Current Policy Perspectives

FEDERAL RESERVE BANK OF BOSTON™

No. 15-2

Did Abnormal Weather Affect U.S. Employment Growth in Early 2015?

Christopher L. Foote

Abstract:
This research note investigates the relationship between the abnormally severe winter experienced in many parts of the United States and the pattern of monthly employment growth during the first four months of 2015. The results suggest that weather reduced employment growth substantially in March and raised it in April. But the overall weather effect averages out to near zero when the four months are considered as a whole, so weather cannot explain the general slowdown in U.S. employment growth experienced since 2014 ended. More generally, the results show that aligning weather data to be consistent with the point-in-time nature of employment surveys is critical for this type of study. In fact, giving more weight to weather occurring just before survey weeks may deliver better estimates of abnormal weather's effects on employment.

JEL Codes: E24, J23

Christopher L. Foote is a senior economist and policy advisor in the research department at the Federal Reserve Bank of Boston. His e-mail address is chris.foote@bos.frb.org.

Michael Boldin and Elizabeth Murry provided a number of useful comments and Matthew Curtis provided outstanding research assistance.

This paper, which may be revised, is available on the web site of the Federal Reserve Bank of Boston at http://www.bostonfed.org/economic/current-policy-perspectives/index.htm.

This version: June 4, 2015

1 Introduction

The winter of 2015 was an abnormally severe one for many parts of the United States, including New England. Also, in 2015:Q1, U.S. GDP declined at an annual rate of 0.7 percent while monthly payroll employment growth slowed by more than 100,000 jobs relative to 2014:Q4. Policymakers are now trying to sort out the potential relationship between the severe winter weather and recent economic data in order to assess the underlying momentum of the economy. This research note uses a state-level model to investigate the effects of abnormal weather on employment growth and has two main findings:

- Unusually harsh weather conditions had an important effect on the pattern of monthly payroll employment growth during the first four months of 2015. Unseasonably cold weather explains much of the surprising March dip in employment growth and a substantial portion of the rebound in April. As suggested by previous research, recognizing these effects requires the construction of a weather dataset that respects the point-in-time nature of the government's employment surveys, which measure employment near the 12th day of each month.

- Significantly negative effects of abnormal weather on employment do not emerge in 2015 until the March survey, and these effects are largely reversed in April. Consequently, the effect of abnormal weather on employment averages to essentially zero over the first four months of this year. While the results reported in this note do not speak to how weather could have affected GDP, bad weather appears responsible for virtually none of the slowdown in average monthly employment growth over the first four months of this year.

2 Estimating the Effects of Abnormal Weather

At several points during the past few years, unseasonable winter weather has been considered as a source of employment fluctuations. In 2012, the exceptionally warm winter was thought to have temporarily raised employment relative to the normal seasonal cycle. Two years later, the so-called polar vortex winter of 2014 was thought to have lowered employment. Perhaps the most common way to quantify the effects of abnormal weather on employment is to regress monthly employment data that has been seasonally adjusted on weather-related variables (Macroeconomic Advisers 2012; Bloesch and Gourio 2015). To the extent that estimates of the regular seasonal adjustments have not been contaminated by unseasonable weather in the past, this method generates an estimate of the effects of abnormal weather on the labor market.

A more ambitious way to adjust for abnormal weather is to account for these effects directly when estimating the regular seasonal adjustments, as in Boldin and Wright (2015). The Boldin-Wright method enters weather-related variables into a time-series regression that is already a part of the standard procedure that estimates regular seasonal factors.[1] Estimating the abnormal-weather effects jointly with the regular seasonal factors is conceptually cleaner, but the Boldin-Wright approach also requires the analyst to make several auxiliary judgments regarding the usual details of seasonal adjustment—including the treatment of outliers, whether seasonal adjustments should be estimated additively or multiplicatively, and the types of filters used to separate the unadjusted data into trend, cyclic, irregular, and seasonal components. It is hard to know how these judgments should be affected by folding the abnormal-weather adjustments into the usual seasonal-adjustment algorithm.

This note uses the simpler method of estimating regressions on seasonally adjusted data, but it stands on the shoulders of Boldin and Wright (2015) in an important way. As part of that study, Boldin and Wright also investigate the calendar dates on which abnormal weather is likely to have the biggest effects on payroll employment. The Current Employment Statistics (CES) program at the Bureau of Labor Statistics (BLS) queries firms about their employment levels during their pay periods that include the 12th day of each month.[2] Boldin and Wright reason that on that basis alone, bad weather that occurs in (say) late March should have virtually no effect on measured employment in March, because this weather would have deterred few people from being employed on or around March 12. Boldin and Wright then incorporate some daily weather data into a statistical model to show that bad weather has the biggest effect on measured employment when it occurs on or shortly before the 12th day of the month. The effect of weather on employment declines nearly linearly as the weather occurs progressively earlier in time (and thereby moves closer to the previous month's employment survey). Using the March example, this finding suggests that weather in late February can also affect employment in March, though these effects will be smaller than the effects of early March weather.

An important implication of this finding is that researchers should not use calendar-month averages of weather data to study abnormal-weather effects. In the March example, calendar-month averages would link late February weather to February employment data, not March employment data.[3] One alternative to using calendar-month averages is to calculate the

[1]Among other things, this regression is used to project employment estimates into the future and thereby improve the estimation of seasonal factors corresponding to current data. For a summary of the government's seasonal-adjustment methods, see Wright (2013).

[2]Similarly, the Current Population Survey (CPS), which generates the unemployment rate, asks respondents about their employment status as of the week (not pay period) that includes the 12th day of each month.

[3]Boldin and Wright are perhaps to the first to show statistically that the effect of weather conditions on employment is most pronounced on or before the survey week, with smaller effects for earlier data. But other researchers have also recognized the general importance of considering weather conditions between survey

simple average of daily weather data between the 12th day of each month. But an even better way to incorporate the lessons of Boldin and Wright (2015) is to construct weighted averages of daily weather data for which the weights rise as the days approach the 12th day of each month; using the previous example, these weights would downweight late February data and upweight early March data. As we will see, constructing weather data that is consistent with the point-in-time nature of U.S. employment surveys makes a difference when interpreting how weather conditions affected employment during the first third of 2015.

3 The Winter of 2015 in Retrospect

Figure 1 displays national temperature rankings from October 2014 through March 2015, using maps produced by the National Climatic Data Center (NCDC).[4] The color of each map turns from blue to white to red as the month rises in the historical temperature ranking, which is depicted as the number in the center of the map (higher numbers denoting warmer months). October, December, and March are red because each of those months was among the warmest since 1895. Specifically, October 2014 ranked 117th out of 120 previous Octobers, December ranked 119th out of 120 and March ranked 110th out of 121. The map for February is white because its average temperature was relatively typical, ranking 53rd out of 121. Yet February's mild national average belied some notable state-level extremes. Figure 2 provides the same information for each of the 48 contiguous states.[5] In February, many states in the Northeast were enduring their second-coldest February on record, while other states in the eastern half of the country had only slightly warmer rankings. Yet in the West, California, Washington, Arizona and Utah each experienced their warmest February on record, and the relative rankings for Oregon, Idaho, Nevada, and Wyoming were only slightly cooler.[6] The regional nature of abnormal temperatures during this period suggests that a state-level model is a good way to study recent weather effects, and this approach is used below.

The national and state-level temperature rankings reflect calendar-month averages, but what was going on between monthly employment surveys? Figure 3 displays national, population-weighted heating-degree days (HDDs), by week, from January 1, 2014 through

weeks when evaluating the effect of abnormal weather on employment. For example, a recent report by the Macroeconomic Advisers forecasting group hypothesized that weather between the February and March surveys was partly to blame for low employment growth in March.

[4]Like most of the weather data used in this note, the data in Figure 1 correspond to the 48 contiguous states.

[5]State-level analysis of temperature data is especially useful because the temperature averages depicted in Figures 1 and 2 are area-weighted, not population-weighted. Below, I make extensive use of data on heating-degree days, which are population-weighted.

[6]As noted by at least one national newspaper, the state-level temperature distribution in early 2015 calls to mind the old joke about the definition of a statistician: someone who can put one hand in a bucket of ice, the other on a hot stove, and say, "On average, I feel fine."

April 30, 2015.[7] The top panel illustrates the usual seasonal pattern, with high HDD levels in the winter falling off to near-zero levels in the summer. The blue dots in this panel correspond to the weeks that include the 12th day of each month. Though the HDDs followed the usual pattern downward in early 2015, there was a snap of cold weather and a consequent spike in HDDs between the February and March employment surveys. Panel B depicts the deviations of weekly HDDs from their normal values over the 1981–2010 period.[8] In this lower panel, the February-March spike shows up as an abnormally large amount of HDDs relative to past history. But the red dots, which denote the calendar-month averages of weekly HDDs, indicate that this spike had a much larger effect on the calendar-month average for February than it did for the calendar-month average for March, even though the spike should influence the March employment survey, not the February survey.[9]

Figure 4 shows the effect of calculating HDD averages in different ways for a sample state, Massachusetts.[10] Among the daily data in Panel A, the calendar-month average is denoted by the blue line and the trailing 28-day simple average by the red line. The green line denotes a trailing 28-day weighted average that uses linearly declining weights.[11] The monthly data in Panel B are constructed by taking the daily HDD averages from the 12th day of each month from Panel A, and Panel C depicts the deviation of those 12th-day averages from their usual month-specific values starting in 1981. To be sure, each of the three deviations in Panel C indicates that in Massachusetts the recent winter was colder than average. But there are important differences among the measures as to precisely when the Bay State's winter turned so severe.

