Statistics Netherlands

Discussion Paper

How unusual weather influences GDP

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remarks The views expressed in this paper are those of the author and do not necessarily reflect the policies of Statistics Netherlands.

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Summary

This study concerns the effect of unusual weather on the Dutch GDP (Gross Domestic Product). This in contrast with the influence of average weather conditions, which can be captured by analysing seasonal patterns. The effect of weather on GDP is interesting in itself, but in the case of large deviations from average conditions (very mild or severe winters for example), the weather effect can cloud the economic developments of interest. Corrected data can then reveal the real developments.

The influence of the weather on the economy can take many forms; frost and snow can hinder construction and transport, whilst very hot weather can be advantageous for café's, but not for the retail trade. Therefore we performed the analysis on a sectoral level of more homogeneous composition, and tested a score of different, potentially relevant, weather effects. The influence on GDP was then computed by aggregation. We found that on a quarterly basis, several industries exhibit a significant weather effect. Energy and Mining & Quarrying were influenced by so-called degree-days, whilst manufacturing and construction suffer under conditions of frost. Finally, there was a small positive effect of the maximum daily temperature on the catering industry.

Often, the net effect of unusual weather on GDP as a whole is rather modest, as a result of sectoral effects having opposite signs. For example, the positive effect of colder weather via increased energy consumption may be more or less compensated by the negative effect of more days with frost on construction and manufacturing. In some periods, however, the effect is more substantial. For instance, the weather adjusted year-on-year volume growth rate of total GDP for the first quarter of 2013 differed by 0.8 percentage points from the original (unadjusted) growth rate.

Keywords

Weather, GDP, regARIMA-models

1. Introduction

Weather influences many parts of the economy. For example, retail trade is assumed to decrease when it rains, and the construction industry may be hindered by frost. The effects probably differ from sector to sector, as does the type of weather effect expected to be of influence. Adjusting data for these effects can help us in obtaining a clearer view of the underlying developments, especially in case of e.g., extremely cold or mild winters, or hot summers. In many parts of the economy, growth is to a larger or smaller extent influenced by the weather, and it is therefore important to be able to indicate how large these effects are.

The effects of weather can be separated into a seasonal and an additional, nonseasonal part. The seasonal part consists of all annually recurring fluctuations due to usual weather patterns. For example, energy consumption will always be higher in winter and lower in summer. Together with other recurring time series fluctuations it forms the seasonal component of a time series, and represents the average influence of the time of the year on economic activity. The magnitude of this time series component can easily be determined by seasonal adjustment procedures. In this paper, however, we are interested in weather effects in case of periods with aberrant weather behaviour. For example, the additional household energy consumption in case of a period of severe cold. This part of weather cannot be captured by seasonal adjustment, and has to be modelled separately.

The objective of the paper is not to produce weather adjusted series, just as series are adjusted for calendar and seasonal effects. The goal is to distinguish irregular behaviour from structural economic changes, and to give an indication of the magnitude of the weather effects.

In this paper, we investigate the influence of a number of weather variables on several sectors that make up the GDP (Gross Domestic Product) in the Netherlands. We find that for several sectors a significant effect is present and quantify the magnitude of the effect.

In Section 2, we begin by describing the data used, and describe how the weather variables were constructed. Section 3 describes the approach for modelling time series with weather effects. Section 4 presents the results. We finish with the conclusions in Section 5.

2. Sectors and weather variables

In this section, we describe the data used for this study. We chose to analyse weather effects at the sectoral level, as it seemed plausible that different industries would exhibit different weather effects. The influence on GDP as a whole is then likely to be a mix of different weather effects, making a direct analysis at the aggregate level problematic. We focus on sectors in which we expect a weather effect to be present with some probability[1]. The sectoral classification of the National Accounts was used (NACE). We deemed 1-digit sectors to be homogenous enough for this analysis, with the exception of Manufacturing and 'other commercial services', where we also analysed subsectors. In Table 1 we list the sectors and subsectors investigated, according to the NACE classification.

