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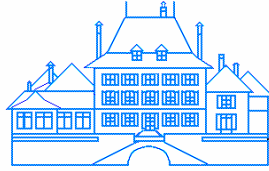
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STUDIENZENTRUM GERZENSEE

STIFTUNG DER SCHWEIZERISCHEN NATIONALBANK



Sequential Information Flow and Real-Time Diagnosis of Swiss Inflation:

Intra-Monthly DCF Estimates for a Low-Inflation Environment*

Marlene Amstad and Andreas M. Fischer

Working Paper No. 04.06

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Sequential Information Flow and Real-Time Diagnosis of Swiss Inflation:

Intra-Monthly DCF Estimates for a Low-Inflation Environment*

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Abstract

The timely release of macroeconomic data imposes a distinct structure on the panel: the clustering and sequential ordering of real and nominal variables. We call this orderly release of economic data *sequential information flow*. The ordered panel generates a new class of restrictions that are helpful in interpreting the real-time estimates of monthly core inflation through the identification of turning points and structural shocks. After establishing the sought-after properties (of smoothness, stability, and forecasting) for core inflation, we turn to the discussion of real-time diagnosis for a low inflation environment. This is done in the context of weekly estimates of Swiss inflation. The intra-monthly estimates for core inflation find that it is worthwhile to update this measure at least twice a month.

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Introduction

Coincident indexes based on monthly panel data have established themselves as popular measures of core inflation. The empirical framework follows either the dimension reduction techniques of Stock and Watson (1999) or Forni *et al.* (2000). Examples include Stock and Watson (2002) for the United States, Cristadoro *et al.* (2002) for the euro area, Gosselin and Tkacz (2001) for Canada, and Camacho and Sancho (2003) for Spain. To be useful for policymakers, it is commonly recognized that the coincident indexes should exhibit three properties. The first is smoothness. Idiosyncratic noise should be purged from core inflation such that the sought-after measure captures only the long-run cycle. This implies that core inflation should exhibit lower volatility and greater persistence than inflation measured by the Consumer Price Index (CPI). Next, the most recent observations of core inflation should not be heavily influenced through filtering procedures or future data revisions. This second property implies that the core's estimates of the underlying price pressure, even if based on limited information, should be relatively stable. A further property, which has received considerable attention, is forecasting. At a minimum, the third property says that the core measure should lead inflation.

An important feature, however, missing in the dynamic factor analysis of the above mentioned studies is that they do not make use of what we call *sequential information flow*: the timely release of real and nominal data imposes a distinct structure on the panel. When data releases are clustered, we argue it is worthwhile to estimate core inflation at intervals shorter than a month. First, the updated estimates can change after embodying information from the bunched releases. If the model’s innovations are highly autocorrelated, then this may provide ‘confirming’ information of a turning point. Second, if the clustered data releases follow a particular ordering, i.e., the month’s nominal variables precede the real variables, the timing sequence of information flow provides a useful restriction in shock identification. Such information and the need to weigh incoming information against what is already known is important, in particular, for policymakers that review their monetary policy stance more than once a month: examples include the European Central Bank and the Swiss National Bank (SNB).¹

The paper’s objective is to show that intra-monthly estimates of core inflation offer important information for policymakers and model identification

¹The board of both central banks hold regularly scheduled meetings that discuss monetary policy and conjunctural issues on a bi-weekly basis.

beyond that is established by the properties of smoothness, stability, and forecasting. The real-time diagnosis of core inflation uses the restrictions that arise from sequential information flow to identify turning points and structural shocks. The empirical framework employs the dynamic common factor methodology of Forni *et al.* (2000 and 2003) with a strong emphasis on cross-sectional smoothing for Swiss inflation from 1994 to 2004: a period where Swiss inflation averaged below 1.0%. Our challenge is thus to show that it is possible to construct useful measures of core inflation for real-time policymaking even in a low inflation environment.

The paper is organized as follows. Section one motivates the need for intra-monthly estimates of core inflation: both from the perspective of monetary policy analysis and in understanding the influence of sequential information flow on core inflation. Next, the main features of our data set and the decisions motivating our choices are outlined in section two. The empirical estimates of the monthly Swiss coincident index, hereafter Swiss Coin, are presented in section three. Here, the attributes of Swiss Coin are discussed in the context of smoothing, stability, and forecasting. This is done to show that the information from the intra-monthly estimates stem from sequential information flow and not from model instability. After establishing that the

sought-after properties are fulfilled for our monthly data set, we turn to the paper’s main empirical results of real-time diagnosis in section four. This entails the identification of the turning points and the innovations of Swiss Coin’s intra-monthly estimates. The last section offers concluding remarks.

1. Empirical Framework for Intra-Month Estimation

Sequential order flow and real-time diagnosis are interlinked. To motivate the two concepts, it is first important to demonstrate the timing sequence of daily data releases.² This is followed by the empirical setup along with definitional concepts useful for diagnosing real-time estimates of core inflation.

The Timing Sequence of Data Releases

To illustrate the timing sequence of data releases, Figure 1 shows the Swiss data releases for the month of December 2003. The plot of daily releases encompasses 434 monthly variables, which are divided into real and nominal variables. Two characteristics of data releases are important for understanding sequential information flow. The first is the concentration of

²Studies that review the properties of real-time data, say Runkle (1998), Croushore and Stark (2003, 2000), and Stark (2002), focus on data sets with a monthly cut off point at best. The Philadelphia Fed project, for example, has set its cut off point on the 15th of each month.

monthly releases in the first and third week. There are 274 variables released in the first week and 111 in the third week. The bunched releases suggest that the estimates of core inflation may change considerably as new information comes in after the first and third week of each month. This conjecture is tested in the empirical section on real-time estimates of core inflation.

A second characteristic of the timing sequence is that the releases of nominal variables in Figure 1 are dominated by November's CPI data in the first week and the releases of real variables are driven by the external trade data for November in the third week. Obviously, the ordered division between nominal and real variables is not exact and may vary over time. However, for our real-time diagnosis of core inflation it is important that the Swiss CPI release follows a regular pattern: i.e., bunched releases of nominal variables precede real variable releases. This pattern of sequential information flow illustrated for Switzerland in Figure 1 should be valid for many countries.³

The Intra-Month Setup

To facilitate the discussion of sequential information flow and monetary

³Kliesen and Schmid (2004) show a frequency distribution for releases of 35 macroeconomic variables. Their results support the clustering phenomena but they do not consider the role of ordering between nominal and real variables.

polycymaking in real time, we define a framework for intra-month estimation following Forni *et al.* (2000). Let, $x_t = (x_{1,t}, x_{2,t}, \dots x_{N,t})'$, where $x_{1,t}$ defines monthly CPI inflation. We assume that the N variables in the panel are measured with error and that they can be decomposed into the sum of two orthogonal components: the signal $x_{i,t}^*$ and the measurement error $e_{i,t}$ for variable i for month t is specified as

$$x_{i,t} = x_{i,t}^* + e_{i,t}. \quad (1)$$

Next, under suitable conditions on the variance-covariance of the x 's defined in Forni *et al.* (2000), $x_{i,t}$ is specified as a generalized dynamic factor model:

$$x_{i,t} = \chi_{i,t} + \xi_{i,t}, \quad (2)$$

with the matrix of the common component, χ_t , partitioned into a nominal and real block

$$\begin{aligned} \chi_t &= \begin{pmatrix} \chi_t^n \\ \chi_t^r \end{pmatrix} \\ &= \begin{pmatrix} b_{nn}^0 & b_{nr}^0 \\ b_{rn}^0 & b_{rr}^0 \end{pmatrix} \begin{pmatrix} u_t^n \\ u_t^r \end{pmatrix} + \dots + \begin{pmatrix} b_{nn}^q & b_{nr}^q \\ b_{rn}^q & b_{rr}^q \end{pmatrix} \begin{pmatrix} u_{t-q}^n \\ u_{t-q}^r \end{pmatrix}. \end{aligned}$$

The common component, which captures that part of the series correlated with the rest of the panel, is of rank 2. The two-dimensional vector of common shocks, i.e., nominal and real, is defined by $u_t = (u_t^n, u_t^r)$, $b_i(L)$ is a row vector of polynomials in the lag operator of finite order, and the idiosyncratic component $\xi_{i,t}$ is orthogonal to u_{t-k} for all k and i .

