# Weather Adjusting Economic Data

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**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.

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# 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.[1] Similarly the slowdown in growth in the first quarter of 2015 was widely ascribed to another exceptionally harsh winter and other transitory factors. 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 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. 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 snapback rate of 4.6 percent in the second quarter, it is highly plausible that weather played a significant role in the decline.

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 on state-level employment data. None of these papers integrates weather adjustment

[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.

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 (NCEI) on daily maximum temperatures, precipitation, snowfall and heating degree days (HDDs) [3] at one station in each of the largest 50 Metropolitan Statistical Areas (MSAs) 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 MSAs, with the averages weighted by population. MSA population was 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.[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 $prp_s^*$, $snow_s^*$ and $hdd_s^*$ denote the unusual precipitation, snowfall or HDD on day $s$, relative to the 30-

[3]The HDD at a given station on a given day is defined as $\max(18.3\text{-}\tau, 0)$ where $\tau$ 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 NCEI. 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.

[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. 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.

year average. This is in line with the meteorological convention of defining climate norms from 30-year averages.

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 quite reasonable to assume that unusual weather *after* the 12th day of the month ought to have a negligible effect on employment data for that month.[6]

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 includ-

[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 a bit contrived. In any case, we do evaluate the possibility that weather just after the 12th could affect employment, and find no evidence that it does.

ing 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 be over-parameterized. We shall estimate the parameters of the MIDAS polynomial from aggregate employment data, as described below. 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 handling mixed frequency data in a way that is parsimonious yet flexible—exactly the problem that we face here.

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 NCEI 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. (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. 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 in month $t$, and 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. Each involves estimating a mixed-frequency MIDAS-augmented seasonal ARIMA(0,1,1)x(0,1,1) model[7] for aggregate NSA employment by pseudo-Gaussian maximum likelihood. This is intended as a precursor to incorporating weather effects in CES seasonal adjustment. We want to see which weather measures impact employment, and at what lags. Each 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 $t$ and $\varepsilon_t$ is an i.i.d. error term. The models differ 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.

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

[7]This model—the so called "airline model" —is the default model in the Reg-ARIMA stage of the X-13 program.

the unusual snowfall on the 12th day of month $t$, measured as the population-weighted average across MSAs.

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, $c$ 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, $c$ determines the weight of weather on the 13th and 14th of the month.

In all of these specifications, temperature (or heating degree days) are 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. 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.

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 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.[8] 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.[9] All of the weather indicators that we consider are physical measures of weather that are essentially exogenous,[10] 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.[11] 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 find this unsurprising

[8] The NCEI also categorizes snowstorms on a discrete scale of 1-5. This scale takes into account the typical nature of snowstorms in each region. For example, 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 also constructed a measure of severe snowstorms, 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 NCEI identifies a total of 375 regional storms—only 53 of these are category 3 and above. However, this severe snowstorms index gave a less good fit to aggregate employment than the standard RSI index, and so we did not consider it further.

[9] Another weather indicator that we considered is the value of damage done by large hurriances in the previous month, relative to the 30-year average. This is the value in 2010 dollars, deflated by the price deflator for construction, as discussed in Blake et al. (2011). However, hurricanes did not turn out to be significant when added to specification 4, and so we do not consider hurricanes further.

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

[11] 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.

given the CES timing conventions.

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.

# 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:

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

where $x_t$ is a vector of user-chosen regressors, $\beta$ 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 $\varepsilon_t$ 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. 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[12], interacted with 12 monthly dummies, the unusual snowfall for month $t$ (defined analogously, but not interacted with any dummies), the unusual HDD for month $t$, $hurr_t^*$ 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.[13]

The sample period is January 1990 to May 2015 in all cases. 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

[12]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 $t$.

[13]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.

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. 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).[14]

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

[14] 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.

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

Figure 2 compares total nonfarm payrolls from using ordinary seasonal adjustment and our SWA adjustment, using specification 4. 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.[15] 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

[15] 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."

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.[16] 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.[17]

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 months of the year.

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

[17] 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.

Table 4 gives the minimum, maximum, and standard deviation of the total weather effect in payrolls changes broken out by month.[18] 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 substantial part, but not all, of the total weather effects.

In all, the weather adjustment involves estimating 14 parameters in $\beta^w$ 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.

### 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

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

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 seasonal adjustment using specifications 5 and 7 to construct the weather variables. Specification 5 includes absences from work, and specification 7 adds monthly lags to admit richer dynamics. Figures 5 and 6 show our estimates of the weather effects in these two cases, respectively. In both these cases, the MIDAS function parameters $a$, $b$, $c$ and $d$ were re-estimated applying equation (1) to aggregate employment data.