[7]Heating degree days (HDDs) are determined by subtracting the mean temperature during a 24-hour period from a reference temperature of 65 degrees. The mean temperature is defined as the simple average of the day's high and low temperature. Thus, if the high temperature on a particular day is 60 and the low temperature is 40, the average temperature is 50 degrees and there are 15 HDDs for that day (the 65-degree reference temperature less the 50-degree daily average equals 15 HDDs).

[8]These deviations from 1981–2010 normal values are calculated directly by the NCDC. In the empirical work below, which uses monthly data, I calculate the normal values myself using the entire sample period, which always extends to April 2015.

[9]Note also that the calendar-month HDD average for February 2015 appears to be warm relative to 1981–2010 normal values, while the temperature map in Figure 1 indicated that February was about average relative to more than a century's worth of data. One potential reason that February's HDD measure indicates more warmth than its temperature ranking is that the HDD data are population-weighted, not area-weighted. In February, the warm parts of the country were large and less-densely populated Western states, so the February temperature ranking would tend to be higher than February's HDD ranking.

[10]The daily, state-level population-weighted HDD data used in this note start in 1981 and can be downloaded from the NCDC at ftp://ftp.cpc.ncep.noaa.gov/htdocs/degree_days/weighted/daily_data/.

[11]The weights for this average are set so that $1 \cdot \omega$ is the weight for the current day's HDD, $\frac{27}{28} \cdot \omega$ corresponds to the once-lagged HDD, $\frac{26}{28} \cdot \omega$ corresponds to the twice-lagged HDD, and so on, with $\omega = (1 + \frac{27}{28} + \frac{27}{28} + ... + \frac{1}{28})^{-1}$. Linear weights are roughly consistent with the pattern of daily employment effects presented in Boldin and Wright (2015).

4 State-Level Estimates of Weather Effects

This section uses a state-level framework to quantify the effects of unseasonable weather on monthly employment growth. The dependent variable for all regressions is the log difference of seasonally adjusted nonfarm payroll growth, as measured by the BLS. In addition to the weather variables, discussed below, each regression also includes two lags of the dependent variable, a monthly national recession dummy, and state-level fixed effects.[12] All weather variables are entered as first differences of data that has previously been deviated from state- and month-specific averages, as in Panel C of Figure 4. Because the dependent variable is defined as the change in employment, entering the weather variables as first-differences imposes a levels-levels relationship between abnormal weather and employment.[13] Additionally, deviating the weather data from usual state/month values before taking differences forces the regression to estimate the employment effects of truly abnormal weather, not the effects of typical weather patterns that should already be accounted for by the BLS's seasonal-adjustment program.

Coefficients for a baseline specification and several extensions appear in Table 1. Weather variables for the baseline model shown in column 1 include the (change in the deviated) 28-day weighted average of HDDs and a monthly precipitation variable. To my knowledge, the NCDC does not provide daily data on precipitation in the same format as the HDD data, so all of the precipitation variables used in this note are based on calendar-month averages.[14] Also appearing in the baseline model are the state-month deviations of an "absent-work" variable that is generated by individual-level data from the Current Population Survey (CPS). Each month, the CPS asks employed respondents whether they were absent from work during the survey week, and if so, why. Potential reasons include vacation, illness, a labor dispute, and bad weather. As pointed out in previous research, a variable measuring the share of employed persons who are not at work because of bad weather is an ideal control for a regression investigating abnormal-weather effects on employment. Not only does this variable directly reflect the impact of bad weather, but it also lines up nearly perfectly with the timing of the CES survey that generates the nonfarm payroll figure.[15] Column 1 shows that all of these

[12] Because the regressions are specified in terms of employment growth, the state-level fixed effects allow each state to have a different average growth rate over the sample period. The daily HDD data are available beginning on January 1, 1981, but the trailing 28-day averages used in many specifications cannot be calculated for January 12, 1981, because those averages extend into December 1980. Because some regressions include one lag of the change in weather variables, the baseline sample period is set to begin in April 1981; the sample period ends in April 2015.

[13] A robustness check will add lags of the weather variables, in order to allow for a more complex levels-levels relationship than is possible with contemporaneous weather variables only.

[14] Precipitation is not the same as snowfall. A later section accounts for snowfall explicitly.

[15] In the CPS, the survey week is the calendar week that includes the 12th of the month. As noted earlier, the survey period for the CES is the pay period that includes the 12th of the month, which may be longer than one week. The absent-work variable is a key component of many discussions of abnormal-weather effects

variables enter significantly in the baseline regression.[16]

As discussed earlier, the timing of the employment surveys suggests that averages of daily weather data between survey dates should outperform calendar-month averages in these regressions. Moreover, the results in Boldin and Wright (2015) suggest that a weighted average that puts more emphasis on weather shortly before each survey date should explain employment better than a simple average of daily data between the 12th day of each month. Both of these hypotheses are supported by the data. Column 2 of Table 1 replaces the weighted-average HDD measure with a calendar-month average. The latter average enters significantly when included on its own, but column 3 shows that it drops out of the model when the weighted average is also present. Column 4 indicates that the same is true of the simple average, which is insignificant when the weighted average is also included.[17]

Figure 5 uses the coefficients from the baseline model in column 1 to depict recent weather effects on the level of employment. These effects are calculated as the difference between two dynamic forecasts of employment that both begin on October 2014. The blue line in the top panel depicts the dynamic forecast using actual weather observed from October 2014 onward.[18] The red line shows the dynamic forecast that is generated by assuming that all weather observed on or after October 2014 is normal for each state and month (this is done by setting the deviations for all three weather variables equal to zero). The lower panel depicts the difference between these two forecasts and is therefore the cumulative effect that weather has on the level of national employment.[19] Panel B indicates that during late 2014 and the first two months of 2015, weather had a generally positive effect on U.S. employment, raising its level by about 34,000 jobs as of February. This positive effect of weather is generally consistent with the warm temperatures for October, December, and January depicted in Figure 1.[20] However, weather effects reversed dramatically in March,

from Macroeconomic Advisers, including Macroeconomic Advisers (2012).

[16]To facilitate reporting of the coefficients, the HDD and precipitation variables are divided by 1,000 before they are entered in the regression.

[17]The standard errors in Table 1 are clustered by year to allow for correlation among errors and regressors both within and across states. The possibility of cross-state correlation significantly complicates statistical inference in state-level employment models (Foote 2007). Clustering by year is an imperfect solution to the problem because the year cluster does not account for correlations across years (for example, between the data from Michigan in December 1990 and data for either Michigan or Ohio in January 1991). Even so, clustering by year does allow for cross-state correlation within each year, and Appendix Table A1 indicates that year-clustering is more conservative than clustering by state, which accounts only for within-state correlation. I therefore emphasize the year-clustered standard errors when presenting regression results.

[18]Because the model is estimated in log differences, the employment-level forecast is backed out of a dynamic forecast of log employment changes. And as the model is estimated at the state-level, dynamic forecasts of employment levels for individual states are summed to generate the national dynamic forecast.

[19]The model's lack of data from Alaska, Hawaii, or the District of Columbia means that weather effects in Figure 5 and elsewhere in this note do not account for the effect of abnormal weather in those places.

[20]Of course, the temperature rankings depicted in Figures 1 and 2 should be viewed with the caveat that they depict area-weighted temperature data and not population-weighted HDD data. They also are calendar-month averages, not weighted averages of daily data between survey dates.

reducing the level of employment by about 41,000 below normal for that month, and thereby depressing March employment *growth* by about 75,000 jobs. Part of this reversal is due to the levels-levels specification of the model, which implies that positive weather effects accumulated through February would be partially reversed in March even if weather in March had been normal. However, the abnormally cold weather that occurred between the February and March surveys, shown previously in Figure 3, did its part as well, as it pushed the level of March employment below normal. In actual data, employment growth fell from 266,000 in February to 85,000 in March, a slowdown of 181,000 jobs. Figure 5 implies that weather accounts for slightly more than 40 percent (= 75/181) of that change.

