harvey.cutler@colostate.edu

The Economic Effects of Improved Precipitation Forecasts in the United States Due to Better Commuting Decisions[1]

Brad Hartman

Harvey Cutler (corresponding author)

Martin Shields

Department of Economics

Colorado State University

Dave Turner

Global Systems Laboratory

National Oceanographic Atmospheric Administration

17 May 2021

[1] This work was partially supported by the Office of the Director, NOAA Global Systems Laboratory.

MR. BRADLEY HARTMAN (Orcid ID : 0000-0002-0456-9339)
DR. HARVEY CUTLER (Orcid ID : 0000-0002-4176-9815)

Article type : Original Article

Abstract

Each year the U.S. government makes significant investments in improving weather forecasts from numerical weather prediction models that are run operationally within the National Weather Service. Although the primary purpose is saving lives and property, more accurate forecasts can create substantial efficiency gains when they elicit improved behavioral responses. One example involves commuters, who make daily decisions about when to leave for work based, in part, on expected road conditions. When workers account for potential weather delays, economic losses due to missed work time are reduced. Economists have often looked at such questions with cost-loss models, a partial equilibrium approach investigating gains to individual agents. We extend this idea to examine economy-wide effects, embedding a behavioral model of time allocation with improved information into eight regional computable general equilibrium models of the US economy. Our primary mechanism is that reductions in lost work time lead to gains in firm-level output. This study evaluates the economic impact of improvements to the High-Resolution Rapid Refresh weather forecast models over three different versions on commuting. Aggregating results from comparisons between old and new versions of the HRRR for 206 metropolitan statistical areas, we find that forecasting improvements lead to smaller losses in work time, creating notable gains to the U.S. economy.

The Economic Effects of Improved Precipitation Forecasts in the United States Due to Better Commuting Decisions

1. Introduction

Between 1990 and 2018 the average U.S. commute time increased 20 percent, with the typical American worker now spending nearly one hour every day driving to and from their workplace (Ingraham (2019)). Because it accounts for so much time, workers are likely paying increased attention to factors that may impact their daily commute, including weather-related changes in road conditions.[1] Research has shown that adverse weather conditions such as rain, sleet and snow lead to significant increases in both travel time and driver risk, imposing significant costs on both individuals and the overall on the economy.[2] Little is known, however, about economic gains that result from information improvements when commuters predicate their actions based on weather forecasts, rather than just what they observe.

Each year the U.S. federal government makes significant investments in improving numerical weather forecast models. Although the primary purpose is saving lives and property, these forecasts inform myriad economic decisions, with studies suggesting more accurate forecasts can create substantial economic gains (e.g., Katz and Murphy (2005), Lazo and Chestnut (2002), Rosenzweig and Udry (2014)). In this paper we simulate the economic gains when commuters have access to improved weather forecasts to help decide when to leave for work based on expected road conditions. When commuters account for potential weather delays, economic losses due to missed work time are reduced.

In 2014 the U.S. National Oceanic and Atmospheric Administration (NOAA) began using the High-Resolution Rapid Refresh (HRRR) numerical weather prediction system to provide operational weather forecasts for the National Weather Service (NWS). HRRR is a real-time model with 3-km

1 In 2018, the smartphone route guidance app *Waze* had more than 30 million active users in the US (https://expandedramblings.com/index.php/waze-statistics-facts/). Waze was initially launched in 2006 as FreeMap Israel to aid GPS navigation. In addition, it provides real-time traffic analytics that suggest alternative routing when the normal path is impacted by congestion or an accident. In 2013, Google paid nearly $1 billion to acquire the company.

2 According to the US DOT (2018), each year there are more than 1.2 million weather related motor vehicle crashes in the US, accounting for 21 percent of all motor vehicle accidents. https://ops.fhwa.dot.gov/weather/q1 roadimpact.htm

resolution, updated hourly, and is the premier model used for high-resolution severe weather forecasting by the NWS.[3] As a federal agency, the NWS publicly shares both the forecasts from its collection of models and the observations from its national network of weather stations. Users can access this information i) directly through NWS, or through private companies that use NWS forecasts as part of their own proprietary, ensemble forecasts that they subsequently ii) sell to local news stations and newspapers (e.g., AccuWeather), or iii) offer through subscription or advertiser supporter smartphone apps (e.g., Weather Underground) (Fritz (2016)).[4]

Since its initial release in 2014, the HRRR model was revised in 2016 (version 2) and 2018 (version 3) and 2020 (version 4). We simulate the economic value of the first two updates with respect to commuting times, using forecasts from the first three generations of the HRRR system. We compare forecasts from each model to observed precipitation data for the nation's 206 largest metropolitan statistical areas (MSAs), exploiting the fact that when NOAA introduces an updated model both the current and new version run simultaneously for several months. For this work, we define model "improvements" to have occurred when the revised model provides a more accurate forecast than the previous version for economically significant events; for example, predicting significant rainfall when the previous model did not.

Section 2 presents a literature review relevant to modeling economic impacts of weather and weather forecasting. Section 3 offers a discussion of the HRRR system and Section 4 presents an abbreviated discussion of the theoretical economic model as it has been used extensively in previous publications. Our extension here is providing some theoretical detail on modeled household behavior, with commuters facing a tradeoff between consumption (driven by wage income) and leisure when deciding how to respond to weather forecasts. Section 5 discusses the organization of the HRRR data, the economic regions divided into the eight Bureau of Economic Analysis (BEA) regions and the impacts on travel times as economic agents respond to weather forecasts. Section 6 provides the simulation results and Section 7 is the conclusion.

2. Literature Review

[3] Details on the HRRR are provided in section 3.
[4] Because these companies are privately held, they do not publicly quantify the importance of any given NOAA model to their overall forecast.

2.1 Modeling the value of improved weather forecasts

While the economic impact of weather is a hot topic, studies estimating the value of weather forecasts are much less prominent--though there is a fairly long history of such analyses. Much of this research finds its theoretical basis in the general field of information economics, premised on the idea that information is valuable when it leads to changes in economic behavior that improve economic outcomes, such as profit or welfare. Murphy (1969) is one of the first to apply this idea to weather forecasts, utilizing a "cost-loss" approach.[5] In this framework, decisionmakers face probabilistic forecasts that influence whether or not they take a precautionary action that prevents or reduces the effects of an adverse outcome. For example, an agricultural producer may use forecasts to decide whether or not to protect her crop from a frost event with probability ρ. Because protection is costly, the producer will only take mitigating action (A=1) when expected benefits (i.e., averted losses) exceed the costs of the action (C), or:

A = 1 if ρ*Loss>Cost, else A=0*

The cost-loss ratio is important because it identifies the threshold probability for "taking action." By providing better estimates of ρ, improved weather forecasts can hone the decisionmaker's problem.[6] Lee and Lee (2007) apply a variant of this idea to examine the value of both deterministic and probabilistic, site-specific forecasts for Beijing and Seoul. The authors find cases where greater subjective forecast reliability can enhance firm profitability and suggest estimates of such gains are "a useful way to analyze the value of forecast for various users" (p 462). By construction, cost-loss estimates only look at impacts on individuals or firms, thus they should be seen as partial equilibrium studies. As we suggest later, individual decisions can have important general equilibrium impacts. Thus, our approach allows a more comprehensive accounting of the value of weather forecasts.

Katz and Murphy (2005) provide important contributions to both the theoretical and empirical modeling of valuing improved weather forecasts from an information perspective. They describe a theoretical model where a decisionmaker uses available information in maximizing expected

5 For examples spanning time, see Thompson and Brier (1955), Thompson (1972), Stuart (1982), Mjelde, Sonka and Peel (1989) and Lee and Lee (2007).

6 As formulated, this problem assumes the decisionmaker is risk-neutral. Other risk preferences can be incorporated by converting monetary values into utility.

utility. Agents choose actions based on expectations of the weather and endure welfare consequences based on their action and the realized weather.[7] For a trite example, it may be whether to purchase an umbrella. More consequential actions might be a winter drive to the mountains. When there is no forecast, the decisionmaker has some prior about the weather (perhaps the prior day's weather or a peek out the window) and chooses an action in accordance with their risk-preferences. When new information is introduced (potentially at a cost), the decisionmaker decides whether to change their action, based on the expected changes to utility, given the costs and benefits associated with the alternative action. Katz and Murphy (2005) outline this connection, defining the demand value of information as "the highest amount the decision maker should be willing to pay in order to receive the forecasts" (p 9).

