WORKING PAPERS
RESEARCH DEPARTMENT

WORKING PAPER NO. 15-05
WEATHER-ADJUSTING EMPLOYMENT DATA

Michael Boldin
Federal Reserve Bank of Philadelphia

Jonathan H. Wright
Johns Hopkins University

January 2015

RESEARCH DEPARTMENT, FEDERAL RESERVE BANK OF PHILADELPHIA
Ten Independence Mall, Philadelphia, PA 19106-1574 • www.philadelphiafed.org/research-and-data/

Weather Adjusting Employment Data

Michael Boldin and Jonathan H. Wright*

First version: December 18, 2014
This version: January 12, 2015

Abstract

This paper proposes and implements a statistical methodology for adjusting employment data for the effects of deviation in weather from seasonal norms. This is distinct from seasonal adjustment, which only controls for the normal variation in weather across the year. Unusual weather can distort both the data and the seasonal factors. We 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, snowfall and hurricanes. Weather effects can be very 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.

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

---

*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`. We are grateful to Roc Armenter, Bob Barbera and François Gourio for helpful discussions and to Natsuki Arai for outstanding research assistance. All errors are our sole responsibility.

1 Introduction

Macroeconomic time series are affected by the weather. For example, in the first quarter of 2014, real GDP contracted by 2.1 percent at an annualized rate. Economic forecasters and commentators, including those at the Federal Reserve, attributed part of the decline to an unusually cold winter and large snowstorms that hit the East Coast and the South during the quarter.[1] 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. For example, 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. This is sometimes misunderstood. For example, in March 2014, Edward Lazear wrote an op-ed in the *Wall Street Journal* discussing the labor market and appeared to state that any effect of the unusually bad weather in that winter should be taken care of by seasonal adjustment:

> "Was it the harsh winter in much of the United States? One problem with that explanation is that the numbers are already seasonally adjusted."

To better measure the underlying health and momentum of the economy, we believe that macroeconomic data should also be purged of the effects of anomalous weather. Moreover, we argue that failing to control for abnormal weather effects distorts conventional seasonal adjustment procedures.

[1]Prior to the start of the first quarter of 2014, professional forecasters were expecting a seasonally adjusted increase of around 2.5 percent. With a snap-back rate of 4.6 percent in the second quarter, it is clear that weather played a significant role in the decline.

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)), as weather can be thought of as a truly exogenous driver of economic activity. Statistical agencies sometimes judgmentally adjust extreme observations due to specific weather events before applying their seasonal adjustment procedures.[2] However, we are aware of only a few papers on estimating the effect of unseasonal weather on macroeconomic aggregates. These are *great* (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, and Dell et al. (2012) who implemented a cross-country study of the effects of annual temperature on annual GDP. None of these papers integrates weather adjustment in the seasonal adjustment process. This is what the current paper attempts to do.

We focus 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. 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 can be 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 makes employment growth somewhat stronger in the winter of 2013-2014, although employ-

[2] Even when the BLS does this, the goal is just to prevent the anomalous weather from distorting seasonals, not to actually adjust the data for the effects of the weather.

ment growth was still weak, even after weather adjustment.

The plan for the remainder of this paper is as follows. In Section 2, we describe seasonal adjustment in the CES and how adjustment for unusual weather effects may be added into this. Section 3 reports results on weather effects. Section 4 concludes.

2 Weather and seasonal adjustment

The X-12 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:

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

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, denoted as an ARIMA(p,d,q)x(P,D,Q) specification, is estimated by pseudo-Gaussian 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.

In this paper, we consider payroll employment in the BLS's CES program. Seasonal adjustment in the CES is done 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 151 disaggregates. We used the modeling choices, including ARIMA lag orders in equation (1), 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. The construction of x_t^w is described in the next subsection. The sample period is 1990:01 to 2014:04 in all cases. For each of the 151 series, we compute the seasonally adjusted data net of weather effects, which we refer to as seasonally-and-weather adjusted (SWA). Note that in the SWA data, we remove the weather effect from the data before seasonal adjustment and do *not* add it back in after seasonal factors have been calculated.[3] In this way, we control for both the direct effect of weather on the data and the impact of weather on estimated seasonal factors. The SWA data can then be summed across the 151 disaggregates and can be compared with the standard version that is only seasonally adjusted (SA).[4]

2.1 Measuring unusual weather

To operationalize this methodology, we first need to construct measures of unseasonal weather that are suitable for adjusting the CES survey.

