The influence of weather on non-seasonal and seasonal adjusted employment data in the US

Michael Markovich, A9302393
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Preliminary and incomplete
Comments welcome

The influence of weather on non-seasonal and seasonal adjusted employment data in the US

Michael Markovich

ABSTRACT

The purpose of this article is to analyze the empirical and economic influence of weather on US non-farm payroll data. We are in particular interested in whether deviations from mean temperature or mean precipitation are capable of explaining shifts in month-over-month growth rates in non-farm payrolls, and whether these shifts – if econometrically significant – are economically important.

Keywords: non-farm payrolls, weather influence, seasonal adjustments
JEL Classification: C39, E24, E27, J60

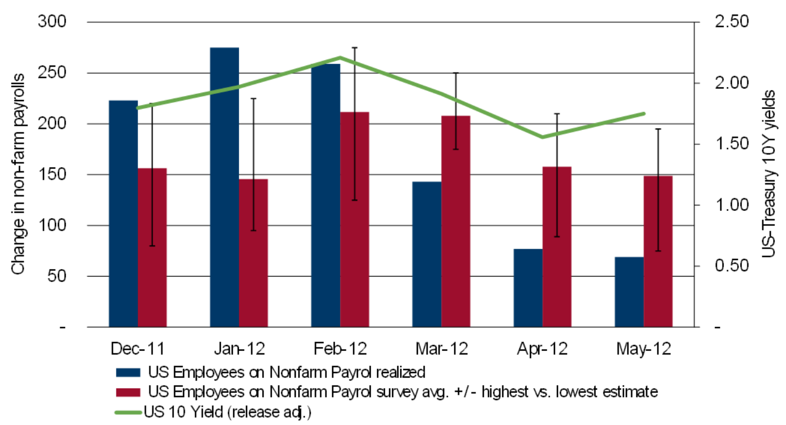
I. Introduction

Monthly non-farm payroll numbers are among the most widely followed employment data for the US economy. Given that payroll data are subject to high seasonal fluctuations – as all employment data – it is important to focus on the drivers of these fluctuations. According to general definition, seasonality can be described as systematic, though not necessarily regular, intra-year movement caused by changes in weather, time of year, and timing of decisions agents of the economy make (see Hylleberg, 1992).

Weather has a strong impact on the employment situation. The question arises whether and to what degree strong weather turbulence – measured as temperature or precipitation deviation from historic long-term means – can affect monthly employment growth beyond that observed over the past half-century.

This question was of particular importance at the beginning of 2012, when employment growth appeared particularly strong and significantly higher than predicted by consensus. Figure 1 shows monthly employment data releases between January and June 2012.[1]

Figure 1: Consensus forecast and realization of non-farm payroll growth along with 10 year US-Treasury yields (one-month lagged)



The first three months are characterized by much higher payroll growth, exceeding in some cases even the highest submitted forecast among members of the panel of economic forecasters.[2] However, March through May show growth that is lower than consensus expectations. Payroll growth in this case is not only

[1] Given that non-farm payroll data are released with a one-month delay – as are most other economic data – observations are labeled according to the month when they were collected and not the month when they were released.

[2] The consensus forecast panel was obtained via Bloomberg.

much lower than anticipated, it is in all cases lower than the lowest submitted forecast in the consensus panel of economic forecasters.

An explanation of how such strong deviations from consensus expectations could materialize was quickly identified: Forecasters blamed it on the weather.

Figure 2: Observed mean temperature and mean precipitation in the US between 1953-2012 along with observations from December 2011 to April 2012.

Panel A: Observed temperature relative to history **Panel B: Observed precipitation relative to history**

