of economic importance, we follow Kogan et al. (2015), and establish patent value, defined as the increase in market value in the three-day period of patent approval announcements after adjusting for benchmark return, idiosyncratic stock return volatility, and various fixed effects.[12] We then sum the patent value of all patents that are invented by an inventor and filed in a year to each inventor-year level (*PatVal*), to measure the economic value of patents generated by each inventor in each year.[13] When there are multiple inventors for a patent, we assign the same patent value to each inventor in the filing year, although additional robustness tests reveal that our results remain unchanged when we divide patent value by the number of co-inventors. This value measure is better than conventional patent measures for two reasons: first, it is based on market valuation and thus reflects the value-relevance of patenting activities; and second, it

[11] To do so, we first assign the latitude and longitude coordinates of the zip code centroid of the inventor's residential location. The weather data contain the latitude and longitude coordinates for each weather station. Using the Haversine formula and the latitude and longitude coordinates for both inventors and weather stations, we identify weather stations within a 50-kilometer radius of the inventors. The Harvesine formula calculates the distance between location *1* and *2* as $d_{1,2} = 2 \times R \times \arcsin(\min(1, \sqrt{A})$, for which R is the earth's radius (approximately 6,371 kilometers), $A = sin^2\left(\frac{\Delta lat}{2}\right) + \cos(lat_1) + \cos(lat_2) \times sin^2(\frac{\Delta lon}{2})$. In this expression, $\Delta lat = (lat_2 - lat_1)$ and $\Delta lon = (lon_2 - lon_1)$, for which *lat* and *lon* refer to latitude and longitude, respectively.

[12] We obtain the raw patent-level data from Noah Stoffman's webpage (https://iu.app.box.com/v/patents), which provides the dollar value of every patent.

[13] Although patent value is measured at the time that the patent is granted, in our empirical analysis we backdate the value to the time when the patent is applied for. Our results stay qualitatively the same when we construct patent value measures ourselves, in which we use benchmark returns as the 2-digit SIC code industry return or the Fama-French industry portfolio returns.

does not depend on forward-looking information (e.g., forward citations by future patents). The natural logarithm of one plus patent value (*LnPatVal*) is our primary dependent variable throughout the empirical analysis.

Our supplementary measures of economic importance of patenting activity are total patent count, total forward citations and average forward citations per patent. Patent count (*Pat*) captures the total number of patents applied for by an inventor in a given year. Given the vast variation in patent quality, forward citation measures are a more accurate measure of patenting output compared with simple patent count (Trajtenberg, 1990; Hall, Jaffe, and Trajtenberg, 2005; Aghion, Van Reenan, and Zingales, 2013). We therefore sum the number of forward citations of patents filed by each inventor for each year (*Cit*). We also calculate the average forward citations per patent by dividing the total number of forward citations generated of all patents filed by each inventor in each year by the number of patents filed by the inventor in that year (*CitPat*).

4.2.2. Patenting Strategies

In addition to proxies of volume and quality of inventor patenting activity, we also examine patent characteristics to better gauge the effect of sunshine exposure on patenting strategies. Specifically, we define patenting strategies along five dimensions: accessing limited information, risk-taking, creativity, specialization, and experimentation.

To measure whether patents are based on a limited information set, we construct two variables. First, we look at whether the patents are based on old technology or not. Specifically, we measure the age of a patent's backward citations (i.e., how old are the patents that are cited by the focal patent) and take the median age of the cited patents to capture the half-life of citations (*HalfLife*). Patents, which have a higher half-life of citations, are deemed to rely on older technologies. Second, we construct a measure capturing the geographic diversity of citations. Specifically, we identify the residential location of all inventors associated with the cited patents to gauge whether the new patent is relying on local information set or not. For each patent, we identify those cited patents where at least one inventor resided in the same county as the inventor associated with a new patent.[14] For each patent we construct a ratio of the number of locally cited patents to totally cited patents (*LocalCites*). In addition to our main measure of local citations, we construct additional variables to describe the reliance on local

[14] We identify an inventor' county of residence based on his/her zip-code. Since the zip-code captures a relatively narrow geographic area, we concentrate on each inventor's county of residence. In robustness tests, we obtain qualitatively identical results when we conduct our analysis on an inventor's state of residence.

information to measure the effects of local spillovers on patent output. Specifically, we use the number of local citations (*LocalCites*) and the ratio of local citations to total patents (*LocalCitations/Patent*). These variables capture the intensity within an inventor in citing local knowledge in a given year, as a way of examining whether local information spillovers are more pronounced.

In addition, we follow Azoulay, Zivin, and Manso (2011) and Balsemeier et al. (2017) and categorize patents according to how many citations they have received relative to other granted patents that have applied for in the same technology class and year. A patent is considered a "hit", if its forward citations fall within the 10^{th} percentile of comparable patents (i.e., patents in the same technology class and applied for in the same year). A patent is considered average, if its forward citations fall between the 10^{th} of 90^{th} percentile of comparable patents. Finally, a patent is considered a "flop" if its forward citations fall outside the 90^{th} percentile of comparable patents. We aggregate these patent classifications for each inventor and year, to come up with measures of the number of "hit", average, and "flop" patents developed by an inventor in a given year, which are termed "*Top10*", "*NTop10*", and "*NTop90*", respectively. These variables allow us to capture the risk-taking activity of inventors, since a greater portion of "hits" and "flops" represents a more risk-taking strategy. At the same time, these variables allow us to identify inventors' creativity, since a greater portion of "hits" without a corresponding increase in "flops" suggests greater creativity.

To measure specialization we utilize the operational definition of exploitation developed by Benner and Tushman (2002). We classify each patent filed by an inventor as exploitative if 60% or more of its backward citations is within the inventor's existing knowledge pool, defined as the combination of the inventor's patents or the backward citations made by those patents in the past five years. *Exploit* is the number of exploitative patents filed by each inventor in each year. In addition to exploitation, we also measure an inventor's tendency to pursue related patents based on the backward citations that new patents make to the inventor's earlier patents. We define *SelfCite* as the number of backward citations that are made by all patents filed by each inventor in each year and are made to prior patents invented by the same inventor, following Chava, Oetl, Subramanian, Subramanian (2013) and Balsmeier et al. (2017).

To measure experimentation, we also utilize the operational definition of exploration developed by Benner and Tushman (2002). The approach taken is largely the same as when calculating exploitation, except that *Explore* is the number of exploratory patents (i.e., patents with 60% or more of their backward citations that are outside of the inventor's existing knowledge pool) filed by each inventor in each year. It is worth noting that there are often multiple inventors registered in one patent, and one patent may be exploitative to one inventor but exploratory to another inventor. In addition to exploration, we measure the number of patents in new technology classes. *NewTechClass* is defined as the number of patents filed by an inventor in a new technology class; in this case, a new technology class is defined as a category in which the inventor has never filed a patent, following Balsmeier et al. (2017).

4.2.3. Inventor Team Characteristics

We construct a number of patent level variables on team characteristics. Specifically, we measure team size as the number of co-inventors associated with a patent (*Team Size*). Patents generated by a single inventor are assumed to have a team size of zero. A patent generated by two inventors will be coded as a team size of one, since from the inventor's perspective there is one co-inventor involved, and so on. To supplement team size as a team characteristic, we also look at the diversity associated with teams. Specifically, we use the Name Files of the 2000 U.S. Census Data to assign the gender and ethnicity of an inventor based on his/her first name and surname. We then construct a ratio of female inventors to total inventors on the team (*Gender Diversity*) as well as a ratio of inventors from non-Anglo Saxon ethnicity to total inventors on the team (*Ethnic Diversity*).

4.3. Control Variables

In our empirical analysis, we control for a battery of inventor- and firm-level characteristics. We discuss these variables briefly in this section and provide the details in the Appendix. At the inventor-level, we consider an inventor's tenure (the number of years since the inventor first appeared in the patent database), as well as the inventor's past innovative performance. Past innovative performance is calculated as the average patent value, average total citations, or average citations per patent of the inventor received over the 5-year period prior to the observation year.[15]

To account for the fact that innovative output is largely driven by resource input into innovation, we use R&D expenses scaled by the book value of assets (*R&D/Assets*) reported by the firm that hires the inventor as a key control variable. Firm-years with missing R&D data are assigned a value of zero and are kept in the sample. To control for any bias in the results driven by replacing missing values of R&D with zero (Koh and Reeb, 2015), we include in all

[15] In regressions where the dependent variable is patent value, past performance is based on the average patent value, while in regressions where the dependent variable is citation count, past performance is based on the average citation count, and so forth.

regressions an indicator variable (*R&D missing*) equal to one if a missing value has been replaced with zero, and zero otherwise.

Following Hall and Ziedonis (2001), we include controls for firm size and capital intensity. Firm size is proxied by the natural logarithm of book assets (*Ln(Assets)*) and capital intensity by the natural logarithm of the ratio of net property, plant, and equipment scaled by book assets (*Ln(PPE/Asset)*). Additional firm-level controls include return on assets (*ROA*), total debt scaled by book assets (*Book leverage*), growth in sales relative to the previous year (*Sales growth*), market-to-book value (*MTB*), cash holdings (cash and easily convertible securities) scaled by book assets (*Cash holdings/Assets*), and the natural logarithm of firm age (*Ln(Firm age)*).

In addition to standard firm-level controls, we further control for product market competition (*Competition*) that is one minus the Lerner index, which is the price-cost margin scaled by sales. We also control for competition squared ($Competition^2$) as *Competition* to the power of two, as Aghion, Bloom, Blundell, Griffith, and Howitt (2005) report an inverted U-shaped relationship between product market competition and innovation.[16] The ownership of institutional investors (*Total IO*) and analyst coverage (*Ln*(*Analysts*)) are also controlled as Aghion et al. (2013) and He and Tian (2013) find that institutional ownership and analyst coverage affect corporate innovation, respectively. We also control for contemporaneous annual stock returns (*Stock returns*), as the extant literature suggests that sky cover has a significant effect on stock returns (Saunders, 1993; Hirshleifer and Shumway, 2003), which may subsequently affect R&D investments.