We obtained data from the National Climatic Data Center (NCDC) on daily maximum temperatures and snowfalls at the 50 largest airports (by 2012 passenger numbers) in the United States from 1960 to the present. We averaged these across the 50 airports, with the averages weighted by 2012 passenger numbers. This was designed as a way of measuring U.S.-wide temperature and snowfall in a way that makes a long time series easily available and that puts more weight on areas with

[3] In contrast, when the BLS judgmentally adjusts for extreme weather effects before seasonal adjustment, it does add the effect back in. Its 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.

[4] 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.

higher economic activity.[5] 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 $snow_s$ denote the actual average temperature on day s, and define the unusual temperature for that day as $snow_s^* = snow_s - \frac{1}{30}\Sigma_{y=1}^{30} snow_{s,y}$, where $snow_{s,y}$ denotes the temperature on that same day y years previously. That is, we take the deviation from the average for that day over the previous 30 years. This is in line with the meteorological convention of defining climate norms from 30-year averages.

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 quite reasonable to assume that unusual weather *after* the 12th day of the month ought to have a negligible effect on employment data

[5]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. Meanwhile, it is the national numbers that garner virtually all the attention.

for that month.[6]

In solving this problem, we try to let the data speak. Our proposed approach assumes that the relevant temperature/snowfall conditions are a weighted average of the temperature/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. We estimate the parameters of the MIDAS polynomial from aggregate employment data. 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. MIDAS polynomials were proposed by Ghysels et al. (2004, 2005) and Andreou et al. (2010) as a device for dealing with handling mixed frequency data in a way that is parsimonious yet flexible—exactly the problem that we face here.

In addition to temperature and snowfall, hurricanes are another weather phenomenon that we want to consider. We define $hurr_t$ as the value of damage[7] done by hurricanes in the month ending on the 12th day of month t, and let $hurr_t^* = hurr_t - \frac{1}{30}\Sigma_{y=1}^{30} hurr_{t,y}$ where $hurr_{t,y}$ denotes the hurricane damage in that same month y years previously. We treat hurricanes differently from temperature and snowfall as their effect is likely to be longer lasting, and so we just treat hurricane damage as a monthly variable.[8]

We first estimate the following mixed-frequency MIDAS-augmented seasonal

[6]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. Still, this seems to be a very contrived and extreme example.

[7]This is the value in 2010 dollars, deflated by the price deflator for construction. See Blake et al. (2011) for more discussion.

[8]Indeed it seems quite likely that hurricanes will have an effect on employment that lasts for far longer than a month, but the number of large hurricanes in our sample is small, and so we do not attempt to model this.

ARIMA(0,1,1)x(0,1,1) model[9] for aggregate employment by pseudo-Gaussian maximum likelihood:

$$(1-L)(1-L^{12})(y_t - \Sigma_{j=0}^{30} B(\frac{j}{30}, a, b)(\Sigma_{k=1}^{12}\gamma_k d_k temp^*_{s-j} + \gamma_{13} snow^*_{s-j}) - \gamma_{14} hurr^*_t)$$
$$= (1+\theta L)(1+\Theta L^{12})\varepsilon_t, \qquad (2)$$

where y_t is total NSA employment for month t, day s is the 12th day of month t, d_k is a dummy that is 1 if t is the kth month of the year and 0 otherwise, $B(x; a, b) = \frac{\exp(ax+bx^2)}{\Sigma_{j=0}^{30}\exp(a\frac{j}{30}+b(\frac{j}{30})^2)}$ and ε_t is an i.i.d. error term. $B(x; a, b)$ is the MIDAS polynomial. Let $\hat{a}$ and $\hat{b}$ denote the pseudo-maximum likelihood estimates of a and b.

We then 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. Our weather regressor x^w_t consists of the unusual temperature for month t (defined in this way) interacted with 12 monthly dummies, the unusual snowfall for month t (defined analogously, but not interacted with any dummies), and $hurr^*_t$. All in all, this gives a total of 14 elements in x^w_t for inclusion as regressors in the X-12 filter.[10]

The motivation for interacting temperature with month dummies 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 it might even boost it. Likewise, warm weather boosts demand for electricity in summer but weakens demand for electricity in winter. On the other hand, snow falls only in the winter months, and its effect on employment is likely to be similar no matter when it occurs. Hurricanes

[9]This model—the so called "airline model"—is the default model in the Reg-ARIMA stage of the X-12 program.

