Can Work-from-Home Improve Adaptation to Extreme Weather? Evidence from Vehicle Crashes in the US

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Abstract

We examine how work-from-home (WFH) interacts with established adaptation strategies to reduce extreme weather–related risks. Using county-date–level data from ten U.S. states on winter weather forecasts, vehicle crashes, mobile phone location, and WFH adoption, we show that WFH reduces baseline travel, leading to fewer vehicle crashes even on snow-free days. However, in high-WFH counties, winter weather advisories are less effective in reducing auto crashes, potentially due to lower baseline travel and increased flexibility in travel timing. Using mobile phone location data, we further show that WFH changes retail travel patterns, making visits more likely to occur when weather advisories are issued earlier. Our results highlight the importance of accounting for interactions between mitigation measures when designing and allocating resources for adaptation efforts.

Key Words: Adaptation; Work-from-home; Vehicle crashes; Weather forecasts

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1 Introduction

Extreme weather events cause significant economic and health damages. We are investing in various adaptation measures that reduce exposure and vulnerability to such events–from air conditioning that reduces heat-related mortality (Barreca et al., 2016) to weather forecasts that help people avoid outdoor exposure and hazards (Song, 2024; Molina and Rudik, 2022; Shrader et al., 2022). Recent technological advances have enabled new adaptation strategies–such as remote work, drought resistant seeds, and heat pumps–yet these innovations may sometimes substitute for existing measures or make existing adaptations less effective. In order to efficiently allocate resources in developing and implementing new adaptations, it is important to understand how they affect existing ones, and how to quantify their net impacts.

In this paper, we examine one such novel adaptation—remote work technologies. We assess the benefits of remote work in the context of auto crashes during winter weather. We first examine the direct gains from remote work adoption. We then investigate how it interacts with a traditional adaptation measure—winter weather advisories. Specifically, we examine whether remote work makes winter advisories more effective, or whether it reduces the benefits of advisories by lowering baseline travel?

Remote work technologies in the context of winter auto crashes provide a valuable setting to explore our question. Pandemic-related shelter-in-place orders compelled both institutions and individuals to adopt remote work and online transaction technologies. Corporations, offices, schools, and hospitals shifted to remote engagement, while commercial establishments embraced e-commerce. Individuals invested in hardware, software, and skills for online shopping. We collectively refer to these remote work and transaction innovations as "work from home" (WFH) adoption. WFH lets people avoid extreme weather conditions such as snowstorms by working and shopping remotely instead of traveling to an office or store. The abrupt and widespread adoption of WFH technologies during the pandemic provides a useful setting to empirically examine their effects.

Vehicle crashes in the US cause significant loss of life and property. Winter weather further increases the risk of crashes. WFH adoption has allowed many workers and businesses to operate fully or partly from home, while remote transaction infrastructure—such as e-commerce and home delivery—reduces travel needs. On one hand, WFH can directly lessen the impact of winter weather on crashes by lowering the number of vehicles on the road. It also offers flexibility, allowing people to shift travel to safer driving conditions. On the other hand, by permanently reducing baseline travel, WFH may weaken the effectiveness of existing adaptation measures like travel advisories. In this paper, we empirically examine

both the direct and indirect effects of WFH adoption on vehicle crashes in the United States.

To examine our research questions, we combine five datasets at county-date level from ten US states for 2018-2022: (1) vehicle crash data from police accident reports, (2) weather station observations from NOAA's GHCN database, (3) NWS's Winter advisory data with lead times from Iowa Environmental Mesonet, (4) mobile phone location data from SafeGraph covering visits to different establishment types, and (5) WFH adoption rates from the American Community Survey (ACS). First, we compare the vehicle crash levels and the effect of advisory lead times on crashes before, during, after the COVID-19 related shelter in place orders. Then, we use the ACS data to compare estimates between counties with below and above median WFH adoption. We follow the methodology in Anand (2022) to estimate the effect of lead time on vehicle crashes. Specifically, we use the within county-year-month variation in advisory lead times and vehicle crashes controlling for observed weather to estimate the effect of an additional hour of advisory lead time on crashes. To examine the underlying mechanisms driving the traffic crashes, we re-estimate our primary model for the number of visits to different kinds of establishments (leisure, retail, healthcare, education, and commercial).

We find that WFH affects adaptation through two distinct channels. First, WFH directly reduces exposure to weather risk by lowering baseline travel. In counties with above-median WFH adoption, crash rates remain significantly below pre-pandemic levels even on days with no snow. Second, WFH affects how people and institutions respond to weather advisories in two ways: it enables greater flexibility in responding to advisories, while also reducing the baseline need to travel. In counties with low WFH adoption, longer advisory lead times continue to reduce crashes at levels similar to the pre-pandemic period. However, in high WFH counties, longer lead times have no effect on crashes. Our analysis suggests that this may be partially attributed to lower baseline travel that reduces the marginal benefits of advance warnings, and partially to a greater flexibility provided by remote work in planning discretionary travel on bad weather days.

Our analysis of visits using mobile phone location data shows that retail visits increase with longer lead times after WFH adoption, reversing their pre-pandemic behavior. In contrast, visits to educational and healthcare facilities show increased responsiveness to advisories—visits fall with longer lead times after WFH adoption—likely due to increased capabilities of remote instruction and telehealth services.

