Weather Adjusting Economic Data

Michael Boldin and Jonathan H. Wright*

First version: December 18, 2014
This version: October 14, 2015

Abstract

This paper proposes and implements a statistical methodology for adjusting employment data for the effects of deviations in weather from seasonal norms. This is distinct from seasonal adjustment, which only controls for the normal variation in weather across the year. We simultaneously control for both of these effects by integrating a weather adjustment step in the seasonal adjustment process. We use several indicators of weather, including temperature and snowfall. We find that weather effects can be important, shifting the monthly payrolls change number by more than 100,000 in either direction. The effects are largest in the winter and early spring months, and in the construction sector. A similar methodology is constructed and applied to NIPA data, although the manner in which NIPA data are reported makes it impossible fully to integrate weather and seasonal adjustments.

JEL Classifications: C22, C80
Keywords: Weather, employment data, seasonal adjustment, big data.

---

*Federal Reserve Bank of Philadelphia, Ten Independence Mall, Philadelphia, PA 19106, michael.boldin@phil.frb.org and Department of Economics, Johns Hopkins University, 3400 North Charles St. Baltimore, MD 21218, wrightj@jhu.edu. This is a revised version of an earlier manuscript entitled "Weather Adjusting Employment Data". We are grateful to Katharine Abraham, Roc Armenter, Bob Barbera, Mary Bowler, François Gourio, David Romer, Claudia Sahm, Tom Stark and Justin Wolfers for helpful discussions, and to Natsuki Arai for outstanding research assistance. All errors are our sole responsibility. The views expressed here are those of the authors and do not necessarily represent those of the Federal Reserve Bank of Philadelphia or the Federal Reserve System.

1 Introduction

Macroeconomic time series are affected by the weather. For example, in the first quarter of 2014, real GDP contracted by 0.9 percent at an annualized rate. Commentators and Federal Reserve officials attributed part of the decline to an unusually cold winter and large snowstorms that hit the East Coast and the South during the quarter (see Macroeconomic Advisers (2014) and Yellen (2014)).[1] Similarly the slowdown in growth in the first quarter of 2015 was widely ascribed to another exceptionally harsh winter and other transitory factors (Yellen, 2015). While the effects of regular variation in weather within a year should, in principle, be taken care of by the seasonal adjustment procedures that are typically applied to economic data, these adjustments are explicitly *not* supposed to adjust for variations that are driven by deviations from the weather norms for a particular time of year. It is typically cold in February, depressing activity in some sectors, and seasonal adjustment controls for this. But seasonal adjustment does not control for whether a particular February is colder or milder than normal.

Our objective in this paper is to construct and implement a methodology for estimating how the data would have appeared if weather patterns had followed their seasonal norms. Monetary policymakers view weather effects as transitory—given the long and variable lags in monetary policy, they do not generally seek to respond to weather-related factors. It follows that the economic indicators that they are provided with ought, as far as possible, be purged of weather effects. Moreover, we argue that failing to control for abnormal weather effects distorts conventional

[1] In November 2013, the Survey of Professional Forecasters expected a seasonally adjusted increase of 2.5 percent in 2014Q1. The original report for the quarter was 0.1 percent, later revised to -2.1 percent, and subsequently revised to -0.9 in the 2015 annual NIPA adjustments that included revisions to the seasonal adjustment process, as discussed in section 4 below. With a snap-back rate of 4.6 percent in the second quarter, it is highly plausible that weather played a significant role in the decline.

seasonal adjustment procedures.

The measurement of inflation provides a useful analogy. The Federal Reserve focuses on core inflation, excluding food and energy, rather than headline inflation. The motivation is not that food and energy are inherently less important expenditures, but that fluctuations in their inflation rates are transitory. Core inflation is more persistent, and forecastable, and indeed a forecast of core inflation may be the best way of predicting overall inflation (Faust and Wright, 2013). In the same way, economic fluctuations caused by the weather are real, but transitory. We may obtain a better measure of the economy's underlying momentum by removing the effects of abnormal weather.

Economists have studied the effects of the weather on agricultural output for a long time, going back to the work of Fisher (1925). More recently, they have also used weather as an instrumental variable (see, for example, Miguel et al. (2004)), arguing that weather can be thought of as an exogenous driver of economic activity. Statistical agencies sometimes judgmentally adjust extreme observations due to specific weather events before applying their seasonal adjustment procedures.[2] Although there is a long literature on seasonal adjustment, we are aware of only a few papers on estimating the effect of unseasonal weather on macroeconomic aggregates. The few papers on the topic include Macroeconomic Advisers (2014), which regressed seasonally adjusted aggregate GDP on snowfall totals, estimating that snow reduced 2014Q1 GDP by 1.4 percentage points at an annualized rate, Bloesch and Gourio (2014) who likewise studied the relationship between weather and seasonally adjusted data, Dell et al. (2012) who implemented a cross-country study of the effects of annual temperature on annual GDP, and Foote (2015) who studied weather effects

[2] Even when agencies do this, their goal is just to prevent the anomalous weather from distorting seasonals, not to actually adjust the data for the effects of the weather. More on this later.

on state-level employment data. None of these papers integrates weather adjustment in the seasonal adjustment process. This is what the current paper attempts to do.

We focus mainly, but not exclusively, on the seasonal adjustment of the Bureau of Labor Statistics (BLS) current employment statistics (CES) survey (the “establishment” survey) that includes total nonfarm payrolls. We do so because it is clearly the most widely followed monthly economic indicator, and also because it is an indicator for which it is possible for researchers to approximately replicate the official seasonal adjustment process, unlike for National Income and Product Account (NIPA) data. We consider simultaneously adjusting these data for both seasonal effects and for unseasonal weather effects. This can be quite different from ordinary seasonal adjustment, especially during the winter and early spring. Month-over-month changes in nonfarm payrolls are in several cases higher or lower by as much as 100,000 jobs when using the proposed seasonal-and-weather adjustment rather than ordinary seasonal adjustment. Using seasonal-and-weather adjustment increases the estimated pace of employment growth in the winters of 2013-2014 and 2014-2015.

The plan for the remainder of this paper is as follows. In Section 2, we discuss alternative measures of unusual weather and evaluate how they relate to aggregate employment. This is intended to give us guidance on which weather indicators have an important impact on employment data. Section 3 describes seasonal adjustment in the CES and discusses how adjustment for unusual weather effects may be added into this—seasonal adjustment is implemented at the disaggregate level. Section 4 extends the analysis to NIPA data. Section 5 concludes.

2 Measuring unusual weather and its effect on aggregate employment data

We need to construct measures of unseasonal weather that are suitable for adjusting the CES survey. We first obtained data from the National Centers for Environmental Information on daily maximum temperatures, precipitation, snowfall and heating degree days (HDDs)[3] at one station in each of the largest 50 Metropolitan Statistical Areas by population, in the United States from 1960 to the present. The stations were chosen to provide a long and complete history of data,[4] and are listed in Table 1. We averaged these across the 50 Metropolitan Statistical Areas, with the averages weighted by population, determined from the 2010 census. This was designed as a way of measuring U.S.-wide temperature, precipitation and snowfall in a way that makes a long time series easily available and that puts the highest weight on areas with the greatest economic activity. Weather, of course, varies substantially around the country, and it might seem more natural to adjust state-level employment data for state-level weather effects. We used national-level employment data with national-level weather because the BLS produces state and national data separately using different methodologies. National CES numbers are quite different from the "sum of states" numbers. The reason is that both state and national CES numbers are constructed by survey methods, but the national data uses more disaggregated cells. Meanwhile, it is the national numbers that garner virtually all the attention from Wall Street and the Federal Reserve.

[3]The HDD at a given station on a given day is defined as $\max(18.3\text{-}\tau, 0)$ where τ is the average of maximum and minimum temperatures in degrees Celsius.

[4]An alternative measure of snowfall, used by Macroeconomic Advisers (2014), is based on a dataset of daily county-level snowfall maintained by the National Centers for Environmental Information. This clearly has the advantage of greater cross-sectional granularity. However, these data only go back to 2005. Our data go much further back, allowing us to construct a longer history of snowfall effects, and to measure normal snowfall from 30-year averages.

Let $temp_s$ denote the actual average temperature on day s, and define the unusual temperature for that day as $temp_s^* = temp_s - \frac{1}{30}\Sigma_{y=1}^{30} temp_{s,y}$ where $temp_{s,y}$ denotes the temperature on that same day y years previously. Likewise, let prp_s^*, $snow_s^*$ and hdd_s^* denote the unusual precipitation, snowfall or HDD on day s, relative to the 30-year average. This is in line with the meteorological convention of defining climate norms from 30-year averages (World Meteorological Organization, 2011).

In assessing the effect of unusual weather on employment as measured in the CES, we want to take careful account of the within-month timing of the CES survey. The CES survey relates to the pay period that includes the 12th day of the month. Some employers use weekly pay periods, others use biweekly, and a few use monthly. A worker is counted if (s)he works at any point in that pay period. Cold weather or snow seems most likely to affect employment status on the day of that unusual weather, but it is also possible that, for example, heavy snow might affect economic activity for several days after the snowstorm had ceased. Putting all this together, temperature/snowfall conditions in the days up to and including the 12th day of the month are likely to have some effect on measured employment for that month. The further before the 12th day of the month the unusual weather occurred, the less likely it is to have affected a worker's employment status in the pay period bracketing the 12th, and so the less important it should be. But it is hard to know *a priori* how to weight unusual weather on different days up to and including the 12th day of the month. On the other hand, it seems likely that unusual weather *after* the 12th day of the month ought to have little effect on employment data for that month.[5]

[5]There are actually ways in which weather after the 12th could matter for CES employment that month. For example, suppose that a new hire was supposed to begin work on the 13th, and the 13th happens to be the last day of the pay period. She would be counted as employed in that month. But if bad weather caused the worker's start date to be delayed, then she would not be defined as employed in that month. We do however evaluate the possibility that weather just after the 12th could affect employment for that month.

