RESEARCH REPORT SERIES
(Statistics #2022-01)

Accommodating Weather Effects in Seasonal Adjustment: A Look into Adding Weather Regressors for Regional Construction Series

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Report Issued: February 16, 2022

Accommodating Weather Effects in Seasonal Adjustment:
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Abstract

Seasonal adjustment is the process of removing regular seasonal patterns from a time series. While weather effects can be seasonal, their variation from year to year can be greater than what would normally be the case for a regular seasonal pattern. Failure to account for a weather effect may result in observations that are unfortunately regarded as outliers, so there may be some interpretive value in being able to accommodate weather effects for seasonal adjustment. In this paper, we use weather data to construct regressors for use in modeling series likely to experience weather effects. We wish to consider the following questions: (1) Does the use of weather regressors help improve a model that is estimated without them? (2) How well does their inclusion in a model explain outliers that are identified by models without? (3) To what extent does their inclusion affect a seasonal adjustment? We find that the weather regressors used can result in better models, that they do explain some, but not all, outliers, and that the difference between a seasonally adjusted series and a seasonal and weather adjusted series can be quite pronounced for some months.

1 Introduction

A time series is typically viewed as consisting of a trend, cycle, seasonal, and irregular components. That is, for a time series X_t, or some appropriately transformed version $f(X_t)$ of that time series, we have

$$f(X_t) = T_t + C_t + S_t + I_t,$$

where T_t, C_t, S_t, and I_t represent the trend, cycle, seasonal, and irregular components, respectively. For series that are recorded at regular intervals within a year, the seasonal component represents the variation that is related to the calendar. For data analysts, the underlying long-term behavior of the series (represented by the trend and cycle) is generally of greater interest, and seasonal fluctuations are noise that may obfuscate this behavior. Hence, the goal of seasonal adjustment is to separate the seasonal component from the nonseasonal component of the series. While weather is an observable phenomenon that reflects seasonality, its movements from year to year may vary to an extent that is beyond the usual scope of a seasonal component. Many government agencies release seasonally adjusted versions of collected data; when external users observe something unusual in the released seasonal adjustment, a frequent inquiry is whether this anomaly can be explained by the weather.

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Multiple economic papers have explored the relationship between weather abnormalities and economic activity in the past. The real estate market, from the perspective of construction, is one sector where weather can be expected to have an impact. Noting that unusual weather conditions were frequently used to explain unexpected figures for various housing statistics, Goodman (1987) looked at the relationship between weather abnormalities and housing activity. Regressing some housing-specific dependent variables against a derived set of weather regressors plus a set of monthly dummy variables (representing monthly seasonal factors), he found that unseasonal weather patterns had minimal impact at a national level, and only slightly more so for some regions of the U.S.; furthermore, this effect was confined to winter months only. He concluded that sampling error was the more significant determinant for the observed month-to-month changes in housing statistics and that the influence of unusual weather on national housing data was exaggerated.

Like Goodman (1987), Cammarota (1989) also looked at housing starts at both national and regional levels. But while Goodman (1987) only considered a summer effect versus a winter effect, Cammarota (1989) allowed for the impact of unseasonable weather to be different for each month, and his models included lagged effects for both the dependent variables and the various month-specific regressors. He found that unseasonable weather had a significant effect on housing starts in the first quarter of the year, especially at a regional level, but that there was no evidence at either a national or regional level for the existence of an offset in subsequent months to mitigate the effects of those weather abnormalities.

Coulson and Richard (1996) tried a different approach by using a vector autoregression to model temperature, precipitation, housing starts, and housing completions simultaneously for each of the four Census regions.[1] They found similar results to Goodman (1987) and Cammarota (1989) in the existence of a "small, but not insubstantial, effect" for unseasonable weather. They noted that temperature shocks were more prominent in cold regions, that precipitation mattered more than temperature in the South, and that neither mattered much in the West.

Fergus (1999) confirmed some of the previous results, finding that deviations from normal in either precipitation or temperature in January and February had "significant contemporaneous effects on the change in housing starts at the national level," and that the magnitude of these effects was "quite substantial." He also found that there were effects associated with abnormal precipitation in June and December as well as an effect associated with unusual temperature for March. He noted that unusual precipitation or temperature deviations were significant in different months by region. Unlike the previous papers, however, he found that there were statistically significant lagged adjustments that in many cases offset the contemporaneous weather effects, suggesting that the long-term effect of abnormal weather is not pronounced.

Looking at housing price indices instead of housing starts/completions, Ewing et al. (2007) considered severe wind events in a set of metropolitan statistical areas that were vulnerable to hurricanes, tornadoes, or both. They found that while there was a short-term decline in housing prices following a severe wind event, the type of wind event did not appear to matter; that is, even though hurricanes and tornadoes are different in behavior, their impact on the housing market is similar.

More recent research has also examined the link between unusual weather conditions and activity in the retail sector. Bertrand et al. (2015) looked at the impact of unexpected temperature deviations on apparel sales in France. Appelqvist et al. (2016) performed a similar study for sporting goods in Finland and Switzerland, Arunraj and Ahrens (2016) looked at both food and fashion retail in a region of Germany, and Sandqvist and Siliverstovs (2018) investigated Swiss retail sales

[1] These are Northeast, Midwest, South, and West. For a listing of state mapping to region, see `https://www.census.gov/programs-surveys/economic-census/guidance-geographies/levels.html#par_textimage_34`.

data. Steinker et al. (2017) looked at the effect of weather on e-commerce, finding that incorporating weather forecasts could both improve the accuracy of sales forecasts and reduce costs for a large European fashion retailer. Moon et al. (2018) looked at the effect weather events had on consumer spending habits on trips to the grocery store.

On a broader economic level, Saad-Lessler and Tselioudis (2010) considered climate change theories on storms and analyzed the effect of these predicted changes on some U.S. industries (and the overall economy). To do this, they used annual data on storm frequency and intensity and found that yearly deviations from a state-specific or year-specific average had a statistically significant effect for the particular state's gross domestic product (GDP) for a number of industries. Their results suggested that while a predicted drop in storm frequency would result in a small (as a proportion of national GDP) loss, a predicted increase in storm intensity would have no significant impact on the economy; that is, while the effects of storms may be statistically significant, they are not economically significant.

Boldin and Wright (2015) looked at the effect of adjusting a series for both seasonal and weather effects, using employment data as an example. Whereas Goodman (1987) took monthly data for temperature and precipitation from a set of 28 weather stations and then associated the rest of the country with one of those stations in order to construct some national or regional level index, Boldin and Wright (2015) used a weighted average based on passenger numbers from the 50 largest U.S. airports (with passenger numbers treated as a proxy for economic activity). They ultimately used a temperature regressor interacted with monthly dummies, a snowfall regressor, and a monthly regressor for hurricane damage as their set of weather regressors. Using total nonfarm payrolls to illustrate their methodology, they showed that adjusting for seasonality and weather could produce a sizable shift in the jobs estimate relative to adjusting for only seasonality.

Like Boldin and Wright (2015), Schreiber (2017) looked at incorporating adjustments for weather effects into seasonally adjusted data. As was the case for Boldin and Wright (2015), temperature and snowfall are both considered relevant, although Schreiber (2017) adds snow height to his model. The weather regressors used were found to be significant for a batch of monthly German economic series, and the model with weather regressors was found to perform better than a benchmark autoregressive model.

The work in this paper is similar to that of Boldin and Wright (2015) and Schreiber (2017) in that it attempts to answer the questions "Does the inclusion of weather data improve models that have been produced without them?" and "To what extent does the inclusion of weather data affect a seasonal adjustment?" There is an additional question of interest that does not appear to have been addressed previously: "Can the inclusion of weather data explain observations that were previously identified as outliers?" That is, if an observation is deemed an outlier by a model that omits weather, is it still an outlier even after weather effects are included in a model? Section 2 discusses the weather data and how regional regressors were formed using station-specific observations. Section 3 gives a brief overview of how the weather regressors are used as part of a regARIMA model for a time series. Section 4 gives an example applying a set of weather regressors to a regional series on Midwest single-unit housing starts. Section 5 does the same for the Northeast. Section 6 summarizes the findings and considers some other potential avenues to explore.

2 Weather Data

The weather data come from the National Oceanic and Atmospheric Administration's National Centers for Environmental Information (formerly the National Climatic Data Center). Individual weather stations record this data, so our initial plan was to select a sufficiently large number of

Variable	Description
Number of days in a month that satisfy a condition	
DP01	At least 0.1 inch of precipitation
DP05	At least 0.5 inch of precipitation
DP10	At least 1.0 inch of precipitation
DT00	Minimum temperature less than or equal to 0F
DT32	Minimum temperature less than or equal to 32F
DT90	Maximum temperature at least 90F
DX32	Maximum temperature less than or equal to 32F
Monthly extreme values	
EMXP	Maximum daily precipitation
MXSD	Maximum snow depth
EMNT	Minimum temperature
EMXT	Maximum temperature
Monthly totals	
TPCP	Precipitation
TSNW	Snowfall
Monthly averages	
MMNT	Minimum temperature
MMXT	Maximum temperature
MNTM	Average temperature (averaging min. and max. temperatures)

Table 1: Variables from monthly summary data; while the units used in the thresholds of the first group were inches and Fahrenheit, the other groups are metric—mm and Celsius. Note that threshold variables overlap, such that DP01 $\geq$ DP05 $\geq$ DP10 and DX32 $\geq$ DT32 $\geq$ DT00. Data sourced from U.S. National Oceanic and Atmospheric Administration, National Centers for Environmental Information.

stations across the country to cover most major U.S. metropolitan areas, in addition to the state capitals for some smaller states. In total, the weather station data cover 92 cities. The data collected for the time span January 1944 through December 2014 were monthly summary data; the data obtained for more recent years were daily weather records (Menne et al., 2012a,b), which we subsequently aggregated to monthly summary data to maintain consistency with the previously collected data. The weather variables of interest can be classified into one of four categories: (i) the number of days in a month where some condition is satisfied (some of these conditions are contained within others), (ii) the extreme values for a month, (iii) the total values for a month, and (iv) the average value for a month. Table 1 lists the specific variables that fall into each of these categories, with the original four-character monthly designation and a description provided.

2.1 Converting Station Data to City Data

Weather stations are associated with nearby cities, and each city maps uniquely to a state, Census division, and Census region. There may be cases where the same weather station is close enough to two cities that it may be viewed as providing data for both (e.g., Saint Paul/Minneapolis in Minnesota or Norfolk/Virginia Beach in Virginia), just as there may be cases where the geography for a station is different from that of an associated city (a weather station in Arkansas may end up mapped to Memphis, Tennessee, even though Tennessee belongs to the East South Central Census division, while Arkansas is in West South Central). Given that we do not intend to examine geographies finer than Census region, the latter should not prove problematic. The mapping scheme results in each city having an associated set of weather stations. However, monthly weather values are not necessarily available for every variable at every weather station. For any variable in Table

1, to obtain a monthly value for a city, an improvised solution to station-specific missing values is to splice together data from associated weather stations. To illustrate, suppose that for some city and some (weather) variable x, we have data for three weather stations, with the following observations at the beginning of those series:

$$\begin{array}{llllllll}
\text{Station A} & x_{A1} & x_{A2} & & & & x_{A6} & x_{A7}, \\
\text{Station B} & & x_{B2} & x_{B3} & & x_{B5} & & x_{B7}, \\
\text{Station C} & & & & x_{C4} & x_{C5} & x_{C6} & x_{C7}.
\end{array}$$

For the three stations displayed, splicing the data would yield the city series that starts with

$$x_{A1} \quad f(x_{A2}, x_{B2}) \quad x_{B3} \quad x_{C4} \quad f(x_{B5}, x_{C5}) \quad f(x_{A6}, x_{C6}) \quad f(x_{A7}, x_{B7}, x_{C7}).$$

That is, we apply some scalar function f to the available station data at a given time point, with the value of the function treated as the corresponding city value. Any summary measure, such as the minimum/maximum, median, or mean, could be a viable option for this function; this also mitigates the effect of potentially attaching the same station to multiple cities. This report chooses to use the median as this summary function f; while the weather across stations for a single city should not vary considerably, the median protects against the possibility of an erroneous recording better than the mean would. An additional step is performed for weather variables that are counts for the number of days: these values are normalized by dividing by the number of days in the corresponding month. This step may help adjust for minor variations that could arise due to differing length of month (and potential leap year effects). The calendar mean is then subtracted out as follows: if x_t is the monthly value for a variable at time t, then the mean-centered value is given by

$$\tilde{x}_t = x_t - \frac{1}{N} \sum_{\delta=1}^{20} x_{t-12\delta}.$$

Since the splicing process does not guarantee the elimination of all missing values for some cities in some months, N in the expression above depends on the number of records that actually do exist in the 20-year window. Note also that x_t is not included in the calculation of that rolling mean. Even though the first full 20-year window in our data begins at January 1964, our mean-centered series will start at January 1960.

2.2 Using City Data to Obtain Regional Data

The previous discussion outlined one method for aggregating from a station level for weather data to a city level. As our intended data for examples are regional in scope, it is therefore necessary to aggregate these weather variables from a city level to a regional level, but this can be generalized to any geography larger than city (or completely ignored if the geography of interest is city). A weighting scheme that reflects some measure of “size” for each city in its corresponding region would appear to be warranted in this situation; population would appear to be a fairly logical choice, so we consider the following two frameworks for weighting:

1. Weighting by city population only: For a given variable, any city without a recorded value for a particular month is omitted for that month. Every other city is assigned a weight in that month equal to

$$\frac{\text{previous Census population for city}}{\text{sum of previous Census population for nonmissing cities in region}}.$$

Any city with a missing value may be viewed as having a population of zero for that month in this weighting scheme, and the regional value for each variable is thus obtained by computing the weighted average of the available (mean-centered) city values. Hence, if $c_{k,x,t}$ is the weight associated with city k and variable x in a region K at time t and $\tilde{x}_{k,t}$ is the mean-centered value of variable x for city k at time t, then the regional value at time t is given by

$$V_{K,t} = \sum_{k \in K} c_{k,x,t} \tilde{x}_{k,t}.$$

2. Weighting by both city and state population: This process takes two steps, with each step similar in spirit to that of the previous scheme. Again, any city without a recorded value for a given variable in a particular month is omitted for that month (treated as though its population were zero). Every other city is first given an intrastate weight (reflecting its size relative to those of the other in-sample cities in the same state); then that state is given a within-region weight (reflecting its size relative to those of the other in-sample states in the same region), applying a similar calculation. The resulting weight for the city is obtained by multiplying the city's intrastate weight and the state's within-region weight. That is, for any city with an observed value for a particular month, its weight in that month is given by

$$\frac{\text{previous Census population for city}}{\text{sum of previous Census population for nonmissing cities in state}} \times \frac{\text{previous Census population for state}}{\text{sum of previous Census population for states in region}}.$$

The regional value for each variable is thus the corresponding weighted average of the (mean-centered) city values: if $\tilde{c}_{k,x,t}$ is the weight of city k inside state K for variable x at time t, and $s_{K,x,t}$ is the weight of state K inside region L at time t, and $\tilde{x}_{k,t}$ is the mean-centered value of city variable x for city k at time t, then the regional value at time t under this approach is

$$V_{L,t} = \sum_{k \in L} \tilde{c}_{k,x,t} s_{K,x,t} \tilde{x}_{k,t}.$$

There are benefits to each scheme. For an economic series, as more activity tends to occur in cities, the first weighting scheme's favoring of larger cities may make sense. However, it is also possible that within some regions, this weighting scheme may overemphasize one or two dominant cities—e.g., New York in the Northeast. The second weighting scheme adds an extra step in its calculation, but it does reduce the dominance of individual cities; in addition, it can potentially elevate states that have large populations, but not necessarily a single large city—e.g., Ohio and Illinois may be in the same general neighborhood with respect to population, but no city in Ohio compares in population to Chicago.

For population figures, we used decennial Census numbers between 1960 and 2010, inclusive, for the cities and states contained within the weather data. This choice results in the population numbers, and consequently the weights, being held fixed for a decade and thus may not reflect the year-to-year population changes between censuses. Nevertheless, the two weighting schemes described above should suffice for the time being.

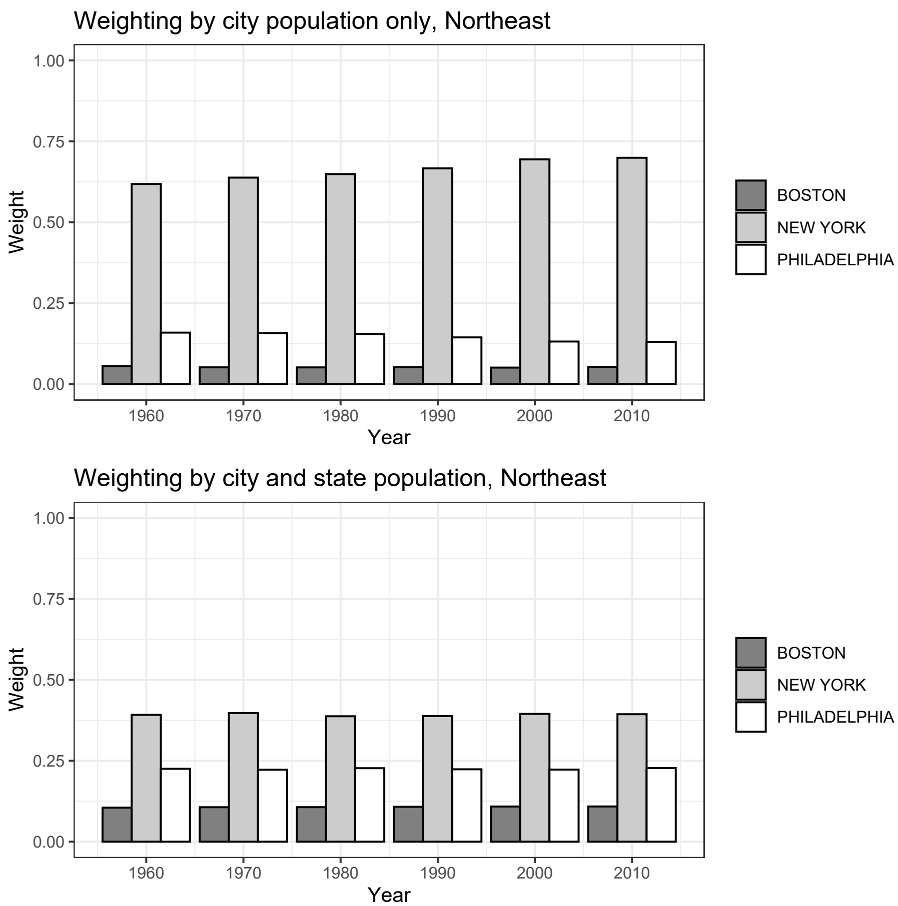

Figure 1: Comparison of weights for the two weighting schemes for 3 Northeast cities: by city population only (top) and by both city and state population (bottom). Population data sourced from U.S. Census Bureau, Decennial Census of Population and Housing, 1960–2010.

