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Erik Haustein and Sven Schreiber[1]

ABSTRACT

While recurring and regular variations of weather conditions are implicitly addressed by standard seasonal adjustment procedures of economic time series, extraordinary weather outcomes are not. We analyze their impact on German total industrial and construction-sector production and find modest but significant effects. The estimated effects of weather deviations can be subtracted from the already seasonally adjusted data to obtain seasonally as well as weather adjusted series. Given the timely availability of the weather data compared to the publication lag of economic measurements, we also show how to exploit this contemporaneous impact in real time to help the nowcasting of industrial production.

[1] Haustein: CA University Kiel; Schreiber (corresponding author): IMK Düsseldorf and Free University Berlin; Hans-Böckler-Str. 39, 40476 Düsseldorf, E-mail svetosch@gmx.net.

Adjusting Production Indices for Varying Weather Effects

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Abstract

While recurring and regular variations of weather conditions are implicitly addressed by standard seasonal adjustment procedures of economic time series, extraordinary weather outcomes are not. We analyze their impact on German total industrial and construction-sector production and find modest but significant effects. The estimated effects of weather deviations can be subtracted from the already seasonally adjusted data to obtain seasonally as well as weather adjusted series. Given the timely availability of the weather data compared to the publication lag of economic measurements, we also show how to exploit this contemporaneous impact in real time to help the nowcasting of industrial production.

Keywords: weather, business cycle, nowcasting

JEL codes: E23 (Production), E32 (Business fluctuations, cycles)

*Haustein: CA University Kiel; Schreiber (corresponding author): IMK Düsseldorf and Free University Berlin; Hans-Böckler-Str. 39, 40476 Düsseldorf, E-mail svetosch@gmx.net.

1 Introduction

Whenever new datapoints of macroeconomic aggregates such as production or (un-) employment are published by statistical agencies, it is often heard that some part of the changes in the respective variables is due to some extraordinary weather effect, such as a mild winter or an unusually snowy spring. However, a precise magnitude of this effect is typically not provided. Therefore, the aim of this paper is to fill this gap by analyzing the impact of unusual weather conditions on several production indices for Germany.

Impacts of weather phenomena on economic variables are usually associated with seasonal patterns and therefore treated as regular. Statistical agencies address this pattern by providing seasonally adjusted series. Nevertheless, one might expect that deviations of weather conditions from their seasonal average may affect economic activities and partly conceal the underlying dynamics. For example, Bloesch and Gourio (2015, p.2) pointed out that whether the economic slowdown in the winter 2013/2014 in the U.S. was due to harsher winter weather or instead due to an underlying economic trend would have had implications for monetary policy. A slowdown of the U.S. economy due to weather effects rather than a negative economic trend might have implied less of a need for adjusting monetary policy.

Depending on the primary objective, controlling for abnormal weather effects and extracting the real economic trend can be accomplished in two different ways: Wright (2013) suggested to include, and Boldin and Wright (2015) then included weather variables in the seasonal adjustment process for U.S. employment and GDP data, resulting in a weather as well as seasonally adjusted time series. They argue that abnormal weather effects may influence the seasonal adjustment procedure. Ouwehand and van Ruth (2014) provided a much differentiated analysis for the Dutch GDP data on the national and sectoral level. Estimating an ARIMA model they concluded that no significant weather effects could be identified for the majority of the sectors. A similar approach was used by the Deutsche Bundesbank for German GDP data (Deutsche Bundesbank, 2014).

In a second type of approach the seasonally adjusted series is taken as given, relying on asymptotic orthogonality between the seasonal component and the unusual weather effects. Bloesch and Gourio (2015) for example found an overall weak but significant weather effect on the nonfarm employment growth rate using a fixed-effects regression model. Also with respect to employment, Hummel, Vosseler, Weber, and Weigand (2015) analyzed the effect of several weather variables like temperature, snowfall, or snow height on a national level, based on 310 representative weather stations in Germany. They identified several weather and catch-up effects in the following months. For instance, a one degree temperature increase in January raises employment by 14.000 persons on average between 2006 and 2014. Also for Germany Döhrn and an de Meulen (2015) showed that including weather variables in a business-cycle oriented forecasting procedure improves the model, but not in a significant way.

There are also attempts to identify longer-run weather (or climate) effects on economic outcomes, see Dell, Jones, and Olken (2014), but in this paper we focus on the shorter-run dynamics of occurrences of abnormal weather. We confirm and follow Hummel, Vosseler, Weber, and Weigand (2015) in their choice of relevant weather measurements, namely air temperature, snowfall, and snow height. We focus on economic output instead of labor inputs, however, namely monthly industrial production. We also provide a separate analysis for the construction sector since any weather effects will be felt there most. A further difference is that we stick to a straightforward model framework that is linear in the parameters, including non-linearities through interaction effects and thereby modelling heterogeneous month-specific effects. Finally, we discuss the use of the weather observations for forecasting purposes in a (pseudo) real-time setting, when the current production data as well as their immediate lags would not have been published yet (often called "nowcasting").

2 Data and empirical approach

The dependent variables that we analyze are the growth rate of German real total industrial production (IP) and the production in the construction sector. Total output represents an important cyclical indicator, while production in the construction sector is the part of economic activity which is most likely to depend on weather conditions. An overview about the different production indices and their hierarchial structure is given in Statistisches Bundesamt (2015). Data are taken from the Bundesbank website. Both indices are calendar and seasonally adjusted.

