



Working Paper

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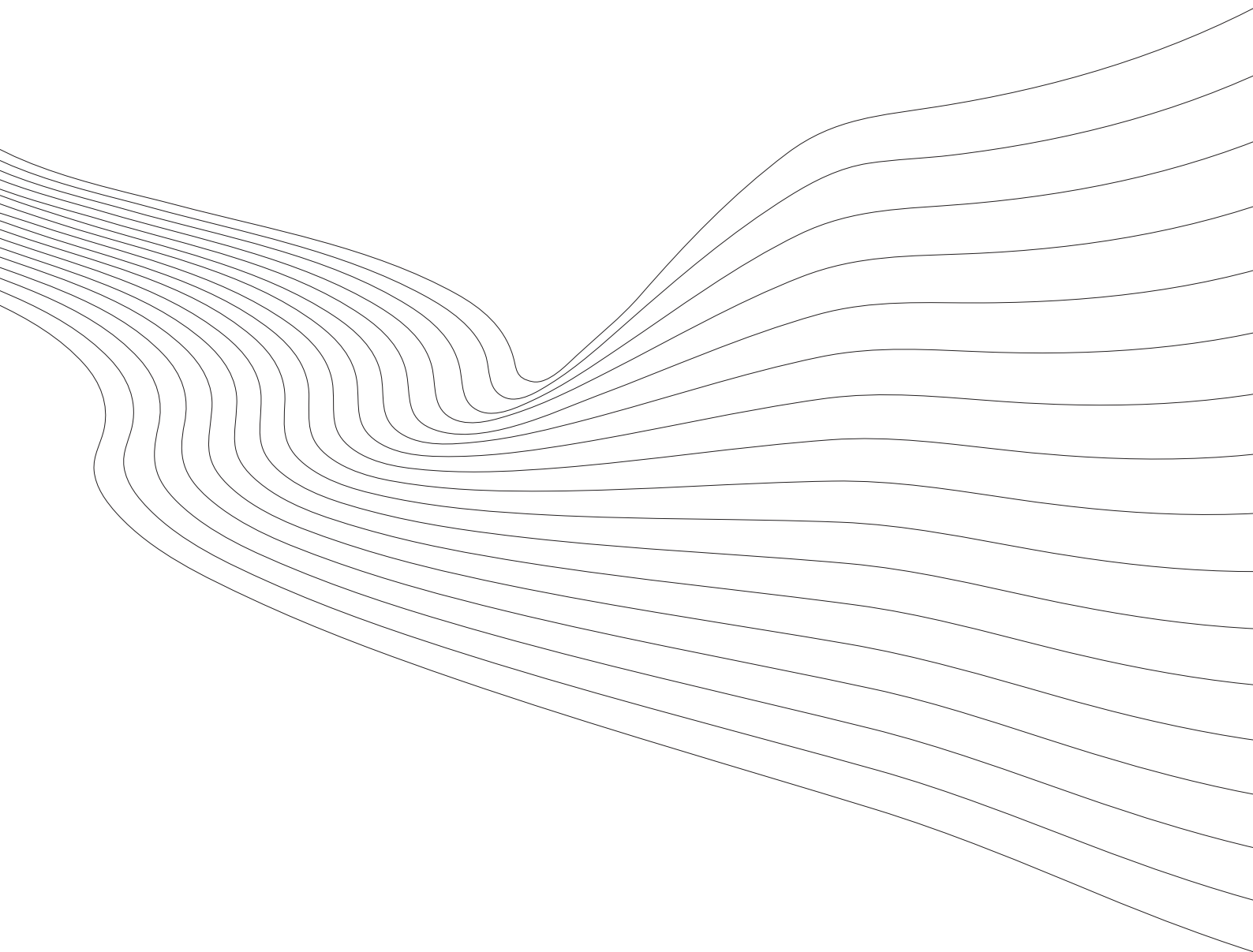
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# KOF Working Papers

The franc shock and Swiss GDP:  
How long does it take to start feeling the pain?

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# The franc shock and Swiss GDP: How long does it take to start feeling the pain?\*

Boriss Siliverstovs\*\*

February 17, 2015

## Abstract

The paper addresses the question on what is the typical time horizon over which a full transmission of movements in the real exchange rate into real economy takes place. To this end, we base our analysis on the mixed-frequency small-scale dynamic factor model of [Siliverstovs \(2012\)](#) fitted to the Swiss data. In this paper, we augment the benchmark model with the real exchange rate of the Swiss franc vis-à-vis currencies of its 24 trading partners, while keeping the rest of model specification intact. We are interested in investigating the relationship between the common latent factor, representing the Swiss business cycle, and the real exchange rate. We explore the temporal relationship between these two variables by varying the time lag with which the real exchange rate enters the factor model by recording magnitude and statistical significance of the factor loading coefficient in the equation pertaining to the real exchange rate variable. Our main conclusion is that the fluctuations in the exchange rate start influencing real economy after one month and their effect is practically over after thirteen months. The largest effect is recorded at the time horizon of about six to nine months.

*Keywords:* Factor model, mixed-frequency data, exchange rate, GDP growth

*JEL code:* C22, E32.

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Words fail me! Jordan is not only the name of the SNB president, but also of a river... and today's SNB action is a tsunami; for the export industry and for tourism, and finally for the entire country.

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*Nick Hayek, Swatch Group CEO*

## 1 Introduction

The decision of the Swiss National Bank (SNB) to lift the cap on the nominal Swiss franc-euro exchange rate on the 15th of January 2015 sent shock waves across financial markets worldwide. In the hectic hours immediately after the cap lifting the Swiss franc sky-rocketed reaching the record level of almost as high as 0.75 CHF per 1 EUR and then stabilising around the one-to-one parity.<sup>1</sup> The Swiss benchmark stock market index (SMI) initially dropped about 14% in a record fall not witnessed since 1989 but closed down about 9% lower in that day. A serious concern regarding the performance of export-oriented Swiss economy and, especially, the tourism branch was also raised among business leaders and policy-makers. The forecasting institutions were forced to abandon their previous forecasts for the Swiss Economy based on the assumption of SNB continuing commitment to the maintenance of the CHF-EUR minimum exchange rate. For example, the KOF Swiss Economic Institute at ETH Zurich significantly lowered its forecast of annual real GDP growth in the current year 2015 from 1.9%, as published in December 2014, to -0.5%. For the next year 2016 the annual GDP growth rate was likewise adjusted downwards from 2.1% (December forecast) to 0.0%.