[10]Note that 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. A nonlinear specification would also be possible.

occur only in the late summer/fall and again their effects are likely to be similar in whichever month they strike.

Figure 1 plots the MIDAS polynomial implied by the pseudo-maximum likelihood estimates of a and b. The estimated polynomial puts most weight on the few days up to and including the 12th of the month.

Note that our methodology uses total employment to estimate the parameters a and b 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-12 methodology at the disaggregate level, as described earlier. Other than a and b (which affect the construction of the monthly weather regressors x_t^w), no parameters from the estimation of equation (2) are used in our seasonal-and-weather adjustment.

3 Results

Figure 2 compares total nonfarm payrolls from using ordinary seasonal adjustment and our SWA construction. 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.

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.[11] 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.

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 33,000 and by 18,000 in January 2014. Meanwhile, we estimate that the weather effect raised the payrolls change for March 2014, by 30,000 as more normal weather returned. The weather effect was quite consequential, but it still does not explain all of the weakness in employment reports during the winter of 2013-2014.

But the winter of 2013-2014 is far from the biggest weather effect in the sample. The data in February and March 2007 contained a large swing as February was colder

[11] 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.

than usual. That fact was not missed by the Federal Reserve's 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."

The data in February and March 1999 contained a very big swing of this sort, as that February was unseasonably mild. According to our estimates, weather drove the month-over-month change in payrolls up by 116,000 in February 1999 and down by 121,000 the next month. 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."

Our estimates provide quantifications of the weather effects in all of these episodes. Table 1 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 months of the year and are generally months of unusual temperature or snowfall.

Table 2 gives the minimum, maximum, and standard deviation of the total weather effect in payrolls changes broken out by month.[12] The standard deviation is the largest in March (65,000) followed by February (55,000). 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.

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

Figure 3 plots the difference between ordinary SA data and SWA data for payrolls changes in the construction sector alone. Weather effects in the construction sector drive a substantial part, but not all, of the total weather effects.

In all, the weather adjustment involves estimating 14 parameters in β^w for each of the 151 disaggregates for a total of 2,114 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. The parameters associated with hurricane damage are significant for some components, but the signs are mixed. Hurricanes have a significantly negative effect on employment in sectors such as air transportation and food services/drinking places. But they have a significantly positive effect on employment in sectors such as community care facilities for the elderly and furniture/home furnishing stores.

3.1 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. To investigate this, we compare the variance and autocorrelation of month-over-month changes in SA and SWA payrolls data, both for total payrolls and for ten industry subaggregates. The results are shown in Table 3.

In the aggregate, month-over-month payrolls changes show a higher degree of autocorrelation using SWA data than using SA data, which primarily reflects the fact that the weather adjustments remove noise from the levels data, which is a source of negative autocorrelation in the month-over-month changes. In fact, in every sector except government, payrolls changes are more autocorrelated 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 A simple diagnostic

As a simple diagnostic to see the effects of weather on different measures of monthly payrolls changes, we regressed the monthly aggregate payrolls change with standard seasonal adjustment on Δx_t^w, the monthly first differences of our unusual weather measures. The coefficients were jointly significant at the 1 percent level,[13] indicating that payrolls changes are materially influenced by the weather. We then reran this regression using our SWA data. Not surprisingly, the weather effect has been purged. The p-value from a joint test on the coefficients on Δx_t^w was 0.83.

We can also regress the weather effect in the level of employment data on the weather variable x_t^w. The estimated coefficients in this regression give a "rule of thumb" for the effect of weather in month t on employment in month t (which does not however take account of the effect of weather in other months operating through the seasonal factors). For example, we estimate that a 1°C decrease in average temperature in March lowers employment by 23,000 and that a 1cm increase in daily snowfall lowers employment by 92,000.

[13] Using Newey-West standard errors with a lag length of 12.

3.3 Alternative snowstorm definitions

The NCDC produces 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. (forthcoming) 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. 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 six regional snowstorm indices to get a national value.[14]

We repeated our seasonal-and-weather adjustment using this RSI measure of snowstorms, along with our temperature variable (constructed exactly as described in subsection 2.1). The full analysis was reworked (including adjustment for average weather patterns on each day of the year and estimation of the MIDAS function). Figure 4 shows our estimates of the weather effects using this alternative snowstorm definition.