Table 1: Sectors and subsectors investigated

B Mining and quarrying

C Manufacturing

- 10-12 Food products, beverages and tobacco
- 13-15 Textiles and textile products and of leather and leather products
- 16-18 Wood products (no furniture), paper (products), printing and reproduction
- 19 Coke and refined petroleum
- 20-21 Chemicals and pharmaceuticals
- 22-23 Rubber, plastic products, construction materials
- 24-25 Basic metals
- 26-27 Electronic and electric products
- 28 Machinery
- 29-30 Vehicles, transport equipment
- 31-33 Furniture and other

D Energy (Electricity, gas, steam and air conditioning supply)

F Construction

G Trade (Wholesale and retail trade; repair of motor vehicles and motorcycles)

H Transporting and storage

I Accommodation and food service activities

J Information and communication

N Administrative and support service activities

- 78 Employment activities
- 79 Travel agency, tour operator and other reservation service and related activities

The analysis was performed on value added data in constant prices (i.e. volume), the main focus of short-term economic analysis. For all sectors, quarterly time series were available running from Q1 1998 to Q3 2012. The time series are index series representing value added based on the 2005 price level.

Weather is expected to influence economic growth in these sectors in various ways. In construction industry, for example, fewer or no activities can be carried out in case of frost. This may also have an effect on suppliers from various industrial branches. The most visible effect, however, can be witnessed in natural gas consumption, which is used for heating houses and offices. Severe winters lead to higher energy consumption. This effect can in fact be computed

[1] Finance, Real estate, Specialized Business Services, Central and local Government, Education, Health services, Cultural Activities were not included in the analysis as we deemed it unlikely that their production would be influenced significantly by weather effects. Agriculture and water and waste management were ignored due to their small size.

more or less directly from gas production on a quarterly basis. For mining and quarrying, a similar effect is expected. In other sectors, the effect of weather can only be computed with model-based approaches.

An important question then is how to quantify weather effects for these sectors. At present, for seasonal adjustment only so called 'degree-days' variables are used. This type of variable measures on how many days temperature dropped below 18°C, in combination with the number of degrees below 18°C. This type of variable is optimised for use as an explanatory variable for gas consumption, but may not be suitable for other sectors. An optimal weather variable should thus be found for each sector individually.

For the construction of weather variables, we used data from the Royal Netherlands Meteorological Institute (KNMI). This data is available freely, and comprises day-to-day recordings of temperature, sunshine, snow, rain, etc. The data are measured at 29 stations throughout the country. Therefore, as a proxy for the average for the entire country, we averaged over all these stations. This averaging was done after all other calculations described below were performed.

Table 2 gives an overview of the weather indicators obtained from the KNMI. Based on these weather indicators, we defined the variables that can be found in Table 3.

Table 2: Weather indicators obtained from KNMI.

KNMI original weather indicators	Description*
Average T	24-h temperature average
Maximum T	24-h temperature maximum
Sun hours	Hours of sunshine
Sun relative	% hours of sunshine compared to maximum hours possible
Rain hours	Number of hours with rain
Precipitation	Rain in mm per 24 hours
Cloud cover	24h average of % cloud coverage
Snow	Mm of snow on ground

* all variables are per day

Table 3: Additional weather indicators constructed based on KNMI data

Transformed indicators	description
Frost	if Average T < 0°C, value = Average T, else value = 0
Frost dummy	if Average T < 0°C, value = 1, else value = 0
Hard Frost	if Average T < -3°C, value = Average T, else value = 0
Hard Frost dummy	if Average T < -3°C, value = 1, else value = 0
Hard Frost 7	if Average T < -7°C, value = Average T, else value = 0
Hard Frost 7 dummy	if Average T < -7°C, value = 1, else value = 0
Degree-days	if Average T<18 then 18-Average T, else value-0
Sunny day dummy	If Sun relative>0.5 then 1, else value=0
Nice day dummy	If Sun relative>0.5 AND Average T>18 then 1, else value=0
Rainy day dummy	If Rain Hours>6 then 1, else value=0
Snow dummy	If Snow day t > Snow day t-1 then 1, else value=0

Based on the above daily variables, we constructed the following quarterly variables (with X any of the above daily variables):

Q(X)	for dummy variables, the quarterly sum per station of the above daily variables, for level variables the daily average over the quarter. Then averaged over all stations to arrive at a country-wide indicator.
QDev(X)	quarterly sum of above daily variables, per station; then taken as a deviation from the average quarterly value for all quarters in the time series; then averaged over all stations.
QDevM(X)	quarterly sum of above daily variables, per station; then taken as a deviation from the average quarterly value for all *the same* quarters in the time series; Then averaged over all stations.

