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ABSTRACT

Winter Weather and Work Hours: Heterogeneous Effects and Regional Adaptation*

Winter weather affects hours worked. We examine how work hours reported in the monthly Current Population Survey (CPS) vary with respect to snowfall in 265 metropolitan areas over the years 2004-2014. The effects of snowfall on work hours vary across types of workers, occupation, industry, and region. Losses in work hours due to snow events are particularly large in the South and among construction workers. An average daily inch of snowfall during a reference week reduces work by about an hour. Few of the hours lost from large snowfalls are "made-up" in subsequent weeks. A "back-of-an-envelope" calculation suggests that in an average year, snow leads to a 0.15 percent loss in annual hours worked, a small but nontrivial impact.

JEL Classification: J22, O4, Q54

Keywords: work hours and snow, regional adaptation, heterogeneity by industry, occupation, work type

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1. Introduction

It is widely recognized that inclement weather affects economic activity. This relationship has often drawn attention from the Federal Reserve Board, among others. For example, in April 2014, Janet Yellen, Chair of the Board of Governors of the Federal Reserve System, gave a speech at the Economic Club of New York stating that part of the softness in economic activity was weather related (Yellen 2014). A year later, Federal Reserve economist Christopher Foote provided evidence that severe weather in early 2015 had slowed employment growth, but some of the decline was offset by faster growth in subsequent months (Foote 2015).

Not all communities handle snow well. An example is the experience of Atlanta, GA during its “snowmaggedon” ice storm in January 2014. Just over two inches of snow and ice paralyzed one of the largest metro areas in the country. “Thousands of drivers were hopelessly stuck for a second day, many without food and water, on paralyzed interstates around Atlanta after a winter storm appeared to take the city by surprise.”[1] It was nearly impossible to travel on the roads the following two days. The movement of 6 million-plus people was squelched by a seemingly minor weather event.

As we show subsequently, the effect of snow on work hours varies substantively across regions, occupations, industries, and types of work. The snow event that paralyzed Atlanta would have had minimal effects in Boston, Chicago, Minneapolis, and other metro areas where snow events are common. Such areas have adapted to winter weather. Local governments and communities invest in road clearing equipment and personnel. Citizens and local governments have acquired behaviors that mitigate the impacts of winter weather. Such behaviors include acquired experience driving in snow, purchase of snow tires and other equipment, use of alternative transportation, and working from home.

In this paper, we examine the relationship between weekly hours worked, as recorded for individuals in the monthly Current Population Survey (CPS), and weather, with a focus on snowfall accumulation. Researchers in multiple disciplines have examined the impact of weather on outcomes such as income, productivity, time-use, health, etc. The economics literature, however, includes relatively few studies on how winter weather affects work hours. CPS monthly employment files have not been widely utilized to examine the relationship between

[1] Retrieved April 23, 2017 at http://usnews.nbcnews.com/_news/2014/01/29/22492664-thousands-still-stranded-on-atlanta-highways-after-snow-catches-south-unprepared

local area working hours and weather during the monthly CPS survey reference week. This is surprising given that the CPS contains large, nationally representative samples of workers reaching back many years in time.

As expected, we find that snowfall during a CPS reference week reduces work hours during that week. Losses in hours worked rise systematically with snow accumulation levels. The relationship between work hours and snow severity differs systematically across regions, types of employment, industry, occupation, and, to a lesser extent, with respect to worker or household demographics. Such relationships have potential policy implications. Climate change and global warming are raising average temperatures and increasing extreme weather events, including winter snow events. As expected, we find that the impact of snow events on work hours differs substantially across regions. For given levels of snowfall, metro areas in regions with infrequent snow events have larger losses in work hours than do areas in regions with frequent snow events. These regional differences no doubt reflect the adaptive behaviors of citizens and local governments in response to prior snow events over time.

The paper is organized as follows. Section 2 briefly summarizes literature related to how weather affects labor-related outcomes. Section 3 presents a brief setup of a labor supply framework that enables us to measure the impact of winter weather (snow events and snowfall accumulation) on work hours. Section 4 presents information on the data sources, including data on climatology, labor inputs, and other relevant measures. Section 5 provides descriptive evidence on work hours and snow. Section 6 presents regression results estimating the impact of snow levels on work hours, with a focus on regional adaptation and heterogeneity with respect to worker types, job types, and location. Section 7 concludes.

2. How Weather Affects Work Hours

Temperature plays a role in determining workers' incomes, although individuals and societies adapt to environmental conditions in ways that mitigate the sensitivity of income with respect to weather variation. Deryugina and Hsiang (2014), studying the 40-year period 1969-2008, conclude that worker productivity decreases with temperature, particularly so for weekdays over 30°C (86°F). These effects changed little over this period. There is rather limited empirical evidence, however, on the relationship between weather conditions and work hours. Severe weather events affect short-run labor supply due to direct effects on worker transportation and mobility, or through indirect effects such as parents staying home with children due to a school closure. Weather affects consumer activity and the demand for goods and services, which in turn affects labor demand, albeit differently depending on the nature of the work and the demand sensitivity. Weather also affects work hours indirectly by changing the relative valuation and costs of alternative uses of time (Connolly 2008; Krüger and Neugart 2018). For example, good weather may increase the demand for leisure activities and thus reduce the supply of market work hours, although increasing demand for some leisure-related activities in turn increases demand for work hours among employees in businesses catering to such demand.

A growing body of research applies various methodologies to examine the climate-related impacts of temperature, precipitation, air pollution, and windstorms on economic activity and outcomes. These studies focus on how changes in climate over time in given spatial areas affect outputs of agriculture and industries, labor productivity, time-use, energy demand, health, conflict, and economic growth (Dell et al. 2014).

Geographer Ellsworth Huntington's (1915) *Civilization and Climate* provided early evidence showing the relationship between temperature and productivity. Huntington finds that productivity was highest in spring and fall when temperatures are moderate, while lowest in summer and winter when temperatures are more extreme. Connolly (2008) examines the impact of rainfall on the labor/leisure choice in the U.S. using the American Time Use Surveys (ATUS). She finds that men substitute about thirty minutes per day, on average, from leisure to work on rainy days. Lee, Gino, and Staats (2014) show that good weather creates distractions that decrease productivity among Japanese bank workers; individuals appear to focus less on work when there are attractive alternate activities. Krüger and Neugart (2018) use German time use data from 2001-2002 linked to weather data. Their study is unique in that it has multiple diary days for individuals, allowing them to use worker fixed effects and measure how day-to-day work hours vary with weather for given workers. Substitution between leisure and work is highest among workers who have jobs with flexible work hours. In contrast to Connolly (2008), the authors find modest interday variation in hours among women but not among men.

Zivin and Neidell (2014) use the individual-level data from the 2003–2006 ATUS linked to weather data from the National Climatic Data Center. They show that fluctuations in temperatures lead to substantive changes in labor supply. They find reductions in work hours in climate-exposed industries such as agriculture, forestry, mining, construction, and utilities, when temperatures exceed 85˚F. Responses were particularly large at very high temperatures. For example, daily work hours in climate-exposed industries decline by as much as one hour at temperatures over 100˚F, as compared to the 76-80˚F range. Ziven and Neidell find little evidence of interday substitution of hours in the workplace.

In contrast to the previous studies focusing on rain and temperatures, there is far less study of how individuals' work hours are affected by snow events. Snow events are less frequent than are rain and extreme temperatures, but potentially have substantial labor supply effects concentrated in time and place. And because snow events are relatively rare and location-specific, it would be problematic to link the relatively small "one-day" samples of individuals recorded in the ATUS.

There is a robust literature focused on climate change and the subsequent need for regional adaptation in response to climate patterns. Kalkuhl and Wenz (2020) examine economic output over time for 1500-plus regions within 77 countries. The authors conclude that increases in regional mean surface temperatures lead to substantively lower productivity levels. The authors do not include damages due to extreme weather events. Using a dataset from more than 180 economies over the period 1950-2015, Acevedo et al. (2020) examine how economic activity is affected by annual variation in temperature and precipitation. The authors conclude that increases in average annual temperatures are followed by lower future levels of investment, which in turn leads to lower output. Gourio and Fries (2020) provide a structural model of adaptation to rising temperatures, which incorporates realistic features of climate and the economy. The principal focus of their model is the effect of rising temperatures on income.