The NCDC furthermore categorizes storms on a discrete scale of 1-5. This scale takes into account the typical nature of snowstorms in each region. For example,

[14]Simple sums are not used in order to avoid double-counting storms that affect multiple regions. Instead, each regional value is multiplied by an estimate of the population in the region that is affected by the storm, and then the sum is normalized across regions by dividing by total U.S. population. A more precise normalization would divide by the population typically affected by large snowstorms, and we are essentially assuming that this value is a constant fraction of the total population.

the same physical snowstorm might have a higher rating in the South than in the Northeast region because the Northeast region is better equipped to handle large snowstorms. We finally repeated our analysis using a measure of severe snowstorms, again along with our temperature variable. The measure of severe snowstorms is defined as the national RSI index but ignoring all category 1 and 2 storms. This is a fairly stringent definition. Summing over the six regions, the NCDC identifies a total of 375 regional storms. But only 53 of these are category 3 and above. Figure 5 shows our estimates of the weather effects using this more stringent alternative snowstorm definition.

The effects of seasonal-and-weather adjustment reported in Figures 4 and 5 are mostly similar to those in the bottom panel of Figure 2 (that simply used the average snowfall measure). But there are several places where the use of an alternative snow measure makes a substantive difference. A prominent example is March 1993. With the baseline snow definition, the total weather effect that month was to lower employment by 92,000. However, using the RSI index instead, the negative effect is much bigger at around 210,000.[15] 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.[16]

4 Conclusions

Seasonal effects in macroeconomic data are enormous. These seasonal effects reflect, among other things, the consequences of regular variation in weather within the year.

[15]Note that there were category 5 snowstorms in three regions of the country in that month.

[16]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.

Seasonal adjustment is not an adjustment for the effects of weather—it does not control for deviations of weather from seasonal norms. Yet, these deviations have material effects on macroeconomic data. This paper has operationalized an approach for simultaneously controlling for both seasonal patterns and unseasonal weather effects in CES employment data. These weather effects include deviation of temperature, snowfall, and hurricanes from seasonal norms. We attempt to purge both the direct effect of weather on the data, and the effect of the data on estimated seasonal factors. 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 SWA data than when using ordinary SA data, suggesting that this gives a better measure of the underlying momentum of the economy.

The methods discussed in this paper can, in principle, be applied to other macroeconomic series. Weather effects may be more important for other series because harsh weather only affects employment numbers if it causes an employee to miss an entire pay period—bad weather seems more likely to impact hours worked or output. Alas, however, these methods cannot be applied to National Income and Product Account (NIPA) data, such as GDP because the Bureau of Economic Analysis stopped releasing not seasonally adjusted NIPA data some years ago as a cost-cutting measure.

References

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

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 Memorandum 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.

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.

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.

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].

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

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*, forthcoming.

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

Table 1: Weather Effect in Monthly Payrolls Changes: Top 10 Absolute Effects

Month	Weather Effect
March 2000	+131
March 1999	-121
Feb 2010	-119
Feb 1999	+116
Feb 2009	+108
Jan 1996	-99
March 2010	+95
April 2010	+92
March 1993	-92
March 2013	-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 151 CES disaggregates, and then adding them up, as described in the text.

Table 2: Weather Effect in Monthly Payrolls Changes: Summary Statistics

	St. Deviation	Min	Max
January	41	-99	74
February	55	-119	116
March	65	-121	131
April	47	-77	92
May	43	-76	79
June	26	-49	39
July	20	-23	40
August	14	-34	28
September	17	-50	29
October	27	-46	59
November	18	-31	35
December	28	-52	68
Overall	37	-121	131