Weather data for Germany have recently begun to be provided on a daily basis and are freely available.[1] The construction of the weather dataset was inspired by the approach of Hummel, Vosseler, Weber, and Weigand (2015), that is we aggregated daily weather data of the 251 weather stations available to the federal state level, then weighing them by the state-level number of employees to obtain aggregated data at the national level. The sample used in this paper is January 1991 through October 2015. We consider three measurable weather aspects, namely air temperature, snow height in cm, and snow fall per week in cm, all time-averaged from daily to monthly series. Other weather variables would also be possible in principle; the Deutsche Bundesbank (2014) for example used the sum of ice-days in a specific time interval (quarter or month), but that information should not differ much from the combined content of snow fall and (cumulated) height.

Given that the weather data are published almost immediately – in contrast to

[1]Original database provided by Deutscher Wetterdienst and freely available at `http://www.dwd.de/`.

the production data that suffer from a publication delay of at least one month – this allows one to predict or "nowcast" the weather effect on a real-time basis. A potential disadvantage, however, is that the most recent data are mostly not yet checked for measurement errors.

What we have in mind as a first approximation is a simple additive framework that distinguishes between different components that together yield the observed realization of the economic variable of interest y in period t:

$$y_t = struc_t + weather_t + \varepsilon_t, \tag{1}$$

where y_t will be a seasonally adjusted growth rate of the underlying economic variable, and $struc_t$ is interpreted as a component which is structural in the sense that it indicates the underlying tendency attributable to purely economic forces and intrinsic dynamics. In contrast, $weather_t$ is an irregular component which measures influences that stem from weather realizations beyond the systematic and regular seasonal cycles. We allow these components to be dynamic, such that they will include lags as well. Finally, ε_t is a purely random error component which should be (close to) white noise.

We proceed by defining the extent of "abnormal weather" as the deviation of the specific variable from the respective month-specific average:

$$\hat{x}_t = x_t - \bar{x}_{t,m} \tag{2}$$

where x_t is a weather variable measurement (temperature, snow height, snow fall) in period t which falls in a month $m \in \{Jan, Feb, ..., Dec\}$, while $\bar{x}_{t,m}$ is the month-specific average of weather variable x_t in period t which happens to be a month m. From now on, the deviation of a weather variable and the name of a weather variable are used synonymously. For example, the deviation of temperature (from its month-

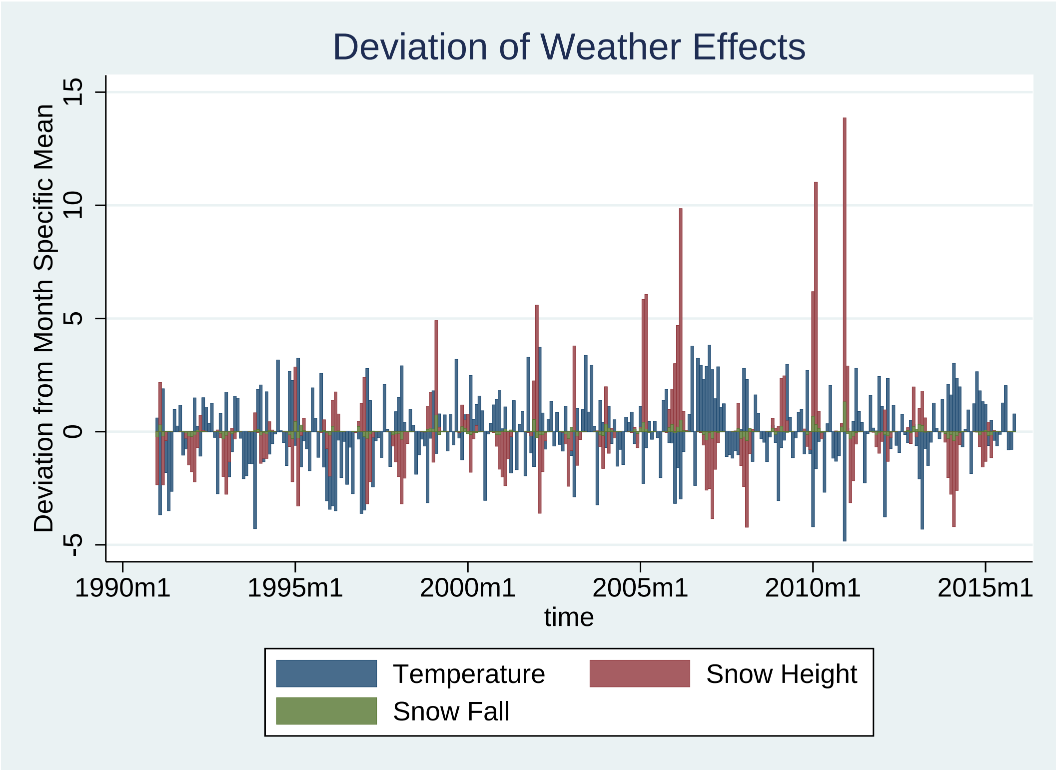


Figure 1: Observed weather deviations

specific average) and temperature are used synonymously, and the absolute level of a weather variable never enters any estimated model. The (month-specific) average refers to the sample period including all observations from September 1991 to April 2015. Figure 1 shows the resulting time series.

