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Construction of a Survey-based Measure of Output Gap

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Abstract

The output gap derived by conventional methods is dependent on data from national accounts statistics. Consequently, the output gap is usually the subject of significant updates if hard data are revised. Reliability of output gap estimates can also be affected by properties of the applied method, for instance the end-point problem (e.g. in the commonly used HP filter). The aim of this paper is to offer a solid methodology to measure output gap using exclusively the output series and surveys that allow for a less uncertain assessment, while eliminating the endpoint problem. We present and apply a method of constructing the output gap from surveys in Slovakia. The method consists of principal component analysis and Kalman smoother applied to the first principal component. The path of the resulting output gap is fairly similar to the path of other measures of output gap, but its revisions (especially during the outbreak of the Great Financial Crisis) are smaller than those of traditional measures.

JEL code: E32
Key words: output gap, survey indicators, principal components, Kalman filter

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1. INTRODUCTION

The decomposition of log output into trend and cycle provides insights into potential output and slack in the economy, i.e. output gap. These variables are important for policy making, both for monetary and for fiscal policies. There are multiple methods of such output decomposition established in the literature.

1. Deriving the output gap from inflation impulses. This framework, pioneered by Kuttner (1994), uses a structural model with a Phillips curve and an IS curve as main ingredients. The output gap is determined with a Kalman filter as a latent variable. This approach was applied to Slovak data by Antoničová and Huček (2006). The structural model can be extended by financial variables (Borio et al., 2013). A reduced form alternative, based on an SVAR, was applied to Slovak data by Benčík (2008).
2. Deriving the trend by purely statistical means using a group of relatively simple methods (deterministic trends, HP filter or band pass filter), usually only the series of log output is used (HP filter can be generalized). These methods are widely used but they have serious shortcomings (for example the endpoint problem). Their application to Slovak data has been pioneered by Bors et al. (1999).
3. Constructing a composite leading indicator as a weighted sum of cyclical components of selected individual indicators leading the reference series, as done by Kľúčik and Haluška (2008).
4. Calculating the output gap as a first principal component of a small set of selected domestic and foreign variables, as done by Ódor and Jurašeková Kucserová (2014). Depending on the data, the resulting gap series may reflect broader relationships than the conventional output gap. Contrary to other methods, the output gap is computed without computing the potential output.
5. Deriving the potential output from a production function – this approach entails explicit modelling of the production process on a macro level, using series for factors of production (labor and capital, possibly other) and computing the equilibrium level of output from the estimated function with equilibrium levels of production factors as arguments. This is a relatively complex and data intensive approach, necessitating many explicit assumptions, for example about equilibrium employment (the current position of output gap requires an assumption about slack in the labor market). This

approach has been used in the framework of big macroeconometric models for Slovakia (for example Livermore, 2004, or Reľovský and Široká, 2009); a stand-alone production function was applied to Slovak data, for example by Benčík (2008).

The aim of this paper is to explore the capacity of available survey data for different sectors of the economy for the determination of output gap. This question has already been studied and is positively answered by Graff and Sturm (2010), who study the ability of (survey-based) capacity utilization to improve the estimates of output gap in a panel setting. They come to the conclusion that capacity utilization can indeed improve the estimates of output gap. Box 5 in the ECB Monthly Bulletin (June 2011) pinpoints the link between capacity utilization and output gap as well. More formal approaches can be fourfold:

1. Generalizing the inflation impulse approach, adding an equation for survey-based unemployment rate (Okun law) and another equation linking the output gap with the capacity utilization in the Kalman filter model, as done by Benes et al. (2010).
2. Generalizing the statistical approach, as in Trimbur (2009), who models the output gap and capacity utilization as stochastic AR(2) processes, using a specification allowing him to specify the period of oscillation and damping factor explicitly. This is also computed using a Kalman filter .
3. Aggregating the information from a smaller set of variables including capacity utilization with principal components, as done by Ódor and Jurašeková Kucserová (2014).
4. Aggregating the information from a broad array (several dozen) of survey data series and filtering/smoothing it with a Kalman filter/smoother. This is done by Hulej and Grabek (2015) for Poland.

The methods for computation of output gap using various macroeconomic variables in structural models are under the negative influence of publication lags and revisions of the series used. Hulej and Grabek (2015) show that their approach minimizes the consequences of the aforementioned problems, as it uses survey data only in the first step and output series in the second step. Simpler methods, like HP filter, have other serious shortcomings (endpoint problem). The aim of our project is to construct an analogous measure for Slovakia in order to obtain estimates of output gap with minimal requirements for National Accounts data, minimizing the uncertainty in the estimates for recent periods. In the first stage, we use principal components to extract the relevant information from survey data for different sectors and in the second stage we smooth them with a Kalman smoother. Subsequently, we examine the stability of our estimates relative to HP filter and the ability of various output gap measures to explain inflation.

The rest of the paper is organized as follows: section 2 lists the data used, section 3 presents the variant of principal components used, section 4 details the computation step by step, section 5 presents the results, section 6 contains the stability statistics, section 7 estimates Phillips curves with different measures of output gap and section 8 concludes.

2. DATA

The history of the Slovak economy is rather short; only two or three business cycles can be identified. We want to use as many series from as many sectors as possible on the one hand, but on the other, we aimed for the series with the highest number of observations possible. The final compromise is to use data from 1997Q1 to 2017Q1. We find it important that this sample captures the boom in 1997 and 1998 and a subsequent bust beginning in 1999, while using at least one indicator for the service sector.

The series used are surveys in the following sectors: construction (15 series), labor (4 series), manufacturing (12 series) and services/retail (6 series). They are listed in Annex 1.[2] Labor market series were retrieved as quarterly; the rest of the series is converted from monthly to quarterly averages. We used indicators for the domestic economy only, as did Hulej and Grabek (2015). Ódor and Jurašeková-Kucserová (2014), however, also included the indicators of trade partners alongside domestic indicators.

3. PRINCIPAL COMPONENT ANALYSIS

[2] The capacity utilization is intentionally included twice, as the series from Eurostat and OECD are different. It can also be argued that the capacity utilization is more closely related to the business cycle than other indicators in this group.

Principal component analysis (PCA) is a common tool used to transform the information contained in a group of series into a set of components (series) that are linear combinations of the original series and are orthogonal to each other. The components mimic the variance of the original set of variables in a way that the first principal component captures the greatest part of the variance of the original set of variables, the second component captures the second greatest part of variance and so forth. This property of principal components allows reduction of the dimension of a large set of variables while retaining a large share of their variance. We use the first principal component in our computations. It explains about a third of the variance of our set of series (see Annex 2). The first principal component explains a smaller part of total variance compared to using standard macroeconomic variables. This indicates that our data is more heterogenous.

We use the variant of principal components with normalized loadings.

