Discussion note

A note on statistical measures of underlying inflation

The price stability objective followed by modern central banks is to maintain annual inflation rates around, say, 2 % in the medium term. Since the HICP comprises hundreds of individual price items, inflation development is often distorted by significant, short-term, and reversible fluctuations of a small group of price sub-components (e.g. volatile energy and/or food prices, temporary large seasonal sales or seasonal price hikes) with a limited information value for monetary policy in practice. To help distinguish between a price signal, relevant for central bankers, and price noise, many central banks routinely monitor various statistical measures of core inflation. This note evaluates some of the popular measures regarding their ability to forecast headline inflation in Slovakia.[1] Our recommendation is to monitor persistence-weighted (PW) and exclusion-based (HICPX) core inflation measures – both having good statistical properties and performing reasonably well in other aspects.[2]

Measures of core inflation

The exclusion measures are based on eliminating traditionally the most volatile sub-components of inflation from the consumption basket. These tend to vary among countries, but in general it boils down to exclusion of food prices, energy prices, indirect taxes, and administrative prices. Two types of exclusion-based measures are considered here: HICP excluding energy, food, alcohol, and tobacco prices (labelled HICPX) and HICP excluding energy, food, and administrative prices (labelled NETX), see Figure 1 for details. The exclusion-based measures are often used by a number of central banks (see, e.g., Khan, Morel, and Sabourin (2015)) since they are easy to calculate, well understood, timely, and transparent. In addition, unlike many other methods, the exclusion-based measures provide a full control over demand- and supply-side factors. However, they do not allow for an ad-hoc adjustment of sudden price changes, implying that close attention needs to be paid to the selection of price components excluded from the basket.

A more flexible method of excluding volatile sub-components of inflation is to trim tails of the marginal distribution of price changes. Unlike standard exclusion measures, trimmed-based measures eliminate the most volatile components of inflation in every period. Although this method is also easy to calculate, timely, and more or less transparent, the resulting core measure might be more difficult to interpret. Probably the biggest shortcoming of this approach is to how determine the "optimal" level of trimming (see Bakhshi and Yates, 1999). The trimming proportion varies basically from 5% to 50%, depending on the country, data transformation, and metric used.[3] For this reason, three trimmed means (labelled TM 10, TM 30, and TM 50) with different trimming proportions (i.e. 10 %, 30 %, and 50 %) are considered in this note, see Figure 2 for details. Another possible shortcoming is that trimming causes a loss of control over demand and supply side shocks which can mask a signal for policymakers and, thus, cause a delay in policy measures (Bullard, 2011). Nevertheless, it seems that a weighted median (i.e. 50 % trimmed mean) exhibits good statistical properties (see, e.g., Smith (2004) and Mayer (2014)).

[1] A dataset employed in this note covers 87 price components of the Harmonised Index of Consumer Prices (HICP) in Slovakia. The data span the period January 2004 – August 2018. The year-on-year growth rates of price components are used in order to bypass a seasonal adjustment of individual components.

[2] Nevertheless, it is worth emphasizing here that the concept of core measures for forecasting headline inflation itself is outdated and new progressive forecasting methods can do a better job in this respect (see Faust and Wright (2013) for a comprehensive survey).

[3] For example, Bakhshi and Yates (1999) find the optimal level of trimming for the UK CPI data between 17 – 47 %; Bryan, Cecchetti, and Wiggins (1997) 9 % for the US CPI data; Brischetto and Richards (2006) report the results between 15 – 35 % for Australia, US, Euro area, and Japan.

Another method gaining increasing attention in recent years is based on a factor structure of price changes. In particular, it is assumed that there exists a small number of factors driving price movements in the economy. For computational simplicity, using principal components is often preferred compared to dynamic factor models (see, e.g., Khan, Morel, and Sabourin (2013)). We follow the mainstream literature and use the first principal component as a measure of core inflation. Although very popular in practice, factor-based core measures may suffer from substantial model uncertainty. In addition, the first principal component usually has a limited explanatory power of price movements (approximately 20 % in Slovakia) and, thus, the results can be difficult to interpret. The estimated first principal component is depicted in Figure 3.