Our work contributes to the literature on how labor and institutions adapt to extreme weather (Li, 2021; Downey et al., 2023; Song, 2024). We show that WFH can improve weather-risk adaptation through both reduced exposure and increased flexibility. We also provide evidence that it can decrease the effectiveness of traditional adaptation measures.

In this respect, our paper is also connected with literature that examines the distributional effects of alternative work arrangements (Papp, 2024; Richard, 2024).

This paper also contributes to the literature on the role of weather forecasts and advisories on environmental risk adaptation (Molina and Rudik, 2022; Shrader, 2020; Shrader et al., 2022; Anand, 2022). We extend this literature by examining how a novel adaptation technology (such as WFH) may interact with our ability to respond to weather forecasts. Our paper highlights the importance of understanding how different adaptation strategies interact. This interaction has important policy implications for designing effective climate adaptation measures.

The paper is structured as follows. Section 2 provides details on the data. Section 3 discusses the empirical design and results. Section 4 concludes.

2 Data and Empirical Design

2.1 Data

In this section, we describe the data sources and sample construction.

2.1.1 Fatal crash data

We obtain fatal crash data in the US from the Fatality Analysis Reporting System (FARS) for the period 2018–2022. Data include all vehicle accidents that resulted in one or more fatalities. We aggregate the number of fatal accidents for each county-date observation in our sample.

2.1.2 Weather Station Observations

We obtain daily snowfall, precipitation, and temperature observations from the National Oceanic and Atmospheric Administration's (NOAA) Global Historical Climate Network (GHCN) database. We aggregate all daily weather observations at county level by estimating the inverse-distance weighted average from the population centroid of the county. We include observations from all weather stations within 20 miles of the county population centroid.

2.1.3 Mobile phone location data

We obtain mobile phone location data from Dewey Data platform for the period 2018–2022. These data are collected by SafeGraph and maintained by Advan Research. Using the geo-

graphic coordinates of the mobile phone location, Safegraph determines the number of visits made to several places of interests (PoI) by unique visitors in a day. We aggregate the number of daily visits to various places in a county. We use North American Industry Classification System (NAICS) classification to categorize the visits in two categories: (a) discretionary visits to retail and leisure services, and (b) non-discretionary visits to educational, healthcare, and commercial places and offices.

2.1.4 Work-from-home adoption

We obtain our WFH data from the 2019 and 2023 waves of the American Community Survey (ACS), administered by the U.S. Census Bureau. For our preliminary analysis, we calculate the average percentage of WFH at the state level using these two years. We then construct a categorical variable indicating whether a state's WFH adoption rate is above or below the median across this period.

2.1.5 Covid-related emergency measures

We also use data on the timing and nature of the federal and state level COVID-related emergency response obtained from Gupta et al. (2021).

3 Preliminary Results

3.1 Effect of WFH on Crashes

We first examine whether the number of vehicle crashes have reduced since the adoption of WFH. We estimate the following regression equation that measures the average daily crashes in a half-year period between Jan 2018 and Dec 2022 relative to that in the second half of year 2019, i.e., Jan 2020 to Jun 2020:

$$y_{ct} = \sum_{h=-3}^{6} \beta_h \mathbb{D}_t^h + \sum_{l=-2}^{2} \Big[\boldsymbol{\gamma_l} \mathbb{W}_{c,t+l} + \boldsymbol{\lambda}_l \mathbb{X}_{c,t+l} \Big] + \alpha_c + \epsilon_{ct} \tag{1}$$

where y_ct is the total number of crashes per 100,000 people in the county c on date t. Our primary variable of interest is a vector of half-year indicator variables $\mathbb{D}_t^h$, where h indexes the half-year periods from 2018 to 2022, such that $h \in \{-3, -2, ..., 5, 6\}$ with $h = 0$ corresponding to July-December 2019. Each indicator $\mathbb{D}_t^h$ equals 1 if date t falls within the corresponding half-year period and 0 otherwise. We omit the indicator for July-December 2019 ($h = 0$) to serve as the reference period. The coefficients β_h measure the difference

in average daily crashes per 100,000 people between each half-year period and the reference period, controlling for other factors.

$\mathbb{W}_{ct}$ captures weather effects through a flexible specification following Barreca et al. (2016). We construct indicator variables for binned values of daily snowfall, rainfall, and temperature. Specifically, $\mathbb{W}_{ct}$ includes indicators $snow^b_{ct}$, $rain^b_{ct}$, and $temp^b_{ct}$, where each indicator equals 1 if the corresponding weather measure falls within bin b. For snowfall, we define eight bins in inches: {less than 0.01, 0.01-0.5, 0.5-1, 1-2, 2-3, 3-5, 5-7, and greater than 7}. Rainfall is categorized into seven bins measured in inches: {less than 0.01, 0.01-0.25, 0.25-0.5, 0.5-1, 1-1.5, 1.5-2, and greater than 2}. Temperature is divided into five bins measured in Celsius: {less than -15, -15 to -5, -5 to 5, 5-15, and greater than 15}. To account for the lead and lag effects of weather on crashes, we construct all weather controls for five days around date t.

