Is Working from Home a Way of Adaptation to Climate Change?

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Abstract

The increase in the intensity and frequency of extreme weather events is one of the consequences of global warming. Investigating the impacts of extreme weather on people's work patterns in the context of work flexibility helps us to better evaluate and adapt to climate change. This paper examines how extreme weather changes people's work patterns theoretically and empirically. The theoretical framework models people's decision of where and for how long to work, and predicts how the decision changes in the presence of extreme weather. The empirical analysis is based on data from American Time Use Survey linked with the Storm Database from NOAA. The results show that job flexibility plays an important role in shaping people's adaptation to extreme weather. Extreme weather events decrease the probability of going out to work by 12.2% on average. For workers who have the flexibility to work at home, during extreme events, about 45 minutes of work time is shifted from their workplace to their home on business days. However, no such location adaptation is detected for workers with little job flexibility. In terms of total work time, extreme weather events reduce labor supply by a small amount of 9 minutes, with this time reallocated to leisure. These findings suggest that job flexibility policies, such as working at home, could be an effective tool of adaptation to climate change because it offers a choice to avoid the risks associated with commuting to work under extreme weather conditions.

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Keywords: climate change, extreme weather, job flexibility, work at home

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I. Introduction

Despite the many efforts to reduce greenhouse gas emissions, the world is not on track to meet its mitigation goals. "Committed emissions" from existing and proposed infrastructure in the energy sector alone already represent more than the entire carbon budget to limit mean warming to 1.5 °C with 50-66% probability (Tong et al., 2019). It is time to seriously consider implications and adaptations for climate change, which seems to be inevitable now.

Among the behavioral adaptations to climate change, shifting work patterns stands out as an effective way to avoid working under extreme weather conditions (Day et al., 2019). Shifting work patterns could be a feasible adaptation if flexibility in work location or work time becomes a regular practice. The advance of telecommunication technology supports alternative work arrangements such as working from homes (Vazquez and Winkler, 2019). According to the American Time Use Survey (ATUS) data, about 7.5% of total work time was spent at the respondent's home in 2003. This number rose to 12.5% in 2019. The work time that takes place outside of the respondents' workplace contributes to 17.5% of the total work time.

Work flexibility options have drastically changed during the recent COVID-19 pandemic. Businesses have been forced to adopt new paradigms and technologies facilitating working from home. Many predict that the pandemic might induce shifting to a new normal, where the work patterns will continue to be highly flexible even after the pandemic is over. Although the promotion of work flexibility options was meant to resolve the COVID-19 crisis, not climate change, it does make work flexibility a much more feasible and promising potential adaptation solution to climate change than ever before.

The impact of extreme weather on people's work patterns has not been extensively explored. In particular, there are two gaps in the existing literature. First, previous studies have been focused on the effects of rising temperatures on economic productivity, but have rarely studied how job flexibility can serve as an adaptation solution. Some studies examined industry-wide or economy-wide productivity impacts, and some others tested how individual worker's productivity is affected.[1] Although the existing literature has studied the impact of adverse weather conditions

[1] See Kjellstrom et al. (2016); Costa et al. (2016); Roson and Sartori (2016); Dunne et al. (2013) for economic-wide impacts, and Graff Zivin and Neidell (2014); Connolly (2008); Heal and Park (2013); Hsiang (2010) for individual impacts.

on work productivity, few studies have looked at the effect of potential adaptation strategies to mitigate such impact.

The second gap is that most existing literature that discusses the impact of weather conditions on people's work patterns only looks at temperature and precipitation, and does not cover other extreme weather conditions. [2] While the implications of high temperatures are widely explored, little has been said on other consequences of climate change. However, the impacts of climate change are multifaceted, extending well beyond an increase in temperature. One of the major consequences is the increase in the frequency and magnitude of extreme weather events. Climate change causes some areas on the planet to become drier, making them more vulnerable to drought and wildfires. At the same time, it makes some other areas becoming significantly wetter, which means more heavy rains, storms, and floods. The rising sea level also results in more frequent coastal floods.

It is therefore necessary to investigate whether and how such work flexibility options, as potential adaptation solutions, affect people's reactions to adverse weather conditions including and beyond heat and precipitation. In particular, the following questions remain to be explored. The first and foremost is to what extent people would take advantage of job flexibility options to mitigate the impact of adverse weather conditions by working at home, and, if so, whether these policies induce "slacking at home", *i.e.* decreasing the total working hours. The second is how the influence of job flexibility compares with other heterogeneity factors such as industries, genders, etc. It is also necessary to explore through which mechanism the work flexibility options influence people's working patterns – whether people decrease their time working at the workplace because they voluntarily avoid going out to work, or because they work for a shorter time period at their workplace due to factors like fatigue. These are important questions for understanding the effectiveness of work flexibility options as an adaptation strategy.

This paper estimates the impacts on individuals' work time and work location of extreme weather, which will likely become more frequent because of global warming. It furthers the discussion of climate impacts on time allocation by being the first paper to empirically evaluate

[2]Even in extreme weather literature, many look at the extremes of temperature and precipitation (Wang et al., 2017; Powell and Reinhard, 2016). Cachon et al. (2012) is among the rare studies that consider multiple extreme weather events such as wind, rain, snow, heat, and cold.

job flexibility as an adaptation option. This paper is also among the few studies to examine extreme weather conditions beyond heat and precipitations, thus filling the gap in the literature.

The analysis comprises a theoretical model and an empirical analysis. The theoretical model describes the individual's decision process of where and for how long to work, and derives the change of people's work time at the workplace both at the extensive margin (the change in the number of people who work at the workplace) and at the intensive margin (the change in work hours at the workplace among those who work at the workplace). The model predicts that under extreme weather, the total work time at the workplace decreases unambiguously at the extensive margin, but may decrease or increase at the intensive margin, depending on what exogenous variables are affected most by the extreme weather. As a result, people are more likely to take the advantage of location flexibility than time flexibility to mitigate extreme weather impacts.

The empirical analysis tests the model predictions based on the 2004-2019 NCDC Storm Event data linked with the ATUS data, which records individual respondents' daily time allocations of different activities. Furthermore, the ATUS 2017-18 Leave and Job Flexibilities Module collected information on job flexibility in terms of location (whether the respondent can work at home or not) and job flexibility in terms of time (whether the respondent has control of his/her work schedule). Using data from this supplementary module, I capture different responses to extreme weather events between employees with high flexibility and their counterparts with low flexibility.

The empirical results show that job flexibility plays a decisive role in determining how people adapt to adverse weather conditions. While the findings suggest a moderate decline in total work time during extreme weather days in general, further analysis reveals significant heterogeneity in the transition of work location based on job flexibility. When their residential areas are affected by extreme weather, workers with the flexibility to work at home reduced work time at their workplace by as much as 45 minutes on average, and this reduction is almost exactly compensated by the increased work hours at home. For workers that can change their work schedule, work time at their workplace is reduced by about 35 minutes on average, and work time at home increases by about 20 minutes. In contrast, no statistically significant response is found among workers with no flexibility in choosing work locations or schedules. This paper also presents the results comparing high-risk v.s. low-risk industries based on climatic exposure, and the results for males and females, respectively. Neither the industrial factor nor the gender factor is as important as job flexibility in terms of shaping the worker's adaptation to extreme weather.

The empirical analysis further explores the intensive margin and extensive margin of the reduced work time at the workplace during extreme weather days. The work time loss in the workplace is almost entirely due to workers' choice to work at home and not going out at all. I find little evidence supporting that workers who already go out to work shorten their time at the workplace at the intensive margin. This result is not consistent with the explanation in previous temperature-based literature that fatigue from prolonged exposure to heat could be the main reason for the decrease in work time (Graff Zivin and Neidell, 2014). Instead, the findings in this paper suggest that the reason for time loss in work time in the workplace is more likely to be the avoidance of traveling so as to keep safe from being exposed to extreme weather.

The remainder of this article is organized as follows. Section II reviews the relevant literature. Section III discusses the theoretical framework. Section IV describes the data, and Section V presents the empirical strategy. The results are discussed in Section VI. Section VII concludes the paper.

II. Related Literature

A. Hypotheses behind adaptation to adverse weather conditions

In order to investigate how job flexibility impacts people's work patterns in the presence of extreme weather conditions, this paper follows two steps. First, it empirically studies how people change their work patterns as an adaptation to extreme weather with an emphasis on the role of job flexibility in shaping people's behavior. Work patterns refer to not just the duration of work time, but also where work time take place. In other words, the adaptation behavior can be either a change of total work hours or a change in locations where the work time is done.

The second step is to explore possible explanations behind these adaptation behaviors, and look for further empirical evidence that supports or rejects these explanations. One of the potential explanations, provided by Connolly (2008), is based on the finding that rainy days shift people's time from leisure to labor. The study proposed a model of inter-temporal substitution of labor supply in which the enjoyment of leisure decreases during bad weather and thus leisure is substituted by labor. Workers might want to modify their work schedule to work more during bad weather, so as to take advantage of good weather conditions for leisure. On the contrary, the findings by Graff Zivin and Neidell (2014) show that temperature increases at the higher end of the distribution largely reduces the work hours in industries with high exposure to climate, with most of this time allocated to indoor leisure. Graff Zivin and Neidell (2014) hypothesize that adverse weather conditions cause fatigue and cognitive impairment, which then decreases labor supply.[3]

One of the findings of this paper in the first step is that people would shift their work time from working at their workplace to working from home. Based on this finding, I propose a third explanation, namely, that the adaptation to adverse weather conditions is driven by people's voluntary avoidance of exposing oneself to danger during travel. The extreme weather events included in the dataset are either very severe in scale or have caused fatalities, injuries, significant property damage, or economic loss. It is possible that people change their work location not because of the decline in comparative utility of labor versus leisure, or because of productivity impacts, but rather due to the incentive to avoid climate exposure during extreme weather so as to reduce the risks and trouble of commuting for work. This is similar to the situation in the COVID-19 pandemic where people are working from home to keep safe from virus exposure. I further probed this hypothesis by identifying whether the work time reduction comes from people who did not travel to work or from people who shortened their work time after traveling to work.

B. Job Flexibility

This paper contributes to the growing literature on job flexibility. The last decade has witnessed the rise in alternative work arrangements (Katz and Krueger, 2019). About 10% of US employees regularly worked from home in 2015 (Bloom et al., 2015). A branch of literature explores the explanation behind this trend. Goldin and Katz (2011) ascribes the increase in workplace flexibility to the increase in the scale of operations, the shifts to corporate ownership

[3]See González-Alonso et al. (1999) and Hancock et al. (2007) for evidences on temperature and performance.

of the business, and the increased numbers of working women. Vazquez and Winkler (2019) find a positive correlation between information and communication technologies (ICT) and job flexibility. Another branch of literature tries to identify who are working from home and if there are compensating wage differentials associated with the benefit of flexibility. It is speculated that women, who are more likely to take the role of caregivers, tend to choose jobs with more flexibility compared to men. However, there is no evidence supporting more flexible schedules for women than men (McCrate, 2005; Schaffer and Westenberg, 2019). Instead, high authority employees, white employees (McCrate, 2005) and high-skill workers (Spreitzer et al., 2017) are found to have more job flexibility. Older Americans have a strong willingness to work if jobs with high flexibility are offered (Ameriks et al., 2020). Empirical research that is based on survey data finds little or no evidence of compensating wage differentials for job flexibility (McCrate, 2005; Schaffer and Westenberg, 2019; White, 2019). On the other hand, Mas and Pallais (2017) adopted a discrete choice experiment in the employment process for a national call center and estimated that the average worker is willing to give up 8 percent of wages for the option to work from home.

