Severe Weather and Automobile Assembly Productivity*

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Abstract

It is apparent that severe weather should hamper the productivity of work that occurs outside. But what is the effect of extreme rain, snow, 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, a week with six or more days of heat exceeding 90° reduces production in that week by 8% on average. The location impacted the least by weather (Princeton, IN) loses on average 0.5% of its production due to severe weather and the location with the most adverse weather (Montgomery, AL) suffers a production loss of 3.0%. Across our sample of plants, severe weather reduces production on average by 1.5%. While it is possible that plants are able to recover these losses at some later date, we do not find evidence that recovery occurs in the week after the event. Furthermore, even if recovery does occur at some point, at the very least, these shocks are costly as they increase the volatility of production. Our findings are useful both for assessing the potential 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. These results can be expected to become more relevant as climate change may increase the severity and frequency of severe 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

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and tourism. Less clear is the impact on "climate-insensitive" sectors such as manufacturing and services (Nordhaud, 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, icy roads or heavy precipitation could cause delays in in-bound delivery of parts from suppliers, possibly due to additional traffic congestion, accidents or cancelled shipments. (See Brodsky and Hakkert (1988); Golob and Recker (2003) for data on precipitation and traffic accidents.). Finished vehicles might be damaged during periods of high wind or hail once they exit the plant. In addition, 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.[1] Alternatively, bad weather outside could influence the affect of employees which in turn may lower their productivity.[2] 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., if 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

[1] 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 Wyon (2001)). Internal temperatures in a automobile plant may exceed this threshold, especially if the outside temperature is high.

[2] 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. However, Lee and Staats (2012) argue that bad weather may increase productivity as it eliminates cognitive distractions associated with good weather.

seasonality; planned shifts to account for known variations in production; weekly dummies to account for national variations in demand, monthly segment dummies (e.g., cars, vans, etc.) to account for segment specific demand seasonality; regional year-month dummies to account for regional differences in weather fluctuations and the possibility that the influence of weather varies by region; and seasonal average weather measures for each plant (e.g., average amount of rain in week t for plant i). 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, within a week, six or more days with a high temperature of 90^oF or one additional day of heavy winds reduces that week's production by approximately 8%, and six or more days of rain within a week reduces production relative to no rain by 6%. Furthermore, we find that average weekly production losses due to weather events (snow, rain, heat and wind) ranges from a low of 0.5% (Princeton, IN) to a high of 3% (Montgomery, AL), with an overall average of 1.5%. 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 collective effect is meaningful.

Our data are suitable for measuring the short term impact of weather on production. An interesting question is how do plants react to the productions shocks we observe? On one extreme, the production could be "lost forever", while at the other extreme, the plant may fully recover the lost production in the same week the weather event occurs. Even if they are able to recover some production in the same week, we find the net impact of severe weather on a week's production to be negative. In addition, we do not find evidence that they are able to recover in the following week - plants are not more likely to schedule overtime in a week that follows bad weather, nor is production higher in weeks following bad weather (all else being equal). Nevertheless, we cannot rule out the possibility that plants recover the production at some point in the future. However, even if they were to fully recover at some point, at the very least, such recovery increases the variability of production (which is costly) and may lead to delayed shipments and stockouts.

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. Using import and export data, Jones and Olken (2010) report results that are consistent with those from Dell et al. (2008). 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 local productivity (a single plant) and we expand the array of observed weather variables beyond temperature and precipitation (e.g., wind). The fine granularity of our data allows us to identify meaningful effects that could be masked in more aggregated data (regional, annual data).

There is a considerable literature on supply chain disruptions. For example, a number of papers investigate sourcing strategies when suppliers have varying reliability (e.g. Tomlin (2006), Wang and Tomlin (2010), Dong and Tomlin (2012)). Some work investigates disruptions empirically (e.g., Hendricks and Singhal (2005)) but in none of these cases is a connection made between the disruption and severe weather. Furthermore, the focus is generally on upstream disruptions whereas we investigate the impact of local disruptions (i.e., local weather).

Our results could be useful in several ways. First, they are related to the issue of climate change. While there is low confidence of the impact of climate change on wind (Pryor (2009)), the Intergovernmental Panel on Climate Change (Field et al. (2012)) projects that climate change is likely to increase the frequency of extreme weather events, such as heat waves and heavy precipitation. It follows that climate change could have a consequential impact even on 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. Third, our results complements the existing literature on productivity in the automobile industry (Lieberman et al. (1990), Lieberman and Demeester (1999), among others) by presenting evidence of the impact of extreme weather on productivity; plant managers may be unaware of the impact of weather on their output (e.g., attributing variation in output to unexplained causes or to mechanisms that are caused by weather, such as absenteeism or parts shortages), and can use our results to implement policies to counteract these negative effects (e.g., accelerating deliveries in anticipation of weather). 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.

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.

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.) Manufacturers report these data to market analysts. In addition, for each plant and each week we obtained data on the number of shifts and hours scheduled from Automotive News, The Harbour Report and the Interuniversity Consortium for Political and Social Research (ICPSR). Similar data were used by (Bresnahan and Ramey, 1994).

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.

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 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 whether a 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.[3]

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:

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

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. The literature in climate and weather research uses two main approaches to measure severe weather: (1) based on the likelihood of occurrence of the event, typically measured as percentiles of the probability distribution for a given time period and location; (2) number of days above specific absolute thresholds of temperature or precipitation (Field et al. (2012) Box 3-1). An advantage of the second (the absolute threshold) approach is that it facilitates the comparison across regions. For this reason, we use this approach in most of our analysis. The main disadvantage is that the impact of an event exceeding a fixed threshold may depend on its location and the time of the year. As a robustness analysis, we also estimated and discuss specifications that allow the impact of weather to vary across geographic regions.