To capture the influence of sequential information and lagged data releases on $\chi_{i,t}$, the variable of interest is a backcast conditional on information that is released in the future, i.e., $\chi_{i,t|j,t+k} = E[\chi_{i,t}|\Omega_{j,t+k}]$, where $\Omega_{j,t+k}$ refers to information from the j th week in the $t+k$ th month. In a similar manner, we define the innovation of inflation's common between week j and week $j-1$ as $\epsilon_{1,t|j,t+1} = \chi_{1,t|j,t+1} - \chi_{1,t|j-1,t+1}$. This includes the innovation of the first week of month $t+1$, which is defined as $\epsilon_{1,t|1,t+1} = \chi_{1,t|1,t+1} - \chi_{1,t|4,t}$.

Useful Concepts for Real-Time Diagnosis

Central banks are reluctant to undertake policy change on the basis of two or three monthly observations. Rather they seek continuous confirmation of directional change through a series of observations that tends to move in the same direction. In a similar manner, real-time estimates of core inflation are able to determine if new incoming information is generating autocorrelated innovations in the common component or if the innovations are random. In

the former case, this would be evidence of what we call *directional confirmation* and would help monetary authorities assess the conjunctural situation. Such information is sought particularly for identifying possible turning points in core inflation. Directional confirmation says something about the breadth of real-time information that is consistently pushing core inflation in a single direction.

A further issue for the policymaker is the identification of the innovation of the common component. The sequential data releases of nominal variables followed by real variables impose a particular structure on the information set (i.e., no contemporaneous information of real shocks during the first week of the month according to Figure 1). As a consequence, when the practitioner projects the panel's variables on the weekly information sets a peculiar result emerges; the common's contemporaneous innovations are generated either by nominal or real shocks. Based on the data releases shown in Figure 1, the model's innovations from the third week of the month, the difference in the estimates between the third and the first week of each month, can be interpreted as real shocks. Similarly, the common's innovations from the first week, i.e., the difference in the estimates between the first week of month t and the third week of month $t-1$, can be interpreted as nominal shocks. This

result hinges on the restriction stemming from sequential information flow together with an economic restriction of contemporaneous price stickiness. The advantage of this identification scheme is that it is possible to interpret the smoothed (contemporaneous) innovation without having to use the SVAR framework as in Giannone, Reichlin, and Sala (2002). The result is shown formally in the Appendix 1.

2. The Data

All series used to construct the data set from 1993:5 to 2004:5 are taken from the SNB's data bank.⁴ A large share of the data is systematically reviewed by SNB economists and thus does not represent new information. The data set's contribution should primarily be regarded as replicating the contours of a data-rich environment in which the central bank operates.

Three key decisions motivated the construction of our data set. The first was to work with daily and monthly data.⁵ Although the SNB's forecasting

⁴The SNB enters the data in its data bank immediately upon arrival. Thus, the lumpiness of the data releases depicted in Figure 1 reflects the information flow from the point of the empirical practitioner. It cannot be excluded that delays exist between the time of the data's public release to the time it is sent to the SNB.

⁵The daily data are financial variables. While Forni *et al.* (2003) motivate their use in

efforts are concentrated at the quarterly frequency, the decision not to work with frequencies greater than a month is intentional for the policy exercise described in the introduction. We are concerned with the problem of how to weigh the most recent information against what we already know at regular intervals less than a month. The SNB is systematically confronted with this issue under its new policy strategy based on inflation forecasting, because the governing board reviews its monetary policy decisions on a bi-weekly basis. This explains why the timing of the SNB's interest rate decisions listed in calendar weeks in Table 1 does not follow a recognizable pattern.

A second concern in constructing the panel was to define the sample length of the so-called low-inflation regime. Officially, the SNB does not have a self-declared regime of low inflation. A time period under 10 years was felt to be too restrictive for the Forni *et al.* (2000) procedure and hence a starting date of May 1993 that coincided with the CPI basket revision was selected.

Third, we follow the advice of Bernanke and Boivin (2003) that *more is* forecasting inflation and output, in our setup they serve as important information for the nowcasts. A list of the financial variables is given in Appendix 2. A complete list of all the variables is available upon request from the authors.

better. More specifically, we sought the largest possible panel with monthly data in the hope to eliminate the idiosyncratic component and to ensure a dynamic structure that captures sufficient variables that lead and lag Swiss CPI inflation. This yielded a total of 434 series. The panel does not include series that are splined from the quarterly level.⁶ Thus, potentially relevant sources of real activity such as (quarterly) Swiss GDP and (quarterly) Swiss industrial production are not considered. This was done intentionally so that the data are not contaminated by data revisions and measurement error in the hope that the intra-month estimates are more stable and informative.⁷

An explicit intention in constructing the data set was to transform the series as little as possible. First, no seasonal filtering is undertaken. This is done because of seasonal filtering's reliance on future information and is therefore not consistent with real-time diagnosis. We will argue in the next section that seasonal adjustment is better handled through cross-sectional

⁶The Swiss GDP estimates rely heavily on monthly surveys, which are included in the panel. This explains in part that our estimates for Swiss Coin remain unchanged when introducing quarterly GDP.

⁷The variables in our data panel are not subject to serious revision errors. Exceptions include the monetary and credit aggregates. Thus our study is trying to avoid many of the issues of revision and vintage addressed in Croushore and Stark (2000) and Stark (2000).

smoothing because of the end-of-sample problem and that the absence of seasonal revisions allows us to interpret better the intra-month innovations in $\epsilon_{1t|jt+k}$.⁸ Second, potential redundant information through newly generated variables, say the creation of interest rate spreads or real balances, impose a choice on the researcher to throw them out before the model is estimated. This route was not taken here. Rather, whenever possible, the model was first estimated using the original series and then the transformed data were introduced and tested at a later stage.

Several data transformations, however, were necessary at the initial stages of estimation. The series were filtered in the following manner. First, to account for possible heteroskedasticity logarithms were taken for nonnegative series that were not in rates or in percentage units. Second, to account for stochastic trends the series were differenced if necessary. Third, the series were taken in deviation from the mean and divided by their standard deviation to remove scalar effects.

3. Monthly Estimates of Swiss Coin

⁸This obviously comes at a cost, because $\hat{\chi}_{t|t+k}$ suffers from a larger idiosyncratic component stemming from seasonality. This issue is discussed in the next section.

Before discussing the intra-monthly estimates, we provide monthly estimates of Swiss core inflation and establish properties of smoothness, stability, and forecasting. This is done for two reasons. The first is to show that Swiss Coin fulfills the standard properties exhibited in Christadoro *et al.* (2002) and other studies of monthly inflation. The second is to show that the jumps in the intra-monthly innovations, discussed in the next section, stem primarily from sequential data flow and not from model instability.

The monthly model of Swiss Coin is specified with two dynamic factors and twelve static factors.⁹ A crucial step in obtaining the smoothness and forecasting results is that the cross-sectional filter of Forni *et al.* (2000) is able to offer a reasonable balance between temporal smoothing and the problem of missing end-of-sample observations.¹⁰ The cross-sectional filter assumes that the panel's series provide leading, contemporaneous, and lagging information with respect to monthly inflation. Rather than applying moving-average or band-pass filters over the time domain, the Forni *et al.* (2000) procedure takes a contemporaneous, cross-sectional average of the panel's variables. The applications of the cross-sectional filter are at the π , $2\pi/12$, and $2\pi/24$ frequency; where the different levels of smoothing in $\chi_{1,t}$ are denoted as

⁹We find that first two factors account for almost 30% of the variance of the data.

