Severe Weather and Automobile Assembly Productivity

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Abstract

It is expected that climate change could lead to an increased frequency of severe weather. In turn, severe weather intuitively should hamper the productivity of work that occurs outside. But what is the effect of rain, snow, fog, heat and wind on work that occurs indoors, such as the production of automobiles? Using weekly production data from 64 automobile plants in the United States over a ten-year period, we find that adverse weather conditions lead to a significant reduction in production. For example, one additional day of high wind advisory by the National Weather Service (i.e., maximum winds generally in excess of 44 miles per hour) reduces production by 26%, which is comparable in order of magnitude to the estimated productivity drop during the launch of a new vehicle. Furthermore, the location with the best weather (Arlington, Texas) only loses 2% of production per year due to the weather, whereas the location with the most adverse weather (Lordstown, OH) suffers an annual production loss of 11%. Our findings are useful both for assessing the potential aggregate productivity shock associated with inclement weather as well as guiding managers on where to locate a new production facility - in addition to the traditional factors considered in plant location (e.g., labor costs, local regulations, proximity to customers, access to suppliers), we add the prevalence of bad weather.

1 Introduction

It is well known that there is a relationship between climate and economic activity. For example, not only are hot countries poorer, temperature even explains variation in economic output within countries (Dell et al., 2009). It is intuitive that climate can impact outdoor activities like agriculture, forestry, construction and tourism. Less clear is the impact on "climate-insensitive" sectors such as manufacturing and services (Nordhaus, 2006).

In this paper we study the relationship between severe weather and weekly automobile production at 64 facilities within the United States over a ten-year period. Although automobiles are made indoors, there are several mechanisms through which bad weather at a plant could influence production. For example, high winds, fog, or heavy precipitation could cause delays in in-bound delivery of parts from suppliers, possibly due to additional traffic congestion, accidents or cancelled shipments.[1] If a plant operates in a "just-in-time" fashion with relatively little buffer stock of parts, the plant may need to delay the start of a shift or cancel a shift altogether due to the absence of needed parts. The same concern applies to "in-bound" employees – production could be curtailed if workers are unable to (or choose not to) travel to the plant. Finally, even if all of the workers and parts are available, it is possible that bad weather could influence employee productivity. For example, with extreme heat conditions outside, even if the plant has a cooling system, it is possible that the indoor temperature rises to a level that slows down the manual labor associated with automobile production.[2] Alternatively, bad weather outside could influence the affect of employees which in turn may lower their productivity.[3] In short, it seems reasonable to conclude that weather could influence seemingly sheltered indoor economic activity.

For our study it is safe (we believe) to assume that production does not cause changes in the weather - whether a plant produces more or fewer cars in a week is unlikely to influence its local weather in that week. Of greater concern is whether weather exerts a causal influence on production - are there omitted variables that could lead to an endogeneity bias? For example, maybe automobile production is seasonal for reasons unrelated to local weather. If production seasonality is correlated with a plant's weather (e.g., fewer cars are made in the summer because demand across the country is lower during the summer), then local weather may only be a proxy for this seasonality. To address this issue we take advantage of the panel structure of our data to include a number of controls: product introduction and ramp-down dummies to account for the possibility that vehicles are introduced at certain times of the year (and their obvious influence on the level of production); plant fixed effects to account for idiosyncratic plant characteristics associated with seasonality; weekly dummies to account for national variations in demand, and regional dummies to account for regional differences in weather fluctuations and the possibility that the influence of weather varies by region. In sum, given our extensive set of controls, we believe we have identified a causal impact of severe weather on production.

We also find that weather has a substantial economic impact on automobile production. For example, we estimate that for an average plant, one additional day of heavy winds in a week reduces that week's

[1]See Brodsky and Hakkert (1988); Golob and Recker (2003) for data on precipitation and traffic accidents.

[2]It has been established that thermal heat stress has a non-linear impact on productivity – the impact of increased temperature begins around 25° C (Ramsey and Morrissey (1978) and DP (2001)). Internal temperatures in a automobile plant may exceed this threshold, especially if the outside temperature is very high.

[3]For example, Simonsohn (2010) finds that the decisions of admissions officers at an academically oriented college are influenced by cloud cover even though admission decisions are not made outside nor should they objectively be influenced by the weather.

production by approximately 26%, and six or more days of rain within a week reduces production relative to no rain by 6.6%. Furthermore, we find that average annual production losses due to weather events ranges from a low of 2% (for a plant in Arlington, Texas) to 11% (for a plant in Lordstown, Ohio). Hence, even though the severe events we identify are not common (e.g., there is only about 2.5 high wind days per year per plant), they are sufficiently common that their cumulative effect is meaningful.

