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The effect of weather on first-quarter GDP

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In a pattern similar to that of the previous year, the U.S. economy appeared to slow down this past winter. The Bureau of Economic Analysis currently estimates that gross domestic product (GDP) grew at 0.6% (at an annualized rate) in the first quarter of 2015. And as in the previous year, harsh winter weather has been cited by some observers as being responsible for the slowdown.[1] However, there is substantial disagreement on the impact of weather on economic activity.

Indeed, many other factors may have been at play last winter, including the sharp decline of oil prices and the appreciation of the dollar relative to other currencies, as well as more idiosyncratic factors, such as strikes in the West Coast ports. Moreover, some have questioned the accuracy of the seasonal adjustment procedure of the Bureau of Economic Analysis.[2] This *Chicago Fed Letter* provides estimates of the effect of weather on measures of economic activity during the past winter.[3]

1. National and Illinois temperature and snow indexes

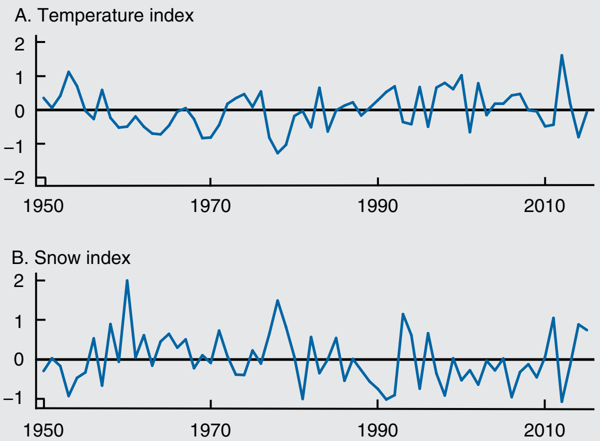
		December	January	February	March
National					
Temperature	2015	1.32	–0.03	–1.76	0.22
	2014	–0.42	–0.76	–0.80	–1.23
Snowfall	2015	–1.58	–0.30	2.47	0.05
	2014	0.49	0.85	1.91	–0.11
Illinois					
Temperature	2015	0.72	–0.13	–2.42	–0.70
	2014	–0.85	–1.29	–2.27	–1.47
Snowfall	2015	–1.84	–0.4	2.58	0.48
	2014	0.73	1.94	2.85	0.41

NOTE: December refers to the previous year.
SOURCE: Author's calculations based on data from the National Climatic Data Center.

First, how bad was the weather? Figure 1 presents temperature and snowfall indexes both for the United States as a whole and for Illinois, for each month of the 2013–14 and 2014–15 winters. The Illinois index is the long-term average across weather stations in the state of the monthly temperature and snowfall (normalized) deviations from the station average. The national index is the employment-weighted average of all the (continental) state indexes. Both indexes are normalized to have mean zero and standard deviation one in the winter months (December through March).[4] These indexes concisely summarize temperature and snowfall deviations from the averages and can be constructed for a long history. It is important to normalize weather indexes to account for the fact that an inch of snow does not have the same effect in Minneapolis as in Atlanta.

Consistent with casual observation, the 2015 winter was significantly worse than usual in February, with temperature 1.76 standard deviations (SD) below the mean and snowfall 2.47 SD above the mean. However, December was better than usual, and January and March were not especially harsh. Of course, this measure is an average, and does not reflect the variety of circumstances experienced in each state. For example, Massachusetts had an especially bad winter (with a snow index of 2.44 SD in January and 6.55 SD in February). Especially interesting is the comparison with the previous winter—while February was worse according to our measure in 2015, the other months (December, January and March) were on balance worse the previous year. Figure 2 presents an annual national index (the sum of the temperature or snowfall index over all winter months) since 1950. Overall, the message is that the 2015 winter, while

2. Annual national index



NOTE: Annual index is average of monthly indexes from December through March.
SOURCE: Author's calculations based on data from the National Climatic Data Center.

worse than average, was not nearly as bad as 2014.

Clear weather effect on some monthly indicators

To estimate the effect of weather on economic activity, I use a simple linear regression model in which the dependent variable is a measure of economic activity, such as the growth rate of industrial production, and the independent variables are current and lagged temperature and snowfall indexes. As described in Bloesch and Gourio (2015), the key result is that weather affects monthly indicators significantly, but there is a strong and nearly complete rebound within a couple of months. Not surprisingly, some indicators are affected more than others, for example, car sales, hours worked, core orders of new capital goods, and all housing-related variables (construction employment and housing starts and permits), and to some extent retail sales and industrial production.

Figure 3 reports, for each indicator, the data as well as the estimated weather effect during each month.[5] If we look at nonfarm payrolls, probably the most closely watched economic indicator, we see relatively strong growth last winter of about 0.2% (250,000 new jobs) per month, slowing down in March to 0.06%. The weather effect is estimated to be small except in February, when it reached –0.07%.[6] The weather effect hence cannot explain the slowdown in nonfarm payrolls, since the timing of the harsh weather (in February) did not coincide with the employment slowdown (in March). Similarly, average hours worked or housing permits (not shown) remained strong in February when we would have expected a large decline based on the weather.