Figure 6 depicts estimates of weather effects using some different specifications of the model. Panel A replaces the 28-day weighted average with the calendar-month average (the regression in column 2 of Table 1). As seen earlier, the high calendar-month average of HDDs for February signaled unusually cold weather, while the corresponding average for March signaled near-normal weather.[21] Accordingly, the calendar-month model in Panel A indicates a negative weather effect in February that is reversed in March. One might think that augmenting this model with lags of the weather variables, including the calendar-month HDD deviation, would ameliorate the problem if the appropriate weather averages are spanned in some sense by the time-t and t–1 values of the calendar-month averages. Panel B shows that this is not the case, as the weather effect in February becomes even more pronounced. Panel C uses the simple 28-day average of HDDs rather than the weighted 28-day average. Unlike the calendar-month models shown in the top two panels, the basic time-series pattern of weather effects in the simple-average model lines up relatively well with that of the weighted-average baseline model, although the early-winter pattern of weather effects in the simple-average model appears more volatile.

Does abnormal weather have smaller effects on states that are used to cold winters? To investigate this possibility, I interacted the weighted-average HDD deviation from the baseline model with dummy variables denoting the eight of the country's nine Census divisions. The omitted interaction corresponds to the New England division, which includes Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont.[22] In this unreported regression, none of the eight interactions are individually significant, although jointly they are nearly significant at the 5 percent level (p-value = 0.0524). Additionally, the signs of the coefficients line up as one might suspect. The coefficients for all of the interactions except one are negative, indicating that cold weather has a larger depressing effect on employment growth for most places outside of New England (perhaps because these places are less accustomed

[21] Specifically, the red dots in the lower panel of Figure 3 are relatively high in February and near zero in March.

[22] For the definition of the Census divisions and regions, see http://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf.

to difficult winters). Indeed, the only division with a (very small) positive interaction is the East North Central division, which includes Indiana, Illinois, Michigan, Ohio, and Wisconsin and which is also relatively cold. In any case, Panel D shows that the model with divisional interactions generates recent weather effects that closely resemble those of the baseline model.

5 Incorporating Snowfall

All models discussed so far have included monthly precipitation as an explanatory variable, but they make no distinction between rain and snow. Some research has begun to incorporate snowfall readings from weather stations around the country into this type of analysis. One example is Bloesch and Gourio (2015), who construct a large dataset from the U.S. Historical Climatology Network to study the impact of both snow and low temperatures during the so-called polar vortex winter of 2014. Another snow-related project was recently undertaken by the Macroeconomic Advisers forecasting group, which assembled daily snowfall readings from a separate NCDC dataset.[23] As outlined in Macroeconomic Advisers (2014), the forecasting group constructs its snowfall dataset by first averaging all of the snowfall readings within each county during each day. The county-level daily snowfall readings are then aggregated into monthly data by summing them within each county and month. Next, usual snowfall totals are calculated by averaging the monthly totals within each county and calendar month. Abnormal snowfall is defined the deviation of a county's actual amount of snowfall from its usual calendar-month total. Finally, two additional variables are constructed. A positive-deviation variable equals the county's actual deviation if the actual deviation is greater than zero (and is set to zero otherwise). In the same way, a negative-deviation variable equals the county's actual deviation if this deviation is less than or equal to zero (and equals zero otherwise). The construction of the positive and negative deviations, which always sum to the actual deviation, allow the researcher to discern whether abnormally low snowfall readings boost economic outcomes to the same extent that abnormally high readings reduce them.

Figure 7 provides some information regarding snowfall intensity experienced during the recent winter. The top panel maps the actual snowfall deviations by county in February 2015. The counties in dark blue experienced more snowfall than they typically receive in February (positive deviations) and the light-blue counties experienced less-than-typical snowfall (negative deviations). The map clearly shows the large amount of February snow that fell in New England and some other parts of the country. The panel also shows that the snowfall dataset does not cover the entire country, as areas with very little snow on average do not report snowfall as often as heavy-snowfall areas and often have missing data.[24] The lower panel

[23]These data begin in July 2005 and are available at http://www1.ncdc.noaa.gov/pub/data/snowmonitoring/fema/.

[24]Counties with missing data in February 2015 are denoted by light brown in the map. When calculating

uses county-level population from the 2010 Census to construct national averages of snowfall deviations, with the blue line denoting the population-weighted actual deviation among all counties.[25] In this graph, the very warm winter of 2012 stands out as having much less snowfall than normal. As we would expect, during early 2012 most counties experienced negative snowfall deviations (gray line), although a few counties experienced positive deviations (red line).

The top panel of Figure 8 permits a sharper focus on snowfall deviations during recent months. Unlike those in Figure 7, the deviations in this panel are based on county-level *averages* of daily snowfall readings rather than county-level *sums* of daily readings. The blue bars display the population-weighted average of all county-level snowfall deviations using averages taken over the corresponding calendar months. These bars depict an abnormally low level of December snowfall and a relatively high amount of February snowfall. The December reading is quite consistent with the national temperature maps for that month as shown in Figures 1 and 2. Specifically, these maps established that the United States as a whole experienced a near-record-setting high average temperature in December and that this warmth was widely felt across the country. In addition, a large amount of February snow is consistent with the severe winter experienced that month in the eastern half of the country.

The light blue and red bars depict snowfall data that are based on weighted averages during the 28 days before the 12th day of the month, not on averages over calendar months. In this way, the light blue and red bars correspond to the timing of the HDD averages used in the baseline model. The light blue bars aggregate all county-level deviations while the red bars aggregate the positive county-level deviations.[26] The positive deviation bars are relatively large in both February and March. High amounts of snowfall before the March survey should not be too surprising, as we have already seen that national HDDs spiked between the February and March surveys. To the extent that cold weather and snowfall are positively correlated, we would therefore expect a lot of snow before the March survey. Also, a strong correlation between HDDs and snowfall data would imply that HDDs may capture some of the variation in employment induced by snowfall, even if snowfall is left out of the model. This correlation is unlikely to be airtight, however. In fact, the lower panel of Figure 3 showed no spike in HDDs between the January and February survey weeks. Thus, the large amount of snow that fell before the February survey is unlikely to be reflected in the pattern of state-level HDDs, so HDDs will be less able to account for any snowfall effect before the

snowfall statistics, a county with missing data is counted as having zero snowfall.

[25] This panel is a replication and update of Figure 2 in Macroeconomic Advisers (2014). The data that generate this panel includes the snowfall in Alaska, but as noted earlier that state is excluded from the regression models in this note, along with Hawaii and the District of Columbia.

[26] Recall that positive deviations are set to zero when the actual deviation is negative or zero. Average negative deviations are not shown, but by definition the height of the negative deviation bars would equal the positive-deviation bars less the all-deviations bars.

February survey.[27]

The last two columns of Table 1 bring snowfall into the formal regression analysis. Column 5 estimates the baseline model over a sample period that begins in October 2005, when snow variables can be constructed.[28] The HDD and absent-work terms remain highly significant while the coefficient on precipitation becomes insignificant. Column 6 shows that including the positive and negative snowfall deviations (and one lag of each) reduces the absolute values of the HDD and absent-work coefficients, although they both remain significant at the 1-percent level. Of the four snowfall terms, all have the expected (negative) sign, but only the contemporaneous positive term is significant.[29]

The lower panel of Figure 8 displays the estimated employment effects from these two models, along with the effects from the full-sample baseline model for comparison. The effects generated by the baseline model estimated on either the full sample or the snowfall sample are nearly identical, indicating that the model is either very stable or that much of the identifying variation for this model comes from post-2005 data. The main difference between these models and the model that includes the snow variables is that the snow-augmented model implies a negative weather effect in February while the models without snow do not. The fact that the snow-augmented model predicts a bigger weather effect in February may reflect the discrepancy between the HDD pattern and the snowfall pattern discussed earlier: both the HDDs and the snowfall data suggest that abnormal weather occurred before the March survey, but only the snowfall data points to bad weather that occurred before the February survey. In any event, all three models imply a negative effect on March employment growth in the neighborhood of 75,000 jobs.

6 Actual versus Adjusted Monthly Employment Growth

With estimates of recent weather effects in hand, we can remove these effects from the pattern of monthly employment growth to get a better picture of the underlying momentum of the labor market. Panel A of Figure 9 depicts actual monthly payroll employment growth that was reported in early May. Job growth slowed over the first four months of 2015 and experienced a noticeable dip in March. Panel B adjusts the monthly totals using the baseline model, estimated over the full sample. Because this model implies a large and negative weather effect on employment growth in March, and a partially offsetting rebound in April,

[27] Precipitation is also included in the baseline model, but as noted earlier, data limitations require precipitation to be entered as a calendar-month average, not a 28-day weighted average. Thus, precipitation's ability to proxy for snowfall before the February survey is also limited.

[28] The raw snow data are available starting in July 2005, but as discussed in footnote 12, the estimation sample for the weather models must begin a few months after raw data become available.

[29] Two of the three insignificant snowfall terms become significant when the standard errors are clustered by state rather than year, as seen by comparing columns 3 and 4 of Table A1.

the baseline adjustment raises March employment growth by about 75,000 jobs and reduces April growth by slightly more than 50,000 jobs. The effect of weather on other months are minor. The pattern of adjusted employment growth over the first four months of the year is much more stable than in actual data and suggests an underlying momentum in employment growth of just less than 200,000 jobs per month.

