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SNB Working Papers
11/2022

SCHWEIZERISCHE NATIONALBANK
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SWISS NATIONAL BANK

Legal Issues

ISSN 1660-7716 (printed version)
ISSN 1660-7724 (online version)

Measuring Swiss employment growth: A measurement-error approach

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26 October 2022

Abstract

The two main employment statistics from the Swiss Federal Statistical Office often show different dynamics on a quarter-by-quarter basis. Applying optimal signal-extraction techniques, this paper constructs a new measure of Swiss employment growth that provides a unified picture of historical employment dynamics. The new measure exhibits higher persistence and stronger co-movement with unemployment than when the underlying employment series are considered separately.

Keywords: Employment, Signal extraction, State-space model, Dynamic-factor model, Switzerland

JEL Classification: E24, E32

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1 Introduction

Employment is an important variable in the analysis of business cycles. In Switzerland, there exist two official statistics that provide a broad-based quarterly measure of employment. These are the employment statistics (ES) and job statistics (JS), compiled by the Swiss Federal Statistical Office (SFSO). A major issue in assessing current developments in the labor market is that these statistics often imply different employment dynamics at the margin. To circumvent complications, typically only one of both statistics is considered when reporting on current labor market developments. However, it may be suboptimal to rely only on one of these statistics, as both may provide valuable information. This paper constructs and assesses employment indicators that combine information from both statistics. The goal is to provide an indicator that reflects the true, although not directly observable, employment dynamics of the economy.

This paper is not the first to provide an indicator to assess the development of Swiss employment. Two prominent examples are the employment purchasing manager index (PMI) produced by the companies procure.ch and Credit Suisse and the KOF employment indicator constructed by the KOF Swiss Economic Institute.[1] The employment PMI shows the balance of firms that increased vs decreased their staffing levels in the previous month. The KOF employment indicator is designed to lead the true development of employment and reflects information on the firms' assessment of their current staffing levels and expectations about the change in their staffing levels over the next 3 months. The main difference from the employment indicators constructed in this paper is that they are based on surveys that complement the ES and JS data. In contrast, the goal of this paper is not to collect new data, but is rather to optimally combine ES and JS to obtain a superior measure of employment.

In terms of methodology, the paper closely follows the framework proposed by Aruoba et al. [2016]. Aruoba et al. [2016] use a measurement-error framework to obtain a superior estimate of US GDP based on expenditure- and income-side GDP estimates. The expenditure- and income-side estimates are interpreted as noisy measures for latent true GDP. Latent true GDP is then estimated based on

[1] The employment PMI is a subcomponent of the overall PMI.

optimal signal extraction techniques. The main difference from the present paper is, of course, the focus on employment rather than GDP. Because the household survey, on which the ES are mainly based, was only conducted once a year before 2010, the paper extends the method of Aruoba et al. [2016] to allow for mixed frequencies in the data. It also goes beyond the parsimonious measurement models of Aruoba et al. [2016] and considers a multivariable model.

This paper provides employment indicators that imply sensible employment dynamics over the business cycle. The employment indicators display a higher correlation with unemployment than each of the underlying data series separately. The indicators also provide a sensible assessment of employment dynamics when the development of the ES and JS are ambiguous. For instance, in 2015, after the Swiss National Bank abandoned the minimum exchange rate, both the ES and JS imply very different quarterly employment dynamics. The JS suggests solid employment growth, while the ES suggests stagnation. Especially in these situations, a proper assessment of the developments in the labor market and the economy as a whole is important for policy-makers to take appropriate actions. The paper's employment indicators help to disentangle noise and signals from the ES and JS and offer a unified view of the true latent labor market dynamics. Finally, the paper assesses to what extent simple (weighted) averages of the ES and JS can proxy the more sophisticated approaches reasonably well. The main advantage of simple (weighted) averages is that they are much easier to communicate. The paper shows that these simple alternative indicators already provide a quite sensible estimate for the development of employment, with a similarly high correlation with unemployment as the more sophisticated indicators. The only major difference from the more sophisticated indicators is that simple (weighted) averages display a lower persistence.

2 Employment statistics and the job statistics

The ES and the JS are compiled by the SFSO. Both provide data on the cyclical development of employment. The ES sheds light on the labor market from the perspective of household labor supply. It is mainly based on the Swiss Labor Force Survey (SLFS), a household survey. The ES cover all employed persons who work for at least one hour per week, in accordance with the definition of the International Labor Organization (ILO). Henceforth, the term employed persons refers always to the number of employed persons according to the ES, and the term employment growth refers to the growth rate of the number of employed persons. In contrast, the JS focuses on the perspective of companies' labor demand. It is based on a firm survey and measures the number of jobs at firms. Henceforth, the term jobs refers always to the number of jobs according to the JS, and the term jobs growth refers to the growth rate of the number of jobs. Figure 1 shows employment and job growth since 1991Q2. The gray shaded areas correspond to peak-to-trough episodes of historical recessions.[2] As seen in the figure, both series do not develop in lockstep to each other. The differences are sometimes even quite large. For instance, quarterly job growth was more than twice as high throughout 1999. After the financial crisis, job growth recovered much faster than employment growth. Especially after 2010, both data series diverge often when considered at a quarterly frequency, making it difficult to assess short-term dynamics. These differences in the data demonstrate the advantage of an estimate that combines both statistics and allows for a unified interpretation of the true latent employment developments.

There are several reasons for the somewhat different development of the two statistics. First, the unit of measure of employment is different. For instance, an employed person can have multiple jobs. Second, the coverage is not exactly the same. While the JS covers only the secondary and tertiary sectors, the ES also covers the primary sector. Furthermore, employees younger than 18 who are not subject to AVS (old age insurance), employees of retirement age with low incomes, and employees in private households are captured only by the ES. Third, and probably most important for the differences in the short term, both statistics are based on different surveys that are subject to idiosyncratic measurement errors.

As Figure 1 shows, there is a structural break in the time series of the number of employed persons in 2010. The time series displays a much higher volatility after 2010. The reason is that before 2010, the SLFS was only conducted once a year. To construct a quarterly series of the numbers of employees before 2010, the SFSO uses the quarterly pattern of the number of jobs from the JS.

[2] To define the peak-to-trough episodes, the OECD recession indicator is relied upon but recessions are excluded in which GDP did not decline in at least two consecutive quarters. The reason for this approach is that the OECD indicator also identifies recessions, which were not labeled as such in the policy debates. With the additional criterion on GDP contraction, the peak-to-trough episodes coincide well with the economic narratives in the policy debates.

This structural break is taken into account when constructing an estimate for employment and only yearly information from the employment statistics pre-2010 is used.