Table 2 defines the main weather variables used in our analysis. *Wind* is the number of days in a week

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

in which a wind advisory was issued by the National Weather Service Forecast Office. A wind advisory is issued when maximum winds in a area achieve a threshold defined for that area, typically in excess of 40 miles per hour. *Rain* and *Snow* are the number of days in which the respective event is recorded in the week. We include *Wind*, *Rain* and *Snow* because each may influence travel to and from a plant. Although foggy conditions may also affect travel, we found some inconsistencies on how this weather variable was recorded and therefore decided to leave it out of the analysis.[4] *Heat* and *Cold* are the number of days in a week in which the extreme temperature for the day exceeds a threshold: 90 degrees Fahrenheit for *Heat* and 15 degrees Fahrenheit for *Cold*. *Heat* is included because it could influence ambient temperature within the plant or employees that must work outside, such as at the loading docks (e.g. Soper (2011)). *Cold* may proxy for hazardous road conditions (e.g., ice). Many of the variables, such as *Wind, Heat* and *Cold*, directly capture extreme weather shocks. To capture extreme events related to the other weather variables, we estimated specifications including multiple levels of the variable to capture potential non-linear effects on production (described in Section 4).

Table 3 shows summary statistics for the weather variables. We defined four regions that cover the locations of the plants in the study: Lakes, Central, Gulf and East, which are illustrated in Figure 1. (The plant in California, not shown in the figure, is included in the Gulf region.) 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. Except for the higher correlation between *Cold* and *Snow*, 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 0.35, 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, total precipitation was unavailable for some weeks in our sample, 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 a sample of weather stations located 30-60 miles away is between 0.47 and 0.85, substantially lower than the other weather variables in our data (see footnote 3 for the sample). To summarize, we feel that the number of days of rain and snow is a more

[4]Between 1994 and 1996, several plants exhibited a frequency of fog that was orders of magnitude higher, which cannot be explained by changes in the weather patterns. This made the estimates of the effect of fog unstable, leading some plants to be highly influential in the estimation.

reliable measure to capture the effect of these weather shocks.

We include weekend observations in each weather variable even though plants are often (though not always) closed on weekends. This is appropriate if weather may have an effect on production that extends a few days before or a few days after the day in which it occurs. For example a weekend snow storm could influence deliveries both on Friday and especially on Monday. In addition, we are using the number of days of an event to proxy for the intensity of an event. A week with 7 days of rain is likely to be more extreme than a week with 5 days of rain. Similarly, a week with snow Friday through Sunday (i.e., three days of snow in our coding) may be more like a week with snow Wednesday through Friday (again, three days of snow in our coding) than a week with snow only on Wednesday (which is one day of snow in our coding, as the first example would be if we ignored the weekend). In addition, plants may attempt to recover lost production during weekdays by working on days off, but this recovery strategy would be limited if bad weather continues through the weekend (see Detroit (2011) for an example on how auto plants attempt to recover production in days off).

$PRODFACTORS$ includes covariates that capture adjustments to the production schedule and changes in productivity. Gopal et al. (2012) 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 temporarily 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.

Using our data on scheduled production, we constructed a new variable capturing the total planned labor hours per week:

$$PLANHRS = Number\ Of\ Shifts \times Hours\ Per\ Shift$$

PLANHRS controls for scheduled shifts in production that may be associated with an anticipated reaction to weather. For example, *PLANHRS* controls for cases in which a plant schedules maintenance in a week in which they expect heavy snow. This may be viewed as a conservative approach as one could argue that if production is reduced due to scheduled maintenance in anticipation of bad weather, then there is indeed a causal effect of bad weather on production. However, it is possible that *PLANHRS* captures seasonality in production schedules that are not due to weather but still correlated with weather. (For example, the plant shuts down for a week in August for vacation no matter if that week turns out to be hot or not.) Hence, we include *PLANHRS* in our regressions.

As just mentioned, 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. These seasonal controls are discussed next.

The first set of controls for seasonality 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 use capture 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, omitting $\rho_{r(i)m(t)}$ 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.[5]

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 $w(t)$ across all of the years in our sample:

$$\bar{W}(i, w(t)) = \frac{1}{5 \cdot N} \left(\sum_{y=0}^{N-1} \sum_{u=-2}^{2} W_{i,w(t)+52y+u} \right)$$

where $N = 10$ is the number of years in our sample. 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 *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 Main results

Table 5 presents the first set of estimation results of regression (1). This specification includes all the seasonality controls: weekly dummies (τ_t), 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 estimates associated to these controls are not reported in the table for space considerations.) Among the weather variables, *Heat*, *Wind* and *Snow* are negative and statistically significant *(Cold* and *Rain* are not significant). We also estimated a specification with fewer seasonal controls – only the weekly dummies – and the results were similar, suggesting that the estimated effect of the weather variables is not driven by potential confounders related to seasonality. In addition, the controls for other production-related factors (grouped as *PRODFACTORS* in regression (1)) are highly statistically significant; these suggest productivity drops associated with production ramp-ups and ramp-downs, and new model introductions. As expected, the total schedule hours (*PLANHRS*) during a week has a positive and significant effect on the number of vehicles produced.

[5]Only four plants in our sample shifted their production from one segment to another.