In solving this problem, we try to let the data speak. Our proposed approach assumes that the relevant temperature/precipitation/snowfall conditions are a weighted average of the temperature/precipitation/snowfall in the 30 days up to and including the 12th day of the month using a Mixed Data Sampling (MIDAS) polynomial as the weights—a model that instead estimated weights on individual days would likely use more parameters than needed. We want to use this specification to collapse the daily weather data that we have into monthly weather measures. We will spell out the details of the MIDAS polynomial and its estimation below. MIDAS polynomials were proposed by Ghysels et al. (2004, 2005) and Andreou et al. (2010) as a device for handling mixed frequency data in a way that is parsimonious yet flexible—exactly the problem that we face here. The presumption is that unusual weather on or just before the 12th day of the month should get more weight than unusual weather well before this date.

In addition to temperature, precipitation, snowfall and HDDs, there are two other weather indicators that we consider. First, as an alternative way of measuring snowfall, the National Centers for Environmental Information produce regional snowfall indices that measure the disruptive impact of significant snowstorms. These indices take into account the area affected by the storm and the population in that area, for six different regions of the country. See Kocin and Uccellini (2004) and Squires et al. (2014) for a discussion of these regional snowfall impact (RSI) indices. They are designed to measure the societal impacts of different storms, which makes them potentially very useful for our purposes. They have the drawback that they do not cover the Western part of the country, but there only two big cities that are not covered and that receive significant snowfall—Denver and Salt Lake City. Any snowstorm affecting a region has an index, a start date, and an end date. We treat the level of snowfall in that region as being equal to the index value from the start to the end date, inclusive. For example, a storm affecting the Southeast region was rated as 10.666, started on February 10, 2014, and ended on February 13, 2014. We treat this index as having a value of 10.666 on each day from February 10 to 13, 2014. On each day, we then create a weighted sum of the 6 regional snowstorm indices to get a national value, where the weights are the populations in the regions (from the 2010 Census). We then used this RSI index as an alternative to the average snowfall. Second, the household Current Population Survey (CPS) asks respondents if they were unable to work because of the weather. We seasonally adjust the number who were absent from work[6] in month t, using the default X-13 filter, and then treat this variable, abs_t, as an additional weather indicator.

We first estimate eight candidate models giving the effects of different weather measures on aggregate employment. Intuitively, we are simply interested in regressing monthly aggregate NSA employment onto a weighted average of daily weather data, where the weights give the best possible fit. This is intended as a precursor to incorporating weather effects in CES seasonal adjustment. However, weather is only a very small part of what drives aggregate employment. We also want the model to allow for trend and seasonal components.

Accordingly, each of our eight candidate models is an "airline model"—the default model in the first stage of the X-13—fitted to aggregate NSA employment, but augmented by weather variables. Each model specifies that there are trend and seasonal components that are nonstationary and consequently require taking first differences and differences from the same month one year earlier. After this differencing, the employment data is driven by weather effects and by moving average errors. The

[6] This is the number with a job, not at work, in non-agricultural industries (Series LNU02036012).

specific model is of the form:

$$(1-L)(1-L^{12})(y_t-\gamma' x_t)=(1+\theta L)(1+\Theta L^{12})\varepsilon_t, \tag{1}$$

where y_t is total NSA employment for month t, L is the lag operator and ε_t is an i.i.d. error term. The eight models differ only in the specification of the regressors in x_t. The specifications that we consider are:

1. **Temperature only**. There are 12 elements in x_t, each of which is $\Sigma_{j=0}^{30} w_j temp^*_{s-j}$ interacted with one of 12 monthly dummies, where day s is the 12th day of month t, $w_j = B(\frac{j}{30}, a, b)$ and $B(x; a, b) = \frac{\exp(ax+bx^2)}{\Sigma_{j=0}^{30}\exp(a\frac{j}{30}+b(\frac{j}{30})^2)}$. $B(x; a, b)$ is the MIDAS polynomial. In all, this model has 17 parameters: the 12 elements of γ along with a, b, θ, Θ and the variance of the error term. Temperature is interacted with month dummies. The motivation for this is that the effect of temperature on the economy depends heavily on the time of year. For example, unusually cold weather in winter lowers building activity, but unusually cold weather in the summer might have little effect on this sector, or might even boost it. Likewise, warm weather boosts demand for electricity in summer but weakens demand for electricity in winter.

2. **HDD only**. There are 12 elements in x_t, each of which is $\Sigma_{j=0}^{30} w_j hdd^*_{s-j}$ interacted with one of 12 monthly dummies where $w_j = B(\frac{j}{30}, a, b)$.

3. **Temperature and snowfall**. There are 13 elements in x_t. The first 12 are as in specification 1. The 13th element is $\Sigma_{j=0}^{30} w_j snow^*_{s-j}$ where $snow^*_s$ denotes the unusual snowfall on the 12th day of month t, measured as the population-weighted average across Metropolitan Statistical Areas. Snow is not interacted with month dummies, because it falls only in the winter months, and its effect

on employment is likely to be similar in any winter month.

4. **Temperature, snowfall (RSI index)**. The specification is as in (3), except using the RSI index to measure snowfall.

5. **Temperature, snowfall (RSI index) and weather-related absences from work**. The specification is as in (3) except that abs_t^* is included as the 14th element of x_t.

6. **Temperature, snowfall (RSI index) and precipitation**. There are 14 elements in x_t. The first 13 are as in specification 4. The 14th element is $\Sigma_{j=0}^{30} w_j prp_{s-j}^*$ where prp_s^* denotes the unusual precipitation on the 12th day of month t, measured as the population-weighted average across MSAs.

7. **Temperature, snowfall (RSI index) and lags of temperature and snowfall**. There are 13 elements in x_t. Each of the first 12 is $\Sigma_{j=0}^{90} w_j temp_{s-j}^*$ interacted with one of 12 monthly dummies, where $w_j = B(\frac{j}{30}, a, b)$ for $j \leq 30$, $w_j = c$ for $31 \leq j \leq 60$ and $w_j = d$ for $j > 60$. The last element is $\Sigma_{j=0}^{90} w_j snow_{s-j}^*$. In this specification, the parameters c and d determine the weight of weather two and three months prior.

8. **Temperature, snowfall (RSI index) and temperature and snowfall just after the CES survey date.** There are 13 elements in x_t. Each of the first 12 is $\Sigma_{j=-2}^{90} w_j temp_{s-j}^*$ interacted with one of 12 monthly dummies, where $w_j = B(\frac{j}{30}, a, b)$ for $j \geq 0$ and $w_j = c$ otherwise. The last element is $\Sigma_{j=-2}^{90} w_j snow_{s+j}^*$. In this specification, we use a MIDAS-weighted average of the days up to and including the 12th, and an extra parameter c, determines the weight of weather on the 13th and 14th of the month.

Note that in all these specifications, we are assuming that the effect is linear in weather; unusually cold and unusually warm temperatures are assumed to have effects of equal magnitude but opposite sign.

All of the weather indicators that we consider are physical measures of weather that are essentially exogenous,[7] except for self-reported work absences due to weather (specification 5). We are consequently a little more cautious about the use of weather-related work absences as a weather measure. Of course, it could be that this variable is giving us more information about the economic costs of weather conditions than any statistical model can hope to obtain. On the other hand, in a strong labor market, employers and employees may make greater efforts to overcome weather disruptions, leading to a problem of endogeneity with this measure.[8]

Table 2 reports the parameter estimates from specifications 1-8. Coefficients on snowfall are generally significantly negative, while coefficients on temperature are generally significantly positive, but only in the winter and early spring months. That is, not surprisingly, unusually warm weather boosts employment (in these months), while unusually snowy weather lowers employment. The estimated coefficients give a "rule of thumb" for the effect of weather in month t on employment in month t. For example, in specification 1 we estimate that a 1°C decrease in average temperature in March lowers employment by 23,000.

Table 2 also reports the maximized log-likelihood from each specification, and p-values from various likelihood ratio tests. We overwhelmingly reject a model with no weather effect in favor of specification 1. Among specifications 1 and 2 (using

[7]Scientists agree that economic activity influences the climate, but this does not mean that it influences deviations of weather from seasonal norms.

[8]Note also that there is a timing issue in using the CPS weather-related absences from work measure. That measure specifically refers to absence from work in the Sunday-Saturday period bracketing the 12th of the month. This lines up with the employment definition in the CES only for establishments with a Sunday-Saturday weekly pay period.

temperature or heating degree days), the former gives the higher log-likelihood, and so we prefer using temperature to heating degree days. We reject specification 1 in favor of specifications 3 and 4, meaning that a snow indicator is important over and above the temperature effect. Among specifications 3 and 4, specification 4 (measuring snowfall using the RSI index) gives the higher log-likelihood, and this RSI index is consequently our preferred snowfall measure. The fact that the RSI index gives a better fit to employment than is obtained using simple snowfall totals indicates that Kocin and Uccellini (2004) and Squires et al. (2014) succeeded in their aim of constructing indices to measure societal impact of snowstorms. However, we reject specification 4 in favor of specifications 5, 6 and 7, meaning that work absences, precipitation and further lags are all important. Finally, there is no significant difference between specifications 4 and 8, meaning that there isn't much evidence for weather on the 13th and 14th of the month having any additional impact.