This theoretical construct underlies empirical studies that attempt to value information via willingness to pay (WTP). Lazo and Chestnut (2002) use this approach to value weather forecast improvements at the national level provided by the National Weather Service (NWS). They conduct a survey where respondents face a binary choice between continued use of current weather technology for no cost or improved technology for an increased cost. Most respondents selected one-day ahead forecasts over multi-day forecasts and there was also preference for highly detailed geographical forecasts (3km, 10km, 20km rather than 40km or greater). At subnational levels, Kenkel and Norris (2007) use WTP to value real time mesoscale forecasts for agricultural producers in Oklahoma, while Rollins and Shaykewich (2003) use the method for select commercial sectors in Toronto.

Not all studies valuing weather forecasts are couched in an information-theoretic context. Instead, some researchers look solely at empirical evidence on observed behavior or market outcomes, eschewing specific assumptions about preferences. For example, Rosenzweig and Udry (2014) analyze the decision making of farmers in India based upon, among other factors, rainfall forecasts. They hypothesize that seasonal forecasts influence migration decisions, with farmworkers less likely to out-migrate when good weather is forecasted. Using a 0.5-degree by 0.5-degree gridded dataset of precipitation radar data and farming observations from 600 Indian districts, Rosenzweig and Udry constructed a general equilibrium model of the agricultural labor market. The authors find a negative effect on wages in cases where

7 We incorporate some of the bigger ideas in this line of research into the labor supply component of our CGE model, discussed in the next section. While our methodology is founded on the prescriptive approach laid out by Katz and Murphy (2005), the focus of our analysis necessitated the use of more descriptive techniques.

realized seasonal rainfall is lower than forecasted. The proffered mechanism is that when actual seasonal rainfall falls short of the forecast, lower crop yields reduce labor demand at harvest time, putting downward pressure on wages. The inverse relationship, where rainfall is greater than forecast, also holds, with farmers bidding up wages at harvest time when labor is scarce.

2.2 Modeling the welfare impacts of increased commuting times and the effects of weather on commuting times

A sprinkling of papers examines the comingled ideas in this sub-section's title, including how commuting choices and travel time are related to weather, productivity, and welfare. Both our theoretical and applied models use many of these ideas as ingredients. We consider two unique threads. In the first, we review research showing that weather and predictions about it can affect commuting and other travel decisions. In the second, we look at various channels by which increased commuting time affects welfare. We use this to set up the household problem in our CGE model, which we describe in section three.

2.2.a Weather, commuting decisions, and travel time[8]

Both the current weather conditions and the forecasts of the anticipated weather affect commuter departure times. With respect to current weather conditions, Khattak and De Palma's (1997) survey of Brussels commuters found that among the 50 percent of respondents that reported changing their travel decisions in adverse weather, 60 percent changed their departure time and 35 percent chose an alternate route. Cools, Moons and Wets (2010) report on a stated preference survey of 586 Belgians. In it they ask about behavior under a variety of weather conditions (e.g., rain, fog, snow) for various trip purposes (e.g., commuting, shopping). Overall, the authors find that behavior changes depend on both the type of weather and the purpose of the trip. For example, snow makes shoppers cancel or postpone trips more frequently than does rain, and shoppers are more likely to cancel or postpone trips than commuters. Still, precipitation events do have notable impacts on commuters in terms of "time of day change," with 52 percent of respondents reporting at least one incident where departure behavior was impacted by snow, while 30 percent reported similar effects of rain.

[8] Böcker, Dijst and Prillwitz (2013) offer a fairly comprehensive review of this literature.

While there is a large body of work on traffic information related to commuting decisions (e.g., Arnott, de Palma and Lindsey (1991), Polak and Jones (1993), Dell'Orco and Marinelli (2017)), only a few studies look at how weather information impacts commuting. For example, Khattak and De Palma (1997) show that close to 75 percent of commuters keep track of weather, primarily using radio and television.[9] Drawing on results of a survey of *en route* Finnish drivers, Kilpeläinen and Summala (2007) suggest that weather forecasts have mixed effects, with only 5.8 percent of more than 1,400 respondents reporting changes in travel plans prior to a trip; yet they do find significant differences in trip planning between drivers that reported actively acquiring weather information relative to those not (16.4 percent vs. 3.5 percent). The changes reported most frequently were allowing more time for the trip (5 percent of all drivers) and altering the time of departure (3 percent). One reason for such small effects may be since drivers were surveyed at service stations, meaning they were already on the road. It is quite reasonable to assume that their behavior is more impacted by the weather they are experiencing, rather than any information about it.

There is an extensive literature on the effects of weather on driving, with much of it looking at how bad weather (e.g., snow and heavy rain) can lead to bad outcomes, such as accidents and fatalities (e.g., Eisenberg and Warner (2005), Black and Mote (2015), Leard and Roth (2015)). Some research, however, also looks at how adverse weather impacts commuting time.[10] For example, Stern et al. (2003) present empirical results showing that precipitation during peak-period traffic can lead to at least an 11 percent increase in travel time, but the authors suggest it is likely much closer to 25 percent. Maze, Agarwal, and Burchett (2006) find rain reduces driving speeds by 6 percent in Minneapolis. Tsapakis, Cheng and Bolbol (2013) report on car level traffic in London during hours of no rain, light rain, moderate rain, and heavy rain. Using correlation analysis, they estimate that light rain (0.01-0.25mm per hour) and moderate rain (0.25-6.35mm per hour) increase travel time between 2 and 4 percent, while heavy rain (> 6.35mm per hour) increases travel time by 4 to 6 percent. In a study of the Washington, D.C. area Stern et al. (2003) find precipitation can increase peak-period travel time between 11 and 25 percent.

2.2.b Travel time and welfare

9 A separate literature describes factors affecting the use/non-use of weather forecasts in decision-making. While this research provides important insights in increasing the value of improved forecasts, it is outside of the scope of our work. For a good overview, see Regnier (2008) or Morss, Lazo, and Demuth (2010).
10 For a somewhat dated review, see Maze, Agarwal, and Burchett (2006).

Not many researchers link weather-to-commuting time-to-welfare, but Sabir et al. (2010) do. Although they find snow has the greatest impact on commuter welfare, they find rain can also have important effects, especially during congested, peak-hour travel times. According to the authors, these impacts range between 9 and 12 percent of total commuting costs during evening commute times. Other papers show that commuters understand time is money. Van Ommermen and Dargay (2006) find the income elasticity of commuting speed is 0.13; as wages increase, people are willing to switch into alternative transportation modes that save time, even if they are costlier. Small, Winston and Yan (2005) finds motorists value both travel time and its predictability. Specifically, they find that the median value of time is about 93% of the average wage rate, while the median revealed preference value of reliability (i.e., the predictability of travel time) is about 85 percent of the average wage rate.

2.3 General equilibrium effects of transport time

As described in sections 2.1 and 2.2, economic valuations of weather forecasts are nearly exclusively partial equilibrium analyses. Our paper extends this work to consider general equilibrium (GE) effects, with the commuting aspects informed by transport related CGE modeling. Robson, Wijayaratna, and Dixit (2018) review such models as applied to a wide range of transportation issues focusing on urban, regional, and spatial structures. Although most of the reviewed models focus on issues related to congestion and mode choice, none address weather-related decisions.

Conceptually, Isard's (1951) 'ideal' IO model is our starting point, modeling interregional trade flows that respond to relative regional price signals while considering freight transport costs.[11] Many spatial CGE modelers adopted this idea, with early versions tending to look at the flow of goods and services, rather than people (e.g., Buckley (1992), Tatano and Tsuchiya (2008), Donaghy (2009)). Although not specifically focused on commuting, Heyndrickx, Koops and Ivanova (2011) model labor flows using the *Transport and Infrastructure General Equilibrium* (TIGER) model in evaluating the effects of an

11 There have been important theoretical treatments of commuting in a GE framework, with many analyzing congestion, land use, and urban form. For example, Anas and Kim (1996) examine a hypothetical linear city where household and firm activities generate commuting trips with travel times modeled endogenously using a congestion function. Anas and Liu (2007) extend this analysis to examine how households optimize subject to time constraints from commuting.

improved railway connection in northern Europe. They find the improved system reduces passenger transit costs and travel time, affecting the household's budget and labor supply, respectively.