A recent paper by Wilson (2019) examines the predictive power of a model in which county-level weather affects employment. Wilson uses the Quarterly Census of Employment and Wages (QCEW), which provides monthly employment counts for state unemployment agencies. The QCEW employment measures include all workers who receive wages subject to Unemployment Insurance (UI). Wilson finds clear-cut changes in employment with respect to temperatures and various weather events, including snow. Colacito et al. (2019) focus on the effects of high temperatures on economic activity (primarily employment), using data on average seasonal temperatures for U.S. states over time. They also find modest employment effects associated with very low temperatures and snowfall.[2]

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[2] A paper by Boldin and Wright (2015) is tangentially related to our analysis. We examine how weather (i.e., snowfall) affects work hours using worker-specific household data (the CPS). Boldin and Wright examine the

3. Measuring Work Hours During Snow Events

We examine the effect of snow events using simple reduced-form labor supply equations. The study of labor supply has a long history in the economics literature; for background, see Pencavel (1986). Hours within a week (or other period) are divided into time devoted to market work, home production, and leisure. Labor supply involves individual or joint decisions made by persons within households over time. Work hour decisions are based on wage opportunities, non-earnings income, and the alternative valuations (preferences) with respect to money income, leisure, and home production activities. Changes in wage opportunities have substitution and income effects of opposite sign. Work hour outcomes, however, are determined by demand-side (employer) as well as supply-side forces.

We estimate reduced-form measures of labor supply (weekly hours of work) as a function of labor supply and demand determinants, excluding an hourly wage measure on the right-hand side.[3] To understand the impact of weather (snow events) on hours worked, we estimate the following relationship:

$$h = f(Weather, X)$$

Here h is a measure of hours worked, X is a vector of variables affecting labor supply and/or demand other than weather (snow) effects. The X vector provides demographic information on age, race, gender, ethnicity, education level, potential work experience (age minus years schooling minus 5), monthly unemployment rate, and sets of dummies for month, CBSA size, region, broad occupation, and broad industry. *Weather* can include temperature, precipitation, and weather events. Our focus is on snowfall accumulation, as described subsequently. Using standard methodology, the general regression form used in this paper is as follows:

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relationship between weather and employment/hours fluctuations in the Current Employment Statistics (CES) establishment surveys from BLS, used along with the CPS in the Bureau of Labor Statistics (BLS) monthly employment reports. The authors explore whether one might construct new "seasonal adjustment" methods that incorporate current monthly weather data. Standard seasonal adjustment methods used by BLS in the monthly reports account for historical fluctuations in monthly employment, but do not adjust for the current month's weather. Boldin and Wright show that it is feasible to use current month/year-specific seasonal adjustments.

[3] In order to use all CPS rotation groups, rather than the quarter samples that report earnings (i.e., the outgoing rotation groups), we exclude a wage variable. Because CPS hourly earnings are calculated as weekly (or annual) earnings divided by hours worked, a labor supply equation with hours (h) on the left-hand side and the implicit wage (E/h) on the right-hand side, there is a "division bias" in which measurement error in h that mechanically drives the wage coefficient (i.e., the labor supply elasticity estimate) toward negative one in a double logarithmic specification (Borjas 1980). Given that such labor supply elasticities are close to zero, we should not expect exclusion of the wage to create substantive bias in measuring the effect of snowfall on hours worked. We confirm that snowfall coefficients are highly similar using ORG quarter samples with a wage variable included.

$$h_{ijt} = \alpha + \beta Weather_{ijt} + \gamma X_{ijt} + \varepsilon_{ijt}$$

where *h*, *Weather*, and *X* are as stated above, i indexes individual workers, *j* indexes the metro area CBSAs, and *t* indexes time (the survey reference week is the second week of each month/year), and ε is the error term.[4] As explained subsequently, we estimate the hours worked equations in linear and semilogarithmic form and use alternative measures of hours worked.[5]

Unlike most other determinants of hours worked, the timing of local area weather events such as snow plausibly varies independently of the other determinants of work hours. In short, weather shock events provide strong identification properties (Dell, Jones, and Olken 2014).

4. Data Description

Four major types of weather data are currently used for econometric analyses in empirical studies: ground station, gridded, satellite, and reanalysis data. The most basic and frequently used weather data are from ground stations, which typically directly record air temperature, precipitation, and snowfall, as well as other measures such as sky cover, sunshine, humidity, water, and wind-related information. Gridded data provide more complete coverage by calculating micro-area weather conditions based on interpolation of information from multiple stations over a wide grid. Satellite data use satellite-based readings to infer various weather variables. Finally, reanalysis data combine information from ground stations, satellites, weather balloons, and other sources, using climate models to estimate weather variables across a grid. Our study uses ground station data, as described below.

4-A. Climatological Data

Our weather data are from the National Oceanic and Atmospheric Administration (NOAA). NOAA's work dates to 1807, providing comprehensive data from "the surface of the sun to the depths of the ocean floor." The National Centers for Environmental Information (NCEI) have integrated three data centers (The National Climatic Data Center, The National Geophysical Data Center, and the National Oceanographic Data Center), which provide comprehensive historical data on oceans, atmosphere, and geography. We use one of the NCEI

[4] The definition of "second week of each month" in the CPS is the week that includes the 12th of the month. In some specifications, we include snow events in weeks prior to the reference week.

[5] In most of our analyses, we do not include dummies (fixed effects) for each of the CBSAs, but provide dummies for region and metro area size. We were reluctant to include CBSA dummies given the large number of CBSAs and a sample size of roughly 2½ million person-week observations. That said, inclusion of CBSA dummies has minimal effect on results. When we estimate our base specification on hours worked results (Table 3, columns 1), we obtain a coefficient of 0.852 on our key snow inches variable. Adding the CBSA fixed effects, the coefficient on snow inches is 0.754. The R-square values are nearly identical. Similar differences are found for other specifications.

datasets from the National Climatic Data Center, the Global Historical Climatological Network-Daily (GHCN-Daily) (Menne, Durre, Vose, Gleason, & Houston, 2012). The GHCN-Daily dataset integrates daily climate observations from approximately 30 different data sources. Version 3, initially released in September 2012, provides 7 days a week data rather than only weekdays. Meteorological elements used in this research are snowfall and weather type from the years 2004 through 2014.[6] The GHCN-Daily, however, is not limited to those variables.

The unit of analysis we choose is the metropolitan area, as delineated by the Census Bureau as Core Business Statistical Areas (CBSAs). Most CBSAs are identified in the Current Population Survey (CPS), the exception being small CBSAs, typically with populations below about 100,000. Relatively few counties are identified in the CPS. The available analysis units in GHCN-Daily include countries, states, counties, cities, and zip codes to divisions and regions, as well as hydrologic units.

To match metropolitan areas (CBSAs) with weather data, we have taken several steps. The first was identifying counties included in each CBSA, using the historical delineation file from the U.S. Census Bureau (2003). There are 370 CBSAs in 50 states (plus the District of Columbia and Puerto Rico) with 1158 counties in the file. The CPS, however, does not identify all CBSAs (nor Puerto Rico).[7] These CBSAs codes were adopted by the CPS beginning in May 2004 and were continued through 2014.[8] As previously stated, the CPS excludes the smallest CBSAs, roughly those with populations below about 100,000. In the CPS, there are a total of 265 CBSAs in 50 states and the District of Columbia, which include 908 counties. Approximately three-quarters of the U.S. population is represented in the CPS metro (CBSA) sample.

Our second step was to identify the most highly-populated county within each CBSA. There are 103 CBSAs that include only one county and 162 CBSAs with two or more counties. For the latter group, it is reasonable to assume that weather recorded from stations within the

[6] There are 12 different weather types; for details see appendix Table A-1. The weather types we define as a “Snow event” in this paper are wt04 which is “Ice pellets, sleet, snow pellets, or small hail”, wt09 which is “Blowing or drifting snow”, and wt18 which is “Snow, snow pellets, snow grains, or ice crystals”. In some of our analyses, we use this comprehensive (albeit categorical) measure of a “snow event” based on there being one or more of these relatively infrequent, but sometimes severe, events that may not produce substantive accumulations on the ground. Most of our analyses use a simple continuous measure of average daily snow accumulations (in inches) over the 7-day CPS reference week, as described below.

[7] Workers not in a designated MSA are in either a small MSA with populations in the 50 to 100K range or are in a non-metro area of the state.

