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## Forecasting unemployment in Finland: A flow approach

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Bank of Finland

# BoF Economics Review

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## Forecasting unemployment in Finland: a flow approach

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### Abstract

In this paper we evaluate whether the accuracy of Finnish unemployment rate forecasts can be improved by utilising the information in the flows into and out of unemployment. We compare and contrast different methodologies for constructing the flows. Our results indicate that Bayesian vector autoregressive models improve forecasts over a simple autoregressive model. Labour market flows improve forecasts over very short forecasting horizons. Additional labour market variables can improve forecast accuracy. The time-series models struggle to improve upon professional forecasts, but a combination of these forecasts proves advantageous especially when forecasting two quarters ahead.

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**JEL codes:** E24, E27, E32

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# Forecasting unemployment in Finland - a flow approach\*

Annika Lindblad<sup>†</sup>

Niklas Gäddnäs<sup>‡</sup>

June 28, 2024

## Abstract

In this paper we evaluate whether the accuracy of Finnish unemployment rate forecasts can be improved by utilising the information in the flows into and out of unemployment. We compare and contrast different methodologies for constructing the flows. Our results indicate that Bayesian vector autoregressive models improve forecasts over a simple autoregressive model. Labour market flows improve forecasts over very short forecasting horizons. Additional labour market variables can improve forecast accuracy. The time-series models struggle to improve upon professional forecasts, but a combination of these forecasts proves advantageous especially when forecasting two quarters ahead.

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# 1 Introduction

Forecasting unemployment accurately is important for policy makers and for understanding the business cycle situation. Using the flows into and out of unemployment provides additional information for forecasting the unemployment rate and can therefore improve predictive accuracy compared to forecasting the rate directly. The central idea behind flow-based unemployment forecasting is that the actual unemployment rate converges towards a steady state rate implied by the labour market flows. As Barnichon et al. (2012) note, these flows have their own time-series properties and by forecasting these flows directly one can capture the dynamics of unemployment and thereby achieve improvements in forecast accuracy.

This paper contributes to the empirical literature on flow-based forecasting and to the literature on Finnish unemployment forecasting by applying the flow-based method developed by Barnichon et al. (2012) to forecast the unemployment rate in Finland. We compare Bayesian vector autoregression (BVAR) models with and without labour market flows, use explanatory variables to try to improve forecast accuracy, condition the unemployment rate forecasts on GDP forecasts, and examine the merits of different methods for constructing the labour market flows for forecasting. We also compare the forecast accuracy of BVAR models to professional forecasters, namely the Bank of Finland staff forecasts. This gives us an overall idea of how useful time series forecasts for the unemployment rate are.

We find that using a BVAR model improves forecasts over a simple AR model. When including data since the pandemic there are some gains in short-term forecasting from including the flows in the BVAR model, but otherwise, we cannot find clear and consistent gains from utilising flows for forecasting. The BVAR models struggle to improve on forecast accuracy compared to Bank of Finland staff forecasts, demonstrating the shortcomings of purely time-series-model-based forecasts. However, compared to professional forecasts the BVAR models are useful for forecasting two quarters ahead. In addition, combining professional forecasts with BVAR forecasts turns out to be fruitful especially when forecasting two quarters ahead. Conditioning on GDP forecasts clearly improves forecast accuracy.

We conclude that for Finland the methodology for constructing labour market flows presented in Shimer (2012) tends to produce forecasts which outperform the forecasts produced using the flow methodology presented in Elsby et al. (2013), high-

lighting the importance of a flexible outflow rate. Many additional labour market variables improve forecast accuracy especially over short forecasting horizons, but no single indicator proved best over all models and horizons. Vacancies do, however, tend to perform well especially over longer forecasting horizons.

This paper builds on the literature concerning the importance of labour market flows for explaining the fluctuations in unemployment, such as Shimer (2005), Shimer (2012), Elsby et al. (2013) and Petrongolo et al. (2008). It is also related to the literature dealing with the challenges in forecasting the unemployment rate, due to, in particular, the asymmetric nature of unemployment over the business cycle, see, for example, Montgomery et al. (1998). In addition, the literature on search and matching models of the labour market by, for example, Mortensen et al. (1994), is related.

However, this paper is most closely related to the literature assessing the forecast accuracy of models based on labour market flows, such as Barnichon et al. (2012) and Meyer et al. (2015). Both papers find, using US data, that flow-based models perform well in forecasting the unemployment rate. Barnichon et al. (2016) find support for using flow-based models in some OECD countries. Goncalves et al. (2019) largely confirm the results using Portuguese data. The flow-based approach is generally found to perform well during recessions and around turning points.

The paper is organised as follows. Section 2 presents the methodology used, including the construction of the flows, the forecasting models and the data set used. Section 3 presents the results of the forecasting exercise and Section 4 concludes.

## 2 Methodology

The first subsection summarises the construction of the labour market flows, the second subsection presents the data used, the third subsection discusses the forecasting models, and the fourth subsection provides information on the overall forecasting set-up.

## 2.1 Labour market flows

The unemployment flows<sup>1</sup> are constructed following the method presented in Shimer (2012) and the method presented in Elsby et al. (2013), which extends the Shimer (2012) methodology by utilising longer unemployment durations. Because of this, according to Elsby et al. (2013) their method could be better suited to infer the flow rates in economies where short-duration unemployment is very noisy, such as in many European economies. We will therefore examine whether the choice of flow construction method impacts forecasting performance for the Finnish unemployment rate.

Since the flows into and out of unemployment are central to our forecasting exercise, we will describe their construction briefly below.<sup>2</sup> Following the presentation in Elsby et al. (2013) we can relate the variation in the number of unemployed,  $u_t$ , to the variation in the underlying inflow rate into unemployment and the outflow rate out of unemployment as:

$$u_t = \beta_t u_t^* + (1 - \beta_t) u_{t-d} , \quad (2.1)$$

where  $d$  denotes monthly duration and the conditional steady state unemployment rate is given by

$$u_t^* = \frac{s_t}{s_t + f_t} , \quad (2.2)$$

and the rate of convergence to the steady state is given by

$$\beta_t = 1 - e^{-d(s_t + f_t)} . \quad (2.3)$$

$s_t$  is the time  $t$  rate of inflow into unemployment, i.e., the job separation rate, which is the rate at which people move from employment into unemployment.  $f_t$  is the time  $t$  rate of outflow out of unemployment, i.e., the job finding rate, which is the rate at which people move from unemployment into employment. As Elsby et al. (2009) note, the steady state unemployment rate,  $u_t^*$ , is an approximation of the actual unemployment rate.

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<sup>1</sup>In this paper we use labour market flows into and out of unemployment. The models also utilising flows into and out of the labour force are left to future research.

<sup>2</sup>See Shimer (2012) and Elsby et al. (2013) for details and the full derivation.

To find the flow rates we follow Elsby et al. (2013) and note that the probability that an unemployed worker exits unemployment within  $d$  months can be written as

$$F_t^{<d} = 1 - \frac{u_{t+d} - u_{t+d}^{<d}}{u_t}. \quad (2.4)$$

The associated outflow rate, which measures the probability that an unemployed worker at time  $t$  exits unemployment within the next  $d$  months, becomes

$$f_t^{<d} = -\ln(1 - F_t^{<d})/d. \quad (2.5)$$

We estimate these rates for  $d = 1, 3, 6, 12$  for Finland. Then these estimates are combined as an optimally weighted average, following the methodology in Elsby et al. (2013), to get the Elsby flow series (denoted Elsby). When we know the outflow rate we can solve for the inflow rate,  $s_t$ , from equation 2.1, as described in Shimer (2012). The inflow rate is therefore always a residual.

The Shimer series are constructed in the same way as the Elsby series, but when determining  $f_t$  Shimer (2012) only utilises the very short term (up to one month, i.e.,  $d = 1$ ) duration data. We denote these flow series Shimer 1M. We also use an alternative specification based on Shimer (2012) for the flow rates, where we consider duration data up to three months (i.e.,  $d = 3$ ). We denote this series Shimer 3M.

The inflow and outflow rates for Finland behave differently depending on the methodology (Figure 1). The Shimer 1M rates are the most volatile and exhibit a clear upward trend, especially since the onset of the COVID-19 pandemic. For very short-term unemployment, represented by the Shimer 1M rates, both the inflow and the outflow rates have increased in recent years, while the flow rates taking into account longer-term unemployment durations have rather decreased (see the Elsby and Shimer 3M series in Figure 1).

As the inflow rate is by construction a residual, it means that if the outflow rate is volatile, as in the case of the Shimer series, then the inflow rate will be relatively stable, and vice versa, as we can see in the case of the Elsby series. The pandemic mainly impacted the job finding rate for the Shimer series, which fell sharply, while the opposite is true for the Elsby series, where the job separation rate rose abruptly in Q2 2020. These differences could have an impact on forecasting performance.