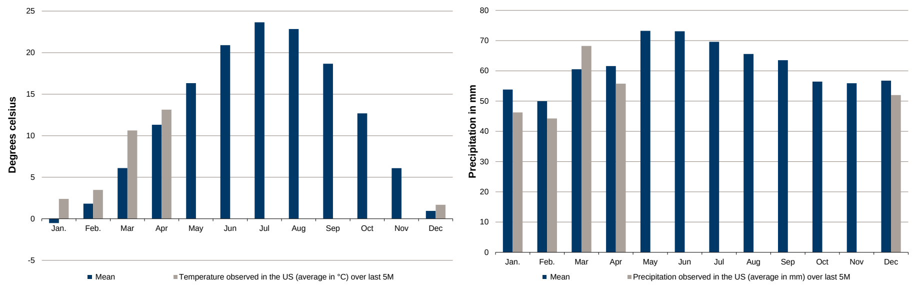


Figure 2, Panel A shows observed temperature for the months between December 2011 and April 2012. As illustrated, temperature was indeed higher than the mean historically observed temperature. In one case –March – the temperature was the highest observed ever for this month and nearly twice as large as the historical mean observation. A similar picture is observed for precipitation (see Panel B). In general precipitation was less than usual. Consequently it was questioned whether the extraordinarily warm temperature during the first quarter of the year frontloaded employment growth and whether, consequently, given that most of the expected increase in employment took place earlier than usual, the dynamic for the second quarter had to weaken.

The purpose of this paper is to analyze whether strong deviations in monthly weather data from mean temperatures and precipitation can statistically affect the mean growth rate of non-farm payroll data, and whether these deviations are economically relevant.

First, we will show that deviations from mean temperature and precipitation have indeed – for some months – a statistically significant influence on mean growth rate in non-farm payroll employment. Second, we will show that these deviations' influence on unconditional growth rate is economically marginal, and that the extraordinary weather turbulence in 2012 cannot account for the strong employment growth observed during the first quarter of 2012.

The remainder of this paper is organized as follows. The next section discusses the anatomy of the data used to highlight the seasonal pattern in different types of employment data (private vs. total) in conjunction with the variables of temperature and precipitation. The third section contains our analysis and results. The final section presents our conclusions.

II. The anatomy of the data (data set and sample)

A. Non-farm payroll data

Non-farm payroll employment data are part of the US Bureau of Labor Statistics' establishment survey, which is released for all employees (total non-farm payrolls including the private and public sectors) and for the private sector only (total private industry non-farm payrolls).[3] The difference between the two series hence represents employment growth in the public sector. Both series are released on a seasonally and non-seasonally adjusted basis during the first week of each month on Friday. Figure 3 shows both seasonally adjusted and non-seasonally adjusted series.

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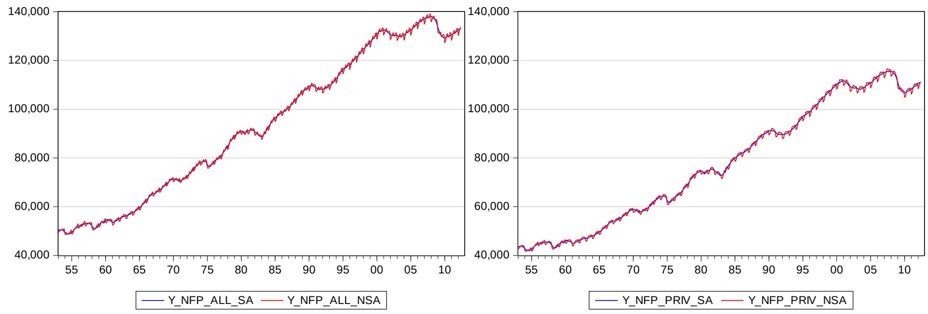
[3] For more details see http://www.bls.gov/opub/hom/pdf/homch2.pdf and http://www.bls.gov/news.release/empsit.htm.

Figure 3: Non-farm payrolls over time for the US economy (establishment survey) – seasonally adjusted (SA) vs. non-seasonally adjusted (NSA)

Panel A: Total non-farm payrolls	**Panel B: Private non-farm payrolls**

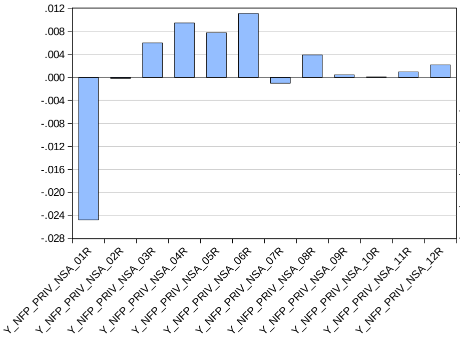


Visual inspection of Figure 3 indicates that non-farm payrolls are non-stationary and increase nearly exponentially (except for the last decade), which would be in line with an exponentially growing population. Consequently, taking the log-difference would be the natural choice for modeling non-farm payrolls.