Apart from weather variables, we also took into account several auxiliary explanatory variables for the construction industry:

Holidays	The deviation from the average (over all the same quarters) number of holidays per quarter. In construction industry, especially in summer the entire industry has holidays for several consecutive weeks.
Days Off	Number of days off and shorter working hours per quarter, deviation from the average (over all the same quarters) per quarter.

Since time series for all explanatory variables start in 1990 (for weather variables) or 1995 (for holidays and 'Days off'), while dependent series end in Q3 2012, we brought all series to the same length:

- For construction all series will run from Q1 1995 tot Q3 2012
- For all other sectors and sub branches all series will run from Q1 1990 to Q3 2012

3. Approach

The goal of this study is to determine for each sector which weather variables have a significant effect on value added and to quantify this effect. In order to get a good estimate of the (additional) weather effects, we should study these in conjunction with other variables that could explain time series fluctuations. We therefore use an approach that combines weather effects with seasonal time series behaviour, calendar effects, and other explanatory variables.

The regARIMA module of the seasonal adjustment program X-12-ARIMA (US Census Bureau, 2011) is very suitable for this. The basis is an ARIMA model, extended by a regression component for the exogenous variables such as weather, calendar effects and other variables that cannot be observed directly.

An ARIMA model is described in the form (AR_{trend} I_{trend} MA_{trend})(AR_{seas} I_{seas} MA_{seas}). As an example, an ARIMA(1 1 2)(1 1 2) model is a model with both period-on-period and year-on-year first differences (the two I's set to 1), an AR(1) term, a MA(2) term, an AR(12) term and a MA(13) term. The dependent is thus transformed to the year-on-year change in the period-on-period change. Indicators representing weather effects can then be added to this model. This is a form of intervention analysis, where the basic dynamics of the series to be explained are described using an ARIMA model and the weather effects are entered in the model as intervention effects, to test whether they add significant explanatory power. In a formula:

$$y_t = a_0 + A(L)y_{t-1} + c_0 z_t + B(L)\varepsilon_t$$

Where: y_t=dependent variable
$A(L)$=AR-structure
z_t=the intervention, i.e. weather indicator
ε_t=residuals
$B(L)$=MA-structure

The "I" in ARIMA points to the order of integration, in practice the transformations needed on the data to render them stationary and thus suitable for ARMA modelling. For the type of economic data considered here, two types of transformation are relevant, trend differencing and seasonal differencing. Trend differencing means computing period-on-period differencing, whilst seasonal differencing amounts to computing year-on-year changes, removing both seasonal effects and (most of) the trend. If a log transformation is used, the result is a growth rate. A seasonal difference is required if one wants to estimate the effects of the weather which are not part of normal seasonal influences. Since an ARIMA model is basically an ARMA model fitted to a differenced series (removing the integrated part), we assume that the above series y_t is sufficiently differenced prior to fitting the above model.

In order to estimate this model, we use the modelling capabilities of X-12-ARIMA. This program has optimization routines to find the optimal ARIMA model while incorporating calendar effects and other auxiliary variables. The routine determines the required transformations and optimal ARIMA form. Usually, this program is used for seasonal adjustment of time series. In this case, we only use the pre-treatment part and modelling routines of the program to adequately determine the contributions of all variables involved. The goal is not to permanently remove weather and seasonal effects from the series, but to identify which effects are significant and to obtain an estimate of the size of the effect.

The use of X-12-ARIMA allows us to take into account the following aspects:

a) Type of transformation: none / log
b) Outlier detection
c) Calendar effects
d) User-defined variables
e) Estimation of the regARIMA-model

In order to model the series we use a basic setup that we apply to all series. In this setup, we use the following settings:

- Period = quarterly
- Modelspan = `(1990.1, 2012.3)`

- Transform = auto
- Outliers: Types = Additive, Critical value = 2.8, Method = addone
- Automdl
- maxdiff = (2,1), maxorder = (2,1)

We test for the significance of the following calendar effects:

- Trading day effects: 6-coefficient or 1-coefficient effect.
- Leap year effect

For the construction industry, we test the following variables:

- Holidays
- DaysOff

Starting from this basic setup, we iteratively worked towards an optimal model. We first tested all weather variables, leap year effect, trading day effects, holiday effects, and outliers separately. Based on their significance, we tested combinations of these variables. Depending on the results, we refined the setup with respect to the critical value for outlier detection and inclusion of regression variables. Alternatively, we also started from a full model, including all possible effects, and iteratively removed insignificant effects. Model selection was done based on the Akaike Information Criterion (AIC). While model fit could be improved by setting more outliers, we kept a conservative approach with regard to the number of outliers in order to avoid overfitting. Although these extreme values may make model estimation more difficult, they are often real economic effects and in our opinion should thus be explained by the underlying time series model or auxiliary variables as much as possible.