Panel C performs a similar adjustment with a model that includes lags of the three weather variables, in order to permit a more complex time-series response to abnormal weather.[30] The broad pattern of adjusted employment growth remains similar to that of the baseline model without lags. Panel D uses a simple rather than a weighted average to calculate the HDDs and generates a pattern of January-to-April employment growth that is similar but somewhat less stable than the pattern in the previous two panels. Panel E uses the baseline model but allows the HDD deviation to have different effects based on its sign (similar to the earlier treatment of the snowfall deviations).[31] There are some minor differences from the baseline model. Finally, Panel F shows the effect of estimating the model on the post-2005 snowfall sample, with the blue bars imposing only the sample restriction on the baseline model and the red bars adding the four snow variables.[32] As discussed earlier, the only appreciable difference in these models occurs in February, when the snow-augmented model implies a larger negative weather effect, and thus a higher adjusted value for February employment growth.

Although the potential adjustments have somewhat different implications for the pattern of monthly employment growth, they all suggest that abnormal weather mostly redistributes this growth among the first four months of 2015 in different ways. As a result, none of the adjustments can explain the significant decline in employment growth experienced in the first four months of 2015 relative to the last three months of 2014. Table 2 illustrates this point by comparing the averages of actual employment growth to corresponding averages implied by different adjustments. The top row of the table shows that employment growth averaged 324,000 jobs in 2014:Q4 but only 194,000 during in the first four months of this year, a slowdown in growth of about 130,000 jobs. The remaining rows show that similar averages are generated by a variety of potential weather adjustments.

7 Conclusion

A key policy concern this year is how weather conditions affect economic activity. Building on previous studies, this note shows that accounting for weather generates a much smoother

[30]See columns 3 and 4 of Table A1 for the coefficients of the lag-augmented baseline model, as well as their standard errors under two potential choices of the clustering variable (year and state).

[31]The regression for Panel E appears in column 7 of Table A1.

[32]Recall that these models are presented in columns 5 and 6 of Table 1.

pattern of employment growth over the first four months of the year, essentially reclassifying employment growth that actually occurred in April to growth that would have occurred in March under more normal weather conditions. This reclassification, however, cannot explain why the average pace of employment growth slowed by more than 100,000 jobs from the end of 2014 through the first four months of 2015. More broadly, the results reported in this note illustrate that aligning weather data with the point-in-time nature of government employment surveys is critical to obtaining useful estimates of abnormal-weather effects. The results also suggest that using a weighted average of daily weather data between the survey dates, as implied by results in Boldin and Wright (2015), gives the most efficient estimates of these effects.

References

Bloesch, Justin, and François Gourio. 2015. "The Effect of Winter Weather on U.S. Economic Activity." Federal Reserve Bank of Chicago *Economic Perspectives*, First Quarter. Available at https://www.chicagofed.org/~/media/publications/economic-perspectives/2015/1q2015-part1-bloesch-gourio-pdf.pdf.

Boldin, Michael, and Jonathan H. Wright. 2015. "Weather Adjusting Employment Data." Federal Reserve Bank of Philadelphia Working Paper No. 15-05. Available at https://www.philadelphiafed.org/research-and-data/publications/working-papers/2015/wp15-05.pdf.

Foote, Christopher L. 2007. "Space and Time in Macroeconomic Panel Data: Young Workers and Unemployment Revisited." Federal Reserve Bank of Boston Working Paper No. 07-10. Available at http://www.bos.frb.org/economic/wp/wp2007/wp0710.pdf.

Macroeconomic Advisers. 2012. "Mild Winter Weather and Payroll Employment." March 21. For a related blog post, see http://macroadvisers.blogspot.com/2012/03/mild-winter-weather-and-payroll.html.

Macroeconomic Advisers. 2014. "Elevated Snowfall Reduced Q1 GDP Growth 1.4 Percentage Points." April 14. For a related blog post, see http://www.macroadvisers.com/2014/04/elevated-snowfall-reduced-q1-gdp-growth-1-4-percentage-points/.

Wright, Jonathan H. 2013. "Unseasonal Seasonals?" *Brookings Papers on Economic Activity* 47(2): 65–110.

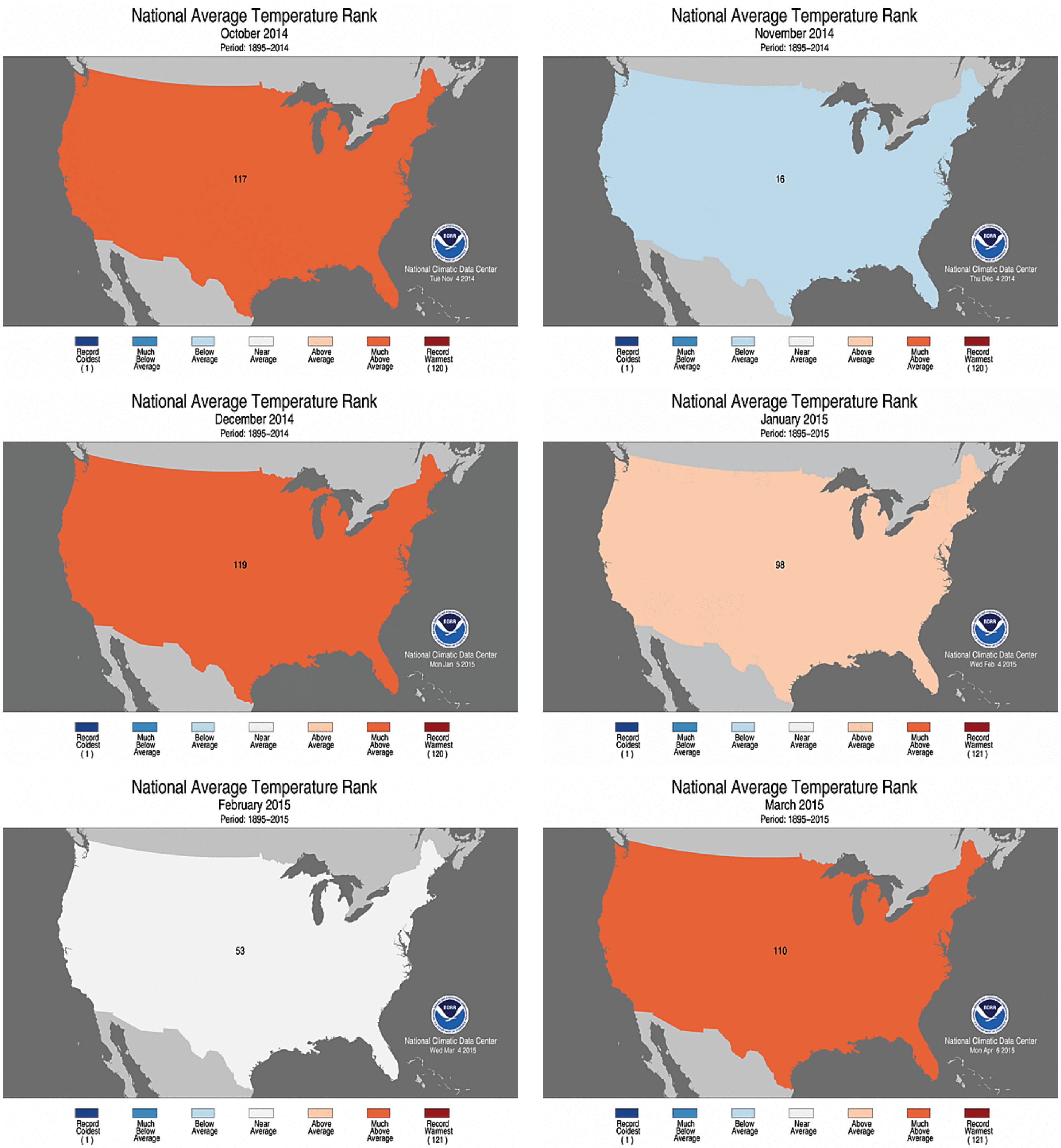

Figure 1. National Temperature Rankings: October 2014–March 2015
Source: National Climatic Data Center, National Oceanic and Atmospheric Administration (http://www.ncdc.noaa.gov/temp-and-precip/us-maps).