We considered some other specifications as well. First, we added the value of damage done by large hurricanes in the previous month,[9] relative to the 30-year average, to specification 4. However, this did not significantly improve specification 4, and so we do not consider hurricanes further.[10] Second, we amended specification 4 to allow for a nonlinearity, whereby positive and negative values of unexpected weather can have asymmetric effects. Again this did not significantly improve specification 4. Third, we modified specification 4 to use a weighted average of temperature in the 9 different climate regions of the US (as defined by the National Centers for Environmental Information), estimating the weights along with all the other parameters to maximize the likelihood of the national employment data. But this gave a barely

[9]This is the value in 2010 dollars, deflated by the price deflator for construction, as discussed in Blake et al. (2011).

[10]We estimate that each billion 2010 dollars in unusual hurricane damage *increases* employment in that month by 287 jobs (95% confidence interval: -919 to +1,493).

significant improvement in likelihood, and the estimated weights were imprecisely estimated and quite implausible in magnitude in some cases (notably the Northeast region received no weight at all). Clearly weather conditions can differ greatly by region, but it doesn't seem that the separate effects of regional weather variation on national employment data are econometrically well identified.[11]

The upper panel of Figure 1 plots the MIDAS polynomial implied by the pseudo-maximum likelihood estimates of a and b in specification 4. The estimated polynomial puts most weight on the few days up to and including the 12th of the month. This pattern can be found in the other specifications as well. The lower panel of Figure plots the lag structure $\{w_j\}_{j=0}^{90}$ corresponding to the estimates of specification 7. This specification allows for richer dynamics of the weather effect. The estimated value of c is positive, meaning that the weather effect in the level of employment lasts into the subsequent month. The estimated value of d is of very small magnitude but is negative. This means that bad weather actually boosts employment two months later. This could be because of a catch-up effect. If bad weather delayed a construction project in February, then this might make the builder employ more workers than otherwise in April to try to get back on schedule. A useful way of thinking of the lag structure in specification 7 is that if the average weight given to weather in the 30 days up to and including the 12th of the month[12] is normalized to 1, then the weights given to weather in the previous two months are 0.6 and -0.1, respectively.

[11] If one were instead trying to model regional employment data, then it would make sense to use regional weather data. However, as discussed earlier, the national employment data receives almost all of the focus in the media and among economists, policymakers and traders in financial markets, and this data cannot be built up from state level data. In addition, there may be spillover effects of weather in one region on economic activity in other regions—e.g., a large local snowstorm may disrupt transportation between regions. Our equations that fit national employment to national weather series are a parsimonious manner to allow for these potential effects.

[12] The weight given to the 30 days up to and including the 12th of the month is not constant—this is the *average* weight given to days in this window. The actual weights are shown in the lower panel of Figure 1.

3 Weather and seasonal adjustment

The X-13 ARIMA seasonal adjustment methodology, used by the BLS and other U.S. statistical agencies, is quite involved. Let y_t be a monthly series (possibly transformed) that is to be seasonally adjusted. The methodology first involves fitting a seasonal ARIMA model:

$$\phi(L)\Phi(L^{12})(1-L)^d(1-L^{12})^D(y_t - \beta' x_t) = \theta(L)\Theta(L^{12})\varepsilon_t, \quad (2)$$

where x_t is a vector of user-chosen regressors, β is a vector of parameters, L denotes the lag operator, $\phi(L)$, $\Phi(L^{12})$, $\theta(L)$ and $\Theta(L^{12})$ are polynomials of orders p, P, q and Q respectively, d and D are integer difference operators and ε_t is an i.i.d. error term. The model is estimated by maximum likelihood. The regression residuals, $y_t - \hat{\beta}' x_t$, are then passed through filters as described in the appendix of Wright (2013), and in more detail in Ladiray and Quenneville (1989) to estimate seasonal factors. Note that our specifications in the previous section are all special cases of equation (2).

Seasonal adjustment in the CES is implemented at the three-digit NAICS level (or more disaggregated for some series), and these series are then aggregated to constructed SA total nonfarm payrolls. In all, there are 150 disaggregates. We used the modeling choices, including ARIMA lag orders in equation (2), chosen by the BLS for each of the disaggregates but simply included measures of unusual weather, x_t^w, in the vector of user-chosen regressors, x_t. We consider the specifications in the previous section. Depending on the specification, our weather regressor x_t^w consists of the unusual temperature for month t, as constructed in the previous section,[13] interacted with 12 monthly dummies, the unusual snowfall for month t (defined analogously, but

[13]In specification 1 for aggregate employment data, let $\hat{a}$ and $\hat{b}$ denote the pseudo-maximum likelihood estimates of a and b. We measure the unusual temperature for month t as $\Sigma_{j=0}^{30} B(\frac{j}{30}, \hat{a}, \hat{b}) temp_{s-j}^*$ where $temp_s^*$ is the unusual temperature on the 12th day of month t.

not interacted with any dummies), and/or abs_t. All in all, this gives a total of 12-14 elements in x_t^w, depending on the specification, for inclusion as regressors in the X-13 filter. As in the previous section, we are assuming that the effect of weather is linear.

The sample period is January 1990 to May 2015 in all cases—the sample period is dictated by the fact that this is the start date for many of the 150 employment disaggregates.[14] For each of the 150 series, we compute the seasonally adjusted data net of weather effects, which we refer to as seasonally-and-weather adjusted (SWA). It is important to note that when we construct the SWA data we remove the weather effect before computing the seasonal adjustment and we do *not* add back these effects. In contrast, when the BLS judgmentally adjusts for extreme weather effects before calculating seasonal adjustments, they add back these initial adjustments. Their aim is not to purge the data of weather effects, but simply to ensure that the unusual weather does not contaminate estimates of seasonal patterns. Our aim for making weather adjustments is not only to improve seasonal adjustment, but also to produce data that are purged of unusual weather effects. A researcher who wants to keep these weather effects in the data, but not to have them affect seasonal patterns, could apply our methodology, and add the weather effects back in after the seasonal adjustments have been made.[15] But in this paper, we control for both the direct effect of weather on the data and the impact of weather on seasonal adjustment. The SWA data can then be summed across the 150 disaggregates and can be compared with the standard version that is only seasonally adjusted (SA).[16]

[14]Our weather data goes back to 1960, allowing us to measure unusual weather by subtracting off a backward looking 30-year average.

[15]This is not what the BLS currently does. The BLS adjusts for specific extreme weather events before computing seasonal factors on case-by-case basis, rather than doing so automatically as we envision.

[16]Our SA data differ somewhat from the official SA data because we use current-vintage data and the current specification files. In contrast, the official seasonal factors in the CES are frozen as estimated five years after the data are first released. Also, we use the full sample back to 1990 for seasonal adjustment. But our SA and SWA data are completely comparable.

The idea of preventing unusual weather from affecting seasonal factors is a little tricky in the presence of climate change because unusual weather might change ones beliefs about seasonal norms. However, climatologists measure seasonal norms from 30-year averages (World Meteorological Organization, 2011), whereas the X-13 filter effectively estimates seasonal factors from averaging just a few years' data. Allowing unusual weather to affect seasonal factors as estimated in the X-13 makes them too volatile.[17]

Note also that our methodology uses aggregate employment to estimate the parameters a, b, c and d that specify how employment is affected by the weather on different days. However, the seasonal-and-weather adjustment is otherwise conducted by applying the full X-13 methodology at the disaggregate level, as described earlier. Other than these parameters (which affect the construction of the monthly weather regressors x_t^w), no parameters from the estimation of equation (1) are used in our seasonal-and-weather adjustment. We use the same lag weights and model specification for each of the disaggregates for reasons of computational cost, parsimony, and ease of interpretation. The price that we pay for this is that we do not allow the persistence of weather effects or the choice of weather indicators to differ across industries. It is important to emphasize that we do allow the magnitude of weather effects to differ across industries—we only restrict the lag structure and choice of weather indicators to be the same.

3.1 Results: Specification 4

We start by considering specification 4 as the baseline case for constructing the weather variables that are used in equation (2) for 150 CES disaggregates. Specifi-

[17]Even preventing unusual weather from affecting seasonal factors, the seasonal factors will *eventually* catch up to climate change because we define unusual weather relative to a rolling 30-year average.

cation 4 includes both temperature and snowfall effects in a straightforward manner, with snowfall measured using the RSI index, and we believe that temperature and snowfall capture a large fraction of the potential weather effects. Results from using other specifications and are discussed in subsection 3.2.

Figure 2 compares total nonfarm payrolls from using ordinary seasonal adjustment and our seasonal-and-weather (SWA) adjustment, using this specification. The top panel shows the month-over-month changes in total payrolls with ordinary seasonal adjustment along with the comparable series that we constructed by adjusting for both abnormal weather and normal seasonal patterns. The bottom panel shows the differences in the two series (ordinary SA less SWA). The differences represent the combination of the directly estimated weather effects that are removed from the SWA series and differences between the seasonal factors in the two series. The latter source of differences is driven by the fact that failing to control for unusual weather events affects estimated seasonal factors.

Of course, the weather effects in the bottom panel of Figure 2 can be either positive or negative. They can be more than 100,000 in absolute magnitude. While these effects are generally small relative to the sampling error in preliminary month-over-month payrolls changes in the CES (standard deviation: 57,000), financial markets, the press, and the Fed are hypersensitive to employment data. The weather adjustments that we propose might often substantially alter their perceptions of the labor market.

3.1.1 Autocorrelation

Figure 3 shows the autocorrelogram of estimated weather effects. At a lag of one month, the weather effects are significantly negatively autocorrelated. This is because they are estimates of the weather effects in month-over-month *changes*. Unusually cold weather in month t will lower the change in payrolls during that month but will boost the change in payrolls for month $t+1$, assuming that normal weather returns in month $t+1$.

The autocorrelation of the weather effect in payrolls changes at lag 12 is also significantly negative. This is because bad weather has some effect on estimated seasonal factors, leading to an "echo" effect of the opposite sign one year later.[18] This underscores the importance of integrating the weather adjustment into the seasonal adjustment process, as opposed to simply attempting to control for the effect of weather on data that have been seasonally adjusted in the usual way.