As the baseline model we fitted an autoregressive model of order 4, including the three weather variables interacted with seasonal (monthly) dummies, allowing for month-specific weather effects. Furthermore, four lags of each weather variable were included to control for possible catching-up effects in the following months. By catching-up effects we mean a shift of production in point of time; for example orders and contracts which could not be carried out in February and March due to a harsh winter might be completed one or two months later. A further concern in time series analysis might be the existence of some structural break. During their analyses, Hummel, Vosseler, Weber, and Weigand (2015) found some evidence for a structural break in 2006, which prompted them to use a smooth transition regression model. The advantage of that model is that weather effects can be flexibly modeled over time. However, the authors assign the structural break in 2006 mainly to the introduction of seasonal short time work benefits (*Saison-Kurzarbeitergeld*), given that they focus on labor market variables. This is not directly relevant for our focus on industrial production. Nevertheless, testing for a structural break might be relevant in the context of the financial crisis and the following deep recession in Germany. Therefore, we tested if a structural break influenced the autoregressive terms of the endogenous variable by applying a standard Chow Test.

A possible break date was determined exogenously by examining the world business cycle at the outbreak of the great recession. Looking at the G-20 GDP growth rate, one observes negative growth rates between the fourth quarter of 2008 and the first quarter of 2009. Hence, we used the beginning of the fourth quarter of 2008 (October of 2008) as the possible break date to be tested.

The baseline model is given as follows:

$$\begin{aligned} y_t =& c_0 + \alpha(L) y_{t-1} \\ &+ \sum_{m=1}^{12} \left[\beta_m (D_{t,m} \times \hat{x}_t^{temp}) + \gamma_m (D_{t,m} \times \hat{x}_t^{sheight}) + \delta_m (D_{t,m} \times \hat{x}_t^{sfall}) \right] \\ &+ \eta(L) \hat{x}_{t-1}^{temp} + \kappa(L) \hat{x}_{t-1}^{sheight} + \lambda(L) \hat{x}_{t-1}^{sfall} + \varepsilon_t \end{aligned} \quad (3)$$

The lag polynomials $\alpha(L)$, $\eta(L)$, $\kappa(L)$, $\lambda(L)$ are defined according to the pattern $\alpha(L) = \alpha_1 + \alpha_2 L + \alpha_3 L^2 + \alpha_4 L^3$. Monthly dummies for month m are denoted by $D_{t,m}$, such that we consider potentially heterogeneous month-specific contemporaneous weather effects, with coefficient sets β_m, γ_m, δ_m. For example, a mild January might be expected to increase economic activity, while the same is probably not true for a hot July. However, we impose homogeneity across months for the lagged effects because the number of parameters would otherwise explode relative to the available observations.

3 Estimating weather influences

3.1 Total industrial production

For overall German industrial production the Chow test yields some evidence for a structural break with respect to the tested four lags of the endogenous variable, with a p-value of 0.08 (see Table 1). Despite the relatively weak evidence these lags interacted with the break dummy are also included in the estimated equation, although only the weather-related terms are explicitly reported. An interaction of the weather variables and the break dummy was not considered, because allowing shifts in all coefficients would entail very high costs in terms of degrees of freedom and efficiency. Especially for estimating the month-specific weather effects only 7 or 8 observations (October 2008 to April 2015) would be available after the break.

In a next step, irrelevant weather components are excluded based on the Akaike Information Criterion (AIC). Our final estimated model consists of four autoregressive terms (and their interaction with the break dummy $D_{Oct2008,t}$) as well as the temperature deviation ($\hat{x}_t^{temp}$) and the snow height deviation ($\hat{x}_t^{sheight}$) interacting with monthly dummies. Furthermore, the four lags of the snow height deviations are also retained in the model.

$$\begin{aligned} y_t = & c_0 + \alpha(L)y_{t-1} + \theta(L)(y_{t-1} \times D_{Oct2008,t}) + \theta_5 D_{Oct2008,t} \\ & + \sum_{m=1}^{12} \left[\beta_m (D_{t,m} \times \hat{x}_t^{temp}) + \gamma_m (D_{t,m} \times \hat{x}_t^{sheight}) \right] \\ & + \kappa(L)\hat{x}_{t-1}^{sheight} + \varepsilon_t \qquad (4) \end{aligned}$$

To account for heteroscedasticity the model was estimated with robust standard errors. The final specification yields an adjusted R^2 of about 0.24, while without the weather variables the value would attain only 0.13, dropping by 0.11, which is not overwhelming but quantitatively important. The deviation of the temperature from seasonal averages plays an important role especially in January, with the expected positive sign. A one-degree extraordinary rise in January increases the monthly (non-annualized) production growth rate by 0.46 percentage points. The temperature effect for October by itself shows the opposite sign, which probably has to be interpreted jointly with the negative snow height effect for the same month.

While the positive snow height effect for September appears surprising, this partial result is driven by an IP growth outlier for September 2010; removing that outlier makes the September effect disappear (drop to a point estimate of 0.16 which is no longer significant). The first lag of the snow height deviation is also significant at a one percent level and does influence the production dynamics in a positive way, supporting the idea of catching-up effects (Table 1).

We can now report the estimated $\widehat{weather}_t$ component by adding together all terms from (4) containing a weather-related variable, using the estimated parameters in place of the unknown truth. The result is shown in Figure 2 in the upper panel. Also in that figure (lower panel) we compare the original with those growth rates of industrial production adjusted for the weather effects. Of course, most of the movements in production are not attributable to weather but to other types of shocks, reflecting the modest R^2 of the estimated equation. Furthermore, the coefficients are estimated with a certain amount of sampling uncertainty, and in Figure 3 we take the associated standard error of $\widehat{weather}_t$ into account, displaying the 95 percent confidence intervals for the weather-adjusted growth of industrial production. In many cases the adjustment produces results that are not significantly different from zero.