This paper is also closely related to the stream of literature that estimates the impact of job flexibility on job performance and satisfaction. Bloom et al. (2015) and Choudhury et al. (2020) find that geographic flexibility increases productivity. Moen et al. (2016) find that workers' greater control of work time can reduce burnout, perceived stress, and psychological distress, and can increase job satisfaction. However, these studies do not consider the effectiveness of job flexibility under sudden adverse conditions like extreme weather events. This research fills this gap and investigates whether and how flexible work policies change people's response to weather conditions. It helps to shed some light on the mechanism of why job flexibility benefits productivity and satisfaction.

III. Theoretical Framework

Consider the following model where an individual worker needs to make a two-step work decision. In the first step, the worker would decide where to work for the day, either from home or on their workplace. In the second step, the worker would decide how long to work for the day.

Formally, if the individual works at the workplace, the decision on the work time is made by solving the following optimization problem:

$$\max_{L,N,I} U(L, I) \tag{1}$$

subject to the time constraint and the budget constraint

$$L + N + m \leq \bar{n}, \tag{1a}$$

$$I \leq (w - c_w)N - f + e, \tag{1b}$$

where L is the total number of hours spent on leisure; N denotes the total number of hours spent on work; I is the net income for the day; m denotes the time spent on commuting; $\bar{n}$ denotes the total number of hours in a day. w is the wage per output. The output per hour is normalized to 1 when the individual is working at their workplace. c_w is the marginal cost of working at the workplace, which includes the risk of working at their workplace, such as fatigue, safety threats, deterioration in health, *etc.*; f is the fixed cost of working at the workplace, which includes costs and risks of commuting, such as transportation fares, parking fees, safety threats, *etc.*; e denotes the endowment, or wealth prior to the day.

$U(L, I)$ is the utility function, which reflects a trade-off between leisure and income earned by working. The utility function satisfies the following assumptions

$$U_L > 0, \quad U_I > 0, \quad U_{LL} < 0, \quad U_{II} < 0, \quad U_{IL} > 0. \tag{2}$$

(1a) is the time constraint, which stipulates that the total number of hours spent on all the activities cannot exceed the total number of hours in a day. (1b) is the budget constraint, which defines the net income.

On the other hand, if the individual works at home, the utility maximization problem becomes

$$\max_{L,N,I} U(L, I) \tag{3}$$

subject to

$$L + N \leq \bar{n}, \tag{3a}$$

$$I \leq (w - c_h)\alpha N + e, \tag{3b}$$

where $\alpha \in [0, 1]$ is the efficiency discount factor of working from home; c_h is the marginal cost of working from home. I assume that on a regular day

$$c_h = c_w < w. \tag{4}$$

Comparing the problems described in (1) and (3), it can be observed that working from home does not have the commuting costs (m and f), but suffers from an efficiency loss. The output per hour is α when the person is working at home. α reflects the adaptability to working from home of different occupations. For occupations whose duties can barely be fulfilled at home, such as construction workers and restaurant service workers, α is close to 0; for occupations whose duties can mostly be performed at home, such as social science researchers and software developers, α is close to 1.

Denote U_w^* as the optimal utility if the worker chooses to work at the workplace; $U_h^*(\alpha)$ as the optimal utility in (3), as a function of α. It can be shown that $U_h^*(\alpha)$ monotonically increases with α, because the higher the α, the less strict the constraint (3b). It can also be shown that

$$U_h^*(1) > U_w^*. \tag{5}$$

This is because when $\alpha = 1$, constraint (3b) is strictly looser than constraint (1b). I further assume that

$$U_h^*(0) < U_w^*, \tag{6}$$

which essentially assumes that for jobs that cannot be performed at home at all, working on site is a better option than resting at home on a normal day.

As can be implied from (5) and (6) combined with the monotonicity of $U_h^*(\alpha)$, there exists an α^*, such that

$$
\begin{aligned}
&\alpha > \alpha^* \quad \Rightarrow \quad U_h^*(\alpha) > U_w^* \quad \Rightarrow \quad \text{The individual works from home,} \\
&\alpha < \alpha^* \quad \Rightarrow \quad U_h^*(\alpha) < U_w^* \quad \Rightarrow \quad \text{The individual works at the workplace.}
\end{aligned} \tag{7}
$$

Now assume that the entire population has all the same exogenous variables but α, which is distributed randomly within $[0, 1]$. Then α^* essentially describes the proportion among the population that chooses to work from home on that day. The lower the α^*, the more people would choose to work from home.

Suppose that extreme weather can change the following exogenous variables: 1) a higher commuting time m, 2) higher commuting cost f, and 3) a higher marginal cost of working at the workplace c_w (still satisfying $c_w < w$). In what follows, I would like to study how these changes would change the work time allocation at the extensive margin, *i.e.* whether more or fewer people would choose to work from home, as well as at the intensive margin, *i.e.* what is the change in work time for those who work from home and those who still work at the workplace.

The Extensive Margin The extensive margin can be derived by computing the derivatives of α^* over the aforementioned exogenous variables. α^* is implicitly defined by $U_h^*(\alpha^*) = U_w^*$. According to the implicit function theorem, for an exogenous variable x ($x \in \{m, f, c_w\}$),

$$
\frac{\partial \alpha^*}{\partial x} = \frac{\partial U_w^*/\partial x - \partial U_h^*/\partial x}{\partial U_h^*/\partial \alpha^*} = \frac{\partial U_w^*/\partial x}{\partial U_h^*/\partial \alpha^*}, \tag{8}
$$

where the denominator on the right-hand side is positive. The second equality is due to the fact that $\{m, f, c_w\}$ do not show up in the maximization problem (3), and hence $\partial U_h^*/\partial x = 0$. According to the Envelope Theorem

$$
\frac{\partial U_w^*}{\partial m} = -\lambda_{w1}^* \le 0, \quad \frac{\partial U_w^*}{\partial f} = -\lambda_{w2}^* \le 0, \quad \frac{\partial U_w^*}{\partial c_w} = -N_w^* \lambda_{w2}^* \le 0, \tag{9}
$$

where λ_{w1}^* and λ_{w2}^* are Lagrange multipliers for constraints (1a) and (1b) respectively which are not greater than zero according to the Karush–Kuhn–Tucker (KKT) conditions; N_w^* denotes the optimal N if the worker chooses to work at the workplace. Combining (8) and (9), it can be concluded that α^* will decrease as m, f and c_w increase, which means the number of people who work from home will unambiguously increase in the presence of extreme weather.

The Intensive Margin Here I would like to investigate whether those who do work at the workplace during the extreme weather would increase or decrease their work time at the workplace, which can be achieved by computing the derivatives of N_w^* over the aforementioned exogenous variables. According to the first-order conditions of the maximization problem (1),

$$-U_L + (w - c_w)U_I = 0. \tag{10}$$

Taking its derivative over an exogenous variable x ($x \in \{m, f, c_w\}$) gives

$$(-U_{LL} + (w - c_w)U_{IL})\frac{\partial L_w^*}{\partial x} + (-U_{LI} + (w - c_w)U_{II})\frac{\partial I_w^*}{\partial x} + \frac{\partial (w - c_w)}{\partial x}U_I = 0, \tag{11}$$

where L_w^* and I_w^* denote the optimal L and I if the worker chooses to work at the workplace.

Let's first consider the exogenous variable m. According to constraints (1a) and (1b), it follows that

$$\frac{\partial L_w^*}{\partial m} = -1 - \frac{\partial N_w^*}{\partial m}, \quad \frac{\partial I_w^*}{\partial m} = (w - c_w)\frac{\partial N_w^*}{\partial m}. \tag{12}$$

Combining equations (11) and (12), we have

$$\frac{\partial N_w^*}{\partial m} = \frac{-U_{LL} + (w - c_w)U_{IL}}{U_{LL} - 2(w - c_w)U_{IL} + (w - c_w)^2 U_{II}} < 0, \tag{13}$$

which implies an increase in commute time will reduce the work hours, because the time constraint gets tighter.

Next, consider the exogenous variable f. According to constraints (1a) and (1b), it follows that

$$\frac{\partial L_w^*}{\partial f} = -\frac{\partial N_w^*}{\partial f}, \quad \frac{\partial I_w^*}{\partial f} = (w - c_w)\frac{\partial N_w^*}{\partial f} - 1. \tag{14}$$

Combining equations (11) and (14), we have

$$\frac{\partial N_w^*}{\partial f} = \frac{-U_{LI} + (w - c_w)U_{II}}{U_{LL} - 2(w - c_w)U_{IL} + (w - c_w)^2 U_{II}} > 0, \tag{15}$$

which implies that an increase in commute cost will increase the work hours, because the individual has to work longer to (partially) recover the increased cost.

Finally, consider the exogenous variable c_w. According to constraints (1a) and (1b), it follows that

$$\frac{\partial L_w^*}{\partial c_w} = -\frac{\partial N_w^*}{\partial c_w}, \quad \frac{\partial I_w^*}{\partial c_w} = (w - c_w)\frac{\partial N_w^*}{\partial c_w} - N_w^*. \tag{16}$$

Combining equations (11) and (16), we have

$$\frac{\partial N_w^*}{\partial c_w} = \frac{(-U_{LI} + (w - c_w)U_{II})N_w^* + U_I}{U_{LL} - 2(w - c_w)U_{IL} + (w - c_w)^2 U_{II}} \quad \text{(ambiguous sign)}, \tag{17}$$

which implies an increase in the marginal cost of working at the workplace will have an ambiguous impact on work hours at the workplace. On one hand, there exists a substitution effect for more leisure because the benefit of working decreases. On the other, there exists an income effect where the individual needs to work longer to recover the increased cost. The sign of equation (17) depends on which of the two terms in the numerator dominates. If the first term dominates, then the derivative will be positive; otherwise, it will be negative. One important determinant of the sign is the magnitude of c_w. If c_w is still small despite the increase, then equation (17) is more likely to be positive. If c_w is large enough, then equation (17) will be negative.

To sum up, the intensive margin of work time at the workplace N_w^* decreases with the commuting time m, increases with the fixed cost associated with working at the workplace f, and change in an ambiguous direction with the marginal cost of working at the workplace c_w. Because extreme weather causes m, f, and c_w to increase, its intensive margin impact is ambiguous.

Model Predictions As the model predicts, the extreme weather will unambiguously reduce the work time at workplace at the extensive margin, *i.e.* fewer people will work at their workplace.

However, the extreme weather has an ambiguous effect at the intensive margin, *i.e.* it is unclear whether people who still work at the workplace will increase or decrease their work time in response to the extreme weather. The intuition behind the ambiguity (instead of a definite decrease at the intensive margin) is that extreme weather primarily influence the commuting costs more than the marginal cost of working at the workplace, with a few exceptions for outdoor occupations and for very serious weather conditions, and therefore it will not impact people's work as much once they get to their workplace. This is different from some other public crises, such as COVID-19, where the major effect is the increase in the marginal cost of working at the workplace (*e.g.* increased exposure to the disease) and thus the hours at workplace are more likely to reduce at the intensive margin. The contrast between the extensive and intensive margin effects of extreme weather suggests that location flexibility plays a much clearer role in mitigating the effect of extreme weather than time flexibility does. In the following sections, I will further explore these propositions empirically.