Our work is related to a growing literature on the impact of climate and weather on economics. A number of studies focus on agriculture (e.g., Crocker and Horst (1981); Mendelsohn et al. (1994); Olesen and Bindi (2002); Deschenes and Greenstone (2007)). Others include more (or all) sectors of the economy. For example, Dell et al. (2008) find in a long time horizon sample that a 1° C increase in temperature in a given year decreases economic growth in a sample of poor countries by 1.1 percentage points. However, they do not find evidence that annual shocks in temperature or precipitation have an impact on growth of "rich" countries.[4] Andersen et al. (2010) report that at the state level, the incidence of lightning strikes influences growth rates in the United States over the period of 1990-2007. Also with U.S. data, Bansal and Ochoa (2009) report a substantial negative correlation (-0.79) between 10-year changes in temperature and 10-year GDP growth. Hsiang (2010) finds that a 1° C temperature increase in a year's average temperature decreases output in 28 Caribbean-basin countries. The largest negative impact is in the "wholesale, retail, restaurants and hotel" sector (-6.5%) and the smallest is in "manufacturing" (+1.4%). Our study differs in that we focus on a single industry (automobile production), we measure the short term effect (weekly data) of local weather on productivity (a single plant) and we expand the array of observed weather variables beyond temperature and precipitation (e.g., wind, fog, cloud cover).

Our results could be useful in several ways. First, they are related to the issue of climate change. The Intergovernmental Panel on Climate Change Fourth Assessment Report (Solomon et al. (2007)) projects that climate change is likely to increase the frequency of extreme weather events, such as heat waves and heavy precipitation, among others. It follows that climate change could have a consequential impact even in indoor economic activities. Second, given that weather varies across the country, our findings should be considered in the location decision for new plants, along with the traditional factors like labor cost and availability, access to suppliers, proximity to markets, etc. Finally, this paper confirms that weather can be used as an exogenous shock in automobile production, which may be useful in the development of valid instruments for other research.

[4] Using import and export data, Jones and Olken (2010) report results that are consistent with those from Dell et al. (2008).

2 Data

Our study combines two main data sets. The first is weekly vehicle production in the United States at the plant-model level. The second includes daily weather conditions at our sample of vehicle assembly plants. Both cover the period of January 1994 to December 2005. In the following subsections these data sets are described in detail.

2.1 Production data

For the period January 1994 to December 2005, we obtained from Wards Auto weekly production of each model produced at all 64 U.S. vehicle assembly plants making light-passenger vehicles, including cars, sport utility vehicles, mini-vans, and pick-up trucks. (We exclude heavy-truck production.) These data were reported by manufacturers to market analysts.

As the production data is reported at the model level, we are able to infer when a plant was closed during a particular week (i.e., zero production), when a particular model was introduced (first week of reported production) or discontinued (last week of reported production). Naturally, we also can infer when a plant is opened or permanently closed.

Table 1 provides descriptive statistics on the production data for the plants in our sample and Figure 1 shows their geographic location.[5]

2.2 Geographic location and weather

For each of the 64 plants in our sample we obtained its address and exact geographic location (longitude and latitude). We identified the closest weather station to each plant. Using the National Weather Service Forecast Office (NWSFO) and the weather.com website, we obtained from these weather stations daily data for the period January 1994 to December 2005. Included in the sample are for each day the day's maximum, mean and minimum values for the following weather variables: temperature, wind speed, humidity, pressure, visibility and dew point. We also obtained information on cloud cover (portion of the sky cover with clouds), and the type of event during a day (rain, thunderstorm, snow, etc.). Finally, we obtained historical weather data for each day: the historical average high, low and mean temperature and the record high and low temperature.

The selected weather stations are close to our plants with a mean and median distance of 13 and 10 miles, respectively. No plant is further than 36 miles from its corresponding weather station. To assess

[5] We exclude from the maps one plant located in California.

whether a weather station's weather is likely to be similar to the weather at its nearby plant, we constructed a sample of weather stations that are between 30 and 60 miles apart. In this sample, the correlation in our weather variables is no less than 95%, suggesting that the weather reported at the nearby weather station is representative of the weather at the plant. [6]

3 Model Specification

Using the collected data on plant production and weather, we constructed a panel dataset that relates weekly plant production to weather-related factors and other control variables. We use i to index a plant (e.g. Fort Wayne, Indiana) and t to index a specific week (e.g. 3rd week of 2002). Because there is substantial heterogeneity in the production volume across plants, we define the dependent variable in the regression as the logarithm of weekly production ($logProd_{it}$). Hence, the impact of weather on production is measured in relative terms (percent of total production) rather than in absolute terms. The covariates in the regression can be grouped into three categories: (i) factors related to local plant weather (denoted $WEATHER_{it}$); (ii) variables related to seasonality, which could potentially vary across plants ($SEASONAL_{it}$); and (iii) other factors that affect plant productivity ($PRODFACTORS_{it}$). The linear regression model can be summarized as follows:

$$logProd_{it} = \beta WEATHER_{it} + \gamma_1 SEASONAL_{it} + \gamma_2 PRODFACTORS_{it} + \delta_i + \varepsilon_{it}. \tag{1}$$