While not analogous, Haddad et al. (2015) are slightly closer to our intent. The authors look at the regional economic impacts of subway system improvements in Sao Paulo, Brazil. Data are observed for regions pre- and post-infrastructure investment, for policy changes that affect worker commute time. Economic impacts are examined by performing a two-step procedure. First, the authors construct a wage equation where commuting time and an accessibility index are used to understand how increased commuting times decrease labor productivity. The estimated reductions in labor productivity are fed into a spatial CGE model to simulate the general equilibrium effects of increased commuting times.

In summary, our paper merges several related research areas with little integration. The *economics du jour* looks at weather and climate impacts, but typically not in the short-term, where forecasts are most accurate. Studies valuing short-term weather forecasts are exclusively partial equilibrium analyses. CGE models allow understanding economy-wide effects, but the commuting studies found in the transportation economics literature have not examined the impacts of short-run weather forecasts. We bridge these approaches.

3. The High-Resolution Rapid Refresh (HRRR) numerical weather prediction model system

The numerical weather forecast models are run operationally by the NWS to provide short-term (hours to days) forecasting guidance for a range of users including general forecasting, severe weather, aviation applications, renewable energy, agriculture and more. These models aid situational awareness, combining observations and a representation of atmospheric physics to provide a best estimate of the weather conditions at some time in the future. We analyze data from the HRRR, which provides forecasts over the conterminous U.S. (Benjamin et al. 2016). The HRRR is reinitialized hourly with current observations, thereby incorporating the most up-to-date information on the atmospheric state, and then integrates this state forward in time using equations to describe the dynamical evolution and physical processes at work in the atmosphere to simulate the evolution of the weather.

HRRR development began in approximately 2008, using the Advanced Weather Research and Forecast (WRF-ARW) model as its baseline (Skamarock et al. 2008). The gridpoint statistical interpolation data assimilation system (Kleist et al. 2009) is used to initialize the atmospheric state of the model using observations from surface met stations, radiosondes, aircraft, and scanning precipitation radar stations. The high-spatial resolution of this model (3-km horizontal, with 50 vertical layers from the surface to the mid-stratosphere) allows this model to resolve most deep convective weather systems; this removes the need to parameterize this important contribution to the overall heating, and thus dynamics of the atmosphere.[12] Additionally, the 3-km resolution helps to improve the representation of the interactions between the atmosphere and the land surface, especially in regions of complex terrain (e.g., valleys, mountains).[13]

The Global Systems Laboratory (GSL) within NOAA is continuously developing the HRRR model, with new versions released to the NWS approximately every 2 years since 2014. Scientists at GSL work to improve both (1) how the model is initialized by improving data assimilation techniques within GSI and incorporating additional observations in the process, and (2) the parameterizations that represent the various atmospheric physical processes. Details on the development of the HRRR modeling system are provided in Dowell et al. (2020) and James et al. (2020). Here, we use HRRR output from versions 1, 2, and 3, wherein the significant changes are shown in Table 1 (full details are provided in Dowell et al. 2020).

[Insert Table 1]

Due to the complex and highly non-linear interactions between myriad physical processes, model output is compared regularly to a range of different atmospheric observations to evaluate if the new changes improved the model. The Model Analysis Tool Suite (MATS), the philosophy and methodology to evaluate the HRRR against observations are described in Turner et al. (2020). This comparison is done in controlled experiments, wherein the code for the new model (v_{x+1}) is frozen and run concurrently with

12 Many atmospheric processes occur at scales too small to be fully resolved by weather forecast models, yet their contribution to the mass or energy budgets need to be included to make a good forecast. These contributions are computed using parameterizations (or simplifications) of the various atmospheric processes. There are many dozens of parameterizations in any weather prediction model, representing processes associated with radiative transfer, turbulent motions, the formation and growth of rain drops, and many more.
13 Doubling the model resolution makes the model approximately $2^4 = 16$ times more computationally expensive and markedly increases the amount of memory and storage needed to run the model and save its output. The rapid increase in computational power with high-performance computing systems has allowed models like the HRRR to be run over such a large domain as the U.S.

the operational model (v_x). These overlap periods are shown in Table 1. Improving the quantitative precipitation forecasts (QPF) is a critical goal for the HRRR development team, and thus comparisons are made regularly against the so-called Stage IV quantitative precipitation estimates (QPE) derived from the network of operational weather radars across the U.S. (Nelson et al. 2016). As precipitation is very heterogeneous over a region, various statistics are computed by MATS to gain different insights into the model performance.

We compared the 12-hour forecasted QPF from different versions of the HRRR from the overlap periods against Stage IV QPE observations. Figure 1 shows the critical success index (CSI) for different precipitation thresholds, where the CSI is computed as the number of times the model correctly forecasted the rain (hits) divided by the sum of the hits and the number of false alarms and misses. The ideal CSI score is 1. Figure 1 clearly shows that v2 was markedly superior to v1 for all precipitation thresholds, and that v3 was better than v2 for precipitation above 0.5 inches in the 6-hour period.

[Insert Figure 1]

Figure 2 illustrates the frequency bias in these precipitation forecasts, wherein the y-axis is the number of times the QPF is above the precipitation threshold divided by the number of times the QPE is above the threshold; the ideal ratio is 1. Figure 2 demonstrates that v2 predicted significantly more events for precipitation above 0.1 inch than the observations (i.e., was actually over predicting these events relative to v1), but that the v3 has by far a better agreement in the frequency of the precipitation events across all thresholds relative to the other two versions. These results (e.g., Figures 1 and 2), which were computed over the eastern side of the U.S. to avoid the observational challenges of the Rocky Mountains, demonstrate that the precipitation performance of the HRRR improved with each subsequent version.

[Insert Figure 2]

4. A CGE Model Incorporating Weather Forecasts in Household Decision Making

In the online Appendix we detail a CGE model that incorporates weather forecasts into the household utility maximization problem. Per standard, utility maximizing households choose how much labor to supply given consumption and leisure preferences, and the prevailing wage rate. We amend this idea such that the quantity of a household's effective labor supply depends, in part, on weather forecasts. When forecasts are perfect, a household optimally allocates its time; when forecasts are incorrect, households may make "mistakes" in apportioning their hours.

Here our concern is when precipitation is under-forecast, meaning workers leave their residences too late to arrive at their jobs on time, resulting in less time spent in production. For households, tardiness means lost income, and household utility suffers. Aggregating such mistakes across households adversely affects aggregate industry labor supply, which subsequently affects sectoral real GDP. General equilibrium impacts are simulated when production and labor income fall, and relative prices change. Most of our discussion describes such a labor market in the context of the CGE model, with the remaining discussion briefly describing the model's other aspects.[14] Additional CGE model construction details related to the simulations are provided in Section 6.

5. Data and Methodology

In this section we describe our weather and commuting datasets and how they are integrated. Building on the intuition of cost-loss models, we define "mistakes" in commuter decisions as cases where we assume commuters rely on what turn out to be inaccurate precipitation forecasts (i.e., underpredictions of meaningful rainfall amounts). We then describe our method for translating individual mistakes into aggregate reductions in labor supply, the effects of which are simulated via the CGE model in Section 6.

[14] Cutler et al. (2016) and Attary et al. (2020) provide detailed discussions of the full CGE model.

5.1 Data

Hourly precipitation forecast data comes from NOAA's HRRR model, which has served as one of the foundational components for local weather forecasts across the U.S. since 2014. HRRR forecasts are made at the 3km-by-3km scale over the contiguous United States. The HRRR is restarted hourly and produces forecasts out to at least 15 hours for each initialization (later versions of the model produce longer forecasts (e.g., out to 36 hours) at regular intervals). For our analysis, we utilize 12-hour ahead forecasts of 1-hour precipitation accumulations for each hour of the day.

Between 2015 and 2018, NOAA released three new HRRR versions (i.e., HRRR1, HRRR2 and HRRR3). Each was tested extensively before its public release. Testing includes simultaneously running the new and previous HRRR versions and recording both forecasts. To evaluate improvements, we analyze the a 15-month testing overlap between HRRR1 and HRRR2 (June 2015 to August 2016). During this period, the operational forecasts reported to the general public were from HRRR1, but experimental HRRR2 forecasts were also stored on NOAA servers. Accordingly, the overlap presents a convenient experiment for evaluating the potential economic impacts of improved weather forecasting.[15] Analogously, we examined the July 2017 to June 2018 for the overlap period between HRRR2 and HRRR3.