Figure 1: All items HICP and exclusion-based core inflation measures

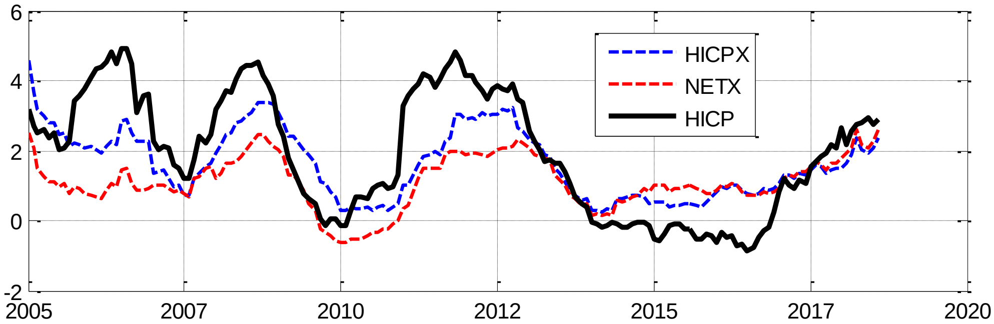
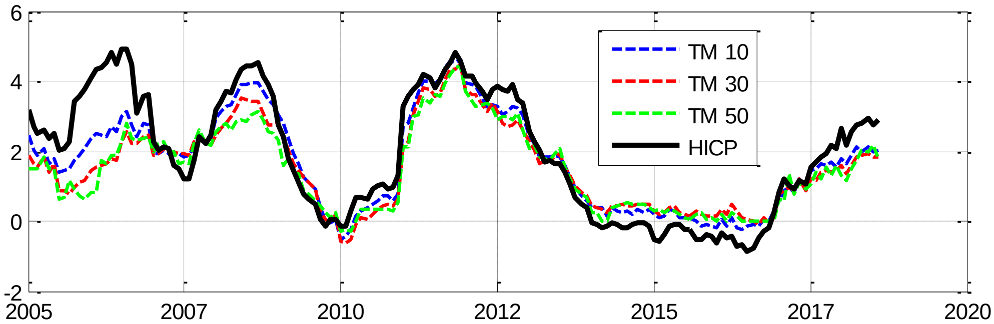


Figure 2: All items HICP and trimmed-based core inflation measures



Finally, we also consider two alternative measures sometimes used in the literature: a volatility-weighted (labelled VW) core inflation measure due to Diewert (1995) and a persistence-weighted (labelled PW) core inflation measure due to Cutler (2001) and Bilke and Stracca (2007). Although easy to calculate, a drawback, limiting their widespread use in practice, is that these methods are purely data-driven and do not necessarily respect HICP expenditure weights.[4] We show that this argument is to some extent odd and that both volatility-weighted and persistence-weighted measures roughly approximate the official HICP expenditure weights in Slovakia (see Figure 5 for details). The mean absolute deviation between the average HICP weights over 2005 – 2018 and the implied VW (PW) weights is only 0.05 (0.03). Both methods correctly down-weight food prices (CP01 category) and housing, water, electricity, and gas prices (CP04 category) in favor of less volatile and/or persistent price categories.

[4] The same argument applies, however, to other measures such as a weighted median, factor- and wavelets-based core inflation measures.

Figure 3: All items HICP and factor-based core inflation measure

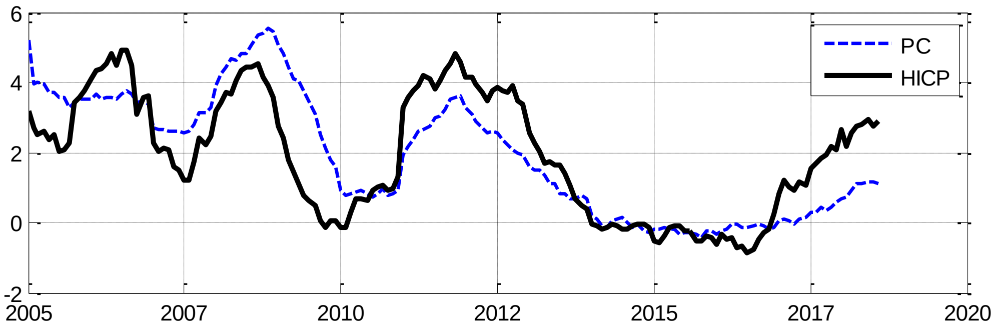


Figure 4: All items HICP and volatility-based and persistence-based core inflation measures