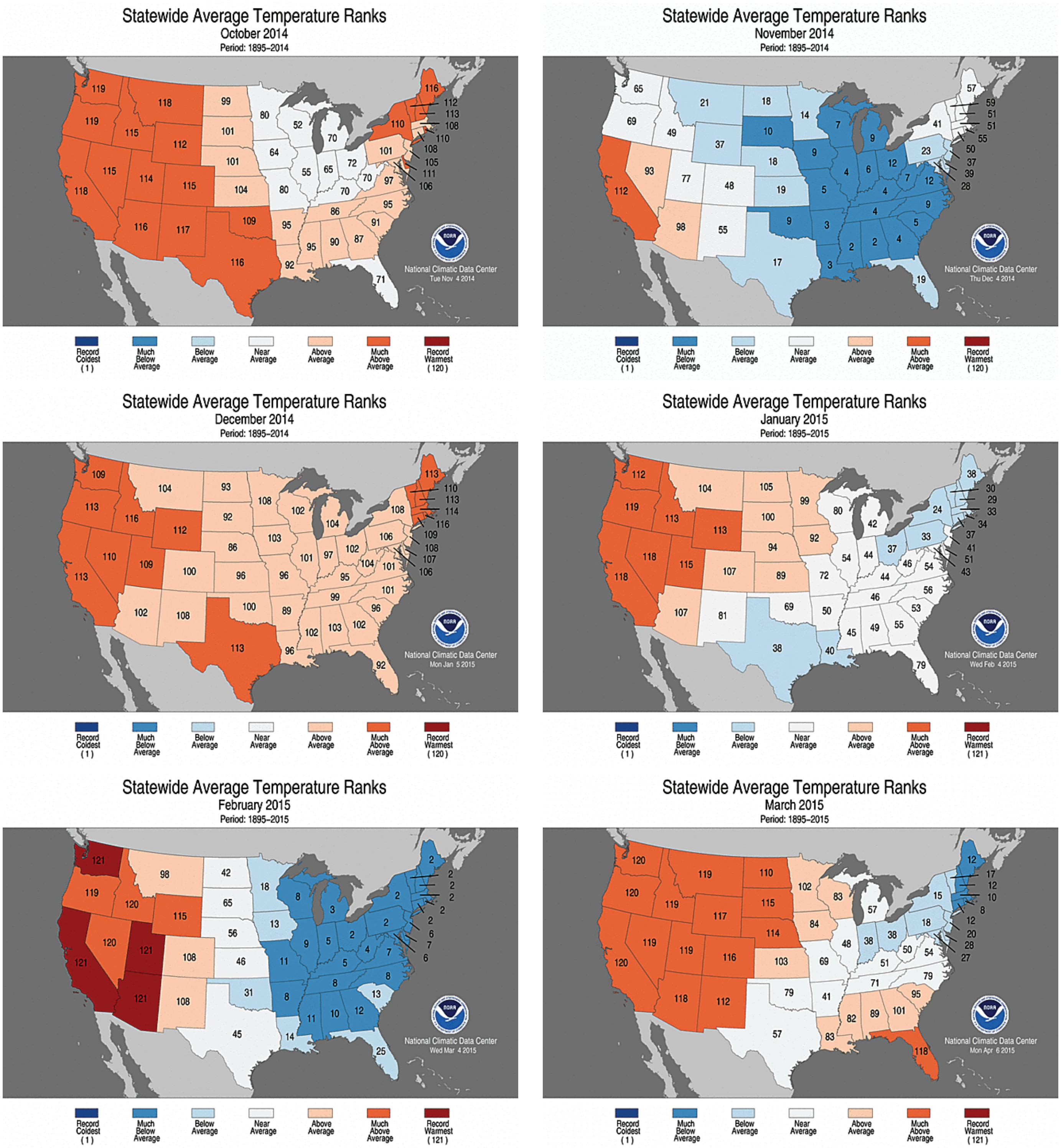

Figure 2. State-Level Temperature Rankings: October 2014–March 2015
Source: National Climatic Data Center, National Oceanic and Atmospheric Administration (http://www.ncdc.noaa.gov/temp-and-precip/us-maps/).

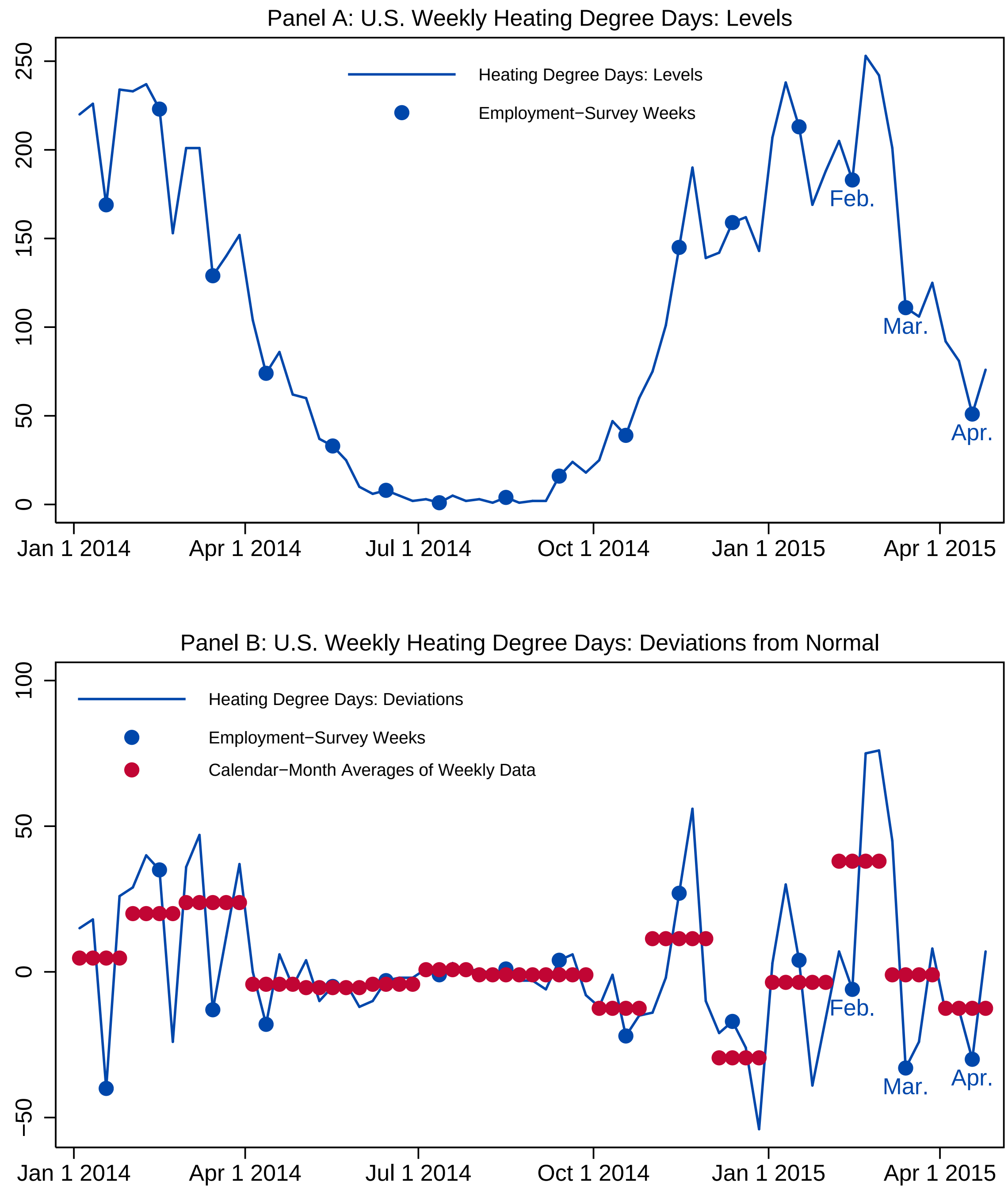

Figure 3. U.S. Weekly Heating-Degree Days (HDDs): January 1, 2014 to April 30, 2015
Source: National Climatic Data Center, National Oceanic and Atmospheric Administration.
Note: Data correspond to population-weighted sums (not averages) of daily HDD data over the given week. The blue dots in the two panels denote the weeks that include the 12th of the month.