The effects of seasonal-and-weather adjustment reported in Figures 5 and 6 are mostly similar to those in the bottom panel of Figure 2 (that simply used temperature and the RSI index). But there are differences. For example, in September 2008, the number who reported absence from work due to weather spiked to levels normally observed only in winter. Consequently, using specification 5, we estimate that the weather effect was to lower monthly payrolls changes by 70,000 in that month, whereas the other specifications find no material weather effect. The weather effects for changes in employment are strongly negatively autocorrelated, but are very slightly little less so when using lags—the autocorrelation at lag one of weather effects on changes in employment rises from -0.50 in specification 4 to -0.48 in specification 7.

The baseline specification 4 forces the effects of weather on the level of employment to dissapear the next month. Specification 7 is more flexible in regards to the dynamics of weather effects. Nonetheless, the estimated weather effect is similar with the more flexible specification.

# 4 NIPA Data

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.[19]

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

[19] 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.

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

where $y_t$ is the quarter-over-quarter growth rate of real GDP or some component thereof, $s_{1t}, ...s_{4t}$ are four quarterly dummies,[20] $w_{1t}$ 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.[21] Our sample period is 1990Q1-2015Q2, using August 2015 vintage data (after the August 27 release). Coefficient estimates are shown in Table 6 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

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

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

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

Table 7 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.

## 4.1 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.[22]

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 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 devia-

[22]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.

tions 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 CES employment data. 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 physical weather indicators considered in this paper are all available on an almost real-time basis—the reporting lag is inconsequential. The NCEI makes daily summaries for 1,600 stations available with a lag of less than 48 hours. In addition, the RSI indices 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.

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**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 |
|---|---|---|---|---|---|---|---|---|
| $\gamma_1$ | 16.4** | -18.2** | 12.6 | 13.8** | 12.5* | 13.7** | 23.4*** | 12.3* |
| $\gamma_2$ | 33.6*** | -38.6*** | 28.8*** | 23.3** | 19.0** | 22.6** | 25.4*** | 23.4*** |
| $\gamma_3$ | 23.3*** | -26.8*** | 16.0** | 18.3** | 20.0*** | 19.0*** | 27.3*** | 17.9*** |
| $\gamma_4$ | -8.5 | 2.9 | -18.1* | -6.3 | -15.6* | -10.6 | 11.8 | -10.3 |
| $\gamma_5$ | 8.7 | -4.1 | 20.7 | 12.3 | 16.8 | 16.3 | 28.6** | 17.0 |
| $\gamma_6$ | 22.7 | 55.0 | 24.4 | 22.3 | 24.6 | 15.9 | 6.4 | 15.0 |
| $\gamma_7$ | 29.5 | 1072 | 26.5 | 30.6 | 56.0 | 38.6 | -6.4 | 28.9 |
| $\gamma_8$ | 30.5 | -183.4 | 26.3 | 30.3 | 44.5 | 29.5 | 18.1** | 26.0 |
| $\gamma_9$ | 6.5 | -42.7 | 1.1 | 6.3 | 26.5 | -11.2 | 12.5 | 12.0 |
| $\gamma_{10}$ | 18.6* | -25.9* | 14.0 | 16.7 | 23.6** | 13.5 | 18.9* | 20.3** |
| $\gamma_{11}$ | 25.2* | -36.3* | 20.7 | 21.5 | 17.0 | 15.4 | 23.9 | 22.6** |
| $\gamma_{12}$ | 16.0* | -16.4 | 11.0 | 14.7 | 11.5 | 15.4 | 22.4** | 13.0 |
| $\gamma_{13}$ | | | -7.62*** | -37.74** | -20.36 | -39.1** | -77.63*** | -24.73* |
| $\gamma_{14}$ | | | | | -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 | 0.32 | Accept 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 $\gamma_{13}$ refers to various snow effects (defined in the text) and $\gamma_{14}$ 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 |
| Jan 1996 | -137 |
| Feb 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: Coefficient Estimates for Equation (3)**