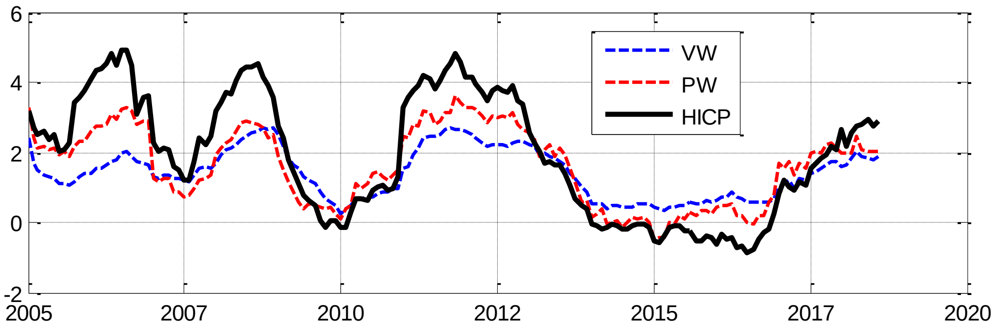
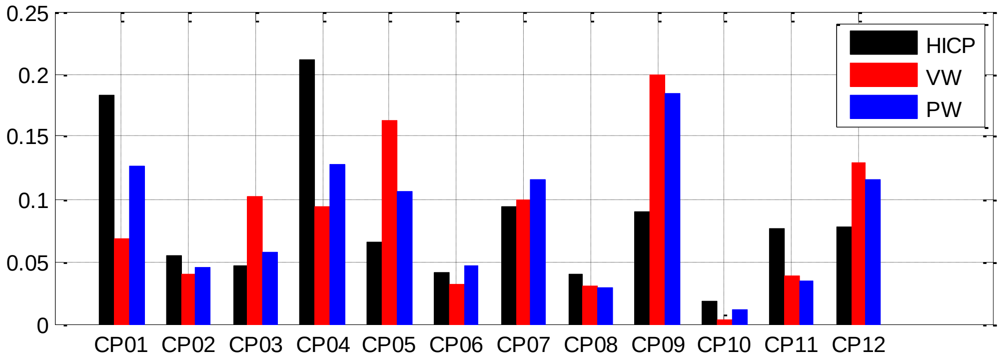


Figure 5: HICP weights and weights implied by VW and PW methods



Note: CP01 = Food & Non-Alcoholic Beverages; CP02 = Alcoholic Beverages, Tobacco & Narcotics; CP03 = Clothing & Footwear; CP04 = Housing, Water, Electricity, Gas & Other Fuels; CP05 = Furnishings, Household Equipment & Routine Household Maintenance; CP06 = Health; CP07 = Transport; CP08 = Communications; CP09 = Recreation & Culture; CP10 = Education; CP11 = Restaurants & Hotels, CP12 = Miscellaneous Goods & Services.

Additionally, there have been other statistical methods developed in the literature to calculate core inflation, for instance:

1. Sticky price CPI [Reiff and Varhegyi (2013)];
2. Wavelets CPI [Baqaee (2010)];
3. Unobserved Component CPI [Stock and Watson (2015)].

It is important to remark here that their contributions to monetary policy analysis are unknown and/or relatively marginal compared to the above listed methods. For this reason, only well-known methods are considered in this note.

Evaluating core inflation measures

Core inflation measures might be evaluated according to many different criteria (see Silver (2007) and Bermingham (2010) for a review). In practice, however, it is important to bear in mind that criteria (and their ordering) depend on the intended purpose of the measures – whether core measures are used for policy analysis or as a predictor of headline inflation. In the latter case (our objective), the core inflation measure should possess the following desirable characteristics (ordered according to their importance):

(i) a good predictor of headline HICP inflation;

(ii) stability of the core inflation estimates over time;

(iii) well understood by professionals and the general public.

Some comments are in order.

Summary statistics: Before we turn our attention to the predictive ability of the selected core inflation measures and their stability over time, it might be worth looking at basic summary statistics (a sample median, an inter-quartile range, and a Spearman (rank) correlation coefficient) of the measures. These are reported in Table 1. We find that core measures very efficient in reducing variance are often highly biased (see, e.g. NETX, TM 50, and VW). Only two measures seem to possess good statistical properties (TM 10 and PW).

Table 1: Summary statistics

	median	iqr	correl. coefficent
HICP	**1.97**	**2.53**	**1.00**
HICP excl. Energy, Food, Alcohol, Tobacco (HICPX)	1.51	1.21	0.81
HICP excl. Energy, Food, Administrative Prices (NETX)	1.02	0.69	0.61
Trimmed Mean (TM 10)	1.83	1.76	0.95
Trimmed Mean (TM 30)	1.55	1.37	0.88
Trimmed Mean (TM 50)	1.48	1.44	0.88
Principal Component (PC)	1.84	2.45	0.79
Volatility Weighted (VW)	1.38	0.92	0.88
Persistence Weighted (PW)	1.87	1.54	0.94