The analysis starts with constructing sample covariance matrix S from original data matrix X. Its eigenvalues (in diagonal matrix Λ) and eigenvectors (in orthogonal matrix) A are computed so that

$$\mathrm{S} = \mathrm{A}\Lambda\mathrm{A}' \qquad (1)$$

and that

$$\mathrm{A}\mathrm{A}' = \mathrm{I} \qquad (2)$$

where I is the identity matrix. The components (scores) are then defined[3] as

$$\mathrm{Z} = \mathrm{X}\mathrm{A} \qquad (3)$$

and the loadings in this variant are equal to the eigenvectors matrix A

The original data can be reconstructed then as

[3] The first principal component from E-views is identical with the first column of the matrix Z, multiplied by a scalar factor. We have split the matrix X and the first column of matrix Λ into blocks corresponding to sectors and recreated the first principal component (scaled by the aforementioned scalar) as a sum of sectoral contributions.

$$X = ZA' \quad (4)$$

Further details about principal components can be found in Jolliffe (2002).

The last step is Kalman smoother, an extension of Kalman filter using the whole sample for computing all observations. Kalman filter is an iterative procedure consisting of predicting, observing and updating. Details can be found for example in Pollock (2002).

4. COMPUTATION OF SURVEY-BASED OUTPUT GAP MEASURE

The following part describes the computations step by step:

1. *Adjusting:* The data for principal component analysis have to be stationary. We assumed that the data for construction, manufacturing and services/retail are stationary by construction. The absolute employment and unemployment series were divided by population in the productive age bracket (15-64 years). As these ratios are bound by construction, we assume them to be stationary as well. The unemployment rate is highly serially correlated, but in the medium term it is mean-reverting, thus was assumed to be stationary.[4]
2. *Normalization:* The retrieved series had obviously different means and variances. In order to homogenize them, we normalized all series used (subtracted its mean and divided the difference by corresponding standard deviation).
3. *Weighting:* We have used the weighting algorithm of Pang (2011) to overcome the problem of the different number of series for each sector (construction, labor,

[4] The unit root tests for these variables are conflicting: both the ADF test and the KPSS test do not reject the null hypothesis (the former indicates non-stationarity, the latter stationarity). When interpreting the results we took two facts into consideration: firstly, that the series are typically very highly autocorrelated and secondly, that due to their construction, shares of employed and unemployed in the total population, as well as the unemployment rate are range-bound and/or mean-reverting in the long run. The high serial correlation is a problem in the ADF test, since this test may only distinguish highly serially correlated (but stationary) series from integrated series. We also consider the long run properties implying stationarity more important than (possible) non-stationarity in the medium-term run. We thus prefer the results of the KPSS test over those of the ADF test and treat the series as stationary. Unit root testing of unemployment rate is complicated by possible nonlinearity of the data generating process as well. Khraief et al (2015) test the stationarity of unemployment rate in most OECD countries (Slovakia is not included) allowing for non-linearity and find it stationary in most countries.

manufacturing and services/trade). Weighting equalizes the sectors with more series with sectors with fewer series avoiding their disproportionate relative importance.[5, 6]

4. *Principal components:* After adjusting, normalizing and weighting the data, we computed the output gap measure in two stages. In the first stage, we computed the first principal component from the set of our survey variables. We used the principal component computation with normalized loadings and computed the normalization for the score so that cross-products match the target.[7] The main results – eigenvalues relating to the shares of variance explained by single principal components and part of eigenvector matrix relating to the loadings of first two principal components – are shown in Annex 2. The first principal component explains almost one third of the variance, two principal components explain more than half. After visual inspection, we determined that the first principal component is most closely related to the business cycle (we present its trajectory later together with the results). This is in accordance with Ódor and Jurašeková Kucserová (2014), who use the first principal component as well. As a robustness check, we included the second principal component in the Kalman smoother alongside the first one, but the second principal component turned out insignificant while the first one retained significance.
5. *Kalman smoother:* The first principal component could still contain short-term noise. We proceeded according to Hulej and Grabek (2015) and constructed a simple Kalman fiter that links the first principal component to the decomposition of log output. By using the output series, certain sensitivily to data revisions is introduced into our measure. However, this would be true even if we linked the information from the first

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[5] Weighting of series in individual group (when there are more groups in the dataset) according to Pang (2011) consists of dividing the individual series by the square root of the number of series in the corresponding group. The series for the construction sector were thus weighted by multiplying them by $\sqrt{1/15}$, for labor by $\sqrt{1/4}$ and for manufacturing by $\sqrt{1/12}$, as there are fifteen, four and twelve series for these sectors. Reflecting the fact that the surveys for retail trade comprise employment tendency and stocks, we assumed that these surveys are linked to services rather than to personal consumption and included them together with the services survey in one sector. For the combined services and retail sector there are six series, but we consider the only service survey more important, as it is defined on a broader base than the series for retail. We implemented this assumption by multiplying the normalized series for retail by $\sqrt{1/7}$ and the series for services by $\sqrt{2/7}$. In this way, the sum of squared weights for every sector is equal to unity, so that the sectors can be supposed to have a comparable influence.

[6] The methodology of Hulej and Grabek (2015) is to a great extent robust to weighting. We have conducted the analysis with normalized series only, for the period from 1995 to 2017, and the results were very similar to the presented results from weighted series.

[7] The computations were carried out in E-views 9.

principal component to output decomposition by some other method.[8] The first principal component thus already corresponds to the cycle series alone (unlike the log output that is a sum of cycle and trend component, which can be separated by those filters). The last stage thus consists of decomposing the log GDP into log potential output and output gap with a Kalman smoother, using the first principal component as an exogenous variable linked to the output gap. The state space model consists of one signal equation and two state equations:

Signal equation:

$$y_t^G = y_t^* + y_t^R, \qquad (5a)$$

where y_t^G is log output, y_t^* is log potential output and y_t^R is (relative) output gap.

State equations:

$$y_t^* = \mu + y_{t-1}^* + \varepsilon_{pt} \qquad \varepsilon_p \sim N(0, \sigma_p) \qquad (5b)$$

and

$$y_t^R = \beta.pc1 + \varepsilon_{yt}, \qquad \varepsilon_g \sim N(0, \sigma_g) \qquad (5c)$$

where μ is drift parameter, ε_p is random element for potential, β is impact parameter, pc1 is the first principal component and ε_y is random element for output gap. We estimated the model using starting values of parameters set to what we considered to be a plausible guess of their value.[9] After estimating the model (parameter values and statistics are presented in Annex 3), we used Kalman smoother with diffuse prior to obtain the state variables. As a robustness check, we computed the states using Kalman filter as well, but their paths were almost identical, so that we report the result from

[8] We tried to use the HP filter on the first principal component (with λ=400), but the results were disappointing – both resulting series (trend and cycle) contained parts of variation attributable to the business cycle, with high ("cycle series") and medium term ("trend series") frequencies.