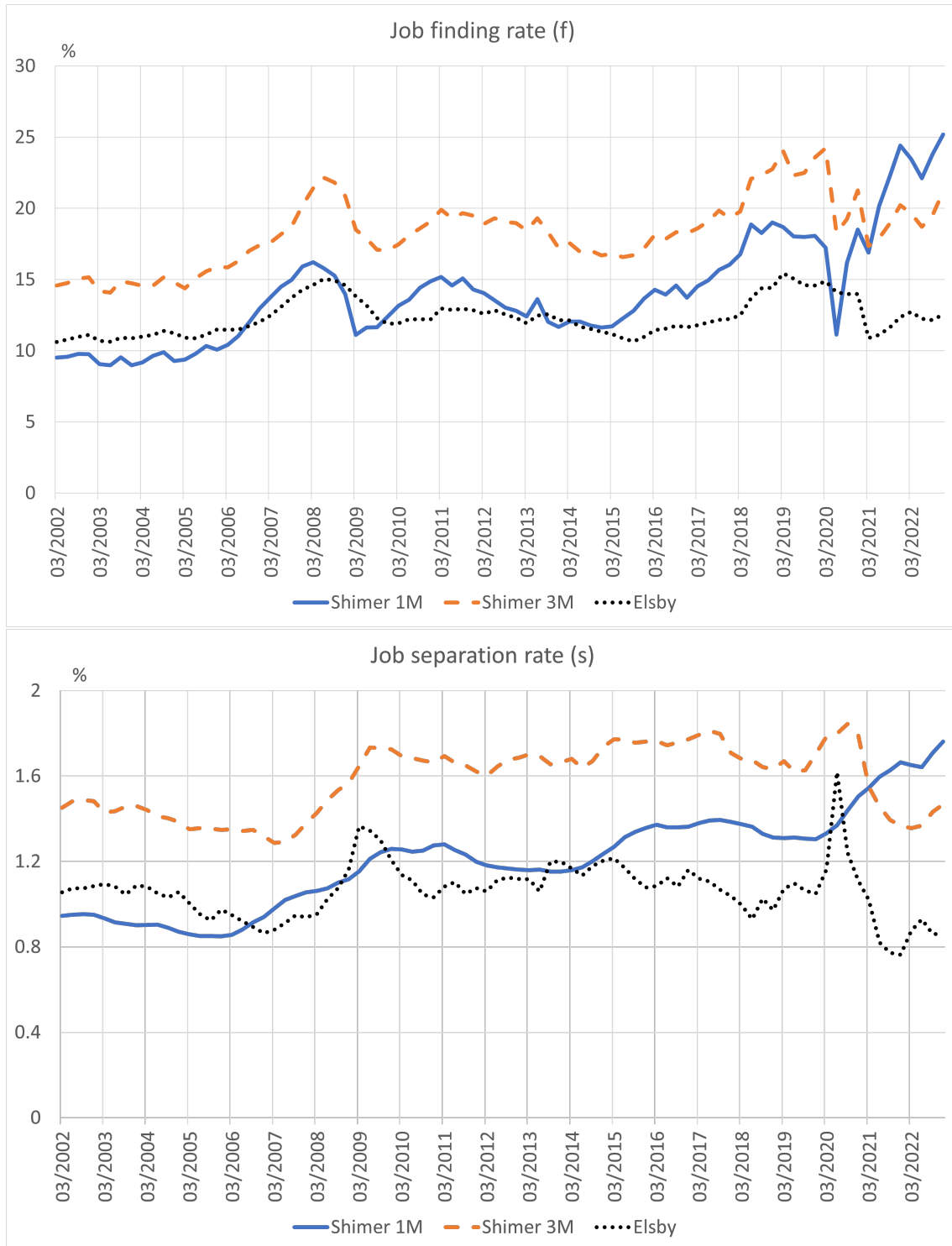


Figure 1: Unemployment flows in Finland constructed using different methodologies

The conditional steady state unemployment rates ( $u^*$ ) implied by the flows (see equation 2.2) are plotted in Figure 2 together with the actual unemployment rate. We can observe that the developments in the steady state unemployment rates tend to precede the developments in the actual unemployment rate. During the pandemic



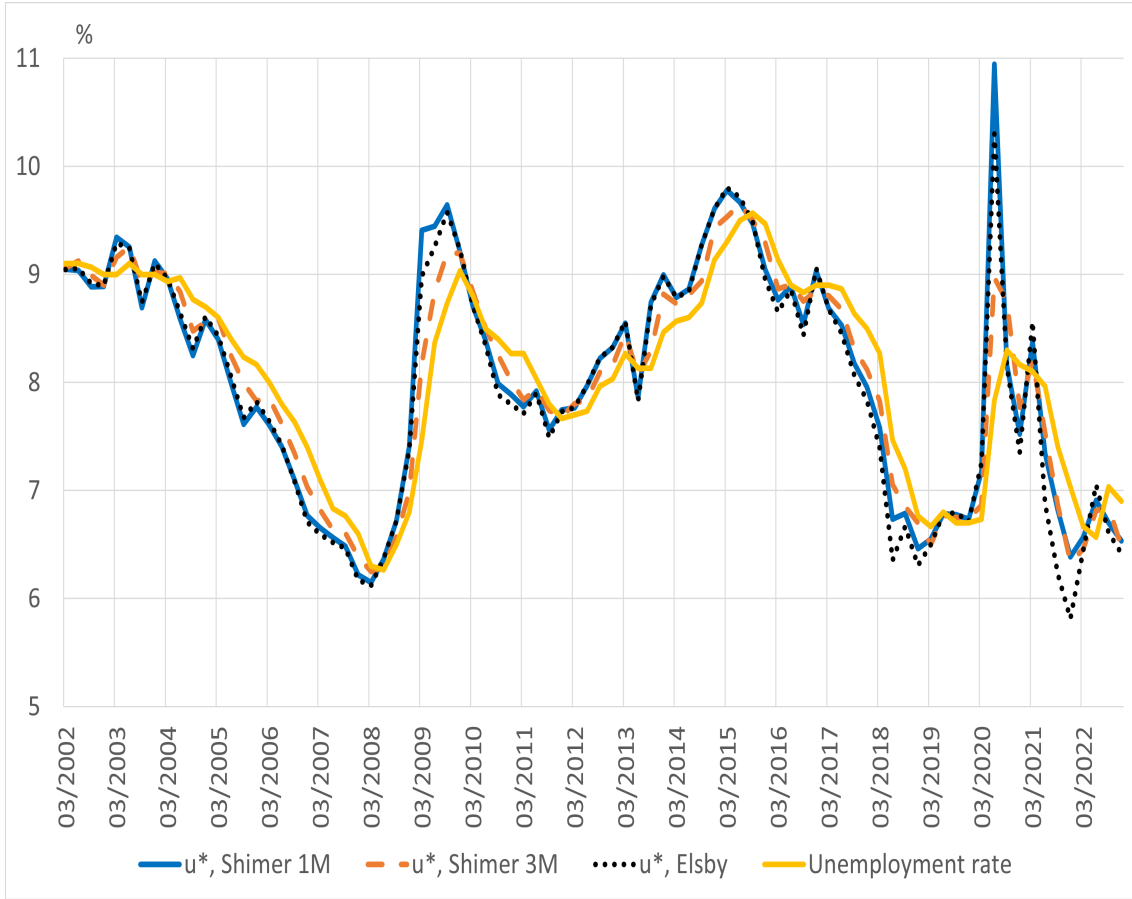


Figure 2: Unemployment rate and conditional steady state unemployment rates ( $u^*$ ) for Finland

the steady state unemployment rate based on the Shimer 3M rates overshoot the actual unemployment rate the least (see Figure 2). It is also clear that the steady state unemployment rates are not as close a match to the actual unemployment rate as for the US (see, for example, Figure 1 in Barnichon et al. (2012)), foreshadowing that the flow-based forecasting models might perform better in the US than in Finland.

## 2.2 Data

To construct the labour market flows we use monthly data on unemployment durations provided by Statistics Finland. The sample starts in January 2001 and ends in December 2022 and includes six time series on unemployment duration: less than one month, between 1 and 3 months, between 3 and 6 months, between 6 and 12 months, between 12 and 24 months, and over 24 months. We separately seasonally

adjust each vintage of the series and the trend series are used in the final analysis. The data is then aggregated, as the forecasting exercise is conducted on a quarterly frequency. As one year of data is needed to construct the flows for the first period, the analysis starts in January 2002 ( $N = 84$ ).

We include several explanatory variables in the forecasting models. Firstly, real-time vintages of GDP and the unemployment rate are included (source: Statistics Finland). GDP is heavily revised in Finland, and using real-time vintages is important in order to provide a realistic assessment of forecasting performance over time, and to be able to compare the forecasts to professional forecasts made at the time.

Secondly, several labour market variables are used, in particular, the number of people on unemployment benefits, the number of people furloughed (source: Ministry of Economics Affairs and Employment of Finland) and vacancies (source: Statistics Finland). For the number of people on unemployment benefits we consider three alternative series: the number of people receiving basic unemployment allowance (source: Social Insurance Institution of Finland), the number of people receiving the labour market subsidy (source: Social Insurance Institution of Finland), and the number of people on earnings-related unemployment allowance (source: the Financial Supervisory Authority). All explanatory variables are seasonally adjusted. In the forecasting exercise the target variable is the unemployment rate from the labour force survey.

The forecasts are timed so that we have a full quarter of unemployment data available when making the forecasts. Unemployment data is released with a roughly one month lag. However, as GDP is released with a roughly two month lag, we use Bank of Finland GDP forecasts<sup>3</sup> to fill in the missing GDP lag.<sup>4</sup> The data for the number of people on earnings-related unemployment allowance is published with a roughly one month lag, meaning that it is available approximately at the same time as the labour force survey. However, the data from the Social Insurance Institution of Finland is published with a roughly four month lag. As we use, nevertheless, the same timing as for the other labour market data, this is not a real-time forecasting exercise with regards to these two series.

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<sup>3</sup>Prior to 2020 GDP forecasts were produced twice a year by the Bank of Finland. Starting in 2020 GDP forecasts are produced four times a year, and published in March, June, September and December.

<sup>4</sup>Note that the quarterly profile of the GDP forecast is not published by the Bank of Finland.

## 2.3 Forecasting models

This section presents the forecasting models used in the analysis. We use three BVAR models. The FLOW-BVAR model (presented in Section 2.3.1) and the BVAR model (presented in Section 2.3.2) both include the labour market flows, but while the BVAR model produces the unemployment rate forecast directly in the BVAR framework, the FLOW-BVAR model uses the flow rate forecasts from the BVAR model and transition equations to form the unemployment rate forecast. The benchmark BVAR model (presented in Section 2.3.2) is the same BVAR model but without the flow rates.

### 2.3.1 The FLOW-BVAR model

Our main forecasting model is the two-state<sup>5</sup> model introduced in Barnichon et al. (2012). Their central idea is that the unemployment rate will gradually move to the conditional steady state level implied by the current flows into and out of unemployment (see equation 2.2). The pace by which this convergence occurs is governed by the flow rates. If the flows change so will the steady state level. According to Barnichon et al. (2012), the conditional steady state level of unemployment therefore provides information regarding the near-term developments of unemployment.