4.4. Other Firm-level Variables

In tests, where we relate a firm's sunshine exposure with corporate policies, we construct a number of variables utilizing data from Compustat and the KLD Socrates database. First, we collect data on Selling, General and Administrative Expenses (SG&A) as a proxy of firm's salary expenditure.[17] We scale SG&A by total asset to construct a variable denoted as *SG&A/Assets*. We also construct an employee treatment index from KLD Socrates database on how well a firm treats its employees along numerous dimensions: employee involvement,

[16] This design follows prior research in the industrial organization literature (Lindenberg and Ross, 1981; Domowitz, Hubbard, and Petersen, 1986; Aghion, Bloom, Blundell, Griffith, and Howitt, 2005).

[17] Direct data on a firm's wage and salary expenditure is sparsely recoded in the Compustat database, which is why we rely on an imperfect proxy of salary expenditure.

health and safety, retirement benefits, cash profit sharing, and other factors. Each dimension is associated with a strength and a concern indicator.[18]

4.5. Migration Data

We measure the effect that sunshine conditions have on a county's net migration using two datasets. First, we utilize the data provided by the Center for Demography and Ecology at the University of Wisconsin-Madison. The data is collected over the period 2000-2010, providing an overall net migration figure for every county over this period. The data is cross-sectional, providing one data point for every county in the sample. The net migration estimates are divided by five-year age cohorts, sex, and by race. We concentrate on the total net migration figure for each county among people of working age (20-65 year old age group). In addition to the raw net migration figure (*Net migration*), we also scale net migration by total population (*Net migration/Population*).

As an alternative to the aggregate total migration data, we also create a variable of county-level inventor migration based on the HBS inventor-level patent records. For each county and year, we measure the number of inventors residing in that county. We take the natural logarithm of one plus the number of inventors residing in a county at a given point in time (*Ln(Number of inventors)*). Increases in the number of inventors represent net migration, while a reduction represents net emigration.

4.6. Local Economic Performance Data

We construct local economic performance variables both at the county level and the state level based on several data sources. First, personal income per capita at county level is collected from the Bureau of Economic Activity regional economic account files (https://www.bea.gov/regional/). We collect this data from 1990 to 2014, which covers the entire period for which we have sunshine data. We take the natural logarithm of one plus nominal personal income per capita (*Ln(Per-Capita Inc.)*). The second proxy of local economic conditions is total sales of all firms headquartered in each county and year. We take the natural

[18] A firm which is exceptionally good (poor) with respect to a particular dimension is assigned a value of one (zero) for the strength indicator and zero (one) for the concern indicator. For each firm-year, we calculate the total strength and concern scores by summing across the seven strength indicators and the seven concern indicators, respectively. The raw employee treatment index is equal to the difference between the strength score and the concern score. Following Deng, Kang, and Low (2013), we divide the strength and concern scores by the respective number of dimensions available in a given year and define the adjusted employee treatment index as the difference between the adjusted total strength score and the adjusted total concern score (Employee treatment). We use the adjusted employee treatment index as our main measure of firm employee treatment. For the test employing employee treatment scores, we limit our sample to the period between 1992 and 2010. The sample period starts in 1992 as this is the earliest year for which data on employee treatment from KLD is available.

logarithm of one plus the sales amount for each county and year (*Ln(Local Sales)*). At the state level, we collect real GDP data from the Bureau of Economic Activity regional economic account files for the period 1990 to 2014. For each state and year, we take the natural logarithm of one plus the nominal real GDP amount (*Ln(Real GDP)*). In addition to real GDP, we collect the state level information about income tax (*Income Tax*) collected by the state in each year between 1995 and 2009 from the US Census Bureau State Governments files.[19]

4.7. Survey Data on Health

The final dataset we compile is a state-level dataset measuring individual's health. We collect data from the Center for Disease Control and Prevention on health indicators across U.S. states spanning the period 1993 to 2010. The data is based on surveys conducted on an annual basis, where respondents are asked to assess their health over the previous 30-day period. The surveys are conducted throughout the year. We specifically rely on two variables: activity limited days, and number of unhealthy days. Activity limited days refers to the number of days within a 30-day period when the respondent's physical activity was limited due to bad health. Unhealthy days are days when the responded felt that their physical condition was not good. For both variables, we take the natural logarithm of one plus the variable, to construct *Ln(Activity limited days)* and *Ln(Unhealthy days)*, respectively, to proxy for the health condition of local residents.

4.8. Survey Data on Working Hours and Leisure

To examine the effect of sunshine exposure on individuals' working and leisure activities, we utilize the American Time Use Survey (ATUS) sponsored by the Bureau of Labor Statistics and conducted by the U.S. Census Bureau. The data are available from 2003 to 2014. The data contains information about every respondent's average working hours around the time of the survey, time spent alone, the number and nature of activities engaged in during the diary week, and the date when the survey was conducted.[20] We construct four variables with this data. First, we take the natural logarithm of one plus the number of hours worked in a week (*Ln(Hours worked)*). Second, we use the natural logarithm of one plus the number of minutes spent alone (*Ln(Time alone)*) to gauge whether sunshine exposure is materially related with social

[19] Income taxes are defined as taxes levied on the gross income of individuals or on net income of corporations and businesses after deducting taxes from gross collections.

[20] The survey requests respondents to keep a diary in which daily activities are recorded. For each respondent, we collect the survey date, the respondents' state of residence, the minutes spent alone, hours worked, and an activity code capturing each activity that the respondent engaged in. We collect the ATUS activity coding lexicon for each year, which identifies the type of activity the respondent engaged in as well as whether the activity was work related, leisure related, or neither.

interactions. Finally, we construct two activity-based variables, which are defined as the number of work related activities scaled by total activities (*Work Activities*) as well as the number of leisure activities scaled by total activities (*Leisure Activities*).

5. Empirical Results

5.1. Inventor's Sunshine Exposure and Patent Value

To examine the overall relation between inventor's sunshine exposure and patent output (as shown in Figure 1), our baseline regression relates an inventor's sunshine exposure in year t with the natural logarithm of the total value of patents applied in year t+1 plus one. To ensure that our baseline results are not driven by omitted variables, we include a large set of controls and fixed effects into our regression model, including the full set of inventor- and firm-level controls described in Section 4.3, inventor fixed effects, industry fixed effects, and year fixed effects.[21] Statistical inferences are based on standard errors clustered at the inventor level to correct for estimation errors with respect to inventor. We present our baseline results in Panel A of Table 2.

The results support our basic proposition that sunshine exposure enhances inventor productivity, as the coefficient estimates on sunshine variables are positive and significant at the 1% level. Columns (1) and (3) show that the coefficients on *sunshine* and *relative sunshine* are 0.005 and 0.004, respectively. Given that the standard deviation of these two variables are 4.42 and 3.61, an one-standard-deviation increase in *sunshine* and *relative sunshine* leads to patent value growth of 2.2% and 1.4%, respectively.

We find even more significant results when the role of team size is taken into account. We interact *sunshine* and *relative sunshine* with *team size*, and expect to observe the strongest association between sunshine exposure and patent value amongst inventors working alone, since the sunshine effect is likely to be uncontaminated by the effect on sunshine of co-inventors. The results in columns (2) and (4) reveal that the coefficients on *sunshine* and *relative sunshine* are strongly positive (0.012 and 0.029, respectively), while the coefficient estimates on the interaction terms are significantly negative. When an inventor is working alone,

[21] The inclusion of inventor fixed effects serves the purpose of relating the change in the relative sunshine exposure that an inventor is exposed to over time with the change in innovative output for an inventor over time. As a consequence, all time invariant inventor-level characteristics, such as inventor quality are held constant. A further benefit of including inventor fixed effects is that the results will not be determined by the level of sunshine or relative sunshine, but rather the change in sunshine and relative sunshine. Furthermore, inventors' working in different industries are expected to produce different levels of patent output. Industry fixed effects control for this cross-industry variation at the 2-digit SIC-code level. To account for macroeconomic factors, as well as time trends in patenting activities and weather patterns, we control for year fixed effects. In robustness tests reported in the online appendix, we replicate our results after replacing inventor fixed effects with ZIP-code fixed effects.

a one-standard-deviation increase in *sunshine* and *relative sunshine* leads to patent value growth of 5.3% and 10.5%, respectively.[22] On the other hand, the positive effect of sunshine on inventor patent output decrease with team size, likely because an individual inventor has less input in the patent generated by a team compared with a patent generated by a single inventor. To address the issue that it could take a long time to develop an invention, we relate an inventor's sunshine exposure in a two- and three-year period *(t*-1 to *t* and *t*-2 to *t)* with the total value of patents applied in year t+1.[23] Our results hold.

In the online appendix, we report a number of additional tests confirming the robustness of the baseline results. Specifically, we show consistent results when using the full sample of inventors (those that both work for publically listed firms and inventors not employed by such firms), when we restrict the sample to inventors not employed by publically listed firms, when we exclude inventor-year observations of zero patents from our sample, after excluding inventors from our sample who have ever resided in rust-belt states, after excluding inventors residing in California, Massachusetts and New York, after limiting the sample to non-relocating inventors to overcome the issue that productive inventors chase nice weather locations, after limiting the sample to inventors residing outside of the firm's headquarter location, and after controlling for firm fixed effects.

In Panel B of Table 2, we consider several non-linear effects of sunshine exposure on inventor productivity. Given that sunshine exposure results in serotonin being released in the brain, a similar effect to taking anti-depressants, too much sunshine exposure can be expected to tire the body and mind resulting in reduced productivity. On the other hand, too much sunshine may reflect extremely hot or dry weather, which may also distract inventors. To address these concerns, we include squared *sunshine* and *relative sunshine* in our regression, and find that the coefficient estimate on $sunshine^2$ and $relative\ sunshine^2$ are negative and significant in columns (1) and (2) of Panel B. These results support some non-linear effects, with too much sunshine actually decreasing productivity. However, the magnitude of the main effect (i.e., the coefficients on *sunshine* and *relative sunshine*) is much greater than the

[22] This is comparable to the economic significance of other significant effects reported in the literature. For example, Aghion et al. (2013) report that a 10% increase in institutional ownership (roughly one standard deviation) is associated with a 7% increase in patent volume relative to its sample mean. Similarly, the economic significance of the relation between analyst following and corporate innovation reported by He and Tian (2013) is roughly 5.5% of the mean citations-per-patent value. These are considered first order determinants of corporate innovation in the literature.