[9] The starting value for the drift parameter of potential output can be inferred from fitting a trend to output. The starting value for the parameter of the first principal component can be inferred from a regression of HP filtered output gap on the principal component. The starting values for variances of the error term were set higher than the SEE of corresponding regressions, as low starting values for these parameters often lead to problems in estimation (for example singular Hessian matrix). As a test for sensitivity with respect to starting values, we made additional eight estimates, multiplying each of the (four) starting values by 0.5 and 1.5 respectively. The estimation always converged to the same maximum of likelihood and the same parameter estimates as with the original starting values.

the smoother only. The smoother has the advantage that it uses data from the whole sample for computing states in all periods.[10, 11]

5. RESULTS

Principal components are linear combinations of original data and it is possible to express the first principal component as a sum of the contributions of sectors in the economy. We depict these contributions together with the first principal component in Figure 1a. The main drivers are the manufacturing and construction sectors. The contributions of these sectors have always the same sign as the first principal component. Services basically copy these two sectors, but their contribution is smaller. The contribution of labor is very small in most quarters, being somewhat significant only at the very beginning and very end of the sample. The results from the Kalman smoother are shown together with HP filtered output gap, the output gap measure calculated by NBS (derived from inflation impulses)[12] and the first principal component in Figure 1b[13]. The latter series is an intermediate result of our computations and we included it in order to show the condensed information extracted from the data and to clarify the impact of the Kalman smoother.

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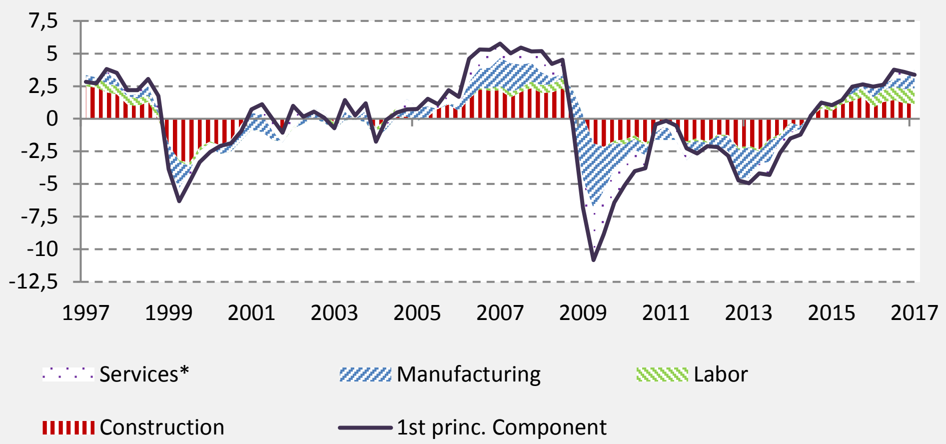
[10] Our version of state space model differs from that of Hulej and Grabek (2015), as we assume the random element in the equation for potential product to be independent from its past values and include drift in the equation, rather than assuming the random element to be a random walk without drift (the random elements will cumulate to a random walk because they enter the lagged value of the potential). We tried a specification similar to the cited paper, but the autoregressive parameter of the random element for potential turned out to be insignificant with Slovak data. The structure of the model of Hulej and Grabek (2015) would have to be literally imposed upon the data, without(?) the data supporting it. Thus, with respect to Occam's razor (the principle that entities are not to be multiplied without necessity) we preferred the simplest model that describes the data well and gives plausible results. The difference in the model specification may be caused by different time series properties of output for Poland and Slovakia.

[11] It is evident that the output growth slowed permanently in the Global Financial Crisis, beginning in 2009. Then it is plausible to ask whether the drift parameter μ shall be constant. We addressed this problem by estimating a version of state space model with a dummy in the equation for potential product, such that it had zero values before 2009 and one in 2009 and afterwards. This dummy, however, turned out insignificant, so we prefer the state space model structure presented above. We tried a model with the first and second principal components as well, but the second principal component turned out insignificant.

[12] This is the official estimate of output gap published by the National Bank of Slovakia, based mainly on Antoničová and Huček (2005).

[13] Unless stated otherwise, the values on the vertical axis of all graphs are fractions of relative output gap (e. g. 0.0x=x%).

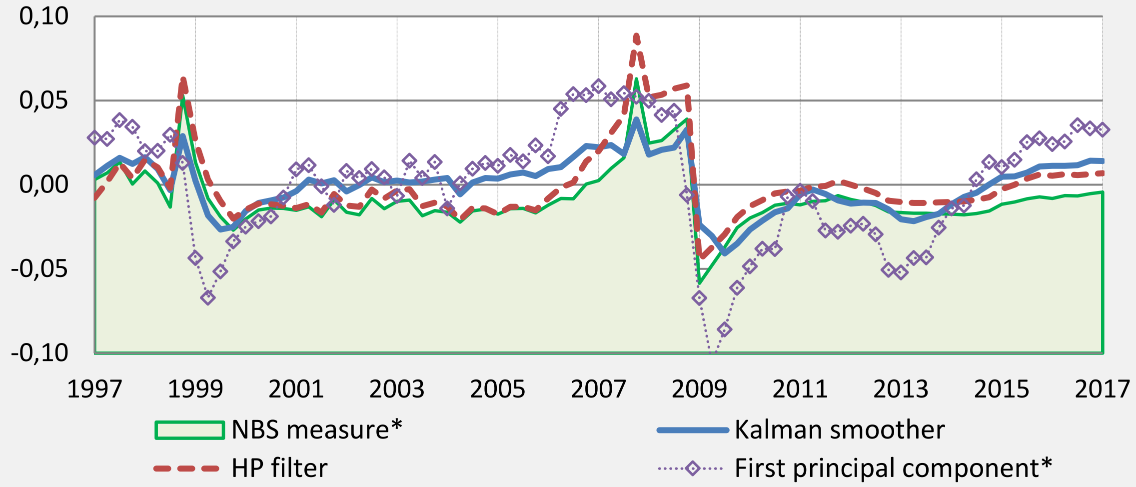
Figure 1a. First principal component and sectoral contributiions



Source: own calculations

*Note: * incl. retail*

Figure 1b. Different measures of output gap – time paths



Source: own calculations, NBS database.