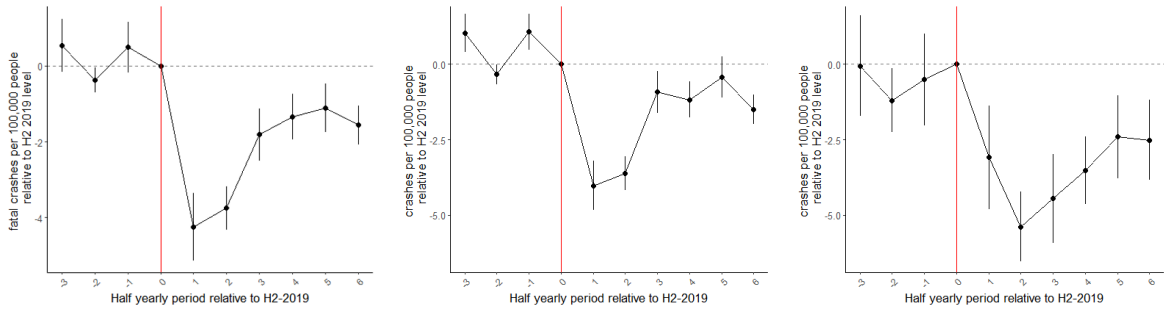
$\mathbb{X}_{ct}$ denotes additional controls. It includes indicator variables to capture the day of the week to control for within week patterns in traffic and crashes. It also includes a variable to capture whether the day is a workday or holiday in the county. Finally, we also control for the seasonal effects by including the week serial number of the year in which the date falls in. α_c is county fixed effects to account for county level time-invariant factors that may affect vehicle crash risk. We weight all regressions by county population. Errors are clustered two-way at county and date level.

Fig 1(a) plots the regression estimates for the change in the daily average crashes in a half-year period relative to the second half-year period in 2019. The bars plot the 95% confidence interval around the estimates. The figure shows that crashes fell sharply after H2-2019, reaching their lowest level in H1-2020. Although crash rates gradually recovered in subsequent periods, they remained consistently below the reference period level through 2022, suggesting a persistent reduction in crash rates following the pandemic onset. The initial large drop is likely due to stay home and shelter in home orders when many offices, businesses, schools, and public places were closed. However, most counties lifted the stay home restrictions by the end of June 2021, i.e., by the half-year period 3 in the graph. This persistent decline in crashes is likely due to the adoption of remote work and home delivery services that reduced the need for travel.

Figures 1(b) and (c) examine how the impact of remote work adoption varies with weather conditions by plotting the estimates separately for days without and with snowfall. Both types of days show a sharp initial decline in crashes following the pandemic onset. However, the subsequent patterns differ. On days without snow, crash rates seem to recover toward pre-pandemic levels by 2022, suggesting a return to normal driving patterns during good weather. In contrast, crash rates on days with snowfall remain lower than pre-pandemic

levels. This difference suggests that the adoption of remote work technologies may have provided people more ways to respond to adverse weather conditions. When faced with snowfall, people appear more likely to utilize remote work options rather than commute, leading to a decrease in weather-related crashes.

Figure 1: Daily average crashes have declined since 2019



(a) All Days (b) No Snow Days (c) Snow Days

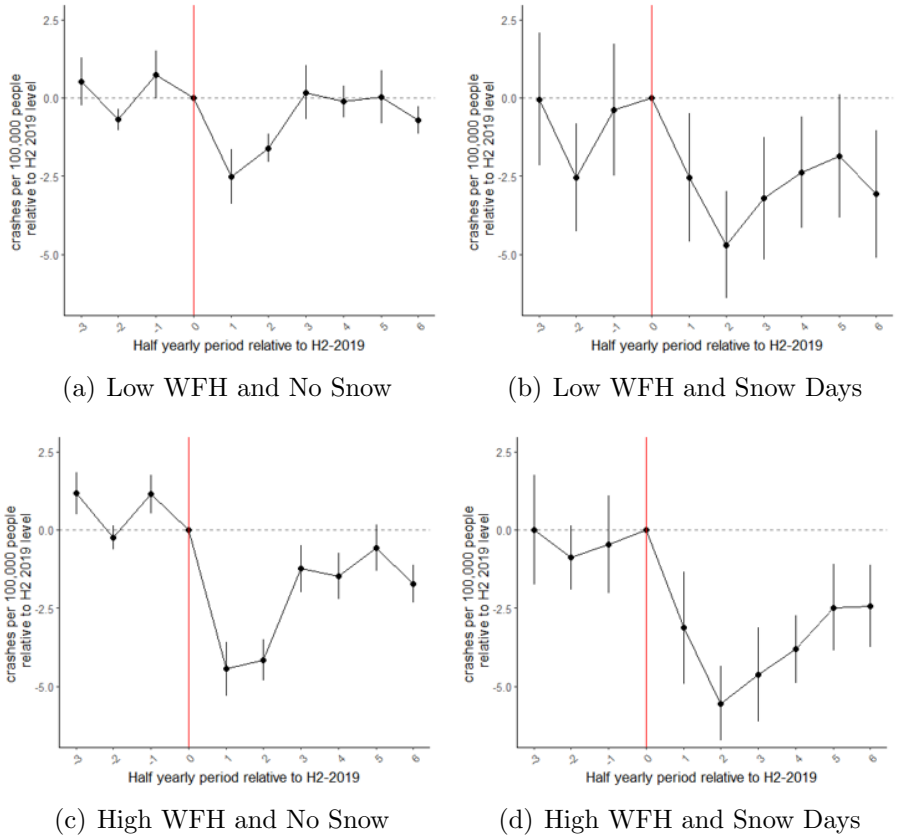
Note: These figures plot the change in daily average crashes (y-axis) in a half-year relative (x-axis) to the second half-year period in 2019 (marked by the red vertical line). Panel (a) shows estimates for all days, panel (b) for days with no snowfall, and panel (c) for days with positive snowfall. The bars plot the 95% confidence interval around estimates. Standard errors are clustered two-way at the county and date level.