In this study we intend to address an important issue of what is the typical response lag of the Swiss economy to volatility of the exchange rate. Or, in other words, how long does it take to transmit exchange rate shocks into the real economy. We base our estimations on the mixed-frequency small-scale dynamic factor model (DFM), first estimated in Siliverstovs (2012). In Siliverstovs (2012) it was shown that the model based on the four survey indicators produces a reliable forecast accuracy of GDP growth during the period 2006Q4—2010Q4. Moreover, it was demonstrated that the DFM model is useful for predicting GDP revisions during the sample period in question.

The contribution of the current study is twofold. First, we introduce the real exchange rate of CHF against the weighted basket of currencies of 24 trading partners into the factor model. The response lag of the Swiss economy to changes in the real exchange rate is measured by comparing different model specifications by varying the lag parameter with which the exchange rate variable enters the factor model. Otherwise the model specification is kept the same as in Siliverstovs (2012). Secondly, we re-estimate the model using more recent data. In this way, we check whether the model estimation results of Siliverstovs (2012) reported for the period that ends in 2011M1 carry over when using an updated data that go through 2015M1.

The paper is organised as follows. Section 2 contains a description of data. The mixed-frequency small-scale dynamic factor model, that forms the basis of our empirical analysis, is presented in Section 3. The estimation results as well as our main findings are presented in Section 4. The final section concludes.

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<sup>1</sup><http://www.schweizer-franken.eu/2015/01/plotzliches-eurchf-mindestkurs-ende.html>.

## 2 Data

The core variables are the same as in [Siliverstovs \(2012\)](#). They comprise the seasonally adjusted real GDP quarterly growth rate, for which we have historical real-time vintages. The use of historical vintages of GDP growth allows us to come as close as possible to simulating real-time information available in the past as well as to check the robustness of our results with respect to changing estimation sample as well as to take into account the influence of GDP revisions, which as shown in [Cuche-Curti et al. \(2008b\)](#), may be rather large in Switzerland, as it would be expected for a small open economy (see [Cuche-Curti et al., 2008a](#), for an international evidence).

We link the GDP growth observed at the quarterly frequency and with a publication lag of about two months after the end of the reference quarter with the following four monthly indicators: Purchasing Managers' Index (PMI) for Switzerland (collected by Credit Suisse) and three monthly business tendency surveys in manufacturing collected at the KOF institute: current assessment of business situation, expected purchase of intermediate goods in the next three months and change in the order backlog compared to the previous month. All the KOF surveys are expressed in terms of *Net Balances*. The value of the PMI index for the current month is released on the first business day of the following month. The PMI time series goes back until January 1995. The KOF surveys are released in the middle of month and contain the most recent observation for the current month. These surveys go back as far as January 1968, thus representing ones of the earliest business tendency surveys collected at KOF.

The DFM estimated in [Siliverstovs \(2012\)](#) was based on these four variables in addition to the GDP growth. In this paper we augment the model with the real exchange rate measured with respect to 24 countries. The index of the real exchange rate takes value of 100 in 1991M1 and goes back to 1973M1. Appreciation of the Swiss Franc is reflected in increased index values. We compute the monthly growth rate by taking first difference of its logarithmic transformation. The real exchange rate is published by the SNB in the beginning of the third *décade* of each month and contains observations through the previous month. Correspondingly, the timing when the factor model is estimated coincides with the release date of the real exchange rate. This means that at that day all variables contain all monthly observations for the previous quarter.

## 3 Dynamic Factor Model

The dynamic factor model links the data observed at mixed frequencies: the observed quarterly  $y_t$ , expressed as the quarter-on-quarter growth rate of real GDP, and a set of monthly indicators  $z_t = (z_t^A, z_t^B, z_t^C, z_t^D, z_t^E)'$  with  $z_t^A$  is the PMI index,  $z_t^B$ —current assessment of business situation,  $z_t^C$ —expected purchase of intermediate goods in the next three months,  $z_t^D$ —change in the order backlog compared to the previous month and  $z_t^E$  represents the real exchange rate. All auxiliary survey indicators enter the model in levels, whereas the real exchange rate is expressed in terms of monthly growth.

Following [Mariano and Murasawa \(2003\)](#), we assume that a common factor  $f_t$ , representing the business

cycle dynamics, is linearly related to the unobserved monthly GDP growth  $y_t^*$ :

$$y_t^* = \beta f_t + u_t,$$

where  $u_t$  is an idiosyncratic component. The observed quarterly GDP growth can be represented in terms of its latent monthly counterpart as follows:

$$y_t = \frac{1}{3}y_t^* + \frac{2}{3}y_{t-1}^* + y_{t-2}^* + \frac{2}{3}y_{t-3}^* + \frac{1}{3}y_{t-4}^*, \quad (1)$$

see [Mariano and Murasawa \(2003\)](#) for more details. Inserting the expression for  $y_t^*$  in the equation above results in the following equation:

$$y_t = \beta \left( \frac{1}{3}f_t + \frac{2}{3}f_{t-1} + f_{t-2} + \frac{2}{3}f_{t-3} + \frac{1}{3}f_{t-4} \right) + \frac{1}{3}u_t + \frac{2}{3}u_{t-1} + u_{t-2} + \frac{2}{3}u_{t-3} + \frac{1}{3}u_{t-4}, \quad (2)$$

linking the observed quarterly GDP growth with the common factor  $f_t$  at the monthly frequency. Here we conform with the literature and assume that GDP values are skip sampled in such a way that these are observed every third month in each quarter.