¹⁰See Cristadoro *et al.* 2002 for a discussion of this issue.

$SC(0)$, $SC(12)$, and $SC(24)$.¹¹ We argue that $SC(12)$ offers an attractive mix between smoothness and the ability to capture information stemming from inflation's dynamics.

The discussion of the monthly estimates is organized as follows. First, several observations regarding the proper level of smoothness are offered. Next, the preferred estimate is matched with actual inflation and other commonly used measures of core inflation. Thereafter, we demonstrate that $SC(12)$ holds up well in a forecasting exercise with other measures. Last, our estimate of $SC(12)$ is discussed in the context of recent interest rate changes.

Defining the Proper Level of Smoothness

Figure 2 plots annualized inflation rates of monthly $SC(0)$, $SC(12)$, and $SC(24)$ from 1994:5 to 2003:12. During this period, CPI inflation averaged 0.8% and the smoothed estimates fluctuate in a tight band between 0.5% and 1.2%. A visual inspection finds only slight differences between the smoothed estimates of $SC(12)$ and $SC(24)$, suggesting that identifying the proper level of smoothing is not of serious concern. This observation is supported by the

¹¹Another way of understanding our annual inflation measures is that $SC(12)$ is close to a centered MA(6) of annual inflation at t .

descriptive statistics offered in Table 2. A noteworthy feature arising out of the graph and the descriptive statistics is that $SC(0)$ is considerably more volatile than the smoothed estimates.

Three differences in the dynamics set the smoothed estimates apart from the non-smoothed estimate. Each suggests that some smoothing is preferable. First, consider the contrasting profile between the $SC(0)$ and the $SC(12)$ estimates when the 1995 VAT tax was introduced. We know with hindsight that the introduction of this tax should only have a temporary effect on inflation. The estimate for $SC(0)$ reacts strongly to the consumption tax, whereas for $SC(12)$ it is mild. Second, as in the case of taxes, some smoothing may be necessary if core inflation is influenced by revisions to the CPI basket in May 2000. Figure 2 also shows that the monthly changes of the non-smoothed estimate increases considerably after the May 2000 revision to the CPI basket, whereas the short-run dynamics of the smoothed estimates do not. This suggests that a smoothed measure of Swiss Coin may be helpful for monetary policy analysis, particularly when considering the post 2000 period. Third, seasonal adjustment of $x_{i,t}$ strongly influences the estimates of $SC(0)$ but not those of $SC(12)$. To see this, Figure 3(a, b, and c) plots the monthly change of $SC(0)$, $SC(12)$, and $SC(24)$ against their seasonally

adjusted equivalents. The plots show that seasonal adjustment is able to reduce the volatility of $SC(0)$, but it still suffers from excess volatility after the 2000 CPI revision. In contrast, the estimates for $SC(12)$ show that the differences are slight between the seasonal-adjusted panel and the non seasonal-adjusted panel. Because we are interested in working with a real-time data set that is continuously updated and not subject to revisions nor forward information assumptions due to seasonal filtering, this motivates our preference to work with a non seasonally-adjusted panel for $SC(12)$.¹²

Next, let us consider how $SC(12)$ matches up with traditional measures of core inflation. Figure 4 plots annual inflation rates measured by four different indexes: the $SC(12)$, the CPI index, the trimmed mean with 15% cut-off tails, and CPI minus food and energy. The traditional measures of core inflation exhibit considerable increases in short-term volatility after the 2000 CPI revision and the 1995 VAT increase. Instead, $SC(12)$ is much smoother than the other core measures. The ratio of the standard deviations of one index over the others is one way to express the Swiss Coin's gain in

¹²As a further check on the influence of non seasonally adjusted data on $\hat{\chi}_{1,t|t+k}$, we compared the estimates of the (long-run and short-term) band filtered estimate, i.e. $\hat{\chi}_{1,t|t+k}^l$ against $\hat{\chi}_{1,t|t+k} - \hat{\chi}_{1,t|t+k}^s$, and found little difference in the estimates.

smoothness. There is a reduction of 64% in the standard deviation of $SC(12)$ with respect to the CPI minus food and energy, 52% for the trimmed mean, and 63% for the median of the CPI basket (figures taken from Table 2).¹³

Forecasting Performance

Crucial for any coincident indicator is its short-run forecasting performance. We test the accuracy of the annual inflation forecasts in two ways. The usefulness of $SC(12)$ against other measures of core inflation is first tested using out-of-sample forecasts from a simple bivariate model: AR(p) model plus core inflation. The simulated equation is estimated from 1994:5 to 1999:12. The second approach uses the random walk forecast, i.e., $E_t(\pi_{t+h} - \pi_t) = 0$, as the benchmark. Atkeson and Ohanian (2001) find that the naive model outperforms a wide combination of NAIRU Phillips curve models for the United States.¹⁴

The results of the two types of forecasts are documented in Table 3. The RMSE's from the out-of-sample forecasts are from 2000:1 to 2003:12. The

¹³Note, there is also considerable variance reduction for $SC(0)$ against the other measures, again see Table 2. This highlights the defects of traditional measures of core inflation that do not encompass information beyond CPI and its subcomponents.

¹⁴See also Gavin and Mandal (2003) for an alternative test of the naive's performance against inflation forecasts of the Blue Chip, the Greenbook, and the FOMC members.

forecasting horizon runs from six months to two years. We compare the forecasts with RMSEs from the models with the core inflation estimates by forming a ratio with RMSEs from the benchmark forecasts: AR(6), AR(3), and the naive forecasts. A ratio greater than one indicates that the benchmark models outperform the models of core inflation. By subtracting one from the ratio and multiplying the result by 100 gives the percentage difference in RMSE between the models of core inflation and the benchmark model.

The RMSEs reveal that the forecasts with $SC(12)$ outperform the models with the other core measures at all horizons and by a considerable margin in most cases. The ratios with $SC(12)$ are always smaller than those with the trimmed mean followed by those from CPI minus food and energy. This result reinforces the view that information outside the CPI basket is important. The RMSEs also reveal that $SC(12)$ offers information beyond the simple benchmark models: the ratios with $SC(12)$ are always less than one. On average the forecasts with $SC(12)$ are 15% better than the benchmark forecasts. This includes the forecasting results against the naive model: a non standard result particularly when inflation is low.¹⁵

¹⁵The RMSE results are unpinning by Diebold and Mariano (1995) sign tests. The null

Swiss Coin and Recent Changes in Monetary Policy

A simple way of demonstrating the usefulness of $SC(12)$ for policy purposes is to confront its profile with recent interest rate changes. Figure 5 does this by plotting three measures of inflation with the SNB's mid-point in the target range of the three-month Libor rate for CHF deposits. Since 2000 when the SNB introduced its new policy strategy based on inflation forecasts, interest rates have followed a hump-shaped path (again see Table 1 for the dates).¹⁶ A simple characterization of SNB policy identifies two phases. The first 'tightening' phase occurred during the first six months of 2000. The three increases in the SNB's target range, which totaled 175 basis points, were an anticipated response to accelerating price pressures captured in the SNB's inflation forecasts. The second phase of policy easing began with a 50 basis point reduction in the target rate in March 2001. Six further rate cuts followed in response to weakening global demand and subdued inflationary pressures.

Figure 5 shows that CPI inflation is 'too noisy' to identify a trend in inflation. The hypothesis that the forecasts with $SC(12)$ are the same as the benchmark forecasts, is strongly rejected.

¹⁶See the discussion in Jordan and Peytrignet (2001) for further details of the SNB's policy of inflation forecasting.

flation that tracks changes in the target range of interest rates. The trimmed mean is less noisy than CPI inflation, however its defect is that it lags by one year changes in the target range. The third inflation measure, $SC(12)$, follows contemporaneously the rise and fall of interest rates. While we recognize that interest rate changes over the last four years were not dictated by inflationary trends alone, we do feel that the profile offered by $SC(12)$ is more informative than the trimmed mean.