[23] We average *sunshine* over a two or three year period to construct the variables *2-year sunshine* and *3-year sunshine*, respectively. We also sum *relative sunshine* over a two or three year period to construct the variables *2-year relative sunshine* and *3-year relative sunshine*, respectively.

magnitude of the squared terms. Thus, the average positive effect of sunshine exposure on inventor productivity is not eliminated by extreme weather conditions.

As an alternative way of addressing the same issue, we develop an indicator variable equal to one for inventors working in counties with above median sunshine exposure. We interact our two primary sunshine variables with this indicator variable, and report the results in columns (3) and (4). The results are consistent with those reported in columns (1) and (2), with the coefficient estimate on the interaction term being negative and significant at the 10% level. These results suggest that abnormal sunshine exposure has a less pronounced effect on those inventors who are exposed to higher amounts of sunshine on a permanent basis. Nevertheless, the magnitude of the main effect is much greater than the magnitude of the interacted term.

To further mitigate the concern that our baseline finding is sensitive to extreme weather issue, in columns (5) and (6) we recalculate the annual *sunshine* and *relative sunshine* variables only based on the sunshine conditions in winter, spring and fall, when temperatures are expected to be milder. We find that the coefficients on these two new sunshine variables are commensurate to their counterparts in columns (1) and (3) of Panel A, suggesting that sunshine during summer months is not a key determinant of our primary results. Finally, we redo our tests after excluding California. California is a unique case, since it is both relatively sunny (average sunshine measures across states in our sample are reported in the online appendix) and is also a key technological hub. Our baseline results might therefore simply pick up the "California effect".[24] We report results excluding inventors residing in California in columns (7) and (8), and obtain consistent results, suggesting that our baseline finding does not merely reflect the "California effect".

In Panel C of Table 2, we examine the effect of inventor relocations on productivity, to examine whether those inventors who relocate to sunnier areas actually an increase in their innovative productivity. Although there are selection issues in such relocation analysis, this test is an important robustness check in that if weather does enhance inventor productivity, we should observe a positive effect on the productivity of inventors who move to more sunny places, even if such an effect is due to inventors' choice or capability. We construct a sample of inventors who relocate only once during the sample (to make the sample as homogenous as possible as well as to exclude inventors who relocate frequently, and who are therefore likely

[24] This concern is mitigated by the fact that we use *relative sunshine* in our analysis, which already strips out the cross-sectional component of sunshine and concentrates on abnormal sunshine.

to have different attributes from other inventors) and have non-missing patent data for at least two years preceding the move as well as two years following the move.

As a result, we have a total of 12,615 relocating inventors. For each relocating inventor, we calculate the average sunshine exposure (*sunshine* and *relative sunshine*) and the average innovation output variables over the two-year period preceding the relocation and the average sunshine over the two years following the relocation. We report the estimation results from regressing the change in average patent value (post-relocation average minus pre-relocation average) on the change in average sunshine exposure between the previous location and the new location (*ΔSunshine* and *ΔRelative sunshine*) in columns (1) and (2).[25] The coefficients of *ΔSunshine* and *ΔRelative sunshine* are 0.013 and 0.015 with statistical significance, confirming that inventors who move to a location with more sunshine become more productive.

In columns (3) and (4), we focus on significant moves in terms of average sunshine exposure. In particular, we construct an indicator variable which identifies inventors that move from a location in the bottom quartile of the sunshine distribution to a location in the top quartile of the sunshine distribution (*Move Low to High*), as well as those that make the opposite move (*Move High to Low*). All other regression specifications are the same as columns (1) and (2). The coefficient estimate of 0.324 on *Move Low to High* in column (3), suggests that moving from a cloudy area to a sunny area is associated with an increase in patent value, which leads to growth of 32.4% in patent value. Conversely, the coefficient estimate of -0.447 on *Move High to Low* in column (4) suggests that moving from a sunny area to a cloudy area leads to growth of -44.7% in patent value.

The results reported in Panel C suggest that inventors who move to places with sunnier weather experience an increase in their productivity, while inventors who move to places with less sunshine experience a reduction in their productivity. One interpretation of this finding is that an individual's choice of where they reside has important implications for their productivity, which can determine their long-term career prospects. Of course, we should not draw too strong an inference based on the inventor relocation results, given that they are potentially affected by selection and endogeneity problems. Nevertheless, the results from the relocation data paint a more complete picture about the role of sunshine in determining inventor productivity.

[25] We further control for the change (post-relocation minus pre-relocation) in all the control variables which we include in our baseline analysis. We also include year fixed effects. Finally, instead of including industry fixed effects, we include an indicator variable into our regression analysis, which captures whether the inventor works for a firm which operates in a different industry, compared with the industry which the inventor worked for when he/she resided in the previous location.

[Insert Table 2 about here]

5.2. Inventor's Sunshine Exposure and Patenting Activities and Strategies

To better understand the relation between sunshine exposure and patent value, we relate an inventor's sunshine exposure in year *t* with the natural logarithm of other patent-based variables in year *t*+1 plus one in this section. In Panel A of Table 3 we utilize the same baseline model as in Panel A of Table 2, except that we replace patent value (*PatVal*) with alternate measure of patent output (*Pat*, *Cit*, and *CitPat*). For brevity, in our regression analysis we only use *relative sunshine* as the primary independent variable throughout the rest of our empirical analyses. The results reported in Table 3 show that sunshine exposure is positively associated with all alternate measures of inventor's patent output, confirming our baseline finding. The results show that higher exposure to more sunshine is associated with greater volume of new patents, and is also associated with higher presumed quality of inventions as measured by citations-per-patent. Panel A thus suggests that inventors with more sunshine exposure are more creative (*Hypothesis 1A*) as they create more forward citations and more forward citations per patent.

Panels B and C of Table 3 dwell deeper into patenting activities by examining the different patent types that inventors influenced by sunshine pursue. In Panel B, we consider patent-based variables related to limited information, risk-taking, creativity, specialization, and experimentation. The results in columns (1) and (2) suggest that inventors with more sunshine exposure rely on latest technologies and resource from a broader knowledge set, as shown in the significantly negative coefficient of relative sunshine for the half-life of backward citations (*HalfLife*) and the ratio of backward citations to local information (*LocalCites*). The results in columns (3) to (5) do not suggest that sunshine exposure results in greater risk taking as sunshine exposure is unrelated with the number of "hit" inventions (*Top10*), but is negatively associated with the number of "flop" inventions (*NTop90*). Also, sunshine exposure is positively associated with average quality inventions (*NTop10*).

We also find that sunshine exposure is associated with greater specialization, as evidenced by the positive relation between sunshine and exploitative patents (*Exploit*) as well as more self-citations (*SelfCite*).[26] Greater exposure to sunshine does not lead to greater

[26] In the online appendix, we show that exploitative patents are not necessarily of lower quality compared with exploratory patents. In fact, our analysis reveals that exploitative patents are more likely to be "hit" inventions and tend to generate more forward citations compared with exploratory patents. For this reason, we assume that pursuing exploitative patents is indicative of specialization, rather than merely pursuing low quality derivative inventions.

experimentation, with sunshine being unrelated to exploratory patents (*Explore*) and negatively associated with patents in new areas (*NewTech*). It is worth noting that the lack of experimentation does not imply that inventors are *less* creative; in fact, as we have shown earlier, inventors with more sunshine exposure create more impactful patents, and use more latest and non-local knowledge in their innovative activities.

In Panel C of Table 3 we repeat the analysis from Panel B but include the interaction of *relative sunshine* with *team size*. The results are largely consistent with those reported in Panel B, except that sunshine exposure becomes significantly positively related with the number of "hit" inventions (*Top10*). This new finding suggests that among inventors working alone, abnormal sunshine increases the number of "hit" inventions, while reducing the number of "flop" inventions. This result does not support more risk-taking from inventors being exposed to more sunshine, but instead supports inventors being more creative and/or better capable to producing more high-quality inventions.

The results reported up to this point are consistent with the notion that sunshine makes individuals more creative and optimistic (*Hypotheses 1A and 1B*).

[Insert Table 3 about here]

5.3. Inventor's Sunshine Exposure and Team-Working

In this section, we examine the effect of sunshine exposure on inventor team and related characteristics. Specifically, we test *Hypothesis 2*, which states that sunshine improves patent output due to the positive effect that sunshine has on collegiality, teamwork, and helping behavior. The results reported in Table 4 are based on the patent-inventor-level data, meaning that we have one observation per patent-inventor pair.[27] In addition to the standard *relative sunshine variable*, we also construct an additional variable, *team relative sunshine*, which is the average *relative sunshine* across all inventors working on a patent. We relate both these sunshine variables in year *t* with *team size*, *gender diversity*, and *ethnic diversity* in year *t*+1, to gauge how sunshine exposure affects the characteristics of inventor teams. In our results reported in Table 4, we include the full set of control variables as those used in Table 2. With respect to fixed effects, given the nature of the data, we do not include inventor and industry fixed effects, but instead include firm and technology class fixed effects. We correct standard errors for clustering at the inventor level.

[27] The sample is limited to only those patents developed by patent teams (i.e., patents developed by more than one inventor).

[Insert Table 4 about here]

Our results show that sunshine exposure is associated with smaller team size, which does not support *Hypothesis 2*. One possible interpretation of this finding is that sunshine exposure leads to inventors being more focused and working more efficiently, rather than having more social activities or enhancing inventors' collegiality, teamwork, and helping behavior.[28] Further evidence is supported by the diversity of inventor teams. Specifically, we find no association between sunshine and gender diversity, and actually observe a negative association between sunshine and ethnic diversity.

5.4. Sunshine Exposure and Managerial Decisions

Next, we examine the effect that sunshine around a firm's headquarters has on corporate policies related to innovation. It is possible that, rather than influencing inventor productivity directly, sunshine around a firm's headquarters affects managers' optimism, firms' employee treatment, and the efficiency of corporate patent attorneys which in turn influence inventor productivity. In the online appendix (Panel G of Table OA.2), we show that our results stay qualitatively unchanged after removing those inventors from our sample that live in either the same county or state as the firm's headquarters. Thus, our baseline results cannot be entirely attributed to the effect of sunshine on managers working in the headquarters.