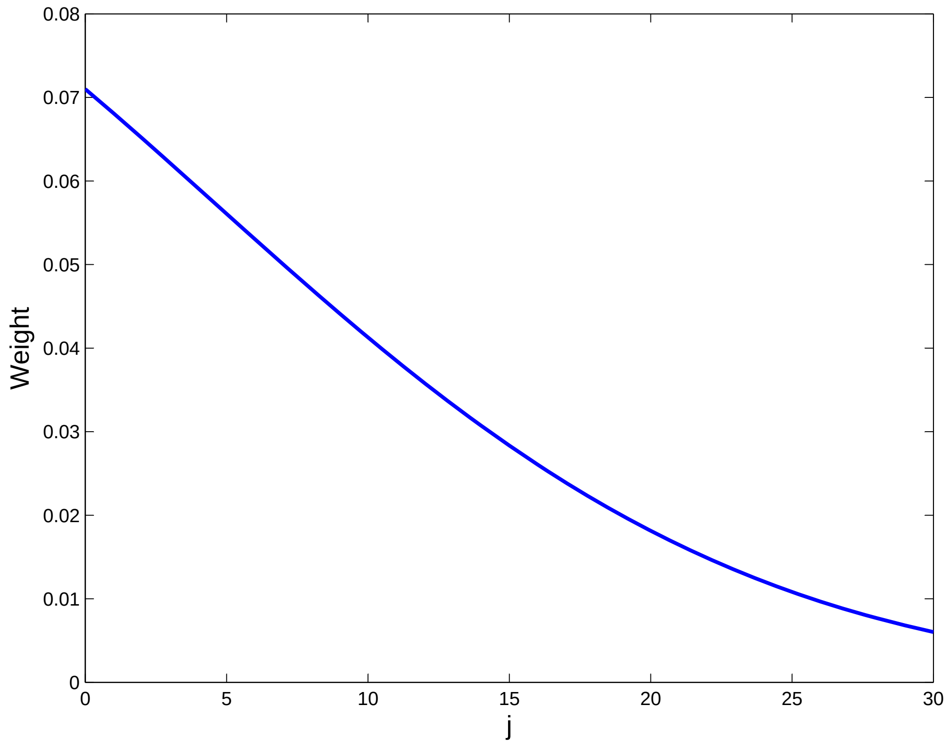
Note: This table shows the standard deviation, minimum and maximum of the difference in monthly payrolls changes (in thousands) that are SA less those that are SWA adjusted, broken out by month. These are constructed by applying either the seasonal adjustment, or the seasonal-and-weather adjustment, to all 151 CES disaggregates, and then adding them up, as described in the text.

Table 3: Autocorrelation of Month-over-Month Changes in SA and SWA Nonfarm Payrolls Data by Sector

Sector	SA data	SWA data
Total	0.798	0.829
Mining and logging	0.650	0.663
Construction	0.585	0.767
Manufacturing	0.729	0.732
Trade, transportation and utilities	0.630	0.640
Information	0.629	0.651
Professional and business services	0.571	0.601
Leisure and hospitality	0.313	0.362
Other services	0.505	0.543
Government	0.057	0.044

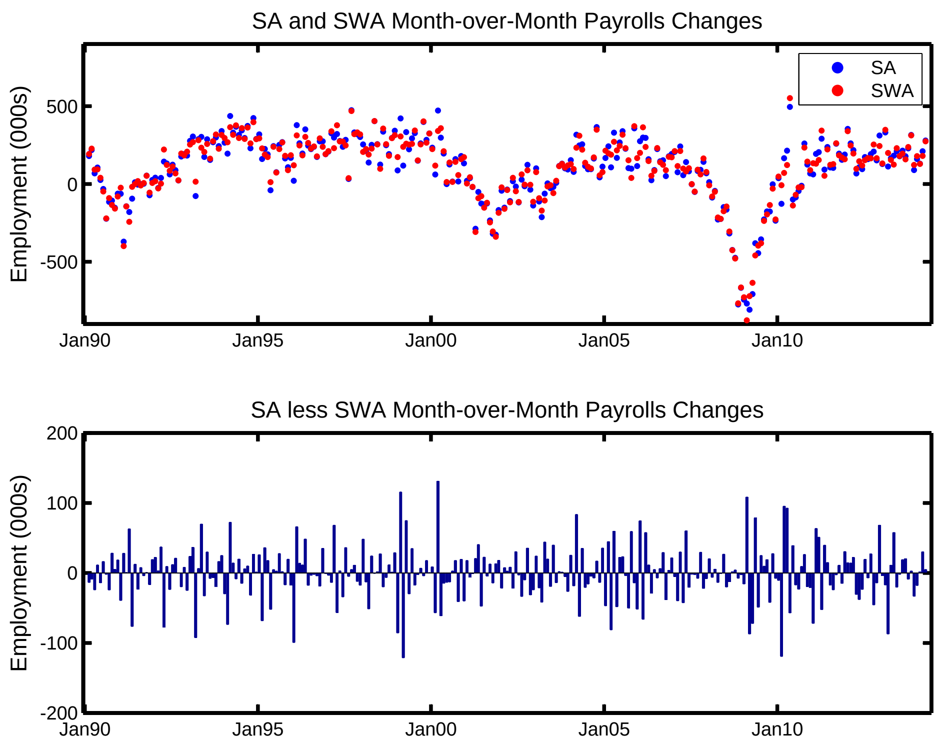
Note: This table reports the first order autocorrelation of SA month-over-month payrolls changes (total and by industry) and of the corresponding SWA data.