IV. Data

A. The American Time Use Survey

The American Time Use Survey (ATUS) provides the time variables and job flexibility variables for this paper. ATUS collects information about how and where Americans spend their time by recording in details the respondents' activities on the diary day, which is the previous day before the interview day. The data files include information from more than 210,000 interviews conducted from 2003 to 2019. The interview dates are spread through out the year and cover most of the days since 2003. Each respondent is interviewed only once about his/her time use, and therefore, the data is pooled cross-sectional. The ATUS sample is drawn from the Current Population Survey (CPS), which allows researchers to link ATUS to CPS data files. From this eligible group, households are selected that represent a range of demographic characteristics. One person aged 15 or over is randomly chosen to attend the ATUS interview, which takes place 2-5 months after the household's final CPS interview. The CPS data files provide demographic information, including age, gender, education, and employment, some of which I use as control variables in the empirical model.

The ATUS also provides the county and the core-based statistical area (CBSA) of the individual's residential location, which can be linked to weather variables. However, for privacy protection, location information is not published for the geographic divisions that have a small population. As a result, only about 40% of the observations report the county codes, and about 70% of them report the CBSA codes. This paper excludes the observations that only have geographic information at the state level. County is used as the primary geographic division. When the CBSA information is published but the county information is not, I use CBSA as a comparable geographic division. The final sample covers 613 divisions, including 407 counties and 206 CBSAs.

Following Connolly (2008), this paper looks at the total minutes spent in three categories of activities: work, leisure, and home production. Although this paper mainly focuses on work time, it also considers the impacts on other activities in order to draw a full picture of how extreme weather affect time allocation. Work time only counts the time spent in the respondent's main job and excludes the time spent in part-time jobs and other income-generating work, etc. This is because the relationship between work time and job flexibility in the respondent's main job will be discussed in section VI. It is more consistent to maintain both the work time variables and the job flexibility variables specific to the main job. According to where the activity takes place, work time is further divided into 3 sub-categories: work at the workplace, work at home, and work at other places. Details of defining the time use variables are listed in Table A1 of the appendix. The following activities are excluded from the analysis: sleeping, eating, personal care, personal activities, education, voluntary work, and transportation. Therefore, the three activity categories considered in this study do not add up to 24 hours, and the effect of the extreme weather on them may not add up to zero either.

In 2017 and 2018, the Leave and Job Flexibilities Module was fielded as a supplement of ATUS. It includes questions on whether the respondent can work from home as part of the main job, and whether the respondent can change the work schedule. This information is used to test whether job flexibilities help people adapting to extreme weather.

B. The Storm Event Database

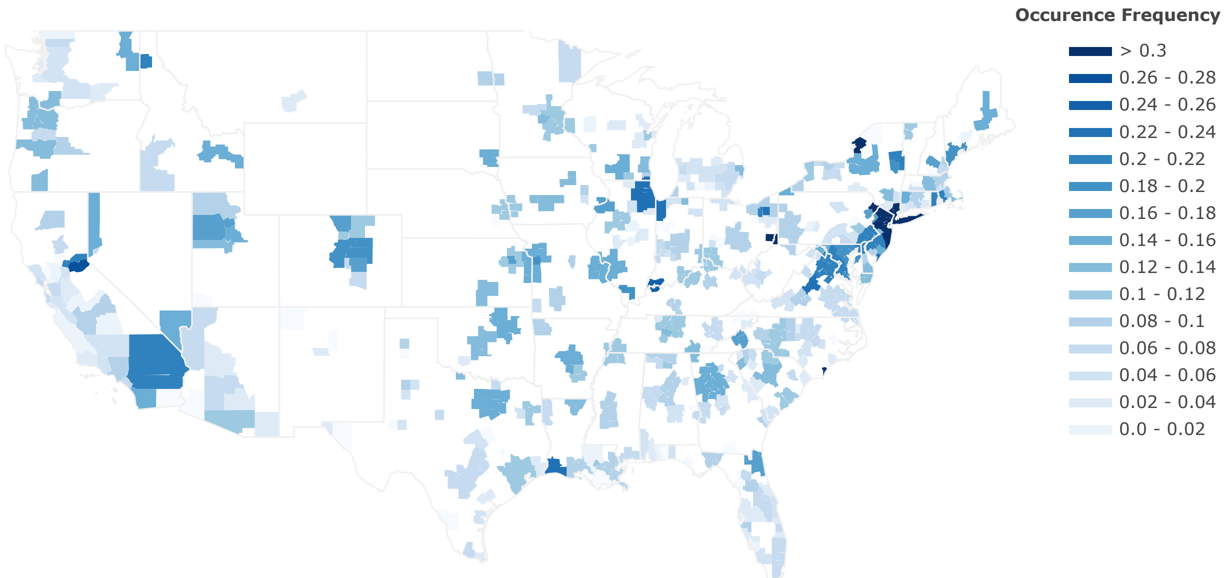
The Storm Event Database is operated by the National Oceanic and Atmospheric Administration (NOAA), which documents the occurrence of storms and other significant weather phenomena having sufficient intensity to cause loss of life, injuries, significant property damage, and/or disruption to commerce. It gathers information from the National Weather Service (NWS), and also the media, law enforcement and/or other government agencies, private companies, individuals, etc. The database contains data from 1950 to 2020. Due to the changes in the data collection and processing procedures over time, the definitions and recording criteria are not consistent across different time periods. However, it is consistent within the latest period, which is from 1996 to the present. During this period, NOAA recorded 48 types of events as defined in NWS Directive 10-1605. The event types that I consider include heat, heavy rain, heavy snow, thunderstorm wind, winter storm, flood, wildfire, strong wind, hail, etc. Excluded from my sample are event types that affect only marine areas, such as marine hurricanes and marine tropical storms. This is because the storm event data is merged with ATUS data using the respondent's residential location, which is always terrestrial. Table A2 presents the full list of events included in this research and their frequency in the sample.

An extreme event is reported in the Storm Event Data whenever the corresponding weather measurement(s) meet or exceed a threshold. For some extreme events, the threshold is a unified standard defined by the NWS. For example, hail 3/4 of an inch or larger in diameter will be entered as an extreme event. This standard does not vary with the location of the hail. For other extreme events, the threshold is locally/regionally established to accommodate climate heterogeneity of different regions. Table A3 in the appendix lists the definition and recording criteria of the 15 most frequent event types in the sample.[4] If the event causes fatalities, injuries, significant property damage, or economic loss, it will be included in the data even when it does not meet the warning criteria. If the event is considered significant, it will be entered into Storm Data, even if it only affected a small area.

For each recorded event, the Storm Data provides the begin time, end time, and the affected

[4] Detailed definitions of all event types can be found in NWS Directive 10-1605.

Figure 1 : Geographic distribution of extreme weather events occurrence frequency rate recorded in the sample. Blank regions indicate no data coverage.



area by NWS public forecast zone. Usually, one county or CBSA consists of multiple forecast zones. The variable of interest in this paper is a dummy variable indicating whether the respondent is affected by extreme weather on the diary day. An observation from ATUS is marked as affected by an event if 1) the diary day overlaps with the time between the begin time and the end time of the event; and 2) at least one of the forecast zone within the residential county/CBSA is reported to be affected by the event. By such definition, the size of a respondent's residential county/CBSA is positively correlated with the frequency of extreme events. However, such heterogeneity can be addressed by including county/CBSA fixed effects in all regressions.

C. Merged Data

I match the ATUS data with the Storm Event data by date and region (county/ CBSA). The merged data set keeps only the respondents that are employed. Eventually, the merged dataset includes 90,722 observations, with 44,427 on business days and 46,295 on non-business days.[5] Summary statistics are shown in Table 1. On business days, people spend about 6.5 hours

[5]The number of observations in business days v.s. non-business days are almost even, which is a deliberate survey design of ATUS.

on working, 3.3 hours on leisure, and 2.3 hours on home production. For non-business days, the number is 1.6 hours on working, 5.6 hours on leisure, and 3.6 hours on home production. People's schedules are very different for business days and non-business days. Therefore, the model is tested on these two groups separately and combined. The main results reported in this paper are based on business days, because these days are found to be most affected by extreme weather. Nonetheless, section VI.D will use the full sample and compare the result of business/non-business days.

The occurrence frequency of extreme weather days is about 9%. The geographic distribution of extreme weather events occurrence frequency rate in the sample is described in Figure 1. Recall that as long as the respondents' residential county/CBSA is affected by one of the event types, the corresponding diary days are marked as extreme weather days. Table A3 presents the frequencies of each event type separately.

On business days, 87% of work time occurs at the respondent's workplace, and 8% of the work time takes place at home. For non-business days, work time at the workplace is 78%, and the proportion of work time at home doubles to 16%. In terms of job flexibility, 35% of the respondents report that they can work at home as part of the job, and 58% of the respondents have flexibilities in changing their work schedules. [6]

V. Empirical Strategy

A. Baseline Model

To study the relationship between extreme weather and time allocation, the following equation is estimated with OLS:

$$T_i = \alpha + \beta E_{c(i),t(i)} + \gamma X_{c(i),t(i)} + D_{t(i)} + \delta_{c(i)} + \varepsilon_i, \tag{18}$$

[6] The work time statistics are based on the full sample, 2004-2019, while the job flexibility statistics are based on the sample of 2017-2018.

where T_i is a vector of time variables, measuring the respondent's total minutes spent in different categories of activity on the diary day. Three main categories are included: work, leisure and home production.[7] The analysis will be focused on three sub-categories of work time according to work location: work at workplace, work at home, and work at other places.

The independent variable of interest is $E_{c(i),t(i)}$, a binary indicator of whether the respondent's residential region is affected by any of the extreme weather events on the diary day. $c(i)$ marks the residential county of the individual i, and $t(i)$ marks the date of observation for the individual i. $X_{c(i),t(i)}$ controls for individual characteristics, as listed in Table 1. In the baseline regressions, $X_{c(i),t(i)}$ includes industry-occupation fixed effects. I will also report the results that are not fixed for industry-occupation. $D_{t(i)}$ represents a series of time-related fixed effects, including year, month, and day of the week. $\delta_{c(i)}$ is the region fixed effect, including 407 counties and 206 core-based statistical areas (CBSAs). The standard errors are robust to heteroskedasticity.

The coefficient of interest, β, measures the impact of extreme weather events on people's time allocation. β identifies the causal relationship between weather and time allocation because the occurrence of extreme weather is a classic natural experiment. Reverse causality is unlikely because it is unlikely that people's decisions of activities affect the weather of the day. [8] There may arise concerns about regional or chronological unobserved heterogeneity. For example, suffering more frequent coastal floods and typhoons, the coastal counties may, at the same time, have work time patterns that are very different from inland counties due to their regional social and economic characteristics. β could also pick up some seasonal shifting of work time and extreme weather. These concerns should be addressed by the fixed effects of year, month, and county/CBSA that are included in all major regressions.

Although the effect of different types of extreme weather could be different, the empirical strategy in this paper estimates the aggregate impact for all extreme event types reported in the Storm Event Data which is captured by the coefficient vector β. This is because extreme weather events are rare. Even for the most common event type, thunderstorm wind, the occurrence rate is as low as 2%. The occurrence rate for all the extreme weather types combined is 9% in the

[7]Leisure includes social activities, sports, relaxing, etc. Home production includes activities such as preparing for food, grocery shopping, and caring for others. Please check Table A1 for the details in time variables definition.