Observed weather data for the concomitant time periods is from the Stage IV Precipitation Accumulation dataset (Nelson et al. 2016) and reported by NOAA's National Centers for Environmental Prediction. This dataset contains recorded precipitation accumulations for the CONU.S. with a resolution at the 4km-by-4km scale and a time frequency of one hour.

The vast size of the datasets presents significant management challenges. Even restricting the analysis to the CONUS, the dataset for forecasted and observed precipitation is approximately 20 terabytes. To parse the data to its most economically important areas, we focus on cities, restricting our analysis to the top 206 most populous MSAs in the country.[16] To associate the weather data with a particular MSA

15 Unfortunately, forecast data was not available for every hour between 2015 and 2018. The servers running and storing the experimental HRRR model forecasts sometimes required maintenance; although forecasts were still made during maintenance periods, they were not stored. As a result, about 10 percent of the forecast data from the experimental HRRR versions for the overlap periods was lost.

16 This count is reduced from the US total of 388 MSAs for two reasons. First, only MSAs that are located within the contiguous US are included. Second, many less populous MSAs are farther than 100 miles from the nearest

we use a GIS shapefile of 2017 city municipal boundaries made available by the Centers for Disease Control and Prevention.

Most U.S. studies analyzing the impact of weather and weather forecasts use weather averages at the county or state scale (e.g., Lazo and Chestnut (2002), Leard and Roth (2015)). Utilizing city-level averages provides a few key advantages. First, because cities are the locus of most U.S. employment, focusing on them as our geographical unit of analysis allows us to capture most commuters.[17] Second, taking averages over a city provides a more precise measurement of the precipitation experienced by that city's commuters. This is because rainfall weather patterns are more consistent over smaller geographic regions than larger ones. For example, the average daily rainfall over the entire U.S. is likely very small while the average precipitation in cities where storm fronts passed that day is likely much larger. In this way, using larger geographic regions diminishes the average precipitation measurement. The same logic in precision applies to state and county averages versus city averages.

As evidenced by Lazo and Chestnut (2002), we assume that drivers respond to precipitation forecasts made at the city scale. It seems reasonable to suggest that a driver responds to the weather conditions reported generally for a city because media reports of weather forecasts are almost exclusively generalized over regions as well.[18] Therefore, we calculate the mean of the forecast and actual precipitation accumulation observations contained within each city. To enhance the accuracy of calculating precipitation means at the city level, we impose an algorithm that computes the minimum bounding box containing the city municipal boundaries. Henceforth, we refer to the city polygons shapefile created by this process as "cityboxes." As a result, for each hour, there are 206 citybox observations of mean precipitation.

The total number of automobile commuters and average commuting time are from the U.S. Census Metropolitan Statistical Area data repository for each year between 2016 and 2018. This data was overlaid with its respective citybox shapes (each contained within the geographic area of the MSA) such that the precipitation actuals and forecasts occurring over those cityboxes could be attributed via GIS. In

NCAR radar station and so to enhance the credibility of observed precipitation these MSAs were dropped from the analysis.

17 The 206 MSAs used in this study capture approximately 68% of total US workers.

18 Recently, several companies have made "hyperlocal" weather data and forecasts available to users for geographic units much smaller than counties (e.g., ClimaCell reports data for 500-meter blocks). We are unsure how extensively commuters use such forecasts.

Map 1 we depict the process by which precipitation forecasts and observations were assigned to each citybox. The black-to-blue-to-red raster image displays concentrations of precipitation accumulation. The orange cityboxes contain municipal city boundaries. The average precipitation accumulation forecasted by HRRR and observed by Stage IV is calculated for each hour for each citybox.

[Insert Map 1]

After assigning annualized average daily commuters to cityboxes and calculating precipitation accumulations, the data are merged and formatted as a panel dataset with date and citybox IDs for each hour for each city. For example, each dataset row includes the citybox name (e.g., Denver), the date and time (e.g., July 15th 2017 at 4pm MDT), the hourly precipitation observed (e.g., 0.1 mm), the 12-hour ahead, 1-hour forecast (e.g., 0.2 mm), the total automobile commuters in that MSA (e.g., 200,000), and the average commute time in that region (e.g., 20 minutes).

5.2 Estimating FTEs lost due to forecast misses

For our purposes, forecast errors are important only when they have the potential for notable economic impacts.19 These are instances where economic decisions might differ according to the specific forecast. As an example, if the forecast implies "no adverse precipitation," yet the observed precipitation is "adverse," then the informed commuter makes a mistake by leaving too late.

19 There is a literature on techniques to evaluate precipitation forecast error (e.g., Ebert el al (2003)). In this paper, our economic concerns about errors are different than those typically discussed in the meteorology and atmospheric science literature.

Building on the cost-loss model described in Section 2.1, Table 2 portrays an expense matrix of possible outcomes resulting from the action (A) to leave early for work or not and the consequent costs associated with the occurrence or absence of adverse precipitation (Y). Our main interest is estimating differences in *losses* across models, which occur when the informed commuter does not leave early (A=0) yet experiences adverse precipitation (Y=1) during their journey, delaying their arrival time to work. Accordingly, we only compare the HRRR versions in cases where one or both models substantially *underestimate* the actual precipitation event. One result of this focus is that we do not estimate the welfare losses arising from *overestimation*, which results from lost leisure when a commuter leaves too early for work (ie, Y=1, A=1).

[Insert Table 2]

Calculating MSA labor hours lost

We categorize precipitation (rain) accumulation as "trivial," "moderate" and "heavy."[20] Consistent with Rosenzweig and Udry (2014), precipitation events less than 0.1mm per hour are "trivial" or light. Per Tsapakis, Cheng and Bolbol (2013), moderate rain is 0.25 to 6.35mm accumulation per hour, while heavy rain is accumulation greater than 6.25mm per hour. We define notable under-forecast events when forecasted precipitation is either zero or trivial, while observed precipitation is either moderate or heavy (i.e., "adverse"). Because we want to ensure that the magnitude of the under-forecast is economically meaningful, we are not troubled by under-forecasting light rain (0.1mm-0.25 mm per hour).[21] For example, we do not want to include situations where 0.009mm was forecast but 0.01mm fell, as such a small difference is economically inconsequential. Although Tsapakis, Cheng and Bolbol (2013) suggest precipitation accumulations less than 0.25mm can still

---

20 The Stage IV precipitation data measures liquid precipitation. Some of this precipitation originally falls in its solid form (i.e., snow). Previous research shows snow has larger impacts on commuting times than does rain. However, our procedure does not allow us to capture differences between rain and snowfall. We did look at instances of precipitation forecast mistakes when the observed temperature is between 28- and 36-degrees Fahrenheit—conditions ripe for snow--but we found very few cases where one HRRR model was correct and the other was not.

21 By comparison, an hourly accumulation of 0.25mm is one quarter of the USGS definition of a "heavy drizzle" (such definitions are available via a USGS online rainfall calculator at https://water.usgs.gov/edu/activity-howmuchrain-metric.html). This means that by using the "light rain" category we would be including under-forecasts where the difference in precipitation was as little as a few extra drops accumulating over the windshield over the course of an hour's drive.

reduce travel time, we believe it is more important to ensure that our analysis captures under-forecasts that reflect seriously upon the underlying performance of the HRRR models.