For illustrative purposes, Figure 1 shows the comparative Northeast weights for Boston, New York, and Philadelphia under the two weighting schemes using decennial Census population counts for both cities and states. The top plot shows the respective city weights (weighting scheme 1), while the bottom plot shows the corresponding city-and-state weights (weighting scheme 2). As noted previously, the first scheme may overemphasize singularly large cities within a region (like New York), while the second scheme reduces the weights attached to those same cities.

2.3 Summary

The procedure suggested for converting monthly summary weather data (or daily weather records that have been aggregated to monthly summary data) into a regional regressor is as follows:

1. Monthly summary data for the set of weather variables is obtained from weather stations.

2. Weather stations within a certain range of a city are assigned to that city (and consequently, to a Census division and region), with the proviso this assignment need not be one-to-one. A city value for each weather variable is obtained by taking some summary statistic (mean,

max, min, median) for those associated weather stations. This report uses the median as the summary statistic.

3. For weather variables that are counts of days in a month, this city value is transformed by dividing the count by the number of days in the corresponding month; this results in a quantity that represents the proportion of the month for which a condition was satisfied.

4. Each city value is then mean-centered by subtracting the corresponding month-specific average over the previous 20 years (subject to missing values).

5. Population weighting is applied to all city values within that region. Cities with a missing value for a particular month are omitted (equivalent to being assigned a weight of 0). Otherwise, the weights proposed are either (1) city population from previous Census divided by total regional population of non-missing cities or (2) city population from previous Census divided by total state population of non-missing cities times state population from previous Census divided by total regional population of nonmissing states.

6. Each city contributes its mean-centered value times its weight to a regional value, and the weighted sum over the cities yields a value for a regional regressor.

This is similar in spirit to the process used by Boldin and Wright (2015), albeit with some differences based on form of weather variable and weighting scheme used. For convenience, we use the variable names from Table 1 interchangeably with the corresponding regressors formed from those variables.

3 Modeling with Weather Regressors

Suppose a time series y_t is a candidate for seasonal adjustment. In the absence of any regressors, an initial step in X-13ARIMA-SEATS would be to fit an ARIMA model, possibly seasonal, to this series:

$$\phi(B)\Phi(B^s)(1-B)^d(1-B^s)^D y_t = \theta(B)\Theta(B^s)a_t,$$

where B is the backshift operator (i.e., $By_t = y_{t-1}$, $B^s y_t = y_{t-s}$), s is the seasonal period, $\phi(B)$ and $\Phi(B^s)$ are the nonseasonal and seasonal autoregressive (AR) polynomials, $\theta(B)$ and $\Theta(B^s)$ are the nonseasonal and seasonal moving average polynomials, and a_t is white noise process with variance σ^2. A model with the form above would be described as an ARIMA $(p\ d\ q)(P\ D\ Q)_s$. Suppose instead that there are regressors (in this report, these would be weather-related) $x_{i,t}$. The previous model is then modified so that the ARIMA model is applied to the residuals of the linear regression of y_t on the set of $x_{i,t}$; i.e., the above is now

$$\phi(B)\Phi(B^s)(1-B)^d(1-B^s)^D \left(y_t - \sum_i \beta_i x_{i,t}\right) = \theta(B)\Theta(B^s)a_t,$$

where the β_i's are the coefficients obtained by performing a linear regression of y_t against the set of $x_{i,t}$.

There are a few points of interest with respect to the inclusion of weather regressors for time series modeling and seasonal adjustment:

1. Is it worth including a weather regressor to model series for which weather effects are suspected to be present? (Model selection)

2. Instead of including a regressor as is, an alternate approach might use the interaction of the regressor with the set of (12) seasonal indicators to form a set of month-specific regressors. If the inclusion of a weather regressor is warranted, would it be better to use a full regressor or to include only a subset of month-specific regressors? (Model selection)

3. What is the effect of accounting for weather in a seasonal adjustment relative to not accounting for weather? That is, is it possible to quantify the extent to which a seasonal adjustment being higher or lower than expected is attributable to the weather?

4. Does the inclusion of a weather effect help explain some previously identified extreme observations in a time series? (Outlier identification)

Monthly data from the Survey of Construction on regional housing starts for single-family housing units will be used to consider these topics.[2] While the data cover a longer span of time, we will focus only on the timespan from January 1970 through December 2019. Similarly, we consider only the series of unadjusted estimates, even though seasonally adjusted estimates are also available. As a first step, a run in X-13ARIMA-SEATS will be performed with no weather regressors; the model form will be fixed as a $(0\ 1\ 1)(0\ 1\ 1)_{12}$ seasonal ARIMA model—the airline model of Box et al. (2015). We use the default settings of X-13ARIMA-SEATS to determine transformation, outliers, and trading-day and Easter regressors. The seasonal adjustments will be obtained using the X-11 procedure within X-13ARIMA-SEATS; note that this approach will yield seasonal adjustments that may not necessarily coincide with the adjustments obtained by the Census staff responsible for this survey. The entire process will be done for the full series, as well as two disjoint subspans of the series: January 1970 through December 1999 and January 2000 through December 2019. Taking the transformation of the response, trading-day and Easter regressors, and automatically identifed outliers chosen by X-13ARIMA-SEATS, we introduce regional regressors based on the weather variables listed in Table 1.

4 Example 1: Midwest Regional Single-Family Housing Starts

4.1 Initial Modeling with Single-Regressor Models

It has been suggested previously that construction series are more affected by winter than by the other seasons; in addition, it has been observed that the regional effects of weather on construction are more pronounced in the Midwest and the Northeast. Hence, our first example looks at regional housing starts in the Midwest. Using X-13ARIMA-SEATS, we fit the aforementioned $(0\ 1\ 1)(0\ 1\ 1)_{12}$ model to the full Midwest Housing Starts series, with the resulting estimated model:

- log transformation;
- 1-coefficient trading-day regressor `td1coef`;[3]
- 7 point (additive) outliers: `AO1973.Jan`, `AO1973.Dec`, `AO1977.Jan`, `AO1981.Feb`, `AO1982.Feb`, `AO2011.Dec`, and `AO2014.Jan`;

[2] The housing starts estimates were obtained at `https://www.census.gov/econ/currentdata/dbsearch?program=RESCONST&startYear=1959&endYear=2020&categories=APERMITS&dataType=TOTAL&geoLevel=US&adjusted=1&notAdjusted=0&errorData=0`. They are subject to sampling and nonsampling error, and possibly measurement error. See `https://www.census.gov/construction/nrc/how_the_data_are_collected/soc.html` for more information on the methodology behind the Survey of Construction.

[3] The regressors used here are defined in Chapter 4 of the X-13ARIMA-SEATS reference manual (U.S. Census Bureau, 2021).

- 5 level shifts: `LS1979.Jan`, `LS1979.Mar`, `LS1980.Jan`, `LS1980.Sep`, and `LS2008.Dec`.

While the individual subspans may yield slightly different outliers, we shall treat this set of outliers as fixed for the time being. Note also that the outliers identified are almost all in winter.

Since the two weighting schemes produce similar values for the regional regressors, we will only provide results for the second one that weights by both city and state population. Each regional regressor is added individually to the above model, and the model is re-estimated. The AICC (Hurvich and Tsai, 1989), an F-adjusted version of the AIC (Akaike, 1973), will be used to determine whether the model with a weather regressor is a better fit to the series than a model without. Table 2 shows the value of AICC for each regression model containing one of the weather regressors, as well as the change in AICC relative to the base model (a negative change corresponds to a drop in AICC). Highlighted rows in the table (and the following tables of this example) indicate regressors whose inclusion decreased the AICC by at least 5 for both subspans.

Looking at Table 2, it is observed that adding the regional regressor derived from the number of days in a month where the maximum temperature is above 90 degrees F (DT90) yields an increase in the AICC relative to the base model with no regressors, and this holds for the full series as well as the two disjoint subspans. Hence, for the Midwest, this weather variable can probably be ignored going forward. On the other hand, adding either the number of days in a month where the maximum temperature is below 32 degrees F (DX32) or the number of days in a month where the minimum temperature is below 0 degrees F (DT00) results in the largest observed decreases in the AICC relative to the base model. That is, in the Midwest, low temperatures seem to be of greater concern than high temperatures. This is also noticeable when considering the regressors derived from extreme monthly temperatures—adding the one based on extreme minimum temperature has a larger effect on the AICC than the one based on the extreme maximum.

The regressors based on snowfall significantly change the AICC when added to the base model. Both have about the same effect on the full series, but their impact on the subspans is different: total snow decreases the AICC slightly more on the first subspan (1970 through 1999), while maximum snow depth decreases the AICC slightly more on the second subspan (2000 through 2019). The regressors based on precipitation appear to be less valuable compared to those based on low temperatures or snowfall. Of the three precipitation thresholds, the lowest (0.1 inch) appears to have the strongest effect on the AICC for the full series and the first subspan of 30 years, whereas the middle (0.5 inch) appears to have a slightly stronger effect for the second subspan of 20 years. Overall, the best individual regressors from an AICC perspective deal with either temperature or snowfall.

Table 3 shows the estimated models when fitting a $(0\ 1\ 1)(0\ 1\ 1)_{12}$ seasonal ARIMA model with one of the city-and-state-weighted weather regressors to a log-transformed housing starts series. The inclusion of a weather regressor does not appear to have much effect on the estimates of the nonseasonal moving average $\widehat{\theta}_1$ and seasonal moving average $\widehat{\theta}_{12}$. We had noted previously that adding a regressor derived from DT90, the number of days where the maximum temperature exceeded 90 degrees F, to the model resulted in a higher AICC than was obtained for the base model. The t-statistics for the regressor over the various spans also reinforce the belief that this variable is not significant. The only other regressor with nonsignificant t-statistics across the board is the one based on extreme maximum precipitation. For the other regressors, the magnitude of the t-statistic in the second subspan tends to be smaller than what is obtained in modeling the full series or the first subspan, but the regressors accounting for the largest drops in AICC do end up also accounting for the largest (in magnitude) t-statistics on the corresponding coefficient estimates. Although multiple temperature regressors are being fit, the information they account for is different—the minimum, maximum, and average temperature regressors are based on temperature

Variable	1970.1–2019.12 AICC	1970.1–2019.12 Δ_{AICC}	1970.1–1999.12 AICC	1970.1–1999.12 Δ_{AICC}	2000.1–2019.12 AICC	2000.1–2019.12 Δ_{AICC}
None	2524.4		1585.2		895.5	
DP01	2509.8	−14.6	1574.3	−10.9	893.7	−1.8
DP05	2515.0	−9.4	1579.9	−5.4	893.3	−2.2
DP10	2522.0	−2.4	1584.1	−1.1	896.3	0.8
DT00	2410.0	−114.4	1506.3	−79.0	856.8	−38.7
DT32	2510.9	−13.5	1574.8	−10.4	893.3	−2.2
DT90	2526.5	2.1	1587.4	2.2	897.5	2.0
DX32	2406.5	−117.9	1490.9	−94.4	862.7	−32.8
EMXP	2524.1	−0.3	1585.8	0.6	896.7	1.2
MXSD	2466.6	−57.8	1553.9	−31.3	869.3	−26.2
EMNT	2478.1	−46.3	1545.5	−39.8	886.3	−9.2
EMXT	2493.4	−31.0	1549.1	−36.2	894.4	−1.1
TPCP	2514.7	−9.7	1578.7	−6.5	894.2	−1.3
TSNW	2466.6	−57.8	1551.3	−33.9	872.9	−22.6
MMNT	2456.5	−67.9	1539.2	−46.0	872.8	−22.7
MMXT	2445.4	−79.0	1526.2	−59.1	873.7	−21.8
MNTM	2447.3	−77.1	1529.8	−55.5	872.4	−23.1

Table 2: AICC and change in AICC when adding city-and-state-weighted Midwest regional regressor to previously estimated model. Highlighted rows indicate regressors whose inclusion results in an AICC decrease of at least 5 in both of the subspans. Housing starts data sourced from U.S. Census Bureau, Survey of Construction.

Variable	1970.1–2019.12 $\widehat{\beta}$	t-stat	$\widehat{\theta}_1$	$\widehat{\theta}_{12}$	1970.1–1999.12 $\widehat{\beta}$	t-stat	$\widehat{\theta}_1$	$\widehat{\theta}_{12}$	2000.1–2019.12 $\widehat{\beta}$	t-stat	$\widehat{\theta}_1$	$\widehat{\theta}_{12}$
None			0.52	0.83			0.45	0.80			0.59	0.94
DP01	−0.384	−4.13	0.51	0.83	−0.425	−3.68	0.43	0.79	−0.319	−2.00	0.59	0.92
DP05	−0.625	−3.42	0.52	0.83	−0.626	−2.77	0.44	0.79	−0.650	−2.10	0.59	0.93
DP10	−0.817	−2.13	0.52	0.83	−0.862	−1.82	0.45	0.80	−0.768	−1.18	0.60	0.93
DT00	−1.388	−11.43	0.50	0.81	−1.332	−9.63	0.42	0.77	−1.570	−6.70	0.60	0.92
DT32	−0.244	−3.99	0.53	0.83	−0.283	−3.59	0.47	0.80	−0.204	−2.12	0.60	0.92
DT90	0.022	0.24	0.52	0.83	−0.010	−0.09	0.45	0.80	0.064	0.40	0.59	0.94
DX32	−0.603	−11.63	0.51	0.80	−0.680	−10.62	0.45	0.76	−0.535	−6.17	0.58	0.91
EMXP	−0.001	−1.55	0.52	0.83	−0.001	−1.25	0.45	0.80	−0.001	−0.98	0.60	0.94
MXSD	−0.010	−8.00	0.53	0.81	−0.011	−5.97	0.48	0.78	−0.011	−5.54	0.59	0.89
EMNT	0.012	7.12	0.53	0.82	0.013	6.69	0.47	0.79	0.011	3.42	0.61	0.93
EMXT	0.012	5.84	0.52	0.83	0.015	6.39	0.45	0.82	0.006	1.82	0.59	0.93
TPCP	−0.001	−3.47	0.52	0.83	−0.001	−2.97	0.44	0.79	−0.001	−1.86	0.60	0.93
TSNW	−0.001	−7.99	0.52	0.81	−0.001	−6.20	0.46	0.77	−0.001	−5.15	0.59	0.90
MMNT	0.022	8.65	0.52	0.82	0.023	7.20	0.47	0.79	0.022	5.13	0.60	0.91
MMXT	0.021	9.35	0.52	0.82	0.024	8.19	0.46	0.79	0.019	5.04	0.59	0.91
MNTM	0.023	9.24	0.52	0.82	0.024	7.93	0.46	0.79	0.021	5.18	0.59	0.91

Table 3: RegARIMA model estimates when adding a city-and-state-weighted regressor to a model of log-transformed Midwest Housing Starts over the designated spans. Housing starts data sourced from U.S. Census Bureau, Survey of Construction.

measures, so positive coefficient estimates are expected, whereas the others are measuring extremes to some extent, so negative coefficient estimates are expected.

4.1.1 Outlier Checking

One of the interests was to see whether anomalous observations (outliers) could be explained by the addition of a weather regressor to a model that did not include them. For this, we use the outlier identification routines contained in the X-13ARIMA-SEATS software. Our previous discussion had kept the set of outliers fixed to the ones identified by the base model. Here, while we retain the log-transformation of the series and one-coefficient trading-day regressor from the base model, we re-estimate all models to obtain regressor- and subspan-specific sets of outliers. The next step is to see whether any of the previously identified outliers are now explainable by the various regressors.

Table 4 shows any dates that have been identified as an outlier in one of the models. For each regressor, we indicate which dates were flagged as outliers, whether the flagging occurred for the full series, the relevant subspan, or both, as well as what type of outlier was identified. For example, in the base model, we see that September 1980 has an entry "LS/"—this means that there was a level shift outlier at September 1980 in the base model when using the full series, but not over the relevant subspan (1970–1999). On the other hand, that same date in a model including average monthly maximum temperature (MMXT) has "/LS" as its entry: there was no level shift outlier when fitting using the full series, but there was one over the subspan.