4. Real-Time Estimates and Diagnosis of Swiss Coin

In the previous section, the stability of $SC(12)$ at the monthly frequency was demonstrated through the properties of smoothness and forecasting. The next step is to show that we can go further by considering the information flow at the intra-month level. In this section, we turn to real-time diagnosis of core inflation by showing in three ways that weekly estimation is informative. First, the weekly innovations of the backcasts provide information that is statistically significant. Second, the weekly innovations can be used as a tool to identify turning points. And last, through the timing sequence of the data releases we are able to attribute whether the weekly innovations are being driven by real or nominal shocks.

Are Weekly Estimates of $SC(12)$ Informative?

To answer this question, our strategy is to apply Wilcoxon rank tests on the weekly innovations of the nowcasts, $SC_{t|j,t}$, and the backcasts, $SC_{t|j,t+k}$ for $k > 0$, to determine whether information flow is pertinent for specific weeks. The tests are performed on weekly estimates of $SC(12)$ using two panels: a real panel from 2003:10 to 2004:5 and a ‘pseudo’ real panel from 2001:1 to 2003:9. The pseudo panel is constructed such that it follows the same pattern of data releases as the months 2004:4 and 2004:5. The motivation for the pseudo real panel stems from the limited size of the real panel.

As a first step, it is important to show that the weekly innovations, $\epsilon_{t|1,t+k} = \chi_{1,t|1,t+k} - \chi_{1,t|4,t+k-1} = SC(12)_{t|1,t+k} - SC(12)_{t|4,t+k-1}$ (i.e., the difference in the core’s estimate from the first week of month $t+k$ and the estimate of $SC(12)$ for the fourth week of month $t+k-1$), $\epsilon_{t|2,t+k} = SC(12)_{t|2,t+k} - SC(12)_{t|1,t+k}$ and so on, do not suffer from unstable estimates of $SC(12)_{t|j,t+k}$ and $SC^*_{t|j,t+k}$. The latter measure of core inflation is based on estimated parameters fixed at the second week of January each year. Under the null hypothesis that the population means of $SC(12)_{t|t}$ and $SC^*(12)_{t|t}$ are the same, the p -values of the rank tests for the real panel and the pseudo real panel are 0.15% and 0.24%. This evidence is consistent with the view that

the weekly estimates of $SC(12)$ do not suffer from parameter instability.

Next, the rank tests of the weekly innovations are presented in Table 4. For both panels, the innovations from the first week are found to provide new information that is not encompassed in the preceding weeks. The p -values of the rank tests are less than 10% for the nowcasts and less than 5% for the backcasts. There is also evidence that new information is coming in during the fourth week. The p -values of the rank tests between $\epsilon_{t|2,t+k}$ and $\epsilon_{t|4,t+k}$ are significant at the 5%. From this evidence, we conclude that it is worthwhile to re-estimate $SC(12)$ at least twice a month.

Directional Change: Identifying Turning Points

The usefulness of identifying turning points with weekly estimates of $SC(12)$ is illustrated with the aid of Figures 6a and 6b. The first figure plots CPI annual inflation (bold line with stars) and 26 weekly estimates of $SC(12)$ from 2003:10 to 2004:2. During this period inflation fell from 1.4% in March 2003 to under 0.1% in February 2004. During the summer 2003, many Swiss economists expressed concern about the economic prospects in their country: inflation forecasts for 2004 were negative coupled with the fear that the awaited economic recovery would not materialize. This was all against a backdrop where Swiss three-month rates stood at 0.25%.

Although it is still too early to say with confidence, the weekly real-time estimates provide a response to the ‘watcherful waiters’ that underlying inflationary pressures have reversed course starting in mid 2003. Figure 6a shows that after a slight decline in the first six months of 2003, the weekly estimates of $SC(12)$ moved consistently in one direction - up. The turning-point result is underscored by the fact that $SC(12)$ is smoothed.

Figure 6b shows the same information as in Figure 6a but it is scaled for $SC(12)$ instead of CPI inflation. For purposes of exposition, the real-time estimates are for weeks 1 and 4 for the months of October and November. Again, the weekly estimates in core inflation confirm the view that information beyond the CPI basket is responsible for the directional change.

Shock Identification: Do Nominal or Real Shocks Drive $SC(12)$?¹⁷

As discussed in section 1, shock identification is possible with the restrictions of sequential information flow and contemporaneous price stickiness. The weekly innovations of $SC(12)$ can be interpreted as real or nominal shocks depending on whether the information released for a specific week is

¹⁷ Policymakers are increasingly recognizing the importance of communicating innovations to the forecast, rather than just emphasizing the consensus forecast. See the discussion in Poole (2004).

dominated by real or nominal variables. Figure 7 provides a plot of this information for week 38 in 2003 to week 9 in 2004. The light-shaded columns are innovations in $SC(12)$ corresponding to releases in real data and the darker-shaded columns are innovations arising from releases in nominal data.

Several remarks regarding the real-time shocks can be offered. First, the CPI release captured in the first or second week of the month (i.e., week 41 October 2003, week 45 November 2003, week 49 December 2003, week 2 January 2004, week 6 February 2004) does not always dominate. The real shocks in the second week of the months December (week 50), January (week 3), and February (week 7) are larger in absolute size than the nominal shocks of the preceding week. Second, in this small data set of real-time releases, it appears that the shocks in the third and fourth weeks of each month (i.e., week 39 and 40, 43 and 44, etc.) are extremely small.

5. Concluding Remarks

The timely release of macroeconomic data imposes a distinct structure on the panel: the clustering and sequential ordering of real and nominal variables. The paper's contribution is to make use of these characteristics of sequential information flow for the weekly analysis of Swiss core inflation.

We show that the innovations of the intra-monthly estimates provide useful information for policymakers even in a low inflation environment. First, the clustering of the data releases means that the weekly innovations of Swiss Coin provide information for identifying turning points. Along the same lines, the rank tests show statistically that it is worthwhile to re-estimate Swiss Coin at least twice a month. Second, the ordering of nominal data releases followed by real data releases aided the identification of structural shocks. This allowed us to identify the core's innovations from the first week as nominal shocks and innovations from the third week as real shocks.

Although several central banks, including the SNB, convene to review and discuss monetary policy issues on a bi-weekly basis, there have been few attempts by analysts to construct estimates of core inflation that supports such an information structure. We feel we have made a step in that direction. In the debate on how frequently should central bankers meet, the intra-monthly estimates underscore the view that policymakers should meet regularly and frequently.

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Appendix 1: Structural Shocks with Cross-Sectional Smoothing

Let the variables in the panel be divided into nominal and real variables, where $x_t = (x_t^n, x_t^r)$. Next, let us assume for convenience that for month t all the nominal variables are released in the first half of the month, i.e., from the first to the fifteenth, and all the real variables are released during the second half of the month, i.e., from the sixteenth and thereafter. As such the grouped data releases define the following information fields for the first and second half of month t as $\Omega_{1,t} = (u_t^n, u_{t-1}^n, u_{t-1}^r, u_{t-2}^n, u_{t-2}^r, \dots)$ and $\Omega_{2,t} = (u_t^n, u_t^r, u_{t-1}^n, u_{t-1}^r, u_{t-2}^n, u_{t-2}^r, \dots)$, where u_t^n and u_t^r are nominal and real shocks at t . For simplicity in this example, we also assume that the data are released with no delay.

We want to show that nominal innovations are driven by either nominal or real shocks depending on the period of the month defined by the timing of the data releases; more formally

$$\epsilon_{t+h|1,t}^n = \chi_{t+h|1,t}^n - \chi_{t+h|2,t-1}^n = f(u_t^n), \quad (3)$$

$$\epsilon_{t+h|2,t}^n = \chi_{t+h|2,t}^n - \chi_{t+h|1,t}^n = g(u_t^r), \quad (4)$$

where $f(u_t^n) = 0$ for $h < 0$ and $g(u_t^r) = 0$ for $h \leq 0$.