[8] In mid-year 2014, the CPS made changes with some code number changes and some small MSAs being added; 17 CBSAs’ codes adopted mid-year in 2014 were converted to the time consistent earlier codes.

most-populated county should have the most substantial economic influences. Moreover, most weather conditions are similar across contiguous counties within the same CBSA. This would generally be the case for such conditions as snow, rain, and temperatures, although far less so for tornadoes or other weather conditions with highly localized coverage.

The third step was calculating snowfall information from the GHCN-Daily database. Each county has multiple stations, with the number of stations varying from 1 to 472 (252 counties contain less than 100 stations). For each county matched to a CBSA we obtain the daily information on snowfall and weather type.[9] The unit of snowfall is inches. Daily snowfall is summed across all stations within a county; our measure of daily snowfall is the average inches across the within-county stations (all stations receive equal weight). For our primary analysis, we calculate the average daily inches of snow across the 7 days in each CPS reference week.

The CPS household employment survey, conducted in the third week of the month, obtains labor information on employment status and hours worked for the previous (second) week of the month (i.e., referred to as the reference week). Hence, our snowfall measure represents the average daily snowfall during the CPS reference week. An alternative "snow event" categorical value is coded as 1 if one or more weather stations within a CBSA record one of the three snow events described previously (footnote 6) during the CPS reference week.

4-B. Labor Data

As a measure of work hours, the Current Population Survey (CPS) provides information on usual hours worked per week in one's primary job, usual hours in a second job if a multiple job holder, and measures of actual hours worked the previous week in the primary job and hours last week in all other jobs. The three measures of hours used in this analysis are (a) hours worked last week on all jobs; (b) usual hours worked per week in one's primary job and a second job (about 5 percent of worker are multiple job holders); and (c) the difference between (a) and (b).

Given the rich set of individual worker controls in the CPS, we can examine how the response to weather varies by type of job (hourly, salaried, or self-employed), occupation, industry, and demographics. The hours worked questions are asked of all CPS rotation groups and not just the quarter sample (the outgoing rotation groups) that are asked questions on earnings and unionization. This also means that we typically observe the same individual in four

[9] All snowfall data values reported provide a quality measurement flag. We exclude snow values designated as having a quality assurance issue (this is a tiny proportion of values, about 0.5% of total observations).

consecutive months and for two adjacent years for those same four months (assuming the household residence remains the same). We do not use the quasi-longitudinal structure of the data (i.e. within-worker monthly differences in hours in response to differences in snowfall).

A downside of using CPS work hours data, as opposed to time diary measures of work, is that worker responses are "heaped" at common work hours. Hirsch (2005), in an analysis of part-time work, examines the frequency distributions of usual hours worked per week (on the principal job) and mean wages by hours worked. He used full CPS-ORG earnings files for September 1995-2002. He found that 53% of women and 57% of men reported their usual hours worked per week as 40. As compared to men, the hours distribution among women contains more low-hour and fewer high-hour observations and is more dispersed. There exist "spikes" or "heaping" at intervals divisible by five, a common survey phenomenon, and an appreciable number of workers at hour intervals divisible by 8, in particular, 24, 32, and 48, in addition to 40. The distribution of "hours worked last week" is more dispersed, with fewer workers reporting exactly 40 hours: 42% among women, 45% among men. Most of our analysis examines hours worked last week (i.e., the reference week). We also examine a measure of deviations from usual hours, defined as hours worked last week minus usual weekly hours.

To avoid high influence observations, we omit the very tiny proportion of individuals reporting more than 90 hours (the hours variables are topcoded at 99 hours). Excluded from analyses using usual weekly hours are those who report usual hours that are "variable" (coded as "-4" by Census). These workers are excluded from analyses using usual weekly hours; most of our analyses use hours worked last week.

Some employed workers may not have worked during the reference week due to being on vacation, ill, weather, etc. For the measure of hours worked last week, the CPS asks employed workers who report zero hours the reason for their not being at work. There are eight reasons for participants to choose from in the survey.[10] Absent weather data, one could examine the frequency of not at work last week due to bad weather. That number, however, is tiny even in high-snow states since it is rare to miss an entire week due to weather. We remove workers who state zero hours worked last week for any reasons, other than those stating bad weather.

The CPS also includes numerous demographic, geographic, and labor market variables.

[10] The 8 reasons in the survey for absence from work are. 1. Own illness; 2. On vacation; 3. Bad weather; 4. Labor dispute; 5. New job to begin within 30 days; 6. Temporary layoff; 7. Indefinite layoff; 8. Other.

We construct variables measuring age, race, ethnicity, gender, educational level, potential experience, and sets of dummies measuring month, CBSA size, region, occupation, and industry.

In our merged CPS-weather dataset, we measure snow in the reference week (the second week of each month), as well as weeks one, two, and three weeks prior to the reference week. Information on prior weather allows us to examine whether there is a "make-up" effect that partially offsets hours lost during a prior snow event. That is, we ask whether we see higher (or lower) work hours in the reference week when there has been snow in previous weeks.

5. Descriptive Evidence on Work Hours and Weather

Figure 1 shows the average hours worked in the weeks prior to the monthly CPS surveys, by major Census region, averaged over the 2004-2014 period. The mean hours worked during the reference week differs across regions, but the differences are relatively stable between May and August. Mean hours are typically lower between October and March, the months over which most snow accumulations occur. On average, the highest hours worked are in the West South Central region and the lowest in New England. Such a pattern is consistent with there being snow effects on work hours. Subsequent analysis examines the direct relationship between snow accumulation and individuals' work hours in the week prior to the monthly CPS surveys.

Figure 1: Total hours worked previous week by U.S. regions by month, 2004-2014

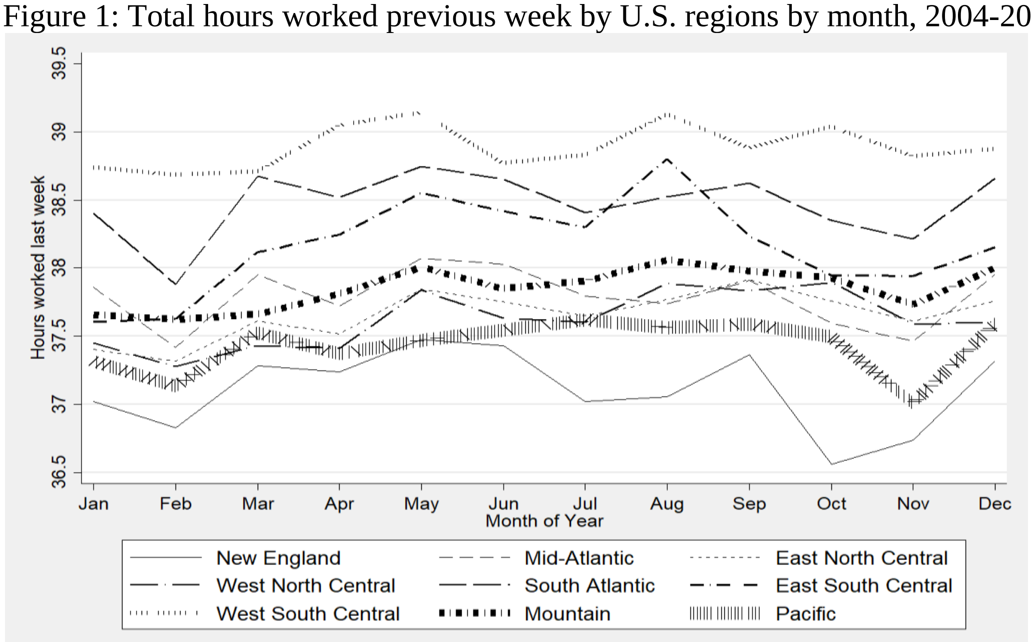


Table 1 provides basic information on hours worked last week measure in our estimation sample. For the overall sample, there are roughly 5.8 million observations of employed workers reporting hours worked in the reference week period (i.e., the second week of each month, prior to conduct of the CPS survey). The mean of hours worked is 37.9 hours per week, about two hours less than the typical modal value of 40 hours per week among full-time workers (part-time workers pull down mean hours). We also consider the mean value of hours worked last week in two subsamples, one for periods with snow and the other with without snow. There are small but substantive differences between the two sample periods, with an average 0.34 hours (20.4 minutes) less work during weeks with snow. We conduct a two-sample adjusted Wald test with equal variances; the mean difference is statistically significant with a F-value of 568.1.