We see that some outliers that existed in the base model fit using the full series drop out when we adjust the model span to one of our two subspans (January 1973, September 1980, December 2011). We also see that some of the regressors when added to the model result in the identification of additional outliers—maximum snow depth (MXSD) adds a level shift at July 1980 when included in a model estimated over the full series, while the number of days where precipitation exceeded 0.5 inches (DP05) adds a point (additive) outlier at January 2009. Many of the weather variables yield regressors whose addition to the model will account for some of the outliers that were identified by the base model. The regressor based on the number of days where the minimum temperature was below 0 degrees Fahrenheit (DT00) appears to be particularly effective in this regard, as its inclusion accounts for outliers from the base model at January 1977, January 1979, March 1979, December 2008, and January 2014 over both the full series and the appropriate subseries. To a lesser extent, the regressors based on snowfall also account for some of the outliers in the base model.

4.2 Using Month-Specific Regressors

As mentioned previously, the interaction of the full regressor with the set of 12 seasonal indicators forms a set of month-specific regressors. This construction reflects the belief that only some months matter for some of the weather variables—e.g., snowfall in summer would be exceedingly rare, so a uniform sequence of zeroes for summer months would not be surprising. Under this modified approach, each regressor in the set is nonzero for the corresponding month only. That is, if V_t is the original regressor series, and $V_t^{(1)}, V_t^{(2)}, \cdots, V_t^{(11)}, V_t^{(12)}$ are the 12 month-specific regressor series, then $V_t^{(i)}$ is equal to V_t for month i and 0 otherwise. We apply this approach to the regressors in Table 2, again preserving the set of outliers originally identified for the base model for comparability.

Before proceeding with any AICC comparisons, the significant months for each variable under this month-specific approach should be determined. Hence, a $(0\ 1\ 1)(0\ 1\ 1)_{12}$ seasonal ARIMA model with a one-coefficient trading-day regressor is fit to the log-transformed starts. Table 5

Variable	1973 Jan	1973 Dec	1977 Jan	1979 Jan	1979 Mar	1980 Jan	1980 Jul	1980 Sep	1981 Feb	1982 Feb	2008 Dec	2009 Jan	2011 Dec	2014 Jan
None	AO/	AO/AO	AO/AO	LS/LS	LS/LS	LS/LS		LS/	AO/AO	AO/AO	LS/LS		AO/	AO/AO
DP01		/AO	AO/AO	LS/LS	LS/LS	LS/LS				AO/AO			AO/	AO/AO
DP05		/AO	AO/AO	LS/LS	LS/LS	LS/LS			/AO	AO/AO		/AO	AO/AO	AO/AO
DP10		/AO	AO/AO	LS/LS	LS/LS	LS/LS			/AO	AO/AO			AO/	AO/AO
DT00		AO/AO				LS/LS			/AO	AO/AO			AO/AO	
DT32		/AO	AO/AO	LS/LS	LS/LS	LS/LS			AO/AO	AO/AO	/LS		AO/	AO/AO
DT90		AO/AO	AO/AO	LS/LS	LS/LS	LS/LS			AO/AO	AO/AO	/LS		AO/	AO/AO
DX32		/AO	AO/AO	LS/LS	LS/LS	LS/LS		/LS	AO/AO	AO/AO				AO/AO
EMXP		/AO	AO/AO	LS/LS	LS/LS	LS/LS			/AO	AO/AO			AO/	AO/AO
MXSD			AO/AO	LS/LS		LS/LS	LS/	/LS	LS/LS	AO/AO				AO/AO
EMNT		AO/AO	AO/AO	LS/LS	LS/LS	LS/LS		LS/LS	LS/LS	AO/AO			AO/	AO/AO
EMXT		AO/AO	AO/AO	LS/LS	LS/LS	LS/LS			AO/AO	AO/AO			AO/AO	AO/AO
TPCP		/AO	AO/AO	LS/LS	LS/LS	LS/LS			/AO	AO/AO			AO/AO	AO/AO
TSNW			AO/AO	LS/LS	LS/LS	LS/LS				AO/AO				AO/AO
MMNT		AO/AO	AO/AO	LS/LS	LS/LS	LS/LS		LS/LS	AO/AO	AO/AO			AO/AO	AO/AO
MMXT		AO/AO	AO/AO	LS/LS	LS/LS	LS/LS		/LS	AO/AO	AO/AO	/LS		AO/AO	AO/AO
MNTM		AO/AO	AO/AO	LS/LS	LS/LS	LS/LS		LS/LS	AO/AO	AO/AO			AO/AO	AO/AO

Table 4: Outliers identified for Midwest Housing Starts using the city-and-state-weighted variables over both full span (first item) and appropriate subspan (second item). Data sourced from U.S. Census Bureau, Survey of Construction.

displays the t-statistics for the month-specific regressors associated with each of the regional regressors under this approach. For each regressor, the top row gives the estimates from using the full series, the middle row from using just the first subspan (1970–1999), and the bottom row from using just the second subspan (2000–2019). Any months that would have produced singularities in the regression matrix (i.e., the values for that month were 0 over the entire modeling span) were omitted and are represented with blank entries in the table.

Looking at Table 5, some general patterns emerge. With few exceptions (mostly among precipitation-based regressors), the month-specific regressors are weaker in the second subspan (2000–2019), judging by the magnitudes of the t-statistics. Regressors based on precipitation tend to see larger t-statistics for spring months (April, May, and to a lesser extent, March). Regressors based on snowfall (MXSD, TSNW) are prominent in winter months (December, January, and February). The regressors based on cold temperature (DT00, DT32, DX32) and the ones based on average temperature also have larger t-statistics in winter months, but there is some additional carryover into March and November. On the other hand, the regressor based on high temperature (DT90) is not significant for any month (in the sense that none of its t-statistics exceed 2 in magnitude).

Hence, the models are re-fit, keeping only the dummies that were significant in each span; the AICC for these new models are computed and will be compared against those for the models using the original regressor. Table 6 shows the AICC associated with using the set of significant month-specific regressors for each of the regressors listed; since DT90 does not yield any significant month-specific regressors for any of the modeled spans, that variable is omitted. For convenience, if we say X is the weather variable (and interchangeably, the regressor based on that variable), and S is the set of significant months for the month-specific variant, then we use X^S to indicate the month-specific regressor. Note that the AICC change displayed in Table 6 is always relative to the AICC of the base model (with no regressors). If none of the month-specific regressors were significant for a particular model span, there will be no entry to match against the AICC for the model with the full regressor over that same span.

Looking at Table 6, we see that the performance of the set of (significant) month-specific regressors relative to the single regressor is mixed. For the two best single regressors from before (DT00 and DX32), the month-specific regressors result in about the same reduction in AICC

Variable	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	−1.34	−1.71	−2.66	−2.24	−2.23	−1.09	−0.52	−1.05	−0.57	0.13	−1.02	−0.32
DP01	−0.40	−1.50	−2.49	−2.27	−2.30	−0.95	−0.66	−0.78	−1.07	−0.04	−0.75	−0.13
	−1.09	−1.16	−1.10	−0.98	−1.07	−0.44	0.15	−0.93	0.30	0.45	−0.74	−0.30
	−1.01	−1.61	−1.83	−1.89	−1.72	−1.22	−0.52	−0.90	−0.95	0.14	−0.96	0.43
DP05	−0.51	−0.73	−1.45	−1.63	−2.18	−1.05	−0.29	−0.39	−1.01	0.12	−0.87	0.31
	−0.48	−1.76	−1.39	−1.15	−0.45	−0.44	−0.34	−1.24	−0.32	0.21	−0.49	0.01
	−1.10	−0.74	−0.18	−1.40	−1.56	−1.11	−0.12	−0.26	−0.64	−0.91	−0.56	1.28
DP10	0.74	0.10	−0.11	−1.93	−2.23	−1.37	0.07	−0.30	−0.36	−0.52	−0.96	1.10
	−1.86	−1.17	−0.35	0.01	−0.28	−0.18	−0.24	−0.23	−0.58	−0.61	0.42	0.51
	−6.75	−9.20	−2.69	−1.16						−1.43	−1.24	−5.16
DT00	−6.41	−6.63	−2.92	−0.76						−1.67	−1.32	−5.22
	−2.77	−6.59	−0.92	−1.85						0.27	−0.09	−1.70
	−3.75	−5.57	0.38	−0.46	0.50	−0.53	0.89		0.69	−0.32	−0.62	−3.38
DT32	−4.50	−4.44	−0.12	1.01	0.55	−0.53	0.97		0.53	0.29	−0.94	−3.08
	−1.39	−3.66	0.34	−1.12	−0.03	−0.33	0.36		1.20	−1.18	0.14	−1.67
			0.90	0.28	0.88	0.34	−0.19	0.73	−0.50	−0.48	−0.35	
DT90			0.94	0.77	−0.10	−0.39	−0.18	0.53	−0.51	−0.47	−0.26	
			0.21	−0.67	1.23	0.87	−0.17	0.66	−0.15	−0.13		
	−6.28	−8.94	−2.44	−1.00	−1.08	0.92		1.10		−1.68	−1.07	−5.83
DX32	−6.89	−7.06	−2.78	0.89	−1.06	0.82				−0.65	−1.62	−4.85
	−2.29	−6.14	−0.58	−2.23		0.87		1.07		−1.86	0.17	−3.37
	−0.99	−0.52	−0.85	−1.03	−2.20	−0.63	0.64	−0.67	−0.84	0.16	−0.01	1.10
EMXP	0.34	0.67	−0.71	−1.75	−2.74	−1.11	0.88	−0.21	−0.69	−0.19	−0.41	0.97
	−1.44	−1.92	−0.87	0.38	−0.38	0.27	0.14	−0.81	−0.56	0.51	0.54	0.36
	−4.99	−6.17	−0.72	−0.94	−0.95				0.60	−0.73	−0.91	−4.79
MXSD	−4.75	−4.31	−1.34	0.16	−0.62				0.59	−0.47	−0.32	−3.93
	−2.00	−5.06	−0.06	−2.02	−0.79				0.40	−0.96	−1.13	−2.77
	5.25	7.73	2.48	0.35	0.23	0.36	0.78	−0.23	−0.98	−0.59	−0.11	4.00
EMNT	5.01	5.58	2.75	−0.59	−0.45	0.74	1.12	0.11	0.04	−1.05	0.01	5.02
	2.59	6.61	1.17	0.95	0.83	−0.14	0.03	−0.90	−1.89	0.91	0.06	0.45
	3.76	4.53	0.74	0.36	0.86	0.26	−0.06	0.41	−0.50	−0.17	3.14	4.09
EMXT	5.29	3.74	1.96	1.34	0.03	−0.69	0.35	0.67	−0.18	−0.26	3.65	3.26
	0.45	2.91	−0.88	−1.74	1.33	1.12	−0.32	−0.08	−0.42	0.12	0.64	2.29
	−1.20	−1.59	−1.85	−1.92	−2.17	−1.21	−0.29	−0.70	−0.88	−0.04	−0.84	0.08
TPCP	−0.06	−0.59	−1.58	−2.09	−2.65	−1.31	−0.29	−0.43	−0.87	−0.12	−0.76	0.11
	−1.10	−1.92	−1.08	−0.64	−0.64	−0.32	0.01	−0.83	−0.41	0.27	−0.41	−0.18
	−4.77	−5.69	−0.32	−1.03	−1.74	−0.83		−0.09	0.72	−0.63	−0.72	−3.94
TSNW	−4.38	−3.68	−0.88	0.62	−2.01				0.73	−0.29	−0.68	−3.49
	−2.30	−4.50	0.33	−2.17	−0.90	−0.77		−0.24	0.42	−0.82	−0.40	−2.35
	7.00	9.36	1.66	1.27	0.20	−0.38	−0.61	−0.05	−0.64	0.47	1.28	5.25
MMNT	7.04	7.14	1.91	−0.04	−0.81	−0.34	−0.46	0.32	−0.29	−0.71	1.75	4.92
	2.89	6.69	0.74	1.43	1.18	−0.15	−0.50	−0.56	−0.51	1.92	0.04	2.32
	6.52	8.98	2.06	2.57	1.07	0.19	−0.41	0.34	−0.76	0.81	2.71	5.80
MMXT	6.90	7.04	3.12	1.83	0.31	−0.25	−0.15	0.66	−0.20	−0.70	2.80	5.12
	2.41	5.95	0.36	1.65	1.32	0.58	−0.45	−0.26	−0.67	1.72	0.88	2.88
	6.89	9.33	1.89	2.03	0.67	−0.10	−0.53	0.15	−0.77	0.66	2.14	5.60
MNTM	7.09	7.24	2.59	1.02	−0.21	−0.32	−0.31	0.51	−0.30	−0.75	2.41	5.10
	2.70	6.39	0.54	1.57	1.27	0.27	−0.50	−0.42	−0.62	1.87	0.55	2.62

Table 5: t-statistics using month-specific regressors for Midwest Housing Starts. Housing starts data sourced from U.S. Census Bureau, Survey of Construction.

	1970.1–2019.12		1970.1–1999.12		2000.1–2019.12	
Variable	AICC	Δ_{AICC}	AICC	Δ_{AICC}	AICC	Δ_{AICC}
None	2524.4		1585.2		895.5	
DP01	2509.8	−14.6	1574.3	−10.9	893.7	−1.8
DP01$^{\{3,4,5\}}$	2515.0	−9.4	1577.2	−8.1		
DP05	2515.0	−9.4	1579.9	−5.4	893.3	−2.2
DP05$^{\{5\}}$			1583.5	−1.7		
DP10	2522.0	−2.4	1584.1	−1.1	896.3	0.8
DP10$^{\{5\}}$			1583.0	−2.3		
DT00	2410.0	−114.4	1506.3	−79.0	856.8	−38.7
DT00$^{\{1,2,3,12\}}$	2406.8	−117.6	1506.6	−78.6		
DT00$^{\{1,2\}}$					857.2	−38.2
DT32	2510.9	−13.5	1574.8	−10.4	893.3	−2.2
DT32$^{\{1,2,12\}}$	2479.1	−45.3	1544.9	−40.3		
DT32$^{\{2\}}$					886.2	−9.2
DX32	2406.5	−117.9	1490.9	−94.4	862.7	−32.8
DX32$^{\{1,2,3,12\}}$	2408.9	−115.5	1496.8	−88.4		
DX32$^{\{1,2,4,12\}}$					856.4	−39.1
EMXP	2524.1	−0.3	1585.8	0.6	896.7	1.2
EMXP$^{\{5\}}$	2522.1	−2.3	1580.9	−4.3		
MXSD	2466.6	−57.8	1553.9	−31.3	869.3	−26.2
MXSD$^{\{1,2,12\}}$	2463.4	−61.0	1551.5	−33.8		
MXSD$^{\{1,2,4,12\}}$					868.5	−27.0
EMNT	2478.1	−46.3	1545.5	−39.8	886.3	−9.2
EMNT$^{\{1,2,3,12\}}$	2440.6	−83.8	1521.6	−63.6		
EMNT$^{\{1,2\}}$					858.6	−36.9
EMXT	2493.4	−31.0	1549.1	−36.2	894.4	−1.1
EMXT$^{\{1,2,11,12\}}$	2479.7	−44.7	1538.0	−47.2		
EMXT$^{\{2,12\}}$					888.0	−7.5
TPCP	2514.7	−9.7	1578.7	−6.5	894.2	−1.3
TPCP$^{\{5\}}$	2522.4	−2.0				
TPCP$^{\{4,5\}}$			1579.6	−5.6		
TSNW	2466.6	−57.8	1551.3	−33.9	872.9	−22.6
TSNW$^{\{1,2,12\}}$	2465.0	−59.4				
TSNW$^{\{1,2,5,12\}}$			1549.7	−35.5		
TSNW$^{\{1,2,4,12\}}$					871.4	−24.1
MMNT	2456.5	−67.9	1539.2	−46.0	872.8	−22.7
MMNT$^{\{1,2,12\}}$	2405.5	−118.9	1501.1	−84.2	854.9	−40.6
MMXT	2445.4	−79.0	1526.2	−59.1	873.7	−21.8
MMXT$^{\{1,2,3,4,11,12\}}$	2402.9	−121.5				
MMXT$^{\{1,2,3,11,12\}}$			1491.4	−93.8		
MMXT$^{\{1,2,12\}}$					862.4	−33.1
MNTM	2447.3	−77.1	1529.8	−55.5	872.4	−23.1
MNTM$^{\{1,2,4,11,12\}}$	2402.2	−122.2				
MNTM$^{\{1,2,3,11,12\}}$			1491.4	−93.9		
MNTM$^{\{1,2,12\}}$					858.0	−37.4

Table 6: AICC and change in AICC using reduced set of month-specific Midwest regressors relative to full Midwest regressors. Housing starts data sourced from U.S. Census Bureau, Survey of Construction.