From equation (1), the common is defined as:

$$\begin{aligned}\chi_t &= \begin{pmatrix} \chi_t^n \\ \chi_t^r \end{pmatrix} \\ &= \begin{pmatrix} b_{nn}^0 & 0 \\ b_{rn}^0 & b_{rr}^0 \end{pmatrix} \begin{pmatrix} u_t^n \\ u_t^r \end{pmatrix} + \dots + \begin{pmatrix} b_{nn}^q & b_{nr}^q \\ b_{rn}^q & b_{rr}^q \end{pmatrix} \begin{pmatrix} u_{t-q}^n \\ u_{t-q}^r \end{pmatrix},\end{aligned}$$

where the restriction of contemporaneous price stickiness sets $b_{nr}^0 = 0$. Consider the projections of x_{t+h}^n for $h = (-H, \dots, 0, \dots, H)$ on $\Omega_{1,t}$ and $\Omega_{2,t}$. In the simple case where $H = 1$, the following nominal innovations for the first half of the month are derived:

$$\epsilon_{t-1|1,t}^n = \chi_{t-1|1,t}^n - \chi_{t-1|2,t-1}^n = 0, \quad (5)$$

$$\epsilon_{t|1,t}^n = \chi_{t|1,t}^n - \chi_{t|2,t-1}^n = b_{nn}^0 u_t^n, \quad (6)$$

$$\epsilon_{t+1|1,t}^n = \chi_{t+1|1,t}^n - \chi_{t+1|2,t-1}^n = b_{nn}^1 u_t^n, \quad (7)$$

and the nominal innovations for the second half of the month yield

$$\epsilon_{t-1|2,t}^n = \chi_{t-1|2,t}^n - \chi_{t-1|1,t}^n = 0 \quad (8)$$

$$\epsilon_{t|2,t}^n = \chi_{t|2,t}^n - \chi_{t|1,t}^n = 0 \quad (9)$$

$$\epsilon_{t+1|2,t}^n = \chi_{t+1|2,t}^n - \chi_{t+1|1,t}^n = b_{nr}^1 u_t^r. \quad (10)$$

In this simple example, it is possible to identify the nominal innovations either as real or nominal shocks depending on whether one projects on information from the first or second half of the month. Any filter of the moving-average class that generates $\frac{1}{2H+1} \sum_{h=-H}^H \epsilon_{t+h|1,t}^n$ and $\frac{1}{2H+1} \sum_{h=-H}^H \epsilon_{t+h|2,t}^n$ is a function of equations (3) and (4). This includes the cross-sectional smoother of Forni *et al.* (2000 and 2003). From equations 5 to 10, it is also easy to show that $\epsilon_{t+h|1,t}^r$ is a function of nominal shocks and $\epsilon_{t+h|2,t}^r$ is a function of real shocks.

In the above example, the timing assumption for the cutoff point between the nominal and real releases can be relaxed so that it is defined for specific days or weeks, which may also vary from month to month. Important is only the assumption that the release of nominal variables precede the release of real variables. Note that this form of ordering in the releases may also be artificially created through the inclusion or exclusion of specific variables in the panel.

The task of shock identification becomes more complex once we are interested in identifying a system with additional shocks. This requires a higher number of dynamic factors in our estimated model (i.e., $r > 2$) and imposes greater restrictions on the information flow. Further, an issue that we do

not treat formally is the fact that the idiosyncratic components (ξ_t^n, ξ_t^r) are not screened from the shocks $f(u_t^n)$ and $g(u_t^r)$. The estimates of $\hat{\chi}_{t+h|1,t}^n$ and $\hat{\chi}_{t+h|2,t}^n$ are in this case dependent on the number of the data releases for periods 1 and periods 2 in t ; respectively N^n and N^r , where $N = N^n + N^r$ defines the number of variables in the cross section. This means that $E_t(\chi_{t+h|1,t}^n) = f(u_t^n) + \frac{1}{N^n} \sum_{j=1}^{N^n} \xi_{j,t}^n$ and $E_t(\chi_{t+h|2,t}^n) = g(u_t^r) + \frac{1}{N^n} \sum_{j=1}^{N^n} \xi_{j,t}^n + \frac{1}{N^r} \sum_{l=1}^{N^r} \xi_{l,t}^r$. Here, the removal of the idiosyncratic component is dependent on the size of N^n and N^r . However, since N^n and N^r are fairly large in our panel, we do not regard this to be of serious concern.

Appendix 2: Data Decomposition

	# monthly series	# daily series	
Prices	6		
CPI-Food & soft drinks	52		
CPI-Alcoholic drinks & tobacco	10		
CPI-Clothes & shoes	30		
CPI-Rent & Energy	5		
CPI-Houshold effects	17		
CPI-Health care	5		
CPI-Traffic, public transport	10		
CPI-News transport, communications	1		
CPI-Leisure activities & culture	21		
CPI-Education	2		
CPI-Restaurants & hotels	9		
CPI-Other products & services	10		
SURVEY	40		
MONEY	9		
EXTERNAL TRADE	83		
EXCHANGE RATES	4	3	
FINANCIAL	6	9	
INTEREST RATES	12	11	
LABOUR	14		
DEMAND	16		
For. IP	8		
For. PR	10		
For. Int.R	8	4	
For.LM	19		
Total	407	27	434