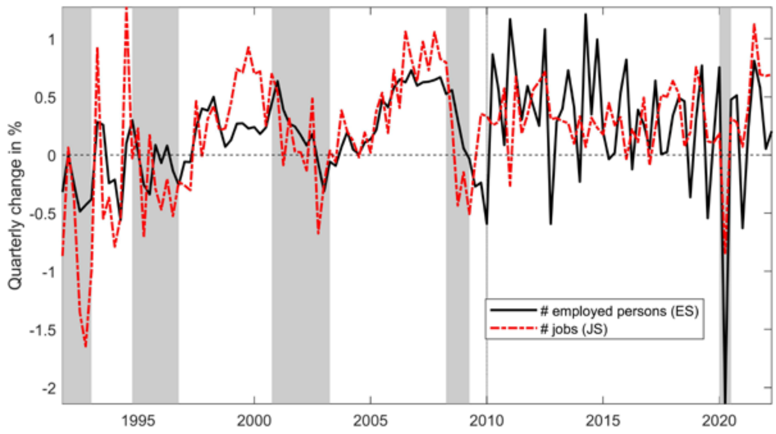

Figure 1: Growth rate of the number of employed persons (employment statistics) and the number of jobs (jobs statistics). Gray shaded areas correspond to peak to trough episodes of historical recessions.

3 Measurement-error models of employment

To estimate the true latent development of employment, a dynamic-factor measurement-error model approach is used. The basic idea of the measurement-error approach is that the number of employed persons $E_{ES,t}$ and the number of jobs $E_{JS,t}$ (and other data) are noisy measures for the latent true number of employed persons E_t. To reveal E_t, filtering techniques must be applied. I consider 3 different models: a 2-measurement, a 3-measurement and a multi-measurement equation model. The first and second models closely follow Aruoba et al. [2016]. All models are defined in terms of growth rates of employment, and all models assume that the growth rate of the latent true number of employed persons ΔE_t follows an AR(1) process. The definition of the true number of employed persons E_t follows the definition of the ES.

3.1 2-measurement equation model

The 2-measurement equation model, which is the baseline model, only uses the growth rates of the number of employed persons $\Delta E_{ES,t}$ and the number of jobs $\Delta E_{JS,t}$ as measures of latent true employment growth. It can be written in the following state-space form:

$$\begin{bmatrix} \Delta E_{ES,t} \\ \Delta E_{JS,t} \end{bmatrix} = \begin{bmatrix} 0 \\ \mu_J \end{bmatrix} + \begin{bmatrix} 1 \\ 1 \end{bmatrix} \Delta E_t + \begin{bmatrix} \varepsilon_{ES,t} \\ \varepsilon_{JS,t} \end{bmatrix} \tag{1}$$

$$\Delta E_t = \mu_E(1-\rho) + \rho \Delta E_{t-1} + \varepsilon_{E,t} \tag{2}$$

The first part represents the measurement equations. The constant μ_J is meant to capture a potential trend in the difference between the ES and JS that results from the different definitions of employment and different coverage of sectors.[3] The last part corresponds to the transition equation. It is assumed that the measurement errors and the transition equation innovation follow a normal distribution with mean 0 and covariance matrix Σ ($(\varepsilon_{E,t}, \varepsilon_{ES,t}, \varepsilon_{JS,t})' \sim N(0, \Sigma)$), where:

$$\Sigma = \begin{bmatrix} \sigma^2_{E,E} & \sigma_{E,ES} & \sigma_{E,JS} \\ \sigma_{ES,E} & \sigma^2_{ES,ES} & \sigma_{ES,JS} \\ \sigma_{JS,E} & \sigma_{JS,ES} & \sigma^2_{JS,JS} \end{bmatrix} \tag{3}$$

As shown by Aruoba et al. [2016], identification of the dynamic system is achieved if at least one element of the covariance matrix of the measurement errors and transition equation innovation Σ is restricted. To achieve identification, it is assumed that both measurement errors are orthogonal to each other, *i.e.*, $\sigma_{ES,JS} = 0$. This assumption seems plausible, as the ES and JS are based on

[3] An anonymous referee pointed out that the number of jobs per employed person could be cyclical. In this case, the measurement errors would be correlated with the business cycle and including only a constant in the measurement equation would not be sufficient. However, empirical evidence suggests that the number of jobs per employed person is acyclical. Testing the null hypothesis that the correlation between the number of jobs per employed persons and the SNB's official measure of the output gap is zero leads to a p-value well above 0.5 for the full sample (bearing in mind that only annual data from the employment statistics are available before 2010) as well as for the sample from 2010 onwards.

two very different surveys, one conducted among households and the other among firms.

3.2 3-measurement equation model

Although the assumption that the measurement errors in $\Delta E_{ES,t}$ and $\Delta E_{JS,t}$ are uncorrelated seems plausible, following Aruoba et al. [2016], a three measurement equation variant is considered that allows for the relaxation of this assumption. The basic idea is to use an additional measure that is correlated with the latent number of employed persons but whose measurement error is independent from the other measurement errors. As additional measure, the employment component of the Swiss manufacturing purchasing manager index provided by procure.ch and Credit Suisse is used. The employment component measures the number of purchasing managers in the survey that reported an increase relative to the number that reported a decrease in staffing levels compared to the previous month. The survey among purchasing managers is very different from those of the employment and job statistics. Hence, it is unlikely that the measurement error in the employment PMI is related to the measurement errors in the employment and job statistics. Using the employment PMI P_t, the state-space form of the new model is

$$\begin{bmatrix} \Delta E_{ES,t} \\ \Delta E_{JS,t} \\ P_t \end{bmatrix} = \begin{bmatrix} 0 \\ \mu_J \\ \mu_P \end{bmatrix} + \begin{bmatrix} 1 \\ 1 \\ \kappa \end{bmatrix} \Delta E_t + \begin{bmatrix} \varepsilon_{E,t} \\ \varepsilon_{J,t} \\ \varepsilon_{P,t} \end{bmatrix} \tag{4}$$

$$\Delta E_t = \mu_E(1-\rho) + \rho \Delta E_{t-1} + \varepsilon_{E,t} \tag{5}$$

$$\Sigma = \begin{bmatrix} \sigma^2_{E,E} & \sigma_{E,ES} & \sigma_{E,JS} & \sigma_{E,P} \\ \sigma_{E,ES} & \sigma^2_{ES,ES} & \sigma_{ES,JS} & 0 \\ \sigma_{JS,E} & \sigma_{JS,ES} & \sigma^2_{JS,JS} & 0 \\ \sigma_{P,E} & 0 & 0 & \sigma^2_{PP} \end{bmatrix} \tag{6}$$

Thanks to the assumption that the measurement error in the employment PMI is unrelated to other measurement errors, I need not to assume that $\sigma_{JS,ES} = 0$ and still achieve identification [Aruoba et al., 2016].