Figure 1: Estimated MIDAS Polynomial



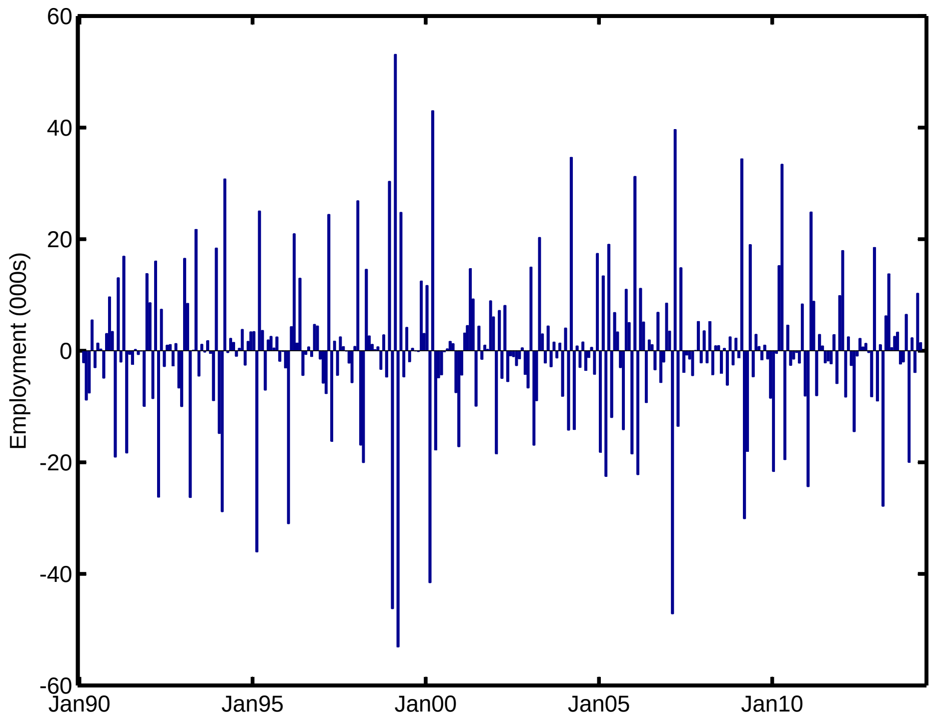
NOTE: This plots the MIDAS polynomial $B(\frac{j}{30}; a, b)$ against j (in days) where a and b are set equal to their maximum likelihood estimates, fitting equation (2) to aggregate NSA employment. The weight for $j = 0$ corresponds to the weight attributed to unsual weather on the 12th day of the month (corresponding to the CES survey date).