*Note: * Values divided by 100*

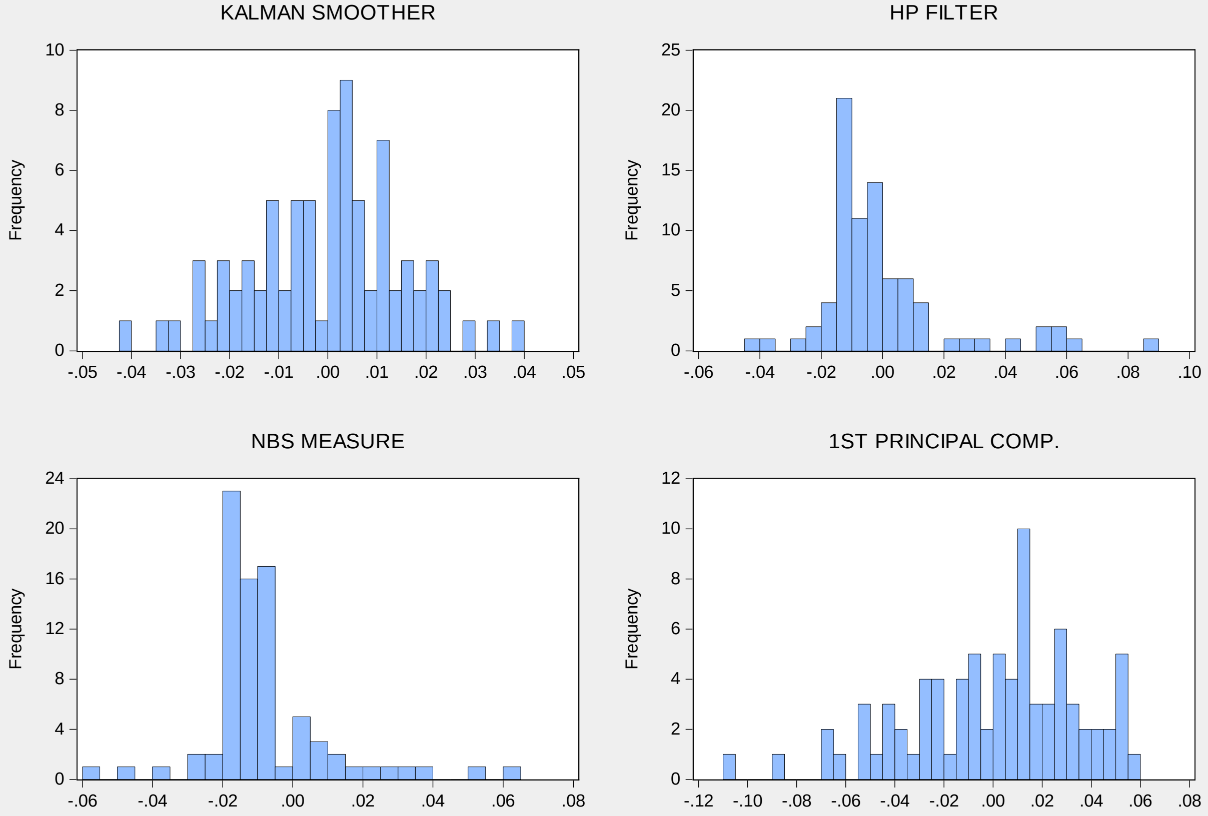
All four series have similar paths. They reflect the unsustainable boom in 1998, subsequent bust in 1999, relatively long period of output languishing slightly below or at the potential, the boom in 2007-2008, the bust during the Global Financial Crisis and a slight overheating after 2013 to present. The measure of the NBS and the HP filter are very similar, the result of Kalman smoother follows them in general, but is closer to zero and less volatile, the first principal component is in general aligned with the rest, but is slightly more volatile, especially after 2005.

The same data as in Figure 1 is presented in Figure 2 in a different form. This graph is included in order to pinpoint the different character of these time series. Distributions of various output gap measures and the first principal component hint at several aspects of their construction.

- First, the asymmetric distributions of HP filtered gap and NBS measure show that the right tail is rather thin and long and is not fully compensated by the left tail. Then, in order to maintain zero mean (mainly in the case of HP filter), the bulk of the mass of the distributions must shift to the left, so that these two distributions have their modes in a negative territory. This means that most observations in these output gap measures are negative and small.
- Second, the distribution of the first principal component is flat, with a distinct peak in positive territory. This means that the sectoral survey series used are aggregated in such a way that their extremes do not offset. The virtual lack of right tail in the distribution relates to a notably high frequency at the mode. The positive mode for this series may mean that the respondents to the surveys are moderately optimistic most of the time, but there are periods of pessimism, sometimes severe. This distribution is thus asymmetric, but not in the way of distributions of the HP filtered gap and the NBS measure.
- Finally, the approximately triangular distribution with modus near zero for the result of Kalman smoother shows that the Kalman smoother decreased the variability of incoming first principal component and centered it at approximately zero mean.

If we compare the distribution of the results of the Kalman smoother and the NBS measure, we can see that the survey-based measure probably will not be able to explain inflation better than the NBS measure, as its mode and general shape are very different from the NBS measure and the HP filtered gap. We will confirm this by estimating Phillips curves in Section 6.

Figure 2. Different measures of output gap – distributions



Source: own calculations, NBS database.

*Note: * Values divided by 100*

6. STABILITY OF THE OUTPUT GAP

In order to explore the stability of the estimates, we want to find out how the survey-based output gap measure changes when more observations are added to the sample and compare its performance with hitherto used output gap measures. The ability to determine the correct value of the output gap early is important for monetary policy especially when the business cycle enters a new phase, since some methods (mainly the HP filter) may have difficulty identifying turning points early. If the output gap estimate must later be revised, the monetary policy based on its original value is suboptimal.

Changes in the estimates of output gap result from two causes: revising existing data points and adding new data points. For output gap measures, both sources can contribute to output gap revisions and we will explore a case when past data is kept constant and only new observations are added (we will use the last vintage of the output series) and a case when both sources of output gap revisions are at work (use all data vintages). If all vintages of output series are used in the HP filter, the results change both due to revisions of past data and the end-point problem. If, however, only the last vintage of output is used, adding observations one by one, only the end-point problem influences the results. Surveys are usually not revised, so for the first principal component all revisions of past values of output gap are caused by adding new observations only. However, as the Kalman filter uses output as a signal, the revisions of past data have some impact in the survey-based measure as well.

The calculations for the HP-filtered output gap from the last data vintage were carried out as follows:

We removed the observations starting in 2009Q2 up to the last one from the sample and computed the survey-based measure and gap from HP filter using observations 1997Q1 – 2009Q1. Then we added the observation 2009Q2 to the sample (leaving the start of the sample the same) and recomputed the output gap measures. We continued by adding the observation 2009Q3 and recomputing and so forth, until we included the last observation from 2017Q1. Note that we normalized and weighted the series for each sample, as we would have done updating the output gap measure with incoming new data.

For the HP–filtered output gap for all vintages and the survey-based measure, we use the matrix of all available vintages of the Slovak GDP from the ECB Data Warehouse, the last observation of the shortest vintage being 2009Q1.[14] We compute the logarithm and perform the HP filter for all columns of this matrix (all available series) for all available observations in every series. Note that we normalized and weighted the series for each sample, as we would have done updating the output gap measure with incoming new data. There are more versions of output gap than in the previous cases, since the output series was updated more often than once in a quarter.

[14] The estimates of parameters of the Kalman filter were unstable for the shortest vintages, probably due to a small number of observations. These vintages were thus omitted.