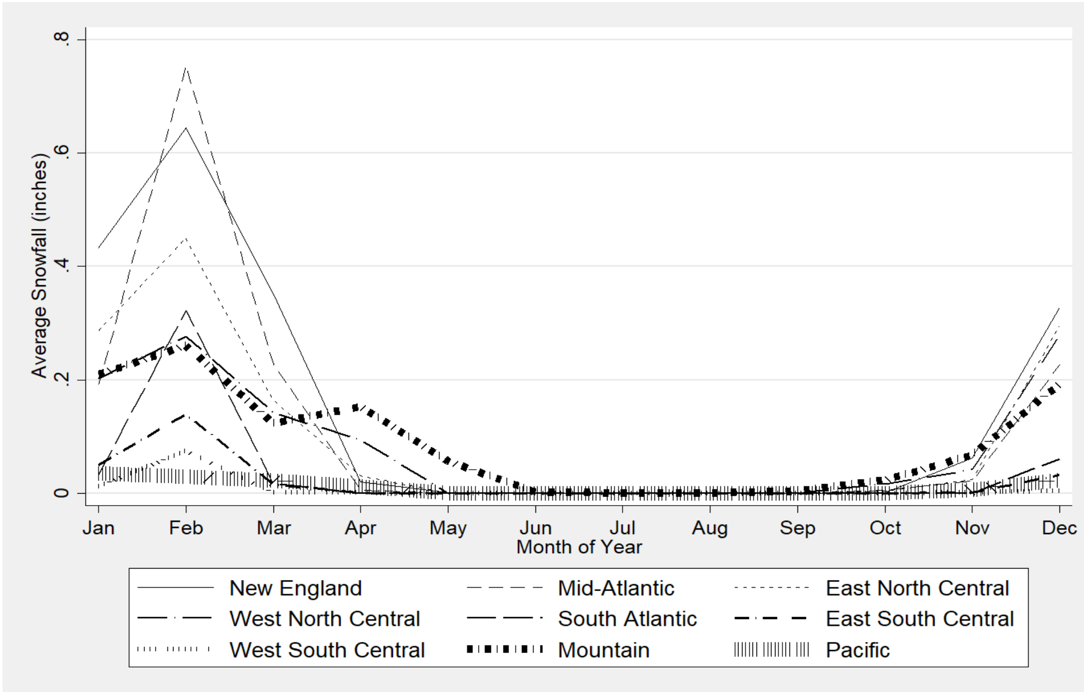
Table 1: Summary of hours worked for weeks with and without snow

	Total Obs.	Mean	Std. Dev.	Min	Max
	All data				
Hours worked last week for full sample with and without snow	5,765,988	37.94	12.56	0	99
	Data conditional on snow				
Hours worked last week for weeks with snow	1,270,219	37.67	12.66	0	99
	Data conditional on no snow or missing				
Hours worked last week for without snow	4,495,769	38.01	12.53	0	99

Note: Included are all employed workers in all months of the Current Population Survey, October 2004–March 2014. Means and standard deviations are weighted using CPS “final weights” accounting for all rotation groups.

Figure 2 (shown below) shows monthly average snowfall for 9 different regions averaged over the years 2004 through 2014. The pattern of snow is consistent with the information on work hours previously seen in Figure 1. Most regions receive their highest snow levels in the first three and last three months of the year (i.e., between October and March). In much of the subsequent analysis, we restrict our sample to these six months. As seen in Figure 2, among the 9 regions, New England received the most snow in the winter period, followed by East North Central and West North Central. The Pacific, East South Central, and West South Central regions receive minimal snow. The other three regions typically have snow events during a year, but the number is small. The evidence on work hours and snow levels for regions by month, as seen in Figures 1 and 2, clearly suggests a possible link between hours worked and snow events.

Figure 2: Average snowfall by U.S. regions by month, 2004-2014



Consistent with the concentration of snow events in winter months, in all regions we observe a slightly higher variation in weekly work hours during winter months. This result is shown in Table 2. The first two columns of Table 2 show the number of observations and coefficients of variation over April to September each year by regions, whereas the last two columns indicate October to March in the following year.

Table 2: Coefficient of Variation (CV) of hours worked by region

	Hours worked April-September		Hours worked October-March	
	(1) Obs.	(2) CV	(3) Obs.	(4) CV
Northeast	292,809	35.45	289,319	36.17
Mid-Atlantic	333,749	32.36	324,975	32.85
East North Central	364,204	34.08	353,529	34.50
West North Central	255,066	34.51	250,302	34.75
South Atlantic	575,364	30.99	564,390	31.49
East South Central	104,225	32.29	101,000	33.13
West South Central	255,964	31.88	251,835	32.07
Mountain	264,373	33.40	260,174	33.79
Pacific	456,489	33.61	448,802	34.11

Note: The table includes all data (all months) for the years 2004-2014. Means and coefficients of variation are weighted using CPS "final weights" that account for all rotation groups. Included are all employed workers in all months of the Current Population Survey.

6. Evidence on Work Hours and Snow: Regional Adaptation and Heterogeneous Effects for Types of Work and Workers

In this section, we examine how weekly work hours are affected by snow events, with emphasis on timing and heterogeneous effects among different types of workers and different types of jobs. Table 3 provides results from our base regressions measuring the relationship between three work hour measures and the inches of snowfall in the CPS reference week for 265 CBSAs over the months of October-March in the years 2004 through 2014 period. Each of the regressions has a rich set of covariates, listed in the table note. Snowfall coefficients absent covariates tend to be slightly larger in absolute value. Column (1) has as its dependent variable the hours worked last week; column (2) the log of hours worked last week (observations with zero hours drop out); and column (3) the difference between hours last week and usual hours worked per week. All regressions are weighted and have standard errors clustered by CBSAs (clustering increases standard errors but does not affect coefficients or R-squares). Results are shown both with and without the full set of CBSAs. A full set of coefficients for the three regressions in Table 3, part A, are provided in Table A-2 of the appendix.

Table 3: The relationship between hours worked last week and snowfall in the reference week

	(1) Hours worked last week	(2) Usual hours minus hours last week	(3) Log of hours worked last week
A. Without CBSA FE			
Inches snow	-0.852***	-0.629***	-0.029***
	(0.173)	(0.153)	(0.0065)
R^2	0.153	0.007	0.125
B. With CBSA FE			
Inches snow	-0.754***	-0.624***	-0.025***
	(0.0270)	(0.0163)	(0.0058)
R^2	0.155	0.007	0.126
Observations	2,490,454	2,487,691	2,486,595

CBSA-clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Note: There are three hours worked regressions with alternative dependent variables. The "hours worked difference" measure in column (3) is defined as hours last week minus usual hours worked per week. The table presents the estimated coefficient (and standard error) on the snow variable. Controls included are for gender, age, race, ethnicity, educational levels, potential experience, CBSAs size levels, regions; occupations, industries, and monthly unemployment rates (national) for October 2004 through March 2014. Month dummies for November-March are included (October is the omitted month). All regressions are weighted by individuals' CPS final weights.

Focusing first on column (1), we find that an inch of average daily snowfall over a week decreases work hours by just under an hour (0.852 hours or 51 minutes). In column (2), the use of the log of hours last week indicates a 3 percent (-0.029) decrease in hours worked. Column (3) provides a rather different dependent variable, measuring the difference between "actual" hours worked in the reference week minus "usual" weekly hours (those with "variable" usual hours are omitted). In principle, this is an attractive measure, reflecting how snow during the week alters person-specific hours of work. Here we obtain a coefficient indicating each inch of average daily snow is associated with 0.63 fewer weekly hours (38 minutes) than usual, less than the 0.85 hour (51 minutes) effect we saw in column (1).

In the lower half of Table 3, we provide regression results in which a full set of CBSA fixed effects are added. Somewhat surprisingly, the addition of CBSA dummies has a rather modest effect on the snow coefficients and R^2 values, reducing just slightly the magnitude of the three snow coefficients. Much of the differences across metro areas in work hours were already accounted for based on controls for region, metro area size, and worker and job attributes.

Note that the interpretation of results is a bit tricky given that our main snow measure represents the daily inches of snow averaged over the entire week. For example, there is no distinction made between there being one inch of snow each day of the week versus there being one day of snow with 7 inches. Given that reported hours are for the entire previous week, it is reasonable to correlate weekly snowfall with weekly hours.