3.3 Multi-measurement equation model

There are many more indicators that contain information on latent employment. Therefore, a multi-measurement equation model is also estimated that additionally includes the change in the unemployment rate Δu_t, the change in the job vacancy rate Δv_t, the employment assessment based on the KOF Business Tendency Surveys K_t and the job security assessment according to the SECO consumer sentiment survey S_t. Details on the data can be found in Appendix Section 6.[4] The state-space representation of the model is

$$\begin{bmatrix} \Delta E_{ES,t} \\ \Delta E_{JS,t} \\ \Delta u_t \\ \Delta v_t \\ K_t \\ P_t \\ S_t \end{bmatrix} = \begin{bmatrix} 0 \\ \mu_J \\ \mu_u \\ \mu_v \\ \mu_K \\ \mu_P \\ \mu_S \end{bmatrix} + \begin{bmatrix} 1 \\ 1 \\ \lambda_u \\ \lambda_v \\ \lambda_K \\ \lambda_P \\ \lambda_S \end{bmatrix} \Delta E_t + \begin{bmatrix} \varepsilon_{E,t} \\ \varepsilon_{J,t} \\ \varepsilon_{u,t} \\ \varepsilon_{v,t} \\ \varepsilon_{K,t} \\ \varepsilon_{P,t} \\ \varepsilon_{S,t} \end{bmatrix} \tag{7}$$

$$\Delta E_t = \mu_E(1-\rho) + \rho \Delta E_{t-1} + \varepsilon_{E,t} \tag{8}$$

$$\Sigma = \begin{bmatrix} \sigma_E^2 & 0 & \dots & 0 \\ 0 & \sigma_{ES}^2 & \dots & 0 \\ \vdots & \ddots & \ddots & \vdots \\ 0 & \dots & \dots & \sigma_S^2 \end{bmatrix} \tag{9}$$

To ensure identification, the common assumption of large-scale indicator models that the variance-

[4]The KOF employment assessment can be viewed as a leading indicator of employment. It reflects the number of businesses in the KOF survey that consider their current staffing levels to be too high compared with those that consider them to be too low. Despite its leading nature, the data published by the KOF is entered contemporaneously into the model. The quarterly data published by the KOF are based on information about the first weeks of the quarter and information about the end of the last quarter only. Hence, it already reflects the leading nature, and no further adjustment should be necessary.

covariance matrix is diagonal is followed (see, e.g., Altissimo et al. [2010], Aruoba et al. [2009], Camacho and Perez-Quiros [2010], Crone and Clayton-Matthews [2005]).

3.4 Mixed-frequency approach

Because the SLFS was only conducted once a year before 2010, only annual information of the ES is used for this period. To incorporate yearly information into the measurement error models, a mixed-frequency approach is used. More specifically, the year-on-year growth rate of the number of employees $\Delta E^y_{ES,t}$ is used for the period before 2010. This involves a change in the measurement equation. To do so, the paper uses the following relation between $\Delta E^y_{ES,t}$ and ΔE_t:

$$\begin{aligned} \Delta E^y_{ES,t} &= \Delta E_{ES,t} + \Delta E_{ES,t-1} + \Delta E_{ES,t-2} + \Delta E_{ES,t-3} \\ &= \Delta E_t + \Delta E_{t-1} + \Delta E_{t-2} + \Delta E_{t-3} + \varepsilon_{ES,t} + \varepsilon_{ES,t-1} + \varepsilon_{ES,t-2} + \varepsilon_{ES,t-3} \qquad (10) \end{aligned}$$

$\Delta E^y_{ES,t}$ is a quarterly series with missing values for all quarters, but each second quarter in the years before 2010. The reason is that the household survey was only performed in the second quarter of each year before 2010. Details on the implementation of the mixed-frequency approach can be found in the Appendix.

4 Data and estimation

To estimate the true latent growth rate of employment, a Bayesian estimation approach is used. Some descriptive statistics of the data are first provided, such that the reader is able to assess my prior definition that follows afterwards. Then, the posterior distribution is shown and discussed. To estimate the parameters of the models, data from 1991Q4 to 2022Q2 is used. A structural break is introduced in 2007Q1 because of the agreement on the free movement of persons, whose implementation is likely to have changed employment dynamics. The agreement was enacted in June 2002, but it was only in 2007 when the movement of persons was effectively fully liberalized [Beerli et al., 2021]. To be precise, it is assumed that all parameters change in 2007Q1. Furthermore, to address COVID-19 outliers, the parameters of the variance-covariance matrix are allowed to change between 2019Q4 and 2022Q2.

4.1 Descriptive statistics

Table 1 shows the standard deviation and the autocorrelation at the first lag for the quarterly growth rate of the number of employed persons and the number of jobs. The statistics are shown for the full sample and various subsamples. In the full sample, employment and job growth are similarly volatile, but the latter displays a considerably higher autocorrelation. The descriptive statistics for the number of employed persons in a sample that includes the years before 2010 have, however, to be treated with caution. Before 2010, the SLFS, on which the ES is based, was only conducted on a yearly basis. To obtain a quarterly time series that goes further back than 2010, an interpolation based on the data of the JS is used. When considering only the subsample from 2010Q2 onwards, employment growth is considerably more volatile than jobs growth. Table 1 also shows descriptive statistics for the different subsamples that are split by the structural breaks. There are two main differences between the pre- and post 2007Q1 samples. First, the volatility in job growth is much lower after 2007Q1. Second, while employment growth was strongly autocorrelated before 2007, the autocorrelation vanished completely after 2007. As mentioned before, however, this might also be to some extent driven by the interpolation method used to obtain a quarterly series before 2010. Finally, considering the pandemic episode between 2020Q1–2022Q2, the volatility of both jobs and employment growth increased strongly, while autocorrelation dropped further.

4.2 Estimation

Here, the prior specification and the posterior distribution of parameters of the baseline model are presented. The posterior distribution of parameters are obtained using a Random-Walk Metropolis-Hastings algorithm. Table 2 shows details of the parameter prior and posterior distribution. The parameter prior and posterior distribution of the 3- and multi-measurement equation model can be found in the Appendix.

Table 1: Data characteristics

D_t	$std(D_t)$	$corr(D_{t+1}, D_t)$
$\Delta E_{ES,t}$	0.44	0.13
$\Delta E_{JS,t}$	0.50	0.48
$\Delta E_{ES,t}^{>2010Q1}$	0.55	-0.21
$\Delta E_{JS,t}^{>2010Q1}$	0.31	0.17
$\Delta E_{ES,t}^{<2007Q1}$	0.30	0.72
$\Delta E_{JS,t}^{<2007Q1}$	0.58	0.44
$\Delta E_{ES,t}^{07Q1-19Q4}$	0.43	-0.03
$\Delta E_{JS,t}^{07Q1-19Q4}$	0.32	0.45
$\Delta E_{ES,t}^{20Q1-22Q2}$	1.00	-0.33
$\Delta E_{JS,t}^{20Q1-22Q2}$	0.56	0.24

Note: The full sample (first and second row) covers 1991Q2–2022Q2

The prior specification is fairly standard. A beta distribution for ρ, inverse gamma distributions for the variance of the innovation in the latent variable and the measurement errors, and normal distributions for the covariances between the measurement errors and the innovation of the latent variable are used. The prior mode of the μ_E's are set equal to the average employment growth of the corresponding subsample. The prior mode of the μ_J's are set equal to the difference of average employment and jobs growth. The prior mode of the ρ's is set to 0.5. Since the standard deviation of all prior distributions is high, the prior distributions are not very informative and, hence, do not restrict estimation considerably.