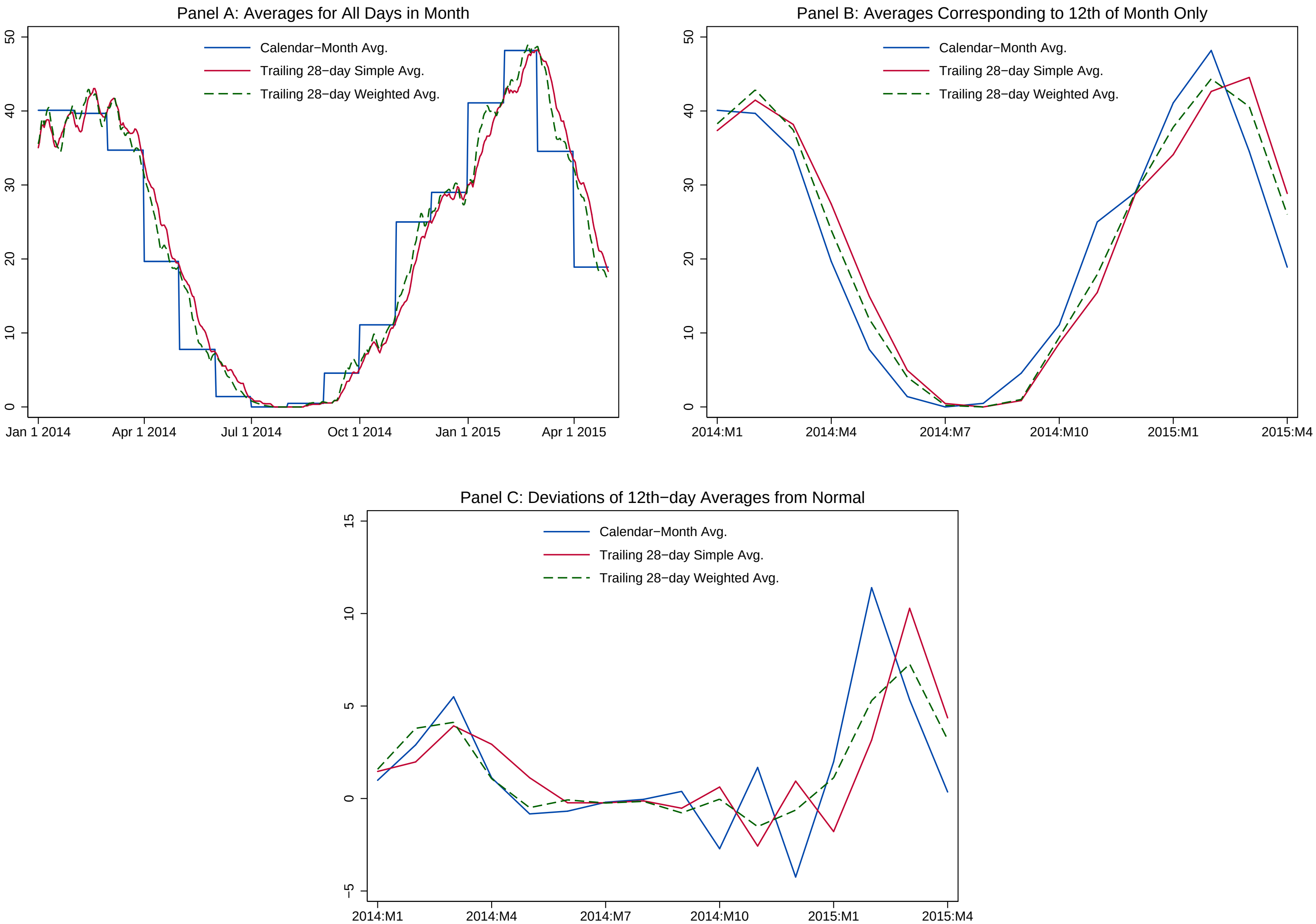

Figure 4. Monthly Averages of Heating-Degree Days, and Deviations from Normal Values, for Massachusetts: January 1, 2014 to April 30, 2015
Source: National Climatic Data Center, National Oceanic and Atmospheric Administration, and author's calculations.
Note: The solid blue lines correspond to calendar-month averages. The solid red lines in each panel correspond to simple (unweighted) averages of HDDs over the current day and the previous 27 days. The green dashed lines take averages over the same history, but use linearly declining weights.

	Baseline Model (1)	(2)	(3)	(4)	(5)	(6)
Dependent variable (lag 1)	0.070*	0.068	0.071*	0.070*	0.17*	0.16*
	(0.033)	(0.034)	(0.033)	(0.034)	(0.062)	(0.064)
Dependent variable (lag 2)	0.15**	0.15**	0.15**	0.15**	0.15	0.16
	(0.050)	(0.050)	(0.050)	(0.050)	(0.082)	(0.084)
Δ HDD (28-day weighted avg.)	–0.080***		–0.075***	–0.075**	–0.073***	–0.059**
	(0.0075)		(0.0093)	(0.023)	(0.014)	(0.013)
Δ Precipitation (inches)	–0.061**	–0.059**	–0.062**	–0.061**	–0.032	–0.032
	(0.018)	(0.018)	(0.018)	(0.018)	(0.027)	(0.026)
Δ Absent work/weather (CPS)	–0.11***	–0.12***	–0.11***	–0.11***	–0.11***	–0.086***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.015)	(0.017)
Δ HDD (calendar-month avg.)		–0.053***	–0.013			
		(0.012)	(0.015)			
Δ HDD (28-day simple avg.)				–0.0063		
				(0.025)		
Δ Snow (Positive deviation, inches)						–0.0025**
						(0.00074)
Δ Snow (Positive deviation, lag)						–0.0011
						(0.00061)
Δ Snow (Negative deviation, inches)						–0.00070
						(0.00075)
Δ Snow (Negative deviation, lag)						–0.0012
						(0.00059)
R-Squared	0.19	0.19	0.19	0.19	0.33	0.34
P-val: Positive snow variables						0.02
P-val: Negative snow variables						0.14
P-val: All snow variables						0.00
Clustering variable	Year	Year	Year	Year	Year	Year
Number of Clusters	35	35	35	35	11	11
Number of Observations	19,632	19,632	19,632	19,632	5,520	5,520

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Δ means "change in."

Table 1. The Effect of Weather on Monthly State-Level Employment Growth
Note: The dependent variable for all regressions is the log change in state-level, seasonally adjusted nonfarm employment. All regressions also include a monthly recession dummy and state-level fixed effects. Weather variables are calculated as deviations from state/calendar-month means. For the snow variables, these deviations are calculated by constructing deviations relative to county/calendar-month means and then population-weighting up to the state level. The sample period for columns 1 through 4 is April 1981 through April 2015. The sample period for columns 5 and 6 is constrained by the availability of snowfall data and begins in October 2005. The heating-degree day (HDD) and precipitation measures are divided by 1,000 before they are entered in the regressions. The absent-work variable is calculated as the share of employed persons who were not at work during the survey week because of bad weather, as measured by the CPS. Data for Alaska, Hawaii, and the District of Columbia are excluded from all regressions.

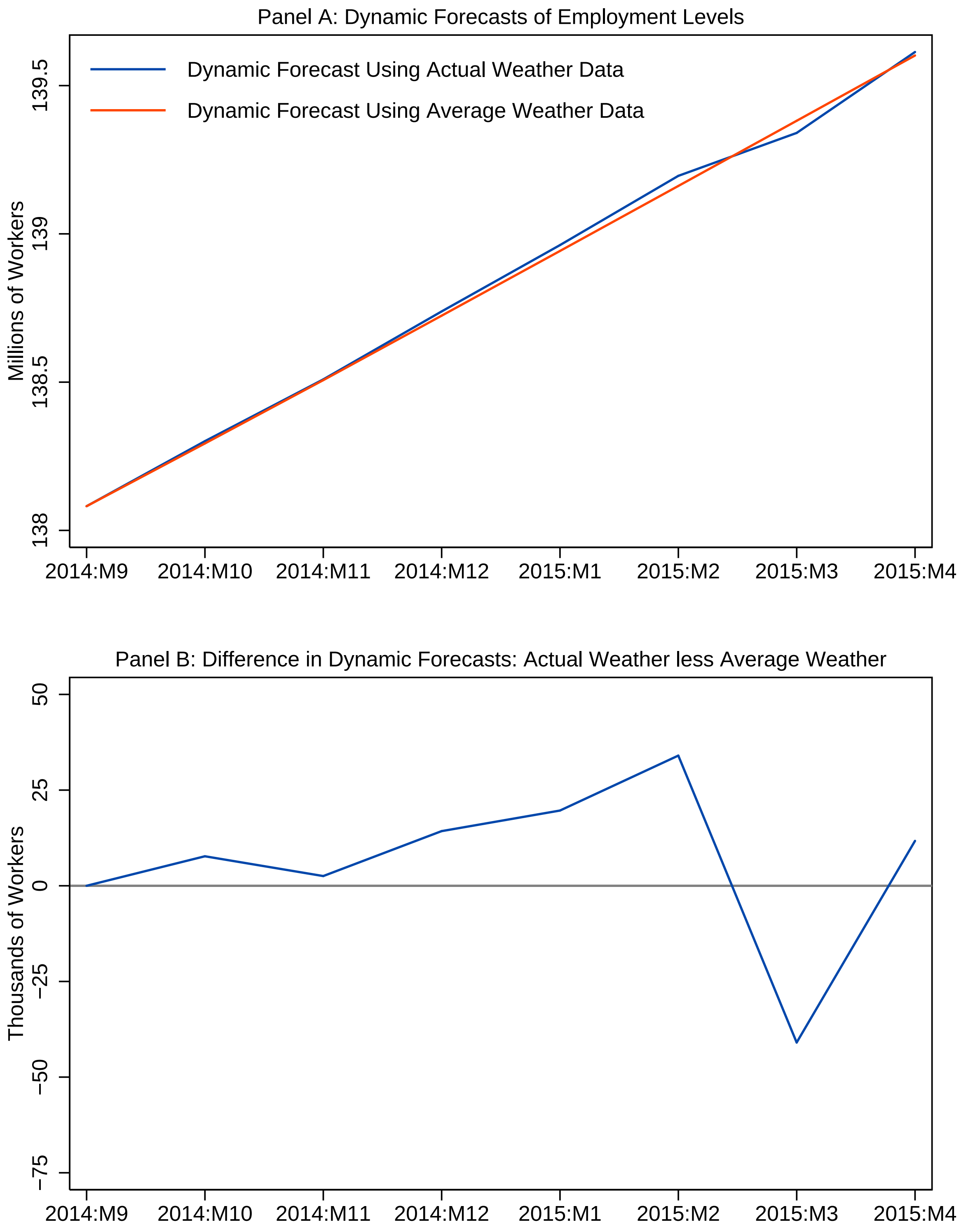

Figure 5. Weather Effects Implied by Baseline Model
Source: Author's calculations.
Note: Estimated effects are generated by the regression in column 1 of Table 1, which uses the 28-day trailing weighted average of heating-degree days (HDDs).