Coefficients on our individual demographic, employment, and other controls are consistent with expectations. Women have lower hours worked the previous week than do men (by 4 hours). Work hours increase with respect to age (experience). Among the "winter" months October through March, hours worked last week were highest in lowest in November and highest in December, the latter result likely reflecting Christmas-related work hours. Weekly work hours over these months are lowest in New England and highest in the West South Central states (1.8 hours difference between the two regions). As one would expect, hours worked are highest in large metro areas.

In all our hours regressions, we control for the monthly unemployment rates at the national level (state and metro level unemployment rates are extremely noisy). The coefficient on the unemployment rate is -0.209, implying 12½ fewer minutes worked weekly associated with a one percentage point increase in the unemployment rate.

In Table 4, we explore the relationship between hours worked and snowfall separately by region. The results provide clear-cut evidence for regional adaptation. We previously showed average snowfalls by region (Figure 2). Results seen in Table 4 show that regions that regularly receive snow tend to have the lowest reductions in work hours for each inch of weekly snow. Residents in the north have adapted to driving, commuting, and shopping with snow on the ground. Northern municipalities have equipment and personnel to clear snow from streets. And office and retail buildings are constructed to allow workers and shoppers to move around cities protected from the cold. Not surprisingly, people and local governments in the south, where snow is infrequent, are not prepared to handle substantive accumulations of snow or ice. Cities in the south may rarely get snow, but small or modest snow accumulations can have substantial effects on mobility and work hours.

As seen in Table 4, snow events provide the largest reductions in work hours in East South Central states such as Alabama and Tennessee (a coefficient of -4.0). Each additional average daily inch of snowfall (an additional 7 inches over a week) is estimated to decrease weekly work by about 4 hours. The South Atlantic region has a coefficient of -3.0 and West South Central -2.3. By contrast, work hours in New England, the Mountain states, and East North Central states are least affected by snow, with snow level coefficients of -0.23, -0.39, and -0.43, respectively. These areas over the winter season may receive substantial snow on a single day, but rarely does this paralyze their communities. As discussed previously, such communities have equipment, personnel, and supplies of salt and sand that allow them to handle large snowfalls. Workers and shoppers have adapted to winter travel conditions and are more likely to maintain their productive activities during winter storms.

The bottom half of Table 4 provides a closely related analysis, restricting the sample to weeks in which there was at least one snow event. Coefficients are similar to those seen previously for the full sample. The largest effects of snow are in the East South Central, West South Central, and South Atlantic regions. The smallest effects are in the Mountain, New England, and East North Central states, where snow events are common.

Table 4: The Relationship between hours worked last week and snowfall in different regions

	(1) New England	(2) Mid-Atlantic	(3) East North Central	(4) West North Central	(5) South Atlantic	(6) East South Central	(7) West South Central	(8) Mountain	(9) Pacific
A. Snow is in the reference week (all data)									
Snow	-0.230***	-0.605***	-0.430***	-0.727***	-3.032***	-3.995***	-2.31***	-0.392**	-0.394
	(0.058)	(0.117)	(0.097)	(0.268)	(0.391)	(0.994)	(0.322)	(0.180)	(0.383)
Observations	261,663	216,180	317,951	234,205	501,061	90,282	233,851	241,964	393,297
R-squared	0.193	0.169	0.188	0.180	0.129	0.156	0.138	0.137	0.142
B. Snow is in the reference week (snow events)									
Snow	-0.211**	-0.824***	-0.435***	-0.665**	-2.174***	-3.725***	-2.194***	0.100	-0.847*
	(0.095)	(0.170)	(0.123)	(0.285)	(0.603)	(1.147)	(0.397)	(0.124)	(0.468)
Observations	85,228	59,202	167,665	118,584	31,412	21,285	42,975	65,741	91,616
R-squared	0.203	0.193	0.188	0.186	0.139	0.154	0.136	0.134	0.142

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: This table presents the estimated coefficient (and standard error), all robust standard errors are clustered at CBSA level in the parenthesis. There are total 18 regressions, and each regression controlled demographic information such as age, race, sex, educational level, experiences as well as five sets of dummies. Month dummies with October omitted, CBSAs size dummies with size 2 omitted; occupation dummies with “Management, Business, Financial” omitted; and industry dummies with “Agriculture, Forestry, Fishing, and Hunting” omitted. All regressions are weighted by individuals’ CPS final weights.

In work available in an appendix (Table A-3), we examine whether work hours are affected by major snow events in previous weeks, all else the same. Of particular interest is whether the loss of hours worked due to snow in prior weeks leads to “make-up” hours in subsequent weeks. We examine the effects of major snow events, those with two or more daily inches occurring in the week prior to the reference week, conditional on no subsequent snow in the reference week. Given that spillover or make-up work effects should only be evident for severe snow events, we restrict the sample to weekly snow amounts averaging 2 inches daily or more, sharply reducing the sample sizes. For major snows in the previous week, we find somewhat lower (-0.24 hours or 14.4 minutes per average daily inch of snow) in the snow-free reference week, suggesting that there exist residual effects of past snow. For major snows two weeks prior to the reference week, we find a substantive positive coefficient (0.44 hours or 26.4 minutes per average daily inch of snow). The positive coefficient suggests that there are partial make-up hours (i.e., production) following particularly severe snow events.

In results presented up to this point, we have measured snowfall in inches, assuming (implicitly) an approximately linear relationship between work hours and average daily inches of snowfall. Alternatively, we estimate hours worked equations using a set of 5 categorical snowfall level dummies to better understand how levels of snowfall affect work hours.

Table 5 shows the results of the relationship between hours worked last week and five categorical snow-level dummies. The omitted category is no “snow event” during the week, based on the three events stated previously in footnote 4. Our included snow-level dummies include increasing ranges of average daily inches. The lowest snow level measure ranges from average daily inches levels of zero to 0.1 inch (many “snow events” produce zero snow accumulation). The additional dummies reflect average daily inch ranges of 0.1-0.5, 0.5-1.0, 1.0-2.0, and 2.0 or more inches.

As expected, higher levels of snow result in larger reductions in hours worked during the reference week, as shown in Table 5. Snow level coefficients range from -0.200 (12 minutes less work in the reference week) for average daily snow of zero to 0.1 inches (many of these are snow events with no accumulation) to a substantial -2.35 fewer hours (141 minutes) in the reference week for average daily snow exceeding 2 inches. Similar results are seen in columns (2) and (3) using the alternative semi-log specification (column 2) or the alternative hours measure (column 3). Using the semi-log specification, we obtain an estimated -0.079 log hours reduction (just under 8 percent) for average daily snow levels greater than 2 inches. In column 3, our estimate is that average snow levels over 2 inches result in 1.9 fewer hours worked in the reference week as compared to usual weekly hours. The overall range of coefficients is from 0.07 hours (5.4 minutes) for snow with minimal accumulation up to nearly 2 hours for the most substantive accumulations. Notable in all three of the specifications are the large increases (in absolute value) of the coefficients once average snow levels exceed the 2-inch threshold. Although such heavy snow events are rare, the magnitude of work loss resulting from such events is substantial, hence the emphasis given to unusual weather by the Federal Reserve Board.

Table 5: The relationship between hours worked last week and snow level

	(1) Hours worked last week	(2) Log hours worked last week	(3) Hours worked difference
Snow from 0 - 0.1’’	-0.200***	-0.006***	-0.068***
	(0.054)	(0.002)	(0.023)
Snow from 0.1’’-0.5’’	-0.392***	-0.012***	-0.150***
	(0.071)	(0.003)	(0.047)
Snow from 0.5’’-1’’	-0.817***	-0.028***	-0.427***
	(0.157)	(0.005)	(0.111)
Snow from 1’’-2’’	-1.01***	-0.034***	-0.583***
	(0.152)	(0.005)	(0.124)
Snow greater than 2’’	-2.354**	-0.079**	-1.926***
	(0.939)	(0.032)	(0.722)
Observations	2,490,454	2,486,595	2,487,691
R-squared	0.153	0.124	0.006

*** p<0.01, ** p<0.05, * p<0.1. CBSA-clustered robust standard errors in parentheses.

Note: This table presents the estimated coefficients (and standard errors) for different weekly snow levels. There are three regressions and different dependent variables. The regressions include controls for gender, age, race, ethnicity, educational levels, potential experience, CBSAs size levels, regions occupations, industries, and monthly national unemployment rates. Month dummies for November-March are included (October is the omitted month). All regressions are weighted by individuals’ CPS final weights.