With regard to the posterior distribution, several results are noteworthy. First, the data are informative. The posterior interquartile intervals are quite tight. In general, the prior mode lies outside the interval. An exception are the prior modes of μ_E and μ_J. However, this is not surprising given that the prior mode is chosen based on the average growth rates of the number of employed persons and the number of jobs observed in the data. Another exception are the parameters estimated based only on the pandemic episode between 2020Q1–2022Q2. This sample is too small to obtain precise estimates. Second, the posterior intervals of the covariance between the measurement errors and the innovation, $\sigma_{E,ES}$ and $\sigma_{E,JS}$, exclude zero, with the minor exception of $\sigma_{E,JS}$ in

2020Q1–2022Q2. Hence, the model indicates that the measurement errors are not independent from innovations in true latent employment growth, which stands in contrast to the common assumption of large indicator models that assume independence between measurement errors and innovations in latent factors. Third, the estimated variance of the measurement error in jobs growth σ^2_{JS} is smaller than the variance of the measurement error in employment growth σ^2_{ES}. This suggests that it is optimal to put more weight on the JS as opposed to ES when assessing employment growth because the signal of the JS is more precise.

These results largely extend to the 3- and multi-measurement equations model (see Appendix Section 6).

5 Results and evaluation

This section shows that the employment indicators imply sensible employment dynamics and are useful when assessing the state of the labor market. For each model, the employment indicator is defined as the posterior median estimate of the smoothed latent state ΔE_t. $\Delta E_{2,t}$ denotes the employment indicator of the baseline model, and $\Delta E_{3,t}$ and $\Delta E_{multi,t}$ are the employment indicators of the 3- and multi-measurement equation model. The posterior distribution of the smoothed latent state are obtained by applying the Kalman smoother conditional on each parameter draw from the Random-Walk Metropolis-Hastings algorithm.

5.1 Descriptive statistics

In general, the employment indicators of the three models are less or, at most, as volatile as the employment and jobs growth according to the ES and JS, and they display a higher persistence. This suggests that true latent employment growth is more predictable based on its own past than what the characteristics of employment and jobs growth suggest separately. Table 3 shows the standard deviation, the autocorrelation at the first lag, and the R-squared of an AR(1) estimation for various objects. These objects are employment and jobs growth $\Delta E_{ES,t}$ and $\Delta E_{JS,t}$, the employment indicators of the three models $\Delta E_{2,t}$, $\Delta E_{3,t}$ and $\Delta E_{multi,t}$, and simple alternative employment

Table 2: Priors and posteriors, 1991Q4-2022Q2

	Prior	Posterior		
	(Mode, Std. Dev.)	25%	50%	75%
1991Q4–2006Q4				
ρ	B(0.5,1)	0.48	0.55	0.62
σ^2_E	IG(0.3,3)	0.18	0.22	0.27
σ^2_{ES}	IG(0.3,3)	0.21	0.25	0.31
σ^2_{JS}	IG(0.3,3)	0.17	0.20	0.23
$\sigma_{E,ES}$	N(0,2)	-0.24	-0.21	-0.18
$\sigma_{E,JS}$	N(0,2)	-0.10	-0.07	-0.04
μ_E	N(0.11,2)	0.07	0.11	0.16
μ_J	N(-0.01,2)	-0.08	-0.03	0.02
2007Q1–2022Q2				
ρ	B(0.5,1)	0.17	0.23	0.31
μ_E	N(0.30,2)	0.31	0.36	0.41
μ_J	N(-0.01,2)	-0.05	-0.00	0.05
2007Q1–2019Q4				
σ^2_E	IG(0.3,3)	0.23	0.28	0.33
σ^2_{ES}	IG(0.3,3)	0.19	0.23	0.27
σ^2_{JS}	IG(0.3,3)	0.15	0.18	0.21
$\sigma_{E,ES}$	N(0,2)	-0.14	-0.12	-0.09
$\sigma_{E,JS}$	N(0,2)	-0.21	-0.18	-0.15
2020Q1–2022Q2				
σ^2_E	IG(0.3,6)	0.28	0.38	0.53
σ^2_{ES}	IG(0.3,6)	0.28	0.37	0.48
σ^2_{JS}	IG(0.3,6)	0.22	0.28	0.35
$\sigma_{E,ES}$	N(0,4)	0.14	0.23	0.31
$\sigma_{E,JS}$	N(0,4)	-0.19	-0.06	0.05

Table 3: Data vs. indicator characteristics

D_t	$std(D_t)$	$corr(D_{t+1}, D_t)$	R^2
ΔE_{ES}	0.44	0.13	0.02
ΔE_{JS}	0.50	0.48	0.23
$\Delta \hat{E}$	0.41	0.43	0.18
ΔE_2	0.45	0.61	0.38
$\Delta \tilde{E}_2$	0.42	0.47	0.22
ΔE_3	0.37	0.76	0.57
$\Delta \tilde{E}_3$	0.42	0.47	0.22
ΔE_{multi}	0.33	0.79	0.62
$\Delta \tilde{E}_{multi}$	0.41	0.46	0.21

Notes: $\Delta E_{ES,t}$ corresponds to the official quarterly time series, which, before 2010, is based on an interpolation using the job statistics. The subscripts $_2$, $_3$, and $_{mult}$ denote the employment indicators of the baseline, the 3- and multi-measurement equation model. $\hat{E}$ denotes the unweighted average of employment growth and job growth. $\tilde{E}$ is the closest convex combination of employment and jobs growth to the respective employment indicator. Details can be found in Section 5.4.

indicators (denoted by $\hat{E}, t$, $\tilde{E}_{2,t}$, $\tilde{E}_{3,t}$ and $\tilde{E}_{mult,t}$) that will be covered later on. As seen in the table, $\Delta E_{3,t}$ and $\Delta E_{multi,t}$ are 10 to 40% less volatile than $\Delta E_{ES,t}$ and $\Delta E_{JS,t}$, while $\Delta E_{2,t}$ is similarly volatile. The baseline employment indicator, and especially the indicators of the 3- and multi-measurement equation models, are much stronger autocorrelated than employment and jobs growth.