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



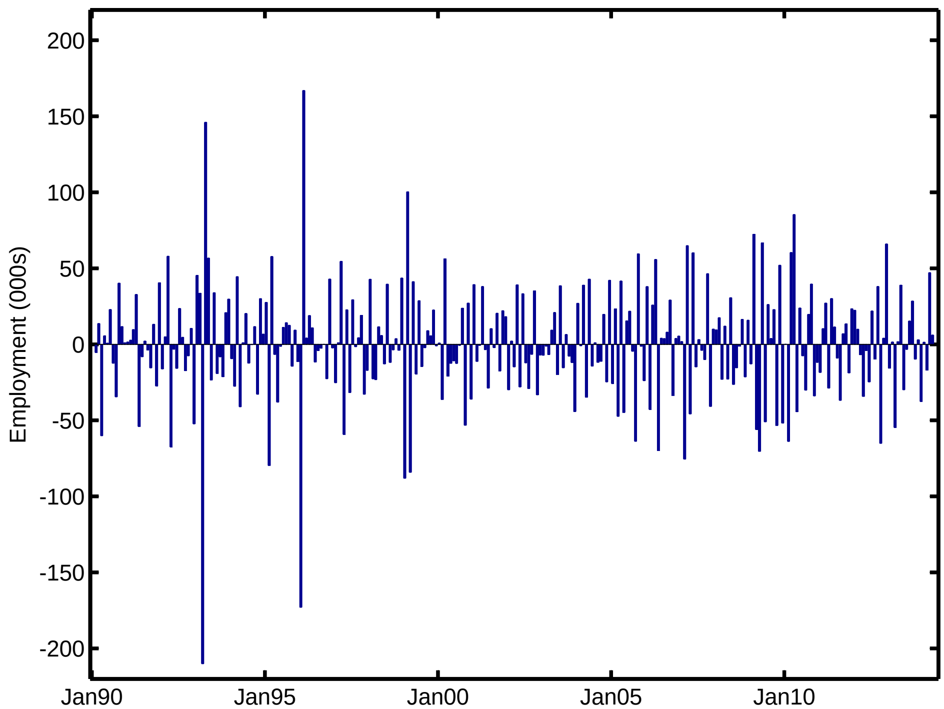
NOTE: This shows the month-over-month change in total nonfarm payrolls using standard seasonal adjustment less the corresponding change using seasonal-and-weather adjustment. This shows the estimated effect of the weather, including the effect of controlling for the weather on seasonal factors.

Figure 3: Difference between SA and SWA Month-over-Month Payrolls Changes in Construction



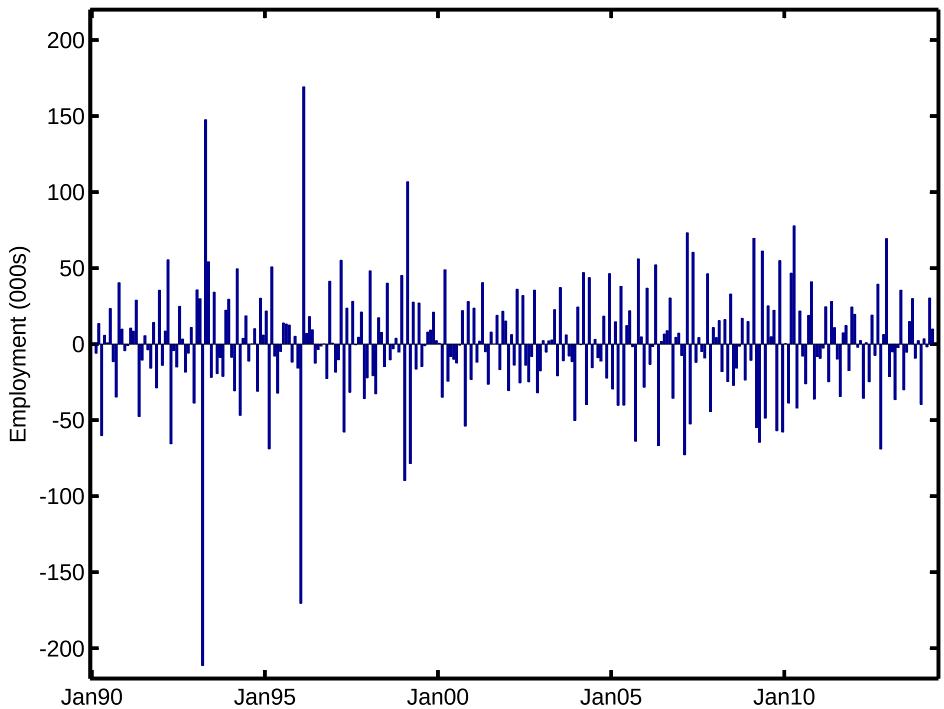
Note: This shows the month-over-month change in construction payrolls using standard seasonal adjustment less the corresponding change using seasonal-and-weather adjustment. This shows the estimated effect of the weather, including the effect of controlling for the weather on seasonal factors.

Figure 4: Difference between SA and SWA Month-over-Month Payrolls Changes: Using RSI Index to Measure Snowstorms



NOTE: As for Figure 2, except that the RSI index described in the text is used as the measure of snowfall

Figure 5: Difference between SA and SWA Month-over-Month Payrolls Changes: Using RSI Index to Measure Snowstorms (Category 3 and above only)



NOTE: As for Figure 4, except that only storms of category 3 and above are included in the RSI index