Nevertheless, we cannot exclude the possibility that sunshine conditions also contributes to inventor productivity through managers, as stated in *Hypothesis 3A and 3B*. To test these hypotheses, we directly relate sunshine around the firm's headquarters and four measures of corporate policies:[29] *SG&A/Assets*, *employee treatment*, *R&D/Assets*, and *PPE/Assets*. We also note that corporate policies with respect to innovative activities are often made at the middle-manager level, and thus interact the headquarters sunshine variable with *Dispersion* (defined as the number of U.S. states mentioned in the firm's annual report that captures the dispersion of a firm's business units from the firm's annual report as in Garcia and Norli (2012)). Assuming that decisions relevant to corporate policies are made at the division level, we should observe a stronger effect of headquarters sunshine for firms that are not geographically dispersed. In the firm-level regression analysis, we include the full set of firm-

[28] This interpretation is consistent with our preceding finding in Table 3 that sunshine exposure results in greater specialization rather than experimentation (ie. inventors becoming more focused).

[29] Specifically, we match the firm's headquarter zip code centroid with weather stations within a 50-kilometer radius.

level control variables, as well as firm and year fixed effects. We correct standard errors for clustering at the firm level.

Our results in Panel A of Table 5 show that sunshine around a firm's headquarter location has no effect on corporate policies. Both sunshine variables are not significantly related with any of the corporate policies, and the interaction terms are insignificant as well. These results thus do not support *Hypotheses 3A and 3B.* In Panel B, we relate the average sunshine conditions around firm divisions with corporate polices, to more directly relate sunshine exposure of middle managers with firms policies relating to innovation activities.[30] The estimation results of division sunshine reported in Panel B of Table 5 are identical to those in Panel A. All divisional sunshine variables are statistically insignificant. Finally, in Panel C of Table 5, we limit the sample to geographically dispersed firms, and separately relate headquarters sunshine or division sunshine around firm's headquarters with corporate policies. Once again, across all regressions we find that neither sunshine around the headquarter location or division location has any effect on corporate policies. In summary, the results presented in this section yield little support for the notion that sunshine-induced managerial decisions are the key determinants behind the positive association between inventor sunshine exposure and productivity.[31]

[Insert Table 5 about here]

In this section, we test *Hypotheses 4A and 4B* by examining whether the positive association between local sunshine and patent value is due to local information spillovers. Local information spillovers can occur both directly and indirectly. Local spillovers can occur directly by enticing local inventors to engage ideas between each other, which is related to helping behaviors or social networking that could be affected by sunshine. In terms of indirect spillovers, better weather can attract skilled migration increasing labor market competition in the local area, which will force inventors to work harder. This might be responsible for the baseline results. We address both potential channels in Table 6.

The results reported in columns (1) to (4) of Panel A are estimation results for migration from running a cross-sectional regression in which the dependent variables are the natural

[30] We multiply the average sunshine conditions in each state by the portion of total mentions for that state, to come up with a business operation weighted measure of firm-level sunshine exposure.

[31] In the online appendix, we show that sunshine conditions around the US Patent and Trademark Office influence the time it takes for a patent to be processed, with more sunshine speeding up the review time. However, in subsequent analysis, we show that this does not drive our main result. In the online appendix, we also show that sunshine conditions around corporate headquarters are unlikely to influence the effectiveness with which patent attorneys prepare patent applications.

logarithm of net migration and net migration scaled by county population over 2000-2010 from the Center for Demography and Ecology at the University of Wisconsin-Madison. The explanatory variables are average *sunshine* or *relative sunshine* over 2000-2010. Across all columns, we find no relation between sunshine exposure and migration. These results do not support the notion that local sunshine influences labor market conditions through attracting skilled migration.

In columns (5) and (6), we address this issue further by relating county level sunshine conditions with the number of inventors residing in each county. These regressions are based on longitudinal data, as we are able to track the number of inventors residing in each county over time. In addition to controlling for the natural logarithm of personal income in the county, we include county and year fixed effects. Again, we find no relation between sunshine and the number of inventors residing in a county. In short, the results reported in Panel A of Table 6 does not support *Hypothesis 4A.*

In Panel B of Table 6, we relate inventor-level sunshine exposure with our two additional local citation intensity measures (*Local cites* and *Local Citations/Patent*) that capture local spillovers. We limit our analysis only to those inventors who have applied for at least one patent, since these measures rely on the citations made in the patent being applied for. Specifically, we relate sunshine exposure with local citations. In our regression analysis, we include the full set of control variables, as well as inventor, industry and year fixed effects. Consistent with the results reported in column (6) of Panel B in Table 3, we find a negative association between sunshine exposure and utilization of local knowledge. Overall, the results do not support *Hypothesis 4B.*

[Insert Table 6 about here]

5.7. Sunshine Exposure, Local Economic Performance

In this section, we relate local sunshine with local economic conditions to test *Hypothesis 5*, which states that sunshine positively influences patent output by enhancing local economy. The results are presented in Table 7. In Columns (1) to (4), we consider two county-level measures of local economic conditions: *Per-Capita Inc.* and *Local Sales*. In columns (5) to (8), we consider two state-level measures of economic conditions: *Real GDP* and *Income Tax*. In the regressions reported in columns (1) to (4) we include county and year fixed effects, while in the regressions reported in columns (5) to (8) we include state and year fixed effects. Our findings show that the coefficients in columns (1) to (4) are insignificant, while in columns (5) to (8) only the relation between *sunshine* and *Ln(Real GDP)* is negative and marginally significant at the 10% level. Overall, the results suggest that sunshine-induced local economic boom does not work as a mechanism for our main finding, and thus do not find any support for *Hypothesis 5*.

[Insert Table 7 about here]

5.8. Local Sunshine and Health

In this section, we relate local sunshine with individual health for a possible relation between sunshine exposure and inventor health. We utilize longitudinal state-level health data covering the period from 1993 to 2010 from the Center for Disease Control and Prevention. Specifically, we use average sunshine for a given state in a given year, and relate it with the number of activity limited days and unhealthy days. In our regression analysis we include state fixed effects (to account states where healthcare is worst leading to lower health) and year fixed effects. Table 8 presents that all coefficient estimates of sunshine variables are insignificant, which does not support the argument that sunshine exposure improves inventors' health and thus increases their productivity.

[Insert Table 8 about here]

5.9. Local Sunshine and Working Hours

Lastly, we relate local sunshine with local residents' working hours for a possible relation between sunshine exposure and inventor's working hours and social behaviors. We utilize ATUS survey data in the results reported in Table 9, in which we relate local sunshine with a number of measures reflecting local residents' use of time. Specifically, we relate the average sunshine conditions in the respondent's state in the month of the survey with *Hours Worked, Time Alone, Work Activities*, and *Leisure Activities*. In columns (1) to (4), we include industry fixed effects, job category fixed effects, state fixed effects, year fixed effects and month fixed effects to account for the heterogeneity in our data.[34] In columns (5) to (8), we include only state, year, and month fixed effects since the dependent variable deals with the split between work and leisure activities. How people split their time between work and leisure is not expected to be highly sensitive to the specific job they perform. We find that both our sunshine measures are not related to any of the dependent variables. This finding indicates that sunshine

[34] Specifically, we control for industry and job category fixed effects, since how people use their time will be strongly related to the job they perform. Similarly, year and month fixed effects are important, since how people use time changes with social and economic trends, plus the use of time will be highly seasonal.

exposure is not a key determinant of how much time people spend at work, and how much time people spend socializing with others.[35]

Empirical evidence presented in Tables 8 and 9 suggest that sunshine exposure has limited effect on local residents' health condition, their working hours, and their time allocation. Two implications are noteworthy: first, these results, together with our earlier finding that inventors produce more patents (especially more influential patents), suggest that inventors become more creative rather than working harder and longer when sunshine exposure increases. Second, sunshine does not seem to enhance inventors' social networks or helping behaviors, which is consistent with our earlier results related to teamwork.

[Insert Table 9 about here]

6. Conclusion

In this paper, we investigate the effect of weather-induced mood on inventors' productivity and the value implication of such an effect. We document that sunshine exposure has a positive effect on inventor productivity. Our main results show that amongst inventors working alone, a one-standard-deviation increase in annual sunshine around the inventor's residential location is associated with an increase in patent value of between 5.3% and 10.5% relative to the mean value. Inventor relocations from areas with low average sunshine to areas with high average sunshine are associated with an improvement in the value of patents generated by an inventor of over 32% relative to the mean of patent value. Sunshine exposure is not only positively associated with patent value but also the number of new patents as well as the forward citations received by new patents. When examining the effect that sunshine exposure has on patenting strategies, we find that inventors exposed to more sunshine produce patents which rely less on old technologies and local knowledge, are more likely to be "hits" rather than "flops", and are more likely to be related to an inventors existing knowledge set rather than in areas entirely new to the inventor.

We examine several channels that have the potential to drive our results and find that sunshine exposure is associated with smaller and less ethnically diverse inventor teams. Coupled with the main results showing that the effect of local sunshine weakens with team size, we conclude that the positive association between sunshine exposure and inventor productivity does not stem from more efficiently operating teams. We find no support for the proposition that our results could be driven by sunshine influencing strategic managerial decisions. We

[35] Seasonality is a key determinant of individuals socializing behavior, with sunshine variables being significantly related with time spent alone when we exclude month fixed effects.

also find no support that sunshine exposure positively influences inventor productivity through local spillovers, local economy, inventor health or working hours. Overall, we interpret our results as showing that sunshine induced good mood has a positive effect on inventor productivity by making inventors more creative and optimistic about the payoffs from their increased effort.

The most significant take-away from our study is that inventor mood has a significant effect on inventor productivity. Given the vital role that inventors play in the economy, our results have important implications for how managers should motivate this important class of economic actors. However, it should be noted that our analysis suggests that good mood facilitates what is termed in the literature as "innovative" creativity (Taylor, 1959; Torrance, 1988); creativity involving improvements through modifications. Although we clearly show that improvements in "innovative" creativity are value relevant for firms, as evidenced by the creation of higher valued patents and patents which are cited heavily by future inventors, good mood is not found to promote "emergenative" creativity; creativity involving the generation of a completely new principle. In this respect, our paper complements Borowiecki (2017), who shows that depressive states are most conducive toward the generation of outstanding and path-breaking creativity ("emergenative" creativity). Given that firm success requires both "innovative" and "emrgenative" creativity from their innovators (Tushman and O'Reilly, 1996), our findings coupled with Borowiecki (2017) have important implications for how emotional states of creative workers affects corporate innovation.