To further investigate the role of remote work in reducing crashes, we examine whether counties with higher work from home adoption experienced larger reductions in crashes. We classify counties into high and low work from home groups based on the share of remote workers reported in the American Community Survey (ACS). The ACS, conducted annually by the U.S. Census Bureau, provides detailed information about work arrangements at the county level based on responses from a representative sample of households. Using these classifications, we estimate Equation (1) separately for four subsamples: counties with above and below median work from home adoption, each categorized again for days with and without snowfall.

Fig 2 plots regression estimates for the change in daily average crashes in each half-year period relative to the second half of 2019, separately for counties with high and low WFH adoption and by snowfall conditions. Panels (a) and (b) show estimates for counties with below-median WFH adoption during no-snow and snow days respectively, while panels (c) and (d) show the corresponding estimates for counties with above-median WFH adoption. The bars plot the 95% confidence intervals around the estimates. The red vertical line marks the reference period (H2-2019).

Figure 2 shows that counties with higher work from home adoption experience larger reductions in crashes. On days without snow, low WFH counties show a complete return

Figure 2: Daily average crashes by WFH and Snowfall



(a) Low WFH and No Snow

(b) Low WFH and Snow Days

(c) High WFH and No Snow

(d) High WFH and Snow Days

Note: These figures plot the change in daily average crashes (y-axis) in a half-year relative (x-axis) to the second half-year period in 2019 (marked by the red vertical line). Panels (a) and (b) show estimates for counties with below-median work from home (WFH) adoption for no-snow and snow days, respectively. Panels (c) and (d) show estimates for counties with above-median WFH adoption for no-snow and snow days, respectively. The bars plot the 95% confidence interval around estimates. Standard errors are clustered two-way at the county and date level.

to pre-pandemic crash levels after stay-home orders were lifted, while high WFH counties maintain lower crash rates. This reduction in crashes during days with no snowfall in high WFH counties likely reflects reduced travel as a direct effect of remote work adoption.

On snow days, both groups of counties exhibit reduced crash rates compared to pre-pandemic levels. The reductions in high WFH counties appear more stable and precisely estimated, suggesting a more consistent pattern in how these counties respond to adverse weather. In low WFH counties, the reduction likely stems from increased institutional flexibility in responding to adverse weather - businesses and schools appear more willing to close or operate remotely when snow is forecast. In high WFH counties, the effect appears to combine this institutional flexibility with an existing baseline of remote work. The established remote work infrastructure in high WFH counties likely enables both consistent reductions in regular commuting and forecast related transitions to remote operations during bad weather.

In the next section, we tease out the effect of these mechanisms by examining the response to winter advisories for low and high WFH counties.

3.2 Effect of WFH on Response to Winter Advisories

The previous analysis suggests that work from home arrangements reduce crashes through a direct adaptation channel–by lowering the average level of travel in high WFH counties, as suggested by reduced crashes even on days without snow. However, WFH adoption may also operate through an indirect adaptation channel by enabling people to respond more flexibly to information about adverse weather conditions. For example, when people have the option to work remotely, they can more easily adjust their travel plans in response to weather advisories. This suggests that WFH adoption may increase the effectiveness of advisories. However, at the same time high WFH adoption may also reduce the marginal benefit of other adaptations like road treatment operations, since fewer people are traveling to begin with. It is not clear how WFH might affect the effectiveness of other adaptation measures.

In this section, we examine how WFH adoption interacts with these other adaptation channels. We focus specifically on how WFH adoption influences the effectiveness of winter weather advisories lead times. Recent evidence shows that winter advisories with longer lead times reduce vehicle crashes by enabling people to adjust their travel plans and allowing more time for snow removal operations (Anand, 2022). Building on these findings, we examine whether the impact of advisory lead times differs between high and low WFH counties. This analysis helps us distinguish between two competing effects: whether the flexibility of remote work enhances the effectiveness of advance weather warnings, or whether reduced baseline travel in high WFH areas diminishes the marginal benefits of such warnings.