Figure 6. Alternative Specifications for Weather Effects on Employment Levels

Source: Author's calculations.

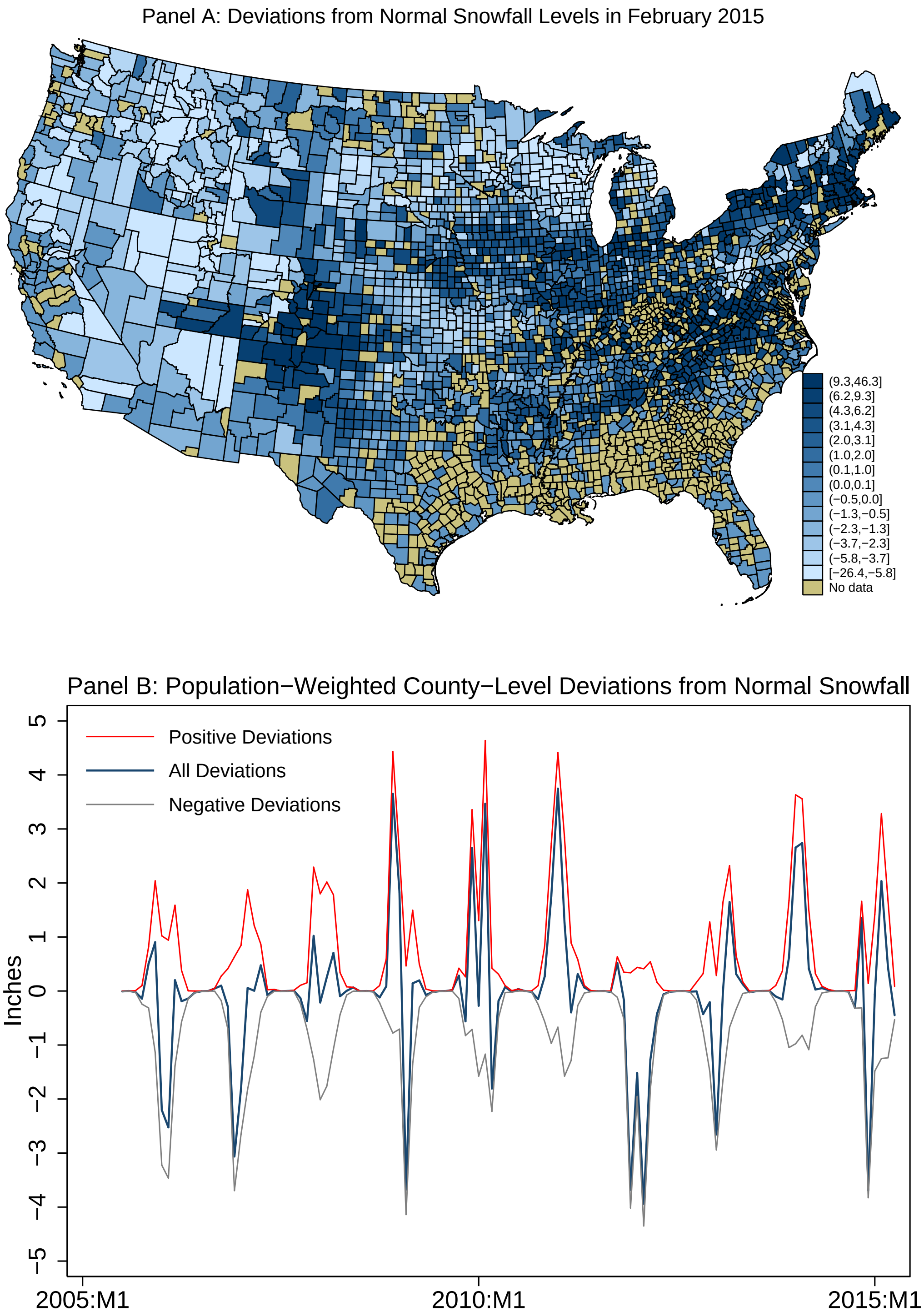

Figure 7. Relative Snowfall Levels in the United States

Source: National Climatic Data Center, National Oceanic and Atmospheric Administration (http://www1.ncdc.noaa.gov/pub/data/snowmonitoring/fema/) and author's calculations.

Note: Snowfall deviations are calculated by taking sums of daily snowfall levels at the county/calendar-month level, then deviating those sums relative to usual county/calendar-month values. Panel A shows these deviations for a single month (February 2015). Panel B uses county-level population weights to construct national values of the snowfall deviations from July 2005 onward and is a replication and update of Figure 2 of Macroeconomic Advisers (2014).

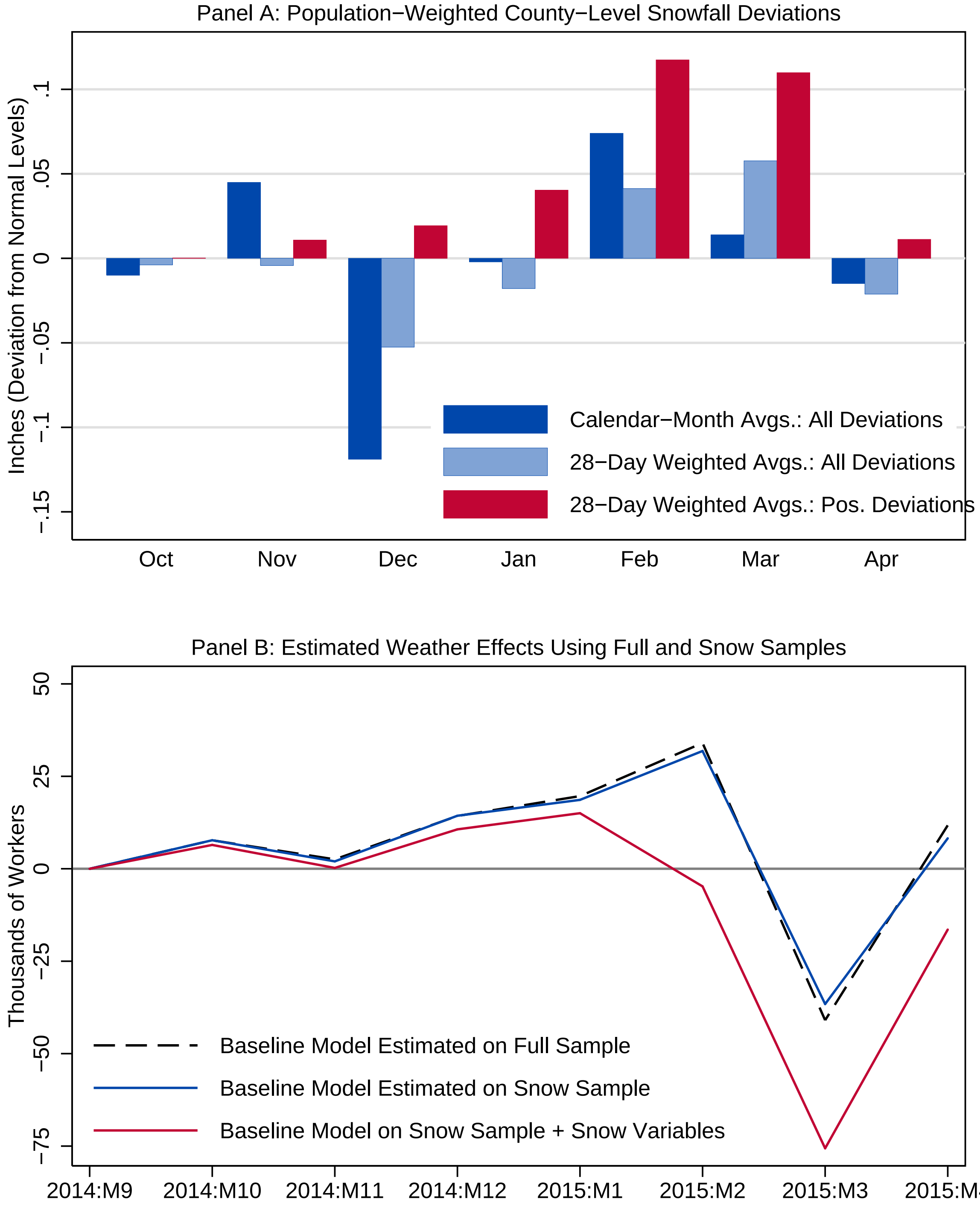

Figure 8. Snowfall Deviations and Their Effects on the Baseline Model
Source: Author's calculations.
Note: Panel A presents population-weighted averages of snowfall deviations, based on averages of daily county-level snowfall readings. The dark blue bars are based on snowfall averages taken over calendar months, and are therefore comparable to the blue line in the lower panel of Figure 7 (which is constructed from sums of daily county-level snowfall readings rather than averages). The light blue and red bars are based on 28-day weighted averages of daily snowfall readings calculated for each county between monthly employment surveys. In Panel B, the dashed black line is generated by column 1 of Table 1, the the blue line is generated by column 5 of Table 1, and the red line is generated by column 6 of Table 1. The full sample is 1981:M4-2015:M4; the snow sample is 2005:M10-2015:M4.