While adverse weather impacts many trip purposes, we only examine commuting. Thus, we restrict our analysis to 12-hour ahead forecasts made for typical morning commuting hours (6:00-10:00 am local time, weekdays only) and assume that all commuters drive to work during this period. Next, the total number of daily commuters in each MSA is evenly allocated across this time window. Accordingly, for every 100 commuters, we assign 25 to each hourly interval. Although this interval does not capture all commuters, most U.S. jobs require that a worker arrive sometime during it. We do not analyze afternoon commuting hours because we assume that workers do not leave their jobs early to return home in the event of inclement weather, thus there are no potential losses. [22]

Translating precipitation into increased commuting time is a critical step. We develop lower and upper bounds for commuting time losses due to unexpected bad weather. For the lower bound we used estimates by Tsapakis, Cheng and Bolbol (2013), who specify that any actualized rainfall between 0.25 to 6.35mm of accumulation increases travel time by three percent and any actualized rainfall greater than 6.35mm increases travel time by five percent. For example, if New York City commuters face an average commute time of 30 minutes, then during a moderate precipitation event that commute will now take 31 minutes. This condition is formulated by the piecewise function $m(Y, \hat{Y})$, where Y is actual precipitation accumulation for the hour, and $\hat{Y}$ is 12-hour ahead forecasted precipitation for that hour.

$$m(Y, \hat{Y}) \begin{cases} 5\%, Y > 6.25 \; and \; \hat{Y} < 0.1 \\ 3\%, 0.35 < y < 6.25 \; and \; \hat{Y} < 0.1 \\ 0\%, Otherwise \end{cases} \tag{7}$$

For each date and hour (t), in each MSA (r), the total commuter count is $Q_{t,r}$. The average commute time for each MSA, in hours, is denoted by $a_{t,r}$.

For the upper bound, we turn to Stern et al. (2003), who collected an expansive data set for Washington, D.C. and estimated travel time delays due to precipitation during peak travel

[22] We acknowledge that workers are sometimes sent home early when adverse weather is predicted and that there can be economically costly "mistakes" when workers are released early, but the adverse weather does not materialize. This is beyond the scope of this work.

periods. Their estimated range varied from 11 to 25 percent, but the authors believed that actual delays were close to 25 percent, so we use this value as the upper bound.

HRRR is a prevalent U.S. weather model, and its forecasts are utilized in NWS reporting of weather alerts and by news agencies across the nation. Additionally, HRRR forecasts inform proprietary forecasting models, such as those of the Weather Channel and AccuWeather (Fritz (2016)). As such, we assume HRRR forecasts (or their derivatives) are the only forecasts that commuters use. Further, we assume all commuters trust HRRR forecasts, with each agent responding positively to them.23 This means that in the event of forecasted moderate or heavy rain, every commuter will choose to leave early for work. Conversely, when zero or trivial precipitation is forecast, no commuter will depart early. As a result, during any commuting hour in any given MSA for which meaningful precipitation under-forecasting occurs, we can express the sectoral labor hours lost (LHL) as a result of this forecast inaccuracy from version v of the HRRR model:

$$LHL^{v}_{t,i,r} = m\left(Y, \hat{Y}\right) * a_{t,r} * (0.25Q_{t,r}) \tag{8}$$

As an example, consider Denver, CO. The average MSA morning commute time is 30 minutes ($a_{t,r}$=0.5), while the total annual average daily number of commuters ($Q_{t,r}$) is 200,000, meaning we estimate 50,000 hourly commuters between 6am and 7am. Multiplying hourly commuters by $a_{t,r}$, we see that 25,000 hours are spent commuting under ideal weather conditions during this time. At 6:00 pm on September 22nd, 2017, HRRR2 forecasted the MSA would see "trivial" precipitation 12 hours later. This forecast, however, turned out wrong, with Denver experiencing "heavy rain" between 6:00 am and 7:00 am on September 23rd. Applying equation (8) with a 5 percent (lower bound) commuting time "penalty" for the under-prediction (i.e., $m(Y, \hat{Y})$=5 percent), the result is 1,250 labor hours lost. For the upper bound, using 25 percent, there are 6,250 labor hours lost. In this way, *LHL* can be considered the sum of household mistakes that cause lateness to work.

23 These are strong assumptions, and (potentially) put an upper bound on our estimates. For example, Lazo (2005) shows that not everyone uses forecasts in their daily decision-making. On the other hand, the changes in driving time estimates due to precipitation we use from Tsapakis, Cheng and Bolbol (2013) are lower than some other published estimates (e.g., Maze, Agarwal and Burchett (2006)), meaning estimated time loss per affected commuter estimates may be conservative. In the simulations in section five, we show how results change when some of these assumptions are relaxed.

Aggregating MSA labor hours lost to full-time equivalent (FTE) losses at the regional level

As noted above and described below, we create eight CGE models, one for each U.S. BEA Region (Map 1 in online Appendix). By looking at sub-national regions, we allow for regional heterogeneity in terms of economic structure, precipitation events and forecast accuracy. Online Appendix B provides a description of how the social accounting matrices (SAM) are constructed for each region.

After determining total labor hours lost for each MSA due to forecast misses, we convert them into a labor metric consistent with the regional CGE models (i.e., annual FTEs, by industry, or $\Delta LB_{i,r}$). To do so we sum the total MSA labor hours lost per meaningful under-forecast for each industry and divide it by the annual average hours worked by an FTE (this is the product of the average number of hours a worker works per week and the average number of weeks a worker works each year). Using data on the divisor for 2015 from the BLS[24] we write this as:

$$\Delta LB_r^v = \sum_t LHL_{t,r}^v / (38.7 * 46.8) = \sum LHL_{t,r}^v / 1{,}811 \tag{9}$$

These FTEs at the MSA level are then aggregated into the eight BEA regions used in the CGE model. A map of the eight BEA regions can be found in the online appendix.

5.3 Data Characteristics[25]

[24] This data can be found here: https://www.bls.gov/news.release/empsit.t18.htm
[25] Additional data descriptions and characteristics can be found in section C of the online appendix.

Tables 3 and 4 report estimates of full-time equivalent workers lost for each region under each forecasting regime using the lower bound. These estimates are based on the number of misses for each region. Overall, we estimate that the total number of “moderate” misses across the eight BEA regions fell from 2,831 to 587, while the number of “heavy” misses declined from 91 to 29 when using HRRR2 instead of HRRR1.When HRRR3 was invoked rather than HRRR2, the total number of “moderate” misses increased from 539 to 777 while the number of heavy misses fell from 34 to 33 (see online Appendix Tables C.2 and C.3 for regional detail).

By construction, our labor hours lost measure (equation 8) is, in part, a function of each MSA’s total number of commuters and their average commute time. Because of this it is possible for regions with lower counts of HRRR misses to lose more labor hours than regions with higher miss counts. As an example, although the Mideast has only 14 MSAs, it has the most commuters and the highest average commuting time. Therefore, a forecast miss in a Mideast MSA may have a substantially larger effect on labor hours lost than a similar miss in any other BEA region.

The third data column is key, showing 1,491.4 more FTE’s lost when HRRR1 was used instead of HRRR2. Although the absolute value of differences in FTE’s lost between the two versions is only a small percentage of total national employment (about 160.7 million), the economic effects can still be notable. (The upper bound estimates of labor lost is represented by multiplying the values in in the first three data columns of Tables 3 and 4 by five.) The implications of Tables 3 and 4 are discussed in detail in section 6.2.

6. CGE Model and Analysis

This section has two parts. In the first we describe how the simulations are implemented and the second section presents the results.

6.1 Setting up the Simulations

Households are linked to production sectors through the labor market. Firms need workers to produce output, but only to the extent to which the value of a worker’s marginal product exceeds the wage the firm must offer to attract an additional worker. As noted in the online Appendix, each household is endowed with time, which they can convert to labor supply if the market wage offer is attractive enough. In equilibrium, the labor demand and supply are equal at a specific wage:

$$\sum_H HW_H\, JOBCOR_{H,L} = \sum_i FD_{LB,i} \tag{10}$$

HW_H is the number of working households across the nine household groups indexed by *H* and it is multiplied by $JOBCOR_{H,L}$. *JOBCOR* is obtained from the PUMS dataset, and represents the average number of workers from each labor group that reside in the nine household groups. Accordingly, the left-hand-side is sectoral labor supply. The right-hand-side is sectoral labor demand ($FD_{LB,i}$). For any loss in labor due to unexpected inclement weather, we would reduce the value of JOBCOR. As an example, consider the Southeast, which sees an estimated gain in 321 workers due to using HRRR2 forecasts instead of HRRR1 forecasts. To account for this increase, we scaled the Southeast JOBCOR by 1.000018 (= 321/39,886,010 = job change/job base).
****

[Insert Tables 3 and 4]

6.2 Simulations and Results

Table 5 presents the HRRR1/HRRR2 and HRRR2/HRRR3 comparisons under the lower and upper bounds with respect to the impact on real GDP. Recall from Table 3 that transitioning from HRRR1 to HRRR2 would effectively increase employment by 1,491 workers in the lower bound case. This results in an increase in real GDP of $57.6 million across the eight BEA regions. The upper bound generates a $212.7 million increase in real GDP.