Similarly as in [Camacho and Perez-Quiros \(2010\)](#), the relationship between the latent common factor and the survey indicators is modelled as a cumulative sum the contemporaneous and eleven lagged values of  $f_t$ :

$$z_t^i = \lambda^i \sum_{j=0}^{11} f_{t-j} + v_t^i, \quad \text{with } i = A, B, C. \quad (3)$$

This modelling approach reflects the fact that surveys tend to be much more persistent than the monthly GDP growth rate. However, since the survey indicator  $z_t^D$  reflects changes in the order backlog compared to the *previous* month we relate it directly to the monthly common factor:

$$z_t^D = \lambda^D f_t + v_t^D.$$

Likewise, we link the monthly real exchange rate growth with the common factor:

$$z_t^E = \lambda^E f_t + v_t^E. \quad (4)$$

Furthermore, [Siliverstovs \(2012\)](#) argues that the comovement between indicators, on what hinges reliable extraction of a common latent factor, can be better captured by exploiting the cross-correlation pattern between the auxiliary indicators by adjusting their lead-lag combination in the DFM specification. For example, the surveys  $z_t^A$  and  $z_t^D$  enter the model in their contemporaneous form, whereas the following lead-lag adjustment  $z_t^{B*} \equiv z_{t+3}^B$  and  $z_t^{C*} \equiv z_{t-3}^C$  was necessary for indicators  $z_t^B$  and  $z_t^C$ , respectively. In doing so, we effectively treat the indicators  $z_t^A$  and  $z_t^D$  as coincident and the indicators  $z_t^C$  and  $z_t^B$  as leading and lagging, respectively. Consequently, the left-hand side of Equation (3) for indicators  $z_t^C$  and  $z_t^B$  needs

to be adjusted.<sup>2</sup>

As in case of certain survey indicators, we can vary the lead-lag with which the real exchange rate enters the model through Equation (4), which can be modified as follows:

$$z_{t-k}^E = \lambda^E f_t + v_t^E. \quad (5)$$

For positive values of the lag parameter  $k$ , the contemporaneous values of the common factor are related to the past values of the real exchange rate, indicating its leading character. For  $k = 0$ , there exists a link between contemporaneous values of the both variables. Finally, for negative values of  $k$ , the real exchange rate serves as a lagging indicator of the business cycle. The empirical conclusion on whether the real exchange rate behaves as a leading, coincident or lagging indicator can be based on the economic and statistical significance of the loading coefficient  $\lambda^E$  in Equation (4). For  $k > 0$ , we expect a negative sign for the loading coefficient, as the franc appreciation generally is expected to execute a dampening effect on the real economy. For  $k < 0$ , we expect that a good performance of the Swiss economy, for example, mirrored in the persistent current account surplus or higher average growth than in the neighbouring countries, will eventually lead to the appreciation of the franc, i.e. a positive sign of the loading coefficient. We vary the value of the lag parameter  $k$  in the interval from -3 to 15, allowing us to estimate a time lag with which fluctuations in the real exchange rate transmit into the real economy and vice versa.

Pooling together the various equations presented above that link observed variables on the one hand and unobserved variables like the common factor and idiosyncratic components on the other hand The relationship between can be represented in what is known as the measurement equation in the state-space models:<sup>3</sup>

$$\begin{pmatrix} y_t \\ z_t^A \\ z_t^{B*} \\ z_t^{C*} \\ z_t^D \\ z_t^{E*} \end{pmatrix} = \begin{pmatrix} \beta(\frac{1}{3}f_t + \frac{2}{3}f_{t-1} + f_{t-2} + \frac{2}{3}f_{t-3} + \frac{1}{3}f_{t-4}) \\ \lambda^A \sum_{j=0}^{11} f_{t-j} \\ \lambda^B \sum_{j=0}^{11} f_{t-j} \\ \lambda^C \sum_{j=0}^{11} f_{t-j} \\ \lambda^D f_t \\ \lambda^E f_t \end{pmatrix} + \begin{pmatrix} \frac{1}{3}u_t + \frac{2}{3}u_{t-1} + u_{t-2} + \frac{2}{3}u_{t-3} + \frac{1}{3}u_{t-4} \\ v_t^A \\ v_t^B \\ v_t^C \\ v_t^D \\ v_t^E \end{pmatrix} \quad (6)$$

with  $z_t^{B*} \equiv z_{t+3}^B$  and  $z_t^{C*} \equiv z_{t-3}^C$  as in the model of [Siliverstovs \(2012\)](#) and  $z_t^{E*} \equiv z_{t-k}^E$  with  $k \in [-3, 15]$ , representing the novelty of the current paper.

## 4 Results

In this section we first report the model estimation results using the exactly the same specification as in [Siliverstovs \(2012\)](#). The purpose of this estimation exercise is to verify whether estimation results reported

<sup>2</sup>[Camacho and Doménech \(2012\)](#) also differentiate between the leading properties of the auxiliary indicators. In their small-scale DFM they selectively allow some financial variables to lead the common factor.

<sup>3</sup>For the sake of brevity, the complete state-space form of the DFM is relegated to the appendix.



in [Siliverstovs \(2012\)](#) are robust with respect to prolongation of the sample and the use of more recent GDP vintages. In the second stage, we augment the DFM with the real exchange rate and re-estimate it using the model specification in Equation (6).

In order to check whether the previous estimation results of the DFM reported in [Siliverstovs \(2012\)](#) hold also in the extended sample, we recursively re-estimate the factor model in the pseudo real time. This means that at each forecast horizon we use the GDP data vintage that was actually available in the past. Since we do not have all historical vintages of the other variables we appropriately truncate them according to their release timing and publication lag. The model is estimated using an expanding estimation window. The initial forecast origin corresponds to the data stand on the 21st of January 2007. At this date, the data at our disposal are: GDP data vintage extends through 2006Q3, the PMI indicator available until December 2006 and the three KOF survey variables available until January 2007. As the starting date for the initial estimation sample we take January 2005—the earliest date for which all monthly indicators are available.<sup>4</sup> The, the initial estimation sample period is 1995M1—2007M1. Simulating the actual data stand in the past at the next forecast origin (the 21st of April 2007), we extend the information set by the new GDP data vintage that has the latest observation for 2006Q4, the PMI variable available until 2007M3 and the KOF surveys available until 2007M4. We proceed in this manner until at the last forecast origin (the 21th of January 2015) the estimation sample covering the period 1995M1—2015M1 is used. In total we have 33 forecast origins and, correspondingly, 33 pseudo real-time data vintages. For each estimation window the model parameters are re-estimated.

The results of the recursive estimation of the loading coefficients of the common factor into the GDP variable ( $\beta$ ) and the four survey variables ( $\lambda^A, \lambda^B, \lambda^C, \lambda^D$ ) using the the same DFM specification as in [Siliverstovs \(2012\)](#) are presented in Figure 1. This figure is to be compared with Figure 2 in [Siliverstovs \(2012, p. 314\)](#) displaying estimation results of the same model carried out four years ago. As seen, expanding the sample by additional four years still yields very similar coefficient estimates and, more importantly, these estimates remain stable across all estimation windows.