Figure 1: Nominal and Real Data Releases for December 2003

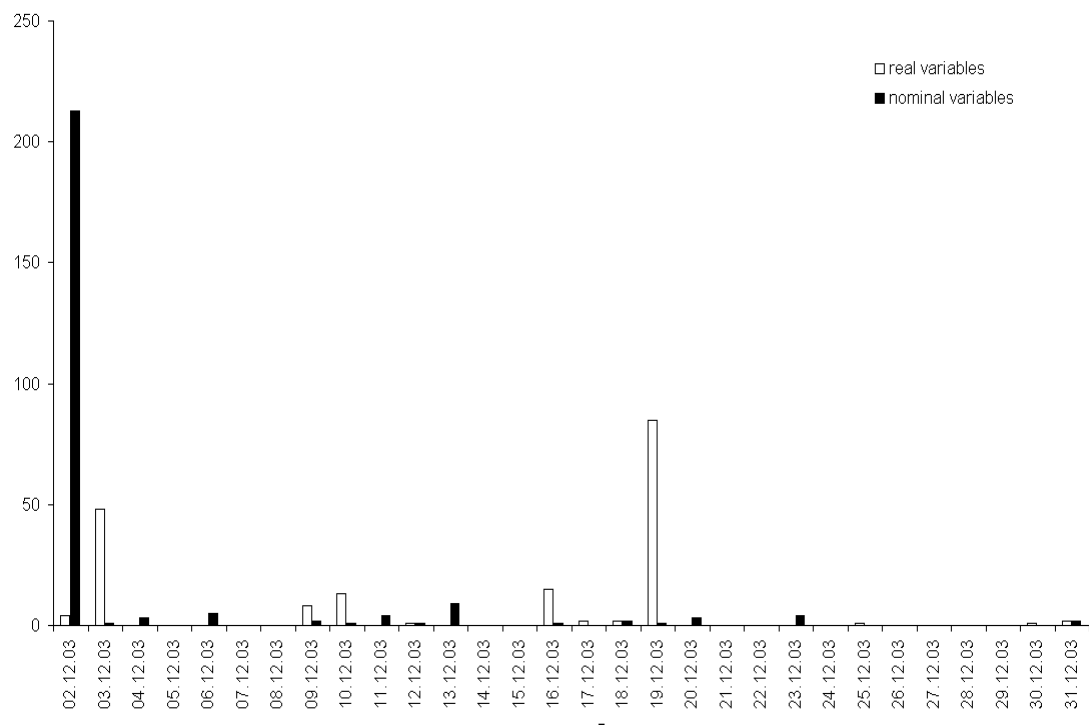


Figure 2: Annualized Swiss Coin

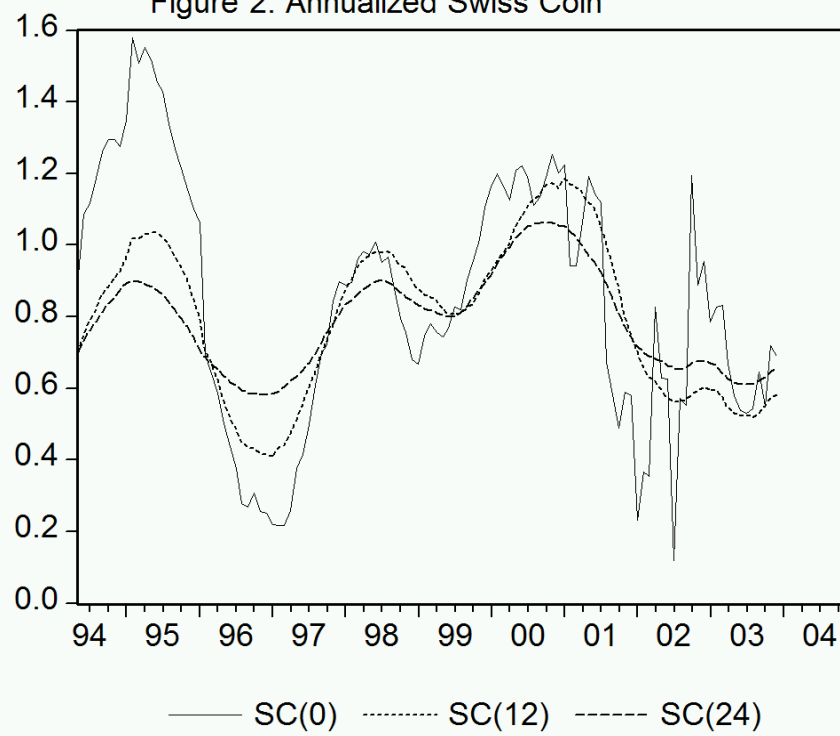


Figure 3(a): Annual Swiss Coin Inflation with no Cross-Sectional Smoothing

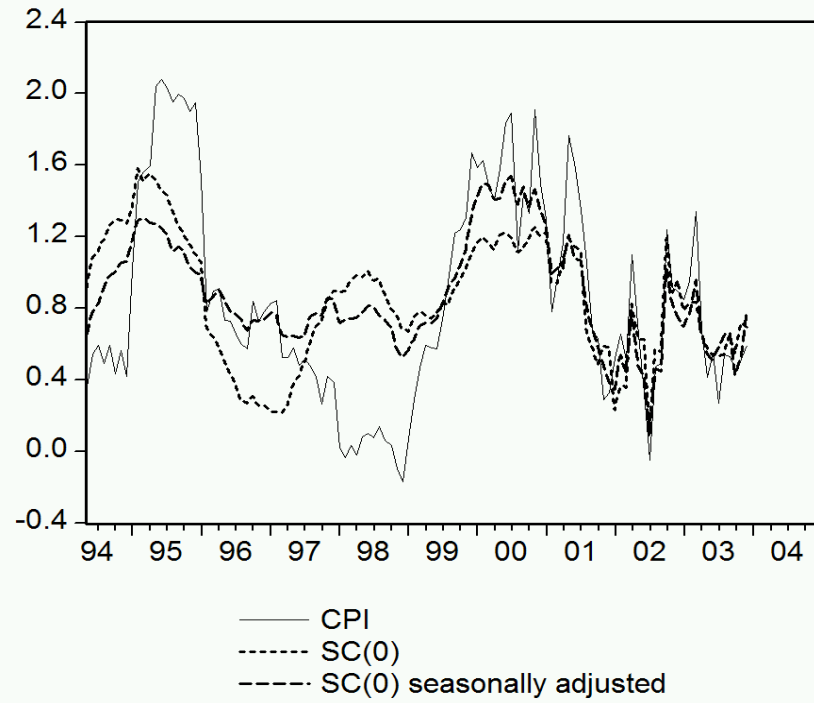


Figure 3(b): Annualized Swiss Coin Inflation with Cross-Sectional Smoothing

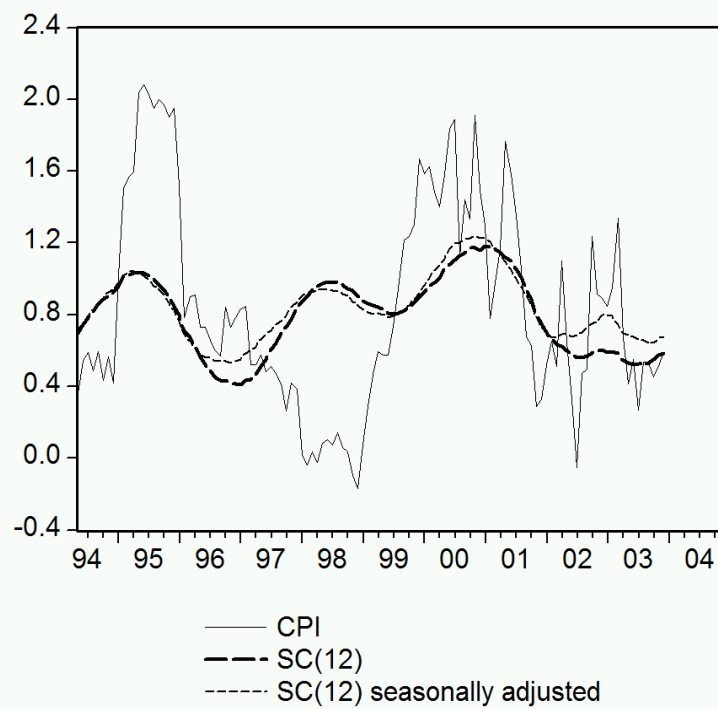
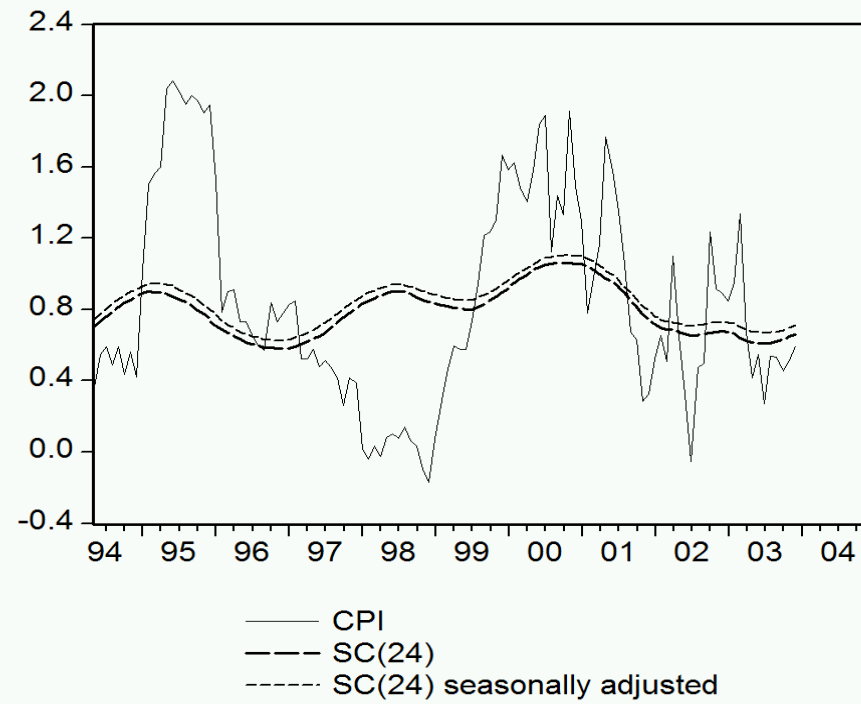


