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Can the inclusion of calendar and temperature effects improve nowcasts and forecasts of construction sector output based on business surveys?

For nowcasting and short term forecasting of industrial production and GDP, business surveys are a vital source of information. They cover information of the recent past as well as developments in the near future. Whereas variations in industrial production indices potentially cover weather conditions as well as variations due to the different number of work days, it is unclear to which extent business surveys mirror them as well. Ignoring such information can lead to model misspecifications if used for nowcasting or forecasting.

This study sheds light on the effects of temperature changes as well as the varying number of work days on business survey results and on the production index of the Austrian construction industry. It was found that survey data do not contain sufficiently the effects of the different number of work days necessary for explaining variations in industrial production in construction. No statistical evidence was found that changing temperatures beyond their typical seasonal pattern influence the survey results and industrial production.

JEL Classification: E27 and E37

Keywords: Business surveys, weather effects, work day effects and nowcasting

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1 Introduction

For guiding economic policy the knowledge about the current state of the economy is vital information. Unfortunately many key statistics – like the quarterly GDP – are released with some delay. This requires bridging this time gap by alternative calculations. For this, economists apply methods similar like those used in forecasting to estimate recent production. Such calculations are usually based on monthly indicators like industrial production (if already available), employment figures, retail sales, etc. which are used to forecast the coming quarterly DGP release. As this does not concern future developments it is often named as nowcasting.

One important source of information for nowcasting and forecasting are business surveys. The drawback of being purely qualitative indices is compensated by their fast availability and that figures are not revised afterwards. For this reasons many studies concerning nowcasting GDP (see e.g. Banbura, Giannone, and Reichlin, 2010; Kuzin, Marcellino, and Schumacher, 2009) make use of business survey indicators.

In most cases these indicators are used in the framework of dynamic factor models and VARs, without explicitly modeling the structure. A reason might be that firstly the data is of qualitative nature, so a parametric linear approach could give misleading results. A further reason might be that questions of the surveys are formulated in a manner, which makes it difficult to understand which time span is compared to which in respect of changes of the business conditions. This makes an explicit modeling strategy based on theoretical considerations cumbersome.

In any case, usually nowcasting techniques do not care for the existence of work day effects or weather conditions in the recent data. But these effects can plague considerably the economic data, leading to misjudgment of the current economic situation. Furthermore, researchers set up their models using data already adjusted for work days and seasonality. The most prominent seasonal adjustment methods – TRAMO-SEATS and X12 – are based on symmetric filters. This requires a forecast of the time series in order to adjust the data at the recent time margin. The ignorance of the influence of the varying number of work days as well as special weather conditions in the underlying data – especially at the recent time margin – can lead to a poor forecast (this is done in most cases by a univariate time series approach) and consequently results in unstable seasonal adjusted data at the recent time margin.

As an alternative strategy this study tries a structural approach. This not only allows working with unadjusted data but also sheds light on the effects of a changing number of work days and weather conditions on output. Furthermore it is tested in how far such effects are already included in the business survey data. This explicit modeling strategy reveals also the reason why there can be found a seasonal pattern in the business survey despite the fact there should not be one, by convention. In order to care for possible differences within the construction industry different models for civil engineering and structural construction are employed.

2 The data

About the usefulness of business survey data exists a large amount of literature. Whereas information about quantitative hard data is only available with a considerable time lag – which makes it less appropriate for judging the economic situation at the recent time margin – business survey data comes in very fast and is not submitted to regular revisions.