At the next step, we augment the factor model with the real exchange rate variable and re-estimate the enlarged factor model using each of the previously defined pseudo real time data vintages. In addition, we vary the lag parameter  $k \in [-3, 15]$  with which the real exchange rate enters the factor model, see Equation (6). Since the main focus of this paper on the lead-lag relationship between the real exchange rate and business cycle dynamics (proxied by the common factor  $f_t$  in the model), we restrict presentation of the estimation results to reporting only estimates of the factor loading coefficient  $\lambda^E$  as a function of a forecast origin and the corresponding estimation window as well as the lag  $k$  of  $z_{t-k}^E$ .<sup>5</sup>

In Figure 2 we report the estimates of the loading coefficient and the associated p-values obtained for the final estimation window 1995M1—2015M1 as a function of the lag parameter  $k$ . The estimates of the loading coefficient  $\widehat{\lambda}^E$  are all negative except for  $k = -3$  and  $k = -2$ . This sign of the estimates indicates that the real exchange rate is the leading indicator for the Swiss business cycle. The magnitude of the estimated

<sup>4</sup>Recall that 1995M1 is the earliest period for which the PMI is available.

<sup>5</sup>We make the complete model estimation results available upon the request.

coefficient also varies with the value of  $p$  forming a U-shaped pattern. The minimum of  $-0.086$  is achieved at the time lag of nine months,  $k = 9$ . According to the tests of statistical significance, we also can reject the null hypothesis that the loading coefficient is not significantly different from zero at the 5% level. The estimates of the loading coefficient are also significant at values of  $k = 8, 9, 10, 11$  at the 5% level. At the 10% level, the estimates are significant for  $k = 3$  and for each value of  $k$  in the interval  $[5, 12]$ , effectively specifying a most likely time span within which changes in the exchange rate transmit to the real economy.

In Figures 3 and 4 we report the p-values and the estimates of the loading coefficient  $\widehat{\lambda}^E$  obtained using all historical data vintages at our disposal, respectively. In Figure 3 the values of the  $p$ -parameter for which estimates  $\widehat{\lambda}^E$  are significant at the 5% and 10% levels are reported in green and yellow colours; the associated p-values above 10% but less than 20% in red, and those above 20%—in black. The main finding is that the familiar U-shape pattern in the reported p-values, shown in Figure 2 for the final data vintage, manifests itself in every data vintage. The p-values below 5% level are generally centred around values of the lag parameter in the interval between five and nine for data vintages up to 2011. For later vintages, we observe a slight shift towards higher value of the lag parameter. It is worthwhile noting, that this shift takes place in the period characterised by the maintenance of the minimum CHF/EUR exchange rate boundary since the 6th of September 2011. Apparently, the introduction of the currency cap somewhat increased the response time of the real economy to the exchange rate shocks. This is also evident consistent with the pattern observed in the estimates of the loading coefficient  $\lambda^E$ , shown in Figure 4. In the period before the introduction of the currency cap the minimal values of the loading coefficient were mostly centred around  $k = 6$ . Since 2011 the troughs in the estimated loading coefficients are around  $k = 9$ .

In Figure 5 we report the unconditional distribution of the incidence of significant estimates of the factor loading coefficient  $\widehat{\lambda}^E$  at the 10% level for each value of  $k \in [-3, 15]$  across all data vintages. The highest incidence of significant estimates occurs at  $k \in [6, 9]$ , suggesting a most likely time horizon when the interaction between the real exchange rate and the latent common factor representing the business cycle dynamics in Switzerland is most intense. The effect of real exchange shocks are felt starting as soon as one month and continuing as late as 13 months. Beyond the horizon of 13 months these effects fade out.

## 5 Conclusion

The recent decision of the SNB to abolish the minimum exchange rate of the Swiss Franc to euro, introduced on the 6th September 2011, set a turmoil in financial markets and raised serious concerns on the future prospects of the Swiss economy. Undoubtedly, this unexpected move also considerably raised an interest in the nexus between exchange rate and economic growth in Switzerland, calling for further exploration of the relationship between them.

In this paper, we attempt to address the question on what is the typical time horizon over which a full transmission of movements in the real exchange rate into real economy takes place. To this end, we base our analysis on the small-scale dynamic factor model proposed in Siliverstovs (2012). This model, which we take as a benchmark, is based on four survey indicators (one is the PMI collected by Credit Suisse and

three surveys in manufacturing collected at KOF Swiss Economic Institute at ETH Zurich). As shown in Siliverstovs (2012), this model, despite its small size, can adequately capture the business cycle dynamics in Switzerland both in sample and, more importantly, out of sample, producing reliable forecasts of GDP growth.

In this paper, we augment the benchmark model with the real exchange rate of the Swiss franc vis-a-vis currencies of its 24 trading partners, while keeping the rest of model specification intact. We are interested in investigating the relationship between the common latent factor, representing the Swiss business cycle, and the real exchange rate. We explore the temporal relationship between these two variables by varying the time lag with which the real exchange rate enters the factor model. In particular, we keep the track of the magnitude and statistical significance of the coefficient with which a common factor loads into the real exchange rate variable as function of the time lag parameter. Our main conclusion is that the fluctuations in the exchange rate start influencing real economy as soon as after one month and their effect is practically over after thirteen months. The largest effect is recorded at the horizon of about six to nine months. We also record that since the introduction of the currency cap in 2011, it takes a longer time for the full transmission of the real exchange rate shocks into the real economy, compared to the earlier period.