5.2 Historical episodes

The employment indicators suggest a sensible development of employment during historical episodes. Figure 2 shows the baseline employment indicator, the corresponding posterior interquartile interval and the underlying data from the ES and JS. The gray shaded areas correspond to the peak-to-trough episodes. In line with the economic narrative, the baseline indicator points to a strong decline in employment growth during the double-dip recessions in the 1990s, the recession associated with the dot-com bubble, the financial crisis and the pandemic. When taking a closer look, the baseline indicator seems to follow the JS more closely than the ES. For instance, during the financial crisis, the baseline indicator and the JS suggest an immediate decline in latent employment growth, whereas the ES points to a much more sluggish reaction in employment dynamics. Additionally, the baseline indicator points to a similarly strong decline in employment at the onset of the pandemic as the JS, whereas the ES suggest a more than twice as strong decline. Intuitively, the stronger weighting of jobs vs employment growth is because the estimated measurement error variance in the former is lower. It is optimal to put more weight on more precise measures.

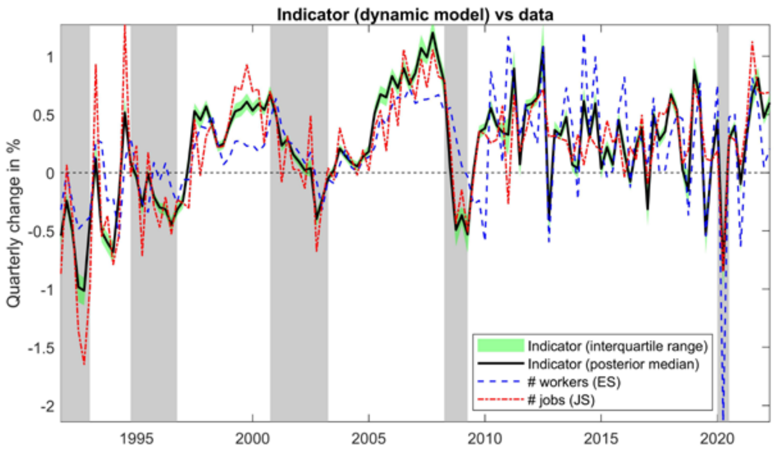

Figure 2: Baseline employment indicator vs. data

Overall, the employment indicators of the 3- and multi-measurement equation models display similar dynamics as the baseline indicator. Figures 3 and 4 show the baseline indicator with its posterior interquartile interval compared to the indicator based on the 3- and the multi-measurement equation model, respectively. The main difference between the baseline and the 3-measurement equation's employment indicator concerns the recession associated with the dot-com bubble. According to the 3-measurement equation's employment indicator, employment growth dropped more sharply in the beginning of the recession. Otherwise, both indicators are quite close to each other. The multi-measurement equation employment indicator is very similar to the baseline indicator up to 2005. Thereafter, the dynamics are still similar, but the multi-measurement equation model displays smaller fluctuations, with the exception of the outbreak of the pandemic.

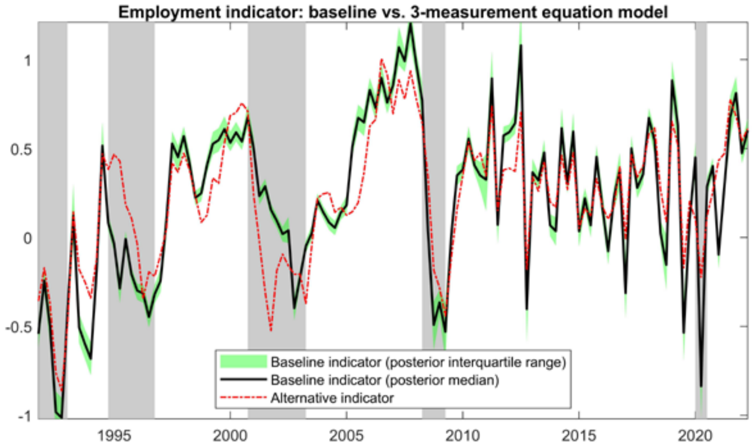

Figure 3: Baseline vs 3-measurement equation model employment indicator

At this point, it should be highlighted that the benefits of a blended estimate are particularly evident for important episodes, such as the financial crisis, the period after 2015 (abandonment of the minimum exchange rate floor), or the pandemic. For instance, in 2015Q2, employment growth turned negative, while jobs growth increased by almost 2 percentage points on an annualized basis. In such a case, the employment indicators help to disentangle the noise from the signal and provide a useful measure for the assessment of the state of the labor market.

5.3 Comovement with unemployment

A further possibility to assess the employment indicator's plausibility is to examine co-movement with unemployment. Unemployment is a natural counterpart to employment and, hence, should co-move closely with employment.

The employment indicators display a strong co-movement with unemployment — a co-movement that is stronger than when regarding the underlying data series separately. Table 4 shows the cross-correlations of employment growth, job growth and the employment indicators with the change in the unemployment rate. All employment indicators $\Delta E_{2,t}$, $\Delta E_{3,t}$ and $\Delta E_{multi,t}$ display a higher absolute contemporaneous correlation with the change in the unemployment rate than employ-

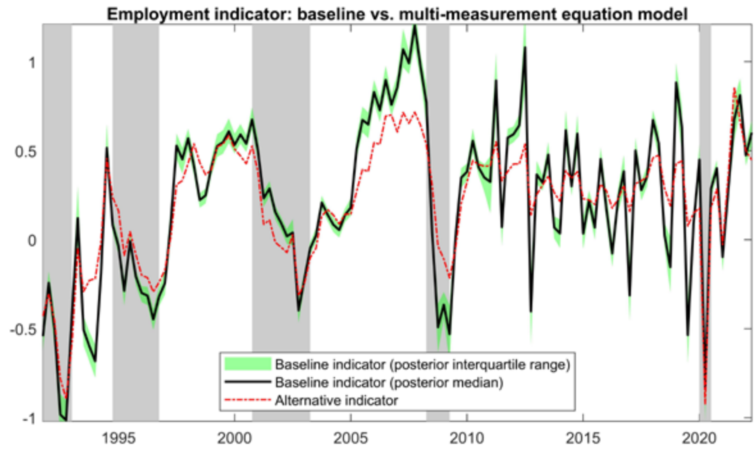

Figure 4: Baseline vs multi-measurement equation model employment indicator

ment and job growth. The strong correlation of $\Delta E_{mult,t}$ must be treated with caution because unemployment is also part of the dataset with which $\Delta E_{mult,t}$ is constructed. With regard to the cross-correlation at leads and lags, there is no clear pattern. However, the cross-correlations at leads and lags are smaller than the contemporaneous correlation, indicating contemporaneous co-movement. The stronger co-movement of the employment indicator with unemployment is economically sensible and suggests that the employment indicators are superior measures to assess employment dynamics compared to jobs or employment growth data on their own.