For each of the sectors, these two approaches gave us the optimal model per sector, with a coefficient indicating the effect of weather on value added. The way this analysis is carried out, means that this is the additional effect of weather, on top of the 'usual' weather effects as they appear in the seasonal pattern. From this model we can compute the net effect of weather on turnover in a particular period, by taking $c_i z_t$, with c_i the estimated coefficient of the i^{th} weather variable and z_t the value of the weather variable in period t.

4. Results

For all sectors a large number of models was evaluated, in order to determine which weather variables were most significant for each series. For the majority of the sectors , no significant weather effect could be identified. For quarterly time series, this is not that surprising as most weather effects will tend to average out over a quarter. A drop in activity in one day or week can easily be compensated by more activity in a later day/week. For example retail sales will

probably suffer from a very rainy week or month, but this will usually be followed by a more "normal" week/month, which will probably result in "catch-up" sales.
Another important result is that apart from temperature related weather variables, no weather variable had a significant effect on quarterly economic developments. So we could identify no net influence of rain, snow or sunshine. The main effects are due to hot and cold weather. Table 4 summarizes the results for sectors with significant weather effects, including model specification and diagnostics.

Table 4: Sectors with significant weather effects and their respective best models

Sector	**Mining (B)**	**Manufacturing (C)**	**Energy (D)**	**Construction (F)**	**Accommodation and food service activities (I)**
Weather variable	Degree-days	Frost dummy	Degree-days	Hard frost dummy	Maximum temperature
Coefficient (sig.)	0.04 (26.00)	-0.0011 (-4.00)	25.16 (6.13)	-66 (-11.9)	0.0051 (5.54)
Variant	-	QDevM	-	QDevM	QDevM
Transformation	Log	Log	None	None	Log
ARIMA-model	(0,0,2)(0,1,1)	(0,1,0)(0,1,1)	(1,0,0)(0,1,0)	(0,1,1)(0,1,0)	(1,1,0)(0,1,0)
AIC	1127	1245	947	881	786
Critical value outliers	2.8	2.8	2.8	2.8	2.8
Other significant variables	Trading days (1 coefficient)	Leap Year	-	Leap year Holidays Days off	-

As expected, Energy and Mining have degree-days as a significant weather variable, reflecting heating needs, while Construction and Manufacturing are sensitive to frost, hindering building activity and possibly transport. Although we do not present all models that were tested, nor results for all subbranches of Manuafacturing, we made the following observations during testing:

- For sectors with significant weather effects, the relevant weather indicator varies. Thus, a direct analysis of the effect of weather conditions on aggregate GDP would probably be misspecified. It also means that the relation between GDP as a whole and weather may be less clear. A quarterly temperature of 1°C more or less than average does not directly translate into a standard change in GDP. In order to quantify the net effect, we suggest to compute the effect for each branche separately and then aggregate results. This is what we will do below.

- The precise construction of a weather variable did not have a large impact. For all weather variables we constructed the variants Q(X) , QDev(X) and QDevM(X), with X the weather variable. If one of these was significant, then the other two in most cases were significant as well. In the results in Table 4, we therefore used the most significant one.

- For the Construction industry, all weather variants based on frost were clearly significant. There were some differences in t-values, but all variants based on normal frost or hard frost, and also variants based on dummy variables, had high absolute t-values. Auxiliary variables for holidays and days off were also significant in most models tested.

- For Energy and Mining, several of the frost-related variables were significant, but the relation was not as clear as for Construction. For these sectors, degree-days proved to be a better explanatory variable, with much higer t-values.

- For the 11 subbranches of manufacturing that were tested, many did not exhibit a significant weather effect. Only 'Wood products', 'Basic materials' (which are supplied to the construction industry), and 'Furniture and other' showed significant results for most frost-related variables. 'Vehicles, transport equipment' showed a significant relation with dummy variants of frost variables. This gives some idea of the sources of the weather effect on aggregate manufacturing. The retail-subbranche of the trade sector exhibited no significant weather effect on a quarterly basis.