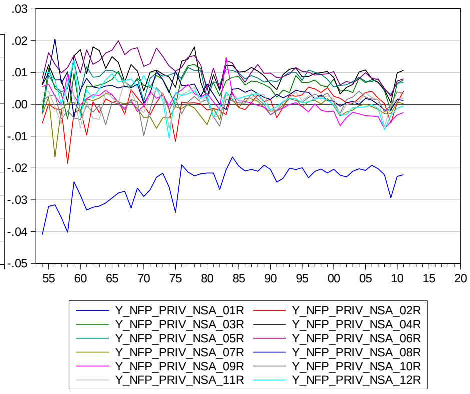
Indeed, as shown in Figure 4, when looking at the log-differences, grouped along identical season (i.e. sampled annually), we can observe that the different seasons have relatively similar paths but different (although nearly constant) mean growth rates (especially after 1975), which indicates that log-changes in payroll data can be modeled as deterministic seasonal processes.

Figure 4: Monthly growth rates of non-farm payroll data (total and private). Sample between 1953-2012, non-seasonally adjusted data.

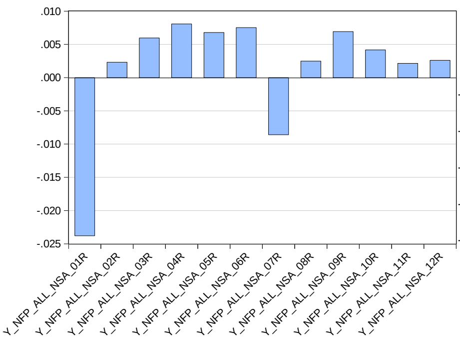
Panel A: Monthly NSA growth rate (average – private non-farm payrolls)



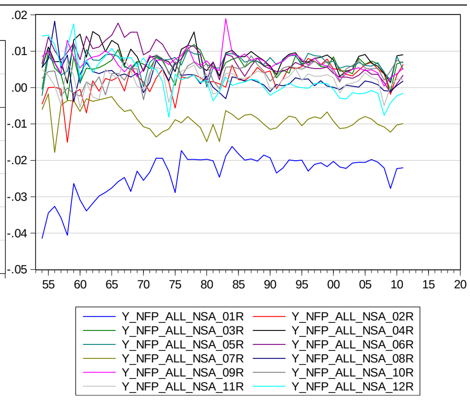
Panel B: Monthly NSA growth rates over time (private non-farm payrolls)



Panel C: Monthly NSA growth rate (average – total non-farm payrolls)



Panel D: Monthly NSA growth rates over time (total non-farm payrolls)



To confirm our assumption we run several unit-root tests (individual and common unit-root tests) for the two payroll datasets. The results are shown in Figure 5. They confirm that a unit-root process can be rejected across all different test specifications. We therefore assume that non-farm payroll data follow a stochastic trend process with deterministic seasonality (seasonality in the mean of the log-difference process).

Figure 5: Testing seasonally grouped log-changes of non-farm payroll data for common and individual unit-roots.

Panel A: Total non-farm payrolls

Group unit root test: Summary
Series: Y_NFP_ALL_NSA_01R, Y_NFP_ALL_NSA_02R,
Y_NFP_ALL_NSA_03R, Y_NFP_ALL_NSA_04R,
Y_NFP_ALL_NSA_05R, Y_NFP_ALL_NSA_06R,
Y_NFP_ALL_NSA_07R, Y_NFP_ALL_NSA_08R,
Y_NFP_ALL_NSA_09R, Y_NFP_ALL_NSA_10R,
Y_NFP_ALL_NSA_11R, Y_NFP_ALL_NSA_12R
Date: 25/06/12 Time: 21:47
Sample: 1953 2020
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-14.8575	0.0000	12	684
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-14.5994	0.0000	12	684
ADF - Fisher Chi-square	236.375	0.0000	12	684
PP - Fisher Chi-square	234.711	0.0000	12	684

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel B: Private non-farm payrolls