| | Real GDP | C | I | G | X | Z |
|---|---|---|---|---|---|---|
| $\gamma_1$ | 0.08*** | 0.04** | 0.19 | 0.06 | 0.26** | 0.15* |
| | (0.03) | (0.02) | (0.12) | (0.03) | (0.11) | (0.09) |
| $\gamma_2$ | 0.11** | 0.06 | 0.29 | -0.08 | 0.28 | 0.09 |
| | (0.05) | (0.05) | (0.28) | (0.06) | (0.18) | (0.13) |
| $\gamma_3$ | 0.04 | 0.01 | -0.33 | 0.07 | 0.08 | -0.27 |
| | (0.04) | (0.05) | (0.37) | (0.05) | (0.23) | (0.19) |
| $\gamma_4$ | 0.05 | 0.02 | -0.09 | 0.07 | 0.12 | -0.10 |
| | (0.04) | (0.04) | (0.22) | (0.05) | (0.14) | (0.11) |
| $\gamma_5$ | 0.21 | -0.06 | 7.29* | -2.83** | 0.68 | -1.22 |
| | (0.80) | (0.56) | (4.16) | (1.41) | (2.90) | (2.85) |

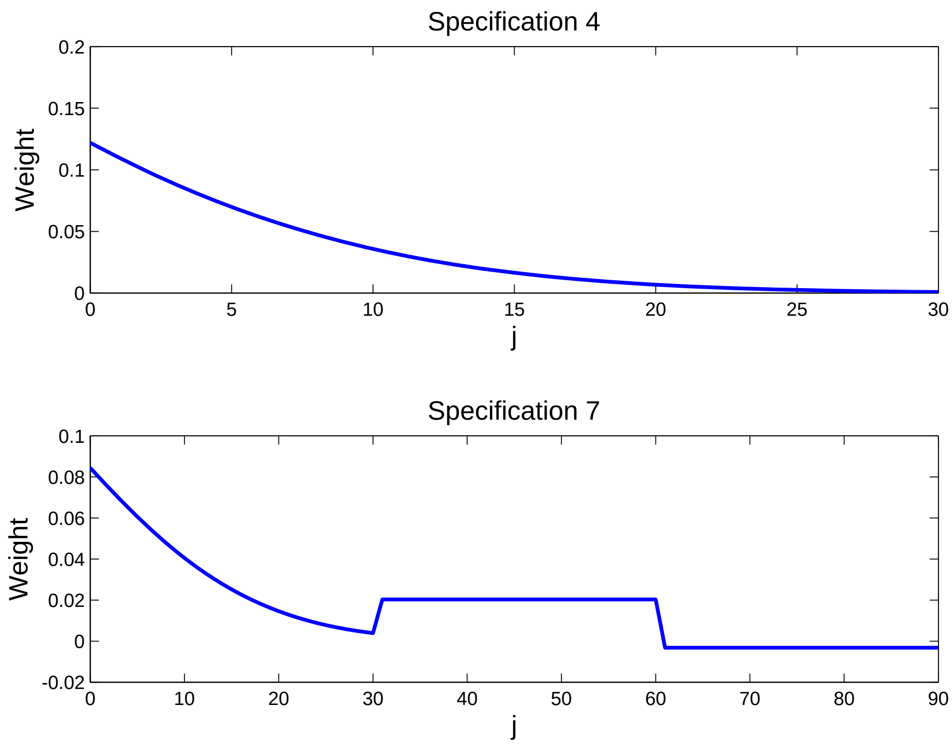
Note: This table shows the coefficient estimates for the weather variables only when estimating equation (3) for real GDP growth and five components thereof. Standard errors are included in parentheses. The sample period is 1990Q1-2015Q2 (August 2015 vintage data). Data units are as follows—NIPA growth 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 7: Adjustments to NIPA variable growth rates in 2015**

| | | SA data | SWA data | SSWA data |
|---|---|---|---|---|
| Real GDP | 2015 Q1 | 0.6 | 1.4 | 3.2 |
| | 2015 Q2 | 3.7 | 2.8 | 2.4 |
| C | 2015 Q1 | 1.7 | 2.0 | 2.3 |
| | 2015 Q2 | 3.1 | 2.7 | 3.0 |
| I | 2015 Q1 | 8.6 | 9.6 | 12.7 |
| | 2015 Q2 | 5.2 | 3.2 | 1.2 |
| 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 | 5.2 | 3.1 | 1.0 |
| Z | 2015 Q1 | 7.1 | 8.4 | 8.4 |
| | 2015 Q2 | 2.8 | 2.0 | 1.5 |