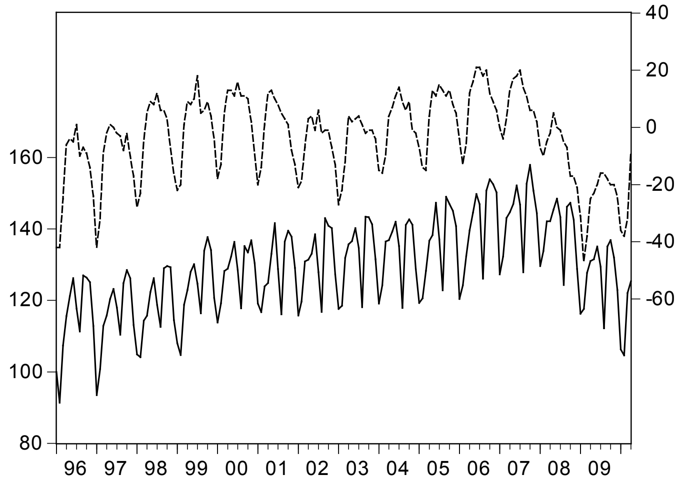
However the nature of this data makes it very difficult to use it within the frame work of structural models. First of all the data is qualitative. Enterprises are just asked whether their business conditions will improve, stay the same or are expected to deteriorate. These answers are aggregated by giving the same weight to each irrespective of the size of the enterprise. By this method it seems difficult to deduce the strength of economic changes as its nature is more a diffusion index. It is more an indicator of the dispersion of the cycle than its momentum.

Another problem presents the fact that while industrial production shows a trend, business survey data do not. What raises the question of how enterprises disentangle trend from cyclical movements. This leads to the second caveat for the use of business cycle data. The questions in the template for the enterprises are not specific enough for judging the period to which the entrepreneur compares. One of the questions of the survey used in this study for nowcasting is:

> How has demand (turnover) for your company's services changed over the past 3 months? It has...
> + increased
> = remained unchanged
> - decreased
>
> *Source: European Commission (2006)*

From this it remains more or less unclear with which reference period the production of the past 3 month is compared by the respondent: with the 3 month average shifted by one month backward, with the foregoing 3-month period or with the quarter of the year before? A hint may be the seasonality in the data. If the answers to the business survey show no seasonal fluctuations, this could point to a comparison to the respective period one year ago and the other way round. There are strong indications that this kind of formulation even confuses respondents. Figure 1 shows the production index of the EU construction industry. It shows clear seasonal movements. The business survey answers – plotted in the same graph – to the change of production in the past 3 month show a pronounced seasonal pattern as well. However, in the EU manufacturing sector the same business survey question shows no seasonal fluctuations but the corresponding industrial production index does. According to the European Commission's manual to the Joint Harmonised EU Programme of Business and Consumer Surveys (2006) there should not be one: ["Even though respondents are explicitly asked not to take into account such seasonal variations, in practice the answers frequently show seasonal patterns"].

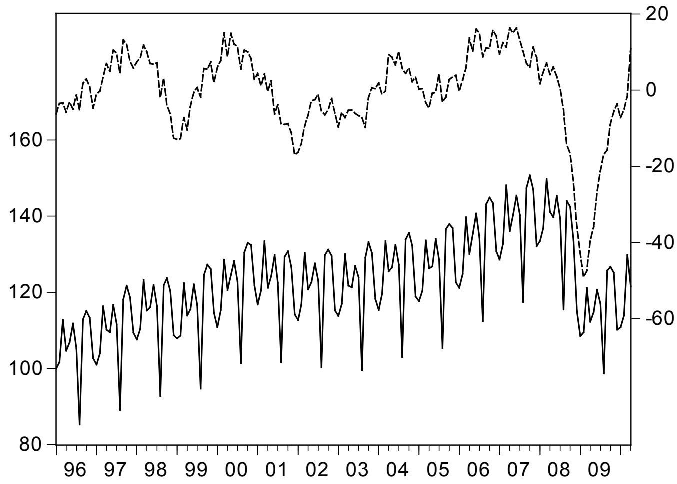
Figure 1: Seasonality in euro area construction industry



Production Index Construction EU
Business Survey Construction EU

For all those reasons it seems to be difficult to set up a model with structures derived by theoretical considerations. In most cases some data mining leads to faster results. As an alternative I set up models with different structures which are tested.