3.1.2 Recent Winters

In Figure 2, the effects of the unusually cold winter of 2013-2014 can be seen. We estimate that weather effects lower the month-over-month payrolls change for December 2013 by 62,000 and by 64,000 in February 2014. Meanwhile, we estimate that the weather effect raised the payrolls change for March 2014 by 85,000, as more normal weather returned. The weather effect was quite consequential, but still does not explain all of the weakness in employment reports during the winter of 2013-2014. In March 2015, colder-than-normal weather is estimated to have lowered monthly payroll changes by 36,000.

3.1.3 Historical Effects

The winters of 2013-2014 and 2014-2015 are far from the biggest weather effects in the sample. The data in February and March 2007 contained a large swing as that February was colder than usual. That fact was not missed by the Federal Reserve's

[18] Wright (2013) argues that the job losses in the winter of 2008-2009 produced an echo effect of this sort in subsequent years. The distortionary effects of the Great Recession on seasonals are of course far bigger than the effects of any weather-related disturbances.

Greenbook which noted in March 2007 that:

> "In February, private nonfarm payroll employment increased only 58,000, as severe winter weather likely contributed to a 62,000 decline in construction employment."

Payrolls changes were weak in April and May 2012. Then Fed Chairman Ben Bernanke, in testimony to the Joint Economic Committee, attributed part of this to weather effects, noting that:

> "the unusually warm weather this past winter may have brought forward some hiring in sectors such as construction, where activity normally is subdued during the coldest months; thus, some of the slower pace of job gains this spring may have represented a payback for that earlier hiring." (Bernanke, 2012)

The data in February and March 1999 contained a big swing, as that February was unseasonably mild. According to our estimates, weather drove the month-over-month change in payrolls up by 90,000 in February 1999 and down by 115,000 the next month. The biggest effect in the sample was March 1993 where weather is estimated to have lowered employment growth by 178,000.[19] This is an enormous estimated weather effect, but does not seem unreasonable: In March 1993, reported nonfarm payrolls fell by 49,000, while employment growth was robust in the previous and subsequent few months.[20]

Table 3 lists the ten months in which the weather effect (the bottom panel of Figure 2) is the largest in absolute magnitude. These all occur in the first four

[19]Note that there were very big snowstorms in three regions of the country in that month.

[20]These are current-data-vintage numbers, with ordinary seasonal adjustment. The first released number for March 1993 was minus 22,000. The BLS employment situation write-up for that month made reference to the effects of the weather. But the BLS made no attempt to quantify the weather effect.

months of the year. They turn out to be 5 pairs of adjacent months as the effects of unusual weather are followed by bouncebacks when more seasonal weather returns.

Table 4 gives the minimum, maximum, and standard deviation of the total weather effect in payrolls changes broken out by month.[21] The standard deviation is the largest in March (68,000), followed by February (58,000). The standard deviations show that weather effects are potentially economically significant in winter and early spring, but they are relatively small in the summer months.

Figure 4 plots the difference between ordinary SA data and SWA data for payrolls changes in the construction sector alone (again using specification 4). Weather effects in the construction sector drive a bit less than half of total weather effects.

In all, the weather adjustment involves estimating 14 parameters in β^w for each of the 150 disaggregates for a total of 2,100 parameters. We do not report all of these parameter estimates. Most of the parameters are individually statistically insignificant. But the parameters associated with temperature in December, January, February and March, and the parameters associated with snowfall, are significantly negative for components of construction employment.

We would comment that we deliberately decided against a strategy of setting parameter estimates that are individually insignificant to zero. In general, assuming that a parameter is precisely zero because it is not statistically significant seems a dubious decision theoretic approach. But this may be particularly true when doing a "bottom up" adjustment for weather effects. For an individual disaggregate, a weather effect might be minor, but these weather effects are likely to be positively correlated across disaggregates, and so the weather effect might be much more important in the aggregate data that we ultimately care about.

[21]Means are not shown because they are close to zero by construction.

3.1.4 Persistence

Purging employment data of the weather effect might make the resulting series more persistent, in much the same way as purging CPI inflation of the volatile food-and-energy component makes the resulting core inflation series smoother, as discussed in the introduction. To investigate this, we compare the standard deviation and autocorrelation of month-over-month changes in SA and SWA payrolls data, both for total payrolls and for nine industry subaggregates. The results are shown in Table 5.

In the aggregate, month-over-month payrolls changes show a higher degree of autocorrelation using SWA data than using SA data. This primarily reflects the fact that the weather adjustments remove noise from the levels data which is a source of negative autocorrelation in month-over-month changes. In fact, in every sector except government, payrolls changes show a higher degree of autocorrelation using SWA data than using SA data. But the effect is small in most sectors. The exception is construction, where the proposed weather adjustment raises autocorrelation from 0.59 to 0.77. Particularly in the construction sector, weather adjustment removes noise that is unrelated to the trend, cyclical or seasonal components. This gives a better measure of the underlying strength of the economy.

3.2 Results with other specifications

We also considered the effects on seasonal adjustments from using other specifications discussed in section 2. In particular, we considered specifications 5, 6, 7 and 8 as alternatives to specification 4. Specification 5 includes absences from work, specification 6 includes precipitation, specification 7 adds monthly lags to admit richer dynamics and specification 8 includes weather on the 13th and 14th of the month. Figure 5 shows the *difference* between SWA data in each of these specifications and the SWA data in specification 4 (that simply used temperature and the RSI index). These charts show that only specification 7 produces noticeably different results. Since the more complicated models make little difference to the weather adjustment, and since simpler models are easier to understand, we prefer specification 4 to specifications 5, 6 and 8.[22]

Including monthly lags (specification 7) does however make a material difference to SWA data, and so we do think of this as an alternative benchmark approach to weather adjustment. Specification 4 forces the effects of unusual weather on the level of employment to disappear the next month, whereas specification 7 is more flexible in regards to the dynamics of weather effects. Figure 6 shows the difference between month-over-month payrolls changes using ordinary seasonal adjustment and SWA data using specification 7. The weather effects for changes in employment are still negatively autocorrelated, but are much less so when using lags—the first autocorrelation is -0.5 in specification 4, but -0.2 in specification 7.

Table 6 lists the ten months in which the weather effect from using this specification are largest in absolute magnitude. Only five of these months are also found in Table 3. It is interesting to note that Table 6 only includes only one pair of adjacent months (February and March 2010), while all of the months in Table 3 are paired with an adjacent month, which is not entirely surprising because the bounceback phenomenon from specification 7 is weaker. We computed analogs of Tables 4 and 5 for specification 7, but they are similar to the original tables, and so we do not include them in the paper.

[22]While including absences from work in specification 5 seldom makes a material difference, an exception is September 2008. In this month, the number who reported absence from work due to weather spiked to levels normally observed only in winter. We speculate that this might owe to the fact that hurricane Ike was moving towards Texas during the survey week.

4 NIPA Data

4.1 NIPA Weather Adjustment

Our focus in this paper has been on the employment report because it is the most widely-followed economic news release, and because it is possible closely to replicate the seasonal adjustment process that the BLS uses in the reported CES data. GDP and other NIPA-based economic data are also widely followed, and are also potentially subject to weather effects. In fact, weather effects could be more important for these series because harsh weather only affects employment statistics when it causes an employee to miss an entire pay period, but it could have broader effects on NIPA series by lowering hours worked or consumer spending. On the other hand, weather effects on NIPA series could be mitigated by the fact that NIPA data are averaged over a whole quarter, not just a pay period. Unfortunately, the SWA steps described above cannot be applied to NIPA data because there is no way for researchers to replicate the seasonal adjustment process in these data, let alone to add weather effects to it.[23]

As an alternative, we instead apply weather adjustments directly to seasonally adjusted NIPA aggregates. We consider the model:

$$\begin{aligned} y_t = {} & \mu_1 s_{1t} + \mu_2 s_{2t} + \mu_3 s_{3t} + \mu_4 s_{4t} + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \phi_3 y_{t-3} + \phi_4 y_{t-4} \\ & + \gamma_1 w_{1t} d_{1t} + \gamma_2 w_{1t} d_{2t} + \gamma_3 w_{1t} d_{3t} + \gamma_4 w_{1t} d_{4t} + \gamma_5 (w_{2t} - w_{2t-1}) + \varepsilon_t, \end{aligned} \quad (3)$$

where y_t is the quarter-over-quarter growth rate of real GDP or some component

[23] Although the BEA compiles NIPA data, seasonal adjustment is done at a highly disaggregated level, and many series are passed from other agencies to the BEA in seasonally adjusted form. As noted in Wright (2013) and Manski (2015), while the BEA used to compile not-seasonally-adjusted NIPA data, they stopped doing so a few years back as a cost-cutting measure. Happily, the June 2015 Survey of Current Business indicated plans to resume publication of not-seasonally-adjusted aggregate data, but this will still not allow researchers to replicate the seasonal adjustment process.

thereof, $s_{1t}, ...s_{4t}$ are four quarterly dummies,[24] w_{1t} is the unusual temperature in quarter t (defined as the simple average of daily values in that quarter), w_{2t} is the unusual snowfall in quarter t (using the RSI index) and $d_{1t}, ...d_{4t}$ are four quarterly variables, each of which takes on the value one in a particular quarter, minus one in the next quarter, and zero otherwise. The particular specification in equation (3) has the property that no weather shock can ever have a permanent effect on the *level* of real GDP—any weather effect on growth has to be "paid back" eventually, although not necessarily in the subsequent quarter, given the lagged dependent variables.[25] Our sample period is 1990Q1-2015Q2, using September 2015 vintage data. Coefficient estimates are shown in Table 7 for real GDP growth and selected components. For real GDP growth, unusual temperature is statistically significant in the first and second quarters.