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Table 1 Summary Statistics of Key Variables

	Mean	Std.	P25	Median	P75	N
Panel A: Key dependent variables						
LnPatVal	1.386	1.655	0	1.450	3.013	1,029,524
LnPat	0.708	0.571	0	0.693	1.098	1,029,524
LnCit	2.038	1.775	0	2.113	3.419	1,029,524
LnCitPat	1.563	1.418	0	1.519	2.639	1,029,524
LnExploit	0.172	0.666	0	0	0	1,029,524
LnSelfCite	0.064	0.287	0	0	0	1,029,524
LnExplore	0.582	1.122	0	0	0	1,029,524
LnNewTech	0.143	0.332	0	0	0	1,029,524
LnHalfLife	0.594	0.98	0	0	1.386	1,029,524
LocalRatio	0.203	0.42	0	0	0.236	298,730
LnTop10	0.170	0.349	0	0	0	687,581
LnNTop10	0.674	0.501	0.693	0.693	0.693	687,581
LnNTop90	0.013	0.096	0	0	0	687,581
Team Size	2.650	2.591	0	2.333	4.000	1,029,524
Gender Diversity						
Ethnic Diversity						
Panel B: Key independent variables						
Sunshine	10.867	4.423	7.388	10.690	13.694	1,029,524
Relative sunshine	-0.942	3.611	-2.780	-0.084	0.683	1,029,524
2-year Sunshine	10.861	4.241	7.402	10.759	13.714	747,098
2-year relative sunshine	-1.856	5.630	-5.273	-1.524	1.366	747,098
3-year sunshine	10.822	4.113	7.528	10.661	13.697	597,282
3-year relative sunshine	-2.797	8.039	-7.804	-2.318	1.881	597,282

This table presents the descriptive statistics of the key variables used in this study. The sample period is 1990 to 2007. The table presents the means, standard deviations, 25th percentile, median, 75th percentile and number of observations for each variable.

Table 2 Sunshine Exposure and Inventors' Patent Value

Panel A: Baseline results

	Ln(Patent Value)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sunshine	0.005***	0.012***						
	(0.00)	(0.00)						
Sunshine × Team size		-0.003***						
		(0.00)						
Relative sunshine			0.004***	0.029***				
			(0.00)	(0.00)				
Relative sunshine × Team size				-0.011***				
				(0.00)				
2-year sunshine					0.010***			
					(0.00)			
2-year relative sunshine						0.004***		
						(0.00)		
3-year sunshine							0.015***	
							(0.00)	
3-year relative sunshine								0.004***
								(0.00)
Team size		0.392***		0.356***				
		(0.01)		(0.00)				
All controls	YES	YES	YES	YES	YES	YES	YES	YES
Inventor fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,029,524	730,636	1,029,524	730,636	747,098	747,098	597,282	597,282
Adj R^2	0.52	0.58	0.52	0.58	0.55	0.55	0.56	0.56

Table 2 Sunshine Exposure and Inventors' Patent Value (Cont')

Panel B: Adjusting for Average Sunshine Conditions

	Full Sample						Non-California Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sunshine	0.010***		0.007***				0.004***	
	(0.00)		(0.00)				(0.00)	
Sunshine^2	-0.0001**							
	(0.00)							
Relative sunshine		0.004***		0.006***				0.005***
		(0.00)		(0.00)				(0.00)
Relative sunshine^2		-0.0003**						
		(0.00)						
Sunshine × High sunshine area dummy			-0.003*	-0.003*				
			(0.00)	(0.00)				
Sunshine (non-summer)					0.007***			
					(0.00)			
Relative sunshine (non-summer)						0.004***		
						(0.00)		
All controls	YES	YES	YES	YES	YES	YES	YES	YES
Inventor fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,029,524	1,029,524	1,029,524	1,029,524	1,029,524	1,029,524	868,279	868,279
Adj R^2	0.52	0.52	0.52	0.52	0.52	0.52	0.55	0.55

Table 2 Sunshine Exposure and Inventors' Patent Value (Cont')

Panel C: Inventor Relocations and Patent Value

	ΔLn(Patent Value)			
	(1)	(2)	(3)	(4)
ΔSunshine	0.013***			
	(0.00)			
ΔRelative sunshine		0.015**		
		(0.00)		
Move Low to High			0.324***	
			(0.11)	
Move High to Low				-0.447***
				(0.12)
All controls	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Observations	12,615	12,615	12,615	12,615
Adj R^2	0.05	0.05	0.05	0.05

This table presents the baseline regression results on the relation between inventors' sunshine exposure and patent value. The sample period is 1990 to 2007. Panel A provides the baseline results relating different measures of sunshine exposure with patent value. Panel B examines whether the relation is linear or non-linear. Panel C examines the effect of inventor relocations on patent value. Industry fixed effects are defined at the two-digit SIC code level. Standard errors are corrected for clustering at the inventor level. ***, **, and * denote significance at the 1%, 5%, and 10% significance levels, respectively. Detailed variable descriptions can be found in the Appendix.

Table 3 Sunshine Exposure and Patenting Activity

Panel A: Relative sunshine and patent output

	LnPat	*LnCit*	*LnCitPat*
	(1)	(2)	(3)
Relative sunshine	0.001**	0.005***	0.004***
	(0.00)	(0.00)	(0.00)
All controls	YES	YES	YES
Inventor fixed effects	YES	YES	YES
Industry fixed effects	YES	YES	YES
Year fixed effects	YES	YES	YES
Observations	1,029,524	1,029,524	1,029,524
Adj R^2	0.44	0.46	0.46

Panel B: Relative sunshine and patenting strategy

	Limited Information		Risk-taking/Creativity			Specialization		Experimentation	
	LnHalfLife	*LocalCites*	*LnTop10*	*LnNTop10*	*LnNTop90*	*LnExploit*	*LnSelfCite*	*LnExplore*	*LnNewTech*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Relative sunshine	-0.002***	-0.002***	0.000	0.001*	-0.001**	0.002***	0.001*	0.000	-0.001*
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
All controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Inventor fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,029,524	298,730	687,581	687,581	687,581	1,029,524	1,029,524	1,029,524	1,029,524
Adj R^2	0.43	0.34	0.48	0.54	0.44	0.45	0.50	0.61	0.58

Table 3: Sunshine Exposure and Patenting Activity (Cont')

Panel C: Team size and patenting strategies

	Limited Information		Risk-taking/Creativity			Specialization		Experimentation	
	LnHalfLife	*LocalCites*	*LnTop10*	*LnNTop10*	*LnNTop90*	*LnExploit*	*LnSelfCite*	*LnExplore*	*LnNewTech*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Relative sunshine	-0.003**	-0.006***	0.003***	0.001	-0.001***	0.007***	0.002***	0.001	-0.002***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Relative sunshine×TS	0.000	0.001**	-0.001***	-0.000	0.001***	-0.001***	-0.001***	-0.000	0.001***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Team size (TS)	0.002**	0.007***	0.011***	-0.003***	-0.001***	0.006***	0.001	0.011***	0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
All controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Inventor fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	730,598	287,911	687,581	687,581	687,581	730,636	730,636	730,636	730,636
Adj R^2	0.52	0.34	0.11	0.21	0.05	0.24	0.28	0.52	0.39

This table presents results relating sunshine exposure with patenting activity. The sample period is 1990 to 2007. Panel A provides regressions results relating sunshine exposure with patent output and forward citations. Panel B examines the relation between sunshine exposure and patenting strategies. Panel C also examines the relation between sunshine exposure and patenting strategies, after interacting the sunshine variable with team size. Industry fixed effects are defined at the two-digit SIC code level. Standard errors are corrected for clustering at the inventor level. ***, **, and * denote significance at the 1%, 5%, and 10% significance levels, respectively. Detailed variable descriptions can be found in the Appendix.

Table 4 Sunshine Exposure and Team Characteristics

	Team Size		*Gender Diversity*		*Ethnic Diversity*	
	(1)	(2)	(3)	(4)	(5)	(6)
Team relative sunshine	-0.018***		-0.000		-0.002***	
	(0.00)		(0.01)		(0.00)	
Relative sunshine		-0.016***		-0.000		-0.001***
		(0.00)		(0.01)		(0.00)
All controls	YES	YES	YES	YES	YES	YES
Technology class fixed effects	YES	YES	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES
Observations	424,192	424,192	398,215	398,215	382,691	382,691
Adj R^2	0.16	0.16	0.12	0.12	0.07	0.07

This table provides regression results on the relation between sunshine exposure and team characteristics. The regressions are conducted on a patent-level dataset. Standard errors are corrected for clustering at the patent level. ***, **, and * denote significance at the 1%, 5%, and 10% significance levels, respectively. Detailed variable descriptions can be found in the Appendix.