A second specification, reported in Table 6, includes the weather variables in multiple levels to analyze the extent to which extreme weather events impact productivity. This specification also includes all the seasonality and production factor controls; all the coefficients of the production factors were similar to those in Table 5 and so they are omitted in the table. For *Rain* and *Snow* we include three levels based on the number of days the weather event occurred during the week. The cut-off points are indicated in the variable name and correspond to the 50^{th} and 95^{th} percentile of each measure, conditional on having at least one day of precipitation that week. 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[1]* indicates weeks with one day of snow and *Rain [3,5]* indicates weeks with 3,4 or 5 days of rain. We 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 to 4 days of snow. The highest level of snow is also negative and larger in magnitude, but is not statistically significant at the 5% level (p-value=0.1), possibly due to the small number of observations for this extreme event (see Table 7). Nevertheless, we expect its impact should be as severe and we cannot reject the null hypothesis that the effect of *Snow[5,7]* is larger than *Snow[2,4]*. For rain, the effect is statistically significant for 6 or more days of rain, but not significant for fewer days of rain.

We defined three levels for *Heat*, and *Cold*. The highest level for heat, 6 or 7 days with a high temperature exceeding $90°F$, is closely related to the definition of a heat wave.[6] We find strong evidence of a non-linear effect of *Heat*, but the effect of *Cold* is still insignificant at all levels.

Because days with *Wind* advisory alert are relatively infrequent (See Table 7), levels for this variable were defined based on thresholds of wind-speed. Two levels were defined with cut-offs at 34 and 44 mph, and each level counts the number of days with maximum wind speed on each level's range. For example, *Wind[35,44]* counts the number of days with wind speed between 34 and 44 mph. The results suggest evidence of non-linear effects of *Wind.* Next, we describe the economic significance of these results.

For all the variables reported in Table 6, except for the *Wind* variables, the coefficient represents (approximately) the percentage drop in weekly production when the corresponding weather event occurs during a given week (net of any production recovery that might occur in that week). For *Wind,* the coefficient measures the percentage drop in weekly production of an *additional day* with the indicated wind speed. To put the effect of weather in perspective, the productivity reduction during the first week a vehicle model is introduced is 32%, similar in magnitude to the combined effect of one day of high wind, a heat wave with

[6]The Warm Spell Duration Index (WSDI) – commonly used to characterize the frequency of heat waves – is defined as the fraction of days belonging to spells of at least 6 days with maximum temperature exceeding the 90th percentile (Field et al. (2012)).

6 or more days of high temperature and 6 or more days of rain during a week. But such extreme weather incidents are also rare – for example, weeks with wind-speeds above 44 mph have a frequency of 0.6% in the sample. To estimate the economic impact, we measure the expected production reduction which combines the likelihood of the weather incident with the impact estimated in Table 6. Table 7 reports these calculations for the weather variables that have a statistically significant effect on production as reported in Table 6 along with *Snow[5,7]*, as we cannot reject the null hypothesis that the effect of *Snow[5,7]* is larger than *Snow[2,4]*. Here, we see that snow and rain tend to have the largest economic effect on weekly production.

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 location (this calculation considers all the weather variables included in regression (1)). Table 8 shows the results for the 49 cities in our sample. (Plants in the same city have the same weather and therefore the same effect.) Table 10 shows the average percent loss in productivity due to weather for each of the four regions. While the average loss is not statistically different across regions it is possible to observe a statistically significant difference for the impact of snow and heat across the different regions.

Regression Diagnostics and Robustness Analysis

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 as a robustness check. All of the results are qualitatively similar to the period 1994-2009, but some of the coefficients are estimated with less precision and are not significant (specifically *Heat*). 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.

As the nearest weather stations to the plants are located on average 13 miles away from the plants, a potential concern is measurement error with our weather variables. To address this issue, we estimated the regressions using only plants with corresponding weather stations within 25 miles of the plant. The sample size in this regressions drops to about 26,000 observations. All the results are similar in magnitude and statistical significance, and all the point estimates are within the 95% confidence interval of the results reported in Table 6. This analysis alleviates concerns with potential measurement error in the dependent variable due to the location of weather stations.

The measures of weather used in our main analysis include weather events on weekends even though most plants do not work on weekends. This is reasonable if adverse weather can have an impact on production just before or after the actual weather event. Furthermore, including weekends allows us to better use the duration of the event for a proxy of its intensity. Nevertheless, we estimated our model with weekend weather excluded and found that the results were consistent with those reported in Table 6.

Plant Heterogeneity

Our results provide a measure of the average impact of weather on automobile production. It is possible that individual plants may experience different effects depending on their idiosyncratic features, such as the location of the parts suppliers, or inventory management practices or other operating procedures. For example, while we have measured the impact of severe heat on plants A and B, given the same level of heat, plant A may experience less of an adverse reaction than plant B. As long as the magnitude of the impact of a weather event on a plant is uncorrelated with the frequency of the event at that location, the estimates of the economic impact reported in Tables 7 to 10are unbiased. However, if plant location decisions are endogenous so that plants for which the effect of a weather event is larger are located in areas with lower frequency of these events, then our estimates would overestimate the average economic impact on production even though the estimated impact conditional on an event occurring, i.e., the β coefficients, remain unbiased. This potential bias can be corrected by accounting for the heterogenous effect of weather across plants.

Since it is not possible to estimate a separate coefficient for each plant (the estimates would be too imprecise), we instead categorize plants into groups and estimate a different vector of coefficients for each group. The idea is to group plants based on their weather similarities, so that weather patterns are similar within group but different across groups. If there is any selection based on the incidence of weather events, then one should observe differences in the estimated coefficients across groups.