Group unit root test: Summary
Series: Y_NFP_PRIV_NSA_01R, Y_NFP_PRIV_NSA_02R,
Y_NFP_PRIV_NSA_03R, Y_NFP_PRIV_NSA_04R,
Y_NFP_PRIV_NSA_05R, Y_NFP_PRIV_NSA_06R,
Y_NFP_PRIV_NSA_07R, Y_NFP_PRIV_NSA_08R,
Y_NFP_PRIV_NSA_09R, Y_NFP_PRIV_NSA_10R,
Y_NFP_PRIV_NSA_11R, Y_NFP_PRIV_NSA_12R
Date: 25/06/12 Time: 21:53
Sample: 1953 2020
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 1
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-16.9616	0.0000	12	682
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-16.0932	0.0000	12	682
ADF - Fisher Chi-square	265.447	0.0000	12	682
PP - Fisher Chi-square	269.924	0.0000	12	684

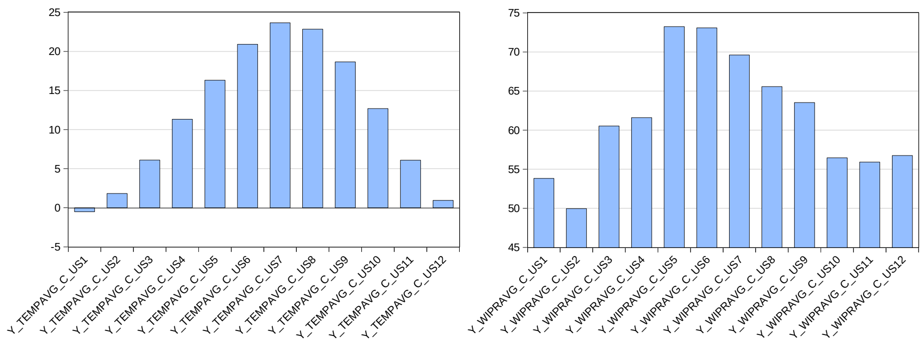
** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

B. Weather data

Monthly weather data were obtained from the National Oceanic & Atmospheric Administration (NOAA). We will focus on two specific series, namely, average monthly temperature and average monthly precipitation. Figure 5 shows the average temperature and precipitation across different months measured between 1953 and 2012.

Figure 6: Average temperature and average precipitation across different months in the USA between 1953 and 2012.

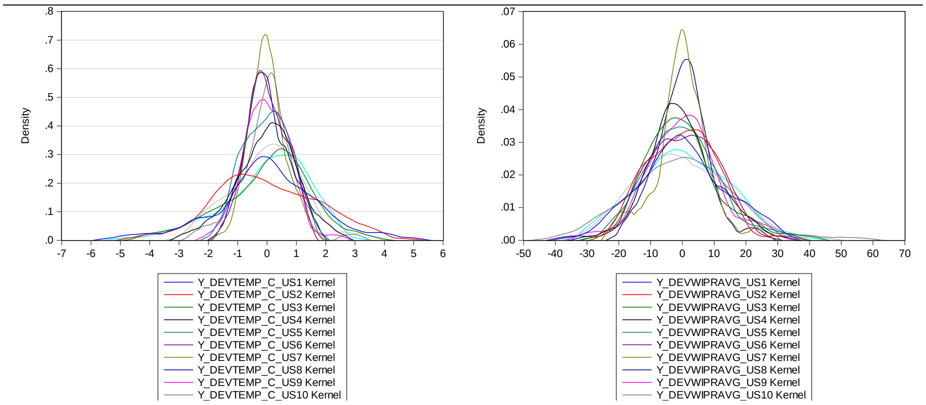
Panel A: Average temperature in °C	Panel B: Average precipitation in mm