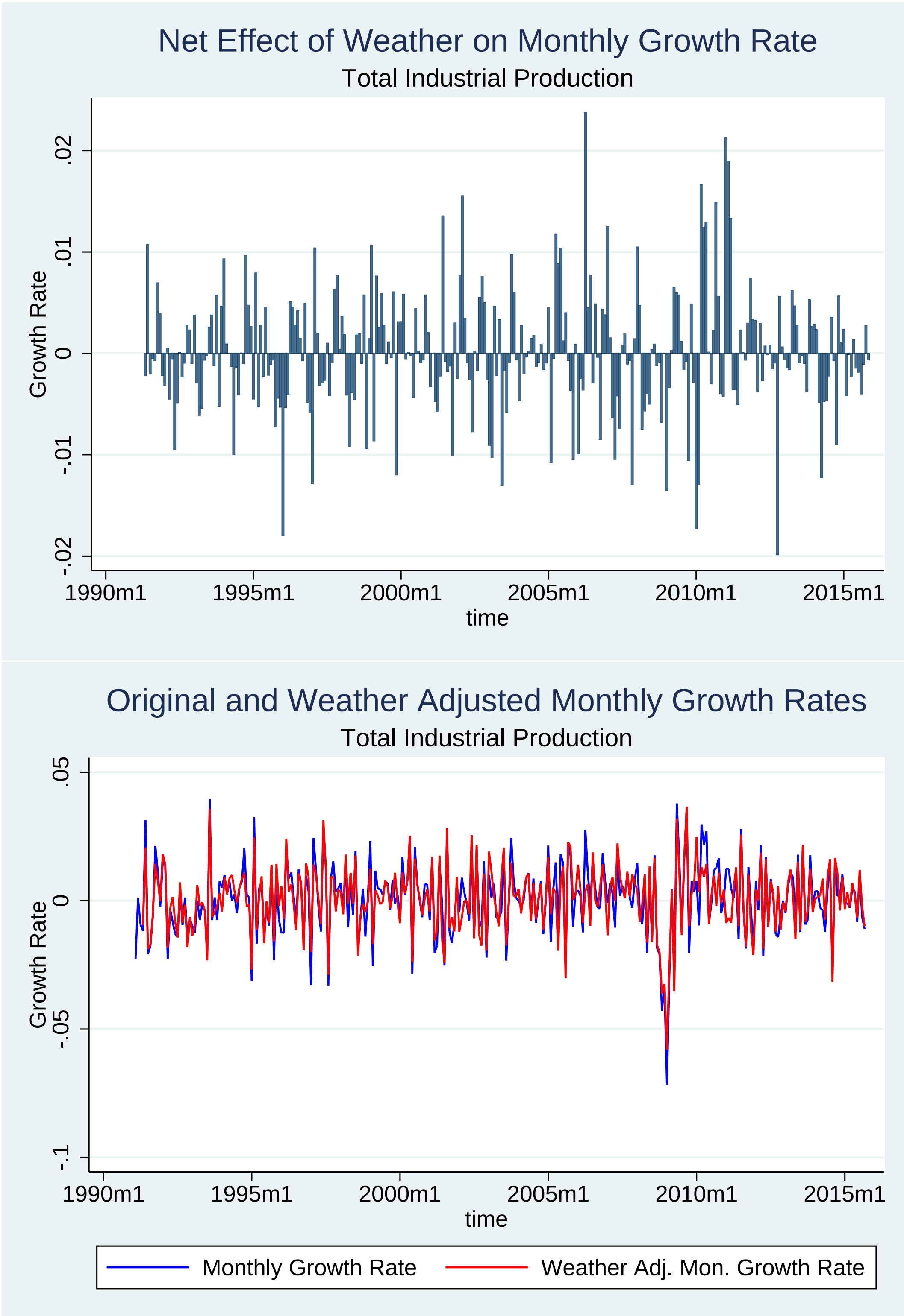


Figure 2: Irregular weather effects on German total industrial production. The upper panel shows the estimated weather component with respect to the monthly (non-annualized) growth rate, i.e. $\widehat{weather_t}$. The lower panel compares the observed growth rate and the result of the weather adjustment, i.e. $y_t - \widehat{weather_t}$.

Table 1: Selected coefficients, total industrial production

Sum of coefficients of lagged endogenous variable	0.608
Temperature×January	0.0046**
Temperature×October	-0.0045***
Snow height×February	-0.0018***
Snow height×September	0.4371**
Snow height×October	-0.1243***
Snow height $(t-1)$	0.0013***
Snow height $(t-2)$	0.0006*
Snow height $(t-3)$	0.0009**
Observations	292
Chow test F(5,256), p-value	1.99, 0.083
R^2	0.329
Adjusted R^2	0.237

Notes: Dependent variable y_t is German total industrial production (growth of an index number, seasonally adjusted). Of each weather component the most significant and largest coefficients in magnitudes are shown. Robust standard errors are used. Symbols: *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$.
For the Snow height×September coefficient see the text.