Regarding the individual regional impacts, the Mideast has the largest economic gains when moving from HRRR1 to HRRR2, a result attributable to the region's unique characteristics (described in more detail in the online Appendix Table 2). In particular, because this region has considerably more commuters than any other BEA region, unexpected precipitation events impact more workers, leading to a larger adverse impact on real GDP. The Southeast has the second largest economic gain, an effect consistent with the fact that this region had the largest number of HRRR1 misses (described in the Online Appendix Table C2).

The impact on federal government tax revenue tells the same story with respect the level and the regional impacts. The lower bound results in an increase in federal tax revenue of $1.68 and for the upper bound, the increase is $6.32 million.

The total impacts for HRRR3 versus HRRR2, however, tell a different story. Our simulations show that real GDP *decreases* when HRRR3 forecasts are utilized instead of HRRR2--although this decrease is an order of magnitude less than the increase in real GDP from HRRR2 versus HRRR1. Referring to online Appendix Table 2, we see that HRRR2 did an overall better job of predicting economically meaningful MSA precipitation events than HRRR3, particularly moderate ones. The differences in the lower and upper bound ranges are consistent with the results from the HRRR1/HRRR2 comparisons.

This does not necessarily suggest HRRR3 is "worse" than HRRR2; our study only compares precipitation forecasts and daily commutes. We do not compare economic gains due to differences in forecast accuracy of each version across myriad other key forecasted weather variables, such as temperature, cloud cover, and wind.[26] Further, our analysis suggests that while HRRR3 does tend to underestimate precipitation more than HRRR2, HRRR3 is more accurate in predicting massive precipitation events such as hurricanes. Additionally, HRRR3 has greater success at predicting zero precipitation events than HRRR2. These two factors likely have economic ramifications that are not measured here.

[Insert Tables 5 and 6]

7. Summary and Conclusions

Improved weather forecasting information can improve economic outcomes. First introduced in 2014, NOAA's HRRR numerical weather prediction system has undergone many enhancements, with the goal of providing increasingly accurate precipitation, temperature, wind, and cloud cover forecasts. In this paper we simulate how improvements in NOAA precipitation forecasts can impact economic activity in the CONUS through better commuting decisions. This has required aligning several disparate research endeavors.

---

26 In companion papers we look at wind forecasts as related to the energy sector and temperature forecasts as related to the agricultural sector.

We use HRRR's 12-hour ahead precipitation forecasts as the information set that commuters use to decide when to leave for work the next morning. When we line up forecasts with measured, actual rainfall, we demonstrate that HRRR1 had many more misses of realized, economically meaningful rainfall events than did HRRR2 during the same time frame. We pair these misses with the work of Tsapakis, Chen, and Bolbol (2013) and Stern et al. (2003) to estimate a lower and upper bound for total labor hours lost due to incorrect forecasts in 206 MSAs in the U.S. These lost hours were aggregated to the level of eight, multi-state regions in the US, and we used CGE models for each region to estimate economic impacts via reductions in labor supply.

While this problem is conceptually straightforward, computationally analyzing these results required making several important assumptions that certainly impact the results. Some potentially bias our results upward, while others may bias them downward. Therefore, it makes more sense to look at our results as the "potential" rather than actual value of changes in HRRR.

Our estimates are too high

While we consider our lower bound estimate "conservative," we make three assumptions that still may bias our results upward. First, we assume that 100 percent of commuters use the 12-hour ahead precipitation forecasts in planning their departure time for work, and then commit to this decision, regardless of how weather patterns and information may deviate from the forecast between the time of the forecast and the time to leave for work. However, as Lazo, Morss and Demuth (2009) note, only about 90 percent of respondents to a national survey indicate that they use weather forecasts daily. Thus, improvements in one weather forecasting system over another are meaningless for non-users. This means that some of the potential benefits are not captured in practice. However, as forecasts become easier and cheaper to access, such as through a weather app on a smartphone, it is likely that a greater share of people are using weather forecasts today than at the time of the Lazo, Morss and Demuth study.

Further, it is quite reasonable to expect that people do update their decisions closer to their departure time for work. For example, a commuter may check the weather before going to bed, and when they wake up, they may check it again, or simply look out their window to see if the current weather is consistent with the forecast. If not, they may simply act on what they see, rather than the earlier forecast. If this is the case, then the information gleaned from any 12-hour ahead forecast is less useful. In future work, we will be comparing HRRR3 to HRRR4 and we will be looking at 1-hour, 3-hour, 6-hour and 12-hour ahead forecasts.[27]

Our third assumption that could bias results upward is that workers leave work on time, even if they showed up late. This assumption is consistent with a recent study of the impacts of increasing congestion on from the Independent Budget Office of the City of New York (2017), which analyzed lost work time from delays in the New York City subway system. An alternative is that workers can stay late to make up some or possibly all their missed time. This may be possible for workers who enjoy flexible start and end times, but other employees may have after-work commitments--such as picking up children from school--that require timely workplace departures. Still other personnel may work on a specific shift and must effectively "clock out" at a set time.

We additionally assume that all workers commute to their jobs between 6 and 10 am, and only work Monday through Friday. This assumption surely does not hold, but there is no statistical reason to think that the average realized performance differences between two versions of HRRR differ for atypical commuters relative to those participating in the forecast window of interest.

Our estimates are too low

We do not examine losses due to diminished worker *productivity* (as opposed to output). However, Sweet (2014) suggests worker effectiveness can be reduced by congestion (an analog of weather-related traffic delays) because it can cause stress. Examining the impacts of subway investments in Brazil, Haddad et al. (2015) simulate the idea of a reduction in labor productivity due to commuting delays using the San Paolo subway system. They estimate labor productivity impacts of different distances traveled where, for over 40 km each way, the gains were between 3-5 percent and for trips around 20

[27] However, HRRR researchers shows that 12-hour ahead forecast differences between versions of the model do not tend to converge as the actualization comes nigh. In other words, if one version of HRRR predicts rain 12-hours ahead and the other does not, these relative predictions are not likely to change much as the time draws nearer. Thus, a user who uses one version of HRRR or another is not likely to get a significantly different forecast when they are about to leave for work than they saw the night before. See Figures 1 and 2.

km each way the labor productivity gains ranged from 1-2 percent. We do not do that here but suspect that these impacts could be large given the Haddad at al. (2015) results.

References

Anas, A., & Kim, I. (1996). General equilibrium models of polycentric urban land use with endogenous congestion and job agglomeration. *Journal of Urban Economics*, *40*(2), 232-256

Anas, A., & Liu, Y. (2007). A regional economy, land use, and transportation model (relu-tran©): formulation, algorithm design, and testing. *Journal of Regional Science*, *47*(3), 415-455.

Arnott, R., De Palma, A., & Lindsey, R. (1991). Does providing information to drivers reduce traffic congestion? *Transportation Research Part A: General*, *25*(5), 309-318.

Attary, N., Cutler, H., Shields, M., & van de Lindt, J. W. (2020). The economic effects of financial relief delays following a natural disaster. *Economic Systems Research*, 1-27.

Benjamin, S.G., and coauthors, 2016: A North American hourly assimilation and model forecast cycle: The rapid refresh. Monthly Wea. Rev., 144, 1669-1694, doi:10.1175/MWR-D-15-0242.1

Berck, P., Golan, E., & Smith, B. (1997). State tax policy, labor, and tax revenue feedback effects. *Industrial Relations: A Journal of Economy and Society*, *36*(4), 399-418.

Black, A. W., & Mote, T. L. (2015). Effects of winter precipitation on automobile collisions, injuries, and fatalities in the United States. *Journal of transport geography*, *48*, 165-175.

Böcker, L., Dijst, M., & Prillwitz, J. (2013). Impact of everyday weather on individual daily travel behaviours in perspective: a literature review. *Transport reviews*, *33*(1), 71-91.

Buckley, P. H. (1992). A transportation-oriented interregional computable general equilibrium model of the United States. *The Annals of Regional Science*, *26*(4), 331-348.