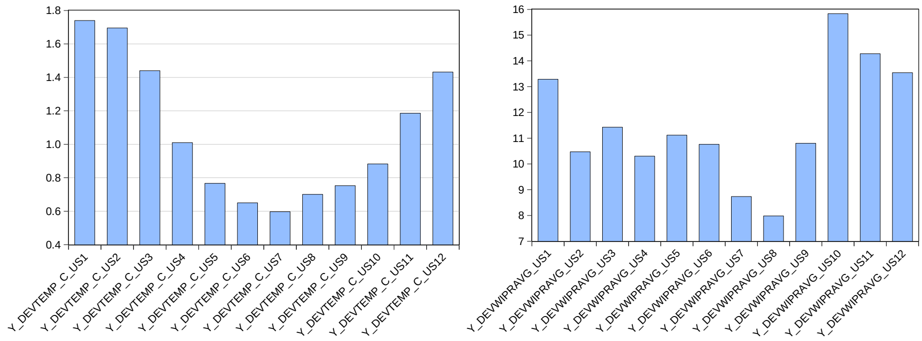
Clearly, temperature and precipitation are highly seasonal as shown above. More interesting in this regard is the distribution of the mean deviation (i.e. the difference between the observed temperature and precipitation and their corresponding sample means). Figure 7 shows for our sample the Kernel density of both weather series. As can be seen in Panel A the distribution patterns change significantly with the seasons. This is particularly true for temperature. A similar pattern, although less pronounced, is observable for precipitation (see Panel B).

Figure 7: Distribution characteristics of deviations from the mean for temperature and precipitation across different months in the US between 1953 and 2012.

Panel A: Temperature deviation in °C (Kernel density)	Panel B: Precipitation deviation in mm (Kernel density)



Panel C: Temperature deviation in °C (standard deviation)	Panel D: Precipitation deviation in mm (standard deviation)



Both weather series indicate that the size of variation during the winter months is much higher compared to the summer season (see Panels C and D for the standard deviations across months). This could lead to a stronger influence of winter-related weather factors on employment growth statistics, a topic that is analyzed in the following section.

III. Empirical Analysis

A. Estimation setup

The econometric model used for our analysis, shown in equation (1), is usually referred to as a periodic autoregressive (PAR) model (see Gladyshev, 1961), since the estimated coefficients change with the seasons of the year. The model is essentially a multivariate vector process (VAR model) of order one where each individual monthly seasonal log-return $(\Delta y_{s\tau})$ for s =1, ...,12 – as shown in Figure 4, Panel B and Panel D – is considered as a separate (annually sampled) time series within the VAR(1) specification.

$$\begin{bmatrix} 1 & 0 & - & - & 0 \\ -\varphi_2 & 1 & - & - & 0 \\ 0 & -\varphi_3 & - & - & \vdots \\ \vdots & \vdots & \vdots & 1 & 0 \\ 0 & 0 & - & -\varphi_{12} & 1 \end{bmatrix} \begin{bmatrix} \Delta y_{1\tau} \\ \Delta y_{2\tau} \\ \vdots \\ \vdots \\ \Delta y_{12\tau} \end{bmatrix} = \begin{bmatrix} 0 & 0 & - & - & \varphi_1 \\ 0 & 0 & - & - & 0 \\ 0 & 0 & - & - & \vdots \\ \vdots & \vdots & \vdots & \vdots & 0 \\ 0 & 0 & - & - & 1 \end{bmatrix} \begin{bmatrix} \Delta y_{1,\tau-1} \\ \Delta y_{2,\tau-1} \\ \vdots \\ \vdots \\ \Delta y_{12,\tau-1} \end{bmatrix} + \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ \vdots \\ c_{12} \end{bmatrix} + \begin{bmatrix} md_1 \\ md_2 \\ \vdots \\ \vdots \\ md_{12} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1\tau} \\ \varepsilon_{2\tau} \\ \vdots \\ \vdots \\ \varepsilon_{12}\tau \end{bmatrix} \qquad (1)$$

Since weather is exogenous, we can include – next to the usual intercept vector (c_s) – the mean-deviation of temperature or precipitation as an additional exogenous vector (md_s) and test its significance.

Given that we allow each seasonal intercept to affect only the corresponding seasonal log-return series (mean-deviation enters as vector and not as matrix in the estimation setup), we need to estimate a restricted VAR model. Following Hamilton (1994) such models are referred to as “models with general coefficient constraints” and should be viewed as a system of seemingly unrelated regressions (SURs). The multivariate time series model is hence estimated as SUR following Zellner (1962).

B. The results

B.1. Statistical significance of the mean deviation coefficients

We have estimated the PAR(1) model using mean deviations from the temperature and precipitation as additional exogenous variables. The results for total and private non-farm payrolls are shown in Table 1.