We think that the assumption that no weather shock can have a permanent effect on the level of GDP is an important and reasonable restriction to impose. But we tested this restriction. We ran a regression of y_t on four quarterly dummies, four lags of y_t, unusual temperature interacted with quarterly dummies, lags of unusual temperature interacted with quarterly dummies, unusual snowfall, and lagged unusual snowfall. In this specification, there were 18 free parameters—equation (3) is a special case of this, imposing 5 constraints, that can be tested by a likelihood ratio test. The restriction is not rejected at the 5 percent level for GDP growth or any of the components, except government spending where the p-value is 0.04.

Having estimated equation (3), we then compute the dynamic weather effect by comparing the original series to a counterfactual series where all unusual weather indicators are equal to zero ($w_{1t} = w_{2t} = 0$), but with the same residuals. The

[24]Their inclusion is motivated by "residual seasonality" discussed further below.

[25]Macroeconomic Advisers (2014) find that snowfall effects on growth are followed by effects of opposite sign and roughly equal magnitude in the next quarter.

difference between the original and counterfactual series is our estimate of the weather effect.

Table 8 shows the quarter-over-quarter growth rates of real GDP and components in 2015 Q1 and Q2 both in the data as reported, and after our proposed weather adjustment. Weather adjustment raises the estimate of growth in the first quarter from 0.6 percentage points at an annualized rate to 1.4 percentage points. However, the estimate of growth in the second quarter is lowered from 3.7 to 2.8 percentage points. Weather adjustment makes the acceleration from the first quarter to the second quarter less marked.

4.2 Residual Seasonality

Our paper is about the effects of weather on economic data effects, not seasonal adjustment. But an unusual pattern has prevailed for some time in which first-quarter real GDP growth is generally lower than growth later in the year, raising the possibility of "residual seasonality"—the Bureau of Economic Analysis (BEA)'s reported data may not adequately correct for regular calendar-based patterns. This is a factor, separate from weather, that might have lowered reported growth in 2015Q1. Rudebusch et al. (2015) apply the X-12 seasonal filter to reported seasonally adjusted aggregate real GDP, and find that their "double adjustment" of GDP makes a substantial difference.[26]

The BEA has subsequently revisited its seasonal adjustment, and made changes in the July 2015 annual revision. The changes might have mitigated residual seasonality, but it important to note that the BEA has not published a complete historical revision

[26] On the other hand, Gilbert et al. (2015) find no statistically significant evidence of residual seasonality. The two papers are asking somewhat different questions. Gilbert et al. (2015) are asking a testing question, and while the hypothesis is not rejected, the p-values are right on the borderline despite a short sample. Rudebusch et al. (2015) are applying an estimation methodology.

to GDP and its components, instead only reporting improved seasonally adjusted data starting in 2012. We did an exercise in the spirit of Rudebusch et al. (2015) by taking our weather-adjusted aggregate real GDP (and components) data, and then putting these through the X-13 filter. This double seasonal adjustment is admittedly an *ad hoc* procedure, especially given that BEA data published for before and after 2012 use different seasonal adjustment procedures, and we consequently treat its results with particular caution. Nonetheless, the resulting growth rates in the first two quarters of 2015 are also shown in Table 7. After these two adjustments, growth was quite strong in the first quarter, but *weaker* in the second quarter, which is the opposite of the picture that one obtains using published data. It is interesting to note that the "double seasonal adjustment" has an especially large effect on investment and exports, suggesting that these are two areas in which seasonal adjustment procedures might benefit from further investigation.

5 Conclusions

Seasonal effects in macroeconomic data are enormous. These seasonal effects reflect, among other things, the consequences of regular variation in weather over the year. The seasonal adjustments that are applied to economic data are not however intended to address deviations of weather from seasonal norms. Yet, these deviations have material effects on macroeconomic data. Recognizing this fact, this paper has operationalized an approach for simultaneously controlling for both normal seasonal patterns and unusual weather effects. Our main focus has been on monthly employment data in the "establishment survey", or CES. The effects of unusual weather can be very important, especially in the construction sector and in the winter and early spring months. Monthly payrolls changes are somewhat more persistent when using seasonally-and-weather adjusted data than when using ordinary seasonally adjusted data, suggesting that this gives a better measure of the underlying momentum of the economy.

The physical weather indicators considered in this paper are all available on an almost real-time basis—the reporting lag is inconsequential. The National Centers for Environmental Information make daily summaries for 1,600 stations available with a lag of less than 48 hours. In addition, the regional snowfall impact indices that we use are typically computed and reported within a few days after a snowstorm ends. One weather indicator that we considered is the number of absences from work due to weather. This has a somewhat longer publication lag, but by construction is still available at the time of the employment report. It would be good if weather adjustments of this sort could be implemented by statistical agencies (as part of their regular data reporting process). Because they have access to the underlying source data, they have more flexibility in doing so than the general public—for example, some of the 150 disaggregates in the CES are not available until the first revision. Statistical agencies want data construction to use transparent methods that avoid *ad hoc* judgmental interventions, but that can be done for weather adjustment. Still U.S. statistical agencies face severe resource constraints, and weather-adjustment may well not be a sufficiently high priority. Weather adjustment can then be implemented by end users of the data. It is not that weather adjusted economic data should ever replace the underlying existing data, but weather adjustment can be a useful supplement to measure underlying economic momentum.

References

Andreou, Elena, Eric Ghysels, and Andros Kourtellos, "Regression Models with Mixed Sampling Frequencies," *Journal of Econometrics*, 2010, *158*, 246–261.

Bernanke, Ben S., "Economic Outlook and Policy," 2012. Testimony to the Joint Economic Committee, U.S. Congress: http://www.federalreserve.gov/newsevents/testimony/bernanke20120607a.htm/ [retrieved September 29, 2015].

Blake, Eric S., Christopher W. Landsea, and Ethan J. Gibney, "The Deadliest, Costliest, and Most Intense United States Tropical Cyclones from 1851 to 2010 (and Other Frequently Requested Hurricane Facts)," 2011. NOAA Technical Memorandom NWS NHC-6.

Bloesch, Justin and François Gourio, "The Effect of Winter Weather on U.S. Economic Activity," 2014. Working paper, Federal Reserve Bank of Chicago.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken, "Temperature Shocks and Economic Growth: Evidence from the Last Half Century," *American Economic Journal: Macroeconomics*, 2012, *4*, 66–95.

Faust, Jon and Jonathan H. Wright, "Forecasting Inflation," in Graham Elliott and Allan Timmermann, eds., *Handbook of Economic Forecasting, Volume 2A*, Amsterdam: North-Holland, 2013, pp. 3–56.

Fisher, Ronald A., "The Influence of Rainfall on the Yield of Wheat at Rothamsted," *Philosophical Transactions of the Royal Society of London. Series B*, 1925, *213*, 89–142.

Foote, Christopher L., "Did Abnormal Weather Affect U.S. Employment Growth in Early 2015?," 2015. Federal Reserve Bank of Boston Current Policy Perspectives 15-2.

Ghysels, Eric, Pedro Santa-Clara, and Rossen Valkanov, "The MIDAS Touch: Mixed Data Sampling Regression Models," 2004. Working paper, UCLA.

Ghysels, Eric, Pedro Santa-Clara, and Rossen Valkanov, "There is a Risk-return Trade-off After All," *Journal of Financial Economics*, 2005, *76*, 509–548.

Gilbert, Charles E., Norman J. Morin, Andrew D. Paciorek, and Claudia R. Sahm, "Residual Seasonality in GDP," 2015. Finance and Economics Discussion Series Notes.

Kocin, Paul J. and Louis W. Uccellini, "A Snowfall Impact Scale Derived from Northeast Snowfall Distributions," *Bulletin of the American Meteorological Society*, 2004, *85*, 177–194.

Ladiray, Dominique and Benoît Quenneville, *Seasonal Adjustment with the X-11 Method*, Springer, 1989.

Macroeconomic Advisers, "Elevated Snowfall reduced Q1 GDP growth 1.4 Percentage Points," 2014. Blog Post: http://www.macroadvisers.com/2014/04/elevated-snowfall-reduced-q1-gdp-growth-1-4-percentage-points/ [retrieved June 25, 2014].

Manski, Charles F., "Communicating Uncertainty in Official Economic Statistics: An Appraisal Fifty Years after Morgenstern," *Journal of Economic Literature*, 2015, *53*, 1–23.

Miguel, Edward, Shanker Satyanath, and Ernest Serengeti, "Economic Shocks and Civil Conflict: An Instrumental Variables Approach," *Journal of Political Economy*, 2004, *112*, 725–753.

Rudebusch, Glenn D., Daniel Wilson, and Tim Mahedy, "The Puzzle of Weak First-Quarter GDP Growth," 2015. Federal Reserve Bank of San Francisco Economic Letter.

Squires, Michael F., Jay H. Lawrimore, Richard R. Heim, David A. Robinson, Mathieu R. Gerbush, Thomas W. Estilow, and Leejah Ross, "The Regional Snowfall Index," *Bulletin of the American Meteorological Society*, 2014, *95*, 1835–1848.

World Meteorological Organization, *Guide to Climatological Practices* 2011.

Wright, Jonathan H., "Unseasonal Seasonals?," *Brookings Papers on Economic Activity*, 2013, *2*, 65–110.

Yellen, Janet L., "Economic Outlook and Policy," 2014. Testimony to the Joint Economic Committee, U.S. Congress: http://www.federalreserve.gov/newsevents/testimony/yellen20140507a.htm/ [retrieved September 29, 2015].