6.1 Visual Inspection

Results from these computations are matrices with triangular section of n.a. values in the lower left corner. The columns of these matrices correspond to individual versions of the output gap for the respective method, rows correspond to quarters. The results are presented in Figure 3a-c.[15] For HP filter, the results are in two variants: first, using the latest series of output only (thus assuming that the series do not get revised) and second using all available vintages from the ECB Data Warehouse. For every quarter at x-axis in these graphs, the width of the array of output gap versions denotes uncertainty in output gap estimates in the respective quarter.

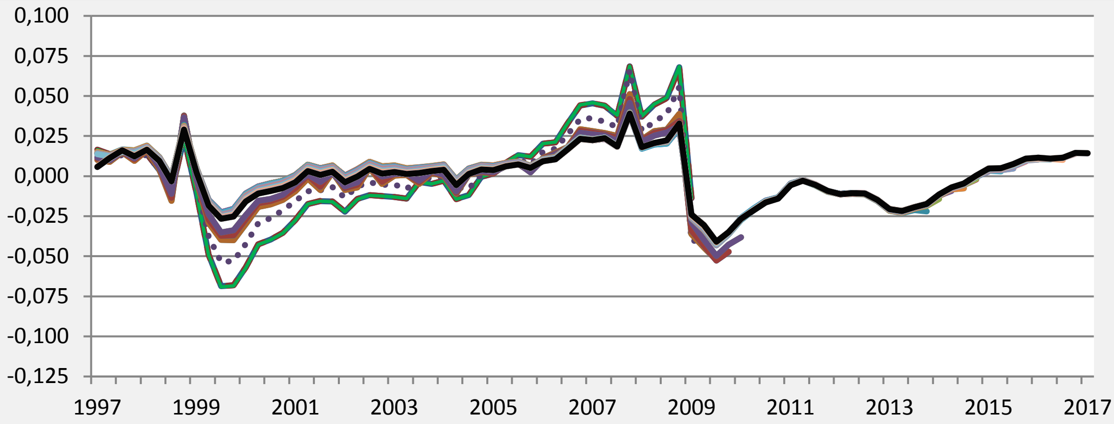
From the shapes of arrays of output gap versions for each method the following observations can be made:

- For the survey-based measure all observations in the sample are subject to visible revisions, including those at the beginning of the sample.
- The HP filter for the last vintage, however, leaves observations at the beginning more or less constant and significantly changes the observations in the (moving) end of the sample (manifesting the endpoint problem of the HP filter).
- The results for the HP filter for various vintages are revised in the whole sample, similarly to the survey-based measure.

The preliminary interpretation from Figures 3a – 3c is that while the HP filter has significant uncertainty at the end of the sample if output suddenly changes, the survey-based measure distributes the uncertainty in the beginning of the sample and the uncertainty in the newest quarters is minor. Thus, if the policy maker is interested in the current phase of the business cycle, the survey-based measure can be more precise than the HP filter. If the revisions of past data are taken into account, the HP–filtered output gap is revised in the more distant past as well. This means that the uncertainty of the HP-filtered estimates is not significantly smaller than the uncertainty of the survey-based measure for the past either.

[15] Every line in the graph depicts a series of output gap for a sample indicated by length of the line. We omitted the legend, as it would clutter up the graphs. For Figure 3a and 3b, every individual series has a different number of observations. For 3c, there are sometimes more than one series ending in the same quarter and having the same number of observations.

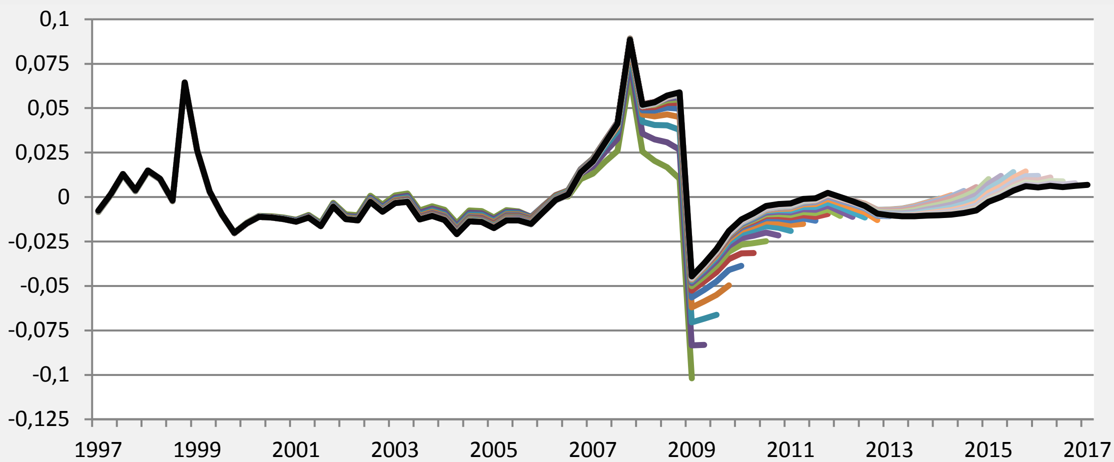
Figure 3a. Recursive estimates of survey-based output gap



Source: own calculations.

Note: See footnote 13 for details

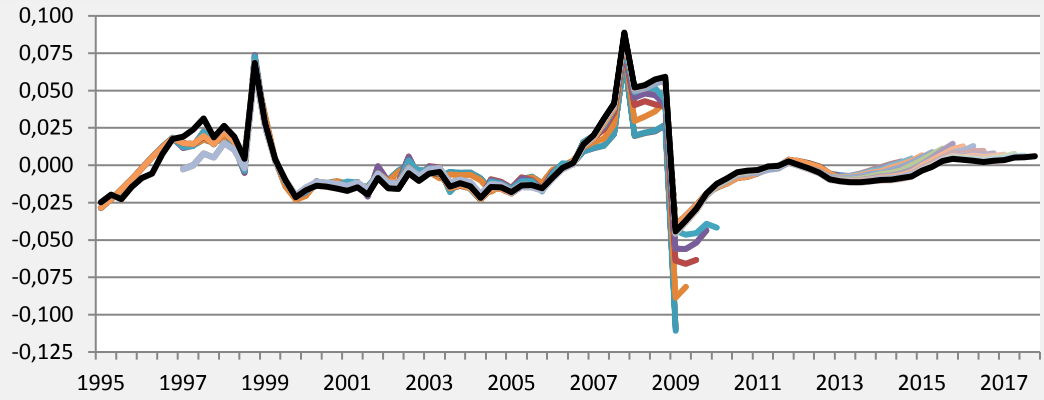
Figure 3-b. Recursive estimates of output gap from HP filter - the last vintage of GDP



Source: own calculations.