Figure 3(c): Annualized Swiss Coin Inflation with Cross-Sectional Smoothing



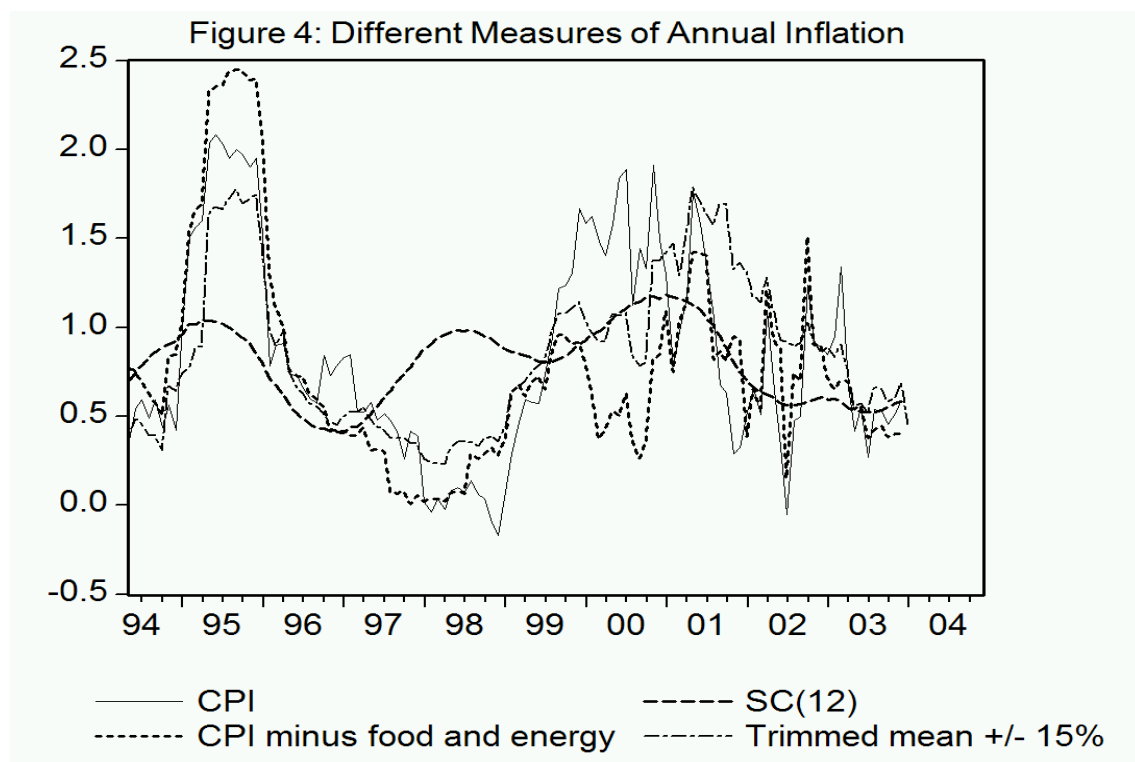


Figure 5: SNB Interest Rate Target Range and Swiss Annual Inflation

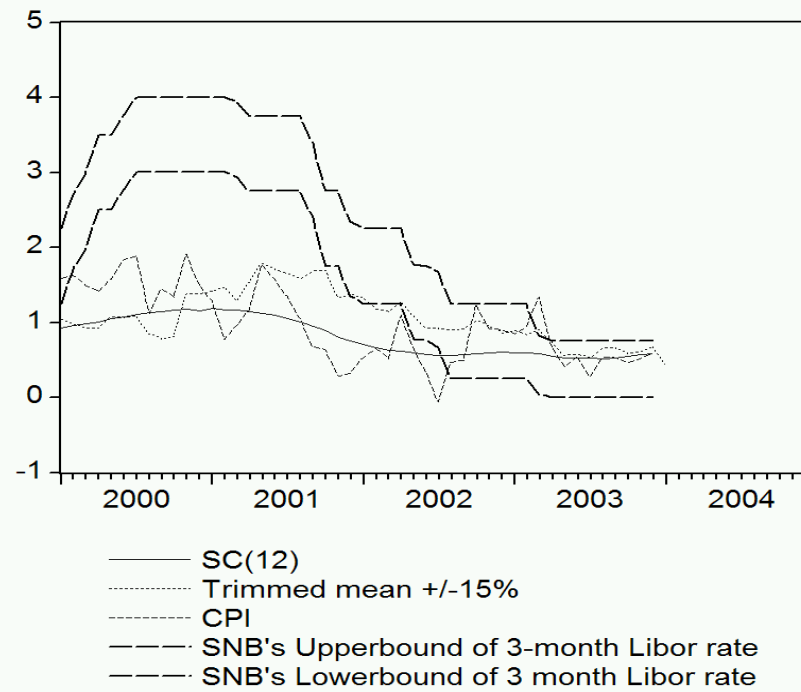


Figure 6a: Weekly Estimates of Annual Inflation

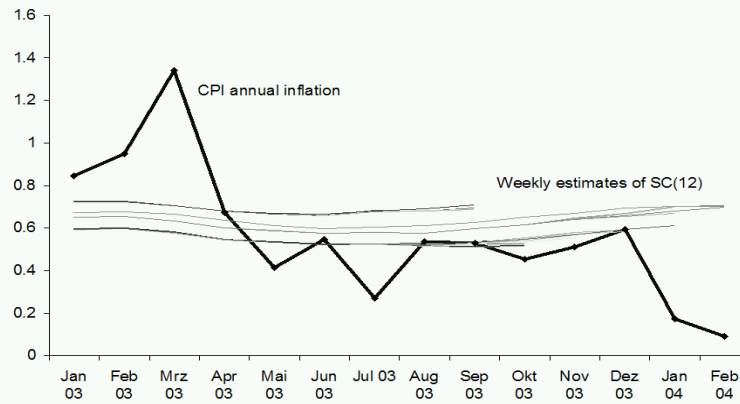
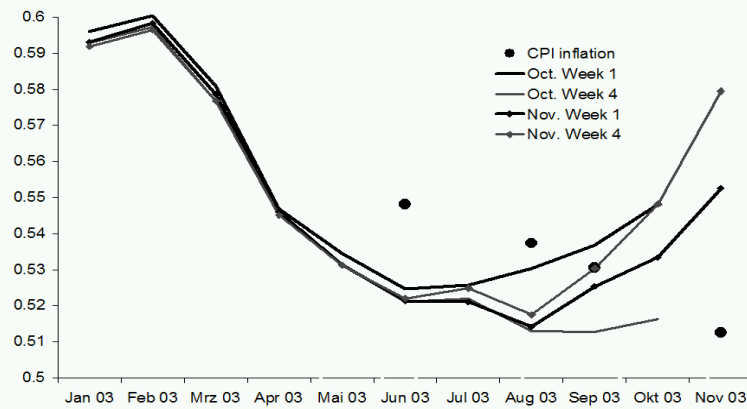