Analysis Q1 2013

Now that we know which weather variables are relevant for analysing the effect of weather conditions on economic growth, we can quantify the effect of weather on the various sectors. For this we can use the estimated coefficients of the regression models above to give quantitative estimates (in millions of euros) of the size of the effect. This shows how the analysis of the weather effect on GDP will be performed on a quarterly basis.

Below, we present results for this. The time series used are not exactly the same as the ones used above. After doing the preceding analysis, new data have become available. As an example, we present results for a recent quarter, Q1 2013. For this, we used the models developed on historical data above. This quarter was a winter quarter with a relatively long period of cold and sub-zero temperatures.

Table 5 gives results for the weather effects in each of the sectors, as well as a total effect on GDP. The GDP effect is indirectly computed as the sum of the sectoral effects. As expected, there is substantial variation of impact over the sectors. The net weather effects are largest in Manufacturing, Energy and Construction. These sectors show opposite effects, which to a large extent level out in GDP as a whole. The total effect on GDP was positive at 94 million, implying that this severe winter increases GDP.

This in itself is news, our analysis shows how the positive effect of colder weather on energy consumption is largely compensated by the negative effect on construction and manufacturing. These results confirms the utility of our approach. Only a sectoral analysis, using selected bespoke weather indicators can identify these opposite effects of weather conditions and show the more substantial effects hidden by the small net effect.

The assessment of the impact of weather, however, is different if one considers the growth rate. Although for this quarter (Q1 2013) the net weather effects cancel out at aggregate level, resulting in a negligible net effect, the year-on-year growth rates for original and weather adjusted data are clearly different for GDP as a whole. The weather adjusted series has a growth rate of -2.5%, whereas the original has a growth rate of -1.7%.

This rather big difference between original and weather adjusted growth rate can be explained by the unusually large weather effect on total GDP in the first quarter of 2012 (see Table 6). Table 6 shows big negative weather effects on manufacturing and construction in the first quarter of 2012, resulting from a period of severe frost. However, effects on mining and energy were almost negligible, resulting from the fact that, on average, the first quarter was not colder than usual, according to the number of degree days.

Table 5: Weather effects in GDP (millions of euro's, volume) and sectors for Q1 2013

	Original	Adjusted	Weather effect	Year-on-year (original, %)	Year-on-year (Adjusted, %)
GDP	134455	134360	94	-1.7	-2.5
B Mining	5368	4798	569	15.5	3.4
C Manufacturing	15782	16009	-227	-4.5	-5.5
D Energy	1922	1860	62	6.1	2.7
F Construction	5331	5618	-287	-11.6	-13.9
I Accommodation and food service	1859	1881	-22	-3.9	-2.6

Weather variables: Mining – degree-days
Manufacturing – number of days of frost
Energy – degree-days
Construction – average number of days of hard frost dummy (-3°c)
Accommodation and food – maximum temperature

Table 6: Weather effects in GDP (millions of euro's, volume) and sectors for Q1 2012

	Original	Adjusted	Weather effect
GDP	136842	137742	-901
B Mining	4646	4641	4
C Manufacturing	16526	16937	-411
D Energy	1811	1810	1
F Construction	6032	6528	-496
I Accommodation and food service	1934	1932	2

Weather variables: same as for Table 5

We also computed the historical effects of weather for the entire time series. Figure 1 shows the historical net effect of weather on GDP, while Figure 2 compares the growth rates of the adjusted and unadjusted GDP series. As can be seen, the effects alternate between positive and negative values, where the effect is not always in the same direction for the same quarter of consecutive years. Over time, the positive and negative effects average out to a large extent. There are however several occasions in which the weather effect is very substantial. As seen above, this may be due to one or two sectors which are very sensitive to changes in weather. In the appendix, similar graphs can be found for each of the sectors. For Energy, Construction and Manufacturing there are clear differences between original and adjusted series.

Figure 1: Net effect of weather on GDP.