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## Appendix

The relationship between observed and latent variables is summarised in the measurement equation:

$$\begin{pmatrix} y_t \\ z_t^A \\ z_t^{B*} \\ z_t^{C*} \\ z_t^D \\ z_t^{E*} \end{pmatrix} = \begin{pmatrix} \beta(\frac{1}{3}f_t + \frac{2}{3}f_{t-1} + f_{t-2} + \frac{2}{3}f_{t-3} + \frac{1}{3}f_{t-4}) \\ \lambda^A \sum_{j=0}^{11} f_{t-j} \\ \lambda^B \sum_{j=0}^{11} f_{t-j} \\ \lambda^C \sum_{j=0}^{11} f_{t-j} \\ \lambda^D f_t \\ \lambda^E f_t \end{pmatrix} + \begin{pmatrix} \frac{1}{3}u_t + \frac{2}{3}u_{t-1} + u_{t-2} + \frac{2}{3}u_{t-3} + \frac{1}{3}u_{t-4} \\ v_t^A \\ v_t^B \\ v_t^C \\ v_t^D \\ v_t^E \end{pmatrix}$$

with  $z_t^{B*} \equiv z_{t+3}^B$ ,  $z_t^{C*} \equiv z_{t-3}^C$  and  $z_t^{D*} \equiv z_{t-k}^E$  with  $k \in [-3, 15]$ .

We further assume that the common factor and idiosyncratic components follow AR(1) processes:

$$\begin{aligned} f_{t+1} &= \psi f_t + \epsilon_t, \\ u_{t+1} &= \theta u_t + \zeta_t, \\ v_{t+1}^A &= \theta_A v_t^A + \zeta_t^A, \\ v_{t+1}^B &= \theta_B v_t^B + \zeta_t^B, \\ v_{t+1}^C &= \theta_C v_t^C + \zeta_t^C, \\ v_{t+1}^D &= \theta_D v_t^D + \zeta_t^D, \\ v_{t+1}^E &= \theta_E v_t^E + \zeta_t^E, \end{aligned}$$

where  $\epsilon_t \sim iidN(0, \sigma_f^2)$ ,  $\zeta_t \sim iidN(0, \sigma^2)$ ,  $\zeta_t^A \sim iidN(0, \sigma_A^2)$ ,  $\zeta_t^B \sim iidN(0, \sigma_B^2)$ ,  $\zeta_t^C \sim iidN(0, \sigma_C^2)$ , and  $\zeta_t^D \sim iidN(0, \sigma_D^2)$  and  $\zeta_t^E \sim iidN(0, \sigma_E^2)$ , so that all the common factor and unit-specific components are orthogonal. We also impose the following identifying restriction  $\sigma_f^2 = 1$ .

The dynamic factor model, defined above, can be compactly written in the state-space form. First, we define the state vector comprising the unobserved variables:

$$s_t = (f_t, f_{t-1}, f_{t-2}, \dots, f_{t-10}, f_{t-11}, u_t, u_{t-1}, \dots, u_{t-4}, v_t^A, v_t^B, v_t^C, v_t^D, v_t^E)'$$

The measurement equation can be written as

$$\begin{pmatrix} y_t \\ z_t^* \end{pmatrix} = H s_t,$$

where  $z_t^* = (z_t^A, z_t^{B*}, z_t^{C*}, z_t^D, z_t^{E*})'$ , with

$$H_{(6 \times 22)} = \begin{bmatrix} H_1 & 0_{(1 \times 6)} & H_2 & 0 & 0 & 0 & 0 & 0 & 0 \\ H_A & H_A & 0_{(1 \times 5)} & 1 & 0 & 0 & 0 & 0 & 0 \\ H_B & H_B & 0_{(1 \times 5)} & 0 & 1 & 0 & 0 & 0 & 0 \\ H_C & H_C & 0_{(1 \times 5)} & 0 & 0 & 1 & 0 & 0 & 0 \\ H_D & 0_{(1 \times 6)} & 0_{(1 \times 5)} & 0 & 0 & 0 & 1 & 0 & 0 \\ H_E & 0_{(1 \times 6)} & 0_{(1 \times 5)} & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix},$$

where

$$\begin{aligned} H_1 &= \left( \frac{1}{3}\beta \quad \frac{2}{3}\beta \quad \beta \quad \frac{2}{3}\beta \quad \frac{1}{3}\beta \quad 0 \right) \\ H_2 &= \left( \frac{1}{3} \quad \frac{2}{3} \quad 1 \quad \frac{2}{3} \quad \frac{1}{3} \right) \\ H_A &= (\lambda_A \quad \lambda_A \quad \lambda_A \quad \lambda_A \quad \lambda_A \quad \lambda_A) \\ H_B &= (\lambda_B \quad \lambda_B \quad \lambda_B \quad \lambda_B \quad \lambda_B \quad \lambda_B) \\ H_C &= (\lambda_C \quad \lambda_C \quad \lambda_C \quad \lambda_C \quad \lambda_C \quad \lambda_C) \\ H_D &= (\lambda_D \quad 0 \quad 0 \quad 0 \quad 0 \quad 0) \\ H_E &= (\lambda_E \quad 0 \quad 0 \quad 0 \quad 0 \quad 0) \end{aligned}$$

The dynamics of the latent factor as well as the idiosyncratic components can be compactly stated in the following transition equation:

$$s_{t+1} = F s_t + \Phi \varsigma_t,$$

where  $\varsigma_t = (\epsilon_t, \zeta_t, \zeta_t^A, \zeta_t^B, \zeta_t^C, \zeta_t^D, \zeta_t^E)'$  and  $\Phi_{(22 \times 7)}$  is a matrix with zeros and seven unit values loading the corresponding elements of the innovation vector into the transition equation.

The state transition matrix  $F$  has the following structure

$$F_{(22 \times 22)} = \begin{bmatrix} F_1 & O_{(12 \times 5)} & O_{(12 \times 5)} \\ O_{(5 \times 12)} & F_2 & O_{(5 \times 5)} \\ O_{(5 \times 12)} & O_{(5 \times 5)} & F_3 \end{bmatrix},$$

where

$$F_1 = \begin{matrix} (12 \times 12) \\ = \end{matrix} \begin{bmatrix} \psi & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}$$

$$F_2 = \begin{matrix} (5 \times 5) \\ = \end{matrix} \begin{bmatrix} \theta & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix},$$

$$F_3 = \begin{matrix} (5 \times 5) \\ = \end{matrix} \begin{bmatrix} \theta_A & 0 & 0 & 0 & 0 \\ 0 & \theta_B & 0 & 0 & 0 \\ 0 & 0 & \theta_C & 0 & 0 \\ 0 & 0 & 0 & \theta_D & 0 \\ 0 & 0 & 0 & 0 & \theta_D \end{bmatrix}.$$