3.2.1 Effect of Advisory Lead Time on Crashes

First, we examine how the effect of winter advisory lead time on crashes changed after the widespread adoption of remote work technologies during the pandemic. Following (Anand, 2022), we estimate the regression model in Equation 2 separately for three time periods: (a) pre-stay-at-home period before March 15, 2020; (b) stay-at-home period between March 16, 2020 and June 30, 2021; and (c) post-stay-at-home period after July 1, 2021. This division allows us to compare the effectiveness of weather advisories during the pre-pandemic period with both the initial phase of mandated stay-at-home period and the subsequent period when remote work became discretionary and more stabilized.

$$y_{ct} = Adv_{ct} + \sum_{j} \beta_j Leadtime_{ctj} + \sum_{l=-2}^{2} \Big[\boldsymbol{\gamma_l} \mathbb{W}_{c,t+l} + \boldsymbol{\lambda}_l \mathbb{X}_{c,t+l} \Big] + \Phi_{cym} + \epsilon_{ct} \tag{2}$$

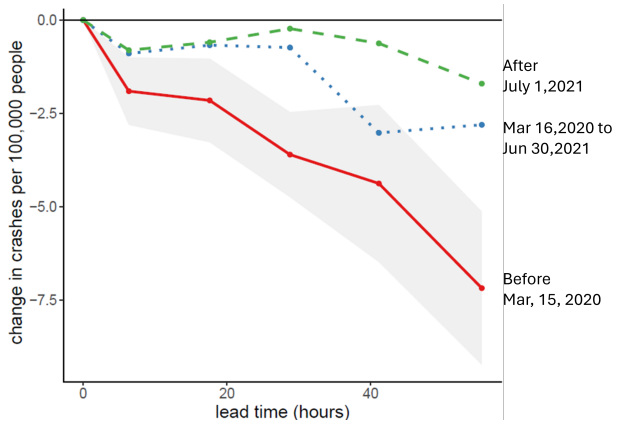
where y_{ct} is the total number of crashes per 100,000 people in county c on date t. Adv_{ct} indicates whether a winter advisory was issued on date t for county c. The key variable of interest, $Leadtime_{ct}$, measures the advisory lead time in hours, with zero lead time assigned to county-dates without an advisory. Thus, Adv_{ct} captures the effect of an advisory issued with zero lead time. To allow for nonlinear effects of lead time, we bin the lead times into five 12-hour intervals $J = \big\{$(0,12], (12-24], (24-36], (36-48], >48$\big\}$. We replace $Leadtime_{ct}$ with five indicator variables $Leadtime_{ctj}$, where coefficient β_j measures the effect of lead time in bin j relative to zero lead time. Since longer lead-times on advisories may cause people to shift their travel to earlier or later days, we examine the cumulative effects of lead time on crash risk. Following Heutel et al. (2021), we use the total number of crashes over a 3-day window centered on the advisory day as our primary outcome variable in equation 2.

$\mathbb{W}_{ct}$ captures weather effects through a flexible specification, as in Equation (1). $\mathbb{X}_{ct}$ denotes additional controls. It includes controls for day of week, holiday, and week serial number. To account for systematic variation in advisory characteristics, We also control for the type of predicted weather event, the advisory signal type (watch, advisory, or warning), and the timing of the advisory. For each control variable, we include both two-day leads and lags to account for how weather conditions and advisories on surrounding days might affect crashes. The model includes county-month-year fixed effects (Φ_{cym}), allowing us to estimate the effect of lead time using within county-month-year variation. All regressions are weighted by county population, and standard errors are two-way clustered at the weather forecast office and date level.

Figure 3 plots the estimates from regression in Equation 2 for three time periods. The y-axis denotes the changes in crashes per 100,000 people relative to days with zero lead time. The x-axis denotes the average lead time in hours within each lead time bin. The red line plots the estimated effect of each lead time bin on crashes during the pre-stay-home period (before March 15, 2020). The dotted blue line shows estimates for the stay-at-home period (March 16, 2020 to June 30, 2021), and the dashed green line shows estimates for the post-stay-home period (after July 1, 2021). The grey ribbon plots the 95% confidence interval for pre-stay-home period estimates.

Figure 3 shows that the effectiveness of advisory lead times in reducing crashes has changed substantially since the adoption of remote work. In the pre-pandemic period, longer

Figure 3: Effect of Advisory Lead Time on Crashes



Note: This figure plots the effect of advisory lead time on crashes for three time periods in the sample using the regression model in Equation (2). The y-axis shows the change in crashes per 100,000 people relative to days with zero lead time. The x-axis shows the average lead time within each lead time bin. The red line plots estimates for the pre-stay-home period (before March 15, 2020), the dotted blue line for the stay-at-home period (March 16, 2020 to June 30, 2021), and the dashed green line for the post-stay-home period (after July 1, 2021). The grey ribbon shows the 95% confidence interval for the pre-stay-home period estimates. Standard errors are two-way clustered at the weather forecast office and date level.

lead times on winter advisories were associated with larger reductions in crashes.[1] The effect is particularly pronounced for longer lead time, with crashes declining by about 7 per 100,000 people when advisories are issued more than 40 hours in advance. However, in the period after July 2021, when remote work became likely more established, the relationship between advisory lead time and crashes disappears. Even advisories issued well in advance show only a small effect on crash rates. These results suggest that the adoption of remote work may have reduced the marginal benefit of advance weather warnings.