[8]The same argument for causal relationship applies to the estimated impacts from extreme weather on people's decisions on going out or not in Section VI.E.

sample. The variation in the treatment variable will be too small to support the estimation if different event types are distinguished. On the other hand, the low treatment rate indicates that the events included in the treatment are very severe, which differentiates this work from previous studies that focus on more common weather conditions such as high temperature and precipitation. For comparison, I also followed the literature and used rainy days (Connolly, 2008) instead of extreme weather as the treatment variable. As shown in Table A4, the magnitude of the impacts of rainy days is smaller compared to the extreme weather events.

B. Heterogeneity: Job Flexibility and More

The baseline model (Equation (18)) only captures the overall impacts of extreme weather on people's work patterns. In order to study how job flexibility plays a role in shaping people's response to extreme weather, I carried out two more sets of estimation that allow different intercept and slope for workers with/without job flexibility. Since the survey questions about job flexibility are available only in 2017 and 2018, the number of observations in these regressions is much smaller compared with the baseline results.

The first set of estimation is group regressions, where the sample is divided into two groups by the availability of certain flexibility options and the baseline model is estimated separately for the two groups. Two flexibility options are studied as the grouping criteria. The first is location flexibility, namely, whether respondents can work at home as part of the main job. The second is time flexibility, namely whether respondents have flexible work hours that allow them to vary or make changes in the times they begin and end work. The second set of estimates is to include the dummy variables of job flexibility (location flexibility or time flexibility) and their interaction terms in the baseline model. The coefficient of the interaction term tests for the different reactions to extreme weather events between workers with and without job flexibility. Industrial and occupational factors may correlate with work patterns and the adaptation to extreme weather at the same time. Therefore, all regressions include industry-occupation fixed effects, which address the potential endogeneity problem with job flexibility due to industrial and occupational heterogeneity.

Industries with more exposure to climate, which are referred to as high-risk industries, may suffer greater impacts from extreme weather. To test for this hypothesis, I estimate the model for high-risk and low-risk industries separately. Gender heterogeneity is also examined. The baseline regressions reveal that, on average, women spend about 50 minutes less on the main job and about 70 minutes more on home production compared to men. If extreme weather affects the marginal utility of work and home production differently, the adaptation behavior for men and women could be different as a result.

VI. Results

A. Baseline Results

Table 2 shows the baseline result of the impacts of extreme weather on time allocation for all employed workers during business days. Some evidence can be found that extreme weather changes people's time allocation. However, the scale of the effect is small. Work time is estimated to decrease by 9 minutes on an extreme weather day. The loss of work time mainly comes from the workplace, and the decrease in work time at their workplace is about 10 minutes. This result is consistent with the conclusion by Graff Zivin and Neidell (2014) that the weather has a moderate impact on the time allocated to labor.[9] The major portion of the time reduction in the workplace is accounted for by an increase in leisure. People spend about 6 minutes more in leisure on extreme weather days. This finding counters the hypothesis that bad weather shocks would impair the utility of leisure, and thus induce workers to forgo some leisure and work longer (Connolly, 2008). Finally, there is no statistically significant evidence that extreme weather changes people's time allocated to home production.

B. Job Flexibility

The analysis in the baseline results, however, cannot show the heterogeneity in job flexibility, which is potentially very important in shaping people's adaptation to extreme weather. Table 3 presents the result of running the baseline model in the group of respondents who can/cannot work at home respectively. On an extreme weather day, respondents who can work at home reduce

[9]In Graff Zivin and Neidell (2014), work time is defined as total minutes spent in the respondent's workplace, which is closely comparable to the result of Table 2 Column (4).

work time at the workplace by 47 minutes on average, which is compensated by 45 minutes increase of work time at home. Overall, the total work time is unaffected. On the contrary, respondents who cannot work at home have a small decrease in work time at all three types of location, and the reduction adds up to 14 minutes in total work time, which is not statistically significant. Testing for the differences in treatment effects between two groups shows that the response in work time at home is significantly different (at 5% level) for people who can work at home and people who cannot. The differences in other regressions are not statistically significant. These findings show that people with location flexibility tend to shift their work time from the workplace to home under extreme weather, while people with little location flexibility maintain their work hours unaffected.

Table 4 shows separately the results for workers who have flexible work schedules and those who do not. For respondents who have a flexible work schedule, work time at the workplace decreases by 33 minutes, work time at other places decreases by about 8 minutes, and the work time at home increases by 21 minutes on an extreme weather day. The increase in the time work at home only makes up for about half the time loss from the other two locations. For respondents who do not have a flexible work schedule, work time is not affected by extreme weather. Although the results show that people with flexible time schedule are more responsive to extreme weather events, the differences in treatment effects between Panel A and Panel B are not statistically significant in any of the four columns, which may be due to the fact that the number of observations in Panel B is much smaller than in other regressions.

Another way to look at the various responses to extreme weather by job flexibility is to allow different intercepts and slopes of extreme weather for different groups. Table 5 includes the dummy variable of location flexibility and its interaction term with extreme weather. According to the results, there is no significant evidence of "slacking at home" because people who can work at home actually work 24 minutes longer on average. Although they work 53 minutes less in their workplace, this time loss is fully and overly compensated by the 69 more minutes working at home. The differentiated response to extreme weather is revealed by the interaction terms. Compared with their counterparts who cannot work at home, workers with location flexibility reduce their work time at the workplace by 36 more minutes during extreme weather, which add up to a 40-minute reduction in the time at the workplace. The difference in the change in work time at home is 38 minutes for these two groups, which means that people with job flexibility increase work time at home by 36 minutes during extreme weather day. For the change in work time at home, the difference is statistically significant between these two groups. However, for the change in work time at work place, the difference is not statistically significant. These findings are consistent with the results in Table 3, but with a smaller magnitude.

Table 6 includes the dummy variable of time flexibility and its interaction term with extreme weather. For ordinary days, allowing the workers to change their work schedule has no impact on the total work time. However, workers with time flexibility switch work location from their workplace to their home for about 24 minutes. In response to extreme weather, workers with flexible work schedules reduce their work time at the workplace by 27 more minutes and increase their work time at home by 24 more minutes than workers who have a more rigid schedule. The difference in treatment effects between groups is statistically significant in the regression of work time at home, but is not statistically significant in the regression of work time at the workplace.

The findings so far suggest that people would only moderately resort to reducing the work time as a means of adaptation. Instead, the major adaptation is to switch the work location from the workplace to home when there is flexibility to do so. Location adaptation is only detected among people with job flexibility. It means that workers would choose to work at home during extreme weather days should their work flexibility permit. In this case, job flexibility improves workers' utility by offering another option.

C. Robustness Check

Table 7 shows the robustness checks for the main result (Table 3) of this paper by varying the specifications of control variables. Here I focus only on work time at home for workers with location flexibility, because this is where the result shows the largest and most significant effects, though outcomes are similar for the other dependent variables and groups shown in this paper.

The estimated work time at home significantly increases during extreme weather days in all specifications. However, the estimated magnitude of the increase varies from 29 minutes to 45 minutes. Note that the industry fixed effects is the most important control in terms of affecting the magnitude of the coefficient of interest. For the regressions with industry fixed effects or industry-occupational fixed effects, the estimated increase in work time at home is at least 37 minutes. One possible explanation is that the impact of extreme weather is correlated with whether the respondent works in an industry that is highly exposed to adverse weather conditions, which is correlated with job flexibility at the same time. Workers in climate-exposed industries, e.g. fishing, construction, etc., may be required to work outdoor or in certain locations that are directly susceptible to extreme weather conditions. Meanwhile, the nature of these jobs makes it impossible for workers to perform the work at home. Omitting these controls will lead to underestimating the magnitude of adaptation to extreme weather day for people with job flexibility. Therefore, industry-occupational fixed effects are included in all of the main regressions in this paper.

I also changed the standard errors from clustering at the state-month level to clustering at county-month, state-year, county-year, and industry. The differences from the main result are negligible and do not affect the significance level of any of the reported coefficients.

D. Other Potential Source of Heterogeneity

This section explores other potential treatment heterogeneity. Compared with the heterogeneity by job flexibility, the differences in treatment effects by industry, gender, and business days/non-business days are small, which indicates that job flexibility is the decisive determinant of people's adaptation behavior among these factors.

Industries

Table 8 compares the impact of extreme weather on workers from high-risk and low-risk industries separately. Following the definition of high-risk industries in Graff Zivin and Neidell (2014), which is also the National Institute for Occupational Safety and Health (NIOSH) definition of heat-exposed industries (NIOSH, 1986), high-risk industries in Panel A include: agriculture, forestry, fishing, and hunting; mining; construction; manufacturing; and transportation and utility industries. The other industries are considered low-risk, and the results for their workers are shown in Panel B.[10] The results show that, compared with low-risk industries, high-risk industries suffer a slightly larger impact on the total work time loss (14 minutes versus 6 minutes), and a slightly smaller impact on the time loss in the workplace (9 minutes versus 11 minutes). However, the magnitude of the difference is rather small. High-risk industry workers decrease work time in all locations, while low-risk industry workers increase the work time at home and at other places. The test of differences in treatment effects between high-risk and low-risk industries show that the difference is statistically significant only in the regression that uses work time at other places as dependent variable, with a small magnitude of 5 minutes. Therefore, there is very limited evidence of industrial heterogeneity. [11]

The findings of this paper provide very weak support to the hypothesis that, because high-risk industries are less sheltered from the climate, there is a larger work time loss in high-risk industries than in low-risk industries. It is possible that although the high-risk industries have suffered greater damages from extreme weather, this does not result in a decrease in demand for labor. The data do not show effective productivity per unit of work time. Perhaps some worker's responsibility during extreme weather had shifted from production to repairing or watching out for accidents. Therefore, suffering greater damage from extreme weather does not necessarily mean that the workers of these industries are kept out of their position by these events and thus reduce their work time more than people from low-risk industries.

Gender

Table 9 shows that both men and women reduce labor supply by about 8 minutes on extreme weather days and there is no gender difference in terms of total work time. However, compared to men, women are more inclined to change work location from the workplace to home as a response. Women decrease work time at their workplace by 13 minutes and increase work time at home by 6 minutes. Men decrease work time at both places. The difference in treatment

[10] Low-risk industries include wholesale trade; retail trade; information; finance and insurance; real estate and rental and leasing; professional and technical services; management, administrative and waste management services; educational services; health care and social services; arts, entertainment, and recreation; accommodation and food services; private households; other services; and public administration.

[11] Other specifications of high-risk/low-risk are also tested. For example, excluding manufacturing from the high-risk, using occupations instead of industries for division, and using both industries and occupations for division. From all these specifications, there is little evidence that workers from high-risk industries/occupations make greater adaptations.

effects by gender is statistically significant only in work time at home, with a magnitude of about 9 minutes. One possible explanation is that women, more often than men, tend to take the role of caregivers to children and the elderly. Extreme weather may cause schools to close or raise more concerns about the safety of children and the elderly. Therefore, working at home becomes favorable for some women to take care of both work and family.

In the job flexibility literature, it is speculated that women tend to choose jobs that offer greater flexibility so that they can also attend to their families. Contrary to this speculation, previous empirical findings suggest that people with work authority, instead of women, have greater job flexibility (McCrate, 2005; Schaffer and Westenberg, 2019). The summary statistics in Table A5 show that 36.8% of men and 34% of women in the sample have location flexibility, and 59.6% of men and 56.8% of women have time flexibility in their jobs. This is consistent with previous literature that women have lower job flexibility.