Note: See footnote 13 for details

Figure 3c. Recursive estimates of output gap from HP filter – all vintages of GDP

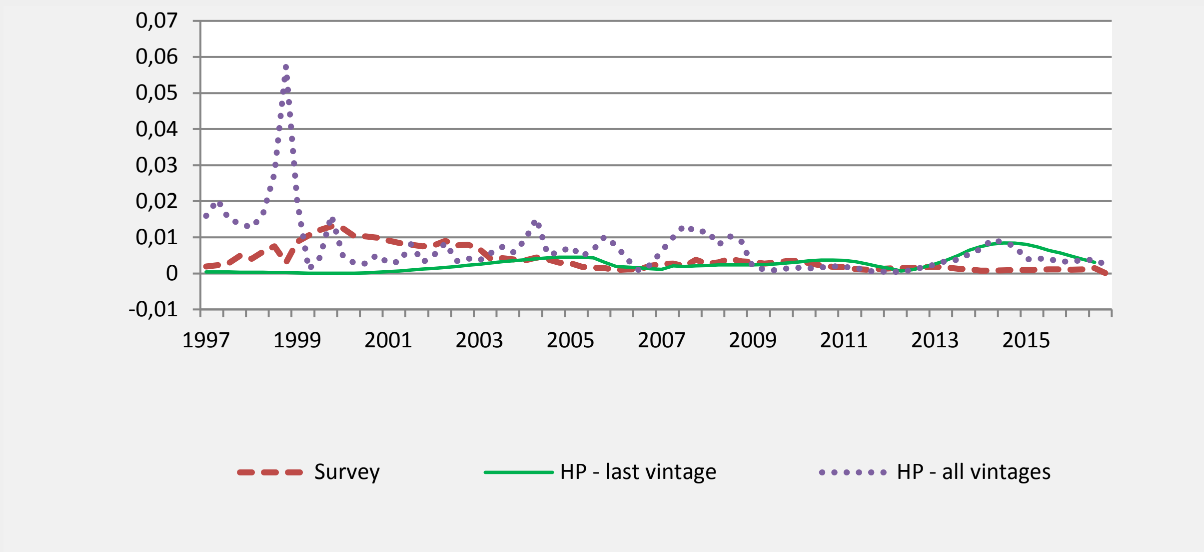


Source: own calculations.

Note: See footnote 13 for details

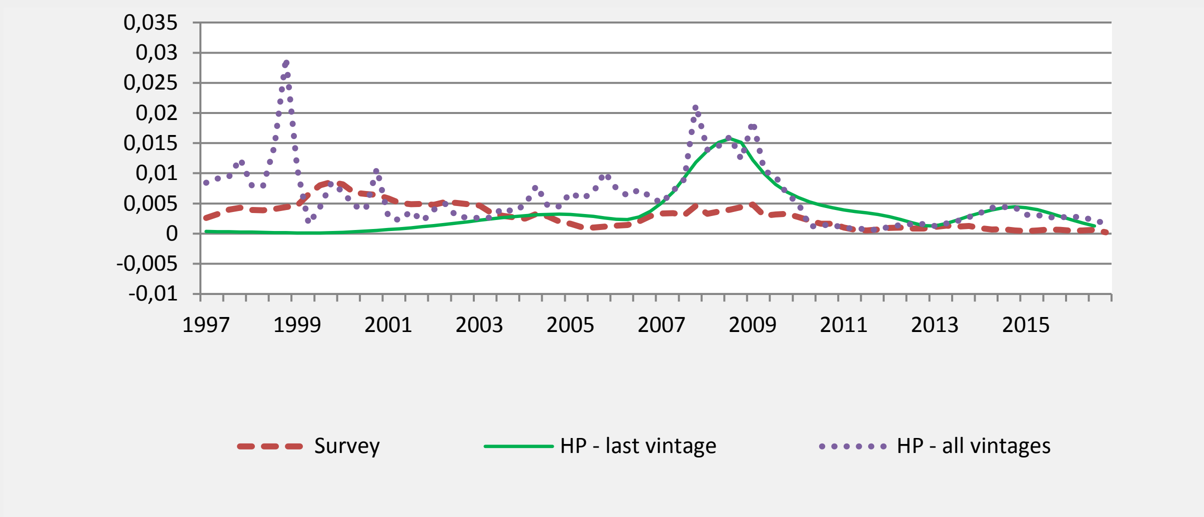
In order to illustrate the uncertainties of output gap estimates, we include the time series of inter-quartile range and standard error of output gap estimates for each period from 1997 to 2016 (there are too few estimates for the very end of the sample). While the inter-quartile range totally ignores the extreme value, standard error uses all observations. Figures 4a and 4b contain the same information as Figures 3a-c, but presented in a different way.

Figure 4-a. Inter-quartile range for output gap estimates



Source: own calculations.

Figure 4-b. Standard error for ouput gap estimates



Source: own calculations.

From the paths of both standard errors and inter-quartile range, it is evident that the instability of survey-based measure is concentrated in the beginning of the sample (and is likely caused by low degrees of freedom), while it is higher in the end of the sample for the HP filter (instability is caused by the end-point problem). It is also evident that the uncertainty of HP filter with all vintages (the realistic version) is higher than that of the survey- based measure in the period 2007 – 2009, when the business cycle turned.

6.2 MEASURES OF MAXIMUM UNCERTAINTY

To quantify the uncertainty of output gap for every aforementioned method, we computed the inter-quartile range and standard error for each quarter and picked the maximum for each method. These statistics are presented in Table 1. The maxima for the survey-based measure occurred in 2000, for HP filter with the last vintage in 2014 and for HP filter with all vintages in 1997. Considering that we study the stability of estimates in period 2009 – 2017, when we add observations, superiority of the survey-based measure is evident from Table 1. The lower variability for the HP filter for the last vintage does not invalidate it, because it was computed from much newer data than the other methods. It was included only in order to illustrate the endpoint problem with HP filter; output gap cannot be computed this way in real time. The survey-based measure has the advantage (compared with the HP filter for all vintages) that estimates for recent periods, that are most relevant for policy purposes, undergo smaller revisions.

Table 1. Maximum inter-quartile range and standard deviation

Statistics \ method	Survey-based – all	HP, last vintage of	HP- all vintages of
IQR	8.81	8.43	23.9
SE	13.0	12.2	18.7

Source: own calculations.

Note: all values multiplied by 1000.

6.3 AGGREGATING REVISIONS IN TIME

We can obtain more information when longer spans of new estimates are compared to a benchmark output gap. Moreover, assessment of the output gap is especially important in times of peaks and troughs of the economic cycle. In the very same period however, output data tend to be significantly revised. Therefore, it is necessary to test for stability of estimates between using revised and real-time information also during these dynamic periods. For this reason, we compute more formal measures in the form of mean compensated revisions (MCR) and mean absolute revisions (MAR) for one, two, four and eight quarters according to the formulas[16]

$$MCR_s = \frac{1}{ns}\sum(y_t|I_{t+s} - y_t|I_t) \qquad (6a)$$

and

$$MAR_s = \frac{1}{ns}\sum|y_t|I_{t+s} - y_t|I_t| \ , \qquad (6b)$$

where n is the number of non-missing revisions, s is step size (1, 2, 4, or 8 quarters), y is the output gap measure and I_t is the information set at time t. The measures are computed for the whole sample and for the year 2009 separately, because we are interested in the size of

[16] The matrix of vintages of the series for GDP contains two groups of series with different base year and there is a gap (some missing vintages) between them. When we compared revisions, we only used series with the same base year for each observation, but when computing the average revisions, we merged the revisions for both groups.

output gap revisions when output growth changes rapidly, as in 2009. The sums run over all non-missing revisions for the respective sample. The results are shown in Table 2.