The term δ_i is a fixed-effect that captures the plant's average production, and ε_{it} is the error term. In what follows, we describe the covariates included in *WEATHER, SEASONAL* and *PRODFACTORS.*

Using daily weather data, we constructed several measures capturing weather conditions at each plant for every week in our sample period. These are listed in Table 2. *Wind* is the number of days in a week in which a wind advisory was issued by the National Weather Service Forecast Office. A wind advisor is issued when maximum winds in a area achieve a threshold defined for that area, typically in excess of 40 miles per hour. We include *Wind*, *Fog*, *Rain* and *Snow* because each may influence travel to and from a plant. *Cloud* could proxy for other inclement weather and could influence employee affect. *High Temp* is included because it could influence ambient temperature within the plant or employees that must work outside (e.g., loading docks). *Low Temp* may proxy for hazardous road conditions (e.g., ice). Many of the variables, such as *Wind, High Temp* and *Low Temp*, directly capture extreme weather shocks. For other measures

[6] The locations consider for this analysis were: Marysville, Ohio and Columbus, Ohio; Washington DC and Baltimore, Maryland; Kansas City, Missouri, and Topeka, Missouri; Lansing, Michigan and Grand Rapids, Michigan.

–specifically for *Rain* and *Snow* – we estimated specifications including multiple levels of the variable to capture potential non-linear effects on production.

Table 3 shows summary statistics for the weather variables. We defined four regions that cover the locations of the plants in the study: Lake, Central, Gulf and East, which are illustrated in Figure 1. The weather statistics are shown by region, and for some weather variables there are marked differences across regions (e.g. *Snow*). Table 4 shows a correlation matrix for the weather variables. Most of the correlations are closed to zero, except for *Rain* and *Cloud* (positive), *Snow* and *Cloud* (positive) and *Snow* and *Rain* (negative); all the correlations are less than 0.4 in magnitude. To check for potential multicollinearity, we regressed each weather variable on the others; the maximum R-square was less than 0.3, suggesting that multicollinearity is not a major concern in identifying the effect of the multiple weather measures in our study.

Note that *Rain* and *Snow* are measured in the number of days with rain and snow in that week. Alternatively, one could use cumulative precipitation to measure the intensity of rain and snow. However, our weather data only includes information about total precipitation, aggregating snow and rain precipitation together. Moreover, we found that for some weeks these precipitation data were missing, usually at the smaller weather stations. The precipitation data also appears to be subject to more measurement error: for example, the correlation for precipitation (measured in inches) across plant stations located 30-60 miles away is between 0.47 and 0.85, substantially lower than the other weather variables in our data. To summarize, we feel that the number of days of rain and snow is a more reliable measure to capture the effect of these weather shocks.

PRODFACTORS includes covariates that capture adjustments to the production schedule and changes in productivity. Goyal et al. (2006) show that productivity is lower during the launch of a new model, so we include the dummy variable *New Model* that indicates the first 9 weeks during which a plant is producing a new model. We also include the dummy variable *Drop Model* to indicate the last 9 weeks before the production of the model is phased out. While *New Model* and *Drop Model* control for changes in productivity during the life-cycle of a model, temporary production stoppages of a model could also affect productivity. Assembly plants can be temporary closed for several reasons, for example, due to holidays, plant re-tooling and also to adjust inventories of finished vehicles in the supply chain (Bresnahan and Ramey (1994)). Two dummy variables, *Prod Start* and *Prod Stop* indicate the week following and preceding a full stoppage of the plant, respectively. Note that all time-invariant factors affecting the productivity of the plant, such as plant capacity and proximity to suppliers, are captured by the fixed effect δ_i.

Seasonality is an important potential confounder in our estimation. For example, seasonality in demand for new vehicles can lead to seasonal production patterns. If these seasonal production patterns are correlated with weather, then we cannot interpret the effect of weather in regression (1) as a causal effect on production. Hence, it is important to include controls in $SEASONAL_{it}$ that capture seasonality patterns in weather and production. However, adding too many controls reduces the power of the regression model to test for weather effects. Hence, we consider several specifications to analyze the robustness of our results with respect to different controls for seasonality.