Table 5 Sunshine Exposure and Managerial Decisions

Panel A: Sunshine around firm's headquarters

	SG&A/Assets		*Employee Treatment*		*R&D/Assets*		*PPE/Assets*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HQ Sunshine	-0.000		0.000		0.000		0.000	
	(0.01)		(0.01)		(0.00)		(0.01)	
HQ Sunshine × Dispersion	0.000		-0.000		-0.000		-0.000	
	(0.01)		(0.00)		(0.00)		(0.01)	
HQ Relative sunshine		0.000		-0.003		0.000		0.000
		(0.01)		(0.01)		(0.01)		(0.00)
HQ Relative sunshine × Dispersion		-0.000		0.000		-0.001		-0.000
		(0.01)		(0.00)		(0.00)		(0.00)
Dispersion	-0.001	-0.000	0.002	0.000	0.001*	0.000	0.001	0.000
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)
All controls	YES	YES	YES	YES	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Observations	10,131	10,131	4,063	4,063	11,536	11,536	11,536	11,536
Adj R^2	0.81	0.81	0.56	0.56	0.82	0.82	0.89	0.89

Panel B: Sunshine around firm's division location

	SG&A/Assets		*Employee Treatment*		*R&D/Assets*		*PPE/Assets*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Division sunshine	-0.001		-0.001		0.000		-0.000	
	(0.01)		(0.01)		(0.01)		(0.01)	
Division relative sunshine		-0.001		0.005		-0.001		0.001
		(0.01)		(0.01)		(0.01)		(0.01)
All controls	YES	YES	YES	YES	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Observations	11,306	11,306	4,720	4,720	12,981	12,981	12,981	12,981
Adj R^2	0.81	0.81	0.54	0.54	0.63	0.63	0.89	0.89

Table 5: Sunshine Exposure and Managerial Decisions (Cont')

Panel C: Sub-sample of geographically dispersed firms

	SG&A/Assets		*Employee Treatment*		*R&D/Assets*		*PPE/Assets*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HQ Sunshine	-0.001		-0.002		-0.000		-0.000	
	(0.01)		(0.01)		(0.00)		(0.01)	
Division sunshine	-0.002		0.003		-0.000		-0.000	
	(0.01)		(0.01)		(0.01)		(0.01)	
HQ Relative sunshine		-0.001		-0.002		-0.000		-0.000
		(0.01)		(0.01)		(0.01)		(0.01)
Division relative sunshine		0.002		0.016		-0.002		0.000
		(0.01)		(0.01)		(0.01)		(0.01)
All controls	YES	YES	YES	YES	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Observations	4,508	4,508	1,932	1,932	4,993	4,993	4,993	4,993
Adj R^2	0.83	0.83	0.56	0.56	0.78	0.78	0.91	0.91

This table provides regression results on the relation between firm-level sunshine exposure and key corporate strategies which have the ability to influence patenting activity. The sample period is 1990 to 2007. The regressions are conducted on a firm-level dataset. Panel A relates sunshine around a firm's headquarters' location and corporate strategies. Panel B relates average sunshine around firms' divisions and corporate strategies. Panel C examines a sub-sample of geographically dispersed firms. Standard errors are corrected for clustering at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% significance levels, respectively. Detailed variable descriptions can be found in the Appendix.

Table 6 Sunshine Exposure and Local Spillovers

Panel A: Sunshine and migration trends

	Overall Migration				Inventor Migration	
	Net migration		*Net migration/Population*		*Ln(Number of Inventors)*	
	(1)	(2)	(3)	(4)	(5)	(6)
Sunshine	0.054		0.001		-0.001	
	(0.05)		(0.01)		(0.01)	
Relative sunshine		-0.005		-0.001		-0.002
		(0.08)		(0.01)		(0.01)
Ln (Median income)	15.130***	14.955***	0.147***	0.147***	0.497***	0.497***
	(1.94)	(2.01)	(0.02)	(0.02)	(0.19)	(0.19)
State fixed effects	YES	YES	YES	YES	NO	NO
County fixed effects	NO	NO	NO	NO	YES	YES
Year fixed effects	NO	NO	NO	NO	YES	YES
Observations	729	729	729	729	19,656	19,656
Adj R^2	0.35	0.35	0.39	0.39	0.95	0.95

Panel B: Sunshine exposure and use of local information set

	Ln(Local citations)		*Local Citations/Patent*	
	(1)	(2)	(3)	(4)
Sunshine	-0.005***		-0.055***	
	(0.00)		(0.00)	
Relative sunshine		-0.002*		-0.045***
		(0.00)		(0.00)
All controls	YES	YES	YES	YES
Inventor fixed effects	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Observations	732,081	732,081	732,081	732,081
Adj R^2	0.46	0.46	0.42	0.42

This table presents the regression results on the effects of local spillovers. Panel A examines the relation between sunshine conditions and local net migration. Overall migrations utilizes county level data on the net migration figures over a ten year period and relates this figure with average sunshine and relative sunshine conditions over a ten year period. The results in columns (1) to (4) are based on a cross-sectional regression. Inventor migration utilized data from the patent data on inventor relocations, and related sunshine conditions in each county-year with net inventor migration in each county-year. In Panel A standard errors are corrected for clustering at the county level. Panel B examines the relation between sunshine conditions and the reliance of inventors on local knowledge. These regressions are conducted on the inventor-level dataset. Standard errors in Panel B are corrected for clustering at the inventor level. ***, **, and * denote significance at the 1%, 5%, and 10% significance levels, respectively. Detailed variable descriptions can be found in the Appendix.

Table 7 Sunshine Exposure and Local Economic Performance

	County Level Analysis				State Level Analysis			
	Ln(Per-Capita Inc.)		*Ln(Local Sales)*		*Ln(Real GDP)*		*Ln(Income Tax)*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sunshine	-0.001		0.015		-0.003*		-0.001	
	(0.01)		(0.01)		(0.00)		(0.01)	
Relative sunshine		-0.001		-0.004		-0.001		-0.001
		(0.01)		(0.02)		(0.01)		(0.01)
County fixed effects	YES	YES	YES	YES	NO	NO	NO	NO
State fixed effects	NO	NO	NO	NO	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Observations	4,830	4,830	4,830	4,830	822	822	580	580
Adj R^2	0.98	0.98	0.87	0.87	0.99	0.99	0.99	0.98

This table presents regression results on the relation between local sunshine conditions and economic performance. The results presented in columns (1) to (4) are based on county-level economic data, while the results presented in columns (5) to (8) are based on state-level economic data. Standard errors in columns (1) to (4) are corrected for clustering at the county level, while standard errors in columns (5) to (8) are corrected for clustering at the state level. ***, **, and * denote significance at the 1%, 5%, and 10% significance levels, respectively. Detailed variable descriptions can be found in the Appendix.

Table 8 Sunshine Exposure and Health

	Ln(Activity limited days)		*Ln(Unhealthy days)*	
	(1)	(2)	(3)	(4)
Sunshine	-0.000		0.003	
	(0.00)		(0.01)	
Relative sunshine		-0.002		-0.000
		(0.01)		(0.01)
State fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Observations	869	869	869	869
Adj R^2	0.76	0.76	0.51	0.51

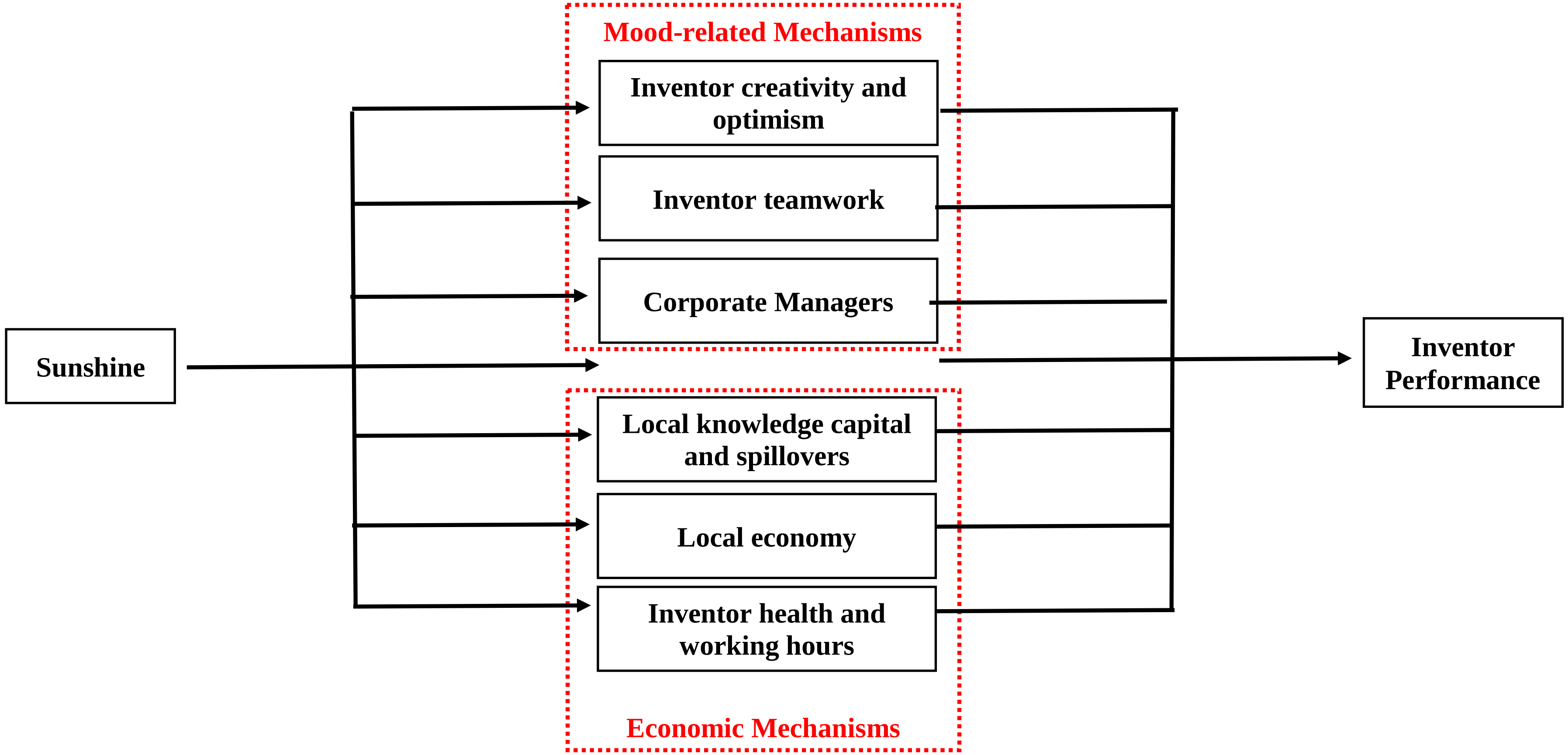
This table presents regression results on the relation between sunshine exposure and health. The results are based on data obtained from the Center for Disease Control and Prevention, which conducts surveys on “healthy days” measures. ***, **, and * denote significance at the 1%, 5%, and 10% significance levels, respectively. Detailed variable descriptions can be found in the Appendix.