Predictive ability: Although predictive ability of core measures can be evaluated in different ways, a regression-based approach is convenient especially in situations where a limited number of data is available.[5] The regression approach is based on estimating the following equation

$$\pi_{t+h} - \pi_t = a + b\,(\pi_t^{core} - \pi_t) + \varepsilon_{t+h}, \qquad (1)$$

where π_t is headline inflation at time t and π_t^{core} is the core measure of inflation at time t. Following Clark (2007), we test for statistical significance of the estimated parameter b and overall goodness of fit by the coefficient of determination R^2. Note that the estimated standard errors, and thus the

[5] Note that a credible out-of-sample analysis is not feasible in our case due to a limited number of observations.

reported p-values, are adjusted for serial correlation and heteroscedasticity in the estimated residuals using the HAC procedure (with automatically selected tuning parameters). The estimation results for different forecast horizons *t+6*, *t+12*, and *t+18* are reported in Table 2. The results suggest that the core measure with the highest predictive content over the 6 – 18 months ahead is the persistence-weighted HICP followed by the volatility-weighted measure. Rather disappointing results are obtained from the trimmed means and the factor model over all forecast horizons.

Table 2: Estimates from predictive regressions

	t + 6			***t + 12***			***t + 18***		
	b	**pval**	**R^2**	***b***	**pval**	**R^2**	***b***	**pval**	**R^2**
HICP excl. Energy, Food, Alcohol, Tobacco (HICPX)	0.15	0.33	0.02	0.74	0.00	0.16	1.14	0.00	0.29
HICP excl. Energy, Food, Administrative Prices (NETX)	0.18	0.17	0.04	0.57	0.00	0.16	0.81	0.00	0.24
Trimmed Mean (TM 10)	0.25	0.48	0.02	0.94	0.04	0.09	1.13	0.00	0.10
Trimmed Mean (TM 30)	0.21	0.39	0.02	0.77	0.02	0.12	0.98	0.00	0.14
Trimmed Mean (TM 50)	0.22	0.35	0.03	0.84	0.01	0.15	1.06	0.00	0.18
Principal Component (PC)	0.05	0.85	0.00	0.49	0.24	0.07	0.84	0.04	0.14
Volatility Weighted (VW)	0.29	0.07	0.07	0.87	0.00	0.24	1.24	0.00	0.38
Persistence Weighted (PW)	**0.57**	**0.03**	**0.12**	**1.51**	**0.00**	**0.33**	**2.08**	**0.00**	**0.45**

Stability over time: Both exclusion-based and trimmed-based measures of core inflation are calculated only from the cross-sectional observations in each period and, thus, robust against estimation uncertainty. However, this is not the case for other approaches discussed in this note (i.e. factor-based, volatility-based, and persistence-based measures). Since all these measures are calculated using both time and cross-sectional information, they are obviously not robust against estimation uncertainty. To make this point clear, we evaluate the robustness of the above measures over time. We start by estimating the selected core inflation measures from a reduced sample spanning the period January 2005 to December 2014. Then we extend the estimation window by 6 months in each step up to reaching the full sample spanning the period January 2005 to June 2018. This approach gives us 8 recursive estimates for each core inflation measure. The results are depicted in Figures 6 – 8. The black line denotes the HICP inflation over the whole period whereas the blue lines represent core measures calculated from different sub-samples. The results clearly demonstrate significant estimation uncertainty of the factor-based core inflation measure in Slovakia. In contrast, both volatility- and persistence-weighted estimates of core inflation are extremely stable over time.