There are likely multiple reasons for the reduction in effectiveness of advisories after the pandemic. One reason could be that with more people having the flexibility to work from home regularly, fewer people need to adjust their travel plans in response to weather advisories, regardless of how early these advisories are issued. This is the direct result of WFH adoption which reduces the baseline travel levels. Another reason could be that WFH adoption allows people the flexibility to move their non-work related travel within the same day, rather than postponing it to another day. For example, WFH may allow a retail store visit to be moved earlier in the day when bad weather is forecast in the afternoon. Without the WFH flexibility, people may resort to cancel or move the travel to another day. Both mechanisms, which may occur together, would result in muted effect of lead time on crashes.

[1]This result is consistent with the result in Anand (2022), relies on observations between the years 2008 and 2019.

To examine the underlying mechanism behind the reduced effectiveness of advisory leadtime after the pandemic, in the next section, we examine the visits made by people to different types of places.

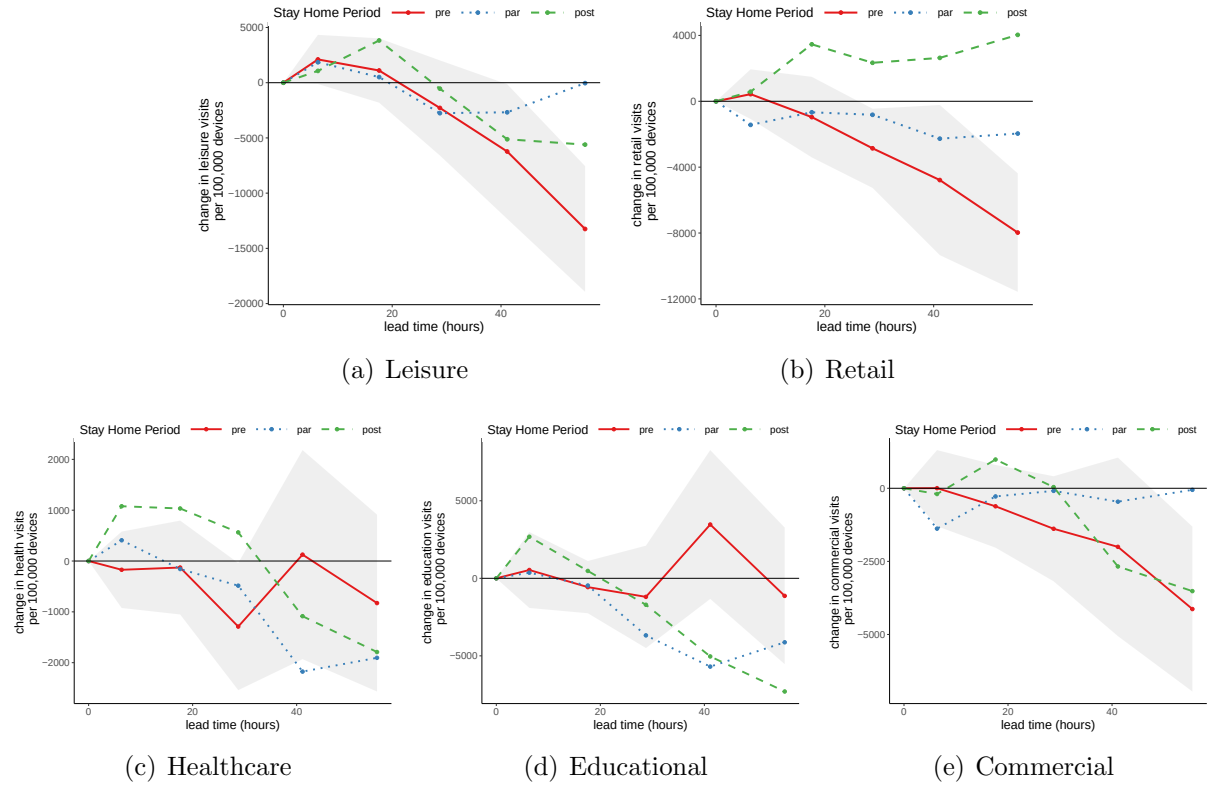
3.2.2 Effect of Advisory Lead Time on Visits

In this section, we examine the effect of lead time on visits to gain insight into the mechanisms behind the change in response to advisory lead time after the WFH adoption. We use the Safegraph smartphone location data to study the number of visits made by people to different places of interest (PoIs). Safegraph uses mobile phone pings to estimate the number of visits to different places, which we classify into five categories based on their North American Industry Classification System (NAICS) codes. These categories are: (a) Leisure (includes restaurants and hotels), (b) Retail (grocery and departmental stores); (c) Healthcare; (d) Education (includes schools, collages, coaching centers); and (e) commercial (includes all types of offices, factories, and manufacturing facilities). Specifically, we estimate the regression model in equation (2) where the dependent variable y_{ct} is the number of visits per 100,000 devices in a county. We estimate the model separately for the five different categories of places of interests.