Table 9 Sunshine Exposure and Working Hours

	Ln(Hours worked)		*Ln(Time alone)*		*Work Activities*		*Leisure Activities*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sunshine	-0.001		-0.000		-0.001		-0.000	
	(0.01)		(0.01)		(0.01)		(0.01)	
Relative sunshine		-0.000		0.000		-0.001		-0.001
		(0.00)		(0.01)		(0.01)		(0.01)
Industry fixed effects	YES	YES	YES	YES	NO	NO	NO	NO
Job category fixed effects	YES	YES	YES	YES	NO	NO	NO	NO
State fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Month fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Observations	94,502	94,502	94,502	94,502	94,502	94,502	94,502	94,502
Adj R^2	0.10	0.10	0.01	0.01	0.16	0.16	0.29	0.29

This table presents regression results on the relation between sunshine exposure and working/leisure hours. ***, **, and * denote significance at the 1%, 5%, and 10% significance levels, respectively. Detailed variable descriptions can be found in the Appendix.

Figure 1 Sunshine Exposure, Inventor Performance, and Mechanisms



Note: This figure illustrates the possible mechanisms through which sunshine exposure influences inventors' performance. All mechanisms are based on a simple model described in Section 2 and motivated by prior literature summarized in Section 3.

In the Mood for Creativity: Weather-induced Mood, Inventor Productivity, and Firm Value

ONLINE APPENDIX

This online appendix reports additional tests referred to in the paper. Table OA.1 provides descriptive statics for our sunshine variables across states. An important question to ask is whether annual sky cover varies sufficiently, both across time and locations, to be able to influence innovation outcomes in an economically significant way. Table OA.1 reveals that states differ significantly in terms of their average sunshine. For example, Alaska only has roughly 5.80 sunny days per month, while Wyoming has roughly 19.25 sunny days per month. Although we would expect that some states are sunnier than others, this assumption raises a potential selection problem; for example, better quality inventors might flock to states with more sunshine. To address this potential problem, we concentrate on *relative sunshine* in our main analysis, which captures the *unexpected* level of sunshine.

[Insert Table OA.1 about here]

Table OA.2 reports the robustness tests for our baseline results reported in Table 2 of the paper. In Panel A, we report baseline results for the full sample of inventors in the patent database (ie. inventors who are both employed by publically listed firms and those that are not). Since the primary dependent variable in Table 2, namely patent value (*PatVal*), is calculated by observing the stock price reaction to patent grants, this measure of patent quality is not available to us when examining inventors who are not employed by publically listed firms. As such, in Panel A we use patent count (*Pat*), forward citations (*Cit*), and citations-per-patent (*CitPat*) as the dependent variables. In addition, we cannot control for any firm-level characteristics in our analysis, since this information is unavailable for inventors not employed by publically listed firms. The model specification is therefore limited to regressing patent output variables on sunshine exposure as well as inventor and year fixed effects. The results in Panel A reveal a positive association between sunshine exposure and inventor's patent output.

In Panel B, we examine the sub-sample of inventors that are not employed by publically listed firms. We use the same empirical set-up as for the results reported in Panel A, and also find a positive association between sunshine exposure and inventor productivity.

In Panel C, we exclude inventor-year observations from our sample where inventors do not apply for any patents. In our baseline analysis, we follow common practice and replace such "missing" years with zeros. We find that our results stay qualitatively unchanged in Panel C.

In Panel D, we address the non-uniformity of inventors distributed geographically by excluding from the sample all inventors who have ever resided in the rust belt states (Pennsylvania, West Virginia, Ohio, Indiana, Michigan, Illinois, Iowa, and Wisconsin). It is possible that our results are somehow contaminated by inventors moving away from rust belt states and older industries to the west. We find consistent results. To address a similar concern, in Panel E, we exclude from our sample those inventors that reside in California, Massachusetts, and New York which are unusually innovative states. Finally, in Panel F we exclude from our sample those inventors that have ever changed locations. This test helps us ensure that the results are not driven by inventors relocating to more sunny areas (ie. California). The results stay qualitatively unchanged.

In Panel G, we remove inventors from our sample that reside in close proximity to the firm's headquarters. In columns (1) and (2) we remove inventors that reside in the same county as the firm is headquartered, while in columns (3) and (4) we remove inventors who reside in the same state. Again, we find that the results stay qualitatively unchanged.

Finally, in Panel H we replace inventor fixed effects with firm fixed effects. This test allows us to examine how inventors residing in different locations but employed by the same firm react to changes in weather. Once again, we report a positive and significant association between sunshine exposure and inventor productivity.

[Insert Table OA.2 about here]

In Table OA.3, we examine the characteristics of exploitative and exploratory patents. Specifically, we utilize our patent-level dataset and run a linear probability model to examine whether exploitative and exploratory patents are more or less likely to be "hits" or "flops". We include technology, firm, and year fixed effects in our regressions. We find that exploitative patents are more likely to be "hits", whereas exploratory patents are less likely to be "hits" and more likely to be of "average" quality. In addition, we run an OLS model in which we regress forward citations on exploitative and exploratory patents and find that exploitative patents generate more forward citations while exploratory patents generate fewer forward citations. Our results highlight that exploitative patents, while by definition not being as path-breaking and "emergenative" as exploratory patents, cannot be considered as lower quality. In fact, by all objective standards, it appears that exploitative patents are higher quality (on average) compared with exploratory patents.

[Insert Table OA.3 about here]

In OA.4 we provide additional results on the effects that team dynamics have on inventor productivity. Specifically, limiting the inventor-level sample to only those inventors that produce at least one patent in a team, and relating *team sunshine* and *team relative sunshine* with patent value, we find a weak positive relation for *team sunshine* and no relation for *team relative sunshine*. In addition, we construct an indicator variable equal to one for inventor-year observations where all co-inventors working on a patent have positive abnormal sunshine. We find that inventor productivity is higher when his/her team members are affected by positive weather, compared with when co-inventors are not similarly affected by good mood. Overall, our result suggest that sunshine has a limited influence on inventor productivity via its effect on teamwork. However, this does not appear to be the primary channel through which sunshine affects productivity, with the effect appearing to be strongest for inventors working alone.

[Insert Table OA.4 about here]

Finally, in Table OA.5 we examine the effect that patent attorneys and patent examiners have on the review process. Specifically, sunshine may improve the mood of patent attorneys, who represent their client firms in preparing, filing, and prosecuting patent applications to USPTO. Although patent attorneys cannot plausibly influence patent quality directly, sunshine exposure might make them more efficient in developing the patent application from a legal standpoint, with a higher quality patent application being less likely to be sent back due to incomplete information and easier to process. As a consequence, the patent might be approved faster, resulting in the technology being patented and brought to the market sooner.

In addition to patent attorneys, sunshine could also improve the mood of outside parties in the patenting process. Patent examiners are employees of the USPTO who review patent applications to determine whether the invention in each of the applications should be granted a patent or not. Since the work of patent examiners involves certain extent of subjective judgments, mood-induced behavioral traits of patent examiners may affect firm patenting success. For example, when patent examiners are in good mood, they are more optimistic and may have an upward bias in the subjective judgment of the quality of the patent application. As a result, they are more likely to approve patent applications that are across-the-border, which leads to greater firm patent output.

In Table OA.5, we examine whether sunshine conditions have the ability to influence the patent review process or the efficiency of patent attorneys. The logic behind these tests is that while patent reviewers and patent lawyers have little impact on the quality of inventions, they do have the ability to slow down, or speed up the time it takes before a patent is granted. For patent reviewers, we examine whether sunshine around the USPTO during the patent review time has an effect on the review length of a patent. For each patent, we measure time under review, as the time between patent application and patent granting. In Panel A, we relate time under review with sunshine conditions around the USPTO during the review time.[36] We

[36] For every patent, we measure the average sunshine exposure during the time when the patent is under review, since this is the time when sunshine exposure has the ability to influence patent reviewers. Towards this end, we

control for all firm level variables pertaining to the firm the patent is assigned to, and include technology class, firm, and year fixed effects. We find that the coefficient estimate on both sunshine variables are negative and significant, meaning that during sunnier periods, patent office workers conduct their duties more efficiently, thus reducing the patent review time.

In Panel B, we relate time under review with sunshine conditions around the headquarters during the review time. Although we have no way of knowing for sure, we assume that patent lawyers work in the firm's headquarters.[37] We also assume that patent lawyers can only have an effect on the patent's quality immediately prior to application, since this is when they will be preparing the patent application. Sunshine exposure might make them more efficient in developing the patent application from a legal standpoint, with a higher quality patent application being less likely to be sent back due to incomplete information and easier to process. The results reported in Panel B show that sunshine conditions around the firm's headquarter location in the month preceding the patent application has no effect on time under review. We conclude that patent lawyers play a limited role in developing patent applications, or that their work has little impact on how quickly the patent is assessed. In Panel C, we examine whether the positive association between inventor sunshine exposure and patent value holds, even after controlling for patent review time. Using the inventor-level sample in which we calculate the average review time for the patents applied for in a given year, we find that the positive association between inventor sunshine exposure and patent value holds, even though the relation between review time and patent value is highly positive and significant. Another important implication is that although sunshine around USPTO results in patent reviewers working more efficiently, this factor does not explain the positive association between the sunshine conditions of inventors and their improved productivity.

[Insert Table OA.5 about here]

measure the sunshine conditions within a 50-kilomemeter radius of the location of the USPTO in Alexandria, Virginia.

[37] For patent attorneys, we measure the sunshine exposure within a 50-killometer radius of the firm's headquarters during the month preceding the patent application.