For total non-farm payroll employment growth the coefficients for temperature mean deviation are statistically significantly different from zero at the 1% to 5% level for the months of January to April (except March) and for December, where the coefficient is statistically significant at the 10% level. For private non-farm payroll employment growth, the picture is very similar, with the coefficients for the months of January to April being statistically significant at the 1% level (except March); again the coefficient for the December observation is statistically significant at the 10% level. The signs are positive, which – as expected – indicates that temperature above the sample mean leads to higher employment growth.

Looking at the estimated coefficients for precipitation, the influence of weather is confirmed. For total non-farm payroll employment growth, the coefficients for precipitation mean deviation are statistically significantly different from zero at the 1% to 5% level for the months of January to April (except March).

For private non-farm payroll employment growth, the picture is similar, with the coefficients for the months of February to April being statistically significant at the 1% level. The signs are negative, which – as expected – indicates that higher precipitation leads to lower employment growth.

We can therefore confirm overall that strong weather fluctuations during the first two quarters of the year leading to much milder weather can increase seasonal employment growth.

However, despite the statistical significance of the estimated coefficients the question remains if the influence of weather is economically relevant in terms of additional employment growth.

Table 1: Estimating the significance of temperature/precipitation deviation from the sample mean on the unconditional growth coefficient of non-farm payrolls in the US.

Panel A: Total and private non-farm payrolls (temperature deviation from the sample mean)

Total non-farm payrolls	Jan.	Feb.	Mrz	Apr	Mai	Jun	Jul	Aug	Sep	Okt	Nov	Dez
coefficients												
intercept	-1.6342%***	0.1299%	0.2909%	0.0412%	-0.1293%	0.1238%	-0.6095%	-1.2806%*	0.042%	-0.6867%	0.7662%	-0.1525%
mean temperature coefficients	0.045%***	0.0301%**	0.0089%	0.0493%**	0.0362%	-0.0171%	0.0295%	-0.0011%	-0.064%*	0.0028%	-0.0037%	0.025%*
p-values												
intercept	0.0091	0.8229	0.5585	0.9405	0.7599	0.8149	0.3046	0.0507	0.9492	0.2503	0.3093	0.8141
mean temperature coefficients	0.0001	0.0462	0.4877	0.0146	0.1322	0.5737	0.4054	0.9691	0.076	0.8867	0.8384	0.0787

Private non-farm payrolls	Jan.	Feb.	Mrz	Apr	Mai	Jun	Jul	Aug	Sep	Okt	Nov	Dez
coefficients												
intercept	-0.5125%	0.3447%	0.7654%**	0.247%	0.8319%***	0.4679%	0.3407%	-0.6875%	-0.8626%**	-0.7242%*	0.2183%	-0.5217%
mean temperature coefficients	0.0483%***	0.0441%***	0.0214%	0.0784%***	0.0353%	0.001%	0.014%	-0.0016%	-0.0374%	0.02%	-0.0048%	0.0328%*
p-values												
intercept	0.2183	0.3848	0.0429	0.5243	0.0026	0.1577	0.4074	0.131	0.0341	0.0568	0.672	0.2329
mean temperature coefficients	0.0003	0.0075	0.1412	0.0012	0.1172	0.9749	0.7575	0.9628	0.3575	0.3541	0.8092	0.0509

Panel B: Total and private non-farm payrolls (precipitation deviation from the sample mean)

Total non-farm payrolls	Jan.	Feb.	Mrz	Apr	Mai	Jun	Jul	Aug	Sep	Okt	Nov	Dez
coefficients												
intercept	-1.9121%***	0.0203%	0.2781%	-0.136%	-0.1151%	-0.0657%	-0.6321%	-1.2985%**	0.2351%	-0.6438%	0.7618%	-0.1145%
mean precipitation coefficients	-0.0035%**	-0.006%***	-0.0013%	-0.0064%***	-0.0022%	-0.003%*	-0.0005%	0.0006%	-0.0002%	-0.0013%	-0.0006%	-0.0019%
p-values												
intercept	0.0021	0.972	0.5785	0.8038	0.7778	0.897	0.2892	0.0474	0.7251	0.2674	0.3149	0.8597
mean precipitation coefficients	0.0235	0.0055	0.4485	0.0011	0.2303	0.0862	0.8223	0.8052	0.9418	0.261	0.6947	0.2622