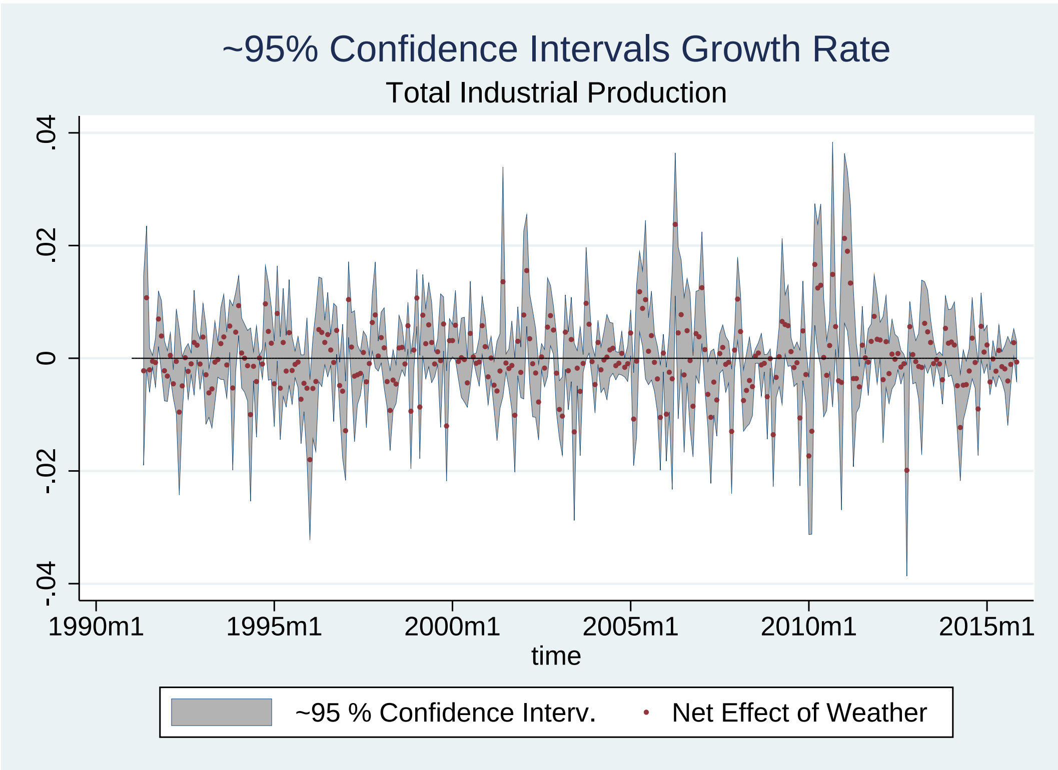


Figure 3: Estimation uncertainty of weather-adjusted industrial production.

3.2 Construction sector

We also analyzed the relationship for the construction sector, which should plausibly be more affected by the weather. The Chow test on the four endogenous lags of production (growth) this time rejects the null hypothesis at an even more borderline p-value of 0.102 (Table 2). As for the total production variant, weather variables interacting with the break dummy were not considered. In a next step further insignificant weather components were excluded and the model simplification was checked by the information criteria. As a result, the lags of snow fall were excluded. The final estimated model includes two weather variables ($\hat{x}_t^{temp}$, $\hat{x}_t^{sheight}$) interacted with a monthly dummy ($D_{t,m}$), the four lags of the temperature deviation ($\eta(L)\hat{x}_{t-1}^{temp}$) and the snow height ($\lambda(L)\hat{x}_{t-1}^{sheight}$) as well as the four autoregressive terms of the independent variables ($\alpha(L)y_{t-1}$).

$$\begin{aligned} y_t =& c_0 + \alpha(L)y_{t-1} \\ &+ \sum_{m=1}^{12} \left[\beta_m(D_{t,m} \times \hat{x}_t^{temp}) + \gamma_m(D_{t,m} \times \hat{x}_t^{sheight})\right] \\ &+ \eta(L)\hat{x}_{t-1}^{temp} + \lambda(L)\hat{x}_{t-1}^{sheight} + \varepsilon_t \end{aligned} \tag{5}$$

Compared to total industrial production, more weather variables play a role for the construction sector. Again heteroscedasticity-robust standard errors were used. This estimate yields an $\bar{R}^2$ of roughly 0.57, of which 0.44 can be attributed to the weather influences, which is of course a much larger share than for total production.

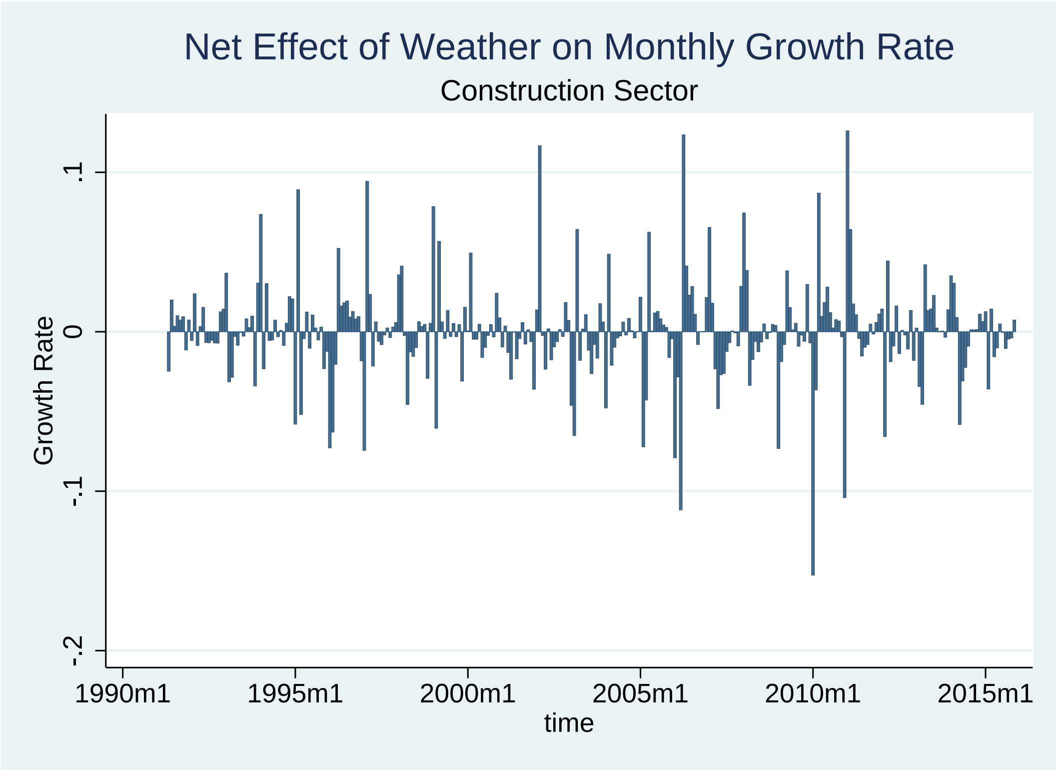
Moreover, all significant weather effects are related to the winter. Consequently, a really hot summer for instance does not affect the dynamics of the construction sector. Comparing the magnitude to the total industrial production, a one degree increase in January raises the monthly construction growth rate by 2.5 percentage points, affecting the construction sector much more than the total industrial production growth rate (Table 2). The lags of the temperature deviation also show the expected negative signs, supporting the hypothesis of catching-up effects. A mild winter would therefore shift the production to some extent into the first months of the year, changing the point in time of production.