The results in Table 5 clearly showed that there are rising work hour losses with respect to higher levels of snow, as one would expect. A rather different, but related, analysis is to examine how weekly work hours are affected by the number of days during the reference week in which there were snow events. Table 6 below provides such an analysis. Multiple days of snow during a week are not common, but our comprehensive data includes metro areas over 10 winter seasons (October-March). Thus, there is a substantial number of cases in which there are multiple days of snow in a week.

In Table 6, we examine how hours worked last week (i.e., the reference week) decrease with respect to the number of days in a week with snow events. The omitted reference group is no snow events during the reference week. In column 1, we show regression results absent controls other than the number of snow days in the week. The intercept of 38.2 is effectively the mean hours worked per week over the entire October-March sample for those weeks without any snow events. The coefficients on the number of snow days provide average weekly hours worked with the number of snow days. Relative to the no-snow average of 38.2, weekly hours fall systematically with respect to the number of snow days. Weeks with one snow day decreases hours worked by .23 of an hour (an average 14 minutes); with two snow days .35 of an hour (21 minutes), and so forth, with the rare 7 days of snow events in a week reduces hours by 1.15 hours (69 minutes). These results are consistent with those seen in Table 4, in which an average *daily* snow of 1-to-2 inches over a week reduces weekly work hours by 1.01 hours.

Table 6: Relationship between hours worked last week and the number of snow days

Variables	(1) OLS w/o controls	(2) OLS w/ controls
Constant	38.20***	20.06***
	(0.082)	(1.363)
If one snow day	-0.232***	-0.162***
	(0.076)	(0.053)
If two snow days	-0.353***	-0.177***
	(0.102)	(0.063)
If three snow days	-0.510***	-0.289***
	(0.147)	(0.086)
If four snow days	-0.641***	-0.355***
	(0.182)	(0.098)
If five snow days	-0.616***	-0.373***
	(0.224)	(0.097)
If six snow days	-0.850***	-0.527***
	(0.186)	(0.115)
If seven snow days	-1.149***	-0.576***
	(0.191)	(0.175)
Observations	2,633,003	2,633,003
R-squared	0.0003	0.151

*** p<0.01, ** p<0.05, * p<0.1; CBSA-clustered robust standard errors in parentheses.

Note: The dependent variable is hours worked in previous week. The table presents estimated coefficients and robust standard errors (in parentheses) clustered at the CBSA level. The regression with controls includes dummies for gender, age, race, ethnicity, education, potential experience, CBSAs size levels, regions; occupations; and industries. Month dummies for November-March are included, with October the omitted month. Monthly unemployment rates (national) for October 2004 through March 2014 are included. Regressions are weighted by individuals' CPS final weights.

We next examine relationships between work hours and snow events for different types of workers and jobs. There may be differences in the ability to vary work hours in response to snow among salaried versus hourly workers. Salaried workers may reduce hours more so than hourly workers since their weekly earnings do not directly vary with hours worked. Salaried workers may also have greater flexibility to work from home during weather events. Hourly workers may be more affected by reductions in labor demand during snow events due to reduced consumer activity when travel is difficult. For example, hourly workers in retail stores may have hours reduced due to lack of demand following snow events. That said, if schools are closed and many adults are home from work, there could be increased demand at restaurants, grocery stores, movie theaters, and the like if travel is feasible.

In results shown in appendix Table A-4, we provide evidence on hours worked during snow events separately for hourly and salaried workers, using both the full sample and the much smaller "snow event" sample. As compared to hourly employees, salaried workers display stronger work hours sensitivity and/or flexibility (i.e., negative snowfall coefficients with larger absolute values) in both the full and snow event samples. Differences between the salaried and hourly workers are small, but consistent across the samples. In the full sample, the snow coefficients are -0.895 for salaried and -0.746 for hourly workers. In the snow event sample, the snow coefficients are -0.733 for salaried and -0.589 for hourly workers.

We next examine differences among wage and salary workers whose primary jobs are wage and salaried in the private sector, wage and salaried in the public sector, and self-employed. Public sector workers are likely to be most affected by the snow given large number of public employees in education. Public schools place a high weight on students' safety; hence, when weather makes travel dangerous, classes are canceled or delayed. In contrast, workers self-employed and in the for-profit private sector are typically less affected (on average) by snow events. Self-employed workers' earnings may be particularly sensitive to hours worked, making it costly to reduce work in response to the weather. Moreover, many workers who are self-employed work out of their home and may be largely unaffected by weather conditions.

As seen in appendix Table A-5, the results are consistent with our expectations. Public sector workers display the most negative hours response to snowfall, twice as large as that seen for the private and self-employed sectors (-1.41 for public, versus -0.76 and -0.72 for private and self-employed workers, respectively). We find the same pattern using the more limited snow event sample, with coefficients of -1.08, -0.63, and -0.41 for the public, private, and self-employed workers. The particularly large work hour responses to snowfall among public employees likely reflects the large share of schoolteachers.

Our final analysis examines the heterogeneity of snow effects on work hours across different industries and occupations. Because of space constraints, we do not show the large industry and occupation tables, but we do provide these tables in our online appendices. Our industry sample is restricted to private sector workers, given that the public sector was examined previously. The sample examining snow effects by occupational groups includes all sectors, since we see workers in many occupations employed in both the public and private sectors.

In our industry analysis (Table A-6), we find negative work hour effects from snowfall in all industries. Coefficients using the snow-event sample tend to be somewhat smaller (in absolute value) as compared to the full sample, but not in all industries. The largest negative impact of snow on work hours is in the construction industry, where a considerable share of the work is outside. In addition to construction, we find substantial work hour effects from snow events in leisure and hospitality, mining, professional and business services, and other service-related industries. The least affected industries tend to be indoor-intensive industries such as information and financial activities. Note that coefficients close to -1.0 reflect a one-hour weekly reduction in work for each average daily inch of snow. Such a magnitude is not large, but that may be misleading. Work hours lost on a snow day within a week may be offset by added hours on other days within the week. Second, many workers routinely report 40 hours of work and/or may not fully report deviations in work hours due to snow (or other) events. Third, our (necessary) analysis linking *weekly* hours worked to weekly snowfall may lessen precision of the analysis. While we have daily measures of snow, we do not have daily measures of work hours.

Our final analysis provides results by broad occupational groups (Table A-7). These results echo those seen for industry groups. Hours worked by those in construction and extraction, farming, fishing, and forestry, and professional occupations are most affected by snow events (each with snow level coefficients of -1.1). Also showing large hours effects are workers in the following occupations: office and administrative support (-0.9), transportation and material moving (-0.8), and management, business, and financial (-0.8). Workers in installation, maintenance, and repair occupations had the lowest reduction (-0.6), not surprising given that some of these workers may increase work hours to provide snow-related repairs.

7. Conclusion

This research has examined the relationship between hour worked and weather conditions, specifically, how snowfall affects people's working hours. Extreme weather events may sharply reduce economic activity, but there is very limited evidence on the overall magnitude of these losses and how work hours respond to various levels of snow accumulation.

The analysis in this study provides several pieces of evidence on how work hours are affected by winter snowfall. First, snowfall reduces work hours. On average, each additional inch of the average daily snow during a week reduces work time by about 1 hour. Second, higher levels of snow systematically lead to larger declines in work times. Third, we find systematic differences in worker responses to snow events based on the type of worker (i.e., paid hourly or salaried), by class of employment (private sector, public sector, or self-employment), by industry of employment, by occupation, and by geographic region. And fourth, we find no compelling evidence that lost hours from snowstorms are "made up" in the subsequent week or weeks. The possible exception is our finding of make-up hours two weeks following unusually severe snowstorms (2 or more average daily inches of snow during a week). The apparent absence of work makeup effects reinforces the concern seen by the Federal Reserve Board and other economic analysts regarding the effect of winter storms on economic activity. Less clear is the aggregate magnitude of lost work hours from a typical winter.