The combination of a more rigid work schedule and a higher need for job flexibility could lead to economic loss, such as uncompensated leave, and stress. This could render women being more vulnerable and bear greater losses from extreme weather.

Business Days and Non-business Days

All the results reported so far are based on business days, and non-business days are excluded. I separate the sample this way because the work patterns are so different accordingly. The average work time is 6.5 hours for business days, and 1.6 hours for non-business days (See Table 1), which is a natural reflection that more people are working during business days. [12] As shown in Table A5, workers who go out to work during business days have greater job flexibility (36.9% can work at home and 59.2% have a flexible schedule) than workers who go out to work during non-business days (15.9% can work at home and 52.8% have a flexible schedule). Table 10 compares the regression results for business days and non-business days. It shows that the work time loss due to extreme weather only happens during business days, and it is not detected in non-business days. For the full sample, the impact is the average of these two groups. The differences in treatment effects between Panel A and Panel B are statistically significant for total work time

[12] The mean of work time is less than 8 hours a day because it also includes observations of people who are off work on the diary day.

(9 minutes) and work time at the workplace (10 minutes).

To sum up, although there is heterogeneity by industry, gender, and business / non-business days, none of the differences is greater than 10 minutes. As a comparison, the difference in impacts by job flexibility is up to 30-45 minutes (See Table 3 to Table 6). Therefore, job flexibility, especially whether the position allows workers to work at home, stands out as the main explanation for the adaptation behavior to extreme weather.

E. Extensive Margin v.s. Intensive Margin

The baseline results show that people reduce work time at the workplace and increase their work time at home during extreme weather days. In order to explore the mechanism behind this shifting of work pattern, I further examine two hypotheses that could explain the time loss at the workplace. The first hypothesis is that the change in work time at the workplace is mainly at the extensive margin. People choose to work at home and not go out to work, possibly trying to avoid exposure to extreme weather during commuting. The second hypothesis is that the change is mainly at the intensive margin and people are forced to start late or end early in their work hours at the workplace because of extreme weather. The latter hypothesis is consistent with Graff Zivin and Neidell (2014)'s explanation that workers have little discretion over labor supply during core business hours but long time exposure to adverse weather conditions causes fatigue, which forces them to shorten the time allocated to labor. The two hypotheses correspond to the extensive and intensive margins as analyzed in Section III.

A linear probability model is estimated to test for the first hypothesis. I keep all the independent variables from the baseline model, but change the dependent variable to a binary indicator of whether the respondent left home to work. Table 11 reports the results with three variations. In column (1) , the dependent variable is equal to 1 if the respondent has worked at any place other than home. In column (2), the dependent variable is equal to 1 if the respondent has reported traveling time for any reason. The result shows that, on average, 1.6% of people stop working outside their homes because of extreme weather. Whether it is for work or any other purpose, the proportion of people who stop going out because of extreme weather is basically the same, which is 1.7%.

Table 11 also reports the results of group regressions based on the information of job flexibility, which is only available in 2017 and 2018. The findings in Table 11 are highly consistent with Table 3 and Table 4 that people with job flexibility change their work location according to the weather while people with little job flexibility do not. The estimated impacts on people with high flexibility are statistically significant and large in magnitude. On average, 12.2% of people who can work at home and 9.2% of people who have flexible work hours refrain from going out to work because of extreme weather. These findings support the hypothesis that the reduction in work hours at the workplace during extreme weather days partly stems from people's choice to not go to the workplace.

In order to test for the second hypothesis, I divide the observations into two groups based on whether the respondent went out to work on the diary day, and estimate the baseline model within these two groups respectively. These group regressions examine the change in labor supply on extreme weather days given the respondent's choice of going out to work or not. Table 12 presents the regression outcomes. For respondents who go out to work on the diary day, extreme weather decreases their total work time by about 5 minutes (not statistically significant), and the reduction in work time at the workplace is almost 6 minutes (significant at 10% level). For respondents who did not go out to work on the diary day, extreme weather increases their work time at home by about 9 minutes, which is not statistically significant. These treatment effects are either small in magnitude or not statistically significant. Although there is some evidence of people adjusting their work time given their choice of going out or not, it is not as strong as that of the first hypothesis. This suggests that fatigue caused by bad weather does result in work time at the workplace to decline. However, it is not the main reason.

The empirical findings above allow us to roughly split the change in the work time at the workplace (estimated to be 10 minutes in Table 2) into the extensive margin and the intensive margin. From summary statistics, the average work time at the workplace is 452 minutes on business days. With this number and the estimated rise in the possibility of people not going to the workplace because of extreme weather, which is 1.6% from Table 11, the average time loss in the workplace due to not going out to work, i.e. the extensive margin, is $452 \times 1.6\% = 8.7$ minutes. Because this calculation only focuses on the work time at the workplace, for people who work at home, the intensive margin is 0. For the respondent who went out to work, the estimated time loss in the workplace is 5.7 minutes. The proportion of people who went out to work is 72%. The weighted average intensive margin for the full sample is $5.7 \times 0.72 + 0 \times 0.28 = 4.1$ minutes. Therefore, the estimated extensive margin (8.7 minutes) is larger than the intensive margin (4.1 minutes). The first hypothesis is the major explanation for work time reduction in the workplace. Of course, the estimated numbers in this paragraph are based on a rough, back-of-the-envelope calculation. The calculated extensive margin and the intensive margin add up to 12.7 minutes, which is larger than the estimation in Table 2.

F. Inter-day Adaptation

The above model describes the short-run adaptation within the extreme weather day. Here I extend the analysis of adaptation by looking for inter-day substitution. When bad weather comes, individuals may postpone some of the work until a good weather day. If there is an effective forecast about the weather condition, people may even shift the work to days before the extreme weather event arrives. However, given the small reduction in total work time found on the very day the extreme weather hits, the inter-day adaptation should be minimal if there is any. Even for workers with job flexibility who are estimated to shifts work time from their workplace to home by about 45 minutes, there should not be large inter-day adaptation if they accomplish their work at home as efficiently as at their workplace.

I include the 1-day forward term (t-1) and 7 lag terms (t+1,...,t+7) to the regressions in Table 2. The results are shown in Figure 2. Only very few coefficients are significant, which means there's not much inter-day adaptation. The largest magnitude in lag terms from all these regressions is found in Panel (b), the model with work time at the workplace as the dependent variable. On the extreme weather day, there's an 8-minute decrease, significant at 10% level, in work time at the workplace which is consistent with the baseline results. The following days display fluctuations. Two days after the extreme weather day, there is a rebound by 13 minutes, significant at 5% level. Starting from 5 days after the extreme event, the impact drops to 0. There is a 6 minutes decrease in leisure two days after the extreme weather. For some unexplained reason, respondents reduce leisure and switch to work two days after the extreme event. This could be a time when people make up for the loss that resulted from the extreme weather. On the whole, the magnitudes of immediate response and inter-day adaptation are both small.

G. Discussion

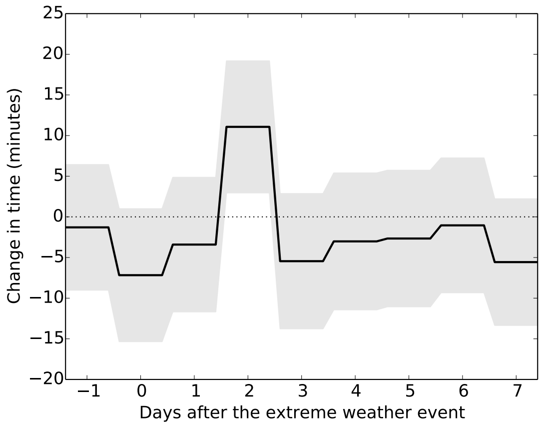
In section II, several possible explanations for the change in labor supply during adverse weather conditions are discussed and a new explanation is proposed. The empirical results presented here can provide some insight into these various explanations.

The empirical results of this paper show the opposite of the hypothesis from the Connolly (2008) inter-temporal substitution model that people would substitute leisure by labor because of decreased utility in outdoor leisure during bad weather. This explanation relies on the assumption that bad weather has a negative influence only on leisure, but not on work, which may not be true in many cases. Even though a majority of Americans work indoors, people have to expose themselves to the outdoor environment when commuting to work. The results from this paper show that people switch from work to leisure during bad weather, which suggests that when outdoor activities are restricted by weather, people may switch to indoor leisure instead of working more.

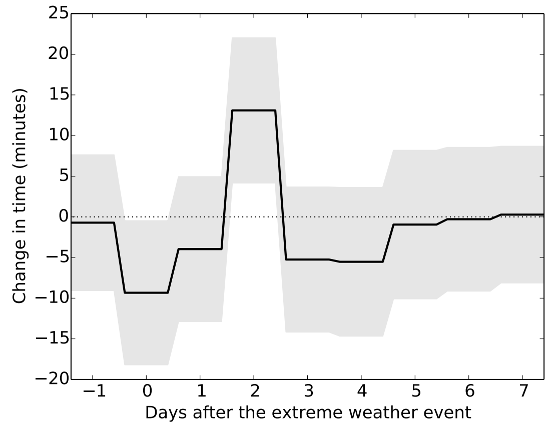
Consistent with the findings of Graff Zivin and Neidell (2014), this paper shows that people reduce work time at the workplace in response to adverse weather conditions, especially for workers with job flexibility. However, my findings suggest a small intensive margin effect, meaning that the work time loss does not mainly come from fatigue or cognitive impairment that forces workers to end work early. Instead, it is mainly a result of people's own decisions to avoid the negative impacts of extreme events by staying home and not going out to work. This is evidence of people actively adapting to adverse environmental conditions when given the chance, rather than passively 'suffering' from them. Of course, the divergence in conclusion with previous literature could stem from the different choices of weather conditions as the treatment. The mechanism behind people's reaction to extreme weather is probably different from that of the response to rainy days and high temperatures.

In addition, consistent with what might be expected, there is a larger reaction in the kind

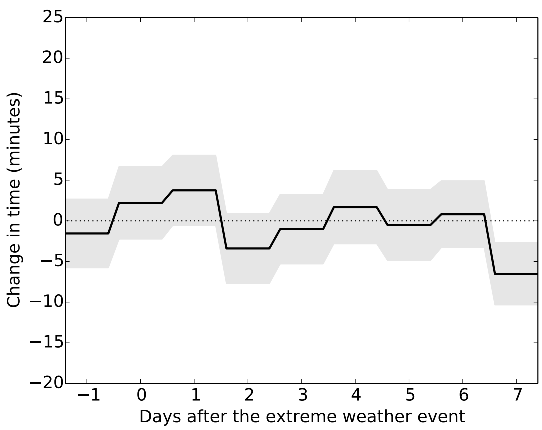
Figure 2 : Estimated change in time (in minutes) in different activities as a function of days after an extreme weather event. The grey shade marks the 95% confidence interval. Time span: 2004-2019. Business days only. N=44,427.