However, weather can help account for the behavior of some other indicators. For example, car sales were weak, especially in February, and rebounded in March. In our model, weather subtracted 2% and 3% from car sales in January and February, respectively, and added almost 4% in March. Similarly, weather helps account for some of the variations in retail sales, industrial production, core orders, and housing starts.

Overall, weather affected some economic statistics in an important way. But consistent with previous work, I find that bad weather does not always coincide with weak economic indicators. Moreover, the effect on the entire first quarter is likely even smaller.

Overall effect on GDP is likely small

There are three simple reasons why the effect of weather on quarterly growth (as measured by GDP) is typically small. First, as illustrated in the car sales example, the bounce-back typically happens very fast, usually the following month. This implies that most of the negative effect of a harsh January or February would be undone by the end of the first quarter. Second, while some economic indicators are affected by temperature or snowfall, others are not affected much or may even benefit from harsh weather. For example, utilities produce more energy (and hence add to GDP growth) when the temperature falls.[7] And third, there is little serial correlation in temperature and snowfall, so that quarterly weather is typically less extreme than monthly weather due to averaging out.

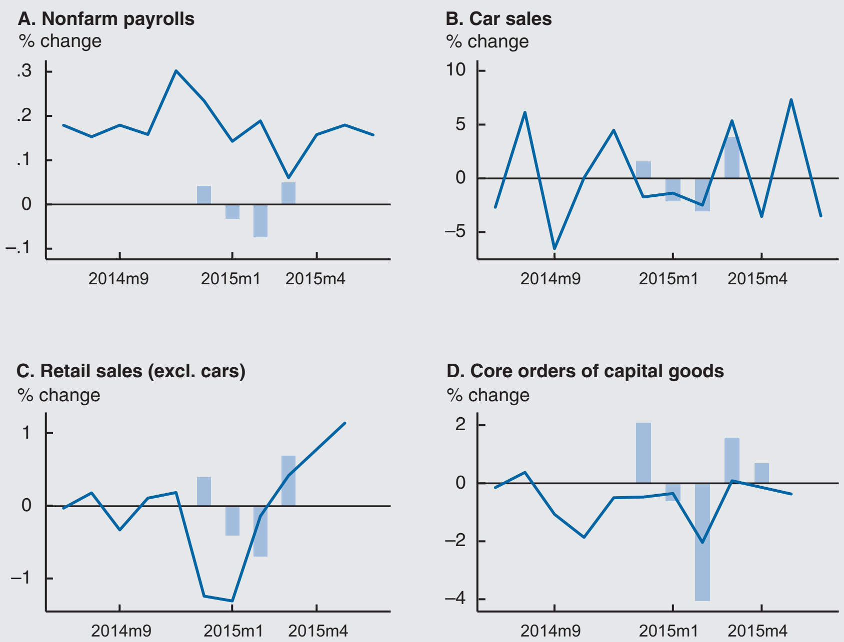
To illustrate this more formally, I construct quarterly temperature and snowfall indexes as the average of temperature and snowfall indexes in each quarter and estimate linear regressions of first-quarter real GDP growth on these quarterly weather indexes (see figure 4). The coefficient estimates have the expected sign: Lower temperature or higher snowfall reduces GDP growth. However, these results are not statistically significant, and the magnitude of the effects is fairly small. For instance, even the very harsh 2013–14 winter is estimated to have reduced GDP growth by only about 0.5% (annualized rate). The 2014–15 winter is roughly half as bad, as shown in figures 1 and 2, so the effect would be even smaller.

GDP can be noisy, so I also tried alternative measures of economic activity, such as gross domestic income (GDI) and final sales to private domestic purchasers (FSDP). The latter measure strips out some volatile components from GDP: net exports, government purchases, and inventories. None of these results are significant. The point estimates of GDI suggest an effect of about 1% in 2013–14 and half that in 2014–15.

It is possible that the model is too simple and that a significant effect might be uncovered using a different model, more efficient statistical techniques, or better data. However, the simple approach works fairly well for monthly indicators, as shown earlier (and in more detail in Bloesch and Gourio, 2015). Why would it generate statistically and economically significant results using monthly indicators and only small, insignificant effects using quarterly data? One interpretation is that an important share of the bounce-back happens very quickly within the quarter.

Another piece of evidence that supports weak effects on quarterly income comes from state-level data on personal income and labor earnings. Studying state-level

3. Data (line) and estimated weather effect (bar)



SOURCE: Author's calculations based on data from Haver Analytics and the National Climatic Data Center.

4. Regressions of economic indicators on temperature and snowfall indexes

	National-level			State-level	
	GDP	GDI	FSDP	PI4	LE4
Temperature	0.252 (0.924)	1.023 (0.835)	0.338 (0.823)	–0.00393 (0.0930)	0.0383 (0.118)
Snowfall	–0.138 (0.924)	0.249 (0.835)	0.175 (0.823)	–0.210** (0.0863)	–0.180* (0.0947)
Observations	66	65	66	2,159	3,071
R-squared	0.006	0.040	0.003	0.688	0.547

NOTES: Regression of real gross domestic product (GDP), gross domestic income (GDI), final sales to domestic purchasers (FSDP), and state-level personal income growth per capita (PI4) or labor earnings (LE4) on national or state-level temperature and snowfall indexes. Regression includes state fixed effects and time fixed effects. Only the first quarter of each year is used. Sample: 1950–2014 for national level and 1969–2014 for state-level. Standard errors are clustered by year for the panel regressions.