Figure 2: Seasonality for EU manufacturing



Production Index Manufacturing EU
Business Survey Manufacturing EU

In the main focus of this study is not on the manufacturing industry but the construction sector. Apart from seasonal fluctuations and the varying number of work days (not already captured by the seasonal component) in construction, weather conditions can play an important role. Despite the fact that the usual weather variations over the year are captured by the seasonal component it will be shown that there still remain some additional fluctuations due to unusual conditions. The problem for the construction industry is not generally bad weather but temperatures below 0° Celsius (32° F). Some building materials like concrete do not harden when there is frost. As no data is available in Austria for frosty conditions, heating degrees per day are used instead here. Even in month apart from winter heating degree data can give positive numbers without frosty conditions. In order to care for this, monthly data outside winter was set to zero. Weather conditions do not influence all types of construction the same way. Considering this, this study observes civil and structural engineering separately.

Whereas the usual changing number of work days between month is captured by the seasonal component (like the shorter February), the different number of weekends per month leads to an additional variation in this data. This goes also for other calendar effects like Eastern, which sometimes is more located in March and sometimes more in April. For both of these calendar effects, a variable has been introduced.

The data used here starts in January 1996 and ends in April 2010. In April 2004 the question concerning the past production changed from asking about the business condition of the recent month to one for the recent past three month. This led to a change in the seasonal pattern in the series which could not be considered within one model. As for that, I shortened the time series to this date. The production indices for civil and structural engineering represent the raw data i. e. not adjusted for work days and seasonal fluctuations. This goes also for business survey data.

One advantage of using raw data is that seasonal adjusted data at the recent time margin can be perturbed by the adjustment process. This is based on the fact that the seasonal adjustment process can be represented by symmetrical filtering the data. For applying this kind of filter forecasting in order to enlarge the series beyond the last observation is necessary. For the latest observation the uncertainty of the forecast adds to the uncertainty of the seasonal adjustment method. However, Artis et al. (2003) found that this problem is overstated in practice for many time series.

3 Modeling recent and future production of construction industry

For nowcasting and forecasting I set up separately for civil and structural engineering simple structural models with constant parameters[1]. In all cases the seasonal pattern of industrial production in construction could not be completely derived from the one included in business survey data, despite different aggregation techniques and shifting the data within reasonable spans in the time domain. In order to capture residual seasonal variations ARMA terms were used additionally.

As the wording of the questions asked in the business surveys give no clear indication to which period respondents compare their answers concerning improvements or deteriorations, three possibilities arise theoretically:

[1] According to a study of Mourougane and Roma (2002) for many euro area countries models with time varying parameters performed worse than those with constant.

I) $\sum_{t=0}^{2} IP_{t+1} - \sum_{t=0}^{2} IP_{t-1}$ (1)

II) $\sum_{t=0}^{2} IP_{t+1} - \sum_{t=0}^{2} IP_{t-3}$ (2)

III) $\sum_{t=0}^{2} IP_{t+1} - \sum_{t=0}^{2} IP_{t-11}$ (3)

with IP being is the industrial production index of the construction sector. In the first case, the coming three month are compared with the three month shifted backward one period. The second equation compares the coming three month with the foregoing ones and the third with the corresponding three month one year ago. As the last transformation cancels out seasonal fluctuations but business survey data show a clear seasonal pattern, it was not considered henceforth.

A further problem arises from the different dates when respondents answer their questionnaires. The enterprises receive their questions at the beginning of the month and some send them back within some days. For them their production situation in past three month refers to a different time period than for the ones who send back their questionnaires towards the end of the month. In this case the three month are overlapping and cover a weighted average of the four preceding month. To consider that possibility I tested two further specifications alternatively to (1) and (2):

IV) $\sum_{t=0}^{3} IP_{t+1} - \sum_{t=0}^{3} IP_{t-4}$ (4)

V) $\sum_{t=0}^{3} IP_{t+1} - \sum_{t=0}^{3} IP_{t-7}$ (5)

The industrial production indices for civil engineering and structures clearly showed some trend and rising seasonal variances. After take log-differences these series were checked by the Phillips-Perron test statistics for unit roots (see Table A1 in the appendix).