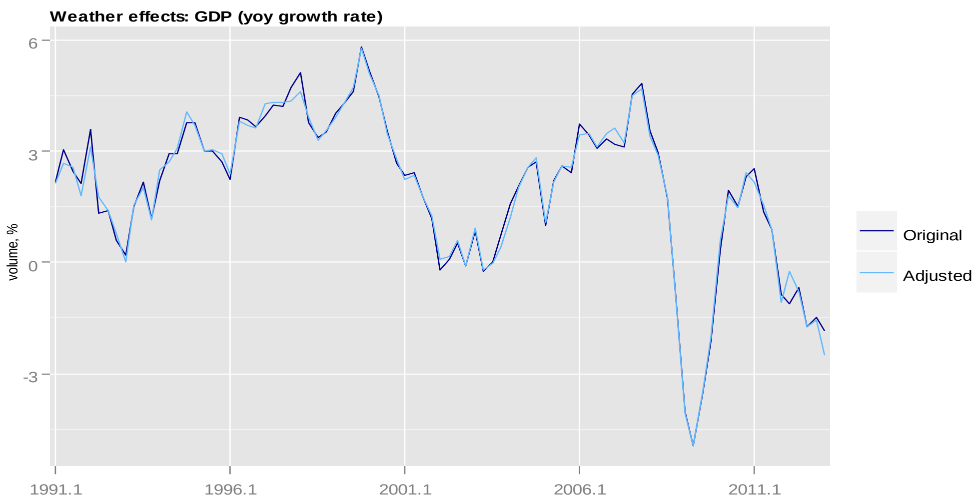

Figure 2: Year-on-year growth rate for GDP, original and adjusted series

5. Conclusions

In this report, we presented an analysis of the effects of weather on GDP. For the most relevant sectors a set of weather variables was tested for their significance in explaining value added, and the effect was quantified. It appears that for the economy as a whole the net effect is relatively small for Q1 2013 (+94 million Euro's), while the difference in growth rate is quite substantial (-0.8%-point). For several component sectors, the net effects were substantial but cancelled out in the aggregate. In manufacturing, about 500 million Euro's of output was lost due to frost, but energy related sectors gained about the same amount due to increased demand for heating.

Every sector is subject to different weather influences, implying that there is no simple and straightforward relation between GDP as a whole and specific weather variables. We therefore recommend computing weather effects for individual sectors first, and then aggregate these to compute the effect on GDP. It should be noted that all the effects considered here are in addition to the normal seasonal weather fluctuations. These are accounted for by standard seasonal adjustments. The effects studied here concern the additional effects of deviations from the average weather conditions normal for the quarter. A whole range of potential influential weather effects was tested, from temperature, snow, rain to sunny & cloudy days. Only temperature-related weather effects were found to influence the economy significantly on a quarterly basis.

Construction and manufacturing were found to be sensitive to frost, with especially severe frost (an average temperature of -3˚C or less) having a negative effect on production. On the other hand, colder weather favours the energy and the mining sectors, as demand for heating increases. This was best captured by the usual degree-days indicator. A final, relatively small effect of temperature was found for the accommodation and food service sector, with value added increasing with maximum daily temperatures. This indicates that relatively hot days have a disproportionate influence on this sector.

Although the results showed significant and substantial weather effects, the results could possibly be improved in several ways. We therefore have the following suggestions for further research:

- Not all industries that make up GDP were studied in detail (see p.3), and not every possible weather variable was considered in this study. Also, we have seen that the weather effect at the GDP level is a mixture of effects at subaggregate level. Nonetheless, it might be useful to study weather effects in GDP because the signal-to-noise ratio is more favourable there, making estimation of regression effects easier.

- The effect of weather may not be constant throughout the time series. For example, houses, nowadays, tend to be better isolated than before, which causes extreme temperatures to have a smaller effect on energy consumption. Also in construction, measures are being taken to be able to continue working in case of bad weather. Models that take into account these time-varying effects may improve the results, but add complexity. An alternative is to compute weather effects over a shorter period of time, e.g., the last 5 years. This however implies that the models and coefficient estimates have to be updated more frequently.

- The analysis described here was performed using quarterly value-added data. Additional weather effects might be found using more high-frequency data, for example monthly or even daily data if available. There would be less opportunity for averaging out. The retail sector would be an interesting candidate.

The quantification of weather effects gives more insight in short term developments in economic series. The net effects can be studied on their own, as done in this study. Also, weather adjusted series can be used for other purposes. For example, weather effects can be taken into account when modelling a series in the pretreatment phase of seasonal adjustment. With this knowledge, seasonal adjustment itself could be improved, giving a more accurate estimate of short term economic growth.