Figure 6b: Weekly Estimates of Annual Inflation



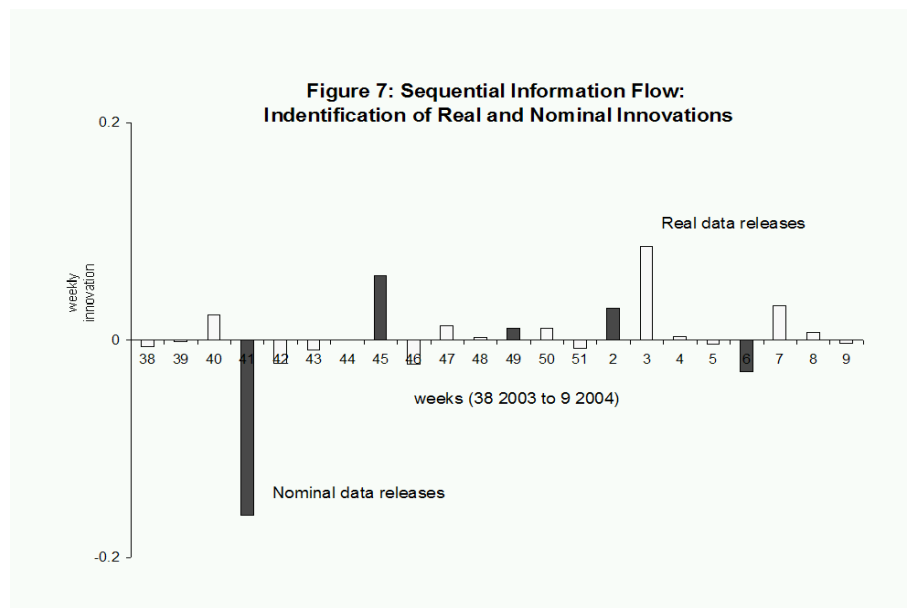


Table 1: SNB's Target Range for the 3-month Libor since 2000

Three-month Libor rate	fixed on	calender week	day of the week
1.75 - 2.75	3.2.2000	5	Thursday
2.50 - 3.50	23.3.2000	12	Thursday
3.00 - 4.00	15.6.2000	24	Thursday
2.75 - 3.75	22.3.2001	12	Thursday
2.25 - 3.25	17.9.2001	38	Monday
1.75 - 2.75	24.9.2001	39	Monday
1.25 - 2.25	7.12.2001	49	Friday
0.75 - 1.75	2.5.2002	18	Thursday
0.25 - 1.25	26.7.2002	30	Friday
0.00 - 0.75	6.3.2003	10	Thursday

Table 2: Descriptive Statistics of Annual Inflation

	<i>CPI</i>	<i>CPI - X</i>	<i>Trimmed</i>	<i>CPI</i>	<i>SC(0)</i>	<i>SC(12)</i>	<i>SC(24)</i>
			<i>Mean</i>	<i>Median</i>			
<i>1994:5 to 2003:12</i>							
mean	0.84	0.77	0.86	0.78	0.85	0.84	0.83
max	2.08	2.45	1.78	1.98	1.57	1.22	1.09
min	-0.17	0.01	0.23	0.00	0.25	0.48	0.062
std. dev.	0.58	0.59	0.44	0.57	0.32	0.21	0.13
Skewness	0.51	1.42	0.58	0.16	0.16	-0.01	0.21
Kurtosis	2.32	4.76	2.29	2.11	2.16	1.96	2.08

Table 3: Out-of-Sample Performance of Annual Inflation from 2000:1 to 2003:12

$\pi_{t+h} = \alpha + \sum_{i=0}^k \beta_i \pi_{t-i} + \gamma \pi_t^{core}$	$RMSE(\pi_{t+h})/RMSE(Benchmark)$			
	$h=6$	$h=12$	$h=18$	$h=24$
<i>Benchmark: AR(6)</i>				
<i>SC(12)</i>	0.839	0.991	0.901	0.804
<i>Trimmed mean</i>	0.972	1.374	1.399	1.254
<i>CPI minus food and energy</i>	2.857	3.099	2.273	1.501
<i>Benchmark: AR(3)</i>				
<i>SC(12)</i>	0.7323	0.956	0.945	0.812
<i>Trimmed mean</i>	1.001	1.089	1.346	1.372
<i>CPI minus food and energy</i>	3.045	2.890	2.314	1.608
<i>Benchmark: Random Walk Model</i>				
<i>SC(12)</i>	0.828	0.818	0.817	0.819
<i>Trimmed mean</i>	1.445	1.129	1.279	1.126
<i>CPI minus food and energy</i>	2.290	2.780	2.114	1.290

Notes: Inflation, π_t , is annual and annual core inflation, π_t^{core} , is *SC(12)*, *trimmed mean*, and *CPI minus food and oil*. Values are RMSEs ratios between the model forecasts with π_t^{core} and the benchmark forecasts. The simulated model is estimated from 1994:5 to 1999:12. The value for k is either 5, 2, 0, depending on whether the benchmark model (with $\gamma = 0$) is *AR(6)*, *AR(3)* or the random walk model.

Table 4: Wilcoxon Rank-Sum Tests of the Weekly Innovations

pseudo real panel						
	$\epsilon_{t 1,k} = \epsilon_{t 2,k}$	$\epsilon_{t 3,k} = \epsilon_{t 2,k}$	$\epsilon_{t 4,k} = \epsilon_{t 3,k}$	$\epsilon_{t 4,k} = \epsilon_{t 2,k}$	$\epsilon_{t 4,k} = \epsilon_{t 1,k}$	$\epsilon_{t 3,k} = \epsilon_{t 1,k}$
$k=t$	0.082	0.773	0.461	0.052	0.352	0.089
$k=t+1$	0.019	0.125	0.074	0.010	0.493	0.031
$k=t+2$	0.002	0.043	0.004	0.000	0.051	0.001
	$\epsilon_{t 1,k}^* = \epsilon_{t 2,k}^*$	$\epsilon_{t 3,k}^* = \epsilon_{t 2,k}^*$	$\epsilon_{t 4,k}^* = \epsilon_{t 3,k}^*$	$\epsilon_{t 4,k}^* = \epsilon_{t 2,k}^*$	$\epsilon_{t 4,k}^* = \epsilon_{t 1,k}^*$	$\epsilon_{t 3,k}^* = \epsilon_{t 1,k}^*$
$k=t$	0.095	0.333	0.393	0.089	0.768	0.160
$k=t+1$	0.020	0.477	0.308	0.009	0.459	0.020
$k=t+2$	0.001	0.052	0.002	0.000	0.003	0.002
real panel						
	$\epsilon_{t 1,k} = \epsilon_{t 2,k}$	$\epsilon_{t 3,k} = \epsilon_{t 2,k}$	$\epsilon_{t 4,k} = \epsilon_{t 3,k}$	$\epsilon_{t 4,k} = \epsilon_{t 2,k}$	$\epsilon_{t 4,k} = \epsilon_{t 1,k}$	$\epsilon_{t 3,k} = \epsilon_{t 1,k}$
$k=t$	0.039	0.796	0.863	0.004	0.791	0.014
$k=t+1$	0.113	0.796	1.000	0.011	1.000	0.018
$k=t+2$	0.093	0.796	0.729	0.009	0.731	0.018
	$\epsilon_{t 1,k}^* = \epsilon_{t 2,k}^*$	$\epsilon_{t 3,k}^* = \epsilon_{t 2,k}^*$	$\epsilon_{t 4,k}^* = \epsilon_{t 3,k}^*$	$\epsilon_{t 4,k}^* = \epsilon_{t 2,k}^*$	$\epsilon_{t 4,k}^* = \epsilon_{t 1,k}^*$	$\epsilon_{t 3,k}^* = \epsilon_{t 1,k}^*$
$k=t$	0.222	1.000	1.000	0.113	0.931	0.113
$k=t+1$	0.161	0.666	0.605	0.139	0.604	0.190
$k=t+2$	0.161	0.222	1.000	0.154	0.422	0.094

Notes: The weekly innovations of the nowcasts are $\epsilon_{t|1,t} = SC(12)_{t|1,t} - SC(12)_{t-1|4,t-1}$, $\epsilon_{t|2,t} = SC(12)_{t|2,t} - SC(12)_{t|1,t}$ and so on. The innovations, which are generated from $SC(12)_{t|jt}$ based on estimated parameters fixed at the second week of January each year, are denoted as $\epsilon_{t|j,t}^*$. The pseudo real panel is from 2001:1 to 2003:9 and the real panel is from 2003:10 to 2004:5.