3.1 Nowcasting civil engineering

In order to find the best transformation of IP of construction industry, cross correlations between the different types of transformation of IP and the business survey data have been checked at various leads and lags. The one presented in (2) was highest and so explained best the characteristics of business survey data. This means that the seasonal pattern of IP can be best derived by the one found in the business survey data when the past three months are compared with the three ones before.

So the following model has been set up:

$$dIP_t^{civil} = ß_0 + ß_1 bs_t^{civil} + ß_2 dwork_t + ß_3\ deast_t + ß_4 dtemp_t \quad (6)$$

with $dIPcivil_t$ being the log-difference of three month sum of industrial production in civil engineering and *bs* the business survey data. In order to avoid multicollinearity of work days (*dwork*), eastern holidays (*deast*) and the temperature data (*dtemp*) with the season included in the business survey data, only their monthly deviations from long term averages are considered which are transformed by taking differences in a manner as applied in *IP*.

Table 1: Nowcast of civil engineering

Dependent Variable: DIPCIVIL
Method: Least Squares
Date: 06/29/10 Time: 14:48
Sample: 2004M09 2010M03
Included observations: 67
Convergence achieved after 13 iterations
MA Backcast: 2003M09 2004M08

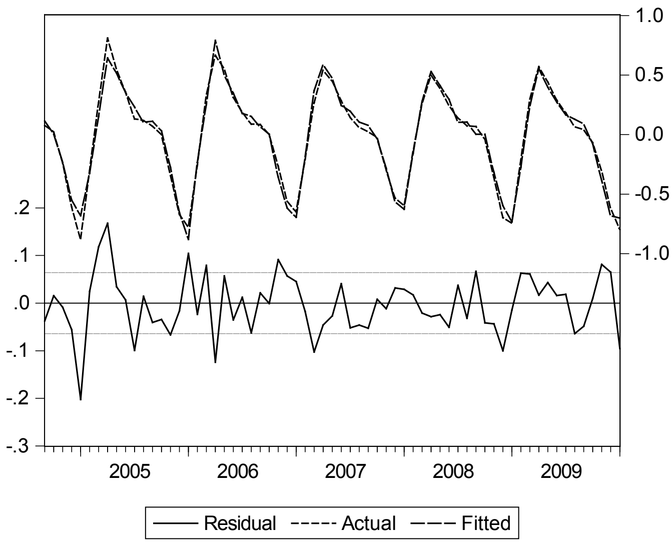
Variable	Coefficient	Std. Error	t-Statistic	Prob.
BS_CIVIL	0.429808	0.080385	5.346872	0.0000
BS_CIVIL(-1)	0.501907	0.084735	5.923273	0.0000
DWORK	0.011064	0.004582	2.414409	0.0188
AR(1)	0.558039	0.121585	4.589689	0.0000
MA(1)	0.768561	0.067696	11.35307	0.0000
MA(12)	0.280138	0.052283	5.358095	0.0000

R-squared	0.918760	Mean dependent var	-0.015844
Adjusted R-squared	0.912101	S.D. dependent var	0.401875
S.E. of regression	0.119147	Akaike info criterion	-1.331635
Sum squared resid	0.865954	Schwarz criterion	-1.134199
Log likelihood	50.60976	Hannan-Quinn criter.	-1.253509
Durbin-Watson stat	1.611114		

Potentially necessary shifts in the regressors have been tested by observing cross-correlations with stepwise remaining residuals. The selection of variables was done according to their significance as represented by their t-value as well as to the Schwarz information criterion. The business survey results were significant both for the coincident results as well as shifted one month backward. This seems to make sense, as the respondent send back there answers over the month. So part of them have a different reference period for the production of the past three month.

As auto-correlation tests applied to the residuals indicated still some remaining auto-regressive behavior, especially in the seasonal frequency domain, ARMA terms entered the equation as well (see Table 1). Eastern, temperature variations as well as the constant turned out to be insignificant but work day effects remained in the equation. This leads to the conclusion that work day variations play still significant role in construction output in Austria and are not taken into consideration by the entrepreneurs when answering their questionnaires. For Eastern and temperature effects it is unclear whether they are either already included in the business survey or do not play a decisive role in production variation. In order to check this, the business survey data was regressed on a seasonal ARMA-model with *dtemp* and *deast* as additional explanatory variables. Whereas *dtemp* could contribute to explain significantly part of the variance *deast* failed to do so (see Table A2 in the appendix). From this it can be concluded that business survey data asking for recent production development includes fluctuations due to unusual weather conditions but do not include work day effect and Eastern effects. The latter one turned out not to be an important factor in civil engineering output variation.