Table 2: Selected coefficients, construction sector production

Sum of coefficients, lagged endogenous variable	-0.7830
Temperature× January	0.0252***
Temperature× February	0.0119**
Snow height× February	-0.0076***
Snow height× March	-0.0150***
Temperature $(t-2)$	-0.0030**
Temperature $(t-4)$	-0.0031*
Snow height $(t-1)$	0.0009***
Observations	292
Chow test F(5,252), p-value	1.50, 0.189
R^2	0.623
Adjusted R^2	0.566

Notes: Dependent variable y_t is production in the German construction sector (growth of an index number, seasonally adjusted). Of each weather component the most significant and largest coefficients in magnitudes are shown. Robust standard errors are used. Symbols: *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$.

Again we report the resulting time series of the estimated weather component and the implied adjusted production series, in the upper and lower panels of Figure 4. And as in the case of the total industrial production index, we display the adjusted series together with its estimation uncertainty stemming from the estimated parameters of the irregular weather components, see Figure 5. This estimation uncertainty is relatively less important in the construction sector given the overall higher variability of this sector-specific production and its weather dependence.



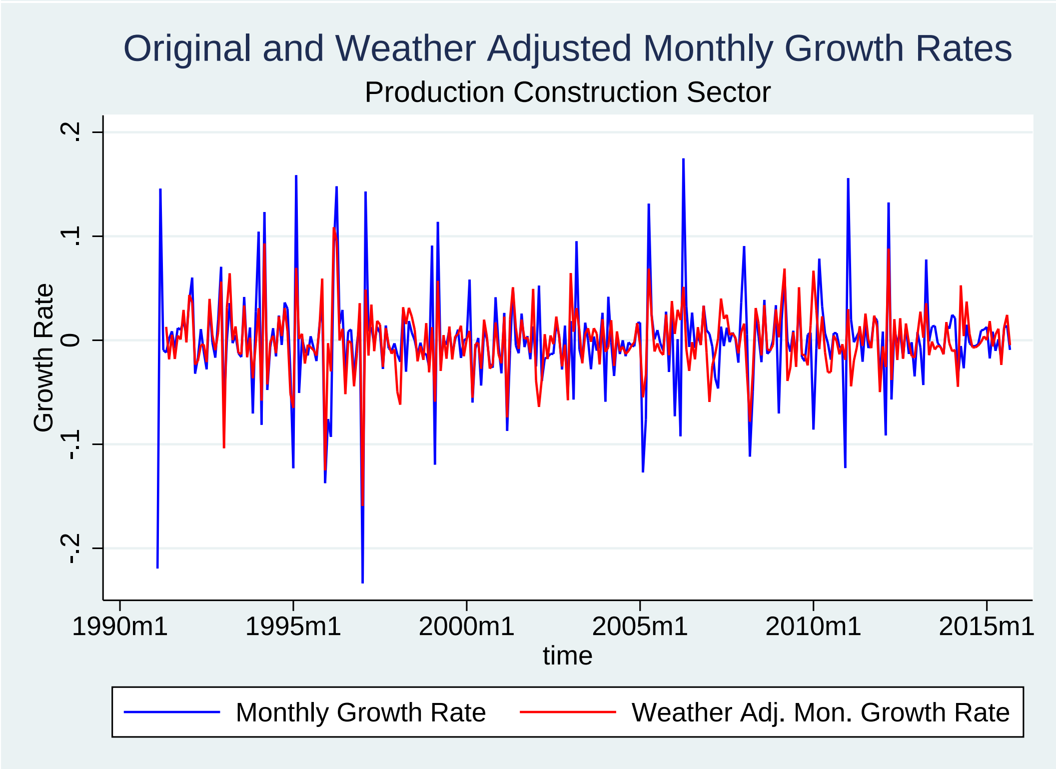


Figure 4: Irregular weather effects on German production in the construction sector. The upper panel shows the estimated weather component with respect to the monthly (non-annualized) growth rate, i.e. $\widehat{weather}_t$. The lower panel compares the observed growth rate and the result of the weather adjustment, i.e. $y_t - \widehat{weather}_t$.