We conducted a hierarchical cluster analysis to segment plants into groups. Let $\bar{X}_{kiq}$ denote the average incidence of weather variable k at plant i during quarter q (using the weather variables defined in Table 2), and $\bar{X}_i$ the vector containing all these weather metrics that characterize a plant i. The cluster analysis calculates the distance between plants based on these metrics, generating a partition of plants into groups. We used Ward's hierarchical clustering method to create the groups (see Johnson and Wichern (1992) for details of the method). For the regression analysis, we considered using two clusters which are shown in

Figure 4. There is a clear geographic segmentation of the two groups, which we name the North and South clusters.

We estimated regression (1) including interactions of the weather variables and an indicator variable for the South cluster. The results of this analysis are presented on Table 11 (the first column, "Main Results", shows the original estimates for comparison; the interactions are labeled "SC"). Given the larger number of coefficients to estimate, the standard errors increase and many of the variables are no longer statistically significant. We focus in testing the null hypotheses of equal coefficients between the North and South clusters, which can be done by testing the significance of the interactions. These results show a difference on the coefficients estimated for the highest level of *Rain* – the effect tends to be higher in magnitude for the South cluster – and no significant difference for the other coefficients. A possible explanation for this difference is that on average the South locations receive 10 inches more of rain per year than the North locations (44 vs 34 inches) even though rain in the South is about as frequent as in the North. Overall, the differences in the coefficients are observed for weather variables whose frequency is similar across the two groups: about 60% of the *Rain[6,7]* events happened in the south cluster. Although there is some heterogeneity across plants, it is not systematically related to the frequency of extreme weather events, and so we conclude that the average economic impact deduced from Tables 7 and 10 are correct.

To the extent that these differences between plants exist, it is worthwhile to know if they are associated with managerial decisions. Unfortunately, while our data is well suited for measuring the average impact, because we have heterogeneity in weather across different plants, it is not particularly well suited for identifying practices that are more or less robust to weather disruptions. To explain, to understand if plant A is more robust to weather than plant B, ideally we want them to have similar weather, or at least weather that is uncorrelated with the practices that make them different. Most of the plants in our sample are located far away from other plants, so few plants have similar weather. Furthermore, we lack data on the specific relevant operational characteristics that could be used to infer differences across plants. Put another way, our panel data is appropriate for identifying the average impact of weather of automobile production, but to understand differences across plants requires a cross-section analysis and that introduces a host of identification challenges. Nevertheless, we can make some initial exploration based on our data.

It is possible that plants owned by GM, Ford and Chrysler (labeled the US group) operate in a different way than all other plants (non-US group). For example, they may be more unionized or use fewer "lean manufacturing" techniques (Bennett et al. (2011) provides some anecdotal evidence on how lean plants may be more prone to disruptions). To test for differences in these two groups, we estimated regression (1) including interactions of the weather variables and a binary variable indicating the non-US group. Again, the estimated coefficients on this analysis are measured with less precision. Interestingly, the results seem to replicate the North/South segmentation reported in Table 11: the *Rain* appears to have a larger impact on plants in the non-US group. Nevertheless, we do not wish to conclude that U.S. plants are better able to cope with *Rain* because of their managerial practices. U.S. plants tend to be located more in northern regions and non-US plants are more prevalent in southern regions (see Figure (1)). Consequently, the differences we observe could be due to differences in the nature of weather in the north relative to the south. For example, six days of rain in Tennessee (which has a non-US plant) may be more intense than six days of rain in Michigan, which is dominated by US plants (as reported earlier, rain tends to be more intense in the south). Therefore, those results may suggests a north/south difference rather than a US/non-US difference.

To further explore this issue, we identified sets of plants which are collocated within 100 miles and have different ownership (US vs non-US). Four pairs of US/non-US plants were identified. We estimated regression (1) with interactions with the non-US group indicator. This regression has little power due to the small sample size, and none of the coefficients are statistically significant. Hence, we believe that with our data and estimation strategy it is not possible to determine if US plants are differentially robust to weather relative to non-US plants or if southern weather is different than northern weather in ways that our main regression does not capture. Put another way, we cannot provide evidence that our average effects are different between US and non-US plants.

Short-term production recovery

Another question of interest is the extent to which plants are able to recover from the short term productivity losses we observe due to weather shocks. At one extreme, plants may be able to recover all of their lost production at some point in the future. Even if this is true, the short term productivity losses would be costly as they can lead to stockouts at dealerships and to volatile production (which could require costly overtime). To further explore the extent of recovery, we analyzed how weather incidents could impact production in the week after the time the incident occurs. Specifically, we estimated regression (1) using "lagged" weather variables. Table 12 shows the results of this analysis. For reference, column (1) reports the estimates of Table 6 and column (2) includes the weather variables that were significant on the main analysis with one week of lag. For the most part, the results when we include the lag variables are similar in sign, magnitude and significance relative to the weekly analysis. In addition, the lagged effects for *Rain [6,7]*, *Snow [5,7]* and *Wind >44* are negative and significant. Not only does this contradict the hypothesis that plants are able to recover their production in the following week of bad weather, it suggests that bad weather may have an impact beyond the week it occurs. Alternatively, it may due to how we code weather events - a six day period of rain that straddles two weeks is probably one weather event, but because we divide time into weeks, it is viewed as two weather events in our analysis. Either way, we do not find evidence suggesting that firms recover their lost production in the week immediately following an adverse weather event. We also considered specifications that added further lags, but these were jointly insignificant.