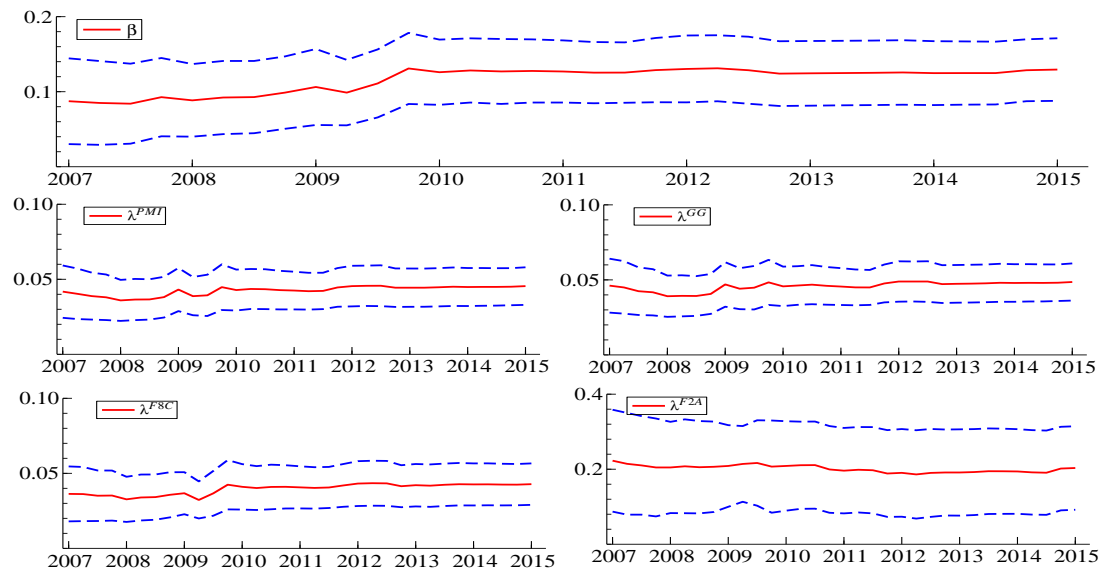


Figure 1: Recursively estimated factor loading coefficients to the GDP and four survey variables with associated  $\pm 2$  s.e. bands using expanding estimation windows. The initial estimation sample is 1995M1—2007M1 and the last is 1995M1—2015M1. The model specification is kept the same as in [Siliverstovs \(2012\)](#).

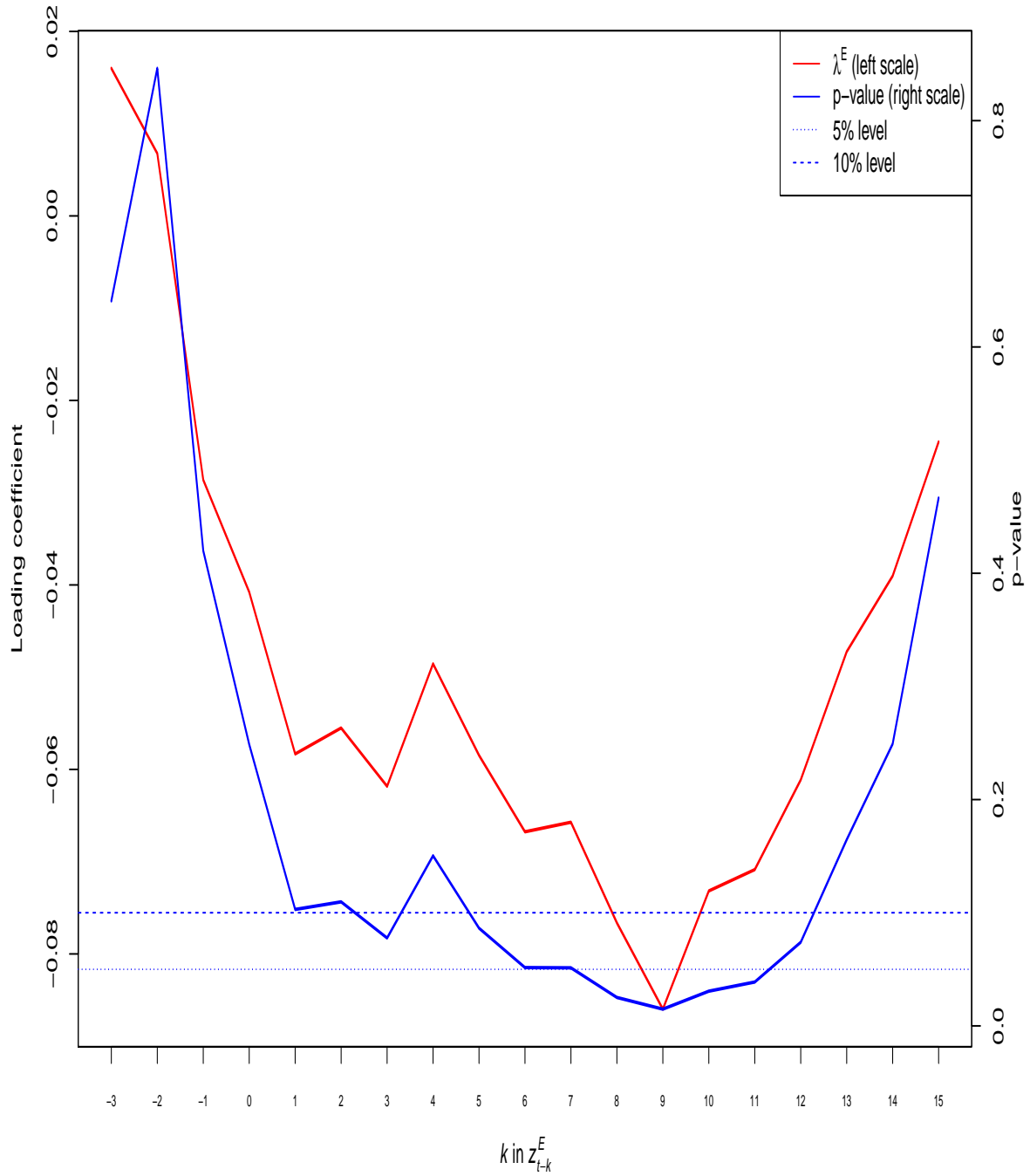


Figure 2: Estimates of the factor loading coefficient ( $\lambda^E$ ) to  $z_t^{E*} \equiv z_{t-k}^E$  in Equation (6) for  $k \in [-3, 15]$  obtained for the final estimation sample 1995M1–2015M1.