Following<sup>6</sup> the derivations in Barnichon et al. (2012) and noting equations 2.1-2.3 we can express the h-period-ahead forecast for the unemployment rate as:

$$\hat{u}_{t+h|t} = \hat{\beta}_{t+h} \hat{u}_{t+h}^* + (1 - \hat{\beta}_{t+h}) \hat{u}_{t+h-1|t} \quad (2.6)$$

where

$$\hat{u}_{t+h}^* = \frac{\hat{s}_{t+h|t}}{\hat{s}_{t+h|t} + \hat{f}_{t+h|t}} \quad (2.7)$$

and

$$\hat{\beta}_{t+h} = 1 - e^{-(\hat{s}_{t+h|t} + \hat{f}_{t+h|t})} . \quad (2.8)$$

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<sup>5</sup>The two-state model includes flows into and out of unemployment, while a three-state model also includes flows into and out of the labour force. Exploring the three-state model is outside the scope of this paper.

<sup>6</sup>See Barnichon et al. (2012) for details on the derivation of the model.

In order to construct forecasts for the unemployment rate we need to forecast the flow rates. As Barnichon et al. (2012) points out, if the flow rates are persistent enough we can use the most recently observed ones as approximations for future rates. However, as we saw from Figure 1, flow rates can vary.<sup>7</sup> We follow the approach in Barnichon et al. (2012) and use a VAR model with leading indicators for labour market flows to forecast the inflow and outflow rates:

$$\mathbf{y}_t = (\ln s_t, \ln f_t, \ln u_t, \Delta \ln gdp_t, \ln Z_t) \quad (2.9)$$

$$\mathbf{y}_t = \mathbf{c} + \Theta_1 \mathbf{y}_{t-1} + \Theta_2 \mathbf{y}_{t-2} + \Theta_3 \mathbf{y}_{t-3} + \Theta_4 \mathbf{y}_{t-4} \quad (2.10)$$

where  $Z_t$  includes a selection of the additional explanatory labour market variables discussed in Section 2.2. Once forecasts for the flow rates are obtained they can be used to produce h-period-ahead forecasts of the unemployment rate (denoted *FLOW-BVAR*) by iterating on the nonlinear labour market relationship in equation 2.6.

### 2.3.2 Other forecasting models

A simple AR(2) model for the unemployment rate is used as a naive yardstick.<sup>8</sup> We also compare the accuracy of our BVAR model forecasts to the unemployment rate forecasts produced by the Bank of Finland in conjunction with the ECB Broad Macroeconomic Projection Exercise.

The BVAR model also produces a forecast for the unemployment rate when the forecasts for the hazard rates are produced (equation 2.10), which can be used in the forecast comparison (denoted *BVAR*). This forecast comparison reveals the benefits of using the nonlinear labour market relationship (equation 2.6) to update the forecast compared to using a linear time-series model utilising the same information. As our benchmark model we use the same BVAR model but without the flow rates (denoted *benchmark*). This forecast comparison reveals the usefulness of labour market

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<sup>7</sup>See Section 3.3 for a comparison between unemployment rate forecasts using fixed and forecasted flow rates.

<sup>8</sup>See Appendix A for details on model selection. Meyer et al. (2015) also utilises a GAR and a SETAR model as nonlinear time series model alternatives, but their results show the improvements in forecast accuracy compared to a simple AR model are either very small or nonexistent. Thus we here focus on using a simple AR model for comparison.

flow data for forecasting the unemployment rate.

## 2.4 General forecasting set-up

The forecasting exercise is undertaken on a quarterly frequency using Bayesian methods and the Ferroni et al. (2021) Matlab toolbox. The toolbox’s standard starting values for the hyper-parameter optimisation are used.<sup>9</sup> We use four lags in the model, which in most cases is the optimal number of lags chosen by the AIC. The parameters of the model are re-estimated every period.

The COVID-19 pandemic was an unusually abrupt and unpredictable shock to the labour market. Going forward the pandemic must be somehow incorporated into forecasting models, as it will continue to impact both parameter estimates and forecasts. We use the heteroskedasticity adjusted BVAR suggested by Lenza et al. (2022) to accomplish this.<sup>10</sup> We use optimised scaling parameters to re-scale the standard deviation of the Q2 and Q3 2020 shocks.

In order to evaluate the forecasting performance of the models we divide the sample period roughly in half, and start the out-of-sample evaluation in Q1 2011. This ensures we have enough data to estimate the models for the first period, but also ensures a long enough forecast evaluation period. We produce forecasts for up to eight quarters ahead. The last forecasts to be compared are for Q4 2022 for all horizons ( $h$ ). We also report the central results for the pre-COVID period in Appendix B.

An expanding window with an initial size of 38 quarters is used when producing the forecasts for the out-of-sample period. Forecasts are mostly compared using their root mean squared forecast errors (RMSFE).

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<sup>9</sup>The results are robust to using fixed hyper-parameter values as well as optimising around different hyper-parameter starting values.

<sup>10</sup>The results are qualitatively similar even if the models are estimated without scaling. Some central results are reported in Appendix C.

## 3 Results

The first subsection discusses the results from the pseudo-out-of-sample forecasting exercise, establishing the relative forecasting performance of the different models and flow methods. The second subsection analyses the role of additional labour market variables, while the third subsection examines the importance of inflow and outflow rates for forecast accuracy. The fourth subsection conditions the unemployment rate forecasts on Bank of Finland GDP forecasts. The last subsection compares the unemployment rate forecasts from the BVAR models to Bank of Finland staff forecasts.

### 3.1 Overall forecasting performance

We start by assessing the forecasting performance of the FLOW-BVAR model, the BVAR model and the benchmark model, i.e. the BVAR model without flows, using the different methodologies for constructing the flows. In this section the benchmark model only contains GDP and the unemployment rate, whereas the FLOW-BVAR model and the BVAR model also contain the unemployment flows.

#### 3.1.1 Evolution of forecast errors for different forecasting models and flow methods

To get an overview of how the different forecasting models and flow methods perform relative to each other over our sample period we look at how the forecast errors evolve in Figure 3.<sup>11</sup> It is clear that all models produce a similar time series of forecast errors. The size and persistence of the forecast errors increase as the forecasting horizon increases.

In the beginning of the forecasting period as well as at the onset of the COVID-19 pandemic the forecast errors are negative, meaning that the realised unemployment rate has been higher than forecast. However, the forecasts made during the early

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<sup>11</sup>The standard deviation of the unemployment rate series is 0.9 over the whole sample.

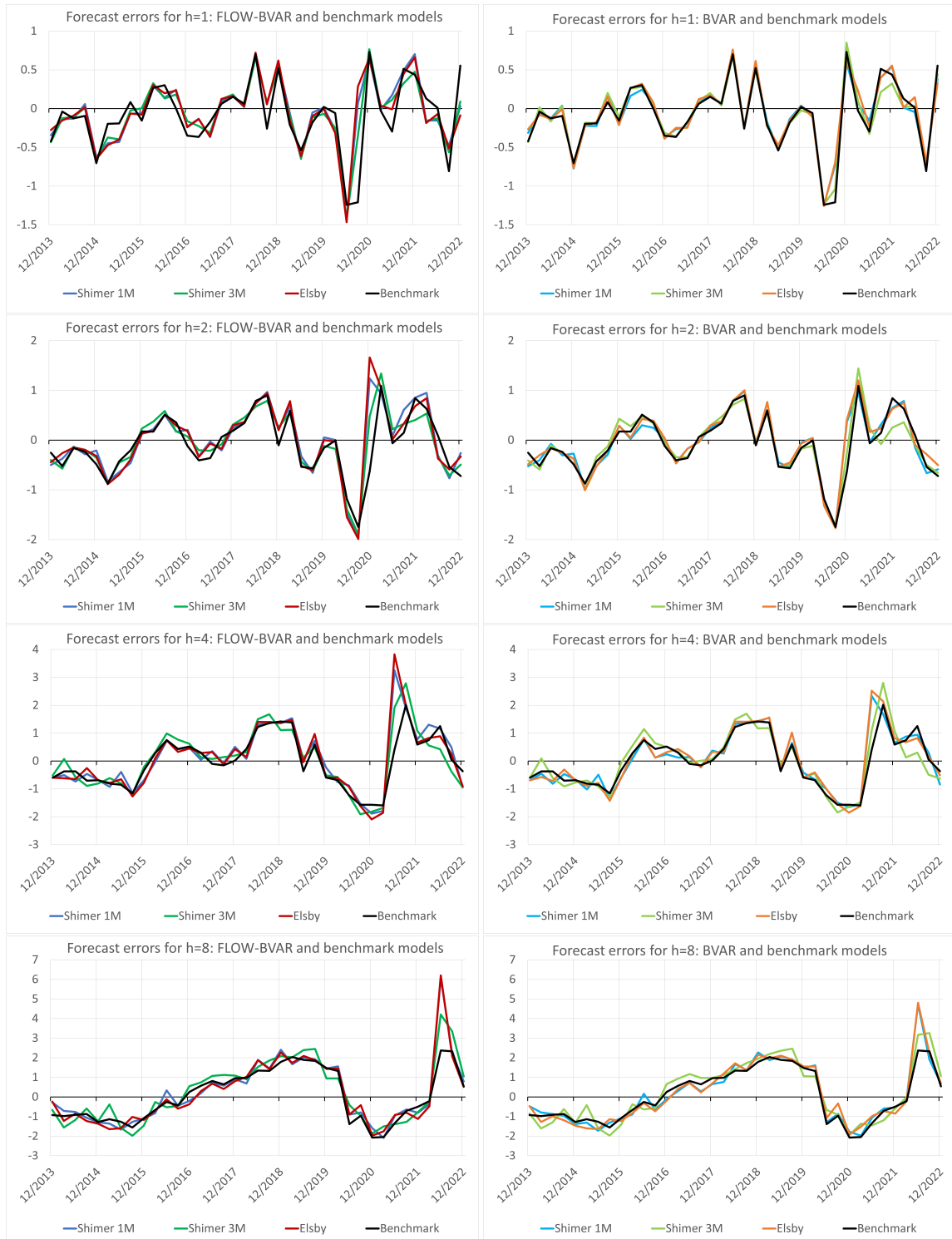


Figure 3: Evolution of forecasts errors over time for selected forecasting horizons. A negative value means realised unemployment has been higher than forecast.

part of the COVID-19 pandemic – in particular in Q2 2020 – tended to overestimate the unemployment rate in late 2020 to 2022, depending on the forecasting horizon, as the sharp shock on the labour market resulted in elevated unemployment rate

forecasts, while the realised unemployment rate fell relatively quickly after the initial shock. The FLOW-BVAR model using the Elsby et al. (2013) labour market flow series overestimated the unemployment rate particularly severely during this time, while the benchmark model performed relatively well. The BVAR model produced mostly smaller forecast errors than the FLOW-BVAR model during this time period.