	DP01	DP05	DP10	EMXP	TPCP	DT00	DT32	DT90	DX32	EMNT	EMXT	MMNT	MMXT	MNTM	MXSD	TSNW
DP01	1.00															
DP05	0.84	1.00														
DP10	0.67	0.84	1.00													
EMXP	0.65	0.80	0.86	1.00												
TPCP	0.90	0.95	0.89	0.87	1.00											
DT00	−0.03	−0.05	−0.04	−0.09	−0.05	1.00										
DT32	−0.19	−0.20	−0.14	−0.18	−0.19	0.31	1.00									
DT90	−0.16	−0.14	−0.09	−0.08	−0.14	−0.00	−0.00	1.00								
DX32	−0.05	−0.11	−0.08	−0.13	−0.08	0.75	0.56	−0.00	1.00							
EMNT	0.06	0.11	0.10	0.14	0.10	−0.65	−0.53	0.12	−0.65	1.00						
EMXT	−0.10	−0.02	0.01	0.06	−0.04	−0.37	−0.47	0.33	−0.48	0.33	1.00					
MMNT	0.12	0.18	0.15	0.21	0.17	−0.68	−0.72	0.25	−0.77	0.79	0.60	1.00				
MMXT	−0.10	−0.01	0.00	0.06	−0.04	−0.57	−0.70	0.33	−0.73	0.68	0.73	0.90	1.00			
MNTM	0.01	0.09	0.08	0.13	0.06	−0.64	−0.73	0.30	−0.77	0.75	0.68	0.97	0.98	1.00		
MXSD	0.12	0.03	0.01	0.00	0.05	0.58	0.39	0.00	0.67	−0.50	−0.38	−0.55	−0.54	−0.56	1.00	
TSNW	0.21	0.07	0.04	0.04	0.11	0.51	0.46	0.00	0.67	−0.47	−0.37	−0.56	−0.55	−0.57	0.80	1.00

Table 7: Correlation matrix for Midwest regressors. Weather data sourced from U.S. National Oceanic and Atmospheric Administration, National Centers for Environmental Information; population data sourced from U.S. Census Bureau, Decennial Census of Population and Housing, 1960–2010.

from the base model, whereas the other temperature threshold variable (DT32) does seem to be improved by using the month-specific variant instead of the single regressor. For the snow-based regressors (MXSD and TSNW), which feature a similarly stark delineation between months, the two approaches are about the same. Precipitation-based regressors (DP01, DP05, DP10, EMXP, and TPCP) do not see much, if any, improvement by opting for the set of significant month-specific regressors, and for some of these, the switch is actually detrimental. On the other hand, the average monthly temperature variables (MMNT, MMXT, MNTM) see a sizable decrease in AICC by using their month-specific variant instead of the single regressor—trying to use a "one-size-fits-all" regressor that covers all months fares worse than simply excluding the nonsignificant months. So, there is some benefit to using a month-specific approach for the regressors based on monthly average temperatures, but not so much for regressors based on any other type of variable.

4.3 Regressor Sets

Instead of including just one regressor (or one set of month-specific regressors), it is worth considering multiple regressors. For the regressors from Table 2, the pairwise correlations are provided in Table 7. Looking at the table, we see that the precipitation-based regressors are fairly weakly correlated with both the temperature-based regressors and the snow-based regressors. The temperature-based regressors are moderately correlated with the snow-based regressors—for the low temperature thresholds, the correlation is positive, whereas for the average monthly temperatures, this correlation is negative. Also, the temperature-based regressors, with the exception of DT90, are all fairly strongly correlated with one another. Since most of the temperature-based thresholds are reflective of cold weather, it is to be expected that the signs are consistent with those observed for the correlations of the snow-based regressors. The three average monthly temperatures (MMNT, MMXT, and MNTM) are nearly perfectly correlated with one another; given the linear relationship between the three, this is not surprising. It is, however, interesting to note that the number of days where the minimum temperature is below 0 degrees Fahrenheit (DT00) is much more strongly correlated with the number of days where the maximum temperature is below 32 degrees Fahrenheit (DX32) than it is with the number of days where the minimum temperature is below 32 degrees Fahrenheit (DT32). So, if we wish to use a set of regressors, we may prefer to only select one from each of the three categories (precipitation, temperature, and snow).

Using the set of outliers previously identified by the base model, we consider sets of up to four regressors as additions to that model, instead of stepping through each addition sequentially. The three- and four-regressor sets are somewhat constrained in that there needs to be at least one temperature, one precipitation, and one snow regressor included, to avoid models that have four temperature regressors or some similarly skewed set. Table 8 shows the AICCs and changes in AICC associated with fitting a $(0\ 1\ 1)(0\ 1\ 1)_{12}$ ARIMA model on the log-transformed Midwest Housing Starts with additional regressors added; only the ten best models for each size of regressor set will be listed, with best being based on the AICC for the model fit to the full series.

The five best one-regressor models are all temperature-related, with the regressors corresponding to low temperature thresholds reducing the AICC more than those corresponding to average monthly temperatures, whereas regressors based on precipitation do not perform that well by themselves. But when we look at the best two-regressor models, there is a noticeable reduction in the AICC by pairing a temperature regressor with a precipitation regressor—the six best models of this type use one of {DT00, DX32} and one of {DP01, DP05, TPCP}. On the other hand, the best three-regressor models do not improve on the best two-regressor models; this may be a consequence of requiring three-regressor models to be of the form {temperature, precipitation, snow}, instead of allowing free selection. Since snow tends to be closely related to low temperature, and since the best single regressors have been the low temperature thresholds, it is possible that including snow in a model that already accounts for low temperature may be somewhat redundant. When we look at the best four-regressor models, we might have expected that the fourth regressor added would be whichever low temperature threshold was not already included, given that the best single regressors measured low temperature thresholds.

The two four-regressor models that are lowest in terms of AICC for the full series model include both the number of days where minimum temperature is below 0 degrees Fahrenheit (DT00) and the number of days where maximum temperature is below 32 degrees Fahrenheit (DX32), the number of days where precipitation exceeded 0.1 inch (DP01), and one of maximum snow depth (MXSD) and total snowfall (TSNW). The results of the two models are almost identical over the full series and the first subspan (1970–1999), although the model with maximum snow depth ekes out a slight advantage in the second subspan (2000–2019).

Table 9 shows the model estimates for these two models over the various spans. There is very little to choose between the two, as the coefficient estimates as well as the effect of including the weather regressors on outliers are similar. Note that the snow regressors are for the most part not significant when the two temperature regressors are in the model, except in the case of maximum snow depth over the second subspan. Recall that for the base model, we had the outliers shown in the first row of Table 10 (taken from Table 4), where the value before the '/' indicates the type of outlier when fitting the full series, and the value after indicates the type when fitting to the subspan. The second row shows the outliers identified by the model with 4 weather regressors (the outlier sets are the same for the two four-regressor models). The models with regressors account for outliers identified at five time points in the base model (and the AO at January 2014 for the model over the second subspan). They identify a level shift outlier at July 1980 that was not in the base model, and the outlier at February 1981 for the full span changes from a point (additive) outlier to a level shift.

4.4 Adjusting for Seasonality versus Adjusting for Seasonality and Weather

We see that adding weather regressors to the best fitted (airline) model for this set of data has accounted for some of the previously identified outliers, but not all. What we are also interested in is the effect adjusting for both seasonality and weather effects has compared to adjusting for

Regressor(s)	1970.1–2019.12 AICC	1970.1–2019.12 Δ_{AICC}	1970.1–1999.12 AICC	1970.1–1999.12 Δ_{AICC}	2000.1–2019.12 AICC	2000.1–2019.12 Δ_{AICC}
None	2524.4		1585.2		895.5	
DX32	2406.5	−117.9	1490.9	−94.4	862.7	−32.8
DT00	2410.0	−114.4	1506.3	−79.0	856.8	−38.7
MMXT	2445.4	−79.0	1526.2	−59.1	873.7	−21.8
MNTM	2447.3	−77.1	1529.8	−55.5	872.4	−23.1
MMNT	2456.5	−67.9	1539.2	−46.0	872.8	−22.7
MXSD	2466.6	−57.8	1553.9	−31.3	869.3	−26.2
TSNW	2466.6	−57.8	1551.3	−33.9	872.9	−22.6
EMNT	2478.1	−46.3	1545.5	−39.8	886.3	−9.2
EMXT	2493.4	−31.0	1549.1	−36.2	894.4	−1.1
DP01	2509.8	−14.6	1574.3	−10.9	893.7	−1.8
DX32 DP01	2380.8	−143.6	1467.8	−117.4	859.3	−36.2
DX32 DP05	2382.7	−141.7	1474.8	−110.5	855.7	−39.8
DX32 TPCP	2384.6	−139.8	1472.9	−112.3	858.6	−36.9
DT00 DP01	2387.4	−137.0	1488.2	−97.0	852.3	−43.2
DT00 TPCP	2393.4	−131.0	1493.7	−91.5	853.1	−42.4
DT00 DP05	2394.7	−129.7	1496.6	−88.6	851.6	−43.8
DX32 DP10	2397.3	−127.1	1482.9	−102.3	861.8	−33.7
DX32 EMXP	2398.1	−126.3	1483.8	−101.4	861.7	−33.8
DT00 TSNW	2401.8	−122.6	1501.5	−83.8	855.3	−40.2
DT00 MXSD	2402.1	−122.3	1504.6	−80.6	851.8	−43.6
DX32 DP01 MXSD	2381.6	−142.8	1470.0	−115.2	857.7	−37.8
DX32 DP01 TSNW	2382.7	−141.7	1469.3	−115.9	861.4	−34.1
DT00 DP01 MXSD	2382.8	−141.6	1488.5	−96.7	848.9	−46.6
DX32 DP05 MXSD	2382.8	−141.6	1476.9	−108.4	853.8	−41.7
DX32 TPCP MXSD	2384.7	−139.7	1475.0	−110.2	856.8	−38.7
DX32 DP05 TSNW	2384.8	−139.6	1477.0	−108.3	857.6	−37.8
DT00 DP01 TSNW	2385.2	−139.2	1487.5	−97.7	852.9	−42.5
DX32 TPCP TSNW	2386.8	−137.6	1475.1	−110.2	860.6	−34.9
DT00 TPCP MXSD	2387.2	−137.2	1493.2	−92.0	848.9	−46.6
DT00 DP05 MXSD	2387.9	−136.5	1496.0	−89.2	846.9	−48.6
DT00 DP01 MXSD DX32	2365.8	−158.6	1464.2	−121.1	849.9	−45.6
DT00 DP01 TSNW DX32	2365.9	−158.5	1463.6	−121.6	852.5	−43.0
DT00 DP05 MXSD DX32	2369.6	−154.8	1472.2	−113.0	847.2	−48.2
DT00 TPCP MXSD DX32	2370.1	−154.3	1469.6	−115.6	849.7	−45.8
DT00 DP05 TSNW DX32	2370.6	−153.8	1472.2	−113.0	850.2	−45.3
DT00 TPCP TSNW DX32	2371.2	−153.2	1469.6	−115.6	852.6	−42.9
DT00 DP01 MXSD MMXT	2374.1	−150.3	1481.1	−104.1	849.3	−46.2
DT00 DP01 MXSD MNTM	2375.8	−148.6	1482.6	−102.6	849.5	−46.0
DT00 DP01 TSNW MMXT	2375.9	−148.5	1481.0	−104.3	852.3	−43.2
DT00 TPCP MXSD MMXT	2377.1	−147.3	1485.4	−99.8	848.8	−46.7

Table 8: AICC results testing sets of Midwest regressors. Housing starts data sourced from U.S. Census Bureau, Survey of Construction.

	1970–2019		1970–1999		2000–2019	
Model	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic
Model using regressor set {DT00, DP01, MXSD, DX32}						
`td1coef`	0.0051	3.72	0.0057	3.52	0.0035	1.33
DT00	−1.0728	−6.45	−0.9611	−5.12	−1.5882	−5.03
DP01	−0.4861	−5.76	−0.5516	−5.39	−0.3782	−2.40
MXSD	−0.0020	−1.32	−0.0008	−0.41	−0.0055	−2.06
DX32	−0.2844	−3.50	−0.4252	−4.25	−0.0287	−0.21
`AO1973.Dec`	−0.4611	−4.36	−0.4529	−4.59		
`LS1979.Jan`	−0.4252	−4.16	−0.4228	−4.07		
`LS1980.Jan`	−0.7611	−7.54	−0.6935	−6.81		
`LS1980.Jul`	0.4558	4.60	0.4272	4.30		
`LS1981.Feb`	−0.4648	−4.63				
`AO1981.Feb`			−0.4407	−4.52		
`AO1982.Feb`	−0.5651	−5.46	−0.5959	−6.21		
`AO2011.Dec`	0.4686	4.53				
`AO2014.Jan`	−0.5182	−4.82				
Nonseasonal MA	0.5346		0.4451		0.5984	
Seasonal MA	0.7635		0.7194		0.9307	
Model using regressor set {DT00, DP01, TSNW, DX32}						
`td1coef`	0.0052	3.78	0.0057	3.52	0.0038	1.43
DT00	−1.1034	−6.69	−0.9746	−5.26	−1.5690	−4.85
DP01	−0.5183	−5.89	−0.5774	−5.47	−0.3444	−2.07
TSNW	0.0000	0.52	0.0001	0.60	−0.0002	−1.46
DX32	−0.3490	−3.96	−0.4669	−4.38	−0.0435	−0.30
`AO1973.Dec`	−0.4858	−4.59	−0.4720	−4.78		
`LS1979.Jan`	−0.4411	−4.33	−0.4300	−4.20		
`LS1980.Jan`	−0.7544	−7.45	−0.6907	−6.78		
`LS1980.Jul`	0.4540	4.56	0.4263	4.29		
`LS1981.Feb`	−0.4687	−4.64				
`AO1981.Feb`			−0.4491	−4.57		
`AO1982.Feb`	−0.5723	−5.53	−0.5931	−6.18		
`AO2011.Dec`	0.4764	4.60				
`AO2014.Jan`	−0.5419	−4.89				
Nonseasonal MA	0.5319		0.4416		0.5977	
Seasonal MA	0.7651		0.7196		0.9314	

Table 9: Estimates from the two best four-regressor models applied to log-transformed Midwest Housing Starts over various spans. Data sourced from U.S. Census Bureau, Survey of Construction.

Model	1973 Jan	1973 Dec	1977 Jan	1979 Jan	1979 Mar	1980 Jan	1980 Jul	1980 Sep	1981 Feb	1982 Feb	2008 Dec	2011 Dec	2014 Jan
No regressor	AO/	AO/AO	AO/AO	LS/LS	LS/LS	LS/LS		LS/	AO/AO	AO/AO	LS/LS	AO/	AO/AO
4 regressors		AO/AO		LS/LS		LS/LS	LS/LS		LS/AO	AO/AO		AO/	AO/

Table 10: Outliers identified for Midwest Housing Starts under the base model (top row) and the model with multiple weather regressors (bottom row). Data sourced from U.S. Census Bureau, Survey of Construction.

only seasonality. So, the seasonally adjusted Midwest Housing Starts series (using a model with no weather regressors) will be compared to the seasonally and weather adjusted series (using the model with the set of 4 weather regressors {DT00, DP01, MXSD, DX32} from before). In both instances, the seasonal adjustment will be done using the X-11 procedure with settings determined by the X-13ARIMA-SEATS software (as noted previously). For this comparison, the outliers will be allowed to vary.

To start, the upper plot in Figure 2 shows the original series (gray) along with a seasonal adjustment from a model with no weather regressors (red) using the full span of data. The circles show the additive outliers, while the triangles show the location of level shifts. The lower plot is similar, with the same base seasonal adjustment from before, but superimposing the seasonal and weather adjusted series from the model with weather regressors (black). Outliers from the new model are denoted as before. Figures 3 and 4 are the corresponding plots using just the first subspan (1970–1999) and the second subspan (2000–2019), respectively.

Visually, the seasonal and weather adjustment appears to be smoother in general than the seasonal-only adjustment. That is, some of the more prominent peaks and troughs in the seasonal-only adjustment are less pronounced for the seasonal and weather adjustment. This is especially noticeable around previously identified outliers that were accounted for by the model with weather regressors; the seasonal and weather adjustment does not decrease as drastically around the beginnings of 1977 and 1979 as the seasonal-only adjustment does (hence, the removal of the additive outlier in 1977 and one of the two level shifts in 1979), It is also worth noting that the seasonal and weather adjustment may move in the opposite direction of the seasonal-only adjustment, as can be seen around the end of 1983.

To get another image of how the additional adjustment for weather effects affects the resulting adjusted series, Figure 5 shows the ratio by month of the seasonal and weather adjusted series to the seasonal-only adjustment, using the model fit to the full span of data. Figures 6 and 7 show the ratios for models fit to the first and second subspan of the data, respectively. The plots show that while the effect is not constant over time, the biggest changes to the adjustments are generally observed in January, February, and December; to a lesser extent, there are also some changes observed in March and November. For the other months, there is some degree of deviation from 1, but over the time span observed, the two sets of adjustments for these months are roughly the same.

Table 11 shows the average absolute percent difference between the seasonal and weather adjusted series versus the seasonal-only adjusted series by month, both for the models using the full span and for the models over the two subspans. For most months, the two sets of adjustments are close over the relevant spans of time. January and February see the largest difference between the two adjustments: on average, the seasonal and weather adjustments for January and February differ by at least 10 percent (in either direction) from the corresponding seasonal-only adjustments, regardless of which span of data is used to fit the models. In fact, there are some Januaries where accounting for weather leads to an adjustment that is almost 75 percent larger (or almost 25 percent smaller). The fluctuations in the ratio for January are slightly more pronounced in the first subspan than they are in the second half of the data, whereas the ratios for February and December experience somewhat larger fluctuations in the second subspan.