Figure 4 plots the estimated effect of lead time on different types of visits. Panel (a) and (b) shows the estimates for discretionary visits to leisure and retail establishments, respectively. Panel (c), (d), and (e) shows the estimates for likely non-discretionary visits made to healthcare, educational, and commercial establishments, respectively. The red line plots estimates for the pre-stay-home period (before March 15, 2020), the dotted blue line for the stay-at-home period (March 16, 2020 to June 30, 2021), and the dashed green line for the post-stay-home period (after July 1, 2021). The grey ribbon shows the 95% confidence interval for the pre-stay-home period estimates. The figure shows changes in how different types of places respond to advisories lead times before and after the adoption of WFH technology.

Panels (a) and (b) show that pre-pandemic leisure and retail visits fall with advisory lead time. After the pandemic, this pattern changes: leisure visits show a smaller decline, while retail visits actually increase relative to zero lead time. The reversal in retail visits is particularly meaningful–there are more visits when advisories arrive with longer lead times. These patterns show how WFH adoption has affected people's response to weather advisories. Before the pandemic, people reduced discretionary trips when advisories came with longer lead times. After WFH adoption, such trips either do not decline or even increase with advisory lead time. It is likely that people move discretionary trips to different times during the day, or even plan additional retail trips to stock up before bad weather when they get

Figure 4: Effect of Lead Time on Visits by Type of Places



(a) Leisure (b) Retail

(c) Healthcare (d) Educational (e) Commercial

Note: The figure plots the effect of advisory lead time on visits to different types of places for three time periods in the sample using the regression model in Equation (2). The dependent variable is the number of visits per 100,000 devices. Panel (a) shows estimates using visits to leisure places such as restaurants, bars, and theaters, panel (b) uses visits to retail places such as stores and malls, panel (c) uses visits to healthcare facilities such as hospitals and clinics, panel (d) uses visits to educational institutions such as schools and colleges, and panel (e) uses visits to commercial places such as offices and factories. The y-axis shows the change in visits relative to days with zero lead time. The x-axis shows the average lead time within each lead time bin. The red line plots estimates for the pre-stay-home period (before March 15, 2020), the dotted blue line for the stay-at-home period (March 16, 2020 to June 30, 2021), and the dashed green line for the post-stay-home period (after July 1, 2021). The grey ribbon shows the 95% confidence interval for the pre-stay-home period estimates. Standard errors are two-way clustered at the WFO and date level.

advance warning. This change in behavior is likely because remote work gives people more flexibility–they can now shop during regular work hours and can plan their trips around expected bad weather instead of just canceling them.

Panels (c)–(e) show estimates for non-discretionary visits. Healthcare and educational visits showed little response to advisory lead times before the pandemic. However, after the adoption of remote work technology, both types show a slight increase in visits for shorter lead times followed by a decline for longer lead times. The decline is more pronounced for educational visits, suggesting that after the remote work adoption, schools and colleges can more easily switch to remote learning when they get enough advance warning of bad weather. Commercial visits show different patterns across periods as well. Before the pandemic, visits

fall gradually with advisory lead time for all lead time horizons. After the pandemic, visits stay constant or even increase slightly for shorter-horizon advisories (less than 24 hours), but fall sharply for longer lead times. These patterns suggest that with shorter lead time, people use WFH flexibility to move their trips around the bad weather rather than canceling them. However, when advisories arrive with longer lead time, institutions have time to respond–schools can switch to remote instruction, healthcare providers and patients can move to tele-health visits, and offices can shift to remote work.

These results help explain why advisory lead times may have become less effective at reducing crashes after WFH adoption. Before the pandemic, longer lead times reduced crashes by reducing overall travel–visits fell across most categories when people got advance warning of bad weather. After WFH adoption, two factors appear to affect crash patterns. First, many visits, especially office visits, do not fall as much with lead time due to lower baseline travel in the post-pandemic period. Second, instead of canceling trips, people now seem to use the flexibility provided by remote work to move their visits to different times–retail visits actually increase with lead time as people shop more to stock up before the storm, while healthcare and commercial visits show increases for shorter lead times as people adjust their schedule around the weather. This likely re-distribution of trips, rather than cancellation, may explain why longer lead times no longer reduce crashes as effectively as they did before the pandemic.

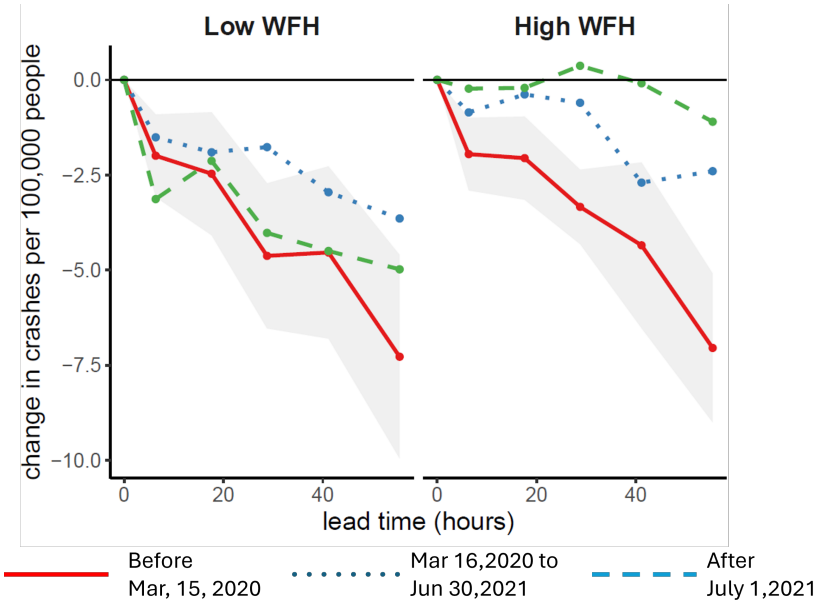
3.2.3 Effect of Advisory Lead Time by WFH Adoption Levels