5.4 Simple alternative employment indicators

A disadvantage of the methodology used to compute the employment indicators is that it is complicated. Hence, it is difficult to explain the employment indicators to a broader audience. For communication purposes, a simpler alternative might be useful. Two simple alternative employment indicators are considered here. The first is the unweighted average of employment and jobs growth. The second, somewhat more sophisticated alternative, is the weighted average of employment and jobs growth that best proxies the more sophisticated employment indicators. More specifically, the weighted average $\Delta \tilde{E}_{x,t}$ that minimizes the sum of squared differences to the more

Table 4: Comovement with unemployment

D_t	$corr(D_{t+k}, \Delta U_t)$				
	k=-2	k=-1	k=0	k=1	k=2
ΔE_{ES}	-0.21	-0.16	-0.53	-0.34	-0.29
ΔE_{JS}	-0.51	-0.41	-0.63	-0.51	-0.48
$\Delta \hat{E}$	-0.44	-0.34	-0.66	-0.47	-0.41
ΔE_2	-0.53	-0.45	-0.66	-0.52	-0.43
$\Delta \tilde{E}_2$	-0.47	-0.37	-0.66	-0.49	-0.42
ΔE_3	-0.66	-0.52	-0.72	-0.62	-0.51
$\Delta \tilde{E}_3$	-0.47	-0.37	-0.66	-0.49	-0.42
ΔE_{multi}	-0.67	-0.53	-0.84	-0.67	-0.56
$\Delta \tilde{E}_{multi}$	-0.46	-0.36	-0.67	-0.48	-0.42

Notes: $\Delta E_{ES,t}$ corresponds to the official quarterly time series, which, before 2010, is based on an interpolation using the job statistics. The subscripts $_2$, $_3$, and $_{mult}$ denote the employment indicators of the baseline, the 3- and multi-measurement equation model. $\hat{E}$ denotes the unweighted average of employment growth and job growth. $\tilde{E}$ is the closest convex combination of employment and jobs growth to the respective employment indicator. Details can be found in Section 5.4.

sophisticated employment indicators $\Delta E_{2,t}$, $\Delta E_{3,t}$ and $\Delta E_{multi,t}$ is computed:

$$
\begin{aligned}
\Delta \tilde{E}_{x,t} =& \lambda \Delta E_{ES,t} + (1-\lambda)\Delta E_{JS,t} \\
with\ \lambda =& argmin \sum_{i=1}^{T} \left(\Delta E_{x,i} - (\lambda \Delta E_{ES,i} + (1-\lambda)\Delta E_{JS,i})\right)^2 \text{ and } \ x \in [2, 3, multi]
\end{aligned}
\tag{11}
$$

In the following, it is shown that especially the weighted average approach delivers alternative indicators that imply sensible employment dynamics and display a similarly high correlation with unemployment as the more sophisticated employment indicators discussed above. The main difference from the more sophisticated indicators is that the alternative indicators are systematically less persistent.

I start with the comparison of the unweighted average $\Delta \hat{E}_t$ with the baseline employment indicator $\Delta E_{2,t}$. Figure 5 shows the development of the unweighted average and the baseline indicator, the latter surrounded by the posterior interquartile interval. The main differences between $\Delta \tilde{E}_t$ and $\Delta E_{2,t}$ concern the years around the financial crisis, and the drop in employment at the onset of the pandemic. On the one hand, the unweighted average points to up to 2 percentage points lower annualized employment growth in the years before the financial crisis. On the other hand, it suggests that employment growth did not drop as strongly during the financial crisis, but was depressed for longer. In 2020 Q2, the unweighted average implies a decline in employment of approximately 6% annualized, while the baseline indicator suggests a drop of approximately 4%. Apart from these examples, the differences are rather small. Considering the descriptive statistics of both series shown in Table 3, the unweighted average is even somewhat less volatile than the baseline employment indicator. Although less volatile, the unweighted average displays a lower autocorrelation, which is also reflected in the lower R-squared from the AR(1) estimate. Finally, as shown in Table 4, the co-movement of the unweighted average to changes in the unemployment rate is similar to that of the baseline model.

The closest weighted average to the baseline indicator $\Delta \tilde{E}_{2,t}$ is based on $\lambda = 0.39$, *i.e.* to 39% on employment and 61% on jobs growth. Thus, the closest weighted average is very similar to

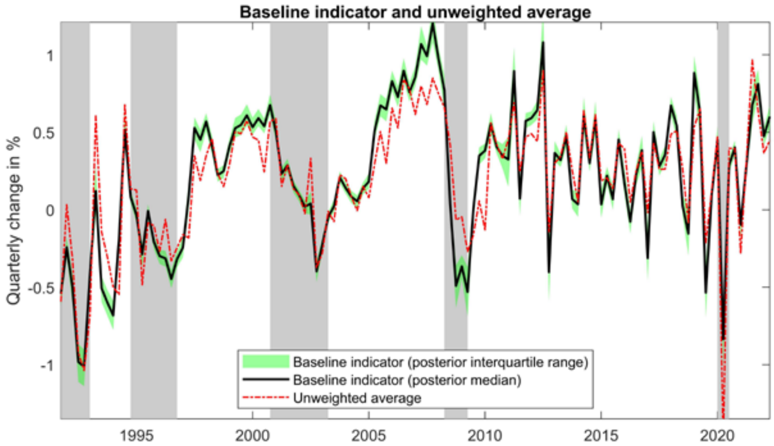

Figure 5: Baseline indicator vs. unweighted average

the unweighted average. The observations from the comparison between the baseline indicator and the unweighted average largely apply to the closest weighted average $\Delta\tilde{E}_{2,t}$. Figure 6 shows the development of $\Delta\tilde{E}_{2,t}$ and of the baseline indicator, the latter surrounded by the posterior interquartile interval. The main differences between $\Delta\tilde{E}_{2,t}$ and $\Delta E_{2,t}$ also concern the years around the financial crisis, and the drop in employment at the onset of the pandemic. As Tables 3 and 4 show, $\Delta\tilde{E}_{2,t}$ is also less volatile, less strongly autocorrelated and displays a similar co-movement with the unemployment rate as the baseline employment indicator.

Similar conclusions are drawn when considering the closest weighted average to the 3- and multi-measurement equation model ($\Delta\tilde{E}_{3,t}$ and $\Delta\tilde{E}_{mult,t}$). $\Delta\tilde{E}_3$ is based on $\lambda = 0.39$ and $\Delta\tilde{E}_{mult,t}$ on $\lambda = 0.43$, *i.e.* both close to the unweighted average. In contrast to the above comparison, however, the closest weighted averages $\Delta\tilde{E}_{3,t}$ and $\Delta\tilde{E}_{mult,t}$ are more volatile than the underlying employment indicators $\Delta E_{3,t}$ and $\Delta E_{mult,t}$ (see Table 3). Additionally, they display a somewhat weaker comovement with unemployment than the underlying employment indicators (see Table 4).