Although we cannot provide a precise estimate of lost work hours and growth due to snow events, a back-of-the-envelope calculation is informative. The mean average daily inches of daily snow over the six "winter" months in our analysis is 0.125 inches. Multiplying the average inches by −0.9, the coefficient from our base equation in Table 3, column 1, we obtain −0.9 x 0.125 = −0.1125, indicating an average weekly reduction of 0.11 hours over the six winter months. Assuming all snow effects occur during winter months, the average weekly reduction over twelve months is half as much, -.05625. Multiplying this by 52 weeks, we get an annual loss of an average 2.925 hours. Average total work hours, based on the 38 hours a week average in the CPS, is 1,976 hours. The 2.925 loss of hours represents a 0.0015 (2.925/1976) or 0.15 percent loss in annual hours worked. We assume the magnitude of labor input reduction will cause an equivalent reduction in economy-wide output. Given that average annual productivity growth has in recent years been only about 1.5 percent, a 0.15 percent annual reduction in work hours due to snowfall is nontrivial. Large year-to-year variations in levels of snow could well distort annual measures of growth rates, particularly so at a regional level. Given that snow effects are highly concentrated in time and location, it is not surprising that the Federal Reserve Board and business analysts often point to severe weather events as affecting short-run growth.

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Appendix Tables

A-1: Different Weather Types in GHCN-Daily Database

# of type	Description of the weather type
01	Fog, ice fog, or freezing fog (may include heavy fog)
02	Heavy fog or heaving freezing fog (not always distinguished from fog)
03	Thunder
04	Ice pellets, sleet, snow pellets, or small hail
05	Hail (may include small hail)
06	Glaze or rime
07	Dust, volcanic ash, blowing dust, blowing sand, or blowing obstruction
08	Smoke or haze
09	Blowing or drifting snow
10	Tornado, waterspout, or funnel cloud
11	High or damaging winds
12	Blowing spray
13	Mist
14	Drizzle
15	Freezing drizzle
16	Rain (may include freezing rain, drizzle, and freezing drizzle)
17	Freezing rain
18	Snow, snow pellets, snow grains, or ice crystals
19	Unknown source of precipitation
21	Ground fog
22	Ice fog or freezing fog

Table A-2: Full Results for Table 3A:

Relationship between hours worked and snowfall in reference week, OLS w/CBSA clustered s.e.

Variables	(1) Hours worked last week	(2) Usual hours minus hours last week	(3) Log hours worked last week
Snow	-0.852***	-0.629***	-0.0294***
	(0.173)	(0.153)	(0.00649)
Unemployment	-0.209***	-0.0392***	-0.00647***
	(0.0112)	(0.00441)	(0.000370)
Demographic			
Female	-3.987***	-0.235***	-0.125***
	(0.0579)	(0.0110)	(0.00290)
Age	0.755***	0.102***	0.0355***
	(0.0591)	(0.00780)	(0.00285)
Hispanic	0.272***	-0.0557**	0.0474***
	(0.0769)	(0.0280)	(0.00319)
Black	0.119*	0.0146	0.0304***
	(0.0687)	(0.0195)	(0.00307)
Asian	0.0500	0.0907*	0.0234***
	(0.152)	(0.0510)	(0.00431)
Other	-0.239**	-0.159***	0.00271
	(0.107)	(0.0355)	(0.00473)
Education and Experiences			
High School	1.820***	0.137***	0.0862***
	(0.0919)	(0.0132)	(0.00440)
Associate Degree	0.545***	0.0213	0.0172***
	(0.0805)	(0.0175)	(0.00312)
Bachelor	0.0798	-0.275***	-0.0265***
	(0.212)	(0.0300)	(0.00902)
Masters	-1.189***	-0.571***	-0.0975***
	(0.313)	(0.0443)	(0.0141)
Professional	2.084***	-0.707***	-0.0432**
	(0.413)	(0.0759)	(0.0181)
Ph.D.	-0.205	-0.732***	-0.111***
	(0.420)	(0.0810)	(0.0188)
Experience	0.612***	-0.163***	0.0212***
	(0.0619)	(0.00865)	(0.00274)
Experience square	-0.0653***	0.00397***	-0.00280***
	(0.00137)	(0.000286)	(7.00e-05)
Experience cube	0.00127***	-0.000102***	5.64e-05***
	(3.78e-05)	(7.50e-06)	(1.70e-06)
Experience quad.	-9.46e-06***	8.70e-07***	-4.31e-07***
	(3.42e-07)	(6.43e-08)	(1.50e-08)

Month Dummy			
January	-0.0465	0.240***	0.00379
	(0.0632)	(0.0699)	(0.00248)
February	-0.118**	0.127**	-0.00267
	(0.0514)	(0.0552)	(0.00189)
March	0.107	0.302***	0.00213
	(0.0647)	(0.0741)	(0.00279)
November	-0.171***	-0.0323	-0.00275**
	(0.0341)	(0.0352)	(0.00117)
December	0.242***	0.435***	0.0122***
	(0.0563)	(0.0701)	(0.00260)
MSA size and Region Dummy			
size3	-0.0972	-0.0212	-0.00826
	(0.122)	(0.0443)	(0.00511)
size4	0.00571	0.000669	0.000113
	(0.124)	(0.0488)	(0.00435)
size5	0.117	-0.00204	0.00248
	(0.107)	(0.0520)	(0.00476)
size6	0.0892	-0.0662	-0.000179
	(0.137)	(0.0687)	(0.00533)
size7	0.369***	0.0898	0.0100**
	(0.111)	(0.0575)	(0.00490)
Mid-Atlantic	0.533***	0.111	0.0211***
	(0.144)	(0.0875)	(0.00384)
East North Central	0.701***	0.263***	0.0226***
	(0.128)	(0.0824)	(0.00360)
West North Central	0.722***	0.0321	0.0213***
	(0.215)	(0.0875)	(0.00704)
South Atlantic	1.203***	-0.0125	0.0479***
	(0.156)	(0.119)	(0.00391)
East South Central	1.010***	0.0368	0.0416***
	(0.152)	(0.106)	(0.00396)
West South Central	1.762***	-0.000212	0.0557***
	(0.199)	(0.102)	(0.00537)
Mountain	1.027***	0.177**	0.0315***
	(0.233)	(0.0800)	(0.0101)
Pacific	0.351***	0.0484	0.0107**
	(0.134)	(0.0894)	(0.00422)
Occupation Dummy			
Professional, Related	-3.409***	-0.0257	-0.0921***
	(0.0696)	(0.0161)	(0.00234)
Services	-4.669***	0.164***	-0.149***
	(0.0949)	(0.0326)	(0.00340)
Sale, Related	-2.506***	0.0668***	-0.0831***
	(0.0658)	(0.0244)	(0.00215)

Office, Admin Support	-3.472***	-0.114***	-0.0868***
	(0.0675)	(0.0165)	(0.00194)
Farming, Fishing, Forestry	-0.548	0.0803	-0.00731
	(0.343)	(0.168)	(0.0120)
Construction, Extraction	-3.884***	-0.590***	-0.0927***
	(0.104)	(0.0429)	(0.00314)
Installation, Maintenance, Repair	-1.908***	0.235***	-0.0348***
	(0.0797)	(0.0295)	(0.00233)
Production	-2.446***	0.186***	-0.0576***
	(0.0853)	(0.0285)	(0.00224)
Transportation, Material, Moving	-3.180***	-0.105***	-0.0972***
	(0.109)	(0.0282)	(0.00302)
Industry Dummy			
Mining	6.963***	1.080***	0.185***
	(0.692)	(0.156)	(0.0127)
Construction	0.702***	0.286***	0.0492***
	(0.0947)	(0.0398)	(0.00305)
Manufacture	2.521***	0.776***	0.112***
	(0.0996)	(0.0354)	(0.00328)
Wholesale Retail Trade	-0.103	0.604***	0.0266***
	(0.101)	(0.0319)	(0.00407)
Transportation, Utility	1.992***	0.634***	0.0795***
	(0.129)	(0.0493)	(0.00375)
Information	1.197***	0.468***	0.0630***
	(0.245)	(0.0416)	(0.00643)
Financial Activities	1.179***	0.268***	0.0769***
	(0.0939)	(0.0397)	(0.00288)
Professional, Business Service	1.179***	0.508***	0.0692***
	(0.106)	(0.0237)	(0.00365)
Education, Health Service	-0.0866	0.553***	0.0131***
	(0.0830)	(0.0332)	(0.00403)
Leisure, Hospitality	-1.315***	0.484***	-0.0204***
	(0.142)	(0.0403)	(0.00743)
Other Services	-0.821***	0.467***	-0.0284***
	(0.132)	(0.0284)	(0.00682)
Constant	19.67***	-2.515***	2.648***
	(1.149)	(0.176)	(0.0566)
Observations	2,490,454	2,487,691	2,486,595
R-squared	0.153	0.007	0.125