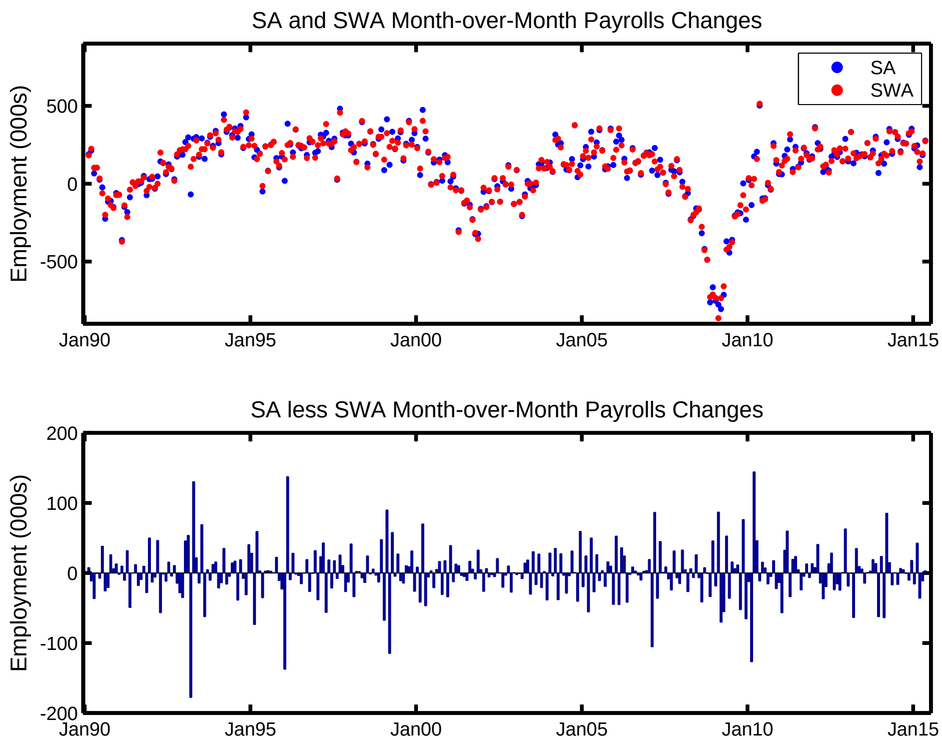
Note: This table shows the quarter-over-quarter growth rates of real GDP and five components thereof in 2015Q1 and 2015 Q2. All entries are in annualized percentage points. The column labeled SA data refers to the published seasonally adjusted data. The column labeled SWA data refers to applying the 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**