In most time periods the different unemployment flow measures as well as the different model specifications seem to perform largely similarly. There are no persistent differences between the forecasts produced by the BVAR and FLOW-BVAR models outside the pandemic period.

### 3.1.2 Forecasting performance of different forecasting models

Next we consider the RMSFEs of the different forecasting models. The benchmark model, i.e. the BVAR model without flows, performs overall very well, indicating that mostly the additional burden of including the flow rates is not beneficial for forecast accuracy (Table 1 and Figure 4).<sup>12</sup> There are, however, some gains in forecast accuracy for very short horizons when using unemployment flows. The differences between the models increase as the forecasting horizon increases.<sup>13</sup> The AR model performs poorly over all horizons.

Table 1: RMSFE ratios of unemployment rate forecasting models

	Shimer 1M		Shimer 3M		Elsby		AR(2) model
	FLOW-BVAR model	BVAR model	FLOW-BVAR	BVAR model	FLOW-BVAR	BVAR model	
h1	0.91	0.90	0.89	0.95	0.92	0.91	1.47
h2	1.12	0.99	1.03	0.99	1.16	1.02	1.10
h4	1.21	1.08	1.16	1.11	1.27	1.14	1.48
h8	1.23	1.12	1.20	1.15	1.24	1.15	11.94

Notes: When the ratio is less than one the RMSFE of the flow-based model or AR model is smaller than the RMSFE of the BVAR model without flows (benchmark model). FLOW-BVAR refers to forecasts produced using the updating equation 2.6 while BVAR refers to forecasts produced directly by the BVAR model (2.10). RMSFEs are calculated over the time period Q4 2012 - Q4 2022 for all models and all horizons ( $h$ ).

The differences between the BVAR model and the FLOW-BVAR model are small

<sup>12</sup>The results are largely robust to using additional explanatory labour market variables, see Appendix D. There are occasional gains over very long forecasting horizons for some variables when using flow-based models, while especially for the Shimer 3M rates there are some gains for some variables in the pre-COVID period for the flow-based models.

<sup>13</sup>This is also true for the pre-COVID sample, see Appendix B.



for very short horizon forecasts, but over longer horizons the BVAR model performs better (Table 1 and Figure 4). The updating equation (2.6) does therefore not seem to improve forecast accuracy in Finland, at least not in this sample. This could reflect the relatively slow convergence to the steady state unemployment rate observed in Finland.

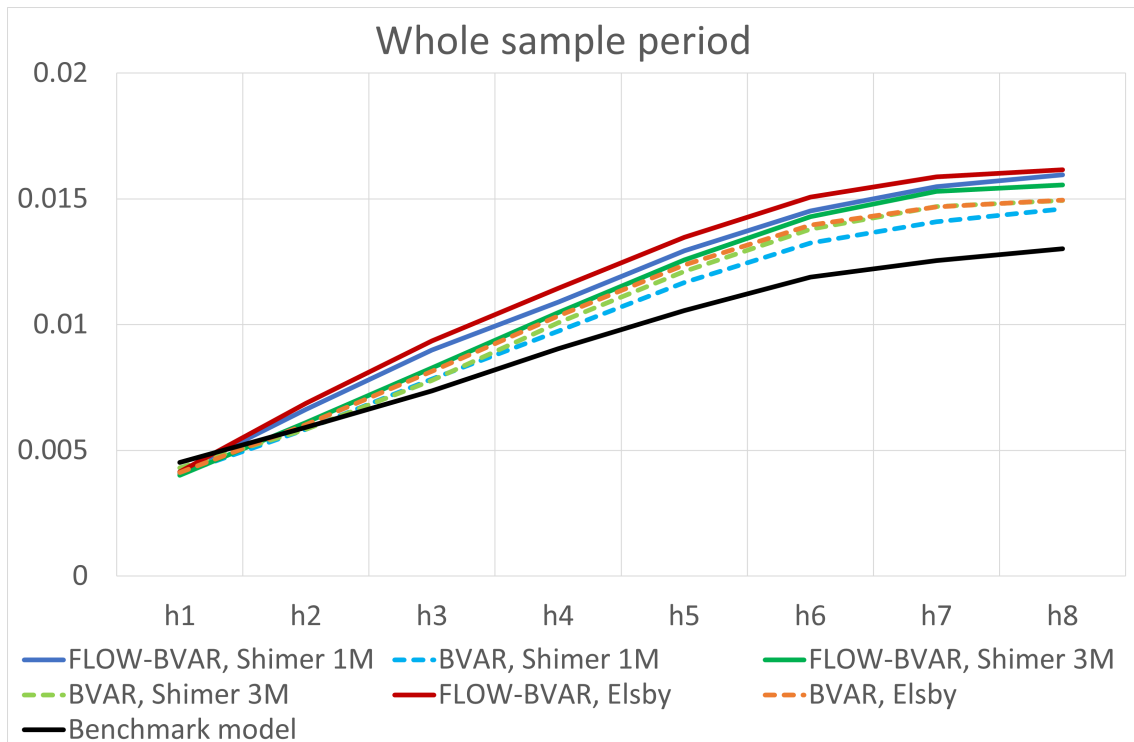


Figure 4: RMSFEs of different forecasting models using different flow methods.

### 3.1.3 Forecasting performance for different flow methods

Comparing the different methods for constructing the flows we conclude that the method by Elsyby et al. (2013) mostly performs worse or roughly equally well compared to the Shimer (2012) method (Table 1 and Figure 4). As could already be surmised from Figure 3, the Elsyby flow series perform worse than the Shimer series, especially since the pandemic. Recalling Figure 1 this would imply that the sharp decline in the job finding rate observed in the Shimer series was important for forecasting performance at the beginning of the pandemic, whereas the strong rise in the job separation rate – observed in the Elsyby series – played a less important role.

Using the Shimer 3M rates produce more accurate forecasts than the Shimer 1M rates for the FLOW-BVAR model, whereas the forecasting performance is in

favour of the Shimer 1M methodology for the BVAR model. Thus, the different developments in the Shimer 1M and 3M inflow and outflow rates observed in Figure 1 does not seem to influence forecasting performance in a clear and consistent way.

### 3.2 Impact of additional labour market variables on forecasting performance

The flow-based models could improve compared to the benchmark when additional explanatory labour market data is included.<sup>14</sup> The additional data could also improve forecasting performance of the models and help in identifying turning points on the labour market.

Earlier we concluded that the best model in our sample period was the benchmark model. This model is outperformed by most specifications including additional explanatory data over short horizons (up to one year), while for the longest horizons the simplest model performs relatively well (see Figure 5). The situation is similar for the FLOW-BVAR and BVAR models and all flow construction methodologies.<sup>15</sup>

In all cases the differences in forecasting performance between different explanatory variables increases as the forecasting horizon increases, and the difference for short forecasting horizons is very small. Especially over long horizons the best explanatory variables include vacancies, a combination of the number of people on earnings-related unemployment allowance and the number of furloughed, as well as a combination of these three explanatory variables. The worst-performing models tend to include the number of people receiving the basic unemployment allowance.<sup>16</sup>

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<sup>14</sup>Not all variables are available in a timely manner in real time, namely the number of people receiving the basic unemployment allowance and the number of people receiving the labour market subsidy.

<sup>15</sup>More detailed results on the performance of specifications including additional explanatory data can be found in Appendix D and Appendix E.

<sup>16</sup>For the pre-COVID sample the results are different, with the simplest model performing worse and the best and worst performing models being very different, see Appendix B. We can thus conclude that the usefulness of different explanatory variables is very dependent on the sample. A way to pre-select the relevant explanatory variables is thus needed. We leave this question to future research.