To test whether the diminished effectiveness of advisory lead times is indeed driven by work from home adoption, we estimate the effect of lead time separately for counties with above and below median WFH adoption. Following our earlier classification using ACS data on WFH levels, we divide counties into high and low WFH groups based on their share of remote workers being above or below the median level, respectively. If WFH reduces the marginal benefit of advance warnings by maintaining lower baseline travel levels, the decline in advisory effectiveness should be more pronounced in high WFH counties. We examine this by replicating the analysis in Figure 3 separately for these two groups of counties.

Figure 5 plots the estimates from regression in Equation 2 separately for counties with below-median (left panel) and above-median (right panel) work from home adoption. For each group, we show estimates for three time periods. The y-axis denotes the changes in crashes per 100,000 people relative to days with zero lead time. The x-axis denotes the average lead time in hours within each lead time bin. The red line plots the estimated effect of each lead time bin on crashes during the pre-stay-home period (before March 15, 2020). The dotted blue line shows estimates for the stay-at-home period (March 16, 2020 to June

30, 2021), and the dashed green line shows estimates for the post-stay-home period (after July 1, 2021). The grey ribbon plots the 95% confidence interval for pre-stay-home period estimates.

Figure 5: Effect of Advisory Lead Time on Crashes by WFH Adoption



Note: This figure plots the effect of advisory lead time on crashes for three time periods separately for counties with below-median (left panel) and above-median (right panel) work from home adoption using the regression model in Equation (2). The y-axis shows the change in crashes per 100,000 people relative to days with zero lead time. The x-axis shows the average lead time within each lead time bin. The red line plots estimates for the pre-stay-home period (before March 15, 2020), the dotted blue line for the stay-at-home period (March 16, 2020 to June 30, 2021), and the dashed green line for the post-stay-home period (after July 1, 2021). The grey ribbon shows the 95% confidence interval for the pre-stay-home period estimates. Counties are classified into high and low WFH groups based on the share of remote workers reported in the American Community Survey. Standard errors are two-way clustered at the weather forecast office and date level.

Figure 5 shows how the effectiveness of advisory lead times varies between high and low WFH counties. In the pre-pandemic period, both groups show similar effects of lead time–vehicle crashes fall with advisory lead times, with larger declines in crashes at longer horizon lead times. For example, advisories issued with longer than 40 hours lead time result in about 7 fewer crashes per 100,000 people. However, after July 2021, these patterns diverge. In low WFH counties, longer lead times continue to reduce crashes, with longer horizon advisories associated with about 5 fewer crashes per 100,000 people. In contrast, crashes in high WFH counties show virtually no response to advisory lead times, with the estimated effect remaining close to zero regardless of how early the advisory is issued. These results suggest that WFH adoption may reduce the marginal benefit of advance weather warnings by maintaining lower baseline travel levels, particularly in areas where WFH is more prevalent.

4 Conclusion and future steps

We examine the role of work-from-home adoption as an adaptation measure to weather-related risks by studying its impact on vehicle crashes during hazardous winter weather. We find that WFH affects adaptation through two distinct channels. First, WFH directly reduces exposure to weather risks by lowering baseline travel, particularly in counties with above-median WFH adoption where crash rates remain below pre-pandemic levels even on days with no snow. Second, WFH has changed how people and institutions respond to weather advisories in two ways: it enables greater flexibility in responding to advisories, while also reducing the baseline need to travel. These effects vary across different types of activities.

We examine how WFH adoption affects the efficacy of advisory lead times in reducing crashes. In counties with low WFH adoption, longer advisory lead times continue to reduce crashes at levels similar to the pre-pandemic period. However, in high WFH counties, longer lead times have no effect on crashes. Our analysis suggests that this may be partially attributed to lower baseline travel that reduces the marginal benefits of advance warnings, and partially due to greater flexibility provided by WFH in planning discretionary travel on bad weather days. Our analysis of visit using mobile phone location data shows that retail visits increase with longer lead times after WFH adoption, reversing their pre-pandemic behavior. In contrast, visits to educational and healthcare facilities show increased responsiveness to advisories—visits fall with longer lead times after WFH adoption—likely due to increased capabilities of remote instruction and telehealth services.

These findings suggest that while WFH technology improves adaptation to weather risks through reduced exposure and increased flexibility, it may also decrease the effectiveness of traditional adaptation measures like weather advisories. This interaction between different adaptation strategies has important implications as climate change increases the frequency and severity of extreme weather events, and society invests more resources in various adaptation measures.

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