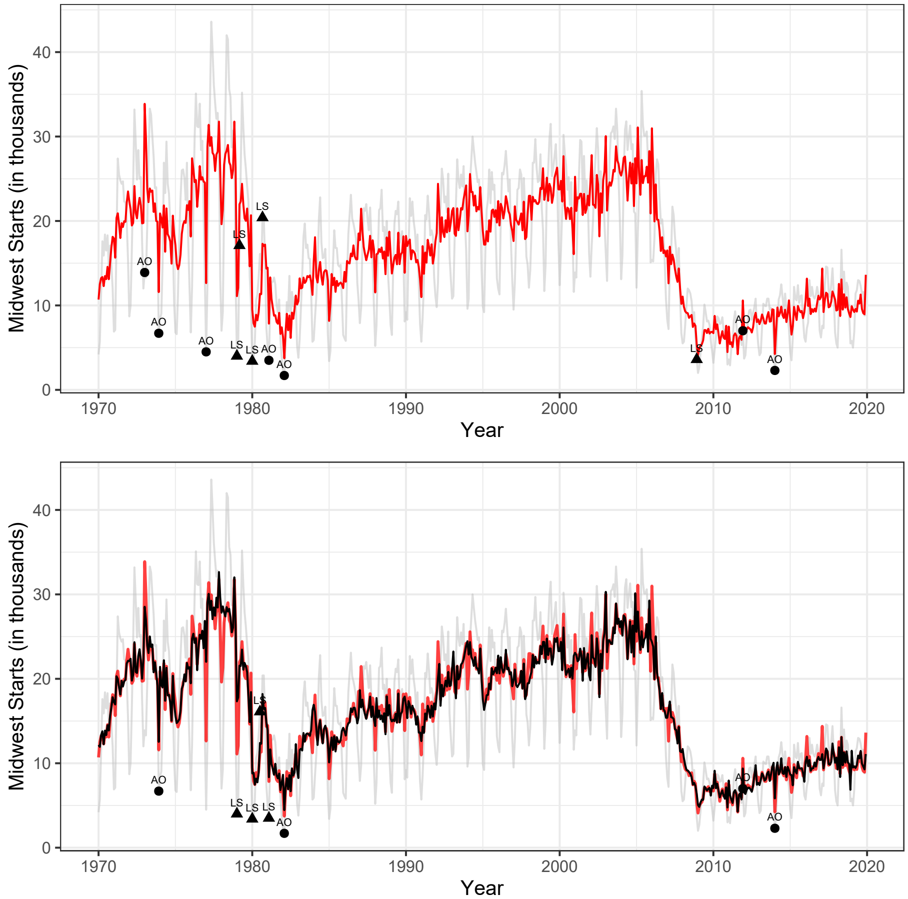

Figure 2: Seasonal-only and seasonal and weather adjustments of Midwest Housing Starts over the full span of data. Data sourced from U.S. Census Bureau, Survey of Construction.

Month	1970–2019	1970–1999	2000–2019
January	13.43	15.46	12.21
February	11.46	11.09	12.33
March	3.10	3.83	2.63
April	3.28	3.05	2.40
May	2.35	2.58	1.60
June	2.66	2.27	2.58
July	2.48	2.90	1.77
August	2.24	2.57	1.88
September	2.27	2.57	1.86
October	2.58	2.54	2.88
November	3.75	4.08	2.83
December	9.84	9.38	11.36

Table 11: Average absolute percent difference between the Midwest seasonal and weather adjustment and the seasonal-only adjustment, by month, modeling over the spans listed. Data sourced from U.S. Census Bureau, Survey of Construction.

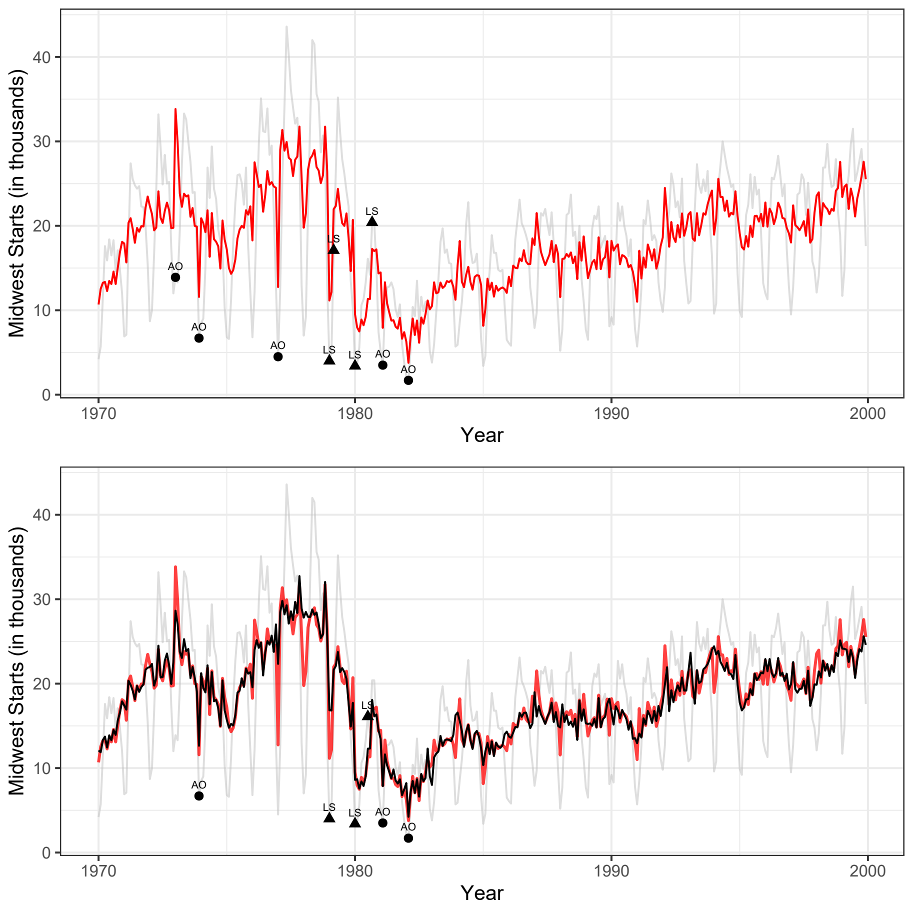

Figure 3: Seasonal-only and seasonal and weather adjustments of Midwest Housing Starts using just data from 1970 through 1999. Data sourced from U.S. Census Bureau, Survey of Construction.

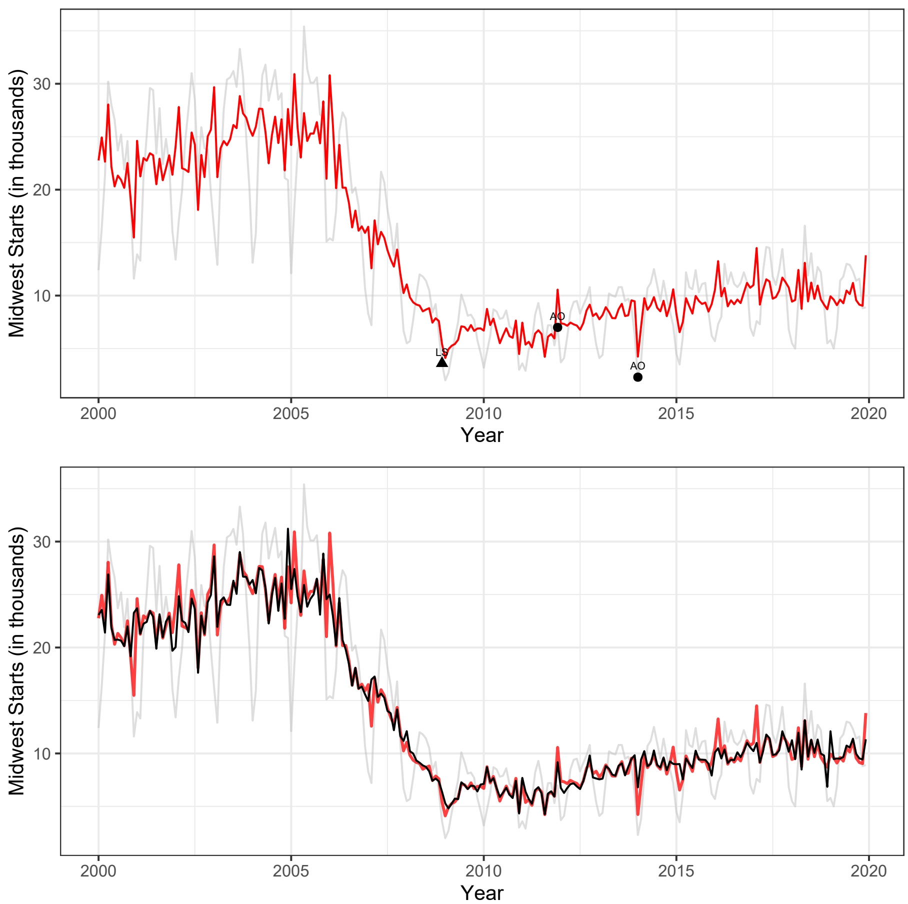

Figure 4: Seasonal-only and seasonal and weather adjustments of Midwest Housing Starts using just data from 2000 through 2019. Data sourced from U.S. Census Bureau, Survey of Construction.

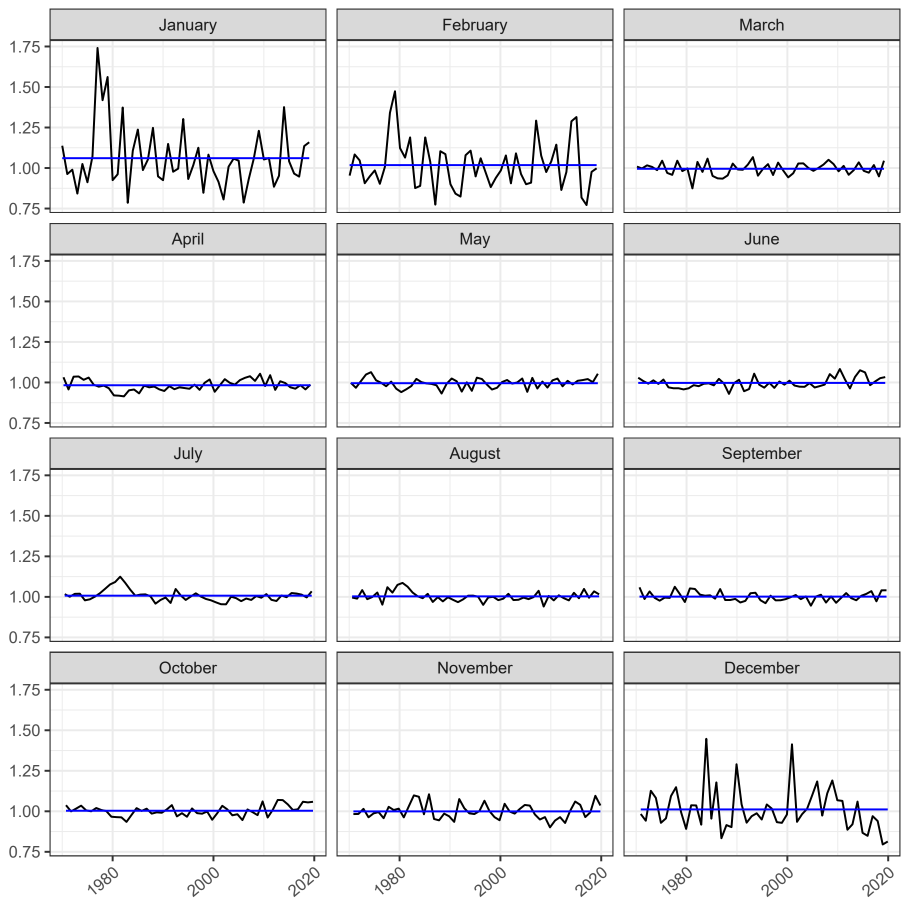

Figure 5: Ratio of Midwest seasonal and weather adjustment to seasonal-only adjustment, by month, using the full span of data. Data sourced from U.S. Census Bureau, Survey of Construction.

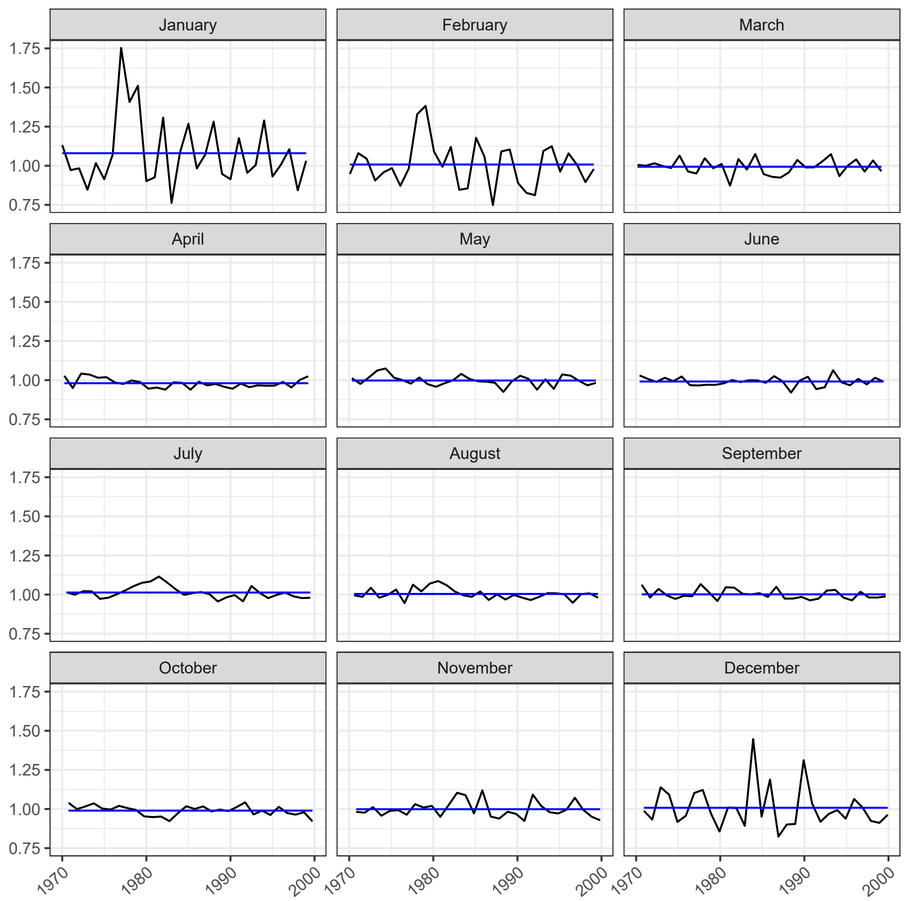

Figure 6: Ratio of Midwest seasonal and weather adjustment to seasonal-only adjustment, by month, for models using just data from 1970 through 1999. Data sourced from U.S. Census Bureau, Survey of Construction.

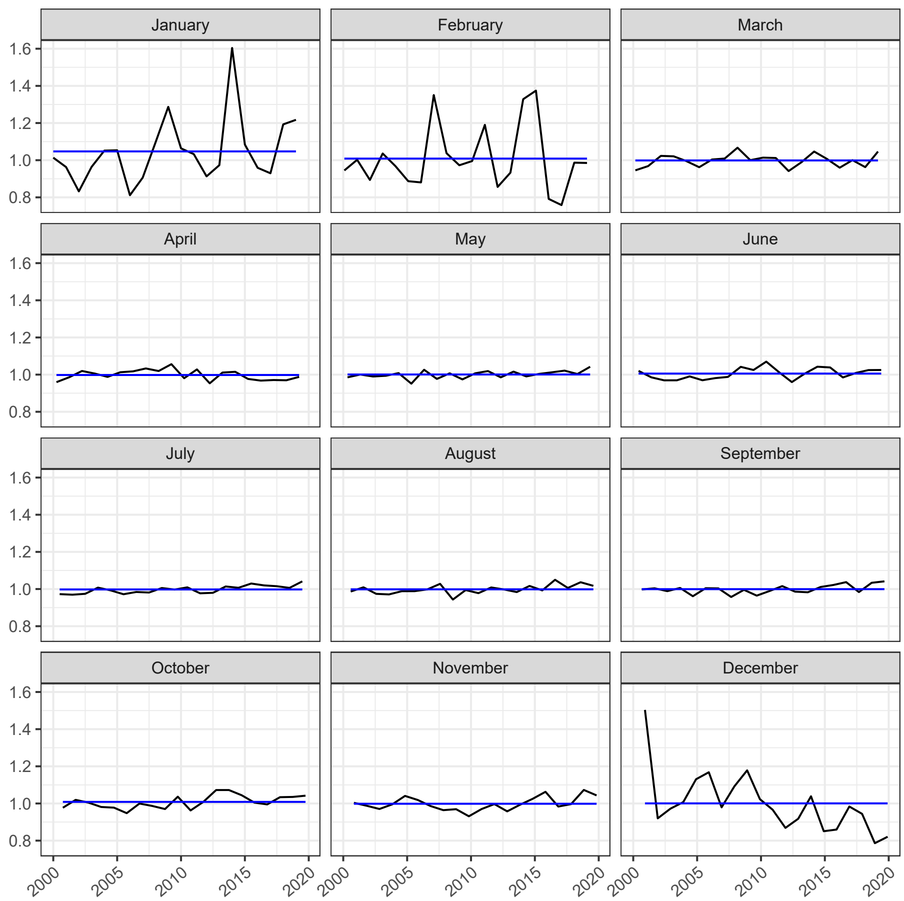

Figure 7: Ratio of Midwest seasonal and weather adjustment to seasonal-only adjustment, by month, for models using just data from 2000 through 2019. Data sourced from U.S. Census Bureau, Survey of Construction.

Variable	1970.1–2019.12 AICC	Δ_{AICC}	1970.1–1999.12 AICC	Δ_{AICC}	2000.1–2019.12 AICC	Δ_{AICC}
None	1999.1		1360.2		612.1	0.0
DP01	1995.3	−3.8	1360.9	0.7	609.3	−2.8
DP05	1994.0	−5.1	1359.3	−0.9	611.0	−1.1
DP10	1991.9	−7.2	1356.7	−3.6	612.2	0.0
DT00	1966.7	−32.4	1340.1	−20.1	599.8	−12.3
DT32	1968.1	−31.0	1327.6	−32.7	610.6	−1.5
DT90	2001.0	1.9	1357.6	−2.6	611.7	−0.4
DX32	1933.5	−65.6	1295.9	−64.3	605.3	−6.9
EMXP	1996.2	−2.9	1358.5	−1.8	613.6	1.4
MXSD	1969.7	−29.4	1326.0	−34.3	611.8	−0.3
EMNT	1981.0	−18.1	1347.5	−12.8	609.6	−2.5
EMXT	1988.3	−10.8	1345.7	−14.5	613.7	1.6
TPCP	1991.8	−7.3	1358.1	−2.1	610.4	−1.8
TSNW	1976.2	−22.9	1325.3	−34.9	613.2	1.1
MMNT	1960.7	−38.4	1319.1	−41.1	610.4	−1.8
MMXT	1945.3	−53.8	1307.8	−52.4	605.7	−6.4
MNTM	1949.8	−49.3	1310.4	−49.8	607.7	−4.4

Table 12: AICC and change in AICC using city-and-state-weighted Northeast regional regressors. Highlighted rows indicate regressors whose inclusion results in an AICC decrease of at least 5 in both of the subspans. Housing starts data sourced from U.S. Census Bureau, Survey of Construction.