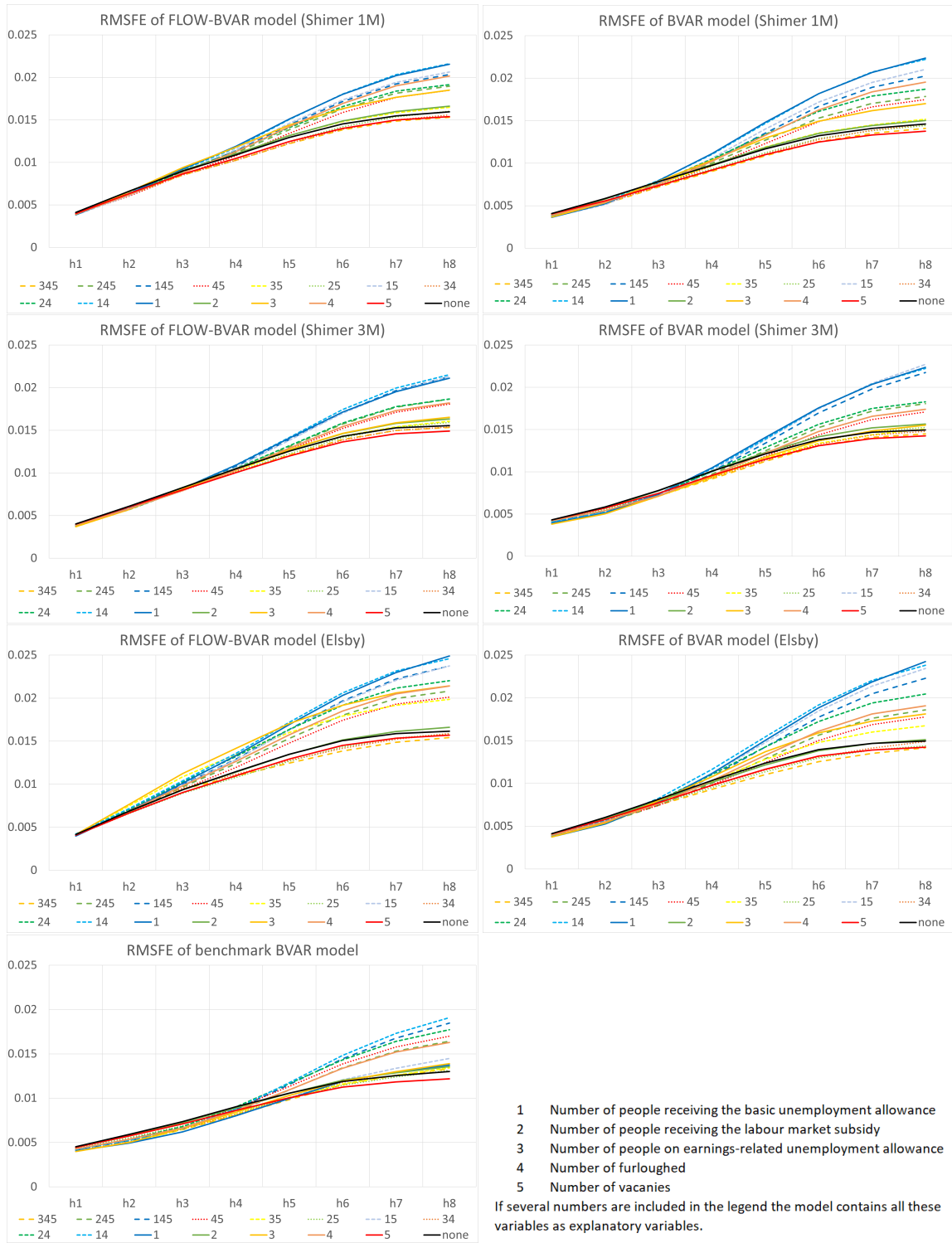


Figure 5: RMSFEs for the BVAR models using additional labour market variables.

### 3.3 Forecasting the inflow and outflow rates

In order to construct forecasts for the unemployment rate we need to forecast the flow rates. First we look at the forecast errors of the inflow and outflow rates (Figure 6).

For the job finding rate, the Elsbey et al. (2013) methodology produces the smallest forecast errors, while for the job separation rate this is only true for the longest forecasting horizon. For the job finding rate the Shimer 1M series is the worst performer, while for the job separation rate the Shimer 1M series forecasts are on most horizons the most accurate. These results seem to reflect the volatility of the series (Figure 1). Overall these results seem to suggest that the accuracy of the job separation rate forecast is more important for the accuracy of the resulting unemployment rate forecasts.

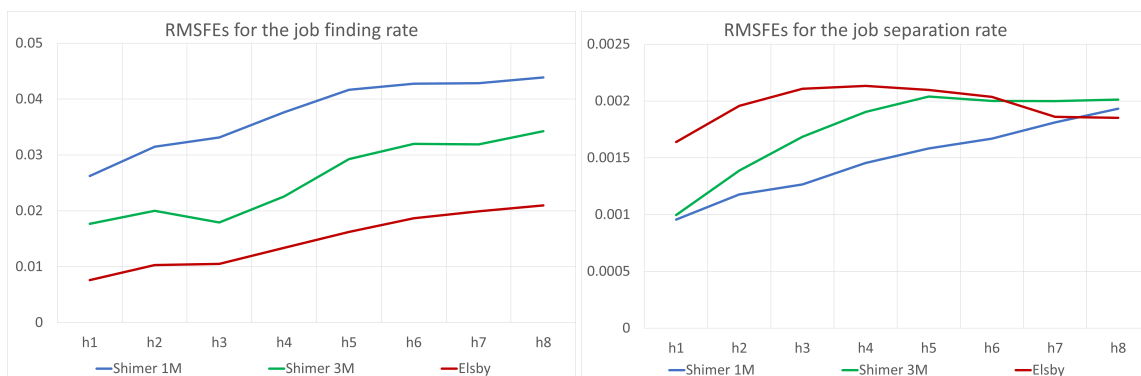


Figure 6: RMSFEs for the inflow and outflow rates.

Next we will establish the importance of inflow and outflow rates for forecasting the unemployment rate in Finland. For example, Barnichon et al. (2012) and Barnichon et al. (2016) found that allowing the inflow and outflow rates to vary is important for forecasting the unemployment rate in the US and some other OECD countries. We consider versions of the model where the job finding rate or the job separation rate is held constant at their latest observed values.

Keeping the inflow or outflow rate constant leads to mostly improved forecast accuracy (Table 2). The main exception is the short term forecasts using the Shimer 3M rates, implying that letting these rates vary could be important for short-term forecast accuracy. The gains are, however, small. The gains from keeping the rates constant grow as the forecast horizon grows. The results are similar across flow construction methods, indicating that the different dynamics of the inflow and

outflow rates do not significantly impact these results.

The results are thus contrary to the results in, for example, Barnichon et al. (2012) and Barnichon et al. (2016). The overall weaker results for Finland could be a result of the conditional steady state unemployment rate implied by the unemployment flows being relative far from the actual unemployment rate in Finland, which is due to the lower levels of the inflow and outflow rates, slowing down the speed of convergence.

Table 2: RMSFE ratios for FLOW-BVAR model forecasts with constant inflow or outflow rates

	Shimer 1M		Shimer 3M		Elsby	
	Fixed s (inflow)	Fixed f (outflow)	Fixed s (inflow)	Fixed f (outflow)	Fixed s (inflow)	Fixed f (outflow)
h1	0.99	1.00	1.02	1.03	0.97	0.99
h2	0.97	1.00	1.01	1.01	0.95	0.95
h4	0.94	0.97	0.95	0.92	0.95	0.87
h8	0.92	0.92	0.93	0.84	1.03	0.77

Notes: When the ratio is less than one the RMSFE of the model with fixed inflow or outflow rates is smaller than the RMSFE of the model with varying rates. f denotes the job finding rate and s the job separation rate. Otherwise, see notes for Table 1.

### 3.4 Conditioning on GDP forecasts

In order to capture the expected economic situation in the unemployment rate forecasts produced by the time series models we condition the BVAR forecasts on the GDP forecasts produced by the Bank of Finland<sup>17</sup>.

Conditioning on the GDP forecasts improves forecast accuracy compared to the unconditional forecast (Table 3).<sup>18</sup> This is true for all flow construction methods and all models. The gains from conditioning are larger for longer forecasting horizons.

The gains in forecast accuracy seem especially large for the pandemic period (compare Figure 7 to Figure 3), indicating that conditioning on GDP forecasts can

<sup>17</sup>The conditioning is accomplished by setting the future path of the GDP variable in the BVAR model to the latest Bank of Finland forecast available at the time of making the forecasts. This is thus a real-time exercise. The standard routines of the Ferroni et al. (2021) Matlab toolbox are used.

<sup>18</sup>This is also very widely true for the pre-COVID sample (see Appendix B) as well as models with additional explanatory labour market data (results available upon request).

help in anchoring the forecasts during turbulent times. Especially the overshooting of the unemployment rate forecasts after the initial pandemic shock is much smaller when conditioning on GDP forecasts.

Conditioning also reduces the differences between the models and flow methods. The gains from conditioning tend to be larger for flow-based models compared to the benchmark model. However, mostly the flow-based models still only improve on the benchmark model for short horizon forecasts (Table 4).

Table 3: RMSFE ratios for forecasts conditional on GDP forecasts relative to unconditional forecasts

	Shimer 1M		Shimer 3M		Elsby		Benchmark model
	FLOW-BVAR	BVAR model	FLOW-BVAR	BVAR model	FLOW-BVAR	BVAR model	
h1	0.95	0.99	0.99	0.99	0.95	0.98	0.99
h2	0.89	0.93	0.95	0.94	0.88	0.91	0.96
h4	0.80	0.84	0.84	0.84	0.77	0.81	0.93
h8	0.78	0.84	0.80	0.83	0.77	0.82	0.94

Notes: When the ratio is less than one the RMSFE of the conditional model is smaller than the RMSFE of the corresponding unconditional model. Benchmark refers to the BVAR model without flow rates. Otherwise, see notes for Table 1.

Table 4: RMSFE ratios for forecasts conditional on GDP forecasts

	Shimer 1M		Shimer 3M		Elsby	
	FLOW-BVAR model	BVAR model	FLOW-BVAR model	BVAR model	FLOW-BVAR model	BVAR model
h1	0.87	0.90	0.89	0.95	0.89	0.91
h2	1.03	0.95	1.02	0.97	1.06	0.96
h4	1.04	0.98	1.05	1.01	1.05	1.00
h8	1.01	1.00	1.02	1.01	1.02	1.00

Notes: When the ratio is less than one the RMSFE of the flow-based model is smaller than the RMSFE of the model without flows. Otherwise, see notes for Table 1.