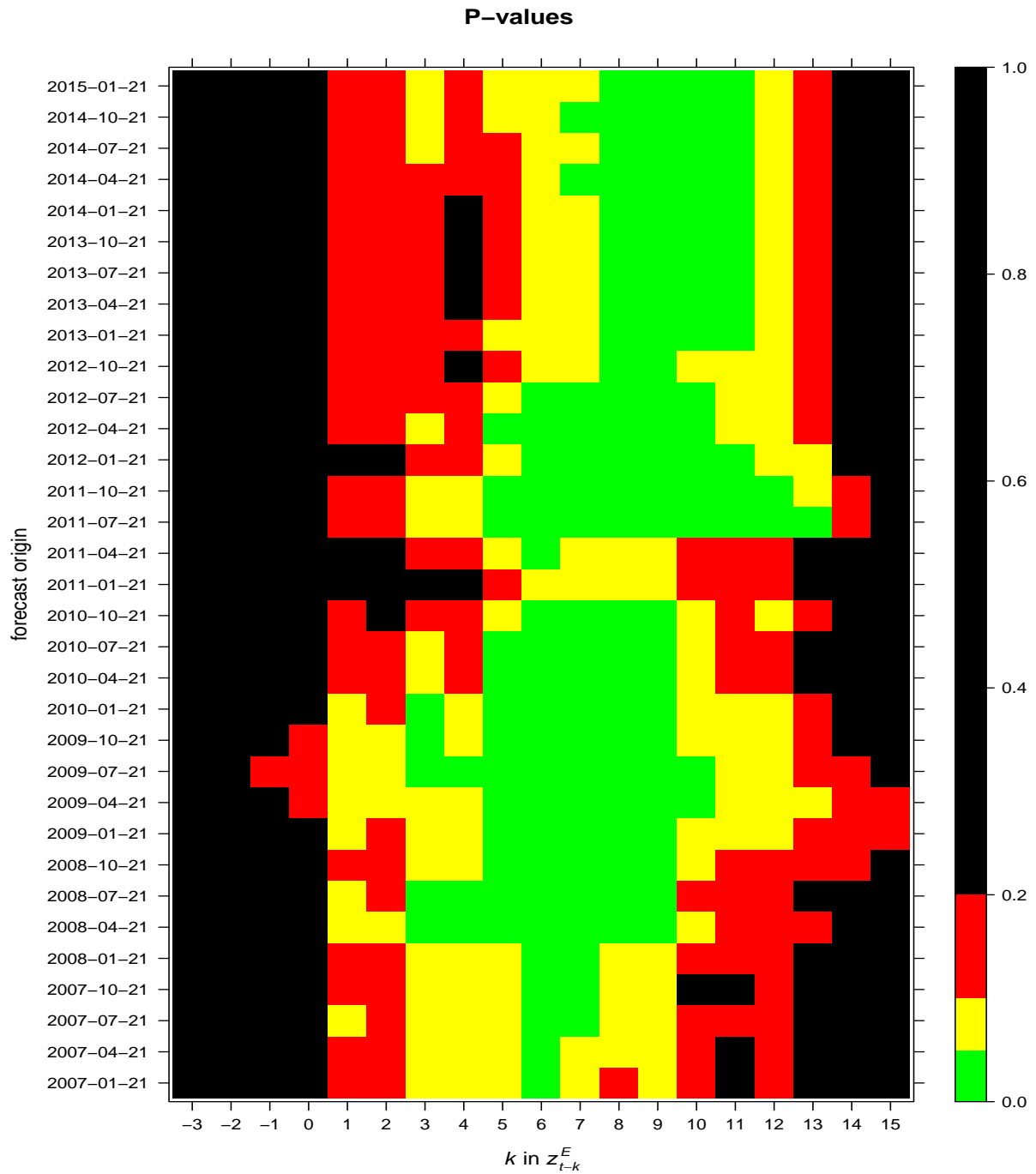


Figure 3: P-values of the recursively estimated factor loading coefficient ( $\lambda^E$ ) to  $z_t^{E*} \equiv z_{t-k}^E$  in Equation (6) for  $k \in [-3, 15]$ . The initial estimation sample is 1995M1–2007M1 and the last is 1995M1–2015M1.