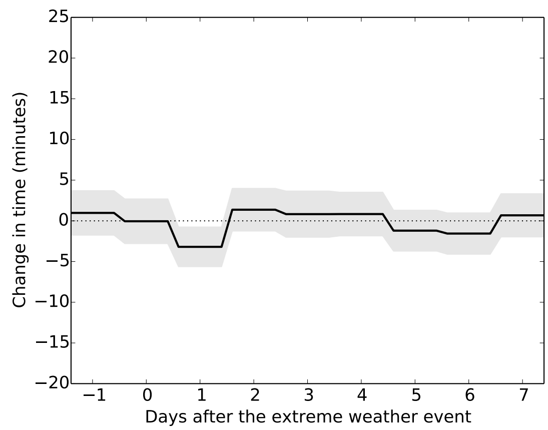
(a) Work (total)



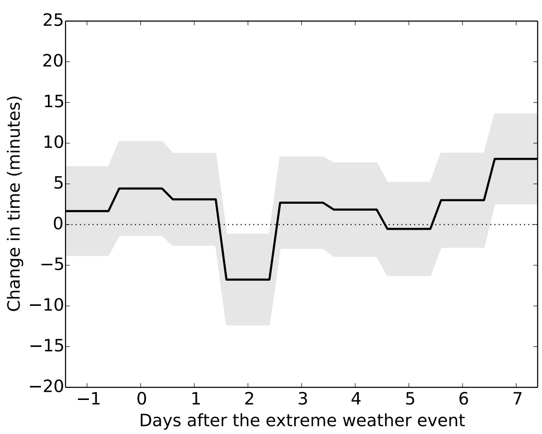
(b) Work at the workplace



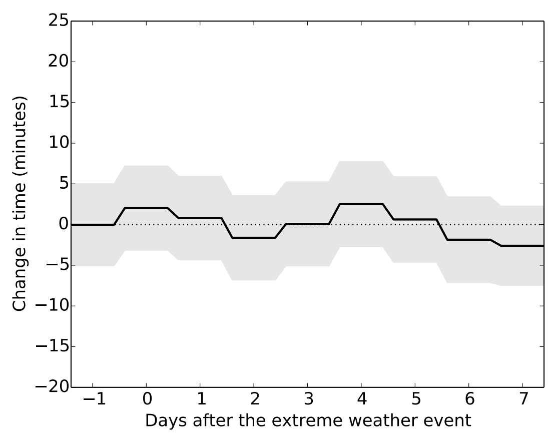
(c) Work at home



(d) Work at other places



(e) Leisure



(f) Home production

of jobs that require workers to work outdoors, although the difference found between climate-exposed industries and other industries is not as large as the difference by job flexibility. Climate-exposed positions cannot shelter from the environment because of the nature of the job, which at the same time means that they usually require workers to work at the workplace, e.g. farmers in agriculture cannot tend to crops away from the field. Therefore, it might be expected that there are greater impacts of extreme weather on people who cannot work at home. This paper finds some evidence, but with a small magnitude, that supports this speculation.

As the outcomes suggest, instead of the nature of the job, institutional factors, such as whether there are job flexibility options for the worker, and whether it is a business day or not, are decisive in people's adaptation to extreme weather. These workplace arrangements explain the largest heterogeneity between people's adaptation, which means that there is a large space for institutional design to guide people's adaptation behavior.

H. Limitations

Although Section V has already mentioned some limitations of the empirical strategy, there are additional limitations that should be noted. First, this paper uses work time as a proxy for individual productivity. However, work time may not be a linear representation of real productivity, especially under abnormal circumstances such as extreme weather. Although the result shows a small decline in total work time under extreme weather, this does not necessarily imply that the negative impact on production is small. Extreme weather could impair productivity by decreasing efficiency given the same work hours. While the findings show that job flexibility increases people's total work time, they cannot reveal whether workers maintain their work quality or become less, if not more, productive working at home than working at the workplace.

In Section V, it is explained why we can identify causal impacts from extreme weather on people's time allocation and their decisions to go out or not. However, in exploring the heterogeneity by job flexibility, the finding that workers with high job flexibility adapt to extreme weather more actively by choosing to work at home instead of going out to work does not establish a causal relationship between job flexibility and the differentiated adaptation behavior. There could be some unobserved confounding variables behind these estimated relationships.

VII. Conclusion

This paper examines the impacts of extreme weather events on individuals' allocation of work time. A simple theoretical model is constructed to model an individual's two-step decision of work location and work time. Assuming that extreme weather will affect the costs associated with working at the workplace, this model distinguishes the extensive and intensive change in work time. The theoretical conclusion is that extreme weather unambiguously reduces the number of people commuting to work, but it is unclear whether people who still work at the workplace will increase or decrease their work time in response to the extreme weather.

The empirical results show that the reduction in total work time is about 8 minutes, which is a modest effect. The major response to extremely bad weather is to work at home in place of commuting to work. This way of adaption is found only for people who have job flexibility that allows them to work at home or change the time schedule of work. On extreme weather days, people with job flexibility shift about 45 minutes of work from their workplace to their home on average. Among respondents with job flexibility, extreme events cause 12.2% more of them to stop going out to work. For people who have already left their homes and traveled to work, there's no evidence of time loss at their workplace. These findings suggest that the avoidance of travel-related risks under extreme weather is probably the main explanation of the impacts on work patterns.

Job flexibility improves workers' welfare by providing the choice of location adaptation, which is not an option and is not observed among workers without job flexibility. In addition to being a means of adapting to climate change, workers who are allowed to work at home are estimated to work 24 minutes longer on average, which should alleviate employers' concerns for 'slacking at home'. Of course, the duration of work time is not an ideal measurement of productivity. If working at home is to be promoted, many questions remain on its implications for individual productivity, cooperation, and worker's health in the short-run and long-run.

Willingly or not, many have experienced working at home or other alternative work arrangements in 2020 and developed skills to do so during the pandemic. The development of telecommunication technology makes working at home more feasible. If alternative work arrangements are to become the new normal, we should pay attention to the differential impacts this could have. Data from ATUS shows that workers who are female, earn less income, with no college degree, work in climate-exposed industries, or go out to work during non-business days have lower access to job flexibility. If job flexibility is an effective adaptation to extreme weather and other adverse conditions, the inequality in job flexibility renders some people more vulnerable than others in coping with these challenges.

REFERENCES

Ameriks, J., Briggs, J., Caplin, A., Lee, M., Shapiro, M. D., and Tonetti, C. (2020). Older americans would work longer if jobs were flexible. *American Economic Journal: Macroeconomics*, 12(1):174–209.

Bloom, N., Liang, J., Roberts, J., and Ying, Z. J. (2015). Does working from home work? evidence from a chinese experiment. *The Quarterly Journal of Economics*, 130(1):165–218.

Cachon, G. P., Gallino, S., and Olivares, M. (2012). Severe weather and automobile assembly productivity. *Columbia Business School Research Paper*, (12/37).

Choudhury, P., Foroughi, C., and Larson, B. Z. (2020). Work-from-anywhere: The productivity effects of geographic flexibility. In *Academy of Management Proceedings*, volume 2020, page 21199. Academy of Management Briarcliff Manor, NY 10510.

Connolly, M. (2008). Here comes the rain again: Weather and the intertemporal substitution of leisure. *Journal of Labor Economics*, 26(1):73–100.

Costa, H., Floater, G., Hooyberghs, H., Verbeke, S., De Ridder, K., et al. (2016). *Climate change, heat stress and labour productivity: A cost methodology for city economies.* Centre for Climate Change Economics and Policy.

Day, E., Fankhauser, S., Kingsmill, N., Costa, H., and Mavrogianni, A. (2019). Upholding labour productivity under climate change: an assessment of adaptation options. *Climate policy*, 19(3):367–385.

Dunne, J. P., Stouffer, R. J., and John, J. G. (2013). Reductions in labour capacity from heat stress under climate warming. *Nature Climate Change*, 3(6):563–566.

Goldin, C. and Katz, L. F. (2011). The cost of workplace flexibility for high-powered professionals. *The Annals of the American Academy of Political and Social Science*, 638(1):45–67.

González-Alonso, J., Teller, C., Andersen, S. L., Jensen, F. B., Hyldig, T., and Nielsen, B. (1999). Influence of body temperature on the development of fatigue during prolonged exercise in the heat. *Journal of applied physiology*, 86(3):1032–1039.

Graff Zivin, J. and Neidell, M. (2014). Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics*, 32(1):1–26.

Hancock, P. A., Ross, J. M., and Szalma, J. L. (2007). A meta-analysis of performance response under thermal stressors. *Human factors*, 49(5):851–877.

Heal, G. and Park, J. (2013). Feeling the heat: Temperature, physiology & the wealth of nations. Technical report, National Bureau of Economic Research.

Hsiang, S. M. (2010). Temperatures and cyclones strongly associated with economic production in the caribbean and central america. *Proceedings of the National Academy of sciences*, 107(35):15367–15372.

Katz, L. F. and Krueger, A. B. (2019). The rise and nature of alternative work arrangements in the united states, 1995–2015. *ILR Review*, 72(2):382–416.

Kjellstrom, T., Briggs, D., Freyberg, C., Lemke, B., Otto, M., and Hyatt, O. (2016). Heat, human performance, and occupational health: a key issue for the assessment of global climate change impacts. *Annual review of public health*, 37:97–112.

Mas, A. and Pallais, A. (2017). Valuing alternative work arrangements. *American Economic Review*, 107(12):3722–59.

McCrate, E. (2005). Flexible hours, workplace authority, and compensating wage differentials in the us. *Feminist Economics*, 11(1):11–39.

Moen, P., Kelly, E. L., Fan, W., Lee, S.-R., Almeida, D., Kossek, E. E., and Buxton, O. M. (2016). Does a flexibility/support organizational initiative improve high-tech employees' well-being? evidence from the work, family, and health network. *American Sociological Review*, 81(1):134–164.

NIOSH (1986). *Working in Hot Environments*. US Department of Health and Human Services, Public Health Service, Centers ....

Powell, J. and Reinhard, S. (2016). Measuring the effects of extreme weather events on yields. *Weather and Climate extremes*, 12:69–79.

Roson, R. and Sartori, M. (2016). *Estimation of climate change damage functions for 140 regions in the GTAP9 database*. The World Bank.

Schaffer, D. L. and Westenberg, J. M. (2019). Time flexibility, women's wages, and the gender wage gap. *Atlantic Economic Journal*, 47(2):217–239.

Spreitzer, G. M., Cameron, L., and Garrett, L. (2017). Alternative work arrangements: Two images of the new world of work. *Annual Review of Organizational Psychology and Organizational Behavior*, 4:473–499.

Tong, D., Zhang, Q., Zheng, Y., Caldeira, K., Shearer, C., Hong, C., Qin, Y., and Davis, S. J. (2019). Committed emissions from existing energy infrastructure jeopardize 1.5 c climate target. *Nature*, 572(7769):373–377.

Vazquez, E. and Winkler, H. (2019). How do telecommunications reforms affect labour market arrangements? evidence from central and western europe. *Economics of Transition and Institutional Change*, 27(3):745–762.

Wang, S. L., Ball, E., Nehring, R., Williams, R., and Chau, T. (2017). Impacts of climate change and extreme weather on us agricultural productivity: Evidence and projection. Technical report, National Bureau of Economic Research.

White, D. R. (2019). Agency theory and work from home. *Labour*, 33(1):1–25.