Table 2. Statistics of revisions of output gap measures

Mean compensated revisions					
Method\step	1	2	4	8	2009
Survey	3.06E-05	6.76E-05	7.87E-05	6.94E-05	-0.006176
HP filter - last vint	1.65E-04	1.38E-04	1.03E-04	7.56E-05	0.012576
HP filter – all vint.	5.11E-05	5.55E-05	5.35E-05	3.51E-05	0.006472
Mean absolute revisions					
Method\step	1	2	4	8	2009
Survey	4.19E-04	4.51E-04	4.34E-04	3.48E-04	0.006176
HP filter - last vint.	3.99E-04	3.54E-04	2.85E-04	1.97E-04	0.012576
HP filter – all vint.	3.96E-04	4.08E-04	4.12E-04	3.30E-04	0.006637

Source: own calculations.

The mean compensated revision shows the systematic change in the average of revisions. Its value in Table 2 show that for steps up to one year the survey-based measure changes less than the HP filter, but for other steps, MCR for survey-based measure rises to the level of the HP filter. The survey-based measure might still be superior in turbulent periods, as the last column shows. Large revisions in 2009 for the HP filter using the last vintage demonstrate the severity of the end-point problem. The MCR for HP filter decreases with longer step, the MCR for survey-based measure does not.

The mean absolute revision is linked more to the variance of revisions caused by adding observations. This indicator is always greater than or equal to the previous one. We can see from Table 2 that MAR decreases for increasing step size for the HP filter, so that in this case the idiosyncratic variation cancels out. Contrary to Hulej and Grabek (2015), whose survey-based measure performed better than the HP filter, the MAR for the survey-based measure for Slovak data is always greater than the MAR for the output gap from the HP filter, even if all vintages of output are used. Contrary to the results for the whole sample, the survey-based measure is again superior in 2009. Additionally, when comparing the results for the whole sample, one should bear in mind that the survey-based measure is revised less for the moving periods at the end of the sample than the HP filter. Mean absolute and relative revisions are identical (apart from sign), all having the same sign for each output gap measure.

The aim of this study is to construct a more robust measture of output gap from survey indicator, as done by Hulej and Grabek (2015). However, contrary to their study for Poland, where the survey-based measure was always superior to HP filter, the results for Slovakia are mixed. When using all available vintages of output since 2009, it is evident from the comparison of absolute and relative revisions that the HP-filtered output gap is slightly superior to the survey-based measure, but the latter performs slightly better when the business cycle turns sharply. Instead of using the survey-based measure as a fully fledged alternative to conventional methods, for Slovakia, the survey-based measure is just a supplement of other methods that can indicate the changing phase of the business cycle. No conclusions shall be made upon the performance of the HP filter for the last vintage, as these computations were made in order to separate the impact of the endpoint problem and the impact of revisions when using this method.

7. ABILITY OF THE OUTPUT GAP MEASURES TO EXPLAIN INFLATION

The modelling of inflation with Slovak data is complicated by the fact that Slovakia is a small open economy, but it is nevertheless worth trying to examine various output gap measures in Phillips curve estimation. Our Phillips curves are analogous to those of Kupkovič (2016). They are homogenous in nominal variables. Three versions with output gap from HP-filter, survey-based measure and official NBS measure are estimated by restricted least squares. The equations have the form:

$$\Delta \log p_{net,t} = c_0 + c_1 * \Delta \log p_{net,t-1} + (1 - c_1) * \pi_t^{ex} + c_2 * y_t^R \qquad (7)$$

where p_{net} denotes net inflation (yearly), π_t^{ex} denotes inflation expectations and y_t^R denotes the output gap measure Parameters of these equations, as well as the t-statistics for output gap, R^2 and Schwarz criterion for each equation are shown in Table 3.

Table 3. Parameters of Phillips curve estimates

	HP	survey	NBS
c_0	0.00	0.00	0.00
c_1	0.87	0.86	0.87
c_2	0.07	0.06	0.09
t-stat	2.23	1.29	2.10
Rsq	0.92	0.92	0.92
Schwarz crit.	-7.26	-7.21	-7.25

Note: The values of c_0 have non-zero digits in higher decimal places

Source: own calculations.

As can be seen from Table 3, the estimates are very similar. However, it seems that the NBS measure and even the HP filtered output gap are better at explaining net inflation than the one based on survey-based measure. As we mentioned before, this may be the consequence of different shapes of distributions for different output gap measures. Furthermore, one can expect that the NBS measure will be superior, as it was derived explicitly from inflation impulses. The Schwarz criterion is lower for NBS measure and output gap from HP filter than for survey-based measure, indicating that the former models are better, but the difference is not statistically significant.

8. Conclusion

Surveys can not only improve the existing methods of estimation of the output gap, they can be used to construct an output gap measure themselves. We have adapted and applied the method of Hulej and Grabek (2015) to the data for the Slovak economy. Our results mimic in general the path of other output gap measures (derived from the Phillips curve, HP-filtered).

The survey-based measure, unlike the other output gap measures, has approximately triangular distribution centered around zero without notable outliers. With respect to stability, the better performing measure was the HP-filtered output gap for the whole sample[17], but the survey-based measure performed better in 2009, when there was a large turning point in the business cycle. The ability of various output gap measures to explain inflation was also tested . The asymmetrically distributed output gap measures (HP filter and NBS measure) fit marginally better into the Phillips curve than the survey-based output gap with a symmetrical distribution.

The survey-based measure has three advantages, compared to output gap measures based on aggregate data:

- lower uncertainty than the HP filter in the presence of steep changes in output growth rate
- the revisions after adding new observations are distributed more evenly in the whole sample, unlike the case of HP filter, when the revisions are concentrated in the end of the sample. A policy maker is mostly concerned about the current position in the business cycle, where the survey-based method gives more precise information.
- Surveys are published with shorter lag than most national accounts indicators, so the survey-based measure can be computed before the complete expenditure structure of GDP is published.

The output gap measure derived from surveys can thus widen the analytical toolbox of policymakers setting the correct monetary policy.

[17] This estimate can only be computed ex post, since it does not take into account revisions of the output series. When the revisions were taken into account, the survey based measure was superior to HP filter.