Private non-farm payrolls	Jan.	Feb.	Mrz	Apr	Mai	Jun	Jul	Aug	Sep	Okt	Nov	Dez
coefficients												
intercept	-0.5735%	0.5314%	0.8391%**	0.2371%	0.8824%***	0.4654%	0.3131%	-0.6878%	-0.7784%*	-0.7188%*	0.2756%	-0.4458%
mean precipitation coefficients	-0.0017%	-0.0065%***	-0.0052%***	-0.0078%***	-0.0025%	-0.0008%	0.0014%	0.0001%	-0.0025%	-0.0015%	-0.0016%	-0.0027%
p-values												
intercept	0.1743	0.1585	0.0307	0.5411	0.0009	0.1484	0.4492	0.1317	0.0531	0.0571	0.6008	0.3113
mean precipitation coefficients	0.3569	0.0037	0.0052	0.0006	0.1427	0.6793	0.5993	0.9663	0.3582	0.2752	0.3827	0.1725

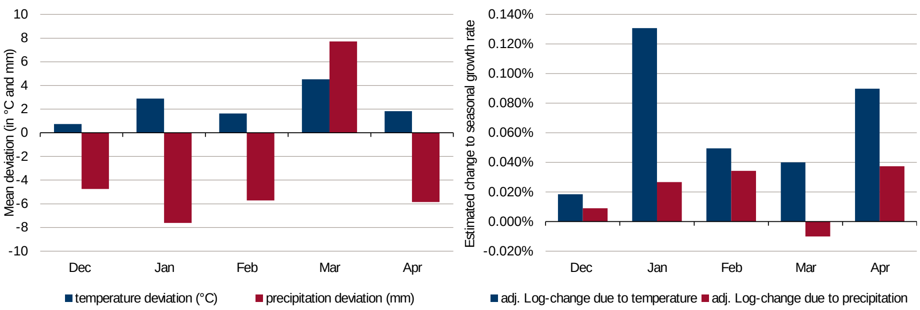
The table shows the estimated intercept and mean deviation coefficients for the specified PAR(1) model in equation 1 along with the corresponding p-values. The estimation methodology for the SUR model is based on simultaneous weighting matrix and coefficient iteration (iterative SUR). Coefficients marked with *** are statistically significant at 1%, coefficients market with ** are statistically significant at 5% while coefficients market with * are statistically significant at 10%.

B.2. Economic significance of the mean deviation coefficients

When looking at the results in Table 1 it becomes clear that the estimated coefficients – despite their statistical significance – are rather small relative to the intercept. In most cases they do not exceed 10% of the intercept (the unconditional seasonal increase or decrease in employment growth). For precipitation it is even smaller at around 1% of the intercept. This casts doubt on the economic significance of the estimated coefficients.

Figure 8: The economic significance of weather mean deviations for monthly growth rates in total non-farm payrolls between December 2011 and April 2012.

Panel A: Observed mean deviation	**Panel B: Estimated impact on employment growth rate (total non-farm payrolls)**



In order to answer the question whether the statically significant coefficients for mean deviation of temperature and precipitation are economically relevant, we have used the most recent five months of weather data to calculate the expected additional boost for employment growth given the mild temperatures and low precipitation. The results for total non-farm payrolls are shown in Figure 8.[4]

[4] The results for private payrolls are similar and hence omitted.

Panel A in Figure 8 shows the observed mean deviation for temperature and precipitation. The strongest deviations have been observed for January and March. Panel B of Figure 8 shows the expected impact on payroll growth. The additional contribution is marginal and can be treated as economically irrelevant.

IV. Conclusion

In this research paper we have analyzed the significance of weather turbulences (measured in the form of deviation in temperature and precipitation from long-term sample means) on non-seasonally adjusted non-farm payroll employment data. We conclude that deviations in temperature and to a lesser extent precipitation from the sample mean does indeed statistically significantly affect the average growth rate of non-farm payrolls during the December to April period. However, economically weather-related changes in employment growth rates are in absolute terms marginal and cannot explain large swings of employment growth.

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