The first set of controls includes weekly dummy variables, τ_t, which control for seasonal production patterns and macro-economic effects affecting production of plants nation-wide. For example, this controls for differences in nation-wide plant productivity during different weeks of the year. But τ_t also controls for any nationwide-trends in production – such trends may be caused by economic shocks affecting aggregate demand for vehicles (e.g. oil prices). The weekly dummies also control for reduced working hours during national holidays. Note that if weather is perfectly correlated across plant locations, we cannot identify its effect separately from the weekly dummy τ_t. However, weather patterns vary substantially across regions. Figures 2 and 3 show two example that illustrate differences in local weather patterns across geographic regions– there is clearly more snow in the Lakes region than in the Gulf region. There is also some variation across plants within the same region – for example, there are differences in the number of *Wind* events among different plants in the East region. Hence, the inclusion of weekly dummies doesn't preclude the identification of the weather effects.

Because τ_t is common to all plants, it does not control for differences in seasonality or trends across plants. Therefore, the second set of controls that we propose captures potential differences in seasonality across plants. In particular, we include region-specific year-month dummy variables, $\rho_{r(i)m(t)}$, where $r(i)$ is the pre-defined region where plant i is located, and $m(t)$ is the month of week t. This controls for monthly seasonality that could differ across regions (e.g., Spring arrives earlier in the year in the Gulf than in the Lakes region). We chose these regions because they have marked differences in their weather patterns; if regional production seasonality is correlated with weather patterns, ommiting $\rho_{r(i)m(t)}$ from the regression would lead to biased estimates. In addition, we also include controls that capture potential differences in *demand* seasonality, which could thereby lead to different production patterns across plants. Specifically, we classified the production of each plant into one of the following segments: cars, vans, sport vehicles and pick-ups. If a plant is producing vehicles on multiple segments, we used the segment with higher production volume to classify the plant. The dummy variables $\psi_{s(i)m(t)}$, where $s(i)$ is the segment of plant i, control for these potential differences in production across plants.

Two plants located in the same region and classified within the same segment could still have differences in their production patterns. If these patterns are related to weather then this could generate a bias in the causal effect we seek to estimate. To mitigate this kind of bias, we propose a third set of controls which captures seasonal average weather patterns specific to a plant. To explain the construction of these controls, let W_{it} be a weather-related variable (e.g. *Wind*) for plant i in week t and let $w(t)$ be week t's number within its year (e.g. the 54^{th} week in the sample is in week 2 of the second year). We define $\bar{W}(i, w(t))$ as the average weather at plant i during a 5 week time window around week $w(t)$, taking all the years in our sample.[7] Hence, if there is correlation between production seasonality at a plant and the seasonality of any of our weather variables at that plant, this should be captured by $\bar{W}(i, w(t))$. We calculated these average weather measures for *Fog, Cloud, Wind, Rain* and *Snow*. Notice that when we include this third set of controls in the model, the β coefficients for these weather variables are estimated using deviation from the weekly average at each plant.

4 Results

Table 5 presents the main estimation results for three different specifications of regression (1). Columns (1) and (2) vary the level of controls included for seasonality: (1) includes weekly dummies only (τ_t) whereas (2) includes weekly dummies, segment-month and region-month dummies ($\rho_{r(i)m(t)}$ and $\psi_{s(i)m(t)}$), and the average weather variables at each location ($\bar{W}(i, w(t))$). (The controls included on each specification are summarized at the bottom of the table.) Column (3) is similar to (2) but includes *Rain* and *Snow* in multiple levels to measure potential non-linear effects.

In the estimates of column (1), all of the coefficients associated with weather variables are negative and most of them are statistically significant (*Low Temp* and *Rain* are not significant at the 5%). The results are qualitatively similar in column (2), which includes more controls for seasonality. In fact, the statistical significance increases for some of the measures, although *Low Temp* and *Rain* continue to be (statistically) insignificant. This suggests that the effect of the weather variables is not driven by potential confounders related to seasonality. If anything, the weather effects become more pronounced when including these additional controls. In addition, for both regressions (1) and (2) the production controls (grouped as *PROD-FACTORS* in regression (1)) are highly statistically significant.

Because the effect of *Rain* is not statistically significant, we explored whether extreme levels of precipitation can have a significant effect on productivity. To do so, we included 3 levels for both *Rain* and *Snow*. The cut-off points are indicated in the variable name and correspond to the 50^{th} and 95^{th} percentile of each

[7] If N is the number of years in our sample, this average can be calculated as: $\bar{W}(i, w(t)) = \frac{1}{5 \cdot N} \sum_{w(u) \in [w(t)-2, w(t)+2]} W_{iu}$

measure, conditional on having at least one day of precipitation that week. So in both cases, the effect of each level is relative to weeks with zero days of the respective precipitation (i.e. the excluded dummies are *Rain=0* and *Snow=0*). For example, *Snow (0,2)* indicates weeks with one day of snow (greater than zero and less than two) and *Rain [3,6)* indicates weeks with 3,4 and 5 days of rain. Interestingly, we do find empirical evidence that the effect of precipitation is non-linear for both rain and snow. One day of snow has no significant effect on production, but the effect is significant for 2 or more days of snow. The magnitude of the point estimate is highest for 6 or more snow days. For rain, the effect is statistically significant for 6 or more days of rain, but not significant for fewer days of rain.