Cools, M., Moons, E., & Wets, G. (2010). Assessing the impact of weather on traffic intensity. *Weather, Climate, and Society*, *2*(1), 60-68.

Cutler, H., & Davies, S. (2007). The Impact of Specific-Sector Changes In Employment On Economic Growth, Labor Market Performance And Migration. *Journal of Regional Science*, *47*(5), 935-963.

Cutler, H., Shields, M., Tavani, D., & Zahran, S. (2016). Integrating engineering outputs from natural disaster models into a dynamic spatial computable general equilibrium model of Centerville. *Sustainable and Resilient Infrastructure*, *1*(3-4), 169-187.

Cutler, H., Shields, M., & Davies, S. (2018). Can State Tax Policy Increase Economic Activity and Reduce Inequality? *Growth and Change*, *49*(1), 142-164.

Dell'Orco, M., & Marinelli, M. (2017). Modeling the dynamic effect of information on drivers' choice behavior in the context of an Advanced Traveler Information System. *Transportation Research Part C: Emerging Technologies*, *85*, 168-183.

Donaghy, K. P. (2009). Modelling the economy as an evolving space of flows. In *Complexity and Spatial Networks* (pp. 151-164). Springer, Berlin, Heidelberg.

Dowell, D.C., and coauthors, 2020: The High-Resolution Rapid Refresh (HRRR): An hourly updating convection-permitting forecast model. Part 1: Motivation and system description. Wea. Forecasting, in preparation.

Ebert, E. E., Damrath, U., Wergen, W., & Baldwin, M. E. (2003). The WGNE assessment of short-term quantitative precipitation forecasts. *Bulletin of the American Meteorological Society*, *84*(4), 481-492.

Eisenberg, D., & Warner, K. E. (2005). Effects of snowfalls on motor vehicle collisions, injuries, and fatalities. *American journal of public health*, *95*(1), 120-124.

Fritz, Angela. "These are the companies and apps that have the most accurate forecasts." Washington Post, 28 Dec. 2016, www.washingtonpost.com/news/capital-weather-gang/wp/2016/12/28/these-are-the-companies-and-apps-that-have-the-most-accurate-forecasts.

Garofalo, G. A., & Yamarik, S. (2002). Regional convergence: Evidence from a new state-by-state capital stock series. *Review of Economics and Statistics*, *84*(2), 316-323.

Haddad, E. A., Hewings, G. J., Porsse, A. A., Van Leeuwen, E. S., & Vieira, R. S. (2015). The underground economy: tracking the higher-order economic impacts of the São Paulo subway system. *Transportation Research Part A: Policy and Practice*, *73*, 18-30.

Heyndrickx, C., Koops, O., & Ivanova, O. (2011). The TIGER Model: Application of detailed passenger and freight transport in a regional CGE setting.

Hsiang, S. M. (2010). Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America. *Proceedings of the National Academy of sciences*, *107*(35), 15367-15372.

Independent Budget Office of the City of New York (2017), "Morning malaise: How much extra time is spent waiting for the subway on your line." October https://ibo.nyc.ny.us/cgi-park2/2017/10/morning-malaise-how-much-extra-time-is-spent-waiting-for-the-subway-on-your-line/

Isard, W. (1951). Interregional and regional input-output analysis: a model of a space-economy. *The review of Economics and Statistics*, 318-328.

Ingraham, Christopher. (2019) "Nine days on the road. Average commute time reached a new record last year." Washington Post, 7 Oct., www.washingtonpost.com/business/2019/10/07/nine-days-road-average-commute-time-reached-new-record-last-year.

James, E., and coauthors, 2020: The High-Resolution Rapid Refresh (HRRR): An hourly updating convection-permitting forecast model. Part 2: Forecast performance. *Weather Forecasting*, in preparation.

Katz, R. W., & Murphy, A. H. (2005). Forecast value: prototype decision-making models in Richard W. Katz and Allan H. Murphy (eds) *Economic value of weather and climate forecasts*. Cambridge University Press.

Kenkel, P. L., & Norris, P. E. (1995). Agricultural producers' willingness to pay for real-time mesoscale weather information. *Journal of Agricultural and Resource Economics*, 356-372.

Khattak, A. J., & De Palma, A. (1997). The impact of adverse weather conditions on the propensity to change travel decisions: a survey of Brussels commuters. *Transportation Research Part A: Policy and Practice*, *31*(3), 181-203.

Kilpeläinen, M., & Summala, H. (2007). Effects of weather and weather forecasts on driver behaviour. *Transportation research part F: traffic psychology and behaviour*, *10*(4), 288-299.

Kleist, D.T., Parrish, D.F., Derber, J.C., Treadon, R., Wu, W.S. & Lord, S. (2009). Introduction of the GSI into the NCEP global data assimilation system. *Weather Forecasting*, 24, 1691-1705, doi:10.1175/2009WAF2222201.1

Lazo, J. K., & Chestnut, L. G. (2002). *Economic Value of Current an Improved Weather Forecasts in the US Household Sector*. U.S. Department of Commerce, National Oceanic and Atmospheric Administration, Office of Program Planning and Integration.

Lazo, J. K., Morss, R. E., & Demuth, J. L. (2009). 300 billion served: Sources, perceptions, uses, and values of weather forecasts. *Bulletin of the American Meteorological Society*, *90*(6), 785-798.

Leard, B., & Roth, K. (2015). Weather, traffic accidents, and climate change. *Resources for the Future Discussion Paper*, 15-19.

Lee, K. K., & Lee, J. W. (2007). The economic value of weather forecasts for decision-making problems in the profit/loss situation. *Meteorological Applications: A journal of forecasting, practical applications, training techniques and modelling*, *14*(4), 455-463.

Maze, T. H., Agarwal, M., & Burchett, G. (2006). Whether weather matters to traffic demand, traffic safety, and traffic operations and flow. *Transportation research record*, *1948*(1), 170-176.

Meade, D. S., Rzeznik, S., & Robinson-Smith, D. (2003). Business Investment by Industry in the US Economy for 1997. *Survey of current business*, *83*(11), 18-70.

Mjelde, J. W., Sonka, S. T., & Peel, D. S. (1989). *The socioeconomic value of climate and weather forecasting: a review*. Illinois State Water Survey.0

Morss, R. E., Lazo, J. K., & Demuth, J. L. (2010). Examining the use of weather forecasts in decision scenarios: results from a US survey with implications for uncertainty communication. *Meteorological Applications*, *17*(2), 149-162.

Murphy, A. H. (1969). On expected-utility measures in cost-loss ratio decision situations. *Journal of Applied Meteorology*, *8*(6), 989-991.

National Weather Service. "About Models." 20 July 2020, www.weather.gov/about/models.

Nelson, B. R., Prat, O. P., Seo, D. J., & Habib, E. (2016). Assessment and implications of NCEP Stage IV quantitative precipitation estimates for product intercomparisons. *Weather and Forecasting*, *31*(2), 371-394.

Nordhaus, W. D. (2006). Geography and macroeconomics: New data and new findings. *Proceedings of the National Academy of Sciences*, *103*(10), 3510-3517.

Polak, J., & Jones, P. (1993). The acquisition of pre-trip information: a stated preference approach. *Transportation*, *20*(2), 179-198.

Regnier, E. (2008). Doing something about the weather. *Omega*, *36*(1), 22-32.

Robson, E. N., Wijayaratna, K. P., & Dixit, V. V. (2018). A review of computable general equilibrium models for transport and their applications in appraisal. *Transportation Research Part A: Policy and Practice*, *116*, 31-53.

Rollins, K. S., & Shaykewich, J. (2003). Using willingness-to-pay to assess the economic value of weather forecasts for multiple commercial sectors. *Meteorological Applications: A journal of forecasting, practical applications, training techniques and modelling*, *10*(1), 31-38.

Rosenzweig, M. R., & Udry, C. (2014). Rainfall forecasts, weather, and wages over the agricultural production cycle. *American Economic Review*, *104*(5), 278-83.

Sabir, M., Koetse, M., Van Ommeren, J., & Rietveld, P. (2010). Weather and travel time of public transport trips. *Integrated transport: from policy to practice*, 275.

Schwarm, W., & Cutler, H. (2003). Building small city and town SAMs and CGE models. *Review of Urban & Regional Development Studies*, *15*(2), 132-147.