To further analyze production recovery after a weather incident, we estimated the impact of weather on the likelihood of scheduling overtime during the weeks after the incident, as overtime is a likely mechanism to recover lost production. We defined an indicator variable that is equal to one if the plant scheduled overtime during the three weeks following any week t. We estimated a Probit regression of this indicator variable, including the weather factors and all the other independent variables of regression (1) as covariates. The estimates suggest that the none of the factors have a significant influence on the probability of overtime (p-values<0.05) The evidence suggest that the production schedule is rarely affected in the weeks immediately following a weather incident.

Although we do not find evidence of a short term recovery, we cannot rule out that recovery occurs with a greater lag. However, plants may choose different lags for recovery - e.g., some may recover in four weeks while others within eight weeks, and even the same plant may take a different amount of time to recover from different events. Hence, it is difficult to use our data to identify this recovery, if it occurs. One possible approach is to aggregate data over time. For example, regress quarterly production on quarterly weather. If recovery occurs within the quarter, we should not observe significant relationships between weather and production. However, this substantially reduces the sample size, thereby complicating the interpretation of the results - failing to reject that null that weather has no adverse impact on production is not the same as accepting the null. Clearly, further research is needed on the long term impact of weather on production. But even if long run recovery is possible, we can conclude that adverse weather has a short term impact on productivity, and therefore leads to a costly increase in the volatility of production.

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 0.5% to 3.0%, with an average of 1.5%. The immediate follow-on question is "Can automobile companies do a better job managing this problem?". The answer depends on the underlying 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 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 productivity 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.

We find that high temperatures reduce 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 $77° F$ (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". About half of companies in a survey, Staff (2011), report that they experienced a weather related disruption to their supply chain, but magnitudes were not estimated and our results suggest that nearly all facilities may experience some form of weather disruption. 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, then 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 are 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 more robust. 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 rain do negatively affect 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 industries. 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. Climate change is forecasted to be associated with increases in severe weather (Field et al. (2012)), in particular with heat and rain, and we find a direct link between severe weather (high winds, high heat, and extensive periods of snow or rain) and productivity losses. Long run forecasts of extreme weather are challenging and there can be uncertainty in the direction of the change (e.g., wind) as well as the magnitude of the change (e.g., temperature). Hence, even though we are not comfortable combining our estimates of productivity losses with extreme weather forecasts to yield a long fun forecast of potential losses in the North American automobile industry due to climate change, we believe 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 (vehicles/plant) (1)	Minimum weekly production (vehicles/plant) (2)	Maximum weekly production (vehicles/plant) (3)	Average utilization (4)
GM	20	4048	231	13155	74%
FORD	16	4547	202	12400	75%
CHRYSLER	9	4666	560	9359	74%
TOYOTA	5	4769	663	12165	76%
HONDA	4	5273	698	11100	74%
ISUZU	2	4031	609	6798	76%
MAZDA	2	3372	874	7382	75%
BMW	1	1640	201	3932	73%
HYUNDAI	1	2516	800	4520	56%
MB	1	1423	223	1990	77%
MITSUBISHI	1	3410	614	5821	75%
NISSAN	1	4800	1619	9165	65%
SUZUKI	1	8270	1814	12972	79%

(1) The average is taken over the companies plants' average weekly production.

(2) This is the minimum number of units produced during a week among all of the company's plant.

(3) This is the maximum number of units produced during a week among all of the company's plant.

(4) To calculate this value, we first obtained the utilization for each plant during each year in our sample as the average production divided by the maximum production value. Then we average across each plant and finally obtain the average across each company.

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 typically in excess of 40 miles per hour.
Rain	Number of days with rain during the week.
Snow	Number of days with snow during the week.
Heat	Number of days with a high temperature above 90 degrees Fahrenheit.
Cold	Number of days with low temperature below 15 degrees Fahrenheit.

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

	Central	East	Gulf	Lakes	Total
Wind	0.006	0.010	0.011	0.007	0.007
	(0.076)	(0.101)	(0.106)	(0.083)	(0.087)
Rain	2.508	2.804	2.678	2.334	2.507
	(1.848)	(1.804)	(1.892)	(1.793)	(1.841)
Snow	0.490	0.264	0.065	0.870	0.518
	(1.128)	(0.712)	(0.336)	(1.524)	(1.193)
Heat	0.480	0.428	1.001	0.211	0.483
	(1.299)	(1.128)	(1.997)	(0.708)	(1.326)
Cold	0.382	0.176	0.038	0.652	0.390
	(1.168)	(0.724)	(0.294)	(1.557)	(1.206)

Table 4: Correlation matrix of weather variables.

	Wind	Rain	Snow	Heat	Cold
Wind	1.000				
Rain	0.021	1.000			
Snow	-0.009	-0.357	1.000		
Heat	0.009	0.013	-0.161	1.000	
Cold	-0.009	-0.314	0.599	-0.117	1.000

Table 5: Estimation results of regression (1).

Production factors		Weather		Additional Controls
Prod. Start	-0.1006***	*Heat*	-0.0127***	*Week*
	(0.0257)		(0.0037)	*Region-Month*
Prod. Stop	-0.0578*	*Cold*	0.0004	*Segment-Month*
	(0.0240)		(0.0043)	*Avg. Weather*
New Model	-0.3236***	*Wind*	-0.0800*	
	(0.0202)		(0.0337)	
Drop Model	-0.0145	*Rain*	-0.0033	
	(0.0121)		(0.0023)	
PLANHRS	0.7272***	*Snow*	-0.0138***	
	(0.0167)		(0.0043)	

Number of observations=31,174. R-square=0.61. Robust Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Estimation results of regression (1) including levels of the weather variables