Figure 6: Recursive estimates of factor-based core inflation measure

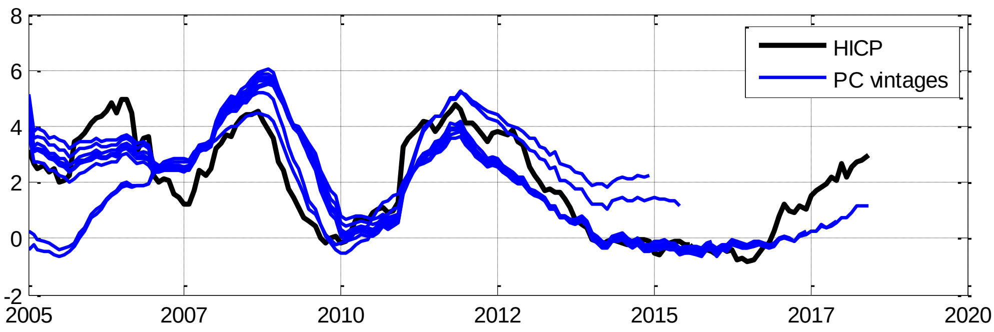


Figure 7: Recursive estimates of volatility-weighted core inflation measure

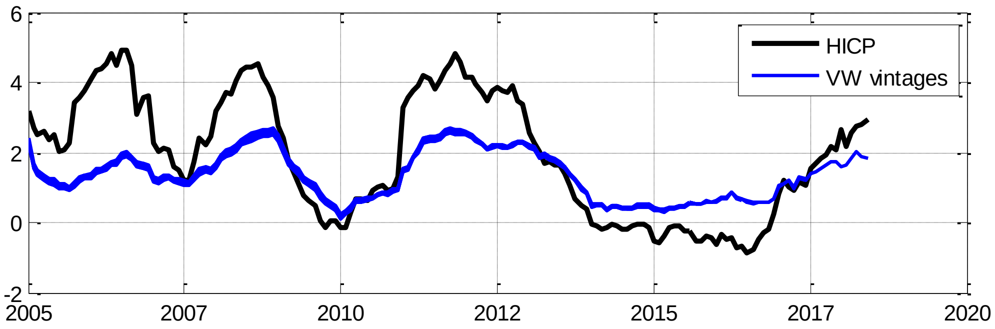
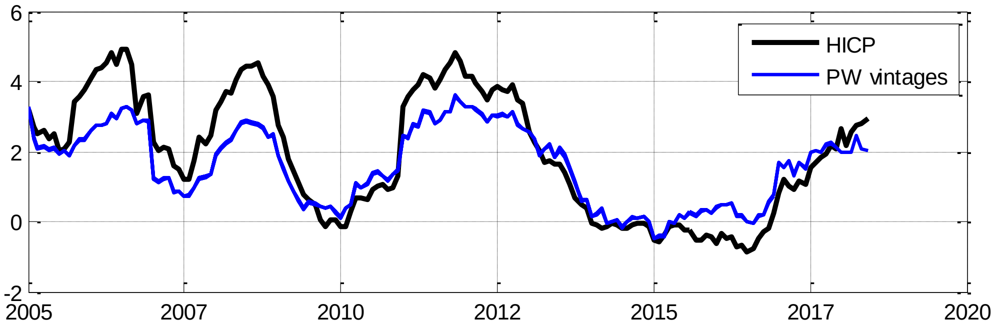


Figure 8: Recursive estimates of persistence-weighted core inflation measure



Summary and conclusion

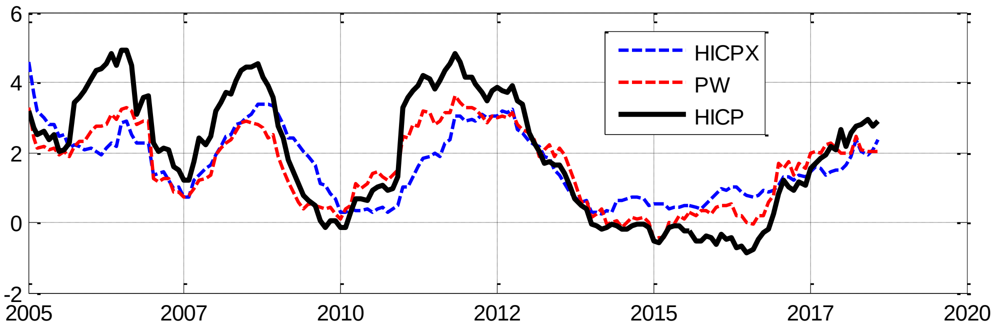
The evaluation criteria for core inflation measures are summarized in Table 3. The factor-based measure is not recommended since it is not sufficiently stable over time, exhibits poor forecasting performance, and we have justified concerns about how well this approach is understood by economic professionals and the general public. Trimmed-based and volatility-weighted measures are not recommended since they are outperformed by other competitors in some key characteristics. This leaves us with two alternatives as preferred core inflation measures – persistence-weighted (PW) and exclusion-based (HICPX) – both having good statistical properties and performing reasonably well in other aspects. The behavior of the two recommended measures is depicted in Figure 9. We conclude by suggesting that future research could be devoted to further improvements of the persistence-weighted core inflation measure (e.g., using bias-correction AR-based persistence, robust measures of persistence, measures of persistence suitable for non-linear time series data, and their combinations).

Table 3: Evaluation of core measures

	Exclussion-based	Trim-based	Factor-based	Volatility-based	Persistence-based
Good predictor	3	4	5	2	1
Stability over time	yes	yes	no	yes	yes
Well understood	yes	yes	no	no	no

Note: "1" denotes the best forecasting performance while "5" the worst forecasting performance among the selected core inflation measures (see text for details); "yes (no)" denotes that a given criterion is (or is not) satisfied.

Figure 9: Comparison of recommended core inflation measures



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