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ANNEX 1 LIST OF SURVEY INDICATORS USED

Identifier	Definition
WN_C_ASSURED	Construction, Duration of Assured Production, Balance, SA
WN_C_BUILD	Construction, Building Activity, Balance, SA
WN_C_BUILD_EXP	Construction, Expected Building Activity, Balance, SA
WN_C_CONF_TOT	Construction, Total, Balance, SA
WN_C_EMPL_EXP	Construction, Employment Expectation, Balance, SA
WN_C_LF_DEM	Construction, Limiting Factors: Insufficient Demand, Balance
WN_C_LF_EQUIP	Construction, Limiting Factors: Shortage of Material and/or Equipment, Balance
WN_C_LF_FIN	Construction, Limiting Factors: Financial Constraints, Balance
WN_C_LF_LAB	Construction, Limiting Factors: Shortage of Labour Force, Balance
WN_C_LF_NONE	Construction, Limiting Factors: None, Balance
WN_C_LF_OTH	Construction, Limiting Factors: Other, Balance
WN_C_LF_WEA	Construction, Limiting Factors: Weather Conditions, Balance
WN_C_ORDER_BOOK	Construction, Order Books, Balance, SA
WN_C_SIT_EXP	Construction, Expected Economic Situation, Balance, SA
WN_C_SPRICE_EXP	Construction, Selling Price Expectation, Balance, SA
WN_L_EMPLP	Labor, Employees (survey)*
WN_L_RU	Labor, Unemployment rate, SA
WN_L_TOTP	Labor, Employment (survey)*
WN_L_UP	Labor, Unemployment (survey)*
WN_M_CAPUTIL	Capacity Utilization, Manufacturing Industry (Eurostat)
WN_M_CAPUTIL_OECD	OECD MEI, Manufacturing Rate Of Capacity Utilisation, SA
WN_M_CONF	OECD MEI, Manufacturing Industrial, SA
WN_M_CONF_INDEX	OECD MEI, Manufacturing Industrial, SA, Index
WN_M_EMPL_FTEND	OECD MEI, Manufacturing Employment Future Tendency, SA
WN_M_FINGOOD_STOCK	OECD MEI, Manufacturing Finished Goods Stocks Level, SA
WN_M_ORDER_BOOK	OECD MEI, Manufacturing Order Books Level, SA
WN_M_ORDER_BOOK_EXP	OECD MEI, Manufacturing Export Order Books Level, SA
WN_M_ORDER_INFLOW	OECD MEI, Manufacturing Orders Inflow Tendency, SA
WN_M_PROD_FTEND	OECD MEI, Manufacturing Production Future Tendency, SA
WN_M_PROD_TEND	OECD MEI, Manufacturing Production Tendency, SA
WN_M_SPRICES_FTEND	OECD MEI, Manufacturing Selling Prices Future Tendency, SA
WN_R_CONF	OECD MEI, Retail Trade, SA
WN_R_CONF_SENT	Eurostat, Sentiment Indicators, Retail, SA
WN_R_EMPL_TEND	OECD MEI, Retail Trade Employment Future Tendency, SA
WN_R_SIT_TEND	OECD MEI, Retail Trade Business Situation Future Tendency, SA
WN_R_STOCKS	OECD MEI, Retail Trade Volume Of Stocks Level, SA
WN_S_CONF_TOT	Service Surveys, SOSR, Services, Total, Balance, SA

*adjusted series

ANNEX 2 EIGENVALUES AND LOADINGS OF FIRST FOUR PRINCIPAL COMPONENTS

Table 1A. Eigenvalues in principal component analysis (first ten)

Nr.	Value	Proportion	Cumulative Value
1	12.17794	0.3291	12.17794
2	7.788029	0.2105	19.96597
3	4.671793	0.1263	24.63776
4	2.452247	0.0663	27.09001
5	1.732672	0.0468	28.82268
6	1.362680	0.0368	30.18536
7	1.225385	0.0331	31.41075
8	1.105609	0.0299	32.51636
9	0.969944	0.0262	33.48630
10	0.520323	0.0141	34.00662

Source: own calculations.

Table 2A. Eigenvectors (loadings) in principal component analysis

Variable	PC 1	PC 2
WN_C_ASSURED	0.075964	-0.267025
WN_C_BUILD	0.218164	-0.117191
WN_C_BUILD_EXP	0.222320	-0.134393
WN_C_CONF_TOT	0.247364	-0.092284
WN_C_EMPL_EXP	0.238986	-0.083204
WN_C_LF_DEM	-0.143093	-0.159885
WN_C_LF_EQUIP	0.134676	0.001417
WN_C_LF_FIN	-0.162435	-0.009056
WN_C_LF_LAB	0.175294	-0.142612
WN_C_LF_NONE	0.131357	-0.203399
WN_C_LF_OTH	0.013115	0.267207
WN_C_LF_WEA	-0.006272	-0.075404
WN_C_ORDER_BOOK	0.242923	-0.096951

WN_C_SIT_EXP	0.230877	-0.110231
WN_C_SPRICE_EXP	0.104950	0.259904
WN_L_EMPLP	0.125036	-0.047788
WN_L_RU	-0.081743	0.297692
WN_L_TOTP	0.070890	-0.299213
WN_L_UP	-0.083178	0.293853
WN_M_CAPUTIL	0.216787	0.087612
WN_M_CAPUTIL_OECD	0.221041	0.087017
WN_M_CONF	0.188051	0.170624
WN_M_CONF_INDEX	0.189501	0.171432
WN_M_EMPL_FTEND	0.118378	-0.125325
WN_M_FINGOOD_STOCK	-0.006167	-0.036125
WN_M_ORDER_BOOK	0.236421	0.065173
WN_M_ORDER_BOOK_EXP	0.229507	0.073307
WN_M_ORDER_INFLOW	0.084015	0.185247
WN_M_PROD_FTEND	0.111812	0.221728
WN_M_PROD_TEND	0.126710	0.162791
WN_M_SPRICES_FTEND	0.062180	0.244023
WN_R_CONF	0.229754	0.026914
WN_R_CONF_SENT	0.229771	0.026821
WN_R_EMPL_TEND	0.121314	-0.062564
WN_R_SIT_TEND	0.202741	0.007974
WN_R_STOCKS	-0.055022	-0.022972
WN_S_CONF_TOT	0.120248	0.292026

Source: own calculations.

ANNEX 3 PARAMETERS OF STATE SPACE MODEL

The parameters are encoded as: μ =c(11), ε_p=c(22), β =c(31), ε_y=c(33)

Table 5A. Parameters of Kalman filter

Method: Maximum likelihood (BFGS / Marquardt steps)

Sample: 1997Q1 2017Q1

Included observations: 81

Initial Values: C(11)=0.01000, C(22)=0.02000, C(31)=0.00300, C(33)=0.01000

Convergence achieved after 58 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(11)	0.008875	0.001898	4.676916	0.0000
C(22)	0.012737	0.001844	6.905649	0.0000
C(31)	0.004329	0.001153	3.753512	0.0002
C(33)	0.007527	0.001667	4.515203	0.0000

Log likelihood 197.7880

Source: own calculations.