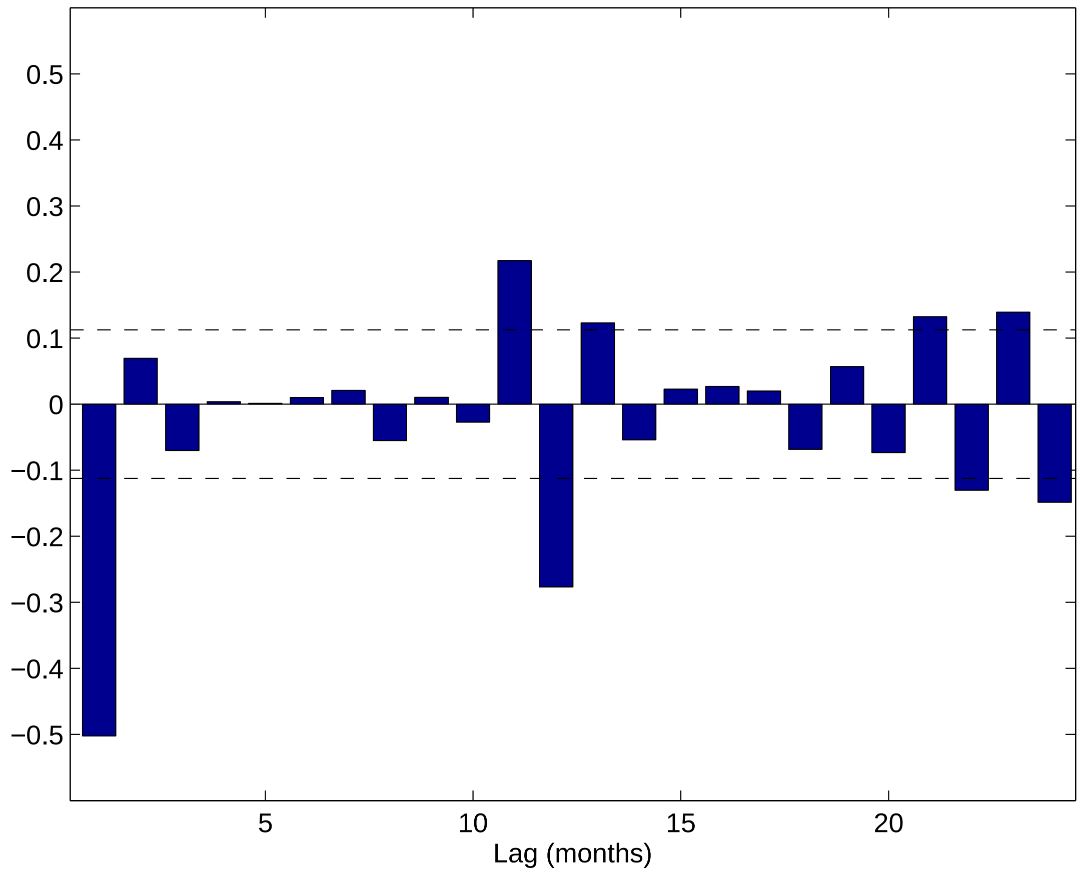

NOTE: This plots the weights $w_j$ against $j$ (in days) where parameters are set equal to their maximum likelihood estimates, fitting equation (1) to aggregate NSA employment, in specifications 4 and 7. The weight for $j = 0$ is the weight attributed to unusual weather on the 12th day of the month (corresponding to the CES survey date).

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



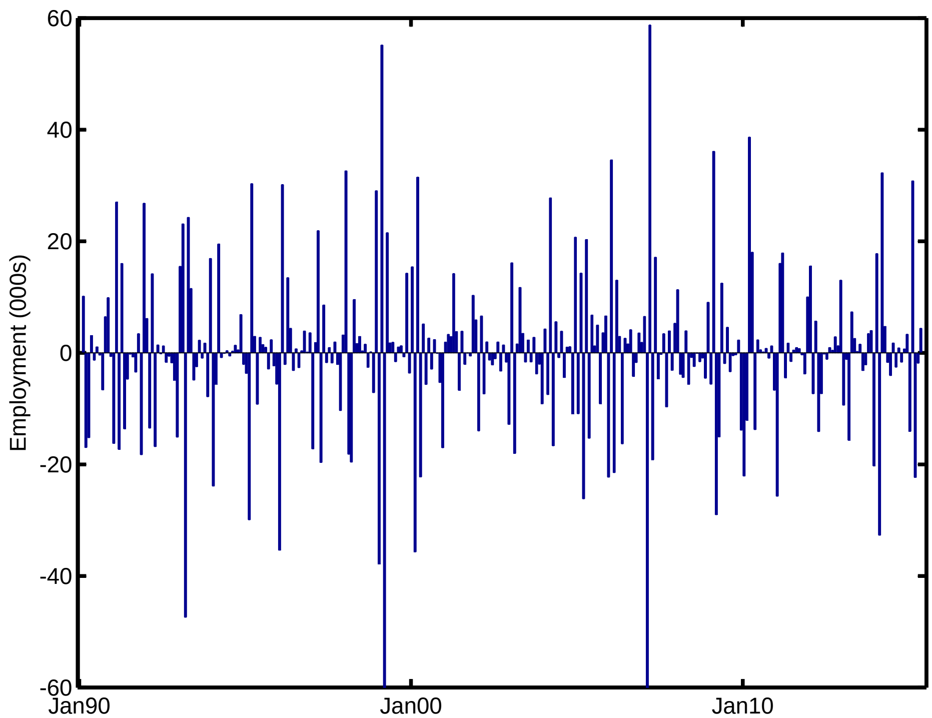

Note: This shows the month-over-month change in total nonfarm payrolls using standard seasonal adjustment less the corresponding change using seasonal-and-weather adjustment. This shows the estimated effect of the weather, including the effect of controlling for the weather on seasonal factors. The exercise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