5 Example 2: Northeast Regional Single-Family Housing Starts

5.1 Initial Modeling with Single-Regressor Models

The same sort of analysis can be applied to the regional housing starts series for the Northeast. An airline model applied to the full Northeast Housing Starts series identifies the following features:

- log transformation;
- 1-coefficient trading-day regressor `td1coef`;[4]
- outliers: `AO1978.Feb`, `LS1980.Feb`, `AO2009.Jan`, and `AO2015.Feb`.

As before, even though individual subspans may yield differences in outliers, the set of outliers from the base model will be held fixed for the time being.

Table 12 provides the values of the AICC for the regional regressors obtained using city-and-state population weighting, with the set of trading-day regressor and outliers from above held fixed. Highlighted variables correspond to those whose inclusion resulted in a drop in the AICC of at least 5 in both the first and second subspan. The most useful individual regressors based on decreasing the AICC are temperature-related. The snow variables appear to be meaningful for the full series and the first subspan, but do not result in a significant decrease in the AICC when modeled over the second subspan. This behavior is shared with many of the other variables—they are significant for the full series and the first subspan, but not for the second subspan. None of the precipitation variables appears to be a useful inclusion over the two subspans, even though DP05, DP10, and TPCP are all significant for the full series, and while the low threshold appeared to have the largest

[4]The regressors used in this analysis are defined in Chapter 4 of the X-13ARIMA-SEATS reference manual (U.S. Census Bureau, 2021)

	1970.1–2019.12				1970.1–1999.12				2000.1–2019.12			
Variable	$\widehat{\beta}$	t-stat	$\widehat{\theta}_1$	$\widehat{\theta}_{12}$	$\widehat{\beta}$	t-stat	$\widehat{\theta}_1$	$\widehat{\theta}_{12}$	$\widehat{\beta}$	t-stat	$\widehat{\theta}_1$	$\widehat{\theta}_{12}$
None			0.62	0.78		0.58	0.71		0.679	0.88		
DP01	−0.212	−2.42	0.62	0.78	−0.132	−1.17	0.58	0.71	−0.315	−2.25	0.68	0.86
DP05	−0.363	−2.69	0.62	0.78	−0.302	−1.73	0.58	0.72	−0.393	−1.82	0.68	0.87
DP10	−0.686	−3.05	0.62	0.79	−0.705	−2.40	0.58	0.72	−0.511	−1.45	0.68	0.88
DT00	−2.041	−5.96	0.62	0.79	−1.767	−4.79	0.58	0.72	−3.535	−3.86	0.68	0.89
DT32	−0.414	−5.85	0.63	0.77	−0.544	−6.06	0.59	0.71	−0.219	−1.94	0.68	0.86
DT90	0.045	0.38	0.62	0.78	0.349	2.20	0.59	0.70	−0.273	−1.64	0.67	0.86
DX32	−0.658	−8.48	0.62	0.79	−0.813	−8.58	0.57	0.74	−0.407	−3.03	0.68	0.88
EMXP	−0.001	−2.24	0.62	0.78	−0.001	−1.97	0.58	0.72	−0.000	−0.83	0.68	0.88
MXSD	−0.005	−5.71	0.63	0.77	−0.008	−6.20	0.59	0.70	−0.002	−1.60	0.68	0.86
EMNT	0.012	4.54	0.63	0.78	0.013	3.90	0.58	0.71	0.009	2.20	0.69	0.86
EMXT	0.008	3.63	0.63	0.77	0.011	4.16	0.60	0.69	0.003	0.73	0.68	0.88
TPCP	−0.000	−3.07	0.62	0.78	−0.000	−2.06	0.58	0.72	−0.000	−1.99	0.68	0.87
TSNW	−0.000	−5.07	0.63	0.77	−0.001	−6.26	0.59	0.70	−0.000	−1.04	0.68	0.87
MMNT	0.024	6.48	0.63	0.78	0.031	6.79	0.58	0.71	0.012	1.99	0.69	0.87
MMXT	0.025	7.67	0.63	0.77	0.031	7.70	0.59	0.69	0.015	2.95	0.69	0.88
MNTM	0.026	7.34	0.63	0.77	0.033	7.49	0.59	0.70	0.015	2.59	0.69	0.87

Table 13: RegARIMA model estimates when adding a city-and-state-weighted regressor to a model of log-transformed Northeast Housing Starts over the designated spans. Data sourced from U.S. Census Bureau, Survey of Construction.

effect on AICC in the Midwest, it is instead the higher threshold in the Northeast for which this holds.

Table 13 shows the results of fitting a $(0\;1\;1)(0\;1\;1)_{12}$ ARIMA model to each span using the listed regressors under the city-and-state population weighting scheme. Although few of the regressors produced a significant reduction in the AICC when added to the base Northeast model previously, the t-statistics would suggest that their effects are statistically significant. As was the case for the Midwest, the only regressor without a significant t-statistic on its coefficient estimate for any modeled span of the series is the number of days where the maximum temperature exceeded 90 degrees Fahrenheit (DT90).

5.1.1 Outlier Checking

As in the previous example, Table 14 displays the outliers that are identified by a model containing any specific regressor. We use the same structure as before, so we see that all outliers identified by the base model over the full span are also considered outliers when the model is instead fit to the two subspans. Hence, a regressor that accounts for more outliers will have more blank entries. These regressors fare poorly in explaining the previously identified outliers, but do detect outliers that were not identified in the base model. For example, the number of days where the maximum temperature is below 32 degrees Fahrenheit (DX32) does account for the one additive outlier in February 2015; it does identify outliers in 3 other Februaries (1981, 1982, and 2013) that were not in the base model. In the same vein, the number of days where the minimum temperature is below 0 degrees Fahrenheit (DT00) explains the outliers in January 2009 and February 2015; it also identifies additional outliers in January 1978 and Februaries 1981 and 1982.

Variable	1978 Jan	1978 Feb	1980 Feb	1981 Feb	1982 Feb	2009 Jan	2013 Feb	2015 Feb
None		AO/AO	LS/LS			AO/AO		AO/AO
DP01		AO/AO	LS/LS			AO/AO		AO/AO
DP05		AO/AO	LS/LS			AO/AO		AO/AO
DP10		AO/AO	LS/LS			AO/AO		AO/AO
DT00	AO/AO	AO/AO	AO/LS	AO/AO	AO/			
DT32		AO/AO	LS/LS	AO/AO		/AO		AO/AO
DT90		AO/AO	LS/LS			AO/AO		AO/AO
DX32		AO/AO	LS/LS	AO/AO	AO/AO		AO/	
EMXP		AO/AO	LS/LS			AO/AO		AO/AO
MXSD		AO/AO	LS/LS	/AO		AO/AO		AO/AO
EMNT		AO/AO	LS/			AO/AO		AO/AO
EMXT		AO/AO	LS/			/AO		AO/AO
TPCP		AO/AO	LS/LS			AO/AO		AO/AO
TSNW		AO/AO	LS/LS	/AO	/AO	AO/AO		AO/AO
MMNT		AO/AO	LS/LS	AO/AO		/AO		AO/AO
MMXT		AO/AO	LS/LS	AO/AO		/AO		AO/AO
MNTM		AO/AO	LS/LS	AO/AO		/AO		AO/AO

Table 14: Outliers identified for Northeast Housing Starts using the city-and-state-weighted variables over both full span (first item) and appropriate subspan (second item). Data sourced from U.S. Census Bureau, Survey of Construction.

5.2 Using Month-Specific Regressors

As before with the Midwest Housing Starts data, it is worth examining the interactions of the weather regressors with the set of seasonal indicators. The t-statistics from fitting the set of 12 month-specific regressors to Northeast Housing Starts over the full span and the 2 disjoint subspans is shown in Table 15. We note that the low temperature thresholds (DT00 and DX32) and snow regressors (MXSD and TSNW) are either absent or nonsignificant for the months of May through October; this is not surprising. On the other hand, there appears to be some presence for the high temperature threshold (DT90) in January, in addition to June and October. The latter two might be explicable, but the first one is puzzling and may warrant some additional investigation of the weather data itself.

For the nonthreshold temperature variables, it also appears to be the case that the most meaningful effects are found in winter months—January, February, and December have fairly strong effects. March may also matter, for atypically long winters, and for the maximum temperatures, June seems to be significant (for at least part of the time span). On the other hand, the gain in adopting a month-specific approach to precipitation-based regressors seems to be limited on a cursory glance.

As a check, we re-fit the models for each span, retaining only those months where the t-statistics were significant. The AICC for these new models are recalculated and compared against those for the models using the original single regressor. Table 16 shows the AICC associated with using the reduced set of significant month-specific regressors for each of the regressors listed; as before, significance means that the t-statistic has at least a magnitude of 2 for the month in question. For the Northeast, the results are mixed. The month-specific approach does appear to reduce the AICC more for the precipitation-based regressors. On the other hand, the snow-based regressors fare better under the original approach. Some of the temperature-based regressors do see some benefit to using the set of (significant) month-specific regressors, but not necessarily over all of the modeled spans.

Variable	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	−1.50	−0.92	−1.54	−0.33	−1.38	−2.77	0.41	−1.03	0.40	−0.47	−1.01	2.17
DP01	−1.22	−0.70	−1.67	−0.05	−0.89	−1.91	0.35	−1.24	1.21	1.85	−1.12	2.35
	−0.32	−0.72	−0.23	−0.61	−1.41	−2.07	0.44	−0.15	−0.47	−2.21	−0.33	0.71
	−1.21	−2.10	−1.66	−0.85	−0.65	−3.18	0.59	−0.72	−0.82	−0.13	−0.78	2.10
DP05	−1.44	−2.26	−1.97	−1.15	−0.24	−1.76	0.65	−1.13	0.02	1.77	−1.05	2.10
	0.97	−0.65	−0.24	−0.02	−1.48	−2.97	0.66	0.07	−1.00	−1.52	0.04	0.86
	−1.47	−2.56	−0.55	−1.17	−0.16	−3.21	0.26	−1.53	−1.40	−0.19	−0.55	1.61
DP10	−2.83	−2.17	−1.00	−1.23	0.11	−1.65	0.45	−1.37	−0.58	1.20	−1.53	1.28
	3.97	−1.66	0.35	−0.26	−0.98	−3.01	0.24	−0.89	−1.17	−1.20	1.33	1.46
	−3.70	−3.51	−2.19	−0.40							0.65	−3.51
DT00	−3.05	−2.22	−3.14	−0.29							0.73	−3.23
	−2.23	−4.05	−1.03	−1.15							0.08	−2.26
	−4.50	−5.04	−1.71	−0.16	0.48	−0.18	0.21	0.66	1.08	−0.28	−0.45	−2.46
DT32	−5.61	−3.79	−1.08	−0.45	0.42	−0.38	0.24	0.82	0.69	−0.89	−0.24	−2.98
	−0.50	−3.21	−1.52	0.48	0.42	0.88	0.21	−2.19	1.05	1.03	−0.32	−0.59
	3.68			−1.40	0.50	2.66	−0.50	0.08	−0.42	−3.68		
DT90	2.77			0.07	0.80	2.66	0.42	1.51	−0.62	−0.30		
				−2.14	−0.27	1.01	−1.40	−1.48	0.22	−3.78		
	−6.10	−4.49	−2.79	−0.18						0.05	−1.22	−3.55
DX32	−6.34	−3.58	−3.40	−0.37						0.16	−1.13	−4.04
	−2.13	−2.37	−0.55	0.67						0.14	−0.39	−0.75
	−0.66	−1.71	−0.70	−0.76	0.16	−2.24	0.35	−1.92	−2.26	0.60	−0.26	2.59
EMXP	−1.56	−1.18	−1.57	−1.55	0.25	−1.34	0.62	−1.82	−1.56	1.43	−1.05	2.45
	3.37	−1.17	0.45	0.17	−0.38	−2.02	−0.17	−0.94	−1.57	−0.29	1.47	1.16
	−4.43	−2.88	−2.77	−0.59	0.67					−0.46	−0.03	−1.26
MXSD	−4.99	−3.04	−2.29	−0.49	0.66					0.39	−0.10	−2.80
	−0.92	−0.85	−1.84	−0.26	−1.11					−0.55	0.02	0.73
	3.58	4.20	2.19	−0.07	−0.58	0.27	0.01	−0.68	−0.59	−0.23	−0.08	3.31
EMNT	3.44	1.75	2.75	0.00	−0.46	0.17	0.03	−0.69	−0.64	0.03	−0.71	3.45
	1.05	4.16	0.79	−0.15	−0.35	0.47	−0.26	−0.03	−0.30	−0.42	0.15	1.27
	3.39	1.21	2.19	−0.74	0.62	2.19	−0.50	0.55	0.09	−0.02	0.73	2.21
EMXT	3.60	1.04	1.79	0.33	0.48	2.52	−0.27	1.63	−0.09	0.21	0.40	2.50
	0.98	0.52	1.37	−1.81	0.23	0.51	−0.60	−0.40	0.42	−0.22	0.94	0.15
	−1.34	−2.24	−1.21	−0.90	−0.68	−3.25	0.55	−1.74	−1.45	0.23	−0.97	2.29
TPCP	−1.61	−2.04	−1.82	−1.29	−0.25	−1.86	0.68	−1.74	−0.38	1.92	−1.38	2.13
	1.82	−1.17	0.31	0.02	−1.45	−2.86	0.37	−0.95	−1.36	−0.90	0.39	1.09
	−4.35	−1.87	−2.42	−0.46	0.76				−0.29	−0.42	−0.60	−1.34
TSNW	−5.27	−2.86	−2.01	−0.43	0.74				−0.23	0.18	−0.61	−2.83
	−0.93	0.11	−1.72	−0.12	−0.91				0.39	−0.58	−0.19	0.52
	5.22	5.46	2.23	0.03	0.79	0.17	−0.59	−0.75	−0.75	1.33	0.96	3.09
MMNT	5.18	3.87	2.07	0.81	0.49	0.90	−0.39	0.11	−0.55	1.45	0.79	3.56
	1.62	3.75	1.30	−0.93	0.63	−0.88	−0.72	−1.04	−0.47	0.53	0.46	0.76
	5.82	4.91	2.61	0.50	1.36	2.58	−0.39	0.02	−0.38	1.63	1.96	3.26
MMXT	5.88	4.09	2.42	1.43	0.72	2.42	−0.24	0.84	−0.96	1.31	1.63	3.69
	1.96	2.38	1.41	−0.83	1.31	1.25	−0.63	−0.69	0.38	1.25	1.02	0.87
	5.58	5.28	2.51	0.33	1.15	1.69	−0.52	−0.39	−0.64	1.53	1.55	3.22
MNTM	5.58	4.07	2.32	1.21	0.61	1.91	−0.34	0.51	−0.88	1.43	1.28	3.69
	1.81	3.03	1.38	−0.89	1.05	0.42	−0.69	−0.89	−0.03	0.95	0.78	0.82

Table 15: t-statistics using month-specific regressors for Northeast Housing Starts. Data sourced from U.S. Census Bureau, Survey of Construction.