Yellen, Janet L., "Semiannual Monetary Policy Report to the Congress," 2015. Testimony to the House Financial Services Committee: http://www.federalreserve.gov/newsevents/testimony/yellen20150715a.htm/ [retrieved September 29, 2015].

Table 1: Weather Stations Used to Measure National Weather

MSA	Station	MSA	Station
New York	New York Central Park	San Antonio	San Antonio Airport
Los Angeles	Los Angeles Airport	Orlando	Orlando Airport
Chicago	Chicago O'Hare Airport	Cincinnati	Cincinnati Northern KY Airport
Dallas	Dallas FAA Airport	Cleveland	Cleveland Hopkins Airport
Philadelphia	Philadelphia Airport	Kansas City	Kansas City Aiport
Houston	Houston Intercontinental Airport	Las Vegas	Las Vegas Mccarran Airport
Washington	Washington Dulles Airport	Columbus	Columbus Port Columbus Airport
Miami	Miami Airport	Indianapolis	Indianapolis Airport
Atlanta	Hartsfield Airport	San Jose	Los Gatos
Boston	Boston Logan Airport	Austin	Austin Camp Mabry
San Francisco	San Francisco Airport	Virginia Beach	Norfolk Airport
Detroit	Detroit City Airport	Nashville	Nashville Airport
Riverside	Riverside Fire Station	Providence	Providence TF Green State Airport
Phoenix	Phoenix Sky Harbor Airport	Milwaukee	Milwaukee Mitchell Airport
Seattle	Sea Tac Airport	Jacksonville	Jacksonville Airport
Minneapolis	Minnesapolis Saint Paul Airport	Memphis	Memphis Airport
San Diego	San Diego Lindbergh Field	Oklahoma City	Oklahoma City Will Rogers World Airport
St Louis	St Louis Lambert Airport	Louisville	Louisville Airport
Tampa	Tampa Airport	Hartford	Hartford Bradley Airport
Baltimore	BWI Airport	Richmond	Richmond Airport
Denver	Denver Stapelton	New Orleans	New Orleans Airport
Pittsburgh	Pittsburgh Airport	Buffalo	Buffalo Niagara Airport
Portland	Portland Airport	Raleigh	Raleigh Durham Airport
Charlotte	Charlotte Douglas Airport	Birmingham	Birmingham Airport
Sacramento	Sacramento Executive Airport	Salt Lake City	Salt Lake City Airport

Note: This Table lists the 50 weather stations used to construct national average daily temperature, snowfall and HDD data. Each weather station corresponds to one of the 50 largest MSAs by population in the 2010 Census.

Table 2: Estimated Effects of Unusual Weather on Aggregate Employment

Spec:	1	2	3	4	5	6	7	8
γ_1	16.4**	-18.2**	12.6	13.8**	12.5*	13.7**	23.4***	12.3*
γ_2	33.6***	-38.6***	28.8***	23.3**	19.0**	22.6**	25.4***	23.4***
γ_3	23.3***	-26.8***	16.0**	18.3**	20.0***	19.0***	27.3***	17.9***
γ_4	-8.5	2.9	-18.1*	-6.3	-15.6*	-10.6	11.8	-10.3
γ_5	8.7	-4.1	20.7	12.3	16.8	16.3	28.6**	17.0
γ_6	22.7	55.0	24.4	22.3	24.6	15.9	6.4	15.0
γ_7	29.5	1072	26.5	30.6	56.0	38.6	-6.4	28.9
γ_8	30.5	-183.4	26.3	30.3	44.5	29.5	18.1**	26.0
γ_9	6.5	-42.7	1.1	6.3	26.5	-11.2	12.5	12.0
γ_{10}	18.6*	-25.9*	14.0	16.7	23.6**	13.5	18.9*	20.3**
γ_{11}	25.2*	-36.3*	20.7	21.5	17.0	15.4	23.9	22.6**
γ_{12}	16.0*	-16.4	11.0	14.7	11.5	15.4	22.4**	13.0
γ_{13}			-7.62***	-37.74**	-20.36	-39.1**	-77.63***	-24.73*
γ_{14}					-0.29***	12.3**		
LogL	-1968.9	-1970.1	-1965.5	-1964.7	-1952.3	-1961.9	-1957.9	-1964.2

LR Tests	p-values	Conclusion
H_0 : No weather vs. Spec 1	0.00	Reject exclusion of temperature
H_0 : Spec 1 vs. Spec 3	0.01	Reject exclusion of snow
H_0 : Spec 1 vs. Spec 4	0.00	Reject exclusion of snow (RSI)
H_0 : Spec 4 vs. Spec 5	0.00	Reject exclusion of absences
H_0 : Spec 4 vs. Spec 6	0.02	Reject exclusion of precipitation
H_0 : Spec 4 vs. Spec 7	0.00	Reject exclusion of lags
H_0 : Spec 4 vs. Spec 8	0.59	Do not reject exclusion of 13th and 14th

Note: The top panel of this table lists the parameter estimates from fitting specifications 1-8 to aggregate employment data. In all cases, $\gamma_1, ..\gamma_{12}$ refer to the coefficients on the unusual temperature variable interacted with dummies for January to December, respectively (except heating degree days for specification 2). Meanwhile γ_{13} refers to various snow effects (defined in the text) and γ_{14} refers to the effects of seasonally adjusted self-reported work absences due to weather and precipitation in specifications 5 and 6, respectively. One, two and three asterisks denote significance at the 10, 5 and 1 percent levels, respectively. The row labeled LogL gives the log-likelihood of each model. The specification with no weather effects at all has a log-likelihood of -1993.7. The bottom panel of the table reports p-values from various likelihood ratio tests comparing alternative specifications. Data units are as follows—employment: thousands, temperature: degrees C, snowfall: mm, RSI: scale that defines that index, precipitation: mm, work absences: thousands.

Table 3: Weather Effect in Monthly Payrolls Changes: Top 10 Absolute Effects

Month	Weather Effect
March 1993	-178
March 2010	+144
Feb 1996	+137
Jan 1996	-137
Apr 1993	+130
Feb 2010	-127
March 1999	-115
Feb 2007	-105
Feb 1999	+90
March 2007	+87

Note: This table shows the difference in monthly payrolls changes (in thousands) that are SA less those that are SWA, for the 10 months where the effects are biggest in absolute magnitude. These are constructed by applying either the seasonal adjustment, or the seasonal-and-weather adjustment, to all 150 CES disaggregates, and then adding them up, as described in the text. The exercise uses temperature interacted with month dummies and RSI snowfall as weather variables (corresponding to specification 4).

Table 4: Weather Effect in Monthly Payrolls Changes: Summary Statistics

	St. Deviation	Min	Max
January	42	-137	53
February	58	-127	137
March	68	-178	144
April	44	-57	130
May	24	-49	53
June	17	-36	27
July	22	29	69
August	18	-63	17
September	15	-24	31
October	20	-52	32
November	26	-40	76
December	38	-66	63
Overall	36	-178	144

Note: This table shows the standard deviation, minimum and maximum of the difference in monthly payrolls changes (in thousands) that are SA less those that are SWA adjusted, broken out by month. These are constructed by applying either the seasonal adjustment, or the seasonal-and-weather adjustment, to all 150 CES disaggregates, and then adding them up, as described in the text. The exercise uses temperature interacted with month dummies and RSI snowfall as weather variables (corresponding to specification 4).

Table 5: Autocorrelation and Standard Deviation of Month-over-Month Changes in SA and SWA Nonfarm Payrolls Data by Sector

Sector	Autocorrelation		Standard Deviation	
	SA data	SWA data	SA data	SWA data
Mining and logging	0.662	0.686	5.1	5.0
Construction	0.586	0.768	39.0	35.9
Manufacturing	0.739	0.756	50.4	50.2
Trade, transportation and utilities	0.631	0.651	53.2	52.7
Information	0.625	0.645	23.2	23.0
Professional and business services	0.572	0.609	53.7	52.9
Leisure and hospitality	0.324	0.374	28.6	27.2
Other services	0.496	0.533	8.9	8.8
Government	0.036	0.034	51.5	51.2
Total	0.800	0.840	214.4	210.7

Note: This table reports the first order autocorrelation and standard deviation of SA month-over-month payrolls changes (in thousands; total and by industry) and of the corresponding SWA data. The exercise uses temperature interacted with month dummies and RSI snowfall as weather variables (corresponding to specification 4).

Table 6: Weather Effect in Monthly Payrolls Changes: Top 10 Absolute Effects Using Specification 7

Month	Weather Effect
March 1993	-196
Jan 1996	-167
Feb 2010	-165
March 2010	+147
May 1993	+120
May 2003	+118
Feb 2007	-102
Feb 2009	+102
April 1990	-98
May 1991	-95

Note: This table shows the difference in monthly payrolls changes (in thousands) that are SA less those that are SWA, for the 10 months where the effects are biggest in absolute magnitude. These are constructed by applying either the seasonal adjustment, or the seasonal-and-weather adjustment, to all 150 CES disaggregates, and then adding them up, as described in the text. The exercise uses temperature interacted with month dummies and RSI snowfall along with two monthly lags as weather variables (corresponding to specification 7).