Based on the results of the current study, a system was built with which the analysis can be repeated every quarter. However, before publishing figures that quantify the effects of recent weather, we suggest to run the model in the background for several quarters.

References

KNMI (Royal Netherlands Meteorogical Institute), www.knmi.nl, historical daily data

US Census Bureau (2011), X-12-ARIMA reference manual, version 0.3

6. Appendix

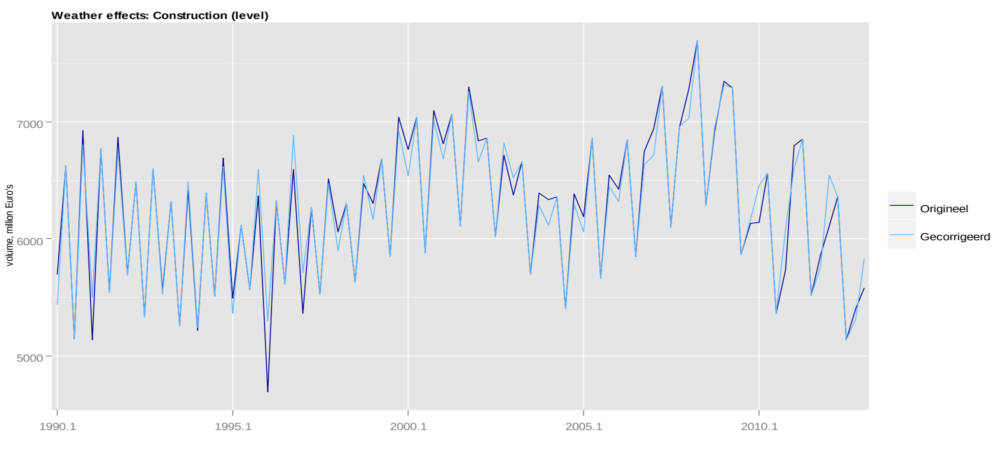

Figure 3: Original and adjusted series for Construction.