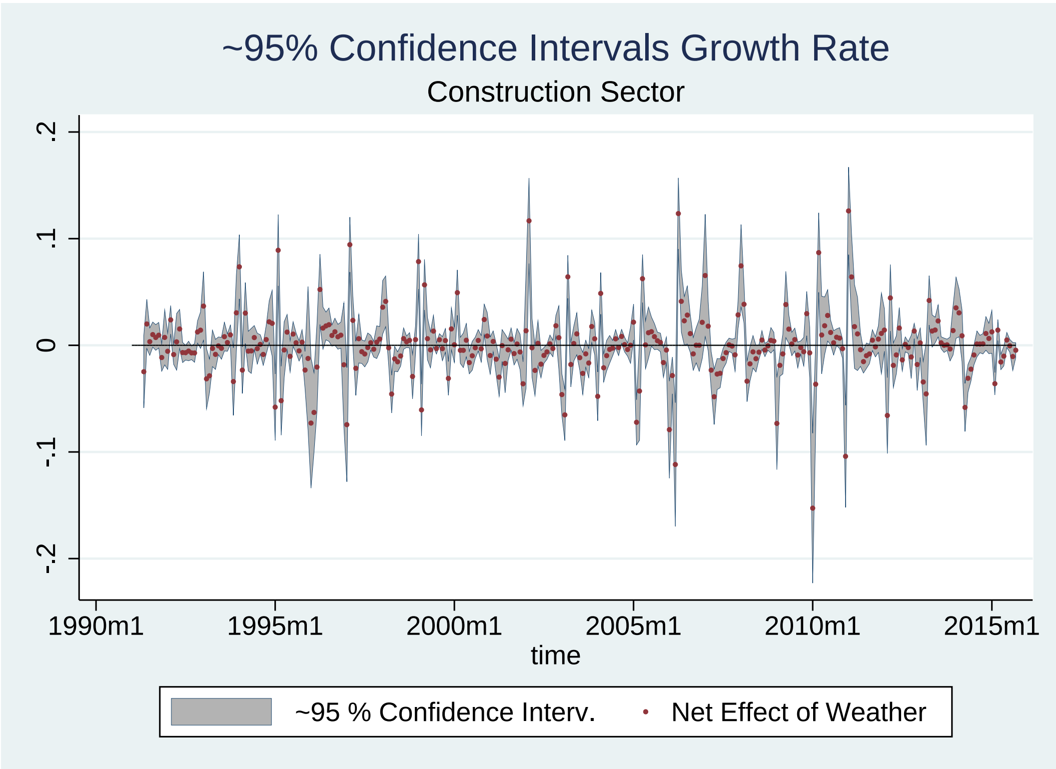


Figure 5: Estimation uncertainty of weather-adjusted production in the construction sector.

4 Improving nowcasting of production measures

In the previous section we performed a historical adjustment of German production time series by estimating the dynamic influences of irregular or abnormal weather conditions. In this section we want to exploit the fact that observations of the weather measures are available much more quickly than the first publications of production values by statistical agencies – in Germany the publication delay for the first and tentative official figures on industrial production is around 38 days, more than one month. Given that we found some significant contemporaneous impact of the weather (deviations), it is natural to take these effects into account when the aim is to produce a short-term forecast of economic activity.

However, our present aim is merely to check whether this is a promising route for future research, and hence we employ some shortcuts. First we do not work with a full real-time dataset but instead continue to use our dataset on industrial and construction-sector production which effectively contains only a single vintage (from 2015). We therefore do not take into account the data revisions occurring after the respective first publications. Secondly, in order to gauge the value added of the weather effects for forecasting, in principle one would have to use a full-fledged forecasting model as the starting point. Instead we will here restrict the non-weather predictive variables to be the lagged endogenous variables available on a pseudo real-time basis. Both the real-time aspect and the use of other predictive variables can be found in Proaño and Theobald (2014) or in Schreiber and Soldatenkova (2016), but only for total industrial production.

The present pseudo real-time exercise for nowcasting thus effectively boils down to removing the first two lags of the dependent variable from the predictive models, because the realizations of industrial (or construction-sector) production of the immediately preceding two months are not yet known when the nowcast would be made. To this end we define the shorter lag polynomials $\alpha^*(L) = \alpha_3 + \alpha_4 L$ and $\theta^*(L) = \theta_3 + \theta_4 L$ which are applied starting at the third lag, such that for total industrial production we obtain the following estimated nowcasting equation:

$$\begin{aligned} y_t = & c_0 + \alpha^*(L) y_{t-3} + \theta^*(L)(y_{t-3} \times D_{Oct2008,t}) + \theta_5 D_{Oct2008,t} \\ & + \sum_{m=1}^{12} \left[\beta_m (D_{t,m} \times \hat{x}_t^{temp}) + \gamma_m (D_{t,m} \times \hat{x}_t^{sheight}) \right] \\ & + \kappa(L) \hat{x}_{t-1}^{sheight} + \varepsilon_t \end{aligned}$$

In Table 3 the important estimated coefficients are reported. By removing the first two lags of the endogenous variable (along with the break interaction terms) the adjusted R^2 drops from 24 to 16 per cent. Here 12 percentage points are due to the weather effects which can be estimated without suffering from a publication delay. The signs of the partial temperature effects for October and December are negative and thus not immediately plausible. In a structural sense there could now be some omitted-variable effects at work in this restricted specification, although for predictive purposes this would be less of a concern.