Precipitation		Temperature		Wind		Additional Controls
Snow [1]	0.0019	*Heat [1]*	-0.0065	*Wind [35,44]*	-0.0196	*Week*
	(0.0106)		(0.0163)		(0.0128)	*Region-Month*
Snow [2,4]	-0.0278*	*Heat [2,5]*	-0.0273	*Wind >44*	-0.0791*	*Segment-Month*
	(0.0133)		(0.0155)		(0.0339)	*Avg. Weather*
Snow [5,7]	-0.0429	*Heat [6,7]*	-0.0875**			*Production Factors*
	(0.0270)		(0.0291)			
Rain [1,2]	-0.0053	*Cold [1]*	-0.0035			
	(0.0101)		(0.0176)			
Rain [3,5]	0.0039	*Cold [2,5]*	-0.0020			
	(0.0117)		(0.0183)			
Rain [6,7]	-0.0590**	*Cold [6,7]*	-0.0212			
	(0.0182)		(0.0297)			

Number of observations=31,174. R-square = 0.61. Robust Standard errors in parentheses.

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

Table 7: Frequency and economic impact of weather variables

Weather incident	Frequency (per week)	Average production reduction (weekly)
Snow [2,4]	11.8%	0.34%
Snow [5,7]	2.1%	0.09%
Rain [6,7]	6.3%	0.37%
Heat [6,7]	1.7%	0.14%
Wind >44	0.6%	0.05%

Table 8: Ranking of average productivity reduction due to weather by location

Rank	*City*	*State*	*Total productivity loss (%)*	*Snow loss (%)*	*Rain loss (%)*	*Temp. loss (%)*	*Wind loss (%)*
1	Montgomery	AL	2.88%	0.00%	0.34%	2.45%	0.10%
2	Arlington	TX	2.41%	0.01%	0.52%	1.71%	0.17%
3	Shreveport	LA	2.18%	0.02%	0.48%	1.56%	0.12%
4	Canton	MS	1.93%	0.00%	0.53%	1.40%	0.00%
5	Avon Lake	OH	1.83%	0.74%	0.54%	0.22%	0.33%
6	St Paul	MN	1.81%	1.03%	0.23%	0.41%	0.14%
7	Oklahoma City	OK	1.81%	0.10%	0.17%	1.23%	0.30%
8	Lorain	OH	1.80%	0.78%	0.45%	0.25%	0.33%
9	Warren	OH	1.78%	1.00%	0.44%	0.21%	0.13%
10	Roanoke	IN	1.77%	0.79%	0.43%	0.29%	0.25%
11	Hazelwood	MI	1.70%	0.35%	0.50%	0.70%	0.16%
12	Lansing	MI	1.66%	0.93%	0.38%	0.27%	0.08%
13	Toledo	OH	1.65%	0.70%	0.42%	0.35%	0.18%
14	Vance	AL	1.63%	0.03%	0.35%	1.10%	0.16%
15	Wayne	MI	1.63%	0.76%	0.35%	0.26%	0.26%
16	Edison	NJ	1.61%	0.28%	0.70%	0.42%	0.21%
17	Linden	NJ	1.59%	0.28%	0.67%	0.38%	0.26%
18	Fenton	MO	1.58%	0.36%	0.32%	0.73%	0.17%
19	Smyrna	TN	1.57%	0.19%	0.54%	0.74%	0.10%
20	Flint	MI	1.55%	0.92%	0.26%	0.28%	0.09%
21	Spring Hill	TN	1.52%	0.17%	0.54%	0.73%	0.08%
22	Lake Orion	MI	1.50%	0.87%	0.26%	0.28%	0.10%
23	Baltimore	MD	1.50%	0.17%	0.67%	0.49%	0.18%
24	Wentzville	MO	1.48%	0.37%	0.27%	0.65%	0.19%
25	Sterling Heights	MI	1.45%	0.98%	0.20%	0.27%	0.00%

Table 9: Ranking of average productivity reduction due to weather by location (continued)

Rank	*City*	*State*	*Total productivity loss (%)*	*Snow loss (%)*	*Rain loss (%)*	*Temp. loss (%)*	*Wind loss (%)*
26	Norfolk	VA	1.44%	0.09%	0.70%	0.47%	0.17%
27	Moraine	OH	1.42%	0.56%	0.38%	0.29%	0.19%
28	Wixom	MI	1.41%	0.92%	0.20%	0.25%	0.03%
29	Belvidere	IL	1.40%	0.58%	0.36%	0.33%	0.13%
30	Spartanburg	SC	1.39%	0.02%	0.62%	0.69%	0.05%
31	Janesville	WI	1.36%	0.62%	0.29%	0.30%	0.15%
32	Kansas City	MO	1.36%	0.28%	0.33%	0.60%	0.15%
33	Louisville	KY	1.33%	0.32%	0.36%	0.53%	0.12%
34	Kansas City	KS	1.33%	0.28%	0.35%	0.55%	0.14%
35	Bowling Green	KY	1.31%	0.19%	0.36%	0.60%	0.16%
36	Pontiac	MI	1.30%	0.83%	0.17%	0.26%	0.04%
37	Lafayette	IN	1.30%	0.43%	0.30%	0.36%	0.20%
38	Lincoln	AL	1.30%	0.03%	0.31%	0.93%	0.03%
39	Georgetown	KY	1.29%	0.30%	0.51%	0.39%	0.08%
40	Normal	IL	1.27%	0.42%	0.29%	0.48%	0.08%
41	Chicago	IL	1.22%	0.60%	0.11%	0.39%	0.12%
42	Marysville	OH	1.19%	0.47%	0.20%	0.28%	0.23%
43	Atlanta	GA	1.15%	0.01%	0.42%	0.55%	0.17%
44	Warren	MI	1.15%	0.67%	0.16%	0.26%	0.06%
45	Wilmington	DE	1.15%	0.14%	0.36%	0.38%	0.27%
46	Dearborn	MI	1.15%	0.66%	0.16%	0.26%	0.06%
47	Detroit	MI	1.14%	0.65%	0.17%	0.26%	0.06%
48	Fremont	CA	0.81%	0.00%	0.61%	0.16%	0.04%
49	Princeton	IN	0.46%	0.05%	0.05%	0.33%	0.03%
	Average		1.50%	0.43%	0.37%	0.56%	0.14%