We now discuss the economic significance of the effects of weather, based on the results of column (3). For all the variables except *Cloud*, the coefficient can be interpreted as the percentage drop in production due to an additional day of the indicated weather (recall *Cloud* is measured in a scale of 0 to 8). The largest drop in productivity is for an additional day of extreme wind *(Wind),* which implies a drop in production of 26%. However, such high winds are also rare, occuring in less than 1% of the weeks and locations in our sample. The second largest effect is for an additional day of intense high temperature (*High Temp*), a drop of 12%. This is a sizable effect, similar to the loss in productivity observed during the first weeks after a plant stoppage, as indicated by the coefficient of *Prod Start.* The combined effect of an additional day of *Wind* and *High Temp* is equivalent to the average reduction in productivity during the launch of a new vehicle, equal to a 36% drop.[8]

The effect of the remaining variables is smaller but still economically significant. A snowy week with 5 or more days of snow reduces production by about 8.5%. A rainy week, with 6-7 days of rain, reduces production by 6.5%, on average. Snow or rain events of such duration probably indicate large and persistent storms.

Based on the average weather variables observed at each location, we calculated the average percent drop in productivity due to weather shocks for each plant. Table 6 shows the results for a selection of the plants. The plants with the greatest loss in productivity are mostly located in the Lakes region. The plants with the least loss in productivity tend to be located in the Gulf region. We conducted an Analysis of Variance to estimate the average productivity loss on each region and test if the differences are statistically significant. The average losses per region are: 7.4% for the Lake region, 5.9% for the Central region, 5.6% for the East region and 4.7% for the Gulf region. We reject the Null hypothesis of equal average losses across regions (p-value less than 10^{-4}). All pairwise t-tests reject the Null of equal means (the largest p-value is 0.01). Hence, the productivity loss due to weather is statistically different across regions, which may

[8]There is one day with such weather in our sample during the month of August, 1996.

have managerial implications for plant location decisions. Moreover, the range of productivity losses due to weather is considerable - from 2.6% to 11.1% with an average loss of about 6%. To put this in perspective, Toyota and Honda may have lost about 25% of their annual production due to the March 2011 earthquake off the coast of Japan, but the productivity losses reported in Table 6 are the estimated annual (i.e., recurring) losses.[9]

We conducted a series of regression diagnostics to analyze the robustness of our results. To check the generalizability of the results to other time periods, we expanded our dataset to include production from 2006 to 2009 using data provided by Automotive News. In 2006, manufacturers stopped reporting weekly production and moved to monthly production reports. Automotive News interpolated weekly production based on monthly production and information on shift patterns, parts shortages, etc. Because we view these data as less reliable we do not use them for our main results, but they are useful for a robustness check. All of the results are qualitatively similar in the period 1994-2009, but some of the coefficients are estimated with less precision and are not significant (specifically *Cloud* and *High Temp*). This is consistent with the larger measurement error associated with the dependent variable for those additional years.

Because some of the weather events are infrequent, we checked for influential points in the data. To do this, we re-estimated the model removing each of the plants (one-at-a-time), and found no significant difference in our results. We conclude that the estimates are not driven by influential locations in the sample.

Another potential concern in our study is measurement error with our weather variables. Recall that the weather stations are located at some distance from the plant, on average 13 miles away. As a robustness check, we estimate the regressions using only plants whose corresponding weather station is within 20 miles of the plant. The sample size in this regressions drops to about twenty four thousand observations. All the results are qualitatively similar, although *Cloud, Fog* and *Wind* are no longer significant. This analysis suggest that potential biases introduced by measurement error in the dependant variable are not a concern.

5 Conclusion

Based on our sample of U.S. automobile assembly plants over a ten-year period, we find that a plant's local weather can have a substantial impact on production, ranging from a reduction of 2% to 11% in annual production. The immediate follow-on question is "Can automobile companies do a better job managing this problem?". The answer depends on the underlining mechanisms. Given that we find heavy winds, snow and rain are associated with production losses, it is possible that disruptions to in-bound deliveries is

[9]The earthquake reduced production by about 50% for six months. See Bunkley (2011).

a major cause. If this is the case, firms could mitigate this factor by carrying more inventory of parts or at least increasing deliveries of parts in anticipation of bad weather. This approach goes against the "just-in-time" philosophy of carrying lean inventory and ensuring a smooth production flow, but avoiding the productivitity losses due to weather may justify a more flexible operating strategy. If, on the other hand, bad weather is problematic because it increases employee absenteeism, then mitigating strategies may be more difficult to develop. For example, it would be costly to "pre-position" workers in anticipation of bad weather - people are not likely to want to live at the plant for an extensive period. However, it may be possible to provide employees with alternative transportation options (company operated shuttles), as long as these transportation options are available during poor weather.