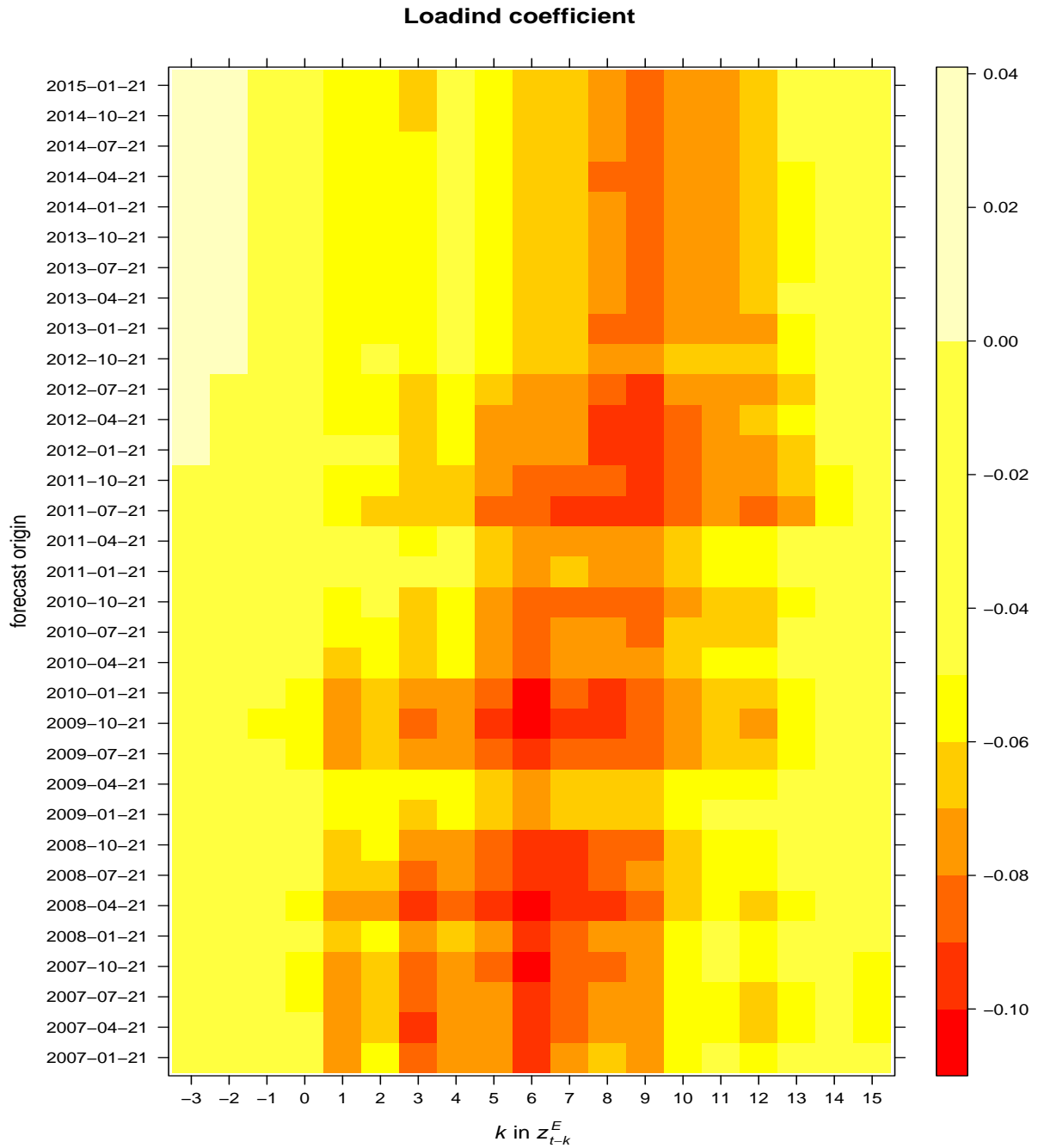


Figure 4: The recursively estimated factor loading coefficient ( $\lambda^E$ ) to  $z_t^{E*} \equiv z_{t-k}^E$  in Equation (6) for  $k \in [-3, 15]$ . The initial estimation sample is 1995M1—2007M1 and the last is 1995M1—2015M1.

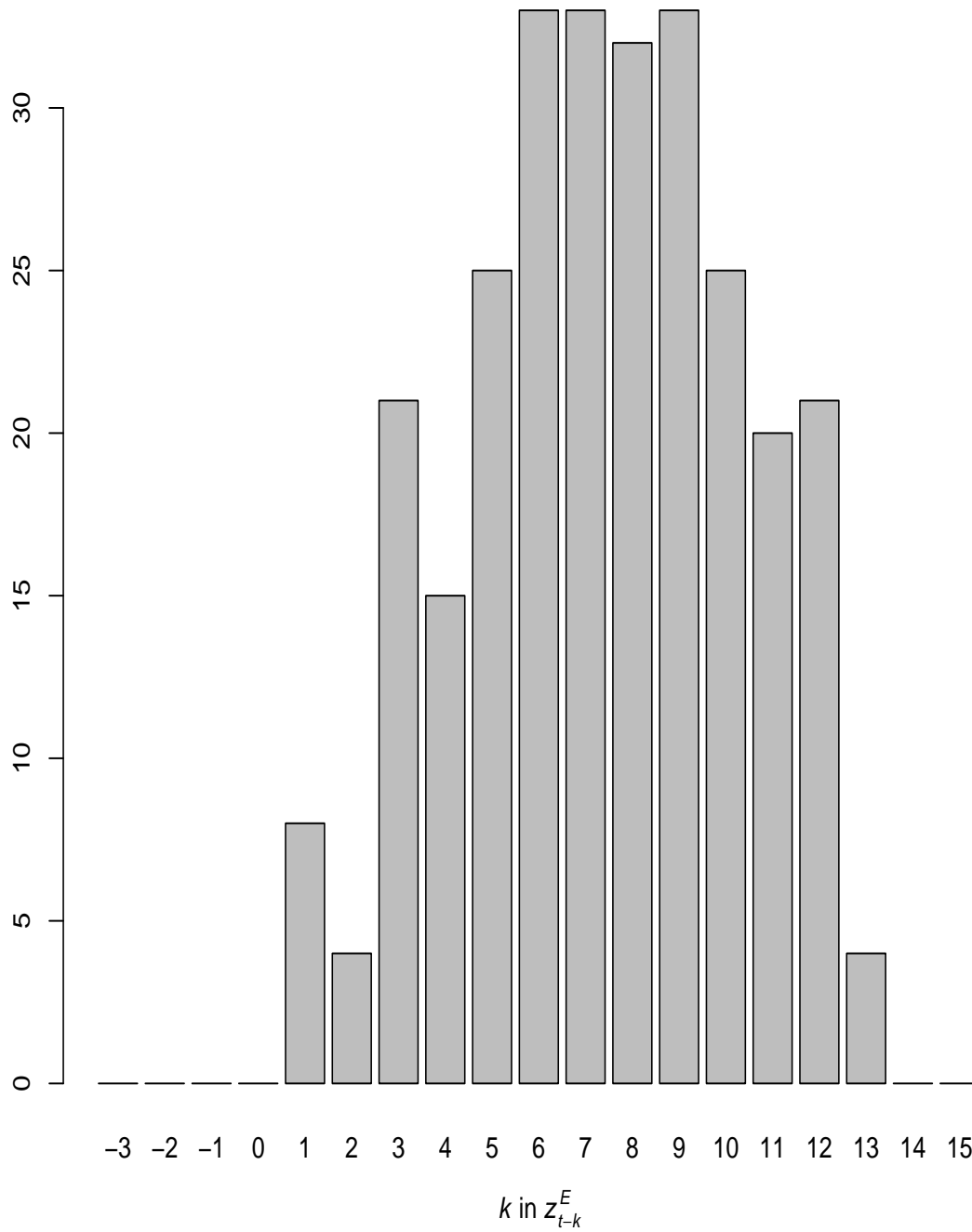


Figure 5: Incidence of p-values associated with  $\widehat{\lambda}^E$  that are less than 0.10 for each  $k \in [-3, 15]$  across all data vintages.