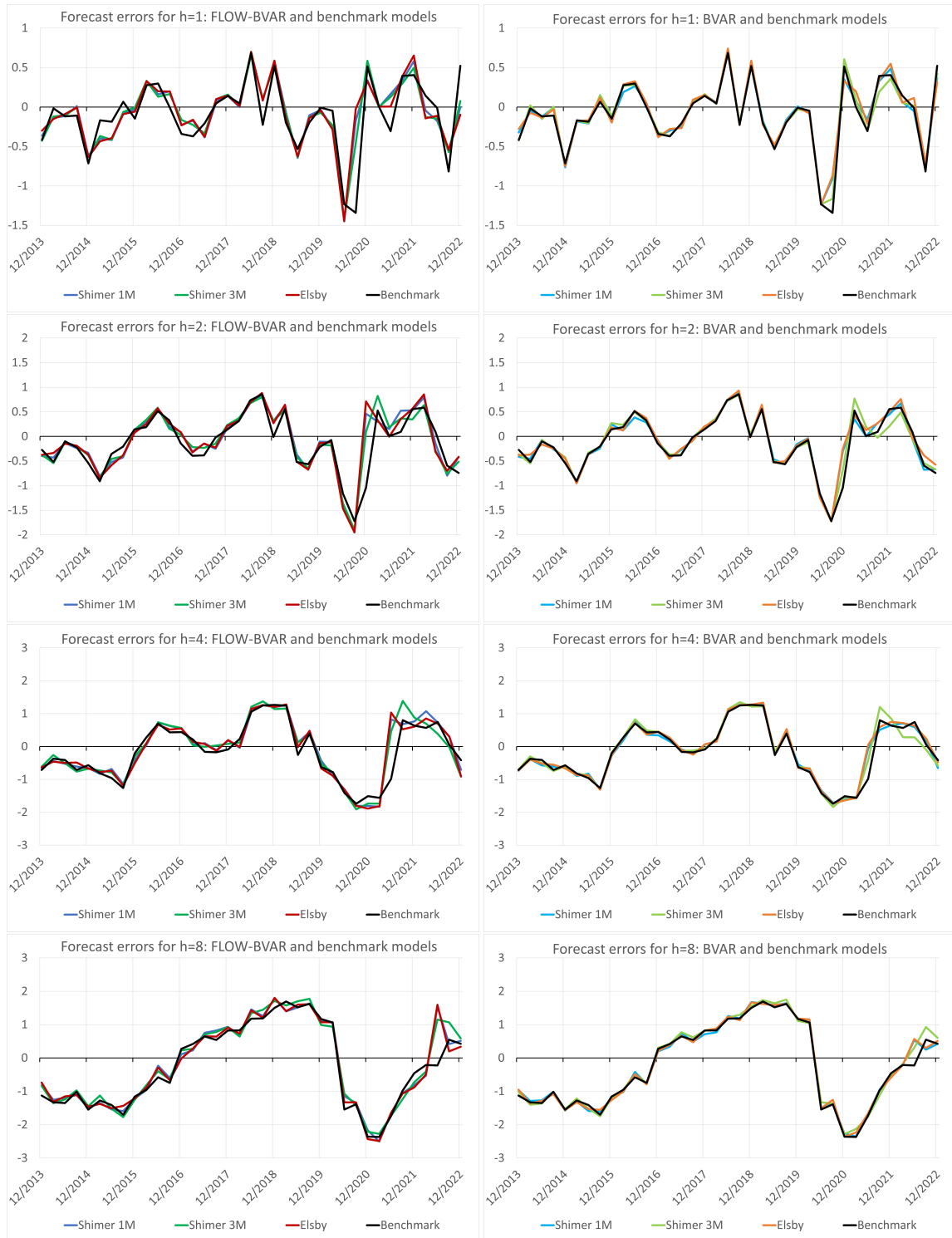


Figure 7: Evolution of forecasts errors over time for selected forecasting horizons. A negative value means realised unemployment has been higher than forecast.

### 3.5 Comparison to Bank of Finland staff forecasts

In this section we compare the forecasts produced by the time series models to those published by the Bank of Finland (BoF)<sup>19</sup>. The Bank of Finland unemployment rate forecasts are published in June and December. To construct comparable measures we pick the forecasts made by the BVAR models using roughly the same information set as was available to the Bank of Finland forecasters at the time of the cut-off dates. This means that in the June forecast labour market data for Q1 is available, while for the December forecast labour market data for Q3 is available.<sup>20</sup>

The Bank of Finland forecast is difficult to beat using BVAR models (Table 5). However, the benchmark model outperforms the BoF forecast when forecasting two quarters ahead. The results for Finland are somewhat weaker than for some other countries, as Barnichon et al. (2016) find that a flow-based model is able to improve on professional forecasts on at least one horizon for several OECD countries.

Although conditioning on the Bank of Finland GDP forecast improves the accuracy of the BVAR forecasts (Table 3), the BoF forecasts are still most of the time more accurate (Table 6). There are some gains in forecast accuracy for the two quarters ahead BVAR forecasts compared to BoF forecasts. This is not true for the pre-COVID period (see Appendix B), implying recent data improves the relative forecasting performance of the BVAR models two quarters ahead.

The BVAR models rely on a similar data set and produce very similar forecasts, and we therefore opt for combining the forecast produced by the benchmark model – often found to be the most accurate model in Section 3.1 – and the Bank of Finland staff forecast.<sup>21</sup> Forecast accuracy compared to the BoF forecast is improved (last column of Tables 5 and 6) with the combined forecast outperforming the BoF forecast in most cases. The improvement is again especially pronounced when forecasting two quarters ahead.

The mean error for the unconditional combined forecast is particularly small (Figure 8): the BoF forecasts tend to overestimate the unemployment rate over short

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<sup>19</sup>Note that the quarterly profile of the BoF unemployment rate forecast is not published.

<sup>20</sup>Note that the Bank of Finland forecasters have one month of the ongoing quarter available when making the forecasts, which is not used for the quarterly time series models. A mixed frequency analysis is beyond the scope of this paper.

<sup>21</sup>Note that the FLOW-BVAR forecasts outperform the benchmark model for  $h = 1$ , but using these forecasts does not significantly change the results for the combined forecast.



forecast horizons and underestimate it over longer forecasting horizons, whereas the opposite is true for the unconditional BVAR forecasts.<sup>22</sup> The forecast errors therefore cancel each other out.

Looking more closely at the forecast errors shows that at the very start of the pandemic the BoF forecast overestimated the future unemployment rate whereas the opposite is true for the BVAR forecasts, rendering the average forecast a good compromise. On the other hand, as the pandemic continued the BoF forecast led to generally smaller forecast errors especially over longer forecasting horizons, as the BVAR models continued to predict higher-than-realised unemployment rates for a long time. While BVAR forecasts provide a good starting point for forecasting the unemployment rate, the pandemic period showed that professional forecasts can improve forecast accuracy around turning points.

When conditioning on the BoF GDP forecast we can see that all the mean forecast errors behave similarly, most likely due to the fact that they now reflect a similar view for GDP over the forecasting horizon. While the mean forecast error for the combination forecast is very small over short forecasting horizons, it grows over longer horizons quite substantially, and becomes eventually larger than for the BoF forecast alone.

Table 5: RMSFE ratios of BVAR model forecasts relative to Bank of Finland staff forecasts

	Shimer 1M		Shimer 3M		Elsby		Benchmark	Combination
	FLOW-BVAR	BVAR model	FLOW-BVAR	BVAR model	FLOW-BVAR	BVAR model		
h1	1.42	1.33	1.37	1.35	1.41	1.35	1.35	0.99
h2	1.04	0.96	1.01	0.98	1.03	0.99	0.94	0.67
h4	1.33	1.25	1.46	1.46	1.34	1.35	1.27	1.01
h8	1.05	1.03	1.26	1.26	1.05	1.07	1.08	0.98

Notes: When the ratio is less than one the RMSFE of the BVAR forecast is smaller than the RMSFE of the Bank of Finland staff forecast.

Benchmark refers to the BVAR model without flows. Combination refers to an average of the Bank of Finland forecast and the benchmark model forecast. The RMSFEs are calculated over the time period Q2 2012 - Q4 2022 for all models and all horizons. Otherwise, see notes for Table 1.

<sup>22</sup>For illustrative purposes we have chosen to only show the FLOW-BVAR and BVAR models using the Shimer 1M flow rates. The mean errors using the Elsby series behave broadly similarly, but the mean errors using the Shimer 3M series are clearly larger over long forecasting horizons.

Table 6: RMSFE ratios of conditional BVAR model forecasts relative to Bank of Finland staff forecasts

	Shimer 1M		Shimer 3M		Elsby		Benchmark	Combination
	FLOW-BVAR	BVAR model	FLOW-BVAR	BVAR model	FLOW-BVAR	BVAR model		
h1	1.35	1.27	1.34	1.29	1.35	1.29	1.29	0.96
h2	0.97	0.89	0.96	0.89	0.96	0.90	0.88	0.64
h4	1.20	1.13	1.23	1.18	1.18	1.15	1.14	0.95
h8	1.02	1.01	1.05	1.04	1.00	1.00	1.02	0.97

Notes: When the ratio is less than one the RMSFE of the conditional BVAR forecast is smaller than the RMSFE of the Bank of Finland staff forecast. Otherwise, see notes for Table 5.

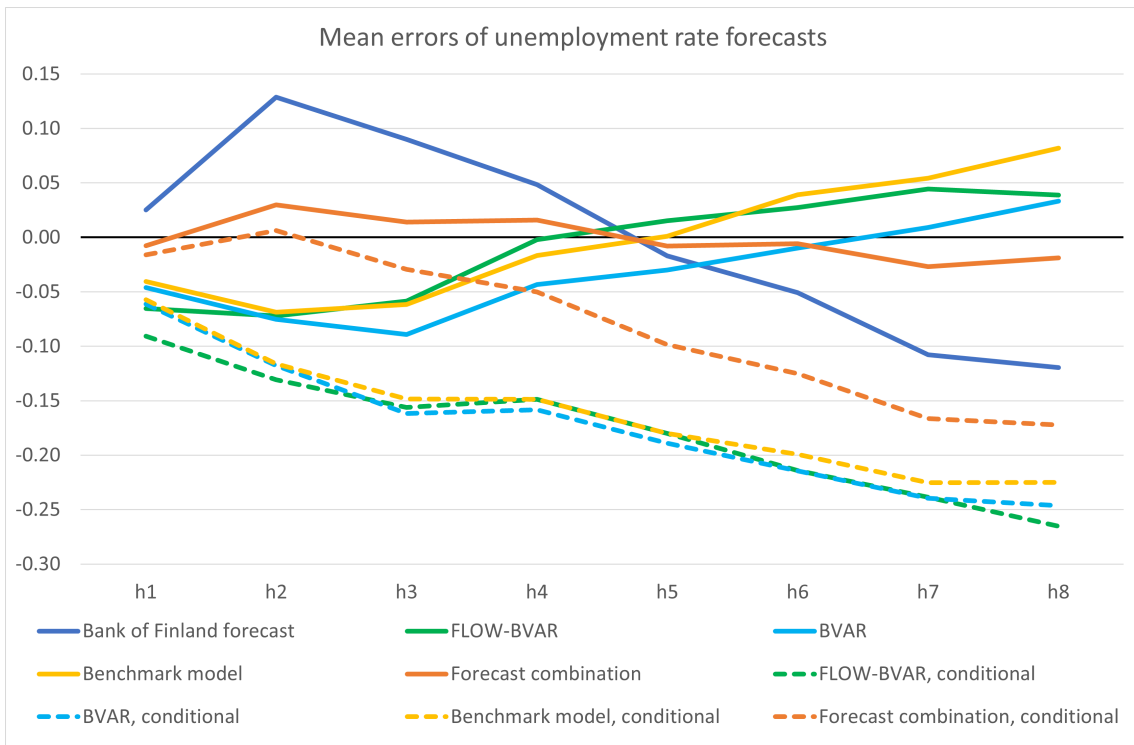


Figure 8: A negative value means the realised unemployment rate has been on average higher than forecast. Shimer 1M flow series are used for the FLOW-BVAR and BVAR models. *Conditional* means conditional on GDP forecasts.