Table 1: Summary Statistics

Time span: 2004-2019	All (N=90,722)		Business Days (N=44,427)		Non Business Days (N=46,295)	
	Mean	SD	Mean	SD	Mean	SD
Time use variables (in minutes)						
Total work	242.10	257.76	392.73	228.27	97.55	193.71
Work at work place	207.77	252.06	344.83	241.79	76.23	181.86
Work at home	25.00	93.79	34.35	114.24	16.02	67.45
Work at other places	9.34	60.95	13.55	73.68	5.29	45.14
Leisure	270.91	190.19	199.96	151.09	338.99	198.78
Home production	177.35	170.03	136.17	144.44	216.86	182.89
Extreme weather						
Extreme weather day [=1]	0.09	0.28	0.09	0.29	0.08	0.28
Individual characteristics						
Age	43.10	13.36	43.24	13.38	42.96	13.35
White [white=1]	0.80	0.40	0.80	0.40	0.80	0.40
Gender[male=1]	0.49	0.50	0.49	0.50	0.49	0.50
Presence of partner[yes=1]	0.58	0.49	0.58	0.49	0.58	0.49
Number of children under 18	0.94	1.13	0.93	1.13	0.95	1.13
Travel status						
Go out to work on diary day [yes=1]	0.46	0.50	0.72	0.45	0.20	0.40
Go out for any reason on diary day [yes=1]	0.92	0.28	0.95	0.21	0.88	0.32

Time span: 2017-2018	All (N= 8,274)		Business Days (N=3,998)		Non Business Days (N=4,276)	
	Mean	SD	Mean	SD	Mean	SD
Job flexibility						
As part of your (main) job, can you work at home?	0.35	0.48	0.36	0.48	0.35	0.48
Do you have flexible work hours that allow you to vary or make changes in the times you begin and end work?	0.58	0.49	0.60	0.49	0.57	0.50

Table 2: OLS Regressions of Time Use on Extreme Weather Day

Panel A: Time use main categories			
	(1)	(2)	(3)
Dependent Variables (in minutes)	Work	Leisure	Home Production
Extreme weather day	-8.607**	6.154**	2.000
	(3.725)	(2.722)	(2.348)
Adjusted R-squared	0.121	0.096	0.145
Panel B: Sub-categories of work time			
	(4)	(5)	(6)
Dependent Variables (in minutes)	Work at workplace	Work at home	Work at other places
Extreme weather day	-10.015**	1.945	-0.538
	(4.014)	(1.992)	(1.223)
Adjusted R-squared	0.096	0.070	0.012

Note: Standard errors clustered on state-month in parentheses. Time span: 2004-2019. These regressions only include respondents that are employed. Non-business days are deleted from the sample. The work time variables only account for the time spent in the respondent's main job. The respondent's total work time in the dairy day is divided into three parts according to different locations (work place, home, and other places). The independent variable of interest is a binary indicator of whether the respondent's residential region is affected by extreme weather on the diary day. The regressions include the following control variables: age, age squared, gender, race (white=1), presence of partner, number of children under 18, dummies for highest level of education completed (16 categories). They are also fixed for Industry-occupation, day of the week, month , year, and county/CBSA.
Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.
Number of observations N=44,427.

Table 3: OLS Regressions of Time Use on Extreme Weather Day, By Location Flexibility

Panel A: Respondents that CAN work at home as part of the main job (N=1,453)				
	(1)	(2)	(3)	(4)
Dependent Variables (in minutes)	Work	Work at workplace	Work at home	Work at other places
Extreme weather day	-6.653	-47.204*	45.338**	-4.788
	(19.547)	(26.895)	(19.806)	(8.867)
Adjusted R-squared	0.146	0.104	0.020	0.074
Panel B: Respondents that CANNOT work at home as part of the main job (N=2,545)				
	(5)	(6)	(7)	(8)
Dependent Variables (in minutes)	Work	Work at workplace	Work at home	Work at other places
Extreme weather day	-14.024	-5.996	-1.957	-6.071
	(16.922)	(17.355)	(1.950)	(5.052)
Adjusted R-squared	0.102	0.090	0.039	0.000

Note: Standard errors clustered on state-month in parentheses. Time span: 2017-2018. These regressions include all the control variables and fixed effects as the baseline regressions.
* Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

Table 4: OLS Regressions of Time Use on Extreme Weather Day, By Time Flexibility

Panel A: Respondents that HAVE flexible work schedule (N=2,397)				
	(1)	(2)	(3)	(4)
Dependent Variables (in minutes)	Work	Work at workplace	Work at home	Work at other places
Extreme weather day	-19.995	-32.597*	20.527*	-7.925
	(15.802)	(19.511)	(11.626)	(4.825)
Adjusted R-squared	0.140	0.076	0.050	0.009
Panel B: Respondents that DO NOT HAVE flexible work schedule (N=1,614)				
	(5)	(6)	(7)	(8)
Dependent Variables (in minutes)	Work	Work at workplace	Work at home	Work at other places
Extreme weather day	5.748	5.717	-0.186	0.217
	(23.710)	(25.526)	(8.670)	(8.957)
Adjusted R-squared	0.083	0.087	-0.013	0.100

Note: Standard errors clustered on state-month in parentheses. Time span: 2017-2018. These regressions include all the control variables and fixed effects as the baseline regressions.
* Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

Table 5: OLS Regressions of Time Use on Extreme Weather Day, Allowing Different Slope and Intercept by Location Flexibility

Dependent Variables (in Minutes)	(1) Work	(2) Work at workplace	(3) Work at home	(4) Work at other places
Extreme weather day	-12.617	-4.142	-2.352	-6.123
	(16.586)	(16.730)	(3.751)	(4.619)
Extreme weather day × Can Work at Home	0.046	-35.773	38.371**	-2.552
	(22.797)	(26.694)	(16.776)	(8.392)
Can Work at Home	24.466***	-53.086***	69.162***	8.390**
	(9.169)	(10.407)	(5.215)	(4.272)
Adjusted R-squared	0.118	0.086	0.122	0.017

Note: Standard errors clustered on state-month in parentheses. Time span: 2017-2018. These regressions include all the control variables and fixed effects as the baseline regressions.
* Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.
Number of observations: N=3,998.

Table 6: OLS Regressions of Time Use on Extreme Weather Day, Allowing Different Slope and Intercept by Time Flexibility

Dependent Variables (in Minutes)	(1) Work	(2) Work at workplace	(3) Work at home	(4) Work at other places
Extreme weather day	-10.245	-1.629	-1.974	-6.642
	(19.165)	(20.790)	(7.800)	(7.140)
Extreme weather day × Flexible work schedule	-3.716	-27.469	24.459*	-0.706
	(22.524)	(26.188)	(12.738)	(8.883)
Flexible work schedule	1.746	-23.219**	24.495***	0.471
	(8.472)	(9.052)	(3.973)	(3.558)
Adjusted R-squared	0.116	0.079	0.069	0.015

Note: Standard errors clustered on state-month in parentheses. Time span: 2017-2018. These regressions include all the control variables and fixed effects as the baseline regressions.
* Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.
Number of observations: N=3,998.

Table 7: OLS Regressions of Work Time on Extreme Weather Day, Robustness check

Dependent Variables : **Work time at home (in Minutes)**	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Extreme weather day	45.338** (19.806)	45.236** (20.421)	37.616* (19.271)	32.246* (19.571)	37.729** (17.089)	41.818** (20.283)	30.128* (15.615)	29.279* (15.560)
Individual characteristics [21]	Yes	Yes	Yes	Yes	Yes	No	Yes	No
Fixed effects:								
Day of the week [6]	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Year-month [185]	No	Yes	No	No	No	No	No	No
Year [16]	Yes	No	Yes	Yes	Yes	Yes	No	No
Month [11]	Yes	No	Yes	Yes	Yes	Yes	No	No
Industry-occupation [199]	Yes	Yes	No	No	Yes	Yes	No	No
Industry [22]	No	No	Yes	No	No	No	No	No
Occupation [11]	No	No	No	Yes	No	No	No	No
County [612]	Yes	Yes	Yes	No	No	Yes	No	No
Adjusted R-squared	0.020	0.026	0.008	0.005	0.038	0.034	0.002	0.002

Note: Standard errors clustered on state-month in parentheses. Time span: 2017-2018. Number of variables in []. Individual characteristics include: age, age squared, gender, race (white=1), presence of partner, number of children under 18, dummies for highest level of education completed (16 categories).

- Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.
- N=1,453

Table 8: OLS Regressions of Time Use on Extreme Weather Day, By Industry

Panel A: High-risk industry (N=9,315)				
	(1)	(2)	(3)	(4)
Dependent Variables (in minutes)	Work	Work at workplace	Work at home	Work at other places
Extreme weather day	-13.891*	-8.715	-0.461	-4.716*
	(8.291)	(8.877)	(3.811)	(2.723)
Adjusted R-squared	0.060	0.055	0.077	0.022
Panel B: Low-risk industry (N=33,206)				
	(5)	(6)	(7)	(8)
Dependent Variables (in minutes)	Work	Work at workplace	Work at home	Work at other places
Extreme weather day	-6.470	-10.738**	3.035	1.233
	(4.340)	(4.708)	(2.364)	(1.481)
Adjusted R-squared	0.096	0.067	0.069	0.008

Note: Standard errors clustered on state-month in parentheses. Time span: 2004-2019. These regressions include all the control variables and fixed effects as the baseline regressions.
* Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

Table 9: OLS Regressions of Time Use on Extreme Weather Day, By Gender

Panel A: Male (N=21,961)				
	(1)	(2)	(3)	(4)
Dependent Variables (in minutes)	Work	Work at workplace	Work at home	Work at other places
Extreme weather day	-8.840*	-7.106	-2.252	0.517
	(5.252)	(5.729)	(2.752)	(2.032)
Adjusted R-squared	0.108	0.080	0.075	0.009
Panel B: Female (N=22,466)				
	(5)	(6)	(7)	(8)
Dependent Variables (in minutes)	Work	Work at workplace	Work at home	Work at other places
Extreme weather day	-8.085	-12.912**	6.315**	-1.488
	(5.390)	(5.728)	(2.885)	(1.470)
Adjusted R-squared	0.106	0.094	0.063	0.010

Note: Standard errors clustered on state-month in parentheses. Time span: 2004-2019. These regressions include all the control variables and fixed effects as the baseline regressions.
* Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

Table 10: OLS Regressions of Time Use on Extreme Weather Day, By Business/Non-business Day

Panel A: Business days (N=44,427)				
	(1)	(2)	(3)	(4)
Dependent Variables (in minutes)	Work	Work at workplace	Work at home	Work at other places
Extreme weather day	-8.607**	-10.015**	1.945	-0.538
	(3.725)	(4.014)	(1.992)	(1.223)
Adjusted R-squared	0.121	0.096	0.070	0.012
Panel B: Non-business days (46,295)				
	(5)	(6)	(7)	(8)
Dependent Variables (in minutes)	Work	Work at workplace	Work at home	Work at other places
Extreme weather day	0.068	-0.234	0.977	-0.675
	(3.148)	(2.906)	(1.134)	(0.713)
Adjusted R-squared	0.097	0.119	0.051	0.016
Panel C: All (N=90,722)				
	(9)	(10)	(11)	(12)
Dependent Variables (in minutes)	Work	Work at workplace	Work at home	Work at other places
Extreme weather day	-4.062	-5.070**	1.546	-0.539
	(2.570)	(2.561)	(1.145)	(0.722)
Adjusted R-squared	0.345	0.308	0.063	0.014

Note: Standard errors clustered on state-month in parentheses. Time span: 2004-2019. These regressions include all the control variables and fixed effects as the baseline regressions.
* Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

Table 11: Linear Probability Model of Going Out to Work on Extreme Weather day

Panel A: All respondents. (N=44,427)		
	(1)	(2)
	Go out to work	Go out for any reason
Extreme weather day	-0.016**	-0.017***
	(0.008)	(0.004)
Panel B: Respondents that CAN work at home as part of the main job. (N=1,453)		
	(3)	(4)
	Go out to work	Go out for any reason
Extreme weather day	-0.122**	-0.081**
	(0.050)	(0.032)
Panel C: Respondents that CANNOT work at home as part of the main job. (N=2,545)		
	(5)	(6)
	Go out to work	Go out for any reason
Extreme weather day	-0.024	-0.027
	(0.035)	(0.019)
Panel D: Respondents that HAVE flexible work schedule. (N=2,397)		
	(7)	(8)
	Go out to work	Go out for any reason
Extreme weather day	-0.092**	-0.064***
	(0.038)	(0.022)
Panel E: Respondents that DO NOT HAVE flexible work schedule. (N=1,614)		
	(9)	(10)
	Go out to work	Go out for any reason
Extreme weather day	0.014	-0.031
	(0.045)	(0.031)

Note: Standard errors clustered on state-month in parentheses. The dependent variable `Go out to work' is equal to 1 if the respondent has worked at any place other than home. The dependent variable `Go out for any reason' is equal to 1 if the respondent has reported traveling time for any reason. These regressions include all the control variables and fixed effects as the baseline regressions.
* Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

Table 12: OLS Regressions of Time Use on Extreme Weather Day, By Work Location

Panel A: Respondents that go out to work on the diary day (N=32,171).