	1970.1–2019.12		1970.1–1999.12		2000.1–2019.12	
Variable	AICC	Δ_{AICC}	AICC	Δ_{AICC}	AICC	Δ_{AICC}
None	1999.1		1360.2		612.1	
DP01	1995.3	−3.8	1360.9	0.7	609.3	−2.8
DP01$^{\{6,12\}}$	1991.2	−7.9				
DP01$^{\{12\}}$			1357.4	−2.8		
DP01$^{\{6,10\}}$					607.9	−4.2
DP05	1994.0	−5.1	1359.3	−0.9	611.0	−1.1
DP05$^{\{2,6,12\}}$	1987.0	−12.1				
DP05$^{\{2,12\}}$			1355.8	−4.4		
DP05$^{\{6\}}$					606.3	−5.8
DP10	1991.9	−7.2	1356.7	−3.6	612.2	0.0
DP10$^{\{2,6\}}$	1986.9	−12.2				
DP10$^{\{1,2\}}$			1353.4	−6.8		
DP10$^{\{1,6\}}$					595.6	−16.5
DT00	1966.7	−32.4	1340.1	−20.1	599.8	−12.3
DT00$^{\{1,2,3,12\}}$	1966.5	−32.6	1335.2	−25.1		
DT00$^{\{1,2,12\}}$					596.1	−16.1
DT32	1968.1	−31.0	1327.6	−32.7	610.6	−1.5
DT32$^{\{1,2,12\}}$	1959.6	−39.5	1316.3	−43.9		
DT32$^{\{2,8\}}$					603.1	−9.1
DT90	2001.0	1.9	1357.6	−2.6	611.7	−0.4
DT90$^{\{1,6,10\}}$	1973.3	−25.8				
DT90$^{\{1,6\}}$			1351.5	−8.8		
DT90$^{\{4,10\}}$					599.6	−12.5
DX32	1933.5	−65.6	1295.9	−64.3	605.3	−6.9
DX32$^{\{1,2,3,12\}}$	1939.0	−60.1	1298.8	−61.4		
DX32$^{\{1,2\}}$					607.1	−5.1
EMXP	1996.2	−2.9	1358.5	−1.8	613.6	1.4
EMXP$^{\{6,9,12\}}$	1989.3	−9.8				
EMXP$^{\{12\}}$			1356.9	−3.3		
EMXP$^{\{1,6\}}$					603.0	−9.1
MXSD	1969.7	−29.4	1326.0	−34.3	611.8	−0.3
MXSD$^{\{1,2,3\}}$	1973.4	−25.6				
MXSD$^{\{1,2,3,12\}}$			1329.2	−31.0		
EMNT	1981.0	−18.1	1347.5	−12.8	609.6	−2.5
EMNT$^{\{1,2,3,12\}}$	1964.7	−34.4				
EMNT$^{\{1,3,12\}}$			1337.7	−22.5		
EMNT$^{\{2\}}$					598.2	−13.9
EMXT	1988.3	−10.8	1345.7	−14.5	613.7	1.6
EMXT$^{\{1,3,6,12\}}$	1982.8	−16.3				
EMXT$^{\{1,6,12\}}$			1342.4	−17.8		
TPCP	1991.8	−7.3	1358.1	−2.1	610.4	−1.8
TPCP$^{\{2,6,12\}}$	1984.9	−14.2				
TPCP$^{\{2,12\}}$			1356.4	−3.8		
TPCP$^{\{6\}}$					606.4	−5.7
TSNW	1976.2	−22.9	1325.3	−34.9	613.2	1.1
TSNW$^{\{1,3\}}$	1980.3	−18.7				
TSNW$^{\{1,2,3,12\}}$			1328.4	−31.9		
MMNT	1960.7	−38.4	1319.1	−41.1	610.4	−1.8
MMNT$^{\{1,2,3,12\}}$	1945.0	−54.1	1316.8	−43.4		
MMNT$^{\{2\}}$					602.9	−9.2
MMXT	1945.3	−53.8	1307.8	−52.4	605.7	−6.4
MMXT$^{\{1,2,3,6,12\}}$	1940.1	−59.0	1305.3	−54.9		
MMXT$^{\{2\}}$					609.9	−2.2
MNTM	1949.8	−49.3	1310.4	−49.8	607.7	−4.4
MNTM$^{\{1,2,3,12\}}$	1943.2	−55.9	1311.4	−48.9		
MNTM$^{\{2\}}$					607.0	−5.1

Table 16: AICC and change in AICC using reduced set of month-specific Northeast regressors relative to full Northeast regressors. Housing starts data sourced from U.S. Census Bureau, Survey of Construction.

	DP01	DP05	DP10	EMXP	TPCP	DT00	DT32	DT90	DX32	EMNT	EMXT	MMNT	MMXT	MNTM	MXSD	TSNW
DP01	1.00															
DP05	0.80	1.00														
DP10	0.57	0.80	1.00													
EMXP	0.45	0.64	0.80	1.00												
TPCP	0.79	0.91	0.89	0.84	1.00											
DT00	−0.06	−0.06	0.02	−0.03	−0.04	1.00										
DT32	−0.11	−0.06	−0.01	−0.04	−0.08	0.42	1.00									
DT90	−0.21	−0.18	−0.15	−0.12	−0.20	0.00	−0.00	1.00								
DX32	−0.09	−0.06	0.02	−0.03	−0.05	0.73	0.66	0.00	1.00							
EMNT	0.02	−0.02	−0.01	0.04	0.02	−0.57	−0.58	0.09	−0.58	1.00						
EMXT	−0.10	−0.10	−0.11	−0.06	−0.10	−0.29	−0.49	0.35	−0.39	0.26	1.00					
MMNT	0.07	0.03	0.00	0.05	0.05	−0.59	−0.81	0.22	−0.73	0.71	0.59	1.00				
MMXT	−0.17	−0.16	−0.16	−0.08	−0.15	−0.48	−0.76	0.32	−0.66	0.57	0.71	0.89	1.00			
MNTM	−0.06	−0.07	−0.08	−0.02	−0.06	−0.55	−0.81	0.28	−0.72	0.65	0.67	0.97	0.97	1.00		
MXSD	0.08	0.12	0.11	0.06	0.09	0.29	0.50	−0.00	0.48	−0.29	−0.30	−0.43	−0.43	−0.44	1.00	
TSNW	0.13	0.16	0.14	0.07	0.12	0.34	0.54	−0.00	0.53	−0.33	−0.34	−0.47	−0.49	−0.50	0.90	1.00

Table 17: Correlation matrix for Northeast regressors. Weather data sourced from U.S. National Oceanic and Atmospheric Administration, National Centers for Environmental Information; population data sourced from U.S. Census Bureau, Decennial Census of Population and Housing, 1960–2010.

5.3 Regressor Sets

As with the Midwest, pairwise correlations of the Northeast regressors are provided in Table 17. The correlation structure is not dissimilar from that of the Midwest; temperature regressors are correlated with each other, but the number of days where the maximum temperature is above 90 degrees Fahrenheit (DT90) is only weakly correlated with every other regressor. The number of days where the minimum temperature is less than 0 degrees Fahrenheit (DT00) has weaker correlations in magnitude in this set, being only moderately correlated with both the number of days where minimum temperature is below 32 degrees Fahrenheit (DT32) and the average monthly maximum temperature (MMXT). The snow regressors are more strongly correlated with one another in the Northeast than they are in the Midwest. The precipitation regressors again have fairly high correlations with each other, but very weak correlations with any of the other two groups.

As we did with the Midwest, we maintain the set of outliers that were previously identified by the base model, and we consider sets of up to four regressors as additions to that model. For picking sets, we adhere to the same constraint of allowing no more than one regressor from each group for models containing three or fewer regressors, with the potential of picking a second from a group when considering four regressors. Table 18 shows the AICCs and changes in AICC associated with fitting a $(0\ 1\ 1)(0\ 1\ 1)_{12}$ ARIMA model with weather regressors added to the log-transformed Northeast Housing Starts. Again, only the ten best models for each size of regressor set will be listed, sorted by the AICC (in ascending order) for the model fit to the full series.

The six best one-regressor models for the Northeast are all temperature-related, with one of the threshold regressors being best in each of the modeled spans (DX32 for the full series and first subspan, DT00 for the second subspan). A model with only one regressor appears to yield the lowest AICC when fit to the second subspan (2000–2019); this may be a consequence of the best sets of regressors all including DX32 instead of DT00, which as noted, is the better regressor for modeling the second subspan. Picking the "best" of the models here is harder than it was for the Midwest, where the best four-regressor models fared better across all spans than any other model. The two-regressor model that decreases the AICC most when fit to the full series—the model containing the number of days where the maximum temperature was below 32 degrees Fahrenheit and total precipitation (DX32 and TPCP, respectively)—does appear to result in a significant change in AICC for each of the spans when compared to the one-regressor model with just DX32.

Regressor(s)	1970.1–2019.12 AICC	1970.1–2019.12 Δ_{AICC}	1970.1–1999.12 AICC	1970.1–1999.12 Δ_{AICC}	2000.1–2019.12 AICC	2000.1–2019.12 Δ_{AICC}
None	1999.1		1360.2		612.1	
DX32	1933.5	−65.6	1295.9	−64.3	605.3	−6.9
MMXT	1945.3	−53.8	1307.8	−52.4	605.7	−6.4
MNTM	1949.8	−49.3	1310.4	−49.8	607.7	−4.4
MMNT	1960.7	−38.4	1319.1	−41.1	610.4	−1.8
DT00	1966.7	−32.4	1340.1	−20.1	599.8	−12.3
DT32	1968.1	−31.0	1327.6	−32.7	610.6	−1.5
MXSD	1969.7	−29.4	1326.0	−34.3	611.8	−0.3
TSNW	1976.2	−22.9	1325.3	−34.9	613.2	1.1
EMNT	1981.0	−18.1	1347.5	−12.8	609.6	−2.5
EMXT	1988.3	−10.8	1345.7	−14.5	613.7	1.6
DX32 TPCP	1919.9	−79.2	1286.9	−73.3	603.0	−9.1
DX32 DP05	1921.8	−77.3	1288.0	−72.2	603.6	−8.5
DX32 DP01	1922.9	−76.2	1290.5	−69.7	601.8	−10.4
DX32 DP10	1925.0	−74.1	1290.3	−70.0	605.4	−6.7
DX32 EMXP	1927.2	−71.9	1289.2	−71.0	606.6	−5.5
DX32 MXSD	1929.5	−69.6	1289.3	−71.0	607.3	−4.9
DX32 TSNW	1934.3	−64.8	1293.1	−67.1	607.3	−4.9
MMXT MXSD	1937.2	−61.9	1294.9	−65.3	607.7	−4.5
MNTM MXSD	1941.5	−57.6	1297.9	−62.3	609.5	−2.6
MMXT TPCP	1942.3	−56.8	1307.6	−52.6	605.6	−6.5
DX32 TPCP MXSD	1918.1	−81.0	1281.9	−78.4	605.2	−7.0
DX32 DP05 MXSD	1920.5	−78.6	1283.6	−76.6	605.8	−6.3
DX32 DP01 MXSD	1921.1	−78.0	1285.3	−74.9	603.9	−8.2
DX32 TPCP TSNW	1921.8	−77.3	1286.2	−74.0	604.5	−7.6
DX32 DP10 MXSD	1922.6	−76.4	1284.7	−75.5	607.6	−4.6
DX32 DP05 TSNW	1923.8	−75.3	1287.6	−72.6	605.0	−7.2
DX32 EMXP MXSD	1924.3	−74.8	1283.3	−76.9	608.7	−3.4
DX32 DP01 TSNW	1924.9	−74.2	1289.7	−70.5	602.9	−9.2
DX32 DP10 TSNW	1926.7	−72.4	1288.9	−71.3	607.2	−5.0
DX32 EMXP TSNW	1928.6	−70.5	1287.5	−72.8	608.6	−3.6
DX32 TPCP MXSD TSNW	1913.5	−85.5	1280.2	−80.0	605.2	−6.9
DX32 DP01 MXSD TSNW	1915.6	−83.5	1283.7	−76.6	603.3	−8.9
DX32 DP05 MXSD TSNW	1915.8	−83.3	1282.4	−77.8	605.6	−6.6
DX32 TPCP MXSD MMXT	1916.5	−82.6	1280.9	−79.3	606.3	−5.9
DX32 TPCP MXSD MNTM	1918.1	−81.0	1282.0	−78.2	606.9	−5.2
DX32 DP05 MXSD MMXT	1918.7	−80.4	1282.6	−77.6	606.9	−5.3
DX32 DP10 MXSD TSNW	1919.1	−80.0	1284.0	−76.2	607.8	−4.3
DX32 TPCP TSNW MMXT	1919.5	−79.6	1285.2	−75.0	605.2	−6.9
DX32 DP01 MXSD MMXT	1919.5	−79.6	1284.5	−75.7	605.0	−7.1
DX32 TPCP MXSD MMNT	1919.6	−79.5	1283.2	−77.0	607.3	−4.8

Table 18: AICC results testing sets of regressors for Northeast Housing Starts. Housing starts data sourced from U.S. Census Bureau, Survey of Construction.

Model	1970–2019 Estimate	1970–2019 t-statistic	1970–1999 Estimate	1970–1999 t-statistic	2000–2019 Estimate	2000–2019 t-statistic
`td1coef`	0.0050	3.00	0.0051	2.58	0.0048	1.66
DX32	−0.8646	−11.91	−0.9817	−10.95	−0.7468	−6.08
TPCP	−0.0004	−3.78	−0.0004	−3.01	−0.0004	−2.13
`AO1978.Feb`	−0.6136	−4.89	−0.5677	−4.80		
`LS1980.Feb`	−0.4902	−4.37	−0.4929	−4.35		
`AO1981.Feb`	−0.6367	−5.06	−0.6690	−5.61		
`AO1982.Feb`	−0.5419	−4.34	−0.5501	−4.67		
`AO2013.Feb`	0.5657	4.56			0.5396	4.01
Nonseasonal MA	0.5923		0.5289		0.6671	
Seasonal MA	0.8229		0.8147		0.8744	

Table 19: Estimates from a $(0\ 1\ 1)(0\ 1\ 1)_{12}$ ARIMA model with DX32 and TPCP weather regressors applied to log-transformed Northeast Housing Starts over various spans. Data sourced from U.S. Census Bureau, Survey of Construction.

But it is not clear that adding a third regressor will yield a model that is uniformly better than the two-regressor model: only the first subspan has a significant decrease in AICC for the third regressor. In the same vein, adding a fourth regressor to the best three-regressor model only results in a significant decrease in the AICC for the full series. So, for the sake of this discussion, we will use the best two-regressor model for comparing the result of a seasonal and weather adjustment to a seasonal-only adjustment.

The outliers identified by the base model were additive outliers at February 1978, January 2009 and February 2015, and a level shift outlier at February 1980; this was consistent for both the full series and the appropriate subspan. Unlike the Midwest model that we selected, which did explain multiple Midwest outliers that had been detected, our two-regressor model for the Northeast only accounts for one of the original set of outliers—the one at January 2009. This model does flag two other additive outliers that were not identified previously: one at February 1981, and the other at February 1982.

5.4 Adjusting for Seasonality versus Adjusting for Seasonality and Weather

One last thing to look at is the comparison of the seasonally adjusted series of Northeast Housing Starts using the base model to the seasonally- and weather-adjusted series using the two-regressor model from the previous section. Again, outliers will be allowed to vary between the two models. The top plot of Figure 8 shows the original series (gray), the seasonal adjustment from a model without weather regressors (red), and the times at which additive outliers (circles) and level shifts (triangles) have been identified. The outliers have also been labeled with the type. The bottom plot layers the seasonal and weather adjustment (black) from the model with the two regressors, with the outliers identified by that model labeled. The corresponding plots for the two disjoint subspans are shown in Figures 9 (for the data from 1970 through 1999) and 10 (for the data from 2000 through 2019).

The seasonal and weather adjustment in these figures does appear to smooth out some of the more ragged movements of the seasonal-only adjustment. That is, some of the peaks and troughs in the seasonal-only adjustment are flattened to some extent. However, just as the model with weather regressors for the Northeast introduces (or identifies) some additional outliers, so too does the resulting seasonal and weather adjustment introduce some ragged movements of its own at times where the seasonal-only adjustment is smoother: the spikes around the beginning of 2001 in

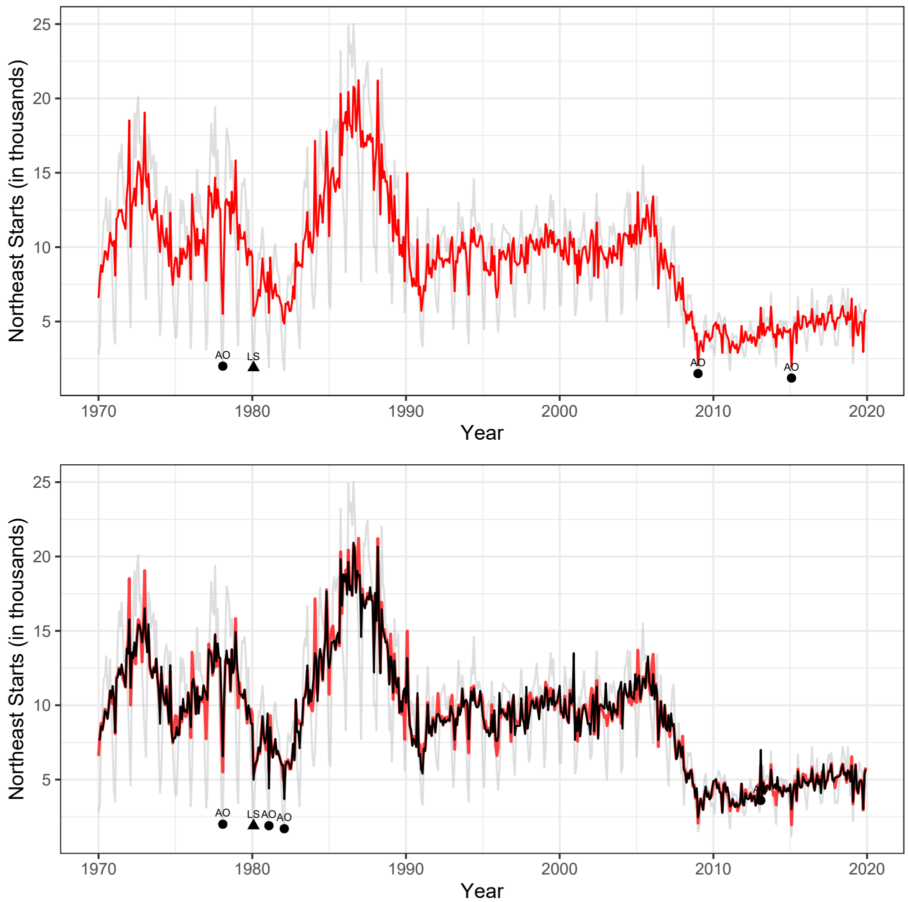

Figure 8: Seasonal-only and seasonal and weather adjustments of Northeast Housing Starts over the full span of data. Data sourced from U.S. Census Bureau, Survey of Construction.

Figure 10 and near February 2013 are two such examples.

Figure 11 shows the ratio, using the full span of data, of the seasonal and weather adjusted series to the seasonal-only adjustment by month. Similarly, Figures 12 and 13 provide the corresponding ratios using the appropriate subspans of the series. These figures also suggest that the largest modifications to the seasonal adjustment through the introduction of weather regressors are in winter months: January, February, and December. While these modifications may not be as substantial as those observed for the Midwest, we still have instances where the seasonal and weather adjustment can be up up to 50 percent larger (or up to 25 percent smaller) than the seasonal-only adjustment. For the remainder of the year, there are some small differences between the two sets of adjustments.