## 4 Conclusion

This paper applies flow-based methods to forecast the unemployment rate in Finland. We find that using unemployment flows in BVAR models do not consistently

and significantly improve forecasting performance compared to a BVAR model without flow rates (the benchmark model), but BVAR models do improve forecast accuracy compared to an AR model. Thus, the additional burden of incorporating the unemployment flows into the forecasting model seems worthwhile only for short forecasting horizons when including recent data. Our results for Finland are overall less encouraging for flow-based forecasting than previous results for other countries, in particular the US, but also for, for example, other OECD countries in Barnichon et al. (2016) and for Portugal in Goncalves et al. (2019). Forecasting the flow rates also seems to worsen forecast accuracy in many cases in Finland.

We included a number of additional explanatory variables related to the labour market and found that many variables improve forecast accuracy especially in the short term. Which variables improve forecast accuracy depends to a high degree on the forecasting horizon and the sample period. However, vacancies tend to perform well over longer forecast horizons.

Different methods for constructing the unemployment flows were compared, with the flow rates by Shimer (2012) seeming to slightly outperform those by Elsby et al. (2013) in our sample. The Elsby series performed particularly badly at the beginning of the pandemic, implying that the sharp decline in the job finding rate was crucial for forecast accuracy at this time.

Conditioning on the GDP forecasts by the Bank of Finland clearly improves forecast accuracy of the BVAR models, with especially large gains during the pandemic. Conditioning thus helps to anchor forecasts during turbulent times. However, even after conditioning, the benchmark model remains difficult to beat, especially beyond the near term.

It is difficult to outperform the Bank of Finland staff forecasts with flow-based models. The main benefit of BVAR models compared to professional forecasts seems to be for forecasting two quarters ahead. Combining professional forecasts with BVAR forecasts turns out to be beneficial especially when forecasting two quarters.

The analysis could be extended into several interesting directions. As we have determined that the BVAR forecasts are the most useful compared to professional forecasts over relatively short horizons, conducting the analysis on a monthly frequency could be interesting. We have also left the three-state labour market model, which is undoubtedly richer in information, to future research. Incorporating the flows into and out of the labour market could increase the importance of the flow-

based models. Analysing the implications for forecasting performance of the different methods for constructing the flows would be interesting for other countries as well. This paper also only considers BVAR models, and a comparison to forecasts produced using a more structural approach, in line with, for example, Tasci (2012), could prove insightful in the Finnish context as well.

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## A Choosing the lag length for the autoregressive model

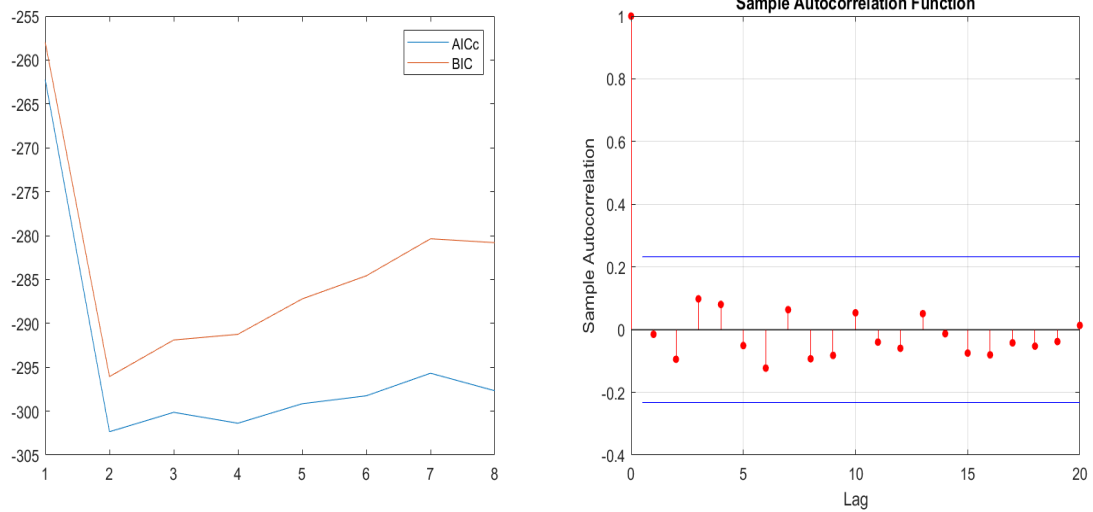


Figure 9: Information criteria for the AR model using up to 8 lags and the autocorrelation function of the AR(2) model.

## B Selected results for the pre-COVID sample

Table 7: RMSFE ratios of unemployment rate forecasting models in the pre-COVID period

	Shimer 1M		Shimer 3M		Elsby		AR(2) model
	FLOW-BVAR model	BVAR model	FLOW-BVAR	BVAR model	FLOW-BVAR	BVAR model	
h1	1.03	1.01	0.99	1.00	1.04	1.03	1.84
h2	1.01	1.01	0.98	1.01	1.04	1.05	1.08
h4	1.02	1.04	1.03	1.08	1.05	1.10	1.49
h8	1.04	1.04	1.15	1.17	1.06	1.09	4.22

Notes: When the ratio is less than one the RMSFE of the flow-based model or AR model is smaller than the RMSFE of the BVAR model without flows. Pre-COVID period: RMSFEs are calculated over the time period: Q4 2012 - Q4 2019 for all models and all horizons. Otherwise, see notes for Table 1.

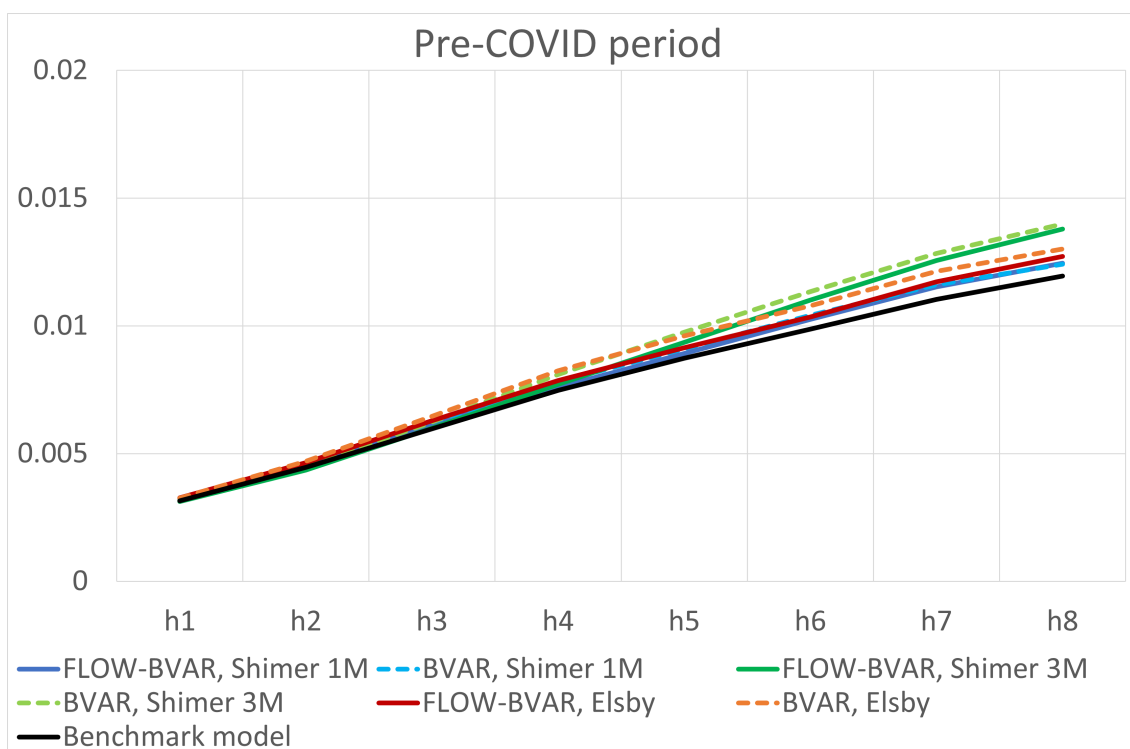


Figure 10: RMSFEs of different forecasting models using different flow methods.