**Figure 3: Autocorrelation of Weather Effects**



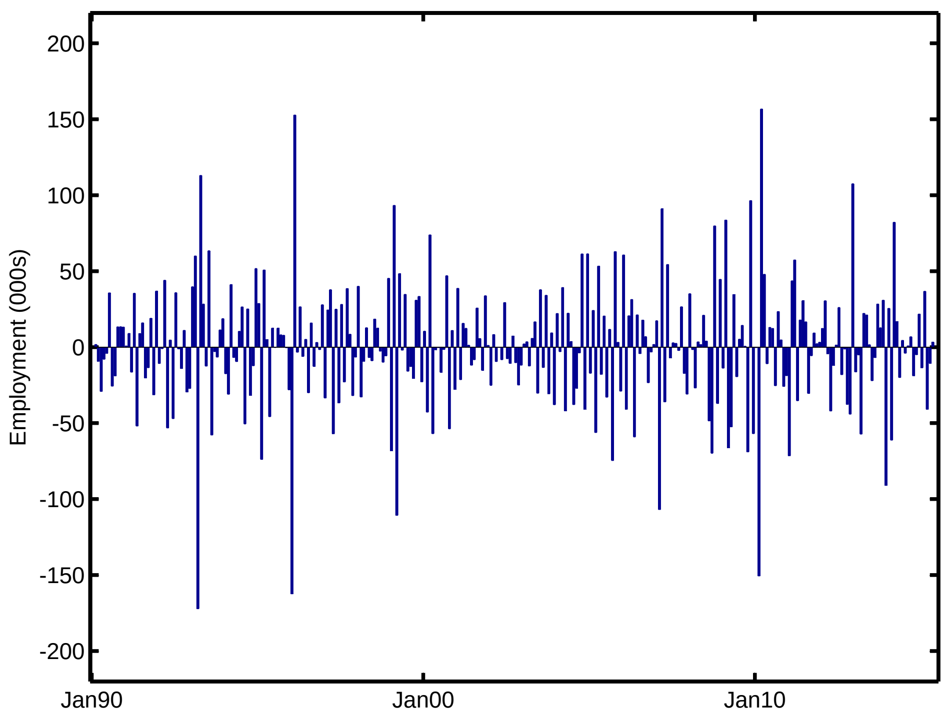

NOTE: This shows the sample autocorrelation function of weather effects, defined as the month-over-month change in total nonfarm payrolls using standard seasonal adjustment less the corresponding change using seasonal-and-weather adjustment. The horizontal dashed lines are the critical values for sample 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**



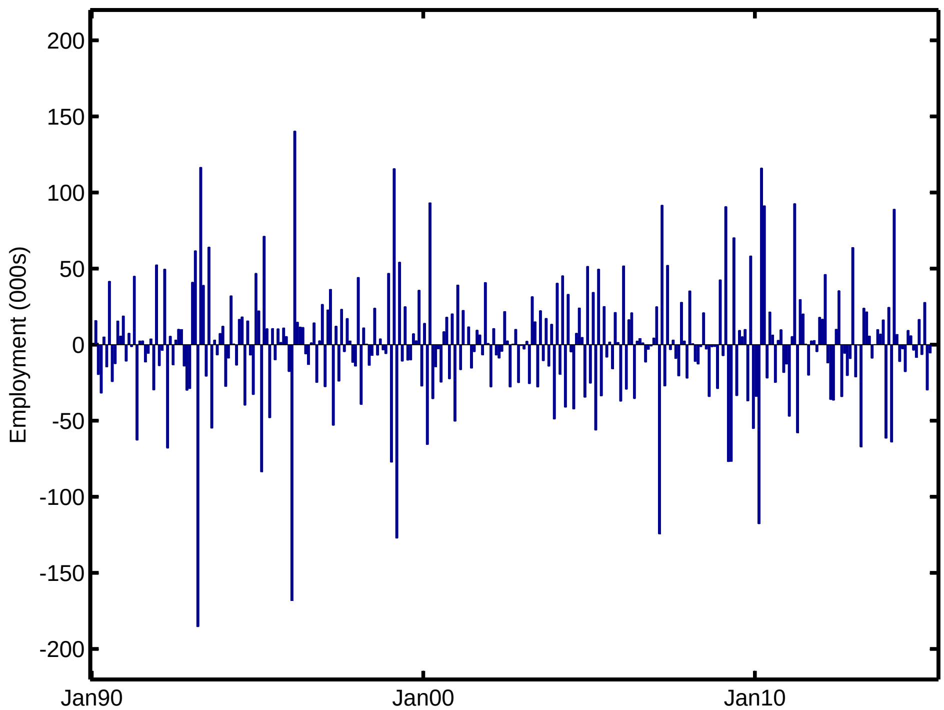

NOTE: This shows the month-over-month change in construction payrolls using standard seasonal adjustment less the corresponding change using seasonal-and-weather adjustment. This shows the estimated effect of the weather, including the effect of controlling for the weather on seasonal factors. The exercise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

**Figure 5: Difference between SA and SWA Month-over-Month Payrolls Changes: Using Specification 5**




NOTE: As for Figure 2, except that CPS work absences due to weather is added as an additional weather variable (as in specification 5).

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




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