Table 20 shows the average absolute percent difference between the seasonal and weather adjusted series compared to the seasonal-only adjusted series by month, both for the models using the full span and for the models over the two distinct subspans. The changes are slightly less severe than those observed for the Midwest, but again, the seasonal and weather adjustments for January and February differ on average by over 10 percent (in either direction) from the seasonal-only adjustments, no matter which span of data is used to fit the models. The differences in March for the Northeast are slightly larger than their counterparts for the Midwest, while the differences in De-

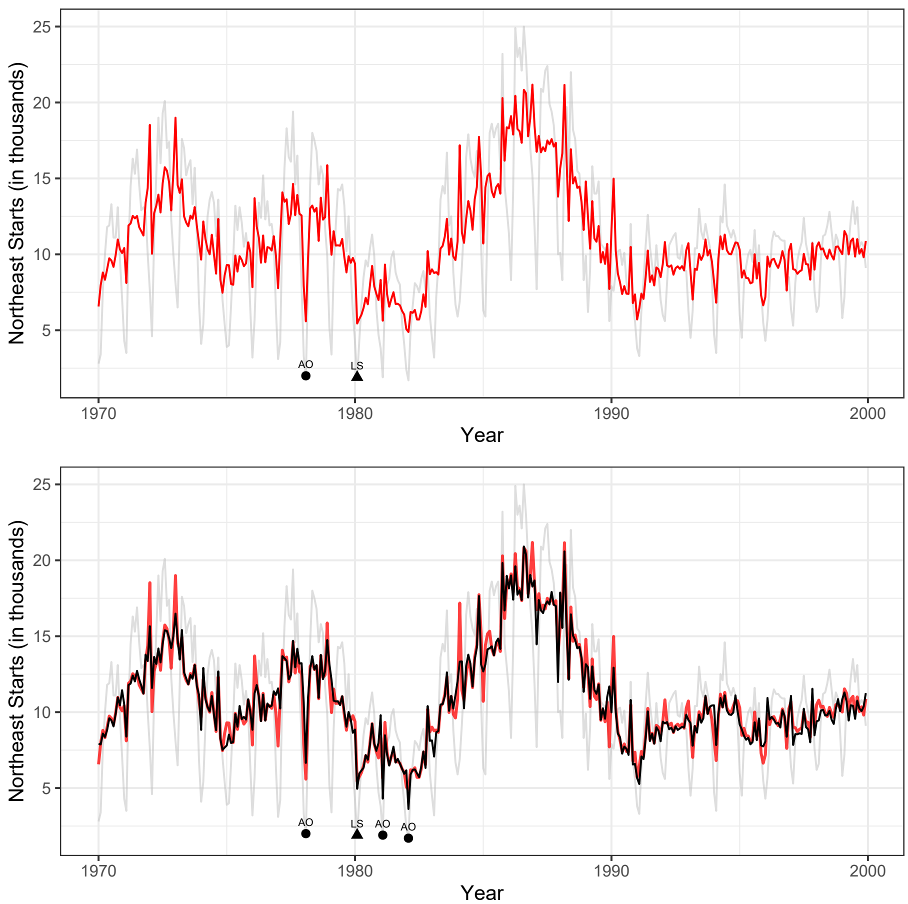

Figure 9: Seasonal-only and seasonal and weather adjustments of Northeast Housing Starts using just data from 1970 through 1999. Data sourced from U.S. Census Bureau, Survey of Construction.

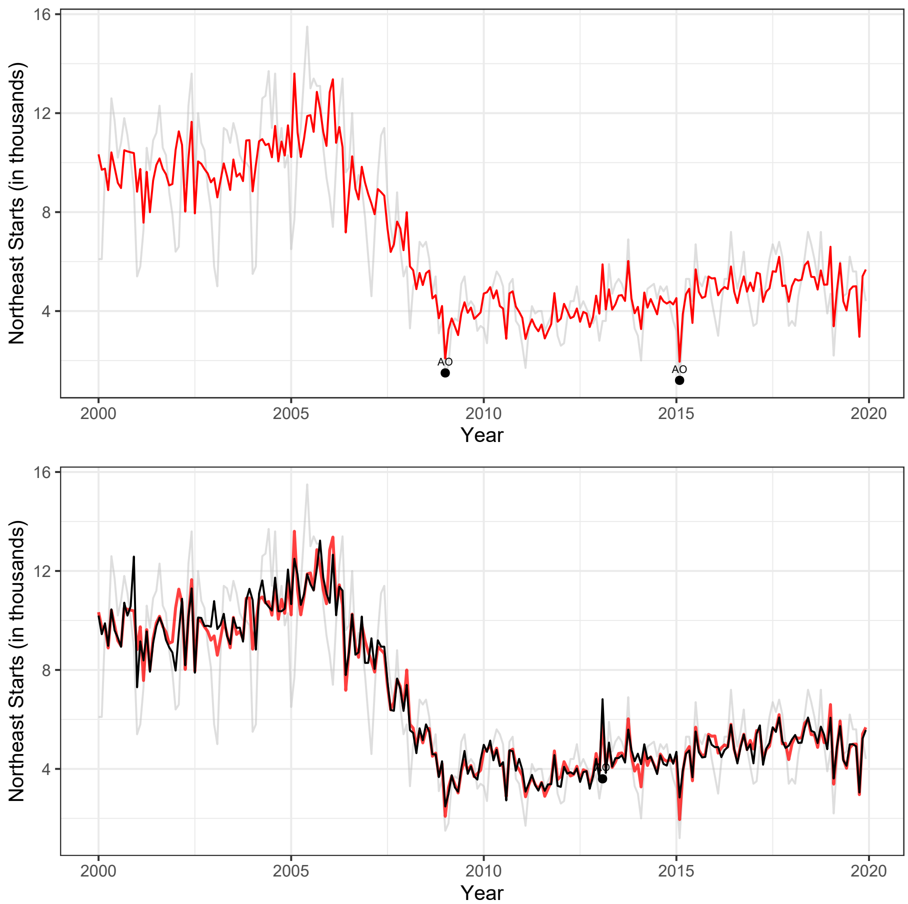

Figure 10: Seasonal-only and seasonal and weather adjustments of Northeast Housing Starts using just data from 2000 through 2019. Data sourced from U.S. Census Bureau, Survey of Construction.

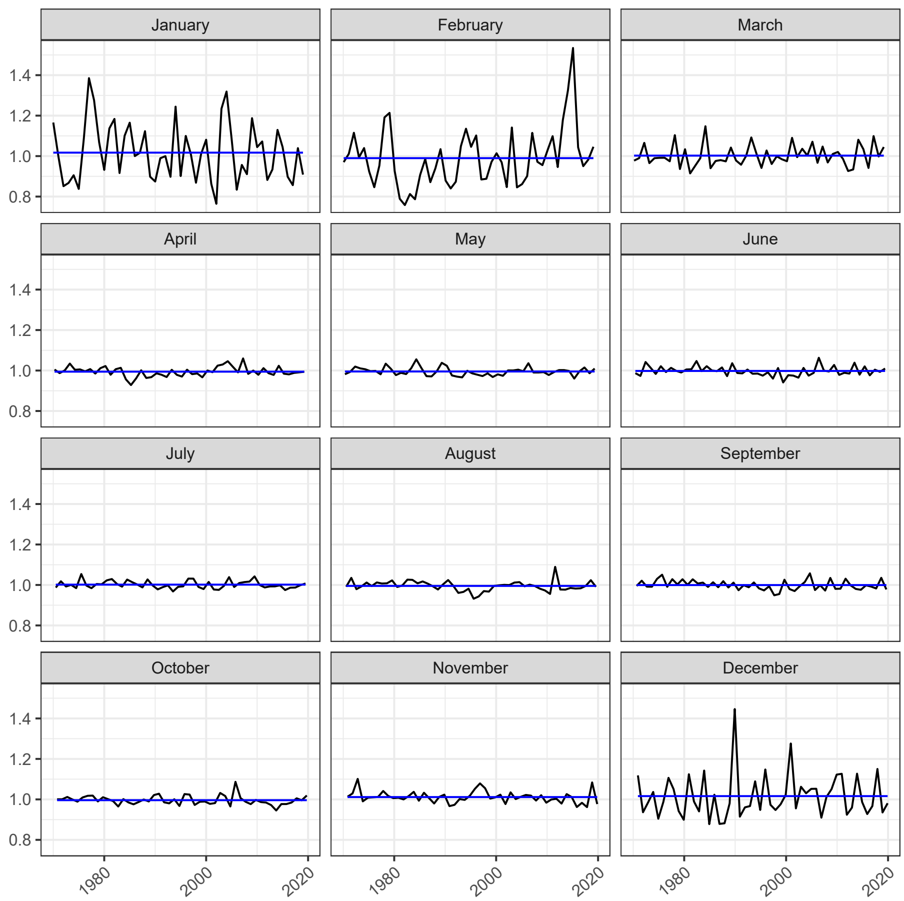

Figure 11: Ratio of Northeast seasonal and weather adjustment to seasonal-only adjustment, by month, using the full span of data. Data sourced from U.S. Census Bureau, Survey of Construction.

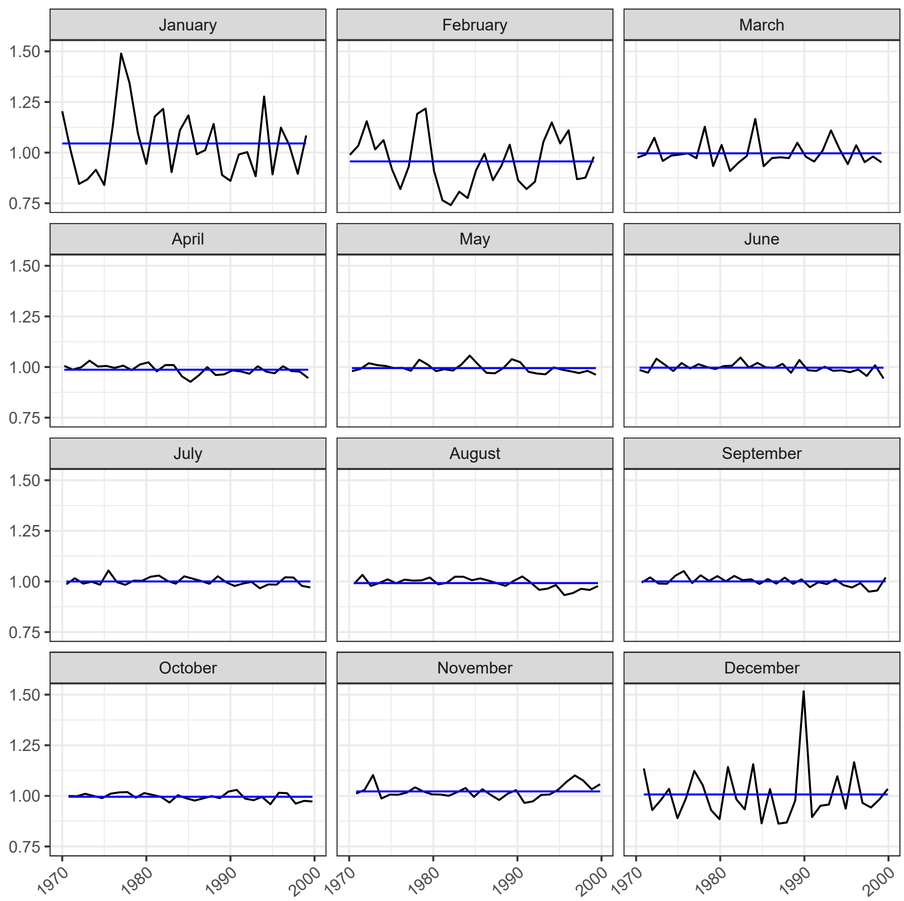

Figure 12: Ratio of Northeast seasonal and weather adjustment to seasonal-only adjustment, by month, for models using just data from 1970 through 1999. Data sourced from U.S. Census Bureau, Survey of Construction.

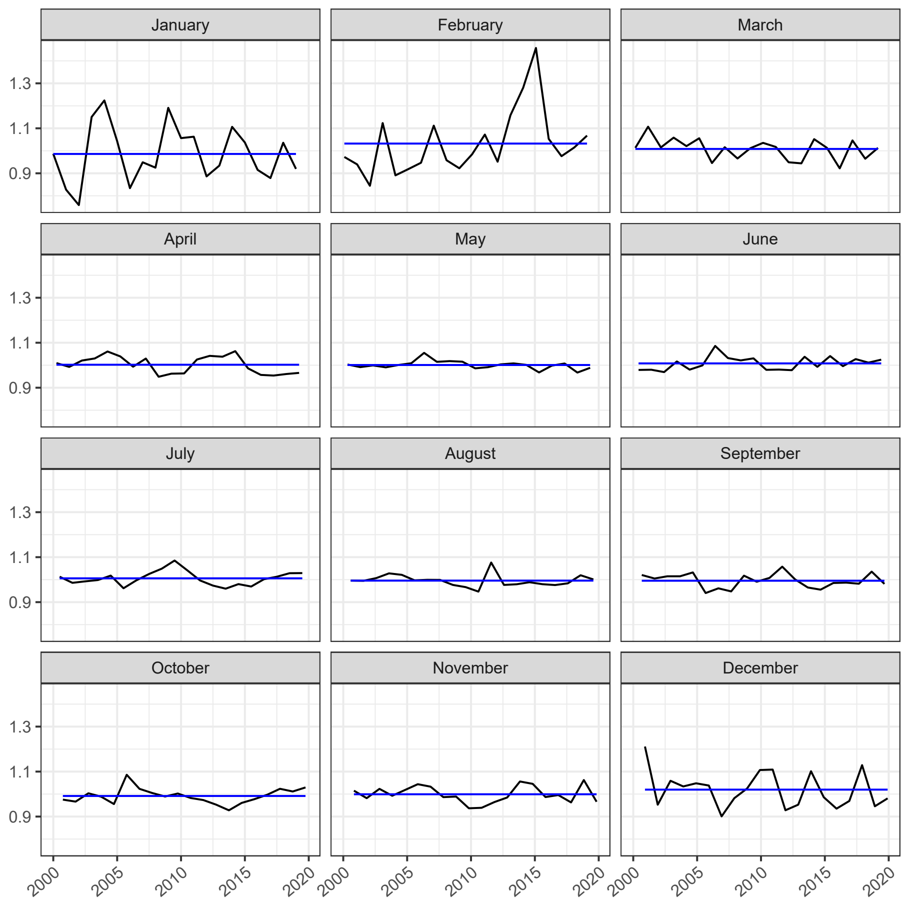

Figure 13: Ratio of Northeast seasonal and weather adjustment to seasonal-only adjustment, by month, for models using just data from 2000 through 2019. Data sourced from U.S. Census Bureau, Survey of Construction.

Month	1970–2019	1970–1999	2000–2019
January	11.53	13.06	10.46
February	10.86	11.49	10.16
March	4.02	4.54	3.92
April	1.89	2.10	3.36
May	1.63	2.04	1.29
June	1.88	1.83	2.47
July	1.49	1.60	2.45
August	1.87	2.03	1.96
September	1.91	1.81	2.56
October	1.75	1.50	2.69
November	2.27	2.87	3.06
December	7.87	9.25	6.64

Table 20: Average absolute percent difference between the Northeast seasonal and weather adjustment and the seasonal-only adjustment, by month, modeling over the spans listed. Data sourced from U.S. Census Bureau, Survey of Construction.

cember are slightly smaller. The rest of the year seems to encounter small deviations as compared to those of the Midwest.

6 Conclusion

Weather data does have some utility in augmenting time series models for economic data. The resulting seasonal and weather adjusted series may yield smaller fluctuations in months that are more likely to be subject to extreme weather events. In addition, the inclusion of weather regressors has the potential to explain some outliers that would have been identified by a model that failed to account for weather effects. These same weather regressors also can identify outliers that may have been previously missed.

The procedure described in the paper above uses weather data collected by stations, which are subsequently associated with cities. Thus, the regressors produced are dependent on what data is being collected by the governing agency (or the weather station, for that matter, as some may only track precipitation, while others may only track temperature). Previous research seemed to consider variables that are akin to monthly averages, whereas we have explored what could be described as thresholding variables. These variables measure the number of days (or transformed, the proportion) of a month for which a particular weather condition is true, or the deviation from the long-term average thereof, and thus may be interpreted as reflecting the persistence of a particular weather condition. These thresholding variables may perform better as regressors relative to monthly averages.

The examples used U.S. regional-level data—Goodman (1987), Cammarota (1989), and Coulson and Richard (1996) had all observed that the effects of weather on economic data in the U.S. appeared to be more pronounced at a regional level than they are at a national level. But conceptually, for any large country, the disparate weather patterns could prove difficult for the examination of national-level data, so the idea of compiling weather data from across such a country into a singular national value may be unwise. However, for smaller countries (or countries with more uniform weather patterns), it may be possible to construct such an aggregate national index.

Our examples chose models with different regressors. There may be some argument that tailoring the regressor set to the region may be overtuning—that using a consistent set across regions may be a more proper approach. We also did not probe too deeply into the inclusion of month-specific regressors into the regressor set. It is apparent that some of the weather variables may actually benefit from adopting a month-specific approach, but given that the retained months may be dependent on the span used for the model, this approach could be prone to overtuning. From the perspective of a practitioner of seasonal adjustment, there may be a question regarding the feasibility of integrating weather data into the production process. At the very least, however, it appears that there can be some value in retroactively checking whether an outlier may have been weather-influenced.

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