Skamarock, W.C. and coauthors. (2008). A description of the Advanced Research WRF version3. NCAR Tech. Note NCAR/TN-475+STR, 113 pp.

Small, K. A., Winston, C., & Yan, J. (2005). Uncovering the distribution of motorists' preferences for travel time and reliability. *Econometrica*, *73*(4), 1367-1382.

Stern, A. D., Shah, V., Goodwin, L., & Pisano, P. (2003). Analysis of weather impacts on traffic flow in metropolitan Washington DC. In *Proceedings of the 19th international conference on interactive information and processing systems (IIPS) for meteorology, oceanography, and hydrology*.

Stuart, A. (1982). On the economic value of probability of precipitation forecasts in Canada. *Journal of Applied Meteorology*, *21*(4), 495-498.

Sweet, M. (2014). Traffic congestion’s economic impacts: Evidence from US metropolitan regions. *Urban Studies*, *51*(10), 2088-2110.

Tatano, H., & Tsuchiya, S. (2008). A framework for economic loss estimation due to seismic transportation network disruption: a spatial computable general equilibrium approach. *Natural Hazards*, *44*(2), 253-265.

Thompson, J. C., & Brier, G. W. (1955). The economic utility of weather forecasts. *Monthly Weather Review*, *83*(11), 249-253.

Thompson, J. C. (1972). The potential economic benefits of improvements in weather forecasting.

Tsapakis, I., Cheng, T., & Bolbol, A. (2013). Impact of weather conditions on macroscopic urban travel times. *Journal of Transport Geography*, *28*, 204-211.

Turner, D.D., Hamilton, J., Moninger, W., Smith, M., Strong, B., Pierce, Hagerty, R. V., Holub, K. & Benjamin, S.G. (2020). A verification approach used in developing the Rapid Refresh and other numerical weather prediction models. Journal of Operational Meteorology, 8, 39-53. doi:10.15191/nwajom.2020.0803

Van Ommeren, J., & Dargay, J. (2006). The optimal choice of commuting speed: consequences for commuting time, distance and costs. *Journal of Transport Economics and Policy (JTEP)*, *40*(2), 279-296.

Wales, T. J. (1978). Labour supply and commuting time: an empirical study. *Journal of Econometrics*, *8*(2), 215-226.

Table 1. HRRR Version Descriptions

Version	Primary update from previous version	Overlap period
v2	First inclusion of sub-gridscale clouds, aerosol particles included in cloud and precipitation processes, fully-cycling of the land surface model	1 Jun 2015 to 1 Aug 2016
v3	Updated turbulence scheme to use non-local mixing, more realistic treatment of sub-gridscale clouds, improved vertical coordinate for simulation above complex terrain, improved data assimilation approach to help retain stratiform clouds	1 July 2017 to 1 June 2018

Table 2. Expense Matrix for Decision Making Model

Weather Event	Do not leave early (A=0)	Leave early (A=1)
No adverse precipitation (Y=0)	0	Cost
Adverse precipitation (Y=1)	Loss	Cost

Table 3. Full-time Equivalent Workers Lost (HRRR1 and HRRR2): Lower Bound*

BEA Region	HRRR 1	HRRR 2	HRRR1 – HRRR2	Percent Reduction in labor hours lost HRRR1 – HRRR2
Southwest	202.4	58.7	143.7	71%
Great Lakes	332.6	76.1	256.5	77
Southeast	416.0	95.1	321.0	77

Mideast	553.2	49.1	504.1	91
Far West	64.8	2.2	62.6	97
Rocky Mountain	33.5	4.8	28.8	86
New England	119.4	10.7	108.7	91
Plains	97.4	31.4	66.0	68
Total	1,819.5	328.2	1,491.4	82

*Because this is a linear estimate, the upper bound can be derived by multiplying these effects by 11 percent/3 percent.

Table 4. Full-time Equivalent Workers Lost (HRRR2 and HRRR3): Lower Bound

BEA Region	**HRRR 2**	**HRRR 3**	**HRRR2 – HRRR3**	**Percent Reduction in labor hours lost HRRR2 – HRRR3**
Southwest	49.8	55.5	-5.7	-10.3%
Great Lakes	90.8	98.0	-7.2	-7.3
Southeast	70.2	94.5	-24.3	-25.7
Mideast	93.4	151.5	-58.1	-38.4
Far West	7.2	33.2	-26.1	-78.5
Rocky Mountain	4.2	4.7	-0.6	-12.2
New England	6.8	24.4	-17.6	-72.3
Plains	33.7	29.1	4.6	15.8
Total	356.0	490.9	-134.9	-27.5

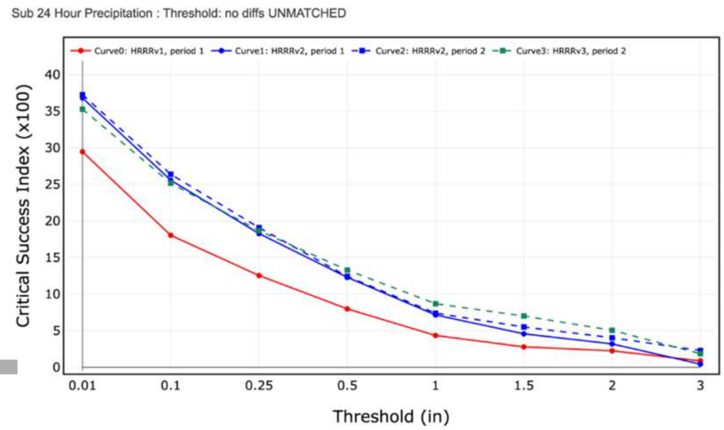
Table 5. Economic Gains from Improved Commuting Decisions (Real GDP in millions of $)

BEA Regions	**Lower Bound HRRR2 vs HRRR1**	**Upper Bound HRRR2 vs HRRR1**	**Lower Bound HRRR3 vs HRRR2**	**Upper Bound HRRR3 vs HRRR2**
Southwest	5.07	15.82	-0.20	-2.43
Great Lakes	9.25	32.18	-0.26	-2.31

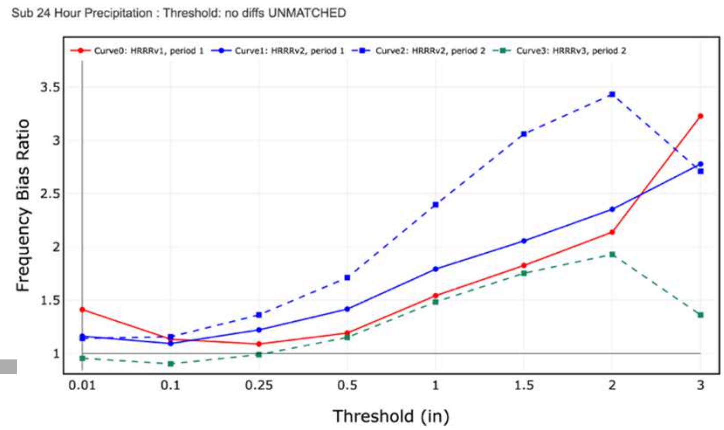
Southeast	11.12	34.82	-0.85	-2.90
Middle East	21.70	75.93	-2.51	-9.10
Far West	2.81	23.06	-1.15	-9.61
Rocky Mountain	1.02	0.85	-0.02	0.00
New England	4.39	18.88	0.16	-3.15
Plains	2.22	11.17	0.54	1.04
Total	57.58	212.70	-4.29	-28.47

Table 6. Changes in Federal Tax Revenue from Improved Commuting Decisions (millions of $)

BEA Regions	**Lower Bound HRRR2 vs HRRR1**	**Upper Bound HRRR2 vs HRRR1**	**Lower Bound HRRR3 vs HRRR2**	**Upper Bound HRRR3 vs HRRR2**
Southwest	0.03	0.10	0.00	-0.02
Great Lakes	0.29	0.95	-0.01	-0.07
Southeast	0.22	0.69	-0.02	-0.06
Middle East	0.89	3.11	-0.10	-0.37
Far West	0.10	0.85	-0.04	-0.35
Rocky Mountain	0.02	0.01	0.00	0.00
New England	0.08	0.33	0.00	-0.05
Plains	0.06	0.30	0.01	0.03
Total	1.68	6.32	-0.16	-0.89



grow_12542_f1.tif



grow_12542_f2.tif