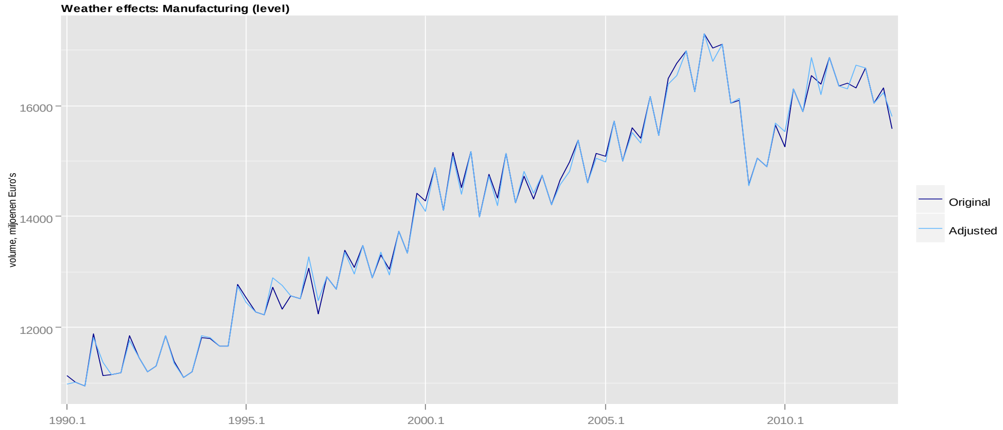

Figure 4: Original and adjusted series for Manufacturing

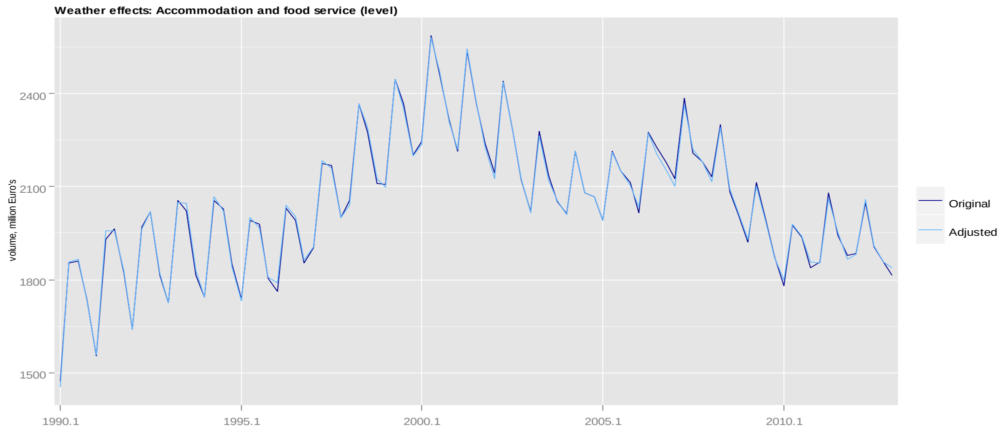

Figure 5: Original and adjusted series for Accommodation and food service.

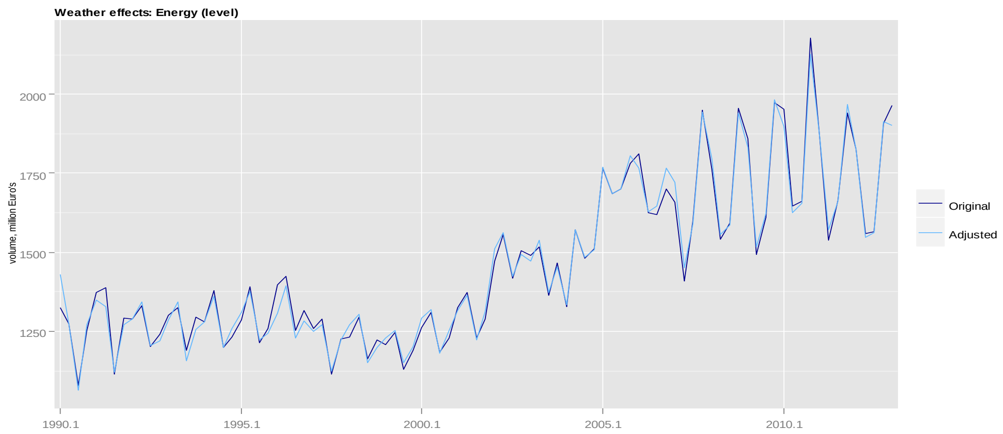

Figure 6: Original and adjusted series for Energy.

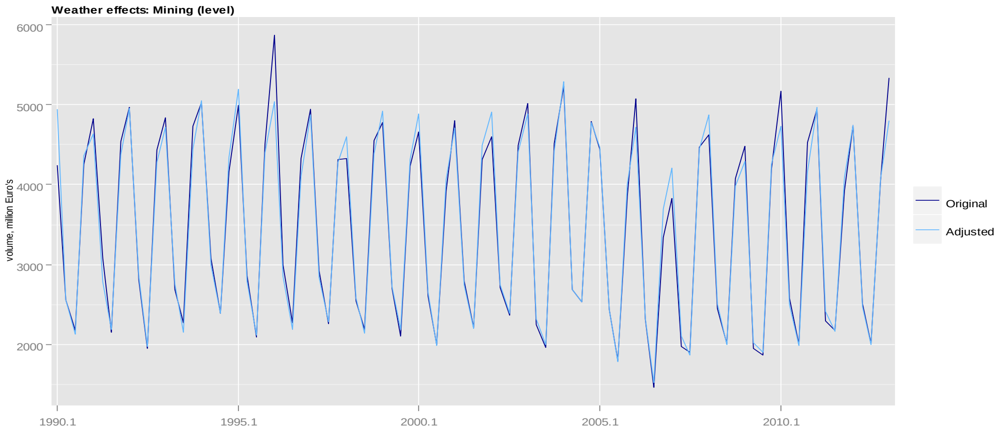

Figure 7: Original and adjusted series for Mining.

Explanation of symbols

.	Data not available
*	Provisional figure
**	Revised provisional figure (but not definite)
x	Publication prohibited (confidential figure)
–	Nil
–	(Between two figures) inclusive
0 (0.0)	Less than half of unit concerned
empty cell	Not applicable
2013–2014	2013 to 2014 inclusive
2013/2014	Average for 2013 to 2014 inclusive
2013/’14	Crop year, financial year, school year, etc., beginning in 2013 and ending in 2014
2011/’12–2013/’14	Crop year, financial year, etc., 2011/’12 to 2013/’14 inclusive

Due to rounding, some totals may not correspond to the sum of the separate figures.

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