Figure 3: Industrial production of civil engineering



All in all, tracking variations of IP production in the construction sector by business survey data turned out to be astonishingly successful and more than 90%[2] of its variation can be explain by this. Figure 3 shows the original IP series of civil engineering as well as the fitted one, together with the residual variation.

3.2 Nowcasting structural construction

For nowcasting the industrial output of the structural construction industry a similar strategy - as outlined at civil engineering - was followed. Here it was possible to construct the model more parsimony. Just the business survey results shifted back by one period (maybe enterprises in the structural construction sector send back their questionnaires faster than in civil engineering) and an AR(1) term were sufficient to explain around 90% of the variations found in the IP data (see Table 2). Surprisingly the business survey data seasonal fluctuations described perfectly the one included in IP series, so no auto-regressive behavior at lag 12 in the residual could be observed. Furthermore work day variations, Eastern effects and unusual temperature fluctuations did not enter the equation due to their low explicative power. In order to check whether these effects are already included in the business survey data, an equation like in civil engineering was set up.

[2] The inclusion of a non-significant constant in order to interpret the adjusted R^2 statistics gave a value of 0.97 together with an F-statistic of higher than 100.

Again the temperature turned out to be significant when modeled the rest of the series as a seasonal ARMA model (see Table A3 in the appendix). Work day effects where only significant if they were shifted 2 month in the future which does not make sense from a theoretic point of view. Eastern holiday variations failed again.

Table 2: Nowcast of structural construction

Dependent Variable: DIPSTRUCT				
Method: Least Squares				
Date: 06/29/10 Time: 15:00				
Sample: 2004M09 2010M03				
Included observations: 67				
Convergence achieved after 6 iterations				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
BS_STRUCT(-1)	0.808955	0.046879	17.25626	0.0000
AR(1)	0.612466	0.099135	6.178093	0.0000
R-squared	0.907339	Mean dependent var		-0.003251
Adjusted R-squared	0.905913	S.D. dependent var		0.235152
S.E. of regression	0.072129	Akaike info criterion		-2.391314
Sum squared resid	0.338172	Schwarz criterion		-2.325502
Log likelihood	82.10901	Hannan-Quinn criter.		-2.365272
Durbin-Watson stat	1.877206			

3.3 Forecasting civil engineering production

Forecasting the production output of the construction sector with the business survey is not straightforward, as there exists no concrete question, like in manufacturing, about the production expectations in the future. Instead, I used here the expectations about the employment in the coming three month as a proxy for business activity. This time the series showed no break due to the change of the question so data back to January 1996 could be used. Again I tried the linear specification as used in (6) with shifting the variables 3 periods in the future (or the business survey regressor in the past).

$$dIP_{t+3}^{civil} = ß_0 + ß_1 bs_t^{civil} + ß_2 dwork_{t+3} + ß_3\ deast_{t+3} + ß_4 dtemp_{t+3} \qquad (7)$$

This time *bs* represents the employment expectation of the civil engineering sector for the coming three month. From a theoretical point of view, these survey results should not include work day variations and Eastern effects, as employment is typically not dependent on this. Of course this data should likewise not include temperature effects, as entrepreneurs cannot forecast weather conditions for the coming three month. So if these factors influence IP in civil engineering at all, they have to be considered separately in the equation.

Table 3 shows the results of the estimation. Instead of shifting all variables three periods into the future, the business survey data was shifted three month into the past. When forecasting the output of civil engineering it turned out that additionally business survey data shifted for a further period in the past to contribute significantly. The coefficient of the work day variable (0.010) gave a value similar to the one found in the nowcasting exercise (0.011). As the business survey and the work day effect variables could not represent all the dynamics found in the IP, ARMA terms were specified, too. Also a constant turned out to be significant.