Table 7: Coefficient Estimates for Equation (3)

	Real GDP	C	I	G	X	Z
γ_1	0.08***	0.04**	0.19	0.06*	0.26**	0.15*
	(0.03)	(0.02)	(0.12)	(0.03)	(0.11)	(0.09)
γ_2	0.11**	0.06	0.29	-0.08	0.28	0.09
	(0.05)	(0.05)	(0.28)	(0.06)	(0.18)	(0.13)
γ_3	0.04	0.01	-0.33	0.07	0.08	-0.27
	(0.04)	(0.05)	(0.37)	(0.05)	(0.23)	(0.19)
γ_4	0.05	0.02	-0.09	0.07	0.12	-0.10
	(0.04)	(0.04)	(0.22)	(0.05)	(0.14)	(0.11)
γ_5	0.22	-0.04	7.28*	-2.83**	0.68	-1.21
	(0.80)	(0.57)	(4.17)	(1.41)	(2.90)	(2.85)

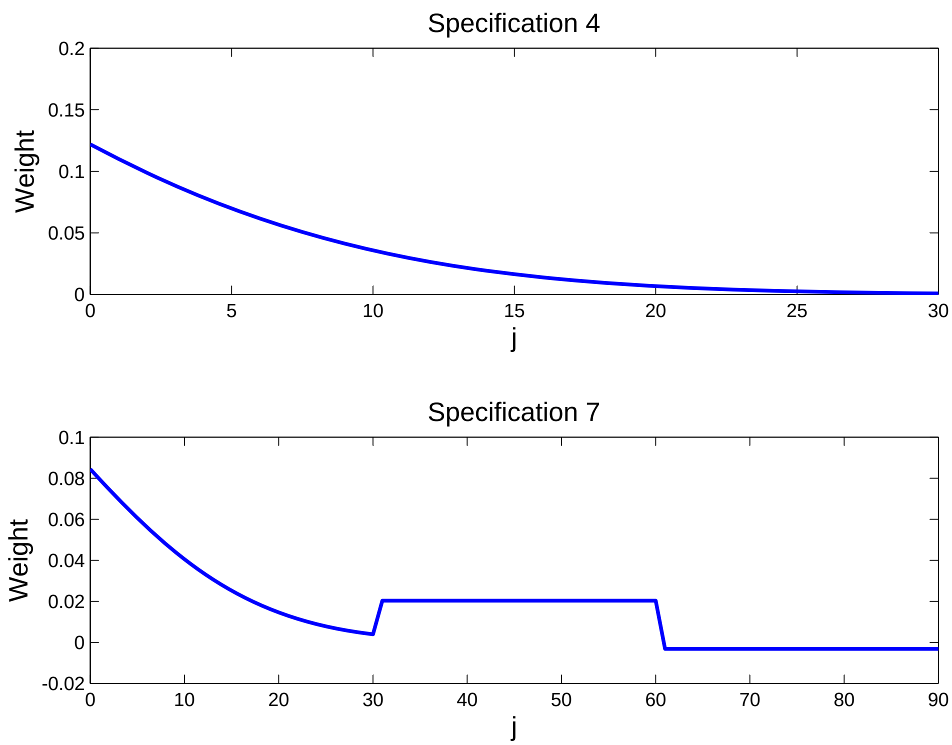
Note: This table shows the coefficient estimates for the weather variables only when estimating equation (3) for real GDP growth and five components thereof. Standard errors are included in parentheses. The sample period is 1990Q1-2015Q2 (September 2015 vintage data). Data units are as follows—NIPA growth rates: annualized percentage points, temperature: degrees C, snowfall: mm. The columns labeled C, I, G, X and Z refer to personal consumption, private investment, government expenditures, export and imports, respectively.

Table 8: Adjustments to NIPA variable growth rates in 2015

		SA data	SWA data	SSWA data
Real GDP	2015 Q1	0.6	1.5	3.3
	2015 Q2	3.9	3.1	2.6
C	2015 Q1	1.7	2.0	2.4
	2015 Q2	3.6	3.2	3.4
I	2015 Q1	8.6	9.6	12.7
	2015 Q2	5.0	3.1	1.0
G	2015 Q1	-0.1	0.6	0.9
	2015 Q2	2.6	2.4	1.3
X	2015 Q1	-6.0	-3.6	2.2
	2015 Q2	5.1	3.0	1.0
Z	2015 Q1	7.1	8.4	8.4
	2015 Q2	3.0	2.2	1.7

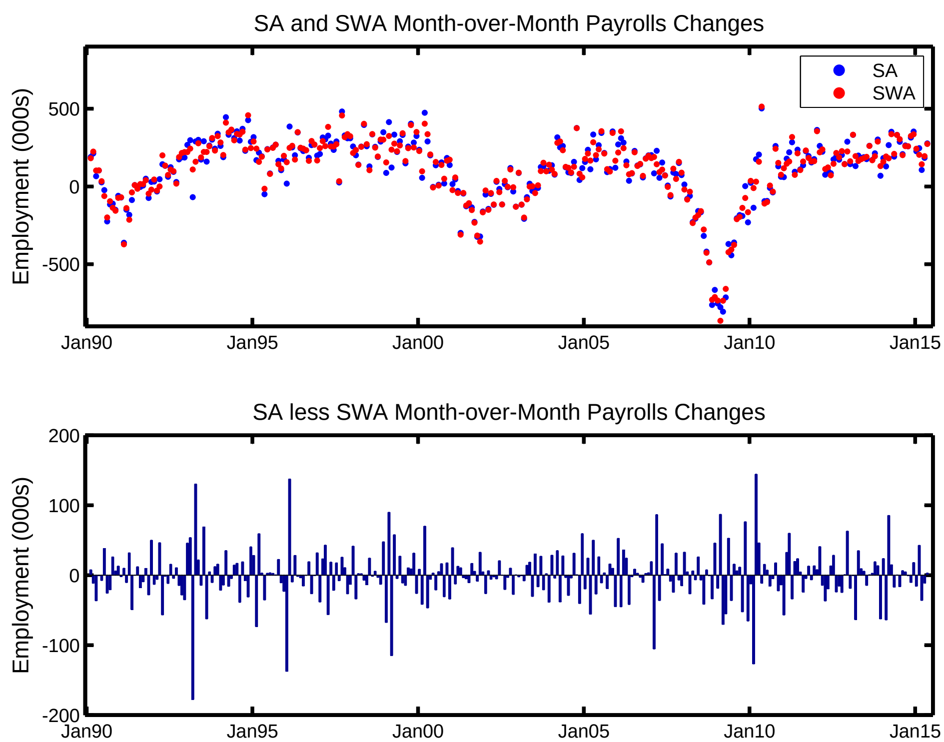
Note: This table shows the quarter-over-quarter growth rates of real GDP and five components thereof in 2015Q1 and 2015 Q2. All entries are in annualized percentage points. The column labeled SA data refers to the published seasonally adjusted data. The column labeled SWA data refers to applying the weather adjustment described in section 4 to the seasonally adjusted series. The column labeled SSWA data refers to applying another round of seasonal adjustment to the SWA series, using the X-13 default settings. The rows labeled C, I, G, X and Z refer to personal consumption, private investment, government expenditures, export and imports, respectively.

Figure 1: Estimated MIDAS Polynomial



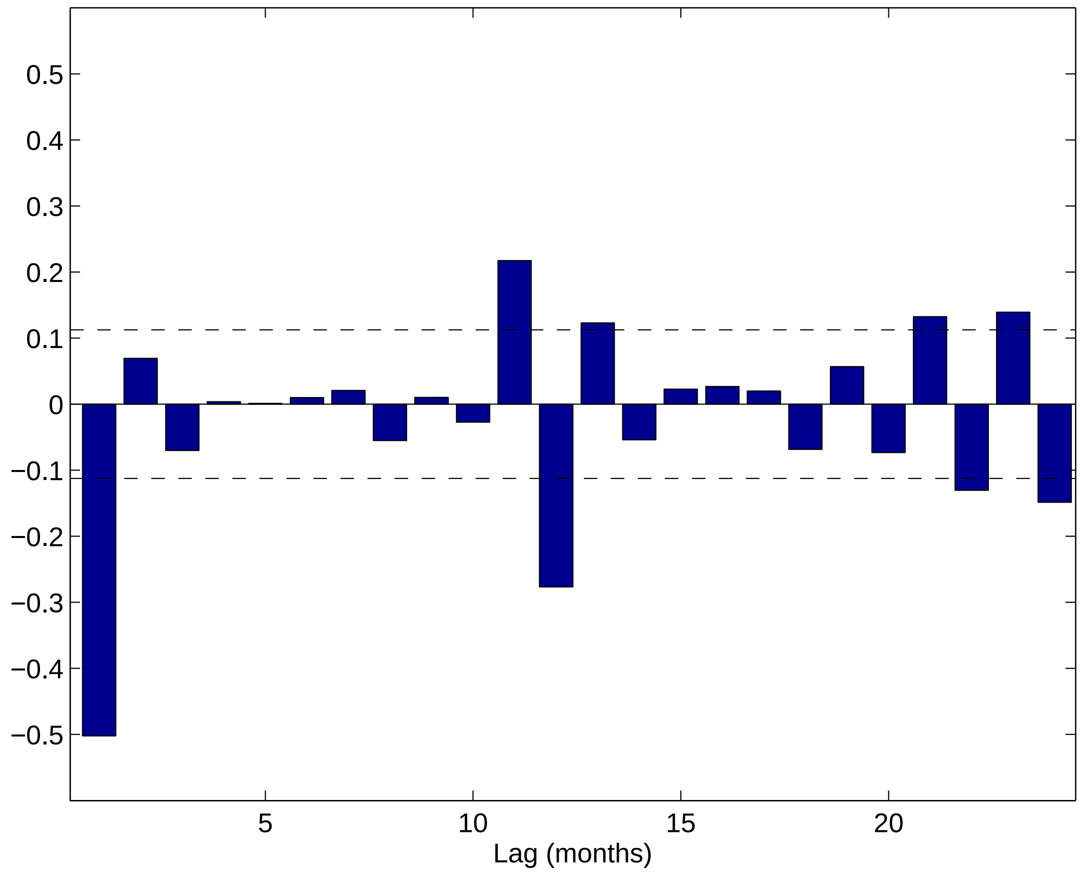
NOTE: This plots the weights w_j against j (in days) where parameters are set equal to their maximum likelihood estimates, fitting equation (1) to aggregate NSA employment, in specifications 4 and 7. The weight for $j = 0$ is the weight attributed to unusual weather on the 12th day of the month (corresponding to the CES survey date). In the top panel, the underlying estimates of a and b are -3 and -2.01, respectively. In the bottom panel, the underlying estimates of a, b, c and d are -1.77, -1.30, 0.02 and -0.003, respectively.