It is interesting that we find that high temperatures reduces production. The obvious mitigating strategy for heat is to provide cooling systems. It is possible that heat is influencing worker productivity in "interface" areas between the outside and inside environments, such as on loading and unloading areas, because these areas may be difficult to cool. Alternatively, if the ambient temperature outside is significant, then it is possible that existing cooling systems are unable to maintain the interior temperature under 25° C (a threshold for heat stress). If this is the case, then maybe an investment in higher capacity cooling systems could be justified.

It is not clear the extent to which automobile companies are aware of the impact of weather on their productivity beyond obvious effects like "a blizzard can disrupt production". If they are indeed not aware, then it is possible that the mitigating strategies discussed above (or others) could improve productivity. But if they are already aware of these effects, they may have already implemented all cost effective mitigating strategies. That would leave only the option to move production to a more weather friendly location. Of course, moving production is costly and raises a host of other issues - labor costs, access to suppliers, etc.

Our study focuses on the automobile industry, which offers several advantages: it is an economically significant industry, there are many geographically dispersed assembly plants operated by a number of different companies, and detailed production data is available over a long period of time (ten years) at the weekly level (rather than monthly, quarterly or annually). However, it is not clear to what extent these results carry over to other industries. Again, the answer depends on the underlining mechanism. If disruptions in in-bound parts deliveries is the cause of the productivity loss, then these effects are likely to occur in any manufacturing industry that operates with limited buffer stocks of inventory. Industries that carry substantial inventory are probably then immune. But if the cause is due to disruptions in in-bound employees, then these effects are likely to be common across many industries, including services. Additional data are needed to tease out which of the mechanisms we have identified (or others) are responsible for these effects.

Our findings provide an interesting contrast with the existing literature on climate change and economic activity. For example, Dell et al. (2008) find that hot years only impact poor countries, but we find that hot temperatures impact production in a "rich" country. Furthermore, they find that rainy years neither impact poor nor rich countries but we find that intense periods of rainy do negatively effect productivity. Similarly, Hsiang (2010) find that adverse weather actually increases manufacturing output in Caribbean basin countries. But those studies work with annual shocks (e.g., a hot year) and annual output measures across a wide range of industries. It is possible that their level of aggregation masks productivity losses in specific industies. Furthermore, because their estimation is based on annual shocks, they are unable to measure short term shocks (e.g., weekly shocks) that nevertheless add up to a substantial annual impact - if the frequency of short term shocks is relatively constant, then there may not be enough variation in annual data to identify their effect (e.g., if there are 5 windy weeks each year and every year, the effect of wind cannot be estimated with annual data).

Finally, our work provides additional evidence on the impact of climate change on economic output. We do not find evidence that changes in averge temperature or rainfall have an impact on productivity, so it is unlikely that long run forecasted increases in average temperatures (e.g., of the order of 2-5° C) are likely to influence automobile assembly productivity directly. However, climite change is also forecasted to be associated with increases in severe weather (Solomon et al. (2007)) and we find a direct link between severe weather (high winds, fog, high heat, and extensive periods of snow or rain) and productivity losses. As a result, the impact of weather on manufacturing productivity is likely to be a growing concern.

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Table 1: Descriptive statistics of assembly plants in the study.

Company	Number of Plants	Average weekly production	Maximum weekly Production
GM	20	3301	16372
FORD	16	3965	22544
CHRYSLER	9	3455	10395
TOYOTA	5	4361	25172
HONDA	4	4081	26929
ISUZU	2	3311	26581
MAZDA	2	2814	7382
SUZUKI	1	6855	21316
MITSUBISHI	1	2731	16112
NISSAN	1	2663	17702
BMW	1	1832	4114
MERCEDES BENZ	1	1537	4780
HYUNDAI	1	1233	7538
TOTAL	64	3242	

Table 2: Weather variables included in the empirical study

Variable	Description
Wind	Number of days in which a wind advisory is issued by the National Weather Service Forecast Office. A wind advisory is issued when maximum wind speed exceeds a threshold for the area which is typicaly in excess of 40 miles per hour.
Cloud	Average cloud cover during the week (0 = no clouds; 8 = sky completely covered).
Fog	Number of days with fog during the week.
Rain	Number of days with rain during the week.
Snow	Number of days with snow during the week.
High Temp	Number of days with a high temperature two standard deviations above of the average historical temperature. The standard deviation for the day is inferred assuming that temperatures are normally distributed with a mean equal to the day's historical average temperature and the record high temperature is the 99^{th} percentile. Only summer and spring weeks are included (i.e., relatively hot weeks in the winter and fall are not included).
Low Temp	Number of days with temperature two standard deviations below the average historical temperature. The standard deviation is evaluated as described for *High Temp.* Only fall and winter weeks are included.