Table 3: Forecast of civil engineering

Dependent Variable: DIPCIVIL
Method: Least Squares
Date: 06/29/10 Time: 18:38
Sample (adjusted): 1996M07 2010M02
Included observations: 164 after adjustments
Convergence achieved after 181 iterations
MA Backcast: 1995M07 1996M06

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMPCIVIL(-3)	0.364042	0.036894	9.867135	0.0000
EMPCIVIL(-4)	0.301940	0.038423	7.858330	0.0000
DWORK(0)	0.010485	0.004437	2.363084	0.0193
C	0.074511	0.033431	2.228783	0.0272
AR(1)	0.519982	0.082374	6.312426	0.0000
MA(1)	0.413703	0.083748	4.939865	0.0000
MA(12)	0.408194	0.071718	5.691666	0.0000

R-squared	0.905714	Mean dependent var	0.009554
Adjusted R-squared	0.902111	S.D. dependent var	0.357216
S.E. of regression	0.111763	Akaike info criterion	-1.503124
Sum squared resid	1.961087	Schwarz criterion	-1.370813
Log likelihood	130.2562	Hannan-Quinn criter.	-1.449411
F-statistic	251.3572	Durbin-Watson stat	1.727462
Prob(F-statistic)	0.000000		

Interestingly the temperature regressor showed no explicative power, whereas there was some evidence that such effects are included in the business survey concerning the past performance and therefore in IP. This result has to be questioned. Nevertheless, again a very large part of the IP variation could be explained as shows an adjusted R^2 value of 0.90.

3.4 Forecasting structural construction production

To study the forecasting power of the business survey in structural construction, a similar equation like (7) was estimated. Again not only the business survey lagged for three month but also the one lagged for four month turned out to explain significantly the variations in IP of the structural construction sector (see Table 4). Once more the explanation seems plausible that the respondents sending back their questionnaires very late have a different reference time for the coming three month than the one doing this earlier in the month. Work day variations beyond the seasonal pattern remained in the equation while temperature and Eastern variations again dropped out.

Table 4: Forecast of structural construction

Dependent Variable: DIPSTRUCT
Method: Least Squares
Date: 06/29/10 Time: 18:35
Sample (adjusted): 1996M07 2010M03
Included observations: 165 after adjustments
Convergence achieved after 13 iterations
MA Backcast: 1995M07 1996M06

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMPSTRUCT(-3)	0.349078	0.036506	9.562206	0.0000
EMPSTRUCT(-4)	0.331875	0.034945	9.497071	0.0000
DWORK	0.004427	0.001769	2.502939	0.0133
C	0.092580	0.029673	3.119974	0.0021
AR(1)	0.700818	0.065003	10.78124	0.0000
MA(12)	0.883622	0.025099	35.20477	0.0000

R-squared	0.942863	Mean dependent var	0.008794
Adjusted R-squared	0.941066	S.D. dependent var	0.246101
S.E. of regression	0.059744	Akaike info criterion	-2.761801
Sum squared resid	0.567531	Schwarz criterion	-2.648858
Log likelihood	233.8486	Hannan-Quinn criter.	-2.715954
F-statistic	524.7553	Durbin-Watson stat	1.570467
Prob(F-statistic)	0.000000		

Like in the other models, it was possible to explain with the again more than 90% of the variation found in IP.

4 Conclusions

Business survey data in construction seem to be a very vital source of information in now- as well as forecasting industrial production. Despite of its purely qualitative nature, quantitative IP changes can be explained very well. Seasonal variations included in the business survey results are in most cases different from those found in the respective IP production, but the residual seasonal pattern can be modeled quite good by seasonal ARMA terms. There remained further some dynamics which made it necessary to include ARMA terms for the cyclical part,too. A reason for that could be that survey data is more a kind of a diffusion index which represents the broadness of the cycle and not so much the strength. This behavior might be captured by cyclical ARMA terms.