Table OA.1 Sunshine across the United States

	Annual Sunny Days per Month		Relative Annual Sunny Days per Month	
	Mean	Std.	Mean	Std.
Alaska	5.80	2.16	-0.51	2.10
Alabama	12.12	5.14	-0.01	3.53
Arkansas	12.07	5.46	0.01	3.25
Arizona	18.82	5.57	0.25	3.74
California	12.66	4.92	-0.23	3.28
Colorado	9.79	5.01	0.11	3.44
Connecticut	10.82	5.01	0.41	4.21
Delaware	15.32	6.22	0.22	3.21
Florida	10.79	7.12	-0.26	3.42
Georgia	13.38	4.77	-0.33	3.24
Hawaii	8.93	6.52	-0.44	2.87
Iowa	11.23	4.53	-0.23	2.31
Idaho	15.10	5.33	-0.01	2.83
Illinois	8.38	4.41	-0.57	2.46
Indiana	10.27	4.69	-0.36	2.80
Kansas	16.47	7.51	0.30	3.77
Kentucky	11.08	5.36	-0.19	2.90
Louisiana	12.65	6.58	-0.20	2.97
Maryland	8.85	4.97	-0.08	3.28
Maine	12.27	4.28	-0.81	2.22
Massachusetts	10.62	3.68	0.15	3.13
Michigan	8.69	4.92	-0.46	2.58
Minnesota	9.41	4.18	-0.19	2.57
Missouri	12.04	7.07	0.17	3.81
Mississippi	14.77	6.61	0.26	3.91
Montana	10.23	5.61	0.16	3.81
North Carolina	11.73	5.33	-0.32	3.07
North Dakota	14.66	3.59	-0.22	2.83
Nebraska	13.02	5.78	0.21	3.25
New Hampshire	7.73	3.72	-0.17	3.09
New Jersey	11.47	6.21	-0.19	3.37
New Mexico	17.12	8.46	0.08	3.77
Nevada	18.27	4.79	0.04	3.10
New York	10.11	5.54	-0.31	3.05
Ohio	8.43	4.79	-0.27	2.87
Oklahoma	14.84	4.24	-0.49	2.71
Oregon	8.78	3.92	0.02	3.26
Pennsylvania	9.73	5.46	-0.29	3.48
Rhode Island	10.18	5.48	0.31	4.23
South Carolina	15.34	7.11	-0.05	3.93
South Dakota	13.14	4.41	0.01	3.20
Tennessee	9.52	3.20	0.17	3.26
Texas	11.89	4.36	-0.46	2.96
Utah	10.76	4.73	0.57	3.83
Virginia	9.40	5.10	-0.16	3.04
Vermont	7.48	3.06	-0.35	1.96
Washington	7.18	3.05	-0.25	2.94
Wisconsin	10.18	4.36	-0.46	2.41
West Virginia	9.68	5.17	-0.39	2.92
Wyoming	19.25	9.63	0.49	3.79

This table reports the average annual number of sunny days per month for each state of the U.S., as well as the average relative annual number of sunny days per month. For each variable, the mean and standard deviation are provided. State-level figures are based on the average across all weather stations for that state in all years. The sample period is 1990 to 2007.

Table OA.2 Additional Robustness

Panel A: Full sample of all inventors employed and not employed by publically listed firms

	LnPat		*LnCit*		*LnCitPat*	
	(1)	(2)	(3)	(4)	(5)	(6)
Sunshine	0.001**		0.002***		0.002***	
	(0.00)		(0.00)		(0.00)	
Relative sunshine		0.001***		0.003		0.002
		(0.00)		(0.00)		(0.00)
Inventor fixed effects	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES
Observations	2,414,288	2,414,288	2,414,288	2,414,288	1,160,256	1,160,256
Adj R^2	0.26	0.26	0.25	0.25	0.57	0.57

Panel B: Sample of inventors not working for publically listed firms

	LnPat		*LnCit*		*LnCitPat*	
	(1)	(2)	(3)	(4)	(5)	(6)
Sunshine	0.000		0.001*		0.002***	
	(0.00)		(0.00)		(0.00)	
Relative sunshine		0.001***		0.002***		0.002***
		(0.00)		(0.00)		(0.00)
Inventor fixed effects	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES
Observations	1,384,764	1,384,764	1,384,764	1,384,764	592,183	592,183
Adj R^2	0.22	0.22	0.22	0.22	0.57	0.57

Table OA.2 (Cont')

Panel C: Sample excluding zero patents

	Ln (Patent value)	
	(1)	(2)
Sunshine	0.004***	
	(0.00)	
Relative sunshine		0.002**
		(0.00)
All controls	YES	YES
Inventor fixed effects	YES	YES
Industry fixed effects	YES	YES
Year fixed effects	YES	YES
Observations	730,636	730,636
Adj R^2	0.58	0.58

Panel D: Sample excluding inventors who have ever resided in rust belt states

	Ln (Patent value)	
	(1)	(2)
Sunshine	0.005***	
	(0.00)	
Relative sunshine		0.004***
		(0.00)
All controls	YES	YES
Inventor fixed effects	YES	YES
Industry fixed effects	YES	YES
Year fixed effects	YES	YES
Observations	801,563	801,563
Adj R^2	0.51	0.51

Table OA.2 (Cont')

Panel E: Sample excluding inventors who reside in California, Massachusetts, or New York

	Ln (Patent value)	
	(1)	(2)
Sunshine	0.005***	
	(0.00)	
Relative sunshine		0.006***
		(0.00)
All controls	YES	YES
Inventor fixed effects	YES	YES
Industry fixed effects	YES	YES
Year fixed effects	YES	YES
Observations	765,849	765,849
Adj R^2	0.57	0.57

Panel F: Sunshine and inventor productivity amongst non-relocating inventors

	Ln (Patent Value)			
	Non-Mover Sample		Non-Mover/Low-Inflow State Sample	
	(1)	(2)	(3)	(4)
Sunshine	0.004***		0.002*	
	(0.00)		(0.00)	
Relative sunshine		0.003**		0.002*
		(0.00)		(0.00)
All controls	YES	YES	YES	YES
Inventor fixed effects	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Observations	724,607	724,607	410,624	410,624
Adj R^2	0.53	0.53	0.60	0.60

Table OA.2 (Cont')

Panel G: Sample of inventors residing outside of headquarter location

	Ln (Patent Value)			
	Different county		Different state	
	(1)	(2)	(3)	(4)
Sunshine	0.003***		0.004***	
	(0.00)		(0.00)	
Relative sunshine		0.003**		0.004***
		(0.00)		(0.00)
All controls	YES	YES	YES	YES
Inventor fixed effects	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Observations	799,684	799,684	661,782	661,782
Adj R^2	0.57	0.57	0.62	0.62

Panel H: Sample of dispersed inventors with firm fixed effects

	Ln (Patent value)	
	(1)	(2)
Sunshine	0.010***	
	(0.00)	
Relative sunshine		0.007***
		(0.00)
All controls	YES	YES
Firm fixed effects	YES	YES
Industry fixed effects	YES	YES
Year fixed effects	YES	YES
Observations	261,375	261,375
Adj R^2	0.52	0.52

This table presents robustness tests to the baseline results reported in Table 2 of the paper. The dependent variable used is indicated at the top of each panel. Standard errors are corrected for clustering at the inventor-level. ***, **, and * denote significance at the 1%, 5%, and 10% significance levels, respectively.

Table OA.3 Exploitative/Exploratory Patents and Patent Quality

	Top10	*NTop10Cited*	*Ntop90Cited*	*LnCit*
	(1)	(2)	(3)	(4)
Exploit	0.008***	-0.003	-0.002	0.051***
	(0.00)	(0.01)	(0.00)	(0.00)
Explore	-0.021***	0.005**	0.004	-0.116***
	(0.00)	(0.00)	(0.00)	(0.01)
All controls	YES	YES	YES	YES
Technology class fixed effects	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Observations	424,192	424,192	424,192	422,881
Adj R^2	0.05	0.14	0.03	0.39

This table presents results relating exploitative and exploratory patents with a number of quality indicators. The tests are conducted at the patent level. Columns (1) to (3) are linear probability models, where the dependent variable tables a value of 1 or zero, depending on how the patents forward citations compare with similar patents. ***, **, and * denote significance at the 1%, 5%, and 10% significance levels, respectively.

Table OA.4 Teams' Sunshine Exposure and Patent Value

	Ln (Patent value)			
	(1)	(2)	(3)	(4)
Team sunshine	0.002***			
	(0.00)			
Team relative sunshine		0.001		
		(0.00)		
Sunshine			0.000	
			(0.00)	
Sunshine × All positive			0.004***	
			(0.00)	
Relative sunshine				-0.007***
				(0.00)
Relative sunshine × All positive				0.023***
				(0.00)
All controls	YES	YES	YES	YES
Inventor fixed effects	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Observations	677,196	677,196	677,196	677,196
Adj R^2	0.54	0.54	0.54	0.54

This table presents regressions results on how team characteristics influence patent value. The tests are conducted on the inventor-level dataset limited to those inventor-years where at least one patent was developed in a team. Standard errors are corrected for clustering at the inventor-level. ***, **, and * denote significance at the 1%, 5%, and 10% significance levels, respectively.

Table OA.5 Sunshine Exposure and Patent Processing Times

Panel A: Sunshine around patent office during review

	Ln(Days under review)	
	(1)	(2)
Sunshine during review	-0.012***	
	(0.00)	
Relative sunshine during review		-0.032***
		(0.00)
All controls	YES	YES
Technology class fixed effects	YES	YES
Firm fixed effects	YES	YES
Year fixed effects	YES	YES
Observations	230,022	230,022
Adj R^2	0.35	0.35

Panel B: Sunshine around firm's headquarters prior to patent application

	Ln(Days under review)	
	(1)	(2)
Pre-application sunshine	-0.000	
	(0.01)	
Pre-application relative sunshine		0.000
		(0.01)
All controls	YES	YES
Technology class fixed effects	YES	YES
Firm fixed effects	YES	YES
Year fixed effects	YES	YES
Observations	273,336	273,336
Adj R^2	0.26	0.26

Panel C: Patent value after controlling for average patent review time

	Ln(Patent Value)	
	(1)	(2)
Sunshine	0.007***	
	(0.00)	
Relative sunshine		0.005**
		(0.00)
Ln(Days under review)	0.081***	0.081***
	(0.01)	(0.01)
All controls	YES	YES
Inventor fixed effects	YES	YES
Industry fixed effects	YES	YES
Year fixed effects	YES	YES
Observations	1,029,524	1,029,524
Adj R^2	0.56	0.56

This table presents the results on the effect of patent office reviewers and corporate patent attorneys on patent review times. The sample period is 1990 to 2007. The regressions are conducted on a patent-level dataset. Panel A relates the average sunshine conditions around the patent office during each patent's review and the review time. Panel B relates sunshine conditions around the firm's headquarters in the month preceding the patent application and the patent review time. Panel C relates inventor's sunshine exposure with patent value after controlling for each patents time under review. Standard errors are corrected for clustering at the patent level. ***, **, and * denote significance at the 1%, 5%, and 10% significance levels, respectively. Detailed variable descriptions can be found in the Appendix.