Table 10: Average productivity reduction due to weather by region

Region	Average productivity loss *(%)*	Average productivity loss due to Snow *(%)*	Average productivity loss due to Rain *(%)*	Average productivity loss due to Heat *(%)*	Average productivity loss due to Wind *(%)*
Central	1.40%	0.45%	0.34%	0.45%	0.16%
East	1.46%	0.19%	0.62%	0.43%	0.22%
Gulf	1.72%	0.05%	0.45%	1.10%	0.11%
Lakes	1.45%	0.79%	0.26%	0.29%	0.11%

Table 11: Estimation results considering two weather clusters

	Main Results	Weather Clusters Results		
		Main Effects	Interactions	
Snow [1]	0.0019	0.0011	*SC*Snow [1]*	0.0143
	(0.0106)	(0.0139)		(0.0189)
Snow [2,4]	-0.0278*	-0.0242	*SC*Snow [2,4]*	-0.0038
	(0.0133)	(0.0162)		(0.0231)
Snow [5,7]	-0.0429	-0.0457	*SC*Snow [5,7]*	-0.0036
	(0.0270)	(0.0296)		(0.0627)
Rain [1,2]	-0.0053	-0.0046	*SC*Rain [1,2]*	-0.0007
	(0.0101)	(0.0142)		(0.0191)
Rain [3,5]	0.0039	-0.0017	*SC*Rain [3,5]*	0.0133
	(0.0117)	(0.0160)		(0.0199)
Rain [6,7]	-0.0590**	0.0013	*SC*Rain [6,7]*	-0.0963***
	(0.0182)	(0.0263)		(0.0307)
Heat [1]	-0.0065	0.0025	*SC*Heat [1]*	-0.0163
	(0.0163)	(0.0260)		(0.0297)
Heat [2,5]	-0.0273	0.0061	*SC*Heat [2,5]*	-0.0477
	(0.0155)	(0.0288)		(0.0289)
Heat [6,7]	-0.0875**	-0.0212	*SC*Heat [6,7]*	-0.0727
	(0.0291)	(0.1181)		(0.1203)
Cold [1]	-0.0035	0.0090	*SC*Cold [1]*	-0.0298
	(0.0176)	(0.0207)		(0.0307)
Cold [2,5]	-0.0020	0.0102	*SC*Cold [2,5]*	-0.0378
	(0.0183)	(0.0215)		(0.0259)
Cold [6,7]	-0.0212	-0.0057	*SC*Cold [6,7]*	-0.1825
	(0.0297)	(0.0294)		(0.1284)
Wind [35,44]	-0.0196	-0.0162	*SC*Wind [35,44]*	-0.0081
	(0.0128)	(0.0178)		(0.0239)
Wind >44	-0.0791*	-0.0779	*SC*Wind >44*	-0.0041
	(0.0339)	(0.0438)		(0.0660)
Additional controls				
Region-Month	YES	YES		
Segment-Month	YES	YES		
Avg. Weather	YES	YES		
Cold (in levels)	YES	YES		
Production Factors	YES	YES		

Number of observations=31,174. R-square = 0.61. Robust Standard errors in parentheses.

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

"SC" = South Cluster

Table 12: Estimation results including lagged effects for the weather variables.

	Main Results	Including Lags		
		Main Effects	Lagged Variables	
Snow [1]	0.0019	0.0015		
	(0.0106)	(0.0105)		
Snow [2,4]	-0.0278*	-0.0287*	*Lagged Snow [2,4]*	-0.0199
	(0.0133)	(0.0130)		(0.0121)
Snow [5,7]	-0.0429	-0.0416	*Lagged Snow [5,7]*	-0.0608*
	(0.0270)	(0.0272)		(0.0280)
Rain [1,2]	-0.0053	-0.0015		
	(0.0101)	(0.0102)		
Rain [3,5]	0.0039	0.0088		
	(0.0117)	(0.0118)		
Rain [6,7]	-0.0590**	-0.0448*	*Lagged Rain [6,7]*	-0.0529***
	(0.0182)	(0.0183)		(0.0159)
Heat [1]	-0.0065	-0.0063		
	(0.0163)	(0.0164)		
Heat [2,5]	-0.0273	-0.0238		
	(0.0155)	(0.0158)		
Heat [6,7]	-0.0875**	-0.0759*	*Lagged Heat [6,7]*	-0.0431
	(0.0291)	(0.0292)		(0.0265)
Wind [35,44]	-0.0196	-0.0195		
	(0.0128)	(0.0127)		
Wind >44	-0.0791*	-0.0793*	*Lagged Wind >44*	-0.1364**
	(0.0339)	(0.0338)		(0.0503)
Additional controls				
Region-Month	YES	YES		
Segment-Month	YES	YES		
Avg. Weather	YES	YES		
Cold (in levels)	YES	YES		
Production Factors	YES	YES		
Observations	31174	30712		
R-square	0.6126	0.6166		