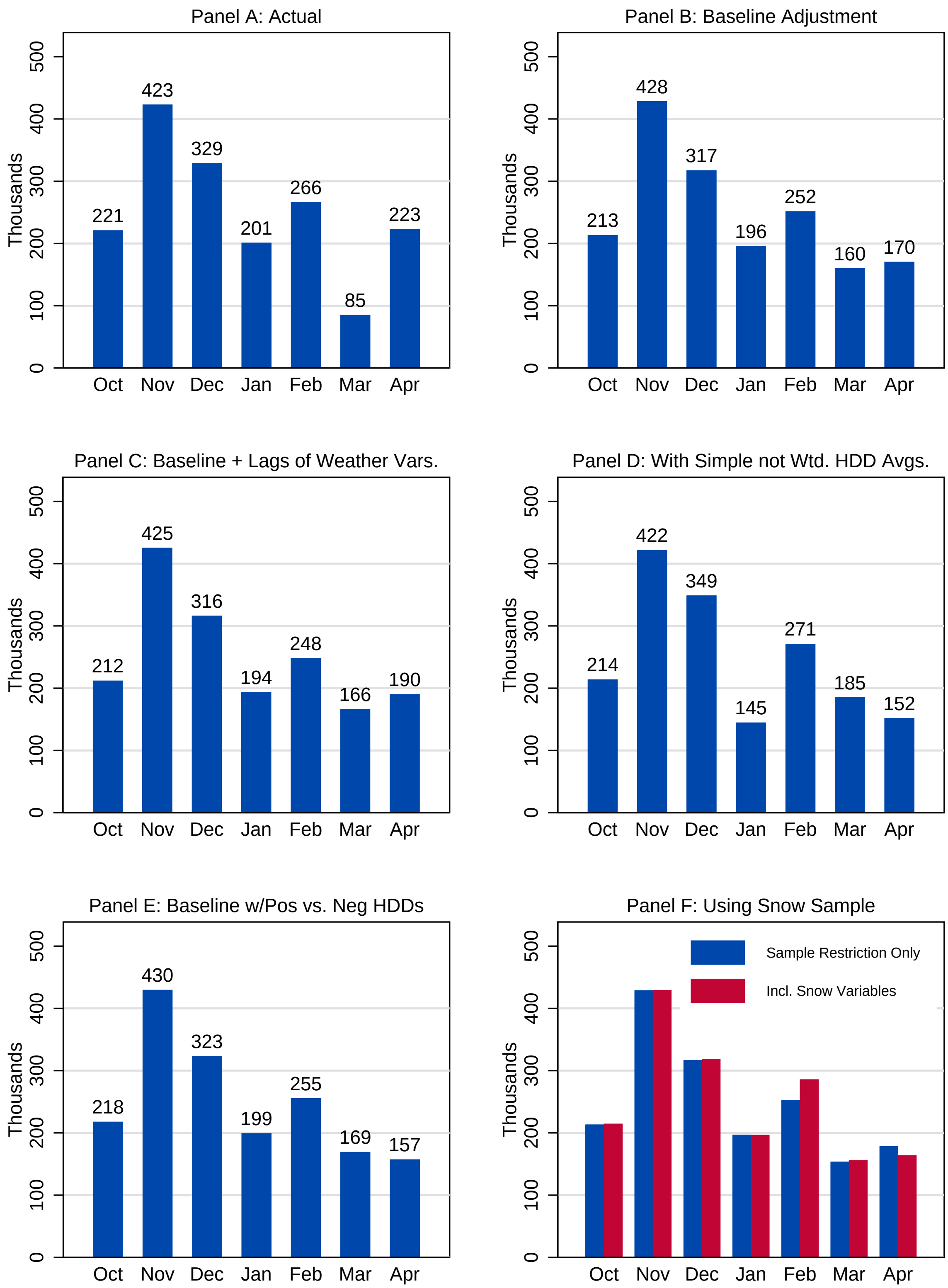

Figure 9. Actual and Weather-Adjusted Monthly Employment Growth: October 2014 to April 2015
Source: Author's calculations.

Model	Average Monthly Payroll Employment Growth 2014 Oct-Dec	2015 Jan-Apr	Implied Slowdown
Actual	324	194	131
Baseline Adjustment (uses weighted 28-day averages of HDDs)	320	194	125
Baseline with Lags of Weather Variables	318	199	118
Using Calendar-month Averages of HDDs	316	200	116
Using Simple 28-day Averages of HDDs	328	188	140
Using Snow Sample (post-2005)	320	195	124
Using Snow Sample & Snow Variables	321	201	120
Baseline with Census Division-specific HDD Effects	319	194	125
Baseline with Positive and Negative HDD Effects	323	195	128

Table 2. Effects of Weather-Related Adjustments for Average Monthly Nonfarm Payroll Growth in Late 2014 (Oct-Dec) and Early 2015 (Jan-Apr)
Source: Author's calculations.
Note: The implied slowdown in the last column may not equal the differences in reported averages because of rounding.

	Baseline Model						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable (lag 1)	0.070*	0.070*	0.16*	0.16***	0.060	0.060*	0.070*
	(0.033)	(0.027)	(0.064)	(0.044)	(0.034)	(0.026)	(0.033)
Dependent variable (lag 2)	0.15**	0.15**	0.16	0.16**	0.16**	0.16**	0.15**
	(0.050)	(0.046)	(0.084)	(0.051)	(0.051)	(0.048)	(0.050)
Δ HDD (28-day weighted avg.)	–0.080***	–0.080***	–0.059**	–0.059***	–0.097***	–0.097***	
	(0.0075)	(0.0068)	(0.013)	(0.0076)	(0.0095)	(0.0080)	
Δ HDD (28-day weighted avg., lag)					–0.036*	–0.036***	
					(0.014)	(0.0088)	
Δ Precipitation (inches)	–0.061**	–0.061***	–0.032	–0.032*	–0.080***	–0.080***	–0.060**
	(0.018)	(0.013)	(0.026)	(0.014)	(0.018)	(0.014)	(0.018)
Δ Precipitation (inches, lag)					–0.036	–0.036*	
					(0.018)	(0.015)	
Δ Absent work/weather (CPS)	–0.11***	–0.11***	–0.086***	–0.086***	–0.13***	–0.13***	–0.11***
	(0.010)	(0.011)	(0.017)	(0.011)	(0.017)	(0.015)	(0.010)
Δ Absent work/weather (CPS, lag)					–0.032	–0.032**	
					(0.016)	(0.012)	
Δ Snow (positive deviation, inches)			–0.0025**	–0.0025***			
			(0.00074)	(0.00045)			
Δ Snow (positive deviation, lag)			–0.0011	–0.0011**			
			(0.00061)	(0.00035)			
Δ Snow (negative deviation, inches)			–0.00070	–0.00070			
			(0.00075)	(0.00041)			
Δ Snow (negative deviation, lag)			–0.0012	–0.0012*			
			(0.00059)	(0.00048)			
Δ Pos HDD (28-day wtd. average)							–0.11***
							(0.014)
Δ Neg HDD (28-day wtd. average)							–0.048**
							(0.015)
R-Squared	0.19	0.19	0.34	0.34	0.20	0.20	0.19
P-val: Positive snow variables			0.02	0.00			
P-val: Negative snow variables			0.14	0.01			
P-val: All snow variables			0.00	0.00			
P-val: Pos HDD effect = Neg HDD effect							0.02
Clustering variable	Year	State	Year	State	Year	State	Year
Number of clusters	35	48	11	48	35	48	35
Number of observations	19,632	19,632	5,520	5,520	19,632	19,632	19,632

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Δ means "change in."

Table A1. Robustness Checks for Monthly Weather Models
Note: See the notes to Table 1 for details regarding variable and sample construction. The point estimates for Columns 1 and 2, for columns 3 and 4, and for columns 5 and 6 are identical; the only differences concern the choice of the clustering variable (year vs. state). Column 1 is identical to column 1 of Table 1, and column 3 is identical to column 6 of Table 1. As in Table 1, all models also include a monthly recession dummy and state-level fixed effects.