Despite the fact that business survey data should not include seasonal variations by convention, the pronounced pattern in this respect leads to the conclusion that enterprises compare the quantitative values of their books when answering the questionnaire. In this case the results should also include variations due to the changing number of work days and potential fluctuations due to weather conditions. Enterprises which do not compare bookkeeping results when answering could disregard such kind of information.

For checking the suitability of nowcasts of IP in construction, I used a survey question concerning the development of the production in the past three month. As such a question was not available for the development in the future, I used the expected changes in employment in the coming three month instead.

In order to check whether additional factors help to describe changes in IP and in how far they are already included in business survey data, I tested separately temperature data and calendar effects like the different number of work days and the Eastern holidays. As these data show pronounced seasonal patterns, which inevitably would lead to multicollinearity problems in the estimation process, I just considered deviations of long term averages.

Temperature effects did not enter in any equation of the forecasting and nowcasting exercises which means either that they are unimportant for explaining IP in construction or that they are already included in the survey results. For the questions concerning the past I found that such variations are included in the survey. The forecasting exercise showed a contradictory result as this variable did neither enter in the forecasting equation nor can it be assumed that it is already included in the survey results of the future. Enterprises typically make no forecast about weather conditions.

Effects due to the change of the number of work days beyond their seasonal fluctuation turned out to be not included in business survey results but contributed significantly to nowcast production. This could be a hint that part of the enterprises do not fill in their questionnaires based on their quantitative results which should include such effects.

The other calendar effect – Eastern holidays – emerged neither to play an important role in industrial production of the construction sector nor to be included in the survey results.

It was shown that with the inclusion of work day effects and ARMA terms business survey results concerning future and past developments can explain in all cases over 90% of the variation in industrial production. Using such data can avoid a preprocessing for adjusting for seasonal variations and work days and therefore the implied endpoint problem at the recent time margin.

Appendix

Table A1

Transformation method	Phillips-Perron test statistics	MacKinnon p-values
I	-2.871	0.0223
II	-3.047	0.0354
III	-3.008	0.0327
IV	-2.966	0.0295
V	-2.732	0.0199

Table A2

Dependent Variable: BS_CIVIL
Method: Least Squares
Date: 06/28/10 Time: 15:33
Sample: 2004M09 2010M03
Included observations: 67
Convergence achieved after 10 iterations
MA Backcast: 2003M09 2004M08

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DTEMP(0)	-0.000459	0.000204	-2.248331	0.0281
AR(12)	0.792127	0.068572	11.55182	0.0000
MA(1)	0.515417	0.084549	6.096064	0.0000
MA(12)	-0.468869	0.089958	-5.212114	0.0000

R-squared	0.761221	Mean dependent var	0.012836
Adjusted R-squared	0.749851	S.D. dependent var	0.315632
S.E. of regression	0.157863	Akaike info criterion	-0.796332
Sum squared resid	1.570008	Schwarz criterion	-0.664708
Log likelihood	30.67711	Hannan-Quinn criter.	-0.744248
Durbin-Watson stat	1.715111		

Table A3

Dependent Variable: BS_STRUCT
Method: Least Squares
Date: 06/29/10 Time: 15:11
Sample: 2004M05 2010M03
Included observations: 71
Convergence achieved after 17 iterations
MA Backcast: 2003M05 2004M04

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DTEMP(-1)	-0.000279	8.70E-05	-3.209571	0.0021
AR(12)	0.900478	0.041875	21.50381	0.0000
MA(12)	-0.570617	0.050901	-11.21027	0.0000
MA(1)	0.682121	0.062170	10.97183	0.0000
MA(2)	0.543792	0.070798	7.680922	0.0000
MA(3)	0.260664	0.039694	6.566915	0.0000

R-squared	0.937692	Mean dependent var	-0.013803

Adjusted R-squared	0.932899	S.D. dependent var	0.277660
S.E. of regression	0.071925	Akaike info criterion	-2.345678
Sum squared resid	0.336254	Schwarz criterion	-2.154465
Log likelihood	89.27156	Hannan-Quinn criter.	-2.269639
Durbin-Watson stat	1.743039		

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