Table 3: Mean and standard deviation (in parentheses) of the weather variables, by geographic region.

	Central	East	Gulf	Lakes	Total
Wind	0.006	0.011	0.009	0.007	0.007
	(0.081)	(0.104)	(0.098)	(0.084)	(0.087)
Cloud	3.975	3.892	3.333	4.431	3.996
	(1.732)	(1.530)	(1.746)	(1.672)	(1.743)
Fog	0.389	0.334	0.459	0.379	0.395
	(0.824)	(0.718)	(0.943)	(0.822)	(0.840)
Rain	2.524	2.801	2.596	2.338	2.498
	(1.822)	(1.759)	(1.860)	(1.783)	(1.816)
Snow	0.523	0.256	0.063	0.913	0.542
	(1.172)	(0.698)	(0.335)	(1.561)	(1.228)
High Temp	0.003	0.004	0.001	0.003	0.002
	(0.067)	(0.061)	(0.039)	(0.051)	(0.057)
Low Temp	0.035	0.033	0.011	0.032	0.029
	(0.241)	(0.240)	(0.125)	(0.240)	(0.223)

Table 4: Correlation matrix of weather variables.

	Wind	Cloud	Fog	Rain	Snow	High Temp	Low Temp
Wind	1.000						
Cloud	0.021	1.000					
Fog	0.017	0.005	1.000				
Rain	0.021	0.217	-0.019	1.000			
Snow	-0.009	0.386	-0.140	-0.357	1.000		
High Temp	0.000	0.007	-0.006	0.013	-0.019	1.000	
Low Temp	0.022	0.074	-0.014	0.030	-0.015	-0.006	1.000

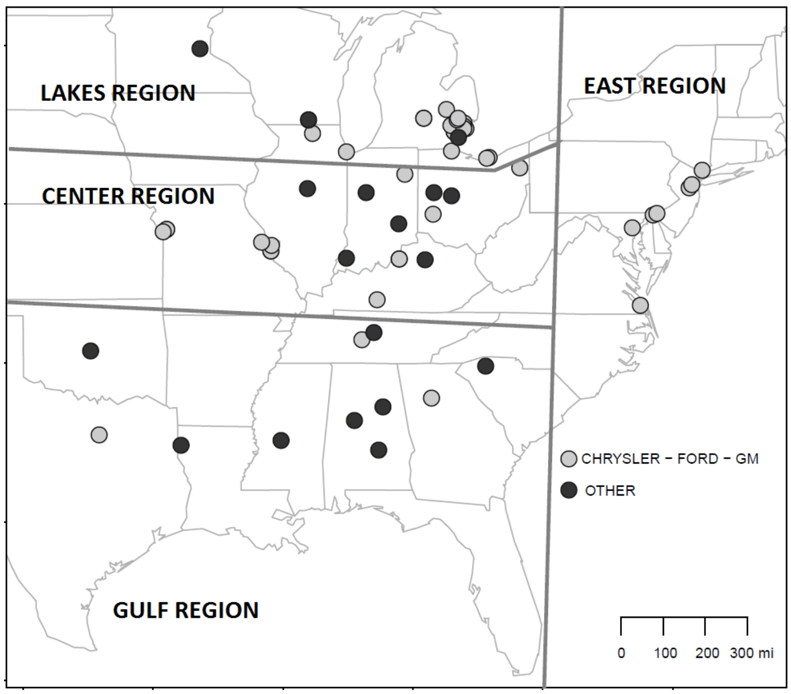

Figure 1: Plant locations and geographic regions.