Robust Standard errors in parentheses

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

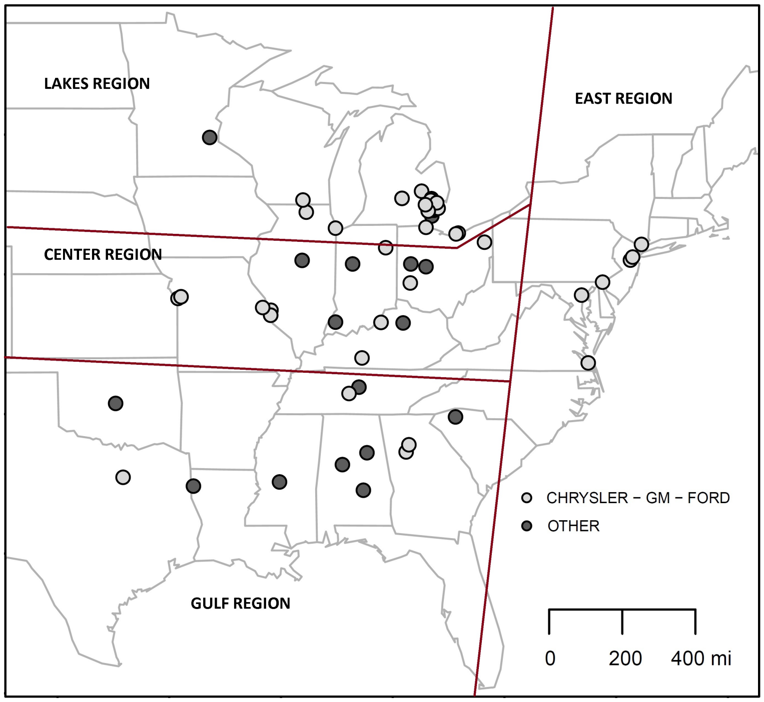

Figure 1: Plant locations and geographic regions. The plant in Fremont, California (not shown) is classified within the Gulf region.

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.

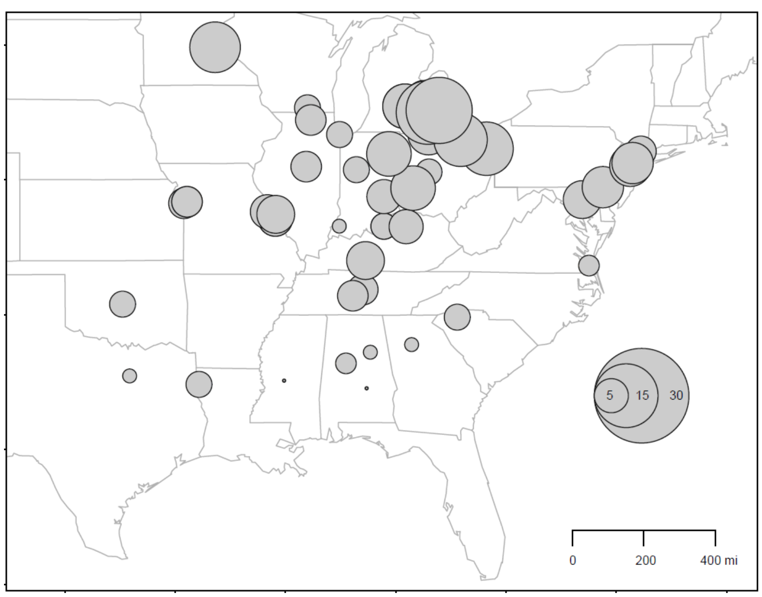

Figure 3: *Snow* map. The scale on the map corresponds to the total number of weeks with more than five days of snow at each location during a 10 year period.

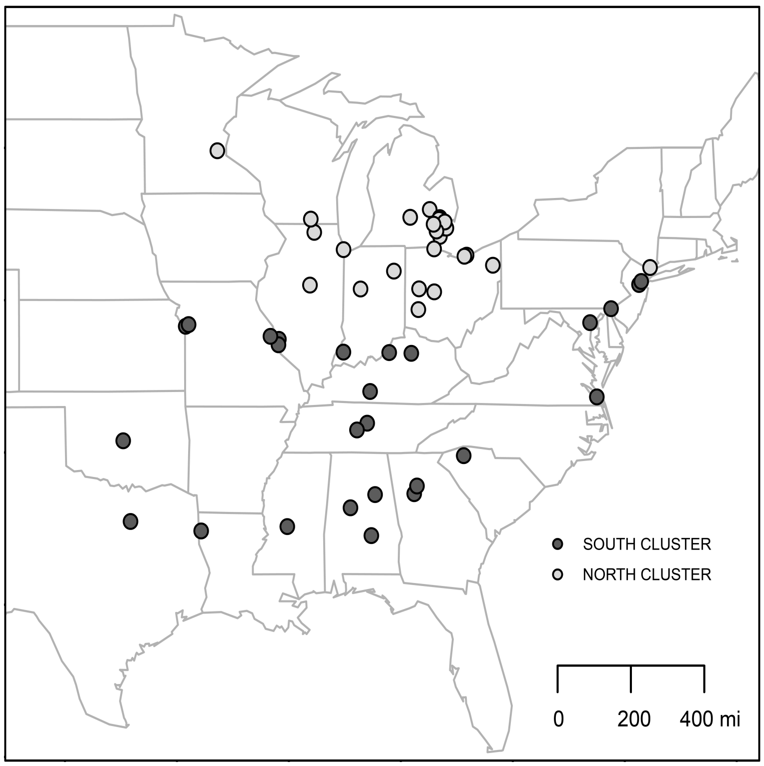

Figure 4: Weather-based clusters. The plant in Fremont, California (not shown) is classified within the South cluster.