Figure 2: Difference between SA and SWA Month-over-Month Payrolls Changes



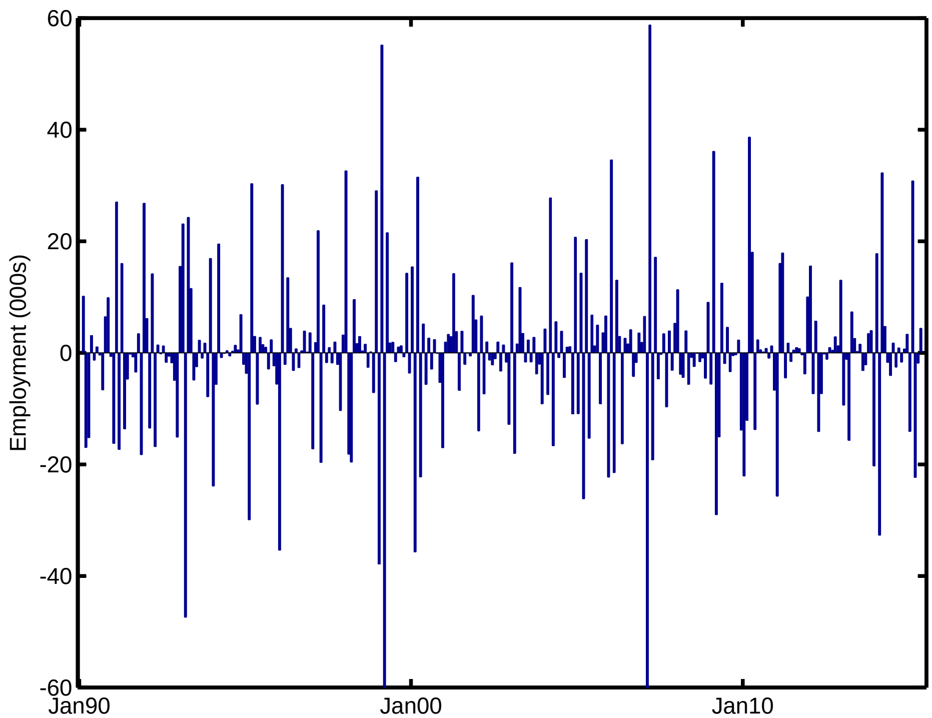
Note: This shows the month-over-month change in total nonfarm payrolls using standard seasonal adjustment less the corresponding change using seasonal-and-weather adjustment. This shows the estimated effect of the weather, including the effect of controlling for the weather on seasonal factors. The exercise uses temperature interacted with month dummies and RSI snowfall as weather variables (corresponding to specification 4).

Figure 3: Autocorrelation of Weather Effects



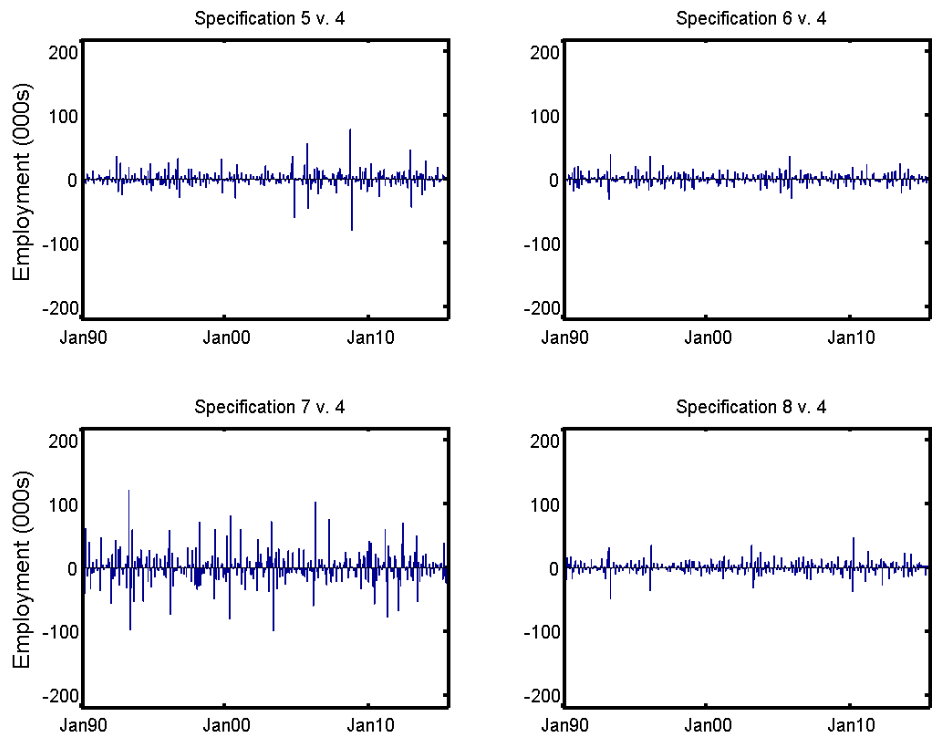
NOTE: This shows the sample autocorrelation function of weather effects, defined as the month-over-month change in total nonfarm payrolls using standard seasonal adjustment less the corresponding change using seasonal-and-weather adjustment. The horizontal dashed lines are the critical values for sample autocorrelations to be statistically significant at the 5 percent level. The exercise uses temperature interacted with month dummies and RSI snowfall as weather variables (corresponding to specification 4).

Figure 4: Difference between SA and SWA Month-over-Month Payrolls Changes in Construction



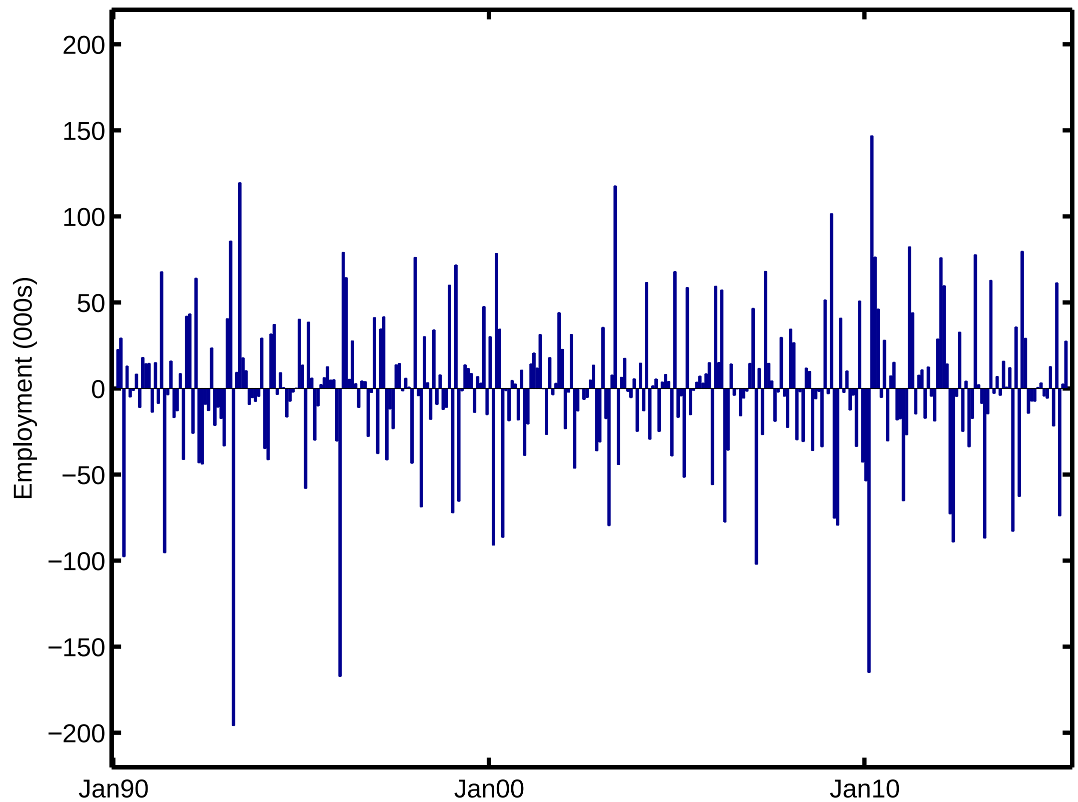
NOTE: This shows the month-over-month change in construction payrolls using standard seasonal adjustment less the corresponding change using seasonal-and-weather adjustment. This shows the estimated effect of the weather, including the effect of controlling for the weather on seasonal factors. The exercise uses temperature interacted with month dummies and RSI snowfall as weather variables (corresponding to specification 4).

Figure 5: Difference between SWA Month-over-Month Payrolls Changes in Alternative Specifications



NOTE: The four subpanels of this figure show the month-over-month payrolls changes using SWA data where the weather variables are as in specifications 5, 6, 7 and 8, respectively, less the corresponding SWA data using specification 4. Relative to specification 4, specification 5 adds CPS work absences due to weather, specification 6 instead adds precipitation, specification 7 instead adds two monthly lags, and specification 8 adds weather on the 13th and 14th of the current month. The figure shows the incremental effects of each of these additions to the specification on SWA data.

Figure 6: Difference between SA and SWA Month-over-Month Payrolls Changes: Using Specification 7



NOTE: As for Figure 2, except that lags of weather indicators in the previous two months are included (as in specification 7).