Table 5: Main results

	(1)	(2)	(3)
Cloud	-0.0079*	-0.0091**	-0.0102**
	(0.0033)	(0.0033)	(0.0033)
High Temp	-0.1176*	-0.1172*	-0.1225*
	(0.0520)	(0.0520)	(0.0520)
Low Temp	-0.0180	-0.0220	-0.0225
	(0.0184)	(0.0184)	(0.0184)
Fog	-0.0748***	-0.0736***	-0.0762***
	(0.0053)	(0.0053)	(0.0053)
Wind	-0.2667***	-0.2645***	-0.2632***
	(0.0420)	(0.0420)	(0.0420)
Rain	-0.0026	-0.0014	
	(0.0028)	(0.0030)	
Snow	-0.0144**	-0.0248***	
	(0.0049)	(0.0055)	
Snow (0,2)			-0.0128
			(0.0159)
Snow [2,5)			-0.0665***
			(0.0181)
Snow >=5			-0.0865*
			(0.0337)
Rain (0,3)			0.0030
			(0.0126)
Rain [3,6)			0.0186
			(0.0146)
Rain >=6			-0.0655**
			(0.0218)
Prod. Start	-0.1123***	-0.1112***	-0.1114***
	(0.0177)	(0.0178)	(0.0178)
Prod. Stop	-0.0812***	-0.0798***	-0.0806***
	(0.0185)	(0.0185)	(0.0185)
New Model	-0.3667***	-0.3670***	-0.3665***
	(0.0139)	(0.0139)	(0.0139)
Drop Model	-0.0520***	-0.0557***	-0.0557***
	(0.0127)	(0.0128)	(0.0128)
Observations	31423	31423	31423
Region/Segment	No	Yes	Yes
Avg. Weather	No	Yes	Yes
R-square(within)	0.1092	0.1151	0.1157

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Ranking of average productivity loss due to weather

Plant	*Company*	*State*	*Productivity Loss (%)*
Top ten			
Lordstown 1	GM	OH	11.1
Orion	GM	MI	10.4
Flint 1	GM	MI	10.3
Sterling Heights	CHRYSLER	MI	9.1
Lansing Delta	GM	MI	8.5
Lansing Grand River	GM	MI	8.5
Pontiac East	GM	MI	8.4
Janesville 1	GM	WI	8.4
Wixom	FORD	MI	8.4
Avon Lake	FORD	OH	7.7
Middle ten			
Shreveport	ISUZU	LA	6.2
Moraine	GM	OH	6.2
Lafayette	TOYOTA	IN	6.1
Marysville	HONDA	OH	6.0
Detroit (Ford)	FORD	MI	5.9
Fairfax	GM	KS	5.9
Kansas City 1	FORD	MO	5.9
Kansas City 2	FORD	MO	5.9
Flat Rock	MAZDA	MI	5.8
Toledo	CHRYSLER	OH	5.8
Bottom ten			
Doraville	GM	GA	4.6
Wilmington	GM	DE	4.5
Newark	CHRYSLER	DE	4.3
Canton	NISSAN	MS	4.2
Princeton	TOYOTA	IN	4.0
Vance	MITSUBISHI	AL	3.6
Fremont 2	TOYOTA	CA	3.6
Fremont 1	TOYOTA	CA	3.6
Spartanburg	BMW	SC	3.6
Arlington	GM	TX	2.6

Figure 2: *Wind* map.The scale on the map corresponds to the total number of high wind days at each location during a 10 year period.

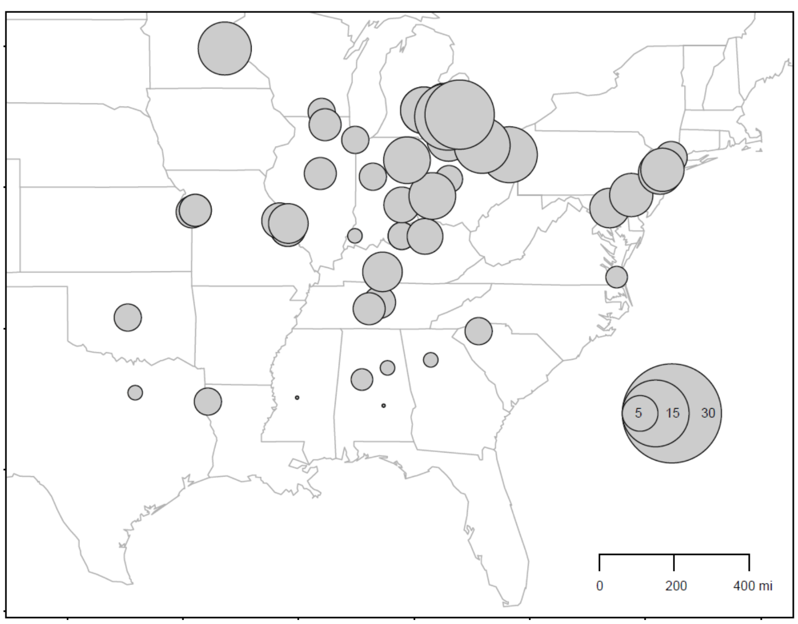

Figure 3: *Snow* map. The scale on the map corresponds to the total number of weeks with more than five days of snow at each location during a 10 year period.