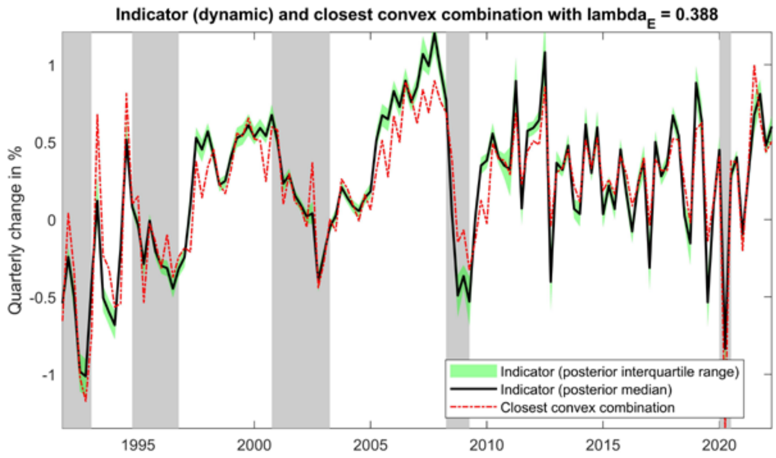

Figure 6: Baseline indicator vs. closest weighted average

6 Conclusion

This paper provides a new measure of Swiss employment growth by applying optimal signal-extraction techniques to noisy measures of employment. In Switzerland, there exist two official statistics that provide a broad-based quarterly measure of employment – the employment statistics and the job statistics. A major issue when using these statistics to assess current developments in the labor market is that both statistics often imply different employment dynamics at the margin. The new measure helps us to obtain a unified picture of employment developments. It provides sensible historical employment dynamics and displays a stronger co-movement with unemployment than each of the underlying data series imply on its own. It also indicates that the persistence in employment dynamics is stronger than previously thought.

The construction of the new measure of Swiss employment growth closely follows Aruoba et al. [2016]. Aruoba et al. [2016] use optimal signal-extraction techniques to noisy income- and expenditure-side estimates of US GDP to obtain a blended estimate. The main difference of this paper with Aruoba et al. [2016] is, of course, the focus on Swiss employment growth. Furthermore, the paper extends their framework to allow for mixed frequencies because the household survey, on which the employment statistics are mainly based, was only conducted once a year before 2010. Additionally, to broaden the analysis, the paper goes beyond the parsimonious measurement-error models of Aruoba et al. [2016] and analyses a multivariable variant. Finally, it compares the results obtained from the measurement-error models with simple (un)weighted averages of the underlying data series. Simple (un)weighted averages imply very similar employment dynamics. This finding and the fact that (un)weighted averages are easily understandable implies that such simple measures are well suited to communicate employment developments.

Appendix

Data of the multi-measurement equation model

In the multi-measurement equation model, data on the change in the unemployment rate, the change in the job vacancy rate, the employment PMI of procure.ch and Credit Suisse, and the job security assessment according to the SECO consumer sentiment survey is used. As a measure of the number of unemployed, the full census data of SECO is used. Data on job vacancies between 1997Q1–2022Q2 stem from the JS. To get a series back to 1991Q4, the data of the JS is linked with the Adecco Group Swiss Job Market Index. The unemployment and vacancy *rate* is computed by dividing the unemployment and job vacancy series by the labor force. The time series of the labor force is based on quarterly data of the ES and low-frequency data used by SECO to calculate the unemployment rate. More precisely, the number of employed and unemployed with permanent residence in Switzerland is used to construct a quarterly series of the labor force, and then this quarterly series is rescaled to match the low-frequency labor force data used by SECO. This is done because the latter is based on a much broader sample and, hence, more reliable. All the data is seasonally adjusted.

Mixed-frequency approach and state-space form

When implementing the mixed frequency approach, the state-space system has to be rewritten as follows:

$$y_t = Cs_t \tag{12}$$

$$s_t = As_{t-1} + Be_t,\ e_t \sim N(0, Q) \tag{13}$$

$$y_t = [\Delta E_t^y - 4\mu_W, \Delta E_t - \mu_W, \Delta J_t - \mu_j - \mu_W, PMI - \mu_P - \mu_W]' \tag{14}$$

$$\begin{aligned} s_t =& [\Delta W_t - \mu_W, \Delta W_{t-1} - \mu_W, \Delta W_{t-2} - \mu_W, ... \\ & ... \, \Delta W_{t-3} - \mu_W, \varepsilon_{E,t}, \varepsilon_{E,t-1}, \varepsilon_{E,t-2}, \varepsilon_{E,t-3}, \varepsilon_{J,t}, \varepsilon_{P,t}]' \end{aligned} \tag{15}$$

$$e_t = [\varepsilon_{W,t}, \varepsilon_{E,t}, \varepsilon_{J,t}, \varepsilon_{P,t}]' \tag{16}$$

$$C = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ \kappa & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}, \tag{17}$$

$$A = \begin{bmatrix} \rho & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{18}$$

$$B = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \; Q = \begin{bmatrix} \sigma_E^2 & \sigma_{E,ES} & \sigma_{E,JS} & \sigma_{E,P} \\ \sigma_{ES,E} & \sigma_{ES}^2 & \sigma_{EJ}^2 & 0 \\ \sigma_{JS,E} & \sigma_{JS,ES} & \sigma_{JS}^2 & 0 \\ \sigma_{P,E} & 0 & 0 & \sigma_P^2 \end{bmatrix} \tag{19}$$

To not loose information on quarterly employment growth between 2010 and 2011, both, the year-on-year as well as the quarterly growth rate is included. To avoid collinearity, data on year-on-year growth are only used up to 2010. When an observable is missing, the state-space system is reduced. That is, the measurement equation for the missing observable is taken out of the system. This ensures identification when year-on-year growth until 2010 and afterwards quarterly growth of the number of employees is used.