Instead of reporting the estimation uncertainty for all observations simultaneously, as we did before in Figure 3 for a different specification, we now focus on the situation at the margin of the sample in 2015. The estimates for the weather effects along with the corresponding confidence intervals are given in Table 4. For example while the estimated weather effect in August is quite large and negative with an impact of roughly -0.4 percent, this estimate is not significantly different from zero, with the confidence interval stretching over 2.8 percentage points (from -1.8 to 1.0 percent). In contrast, for October the effect of irregular weather was estimated as positive at 0.3 percent. At the same time, this estimate is much more precise such that the length of the associated confidence interval shrinks to just over 0.3 percentage points (from 0.2 to 0.5 percent), rendering the estimate significantly

Table 3: Nowcasting total industrial production

Sum of coefficients, lagged endogenous variable	0.36
Temperature×January	0.0042
Temperature×October	-0.0053***
Temperature×December	-0.0022*
Snow height×February	-0.0023***
Snow height×May	-0.1496*
Snow height×October	-0.1251***
Snow height ($t-1$)	0.0018***
Snow height ($t-3$)	0.001**
Observations	292
Chow test F(3,260), p-value	0.19, 0.900
R^2	0.250
Adjusted R^2	0.161

Notes: Dependent variable y_t is total industrial production in Germany (growth of an index number, seasonally adjusted). Of each weather component the most significant and largest coefficients in magnitudes are shown. Robust standard errors are used. Symbols: *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$.

positive.

Obviously we can apply the same nowcasting idea to the construction sector. We obtain the following specification, where the important coefficients are reported in Table 5.

$$\begin{aligned} y_t = c_0 + \alpha^*(L)y_t + \sum_{m=1}^{12} \beta_m (D_{t,m} \times \hat{x}_t^{temp}) \\ + \sum_{m=1}^{12} \gamma_m (D_{t,m} \times \hat{x}_t^{sheight}) + \eta(L)\hat{x}_t^{temp} \\ + \kappa(L)\hat{x}_t^{sheight} + \varepsilon_t \end{aligned}$$

Again the effects are concentrated on the winter months. The signs are as expected, with the exception of the temperature effect for November. The omission of the first two lags of the left hand side variable just induces a surprisingly small drop

Table 4: Weather effects in 2015, total production nowcast

Date	Weather effect point estimate	Upper bound	Lower bound
Oct. 2015	0.00339	0.00504	0.00174
Sept. 2015	-0.00165	0.00137	-0.00468
Aug. 2015	-0.00388	0.00980	-0.01756
July 2015	-0.00241	0.00247	-0.00729

Notes: The upper and lower bounds refer to 95% confidence intervals. For the precise implementation of the nowcast exercise see the text.

of the adjusted R^2 from 56 to 51 percent. Removing the weather variables would induce a drop of the $\bar{R}^2$ by a whopping 50 percentage points, hence the weather adjustment appears particularly promising for the construction sector. On the other hand, the high variation partly stems from a number of peaks in the series as could be seen in Figure 4 (lower panel), but that have appeared less frequently in recent years. This implies that the estimates for less extreme observations are not as precise as might be expected. In Table 6 we again focus on the situation at the current margin of the sample. The point estimates of the weather effect are not significantly different from zero for October and August 2015. For September, however, the confidence interval ranges from -1.5 to -0.3 percent and thus does not cover zero. A large and significant weather effect could also be observed in February 2015 which is included in Table 6 for comparison.

5 Conclusion

We conclude that abnormal weather conditions in Germany affect the construction sector and aggregate production. Generally and not surprisingly, estimated coefficients are larger for the construction sector than for total industrial production. Controlling for measurable weather effects using freely available datasets thus helps to

Table 5: Nowcasting construction-sector production

Sum of coefficients, lagged endogenous variable	-0.17
Temperature×January	0.0235***
Temperature×February	0.0107**
Temperature×November	-0.0099**
Snow height×February	-0.0087***
Snow height×March	-0.0155***
Temperature $(t-2)$	-0.0034**
Snow height $(t-1)$	0.0129***
Observations	292
Chow test F(3,256), p-value	0.541, 0.77
R^2	0.563
Adjusted R^2	0.509

Notes: Dependent variable y_t is production in the German construction sector (growth of an index number, seasonally adjusted). Of each weather component the most significant and largest coefficients in magnitudes are shown. Robust standard errors are used. Symbols: *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$.

Table 6: Weather effects in 2015, construction-sector production nowcast

Date	Weather effect point estimate	Upper bound	Lower bound
Oct. 2015	0.00266	0.00597	-0.01128
Sept. 2015	-0.00920	-0.00321	-0.01519
Aug. 2015	-0.0112	0.00346	-0.02582
Feb. 2015	-0.03570	-0.02458	-0.04682

Notes: The upper and lower bounds refer to 95% confidence intervals. For the precise implementation of the nowcast exercise see the text.

determine the underlying economic dynamics and should lead to a more accurate assessment of the business cycle, ultimately also implying more appropriate stabilization policy advice.

By relying on the (approximate) orthogonality between regular seasonal effects and irregular random weather outcomes we were able to keep the econometric methods simple, using straightforward regression models that are linear in parameters. Within this framework we found it important to allow the effects of the weather variables such as air temperature or snow height (in deviations from seasonal averages) to be month-specific. The specification also had to account for serially correlated production and its dynamic reactions.

Finally we provided initial evidence that the weather effects could also be incorporated to improve the "nowcasting" of production realizations that are still unknown because of the publication delay of such macroeconomic data. This latter part of the analysis used the simplifying shortcut of a pseudo real-time setup, whereas a refined fully real-time estimation would work with a different data vintage for each datapoint. Also, the marginal value added of the weather variables as predictors would have to be assessed relative to a broader information set. Nevertheless, this first set of results was encouraging especially in the case of the construction sector. Also we expect that such irregular weather effects apply to most other economies as well, not only to Germany.

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