SOURCES: Author's calculations based on data from Haver Analytics and the National Climatic Data Center.

data allows me to increase the size of the data, which helps me to measure the effect of weather more precisely. I estimate a simple linear model of personal income growth (nominal, per capita, measured as the growth over the last four quarters) and estimate it using the first quarter of each year. The independent variables include state and time fixed effects and the state-level temperature and snowfall indexes. Figure 4 shows that one obtains a coefficient similar to the one found using national GDP, and it is now statistically significant. Taken at face value, this coefficient suggests that the overall effect of the 2014–15 winter on annualized GDP was about 0.2%.

Conclusion

Weather clearly affects many monthly economic indicators. But there may be a tendency to attribute too much to weather. First, the 2015 winter was not as harsh as that of 2014. Second, the timing of the decline in economic indicators does not coincide with the timing of harsh weather. Third, the rebound following bad weather occurs quickly. Fourth, the direct estimated effects of weather on quarterly GDP or personal income are small (and barely significant). These reasons lead one to have some skepticism that weather had a very important effect on measured GDP in the first quarter. However, there is substantial uncertainty around these estimates, so more work is needed to develop better statistical models to capture the effect of weather on the economy.

[1] See, e.g., *Wall Street Journal*, "Winter snow weighs on first-quarter GDP," http://blogs.wsj.com/economics/2015/02/12/winter-snow-weighs-on-first-quarter-gdp/.

[2] See, e.g., http://www.frbsf.org/economic-research/publications/economic-letter/2015/may/weak-first-quarter-gdp-residual-seasonality-adjustment/; http://www.federalreserve.gov/econresdata/notes/feds-notes/2015/residual-seasonality-in-gdp-20150514.html; and http://libertystreeteconomics.newyorkfed.org/2015/06/the-myth-of-first-quarter-residual-seasonality.html.

[3] This article builds on Justin Bloesch and François Gourio, 2015, "The effect of winter weather on U.S. economic activity," *Economic Perspectives*, Federal Reserve Bank of Chicago, Vol. 39, First Quarter, pp. 1–20, available at https://www.chicagofed.org/~/media/publications/economic-perspectives/2015/1q2015-part1-bloesch-gourio-pdf.pdf. There has been some recent work on the effect of winter weather on high-frequency

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economic statistics. See, e.g., https://www.philadelphiafed.org/research-and-data/publications/working-papers/2015/wp15-05.pdf; and http://www.bostonfed.org/economic/current-policy-perspectives/2015/cpp1502.pdf.

4 We construct these measures from station-level data drawn from the National Climatic Data Center USHCN database. See Bloesch and Gourio (2015) for more details.

5 Figure A1 at the end of this article shows the exact numerical results for more indicators.

6 For a few variables (including employment) that are available at the state level, this model can also be estimated as a panel regression, which leads to another estimate of the weather effect, of –0.13% in this case.

7 For instance, the model estimates that low temperatures in February added 3.7% to industrial production of utilities.

A1. Data during 2014–15 winter and estimated weather effect

		December	January	February	March
Nonfarm payroll	Data	0.23	0.14	0.19	0.06
	Weather effect	0.04	–0.03	–0.07	0.05
	Weather effect (S)	0.07	–0.02	–0.13	0.03
Retail sales (excl. cars)	Data	–1.24	–1.30	–0.14	0.42
	Weather effect	0.40	–0.40	–0.69	0.69
Average hours worked	Data	0.00	–0.30	0.30	–0.30
	Weather effect	0.25	–0.22	–0.41	0.40
Industrial production, manufacturing	Data	0.00	–0.59	–0.20	0.10
	Weather effect	0.39	–0.05	–0.60	0.18
Industrial production, utilities	Data	–5.16	3.15	5.56	–6.05
	Weather effect	–2.03	1.49	3.69	–2.18
Car sales	Data	–1.73	–1.37	–2.49	5.36
	Weather effect	1.57	–2.13	–3.07	3.85
Core orders	Data	–0.48	–0.35	–2.04	0.09
	Weather effect	2.08	–0.62	–4.06	1.57
Housing starts	Data	6.30	–0.84	–16.6	1.96
	Weather effect	6.31	–3.17	–12.28	5.32
	Weather effect (S)	4.93	–3.21	–6.52	5.57
Housing permits	Data	0.00	0.00	3.89	–5.60
	Weather effect	2.97	–1.74	–5.73	2.14
	Weather effect (S)	3.01	–2.08	–5.12	3.75

Note: Weather effects estimated using national or state (S) model.

Sources: Author's calculations based on data from Haver Analytics and the National Climatic Data Center.