Parameter prior and posterior distribution of the 3- and multi-measurement equation model

Table 5: Priors and posteriors 3-measurement equation model Part 1, 1991Q4-2022Q2

	Prior	Posterior		
	(Mode, Std. Dev.)	25%	50%	75%
1991Q4–2006Q4				
ρ	B(0.5,1)	0.62	0.68	0.75
κ	IG(2.6,3)	1.66	1.84	2.05
σ^2_E	IG(0.3,3)	0.12	0.14	0.17
σ^2_{ES}	IG(0.3,3)	0.24	0.30	0.37
σ^2_{JS}	IG(0.3,3)	0.18	0.21	0.23
σ^2_P	IG(0.3,3)	0.16	0.19	0.24
$\sigma_{E,ES}$	N(0,2)	-0.05	-0.03	-0.02
$\sigma_{E,JS}$	N(0,2)	-0.01	0.00	0.02
$\sigma_{E,P}$	N(0,2)	-0.19	-0.16	-0.14
$\sigma_{ES,JS}$	N(0,2)	0.01	0.07	0.12
μ_E	N(0.20,2)	0.12	0.20	0.29
μ_J	N(-0.01,2)	-0.10	-0.06	-0.01
μ_P	N(-0.90,2)	4.84	4.91	5.00
2007Q1–2022Q2				
ρ	B(0.5,1)	0.38	0.49	0.57
κ	IG(2.6,3)	2.32	2.65	3.24
μ_E	N(0.20,2)	0.23	0.29	0.36
μ_J	N(-0.01,2)	-0.03	0.02	0.08
μ_P	N(-0.90,2)	4.75	4.86	4.94

Table 6: Priors and posteriors 3-measurement equation model Part 2, 1991Q4-2022Q2

	Prior	Posterior		
	(Mode, Std. Dev.)	25%	50%	75%
2007Q1–2019Q4				
σ_E^2	IG(0.3,3)	0.12	0.13	0.15
σ_{ES}^2	IG(0.3,3)	0.21	0.25	0.29
σ_{JS}^2	IG(0.3,3)	0.08	0.09	0.11
σ_P^2	IG(0.3,3)	0.42	0.52	0.73
$\sigma_{E,ES}$	N(0,2)	-0.01	-0.00	0.02
$\sigma_{E,JS}$	N(0,2)	-0.04	-0.02	-0.01
$\sigma_{E,P}$	N(0,2)	-0.28	-0.20	-0.16
$\sigma_{ES,JS}$	N(0,2)	-0.15	-0.13	-0.12
2020Q1–2022Q2				
σ_E^2	IG(0.3,3)	0.20	0.24	0.30
σ_{ES}^2	IG(0.3,3)	0.52	0.66	0.87
σ_{JS}^2	IG(0.3,3)	0.23	0.28	0.36
σ_P^2	IG(0.3,3)	0.26	0.34	0.45
$\sigma_{E,ES}$	N(0,2)	-0.00	0.06	0.12
$\sigma_{E,JS}$	N(0,2)	0.08	0.13	0.19
$\sigma_{E,P}$	N(0,2)	-0.27	-0.20	-0.13
$\sigma_{ES,JS}$	N(0,2)	0.18	0.27	0.36

Table 7: Priors and posteriors multi-measurement equation model Part 1, 1991Q4-2022Q2

	Prior	Posterior		
	(Mode, Std. Dev.)	25%	50%	75%
1991Q4–2006Q4				
ρ	B(0.5,1)	0.71	0.82	0.89
λ_u	N(-1,2)	-0.51	-0.48	-0.44
λ_v	N(1,2)	0.17	0.21	0.26
λ_k	N(1,2)	-0.03	0.02	0.06
λ_p	N(1,2)	-0.06	0.01	0.07
λ_s	N(1,2)	0.02	0.07	0.11
σ_E^2	IG(0.2,3)	0.09	0.10	0.12
σ_{ES}^2	IG(0.2,3)	0.14	0.18	0.22
σ_{JS}^2	IG(0.2,3)	0.12	0.14	0.15
σ_U^2	IG(0.2,3)	0.05	0.06	0.07
σ_V^2	IG(0.2,3)	0.05	0.05	0.06
σ_K^2	IG(0.2,3)	0.04	0.04	0.05
σ_P^2	IG(0.2,3)	0.04	0.05	0.05
σ_S^2	IG(0.2,3)	0.04	0.04	0.05
μ_E	N(0.20,1)	0.15	0.25	0.54
μ_J	N(-0.01,1)	-0.06	-0.01	0.02
μ_U	N(-0.19,1)	-0.73	-0.29	-0.16
μ_V	N(-0.20,1)	-0.44	-0.23	-0.14
μ_K	N(-0.21,1)	-0.55	-0.26	-0.16
μ_P	N(-0.15,1)	-0.47	-0.21	-0.10
μ_S	N(-0.28,1)	-0.59	-0.33	-0.23

Table 8: Priors and posteriors multi-measurement equation model Part 2, 1991Q4-2022Q2

	Prior	Posterior		
	(Mode, Std. Dev.)	25%	50%	75%
2007Q1–2022Q2				
ρ	B(0.5,1)	0.42	0.54	0.63
λ_u	N(-1,2)	-0.43	-0.34	-0.25
λ_v	N(1,2)	0.08	0.15	0.24
λ_k	N(1,2)	-0.06	0.01	0.08
λ_p	N(1,2)	-0.05	0.02	0.08
λ_s	N(1,2)	-0.02	0.06	0.12
μ_E	N(0.20,1)	0.25	0.30	0.34
μ_J	N(-0.01,1)	-0.03	0.01	0.07
μ_U	N(-0.19,1)	-0.38	-0.32	-0.24
μ_V	N(-0.20,1)	-0.33	-0.30	-0.24
μ_K	N(-0.21,1)	-0.34	-0.30	-0.24
μ_P	N(-0.15,1)	-0.29	-0.24	-0.19
μ_S	N(-0.28,1)	-0.40	-0.35	-0.31
2007Q1–2019Q4				
σ^2_E	IG(0.2,3)	0.07	0.08	0.09
σ^2_{ES}	IG(0.2,3)	0.14	0.16	0.17
σ^2_{JS}	IG(0.2,3)	0.09	0.10	0.12
σ^2_U	IG(0.2,3)	0.04	0.05	0.06
σ^2_V	IG(0.2,3)	0.04	0.05	0.05
σ^2_K	IG(0.2,3)	0.03	0.04	0.04
σ^2_P	IG(0.2,3)	0.03	0.04	0.04
σ^2_S	IG(0.2,3)	0.03	0.04	0.04

Table 9: Priors and posteriors multi-measurement equation model Part 3, 1991Q4-2022Q2

	Prior	Posterior		
	(Mode, Std. Dev.)	25%	50%	75%
2020Q1–2022Q2				
σ^2_E	IG(0.2,3)	0.59	0.81	1.09
σ^2_{ES}	IG(0.2*4,3)	0.59	0.71	0.90
σ^2_{JS}	IG(0.2*4,3)	0.55	0.67	0.81
σ^2_U	IG(0.2*4,3)	0.49	0.61	0.78
σ^2_V	IG(0.2*4,3)	0.48	0.60	0.74
σ^2_K	IG(0.2*4,3)	0.51	0.63	0.77
σ^2_P	IG(0.2*4,3)	0.48	0.58	0.70
σ^2_S	IG(0.2*4,3)	0.49	0.60	0.75

Acknowledgements

I wish to thank Matthias Lutz, Rolf Scheufele, the participants of the research seminar of the Swiss National Bank and an anonymous referee for helpful discussions and valuable comments.

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