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A-3: The relationship between hours worked last week and past snowfall

	(1) Hours worked last week Full winter sample	(2) Hours worked last week Winter sample with 2” or more snow
A. Snow is one week before the reference week		
Snow	0.009	-0.237
	(0.130)	(0.272)
Observations	1,687,925	19,821
R-squared	0.147	0.217
B. Snow is two weeks before the reference week		
Snow	-0.222**	0.443***
	(0.096)	(0.134)
Observations	1,396,900	12,663
R-squared	0.145	0.187
C. Snow is three weeks before the reference week		
Snow	-0.050	-0.052
	(0.204)	(0.074)
Observations	1,239,392	15,808
R-squared	0.143	0.203

*** p<0.01, ** p<0.05, * p<0.1. CBSA-clustered robust standard errors in parentheses.

Note: This table presents the estimated coefficients and standard errors. Each panel shows the impact of snow on hours worked in the reference week due to snow in prior weeks. The sample requires there is no snowfall in between the current and reference weeks (i.e., we exclude observation with snow following the reference week). The six regressions include controls for gender, age, race, ethnicity, educational levels, potential experience, CBSAs size levels, regions; occupations, industries, and monthly national unemployment rates. Month dummies for November-March are included (October is the omitted month). All regressions are weighted by individuals’ CPS final weights.

Table A-4: Snowfall effects on hours worked for salaried versus hourly workers

	(1) Salaried	(2) Hourly	(3) Salaried	(4) Hourly
	Full sample		Snow event sample	
Snowfall	-0.895***	-0.746***	-0.733***	-0.589***
	(0.239)	(0.164)	(0.136)	(0.142)
Observations	248,566	325,783	65,665	91,936
R-squared	0.086	0.185	0.093	0.202
Difference		-0.149		-0.144
Chow- Test	Chi Square = 1.26		Chi Square = 0.65	
	Prob > Chi-Square = 0.2607		Prob > Chi Square =0.4215	

*** p<0.01, ** p<0.05, * p<0.1; CBSA-clustered robust standard errors in parentheses.

The table presents the estimated coefficient and standard errors. There are four regressions, each including dummies for gender, age, race, ethnicity, educational levels, potential experience, CBSAs size levels, regions; occupations; and industries. Month dummies for November-March are included, with October the omitted month, Monthly national unemployment rates for October 2004 through March 2014 are included., each of which controls for demographic information such as age, race, sex, educational level, experiences as well as five sets of dummies. Month dummies with October omitted, CBSAs size dummies with size 2 omitted; region dummies with New England omitted; occupation dummies with “Management, Business, Financial” omitted; and industry dummies with “Agriculture, Forestry, Fishing, and Hunting” omitted. Regressions are weighted by individuals’ CPS final weights.

Table A-5: Relationship between hours worked and snowfall based on employment type

	(1) Public	(2) Private	(3) Self-Employed	(4) Public	(5) Private	(6) Self-Employed
		Full sample			Snow event sample	
Snow	-1.410***	-0.757***	-0.721***	-1.078***	-0.628***	-0.408**
	(0.337)	(0.139)	(0.217)	(0.185)	(0.091)	(0.203)
Observations	373,464	1,892,618	224,372	94,728	527,375	61,605
R-squared	0.102	0.183	0.112	0.123	0.198	0.110

*** p<0.01, ** p<0.05, * p<0.1; CBSA-clustered robust standard errors in parentheses.

Note: The dependent variable is hours worked in the previous week. There are two sets of regressions, one for the full sample and the other for snow event samples. Controls include dummies for gender, age, race, ethnicity, educational levels, potential experience, CBSAs size levels, regions; occupations; and industries. Month dummies for November-March are included, with October the omitted month, Monthly unemployment rates (national) for October 2004 through March 2014 are included. All regressions are weighted by individuals’ CPS final weights.

Table A-6: Relationship between hours worked last week and snowfall in different industries

	(1) Agriculture, Forestry, Fishing, Hunting	(2) Mining	(3) Con-struction	(4) Manu-facturing.	(5) Wholesale Retail Trade	(6) Transp., Utilities	(7) Infor-mation	(8) Financial Activities	(9) Prof., Business Services	(10) Educ., Health Services	(11) Leisure, Hospi-tality.	(12) Other Services
A. Snow is in the reference week (all data)												
Snow	-0.486	-0.842	-1.372***	-0.549***	-0.638***	-0.785***	-0.260	-0.610***	-0.843***	-0.807***	-1.041***	-0.837***
	(0.614)	(0.718)	(0.216)	(0.110)	(0.133)	(0.173)	(0.163)	(0.131)	(0.246)	(0.163)	(0.159)	(0.294)
Observations	10,975	7,489	119,815	243,874	321,961	87,103	54,565	169,033	235,597	352,599	191,137	98,470
R-squared	0.141	0.112	0.080	0.080	0.236	0.087	0.155	0.105	0.123	0.113	0.295	0.179
B. Snow is in the reference week (snow event sample)												
Snow	-0.663	-0.403	-1.302***	-0.513***	-0.569***	-0.666**	-0.291	-0.541***	-0.612***	-0.672***	-0.841***	-0.353
	(0.942)	(0.676)	(0.256)	(0.111)	(0.131)	(0.248)	(0.202)	(0.129)	(0.136)	(0.146)	(0.165)	(0.238)
Observations	2,265	1,702	29,041	77,556	90,586	23,985	15,297	49,151	61,276	100,383	50,144	25,989
R-squared	0.198	0.115	0.087	0.084	0.248	0.105	0.174	0.119	0.135	0.120	0.309	0.191

*** p<0.01, ** p<0.05, * p<0.1; CBSA-clustered robust standard errors in parentheses.

Note: There are total 24 regressions, In the top half, the full sample is divided into separate regressions (samples) for each of the 12 industry groups. In the bottom half, regressions are estimated for the 12 industry groups, but with samples restricted to have had a snow event during the reference week. Controls are largely the same as in prior tables, the exception being that industry dummies are not included. All regressions are weighted by individuals' CPS final weights.

Table A-7: Relationship between hours worked last week and snowfall in different occupation

	(1) Management, Business Financial	(2) Profes-sional, Related	(3) Services	(4) Sales, Related	(5) Office, Admin Support	(6) Farming, Fishing, Forestry	(7) Construction, Extraction	(8) Installation, Maintenance, Repair	(9) Production	(10) Transportation, Material Moving
A. Snow is in the reference week (all data)										
Snow	-0.799***	-1.052***	-0.698***	-0.796***	-0.865***	-1.107*	-1.100***	-0.504***	-0.535***	-0.778***
	(0.231)	(0.224)	(0.160)	(0.138)	(0.185)	(0.603)	(0.240)	(0.170)	(0.130)	(0.214)
Observations	411,142	634,385	348,176	276,490	342,384	9,371	121,283	82,668	135,301	129,254
R-squared	0.067	0.106	0.188	0.243	0.115	0.138	0.057	0.056	0.073	0.151
B. Snow is in the reference week (snow event)										
Snow	-0.509***	-0.798***	-0.616***	-0.722***	-0.727***	-0.902	-0.881***	-0.244	-0.522***	-0.742***
	(0.105)	(0.145)	(0.129)	(0.133)	(0.164)	(0.729)	(0.305)	(0.173)	(0.146)	(0.202)
Observations	112,879	173,826	91,780	76,240	96,272	1,988	30,258	22,374	42,069	36,022
R-squared	0.071	0.117	0.198	0.254	0.126	0.226	0.057	0.059	0.081	0.155

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Note: This table presents the estimated coefficient (and standard error), all robust standard errors are clustered at CBSA level in the parenthesis. There are total 20 regressions, and each regression controlled demographic information such as age, race, sex, educational level, experiences as well as four sets of dummies. Month dummies with October omitted, CBSAs size dummies with size 2 omitted; region dummies with New England omitted; and industry dummies with "Agriculture, Forestry, Fishing, and Hunting" omitted. All regressions are weighted by individuals' CPS final weights.