	(1)	(2)	(3)	(4)
	Total work time	Work time at workplace	Work time at home	Work time at other places
Extreme weather day	-4.791	-5.742*	0.506	0.446
	(2.954)	(3.472)	(1.313)	(1.620)
Adjusted R-squared	0.091	0.069	0.038	0.012

Panel B: Respondents that did not go out to work on the diary day (N=10,239).

	(5)	(6)	(7)	(8)
	Total work time	Work time at workplace	Work time at home	Work time at other places
Extreme weather day	-	-	8.883	-
			(6.269)	
Adjusted R-squared			0.231	

Note: Standard errors clustered on state-month in parentheses. Time span: 2004-2019. These regressions include all the control variables and fixed effects as the baseline regressions.
* Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

Appendix

Table A1: Time Variables Definition

Time Variable	Activities	Code	locations
Total Work Time	Work, main job	050101	All locations
Work time at workplace	Work, main job	050101	Respondent's workplace.
Work time at home	Work, main job	050101	Respondent's home or yard.
Work time at other places	Work, main job	050101	Places other than respondent's work place and home.
Leisure	Social, relaxing, and leisure; Sports, exercise, and recreation; Religious and spiritual activities; Telephone calls to/from family members, friends, neighbors, or acquaintances.	12xxxx,13xxxx, 14xxxx,160101, 160102	All locations
Home Production	Household activities; caring for and helping others; consumer purchases; using professional and personal care services; using household services; using government services , and civic obligations.	02xxxx,03xxxx, 04xxxx,07xxxx, 08xxxx,09xxxx, 10xxxx	All locations

Note: Time variables are constructed as the total minutes spent in the activity(s) at the designated location(s). The codes are corresponding to the 2003-2019 ATUS Coding Lexicon (PDF).

Table A2: Frequency rate of extreme weather events

Event Type	**Frequency Rate**	**Event Type**	**Frequency Rate**
Astronomical Low Tide	0.21‰	High Wind	5.64‰
Avalanche	0.12‰	Hurricane (Typhoon)	0.07‰
Blizzard	0.57‰	Ice Storm	0.71‰
Coastal Flood	1.48‰	Lake Effect Snow	0.67‰
Cold/Wind Chill	1.42‰	Lake shore Flood	0.24‰
Debris Flow	0.39‰	Landslide	0.08‰
Dense Fog	2.17‰	Lightning	4.50‰
Dense Smoke	0.10‰	Rip Current	0.63‰
Dust Devil	0.07‰	Seiche	0.02‰
Dust Storm	0.19‰	Sleet	0.06‰
Excessive Heat	2.29‰	Sneaker Wave	0.02‰
Extreme Cold/Wind Chill	0.63‰	Storm Surge/Tide	0.20‰
Flash Flood	10.30‰	Strong Wind	3.86‰
Flood	10.91‰	Thunderstorm Wind	19.42‰
Freezing Fog	0.01‰	Tornado	2.56‰
Frost/Freeze	1.29‰	Tropical Depression	0.06‰
Funnel Cloud	1.17‰	Tropical Storm	0.46‰
Hail	13.18‰	Tsunami	0.01‰
Heat	3.60‰	Wildfire	3.89‰
Heavy Rain	3.33‰	Winter Storm	7.24‰
Heavy Snow	4.75‰	Winter Weather	7.51‰
High Surf	1.82‰		

Table A3: Definition of the top 15 most frequent extreme weather events.

Event type	**Definition and recording criteria**
Excessive Heat	Excessive Heat results from a combination of high temperatures (well above normal) and high humidity.An Excessive Heat event occurs and is reported in Storm Data whenever heat index values meet or exceed locally/regionally established excessive heat warning thresholds.
Flash Flood	A life-threatening, rapid rise of water into a normally dry area beginning within minutes to multiple hours of the causative event (e.g., intense rainfall, dam failure, ice jam).
Flood	Any high flow, overflow, or inundation by water which causes damage. In general, this would mean the inundation of a normally dry area caused by an increased water level in an established watercourse, or ponding of water, that poses a threat to life or property.
Hail	Frozen precipitation in the form of balls or irregular lumps of ice. Hail 3/4 of an inch or larger in diameter will be entered.
Heat	Period of heat resulting from the combination of high temperatures (above normal) and relative humidity. A Heat event occurs and is reported in Storm Data whenever heat index values meet or exceed locally/regionally established advisory thresholds.
Heavy Rain	Unusually large amount of rain which does not cause a Flash Flood or Flood event, but causes damage, e.g., roof collapse or other human/economic impact.
Heavy Snow	Snow accumulation meeting or exceeding locally/regionally defined 12 and/or 24 hour warning criteria. This could mean values such as 4, 6, or 8 inches or more in 12 hours or less; or 6, 8, or 10 inches in 24 hours or less.
High Wind	Sustained non-convective winds of 35 knots (40 mph) or greater lasting for 1 hour or longer, or gusts of 50 knots (58 mph) or greater for any duration (or otherwise locally/regionally defined). In some mountainous areas, the above numerical values are 43 knots (50 mph) and 65 knots (75 mph), respectively.
Lightning	A sudden electrical discharge from a thunderstorm, resulting in a fatality, injury, and/or damage.
Strong Wind	Non-convective winds gusting less than 50 knots (58 mph), or sustained winds less than 35 knots (40 mph), resulting in a fatality, injury, or damage. Consistent with regional guidelines, mountain states may have higher criteria.
Thunderstorm Wind	Winds, arising from convection (occurring within 30 minutes of lightning being observed or detected), with speeds of at least 50 knots (58 mph), or winds of any speed (non-severe thunderstorm winds below 50 knots) producing a fatality, injury, or damage.
Tornado	A violently rotating column of air, extending to or from a cumuliform cloud or underneath a cumuliform cloud, to the ground, and often (but not always) visible as a condensation funnel. For a vortex to be classified as a tornado, it must be in contact with the ground and extend to/from the cloud base, and there should be some semblance of ground-based visual effects such as dust/dirt rotational markings/swirls, or structural or vegetative damage or disturbance.
Wildfire	Any significant forest fire, grassland fire, rangeland fire, or wildland-urban interface fire that consumes the natural fuels and spreads in response to its environment. “Significant” is defined as a wildfire that causes one or more fatalities, one or more significant injuries, and/or property damage (optional: include significant damages to firefighting equipment if loss estimates are available). Professional judgment should be used in deciding to include a Wildfire in Storm Data. In general, forest fires smaller than 100 acres, grassland or rangeland fires smaller than 300 acres, and wildland use fires not actively managed as wildfires should not be included. This is consistent with the definitions for significant and/or large fires utilized by most land use agencies.
Winter Storm	A winter weather event that has more than one significant hazard (i.e., heavy snow and blowing snow; snow and ice; snow and sleet; sleet and ice; or snow, sleet and ice) and meets or exceeds locally/regionally defined 12 and/or 24 hour warning criteria for at least one of the precipitation elements. Normally, a Winter Storm would pose a threat to life or property.
Winter Weather	A winter precipitation event that causes a death, injury, or a significant impact to commerce or transportation, but does not meet locally/regionally defined warning criteria. A Winter Weather event could result from one or more winter precipitation types (snow, or blowing/drifting snow, or freezing rain/drizzle). The Winter Weather event can also be used to document out-of-season and other unusual or rare occurrences of snow, or blowing/drifting snow, or freezing rain/drizzle.

Note: If the event causes fatalities, injuries, significant property damage or economic loss, it will be included in the data even when it does not meet the warning criteria. If the event is considered significant, it will be entered into Storm Data, even if it only affected a small area.

Table A4: OLS Regressions of Time Use on Rainy day

Panel A: Time use main categories			
	(1)	(2)	(3)
Dependent Variables (in minutes)	Work	Leisure	Home Production
Rainy day	-4.749**	-0.412	1.980
	(2.417)	(1.622)	(1.529)
Adjusted R-squared	0.122	0.092	0.144
Panel B: Sub-categories of work time			
	(4)	(5)	(6)
Dependent Variables (in minutes)	Work at workplace	Work at home	Work at other places
Rainy day	-5.321**	1.753	-1.181
	(2.608)	(1.242)	(0.839)
Adjusted R-squared	0.096	0.071	0.012

Note: Standard errors clustered on state-month in parentheses. Time span: 2004-2019. These regressions only include respondents that are employed. Non-business days are deleted from the sample. The work time variables only account for the time spent in the respondent's main job. The respondent's total work time in the dairy day is divided into three parts according to different locations (work place, home, and other places). The independent variable of interest is a binary indicator of whether the respondent's residential region is a rainy day on the diary day. Rainy day is defined as a day with at least 0.1 inches of precipitation. The regressions include the following control variables: age, age squared, gender, race (white=1), presence of partner, number of children under 18, dummies for highest level of education completed (16 categories). They are also fixed for Industry-occupation, day of the week, month , year, and county/CBSA.
Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.
Number of observations N=36,868.

Table A5: Job Flexibility and Work At Home Percentage By Individual Characteristics and Work Status On Diary Day

	Number of Obs.	Location flexibility		Time flexibility	
		Mean	Std. Err.	Mean	Std. Err.
High risk industry	1,708	0.308	0.011	0.525	0.012
Low risk industry	6,323	0.374	0.006	0.596	0.006
Male	4,049	0.368	0.008	0.596	0.008
Female	4,225	0.341	0.007	0.568	0.008
High income	4,100	0.497	0.008	0.654	0.007
Low income	4,174	0.214	0.006	0.510	0.008
College degree	4,935	0.486	0.007	0.633	0.007
No college degree	3,339	0.159	0.006	0.505	0.009
Respondents that go out to work during business days	2,982	0.359	0.009	0.592	0.009
Respondents that go out to work during non-business days	798	0.159	0.013	0.528	0.018

Note: The differences in means between pair groups are all significant at 1% level.