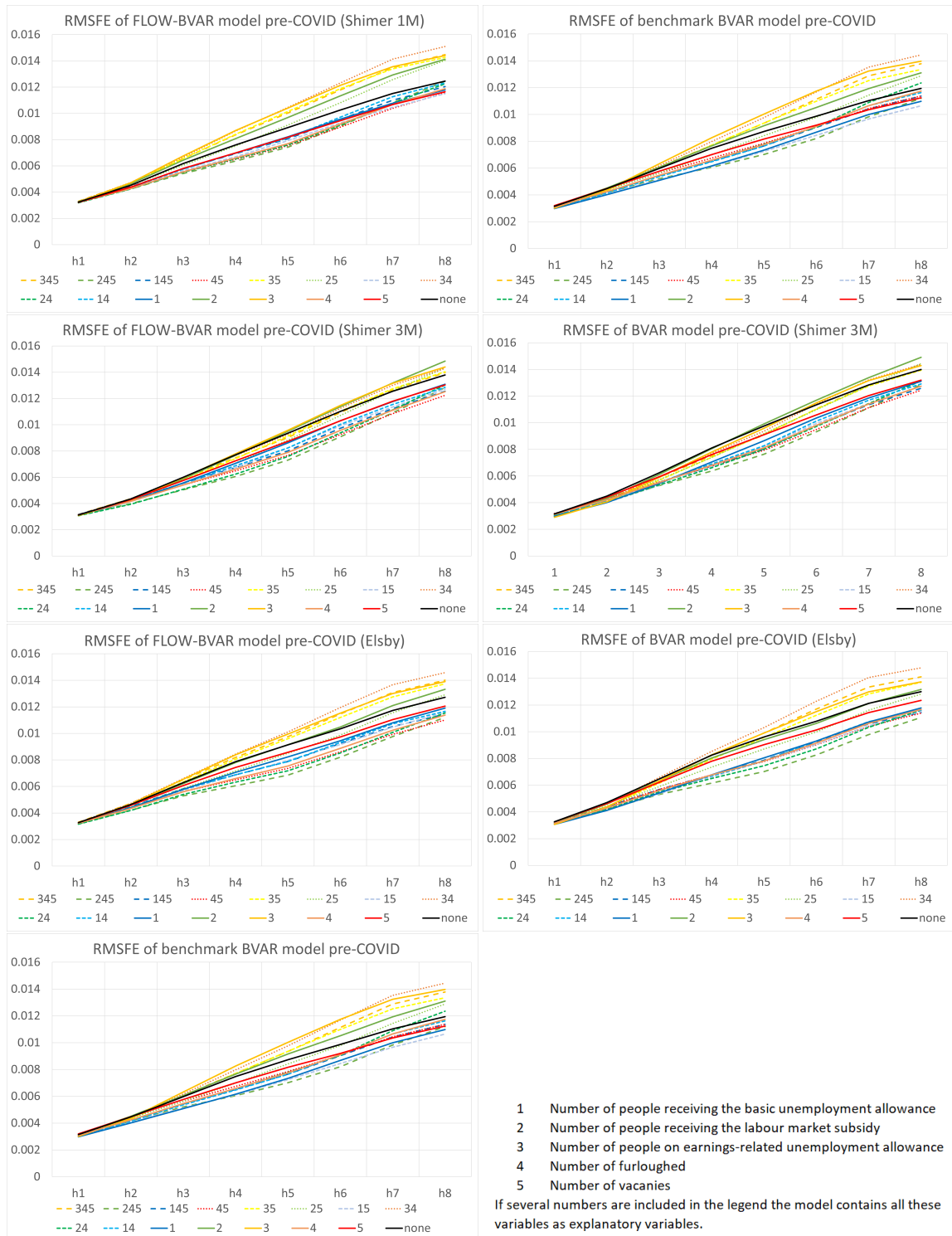


Figure 11: RMSFEs over the pre-COVID sample for the BVAR models using additional labour market variables.



Table 8: RMSFE ratios for FLOW-BVAR model forecasts with constant inflow or outflow rates for the pre-COVID period

	Shimer 1M		Shimer 3M		Elsby	
	Fixed s (inflow)	Fixed f (outflow)	Fixed s (inflow)	Fixed f (outflow)	Fixed s (inflow)	Fixed f (outflow)
h1	1.01	1.00	1.02	1.02	0.99	1.00
h2	0.99	1.05	1.01	1.05	0.98	1.02
h4	0.96	1.08	0.94	1.03	0.96	1.02
h8	0.94	1.10	0.90	0.95	0.92	1.00

Notes: When the ratio is less than one the RMSFE of the model with fixed inflow or outflow rates is smaller than the RMSFE of the model with varying rates. f denotes the job finding rate and s the job separation rate. Otherwise, see notes for Table 1.

Table 9: RMSFE ratios for forecasts conditional on GDP forecasts relative to unconditional forecasts for the pre-COVID period

	Shimer 1M		Shimer 3M		Elsby		Benchmark model
	FLOW-BVAR	BVAR model	FLOW-BVAR	BVAR model	FLOW-BVAR	BVAR model	
h1	0.98	0.98	1.00	0.99	0.99	0.98	0.99
h2	0.96	0.96	0.99	0.97	0.96	0.95	0.98
h4	0.90	0.92	0.90	0.89	0.89	0.88	0.94
h8	0.94	0.95	0.86	0.86	0.91	0.91	0.98

Notes: When the ratio is less than one the RMSFE of the conditional model is smaller than the RMSFE of the corresponding unconditional model. Benchmark refers to the BVAR model without flows. Otherwise, see notes for Table 1.

Table 10: RMSFE ratios for forecasts conditional on GDP forecasts for the pre-COVID period

	Shimer 1M		Shimer 3M		Elsby	
	FLOW-BVAR model	BVAR model	FLOW-BVAR model	BVAR model	FLOW-BVAR model	BVAR model
h1	1.02	1.00	1.00	1.00	1.03	1.02
h2	0.99	0.99	0.98	1.00	1.01	1.02
h4	0.97	1.01	0.98	1.02	0.99	1.03
h8	1.00	1.01	1.01	1.03	0.98	1.01

Notes: When the ratio is less than one the RMSFE of the flow-based model is smaller than the RMSFE of the model without flows. Otherwise, see notes for Table 1.

Table 11: RMSFE ratios of BVAR model forecasts relative to Bank of Finland staff forecasts for the pre-COVID period

	Shimer 1M		Shimer 3M		Elsby		Benchmark	Combination
	FLOW-BVAR	BVAR model	FLOW-BVAR	BVAR model	FLOW-BVAR	BVAR model		
h1	1.12	1.13	1.08	1.10	1.12	1.15	1.09	1.03
h2	1.13	1.14	1.09	1.14	1.15	1.20	1.10	1.02
h4	1.26	1.30	1.28	1.35	1.30	1.37	1.24	1.10
h8	1.10	1.12	1.28	1.31	1.15	1.20	1.13	1.04

Notes: When the ratio is less than one the RMSFE of the BVAR forecast is smaller than the RMSFE of the Bank of Finland staff forecast. Benchmark refers to the BVAR model without flows. Combination refers to an average of the Bank of Finland forecast and the benchmark forecast. Pre-COVID period: the RMSFEs are calculated over the time period: Q2 2012 - Q1 2020 for all models and all horizons. Otherwise, see notes for Table 1.

Table 12: RMSFE ratios of conditional BVAR model forecasts relative to Bank of Finland staff forecasts for the pre-COVID period

	Shimer 1M		Shimer 3M		Elsby		Benchmark	Combination
	FLOW-BVAR	BVAR model	FLOW-BVAR	BVAR model	FLOW-BVAR	BVAR model		
h1	1.10	1.11	1.08	1.09	1.11	1.13	1.09	1.02
h2	1.10	1.11	1.08	1.11	1.11	1.14	1.09	1.02
h4	1.20	1.22	1.19	1.23	1.20	1.24	1.21	1.09
h8	1.07	1.09	1.10	1.13	1.05	1.10	1.10	1.04

Notes: When the ratio is less than one the RMSFE of the conditional BVAR forecast is smaller than the RMSFE of the Bank of Finland staff forecast. Otherwise, see notes for Table 11.

## C Results when the COVID-19 shock is not scaled

This appendix reports the main results of the paper when the COVID-19 shock has not been scaled and a comparison between scaled and non-scaled results.

Table 13: RMSFE ratios of unemployment rate forecasting models

	Shimer 1M		Shimer 3M		Elsby		AR(2) model
	FLOW-BVAR	BVAR model	FLOW-BVAR	BVAR model	FLOW-BVAR	BVAR model	
h1	0.93	0.92	0.88	0.96	0.98	0.94	1.46
h2	1.15	1.02	1.04	1.01	1.27	1.07	1.09
h4	1.24	1.12	1.18	1.14	1.39	1.22	1.43
h8	1.24	1.17	1.18	1.13	1.40	1.25	11.03

Notes: When the ratio is less than one the RMSFE of the flow-based model or AR model is smaller than the RMSFE of the BVAR model without flows. Otherwise, see notes for Table 1.

Table 14: RMSFE ratios for models scaled for the COVID-19 shock relative to non-scaled models

	Shimer 1M		Shimer 3M		Elsby		Benchmark
	FLOW-BVAR	BVAR model	FLOW-BVAR	BVAR model	FLOW-BVAR	BVAR model	
h1	0.97	0.98	1.00	0.99	0.93	0.96	0.99
h2	0.96	0.96	0.98	0.97	0.91	0.94	0.99
h4	0.94	0.93	0.95	0.95	0.88	0.91	0.97
h8	0.92	0.89	0.94	0.94	0.82	0.85	0.92

Notes: When the ratio is less than one the RMSFE of the scaled model is smaller than the RMSFE of the corresponding non-scaled model. Benchmark refers to the BVAR model without flows. Otherwise, see notes for Table 1.

# D Additional results for flow-based models compared to benchmark

This appendix reports results for the FLOW-BVAR and the BVAR model compared to the benchmark model, i.e. the BVAR model without flows, when including additional labour market variables in all models.

Table 15: RMSFE ratios for unemployment rate forecasting models with additional explanatory variables relative to benchmark model

	Shimer 1M					Shimer 3M					Elsby				
	var1	var2	var3	var4	var5	var1	var2	var3	var4	var5	var1	var2	var3	var4	var5
FLOW-BVAR model: Whole sample period															
h1	0.95	0.91	0.98	0.92	0.90	0.94	0.88	0.93	0.91	0.90	0.98	0.91	1.04	0.96	0.91
h2	1.28	1.13	1.30	1.16	1.10	1.17	1.03	1.14	1.08	1.05	1.40	1.17	1.52	1.28	1.16
h4	1.48	1.24	1.40	1.31	1.22	1.36	1.18	1.24	1.20	1.16	1.66	1.28	1.68	1.47	1.27
h8	1.57	1.23	1.33	1.24	1.26	1.54	1.20	1.19	1.12	1.22	1.81	1.22	1.54	1.31	1.29
BVAR model: Whole sample period															
h1	0.90	0.89	0.93	0.92	0.91	0.97	0.94	0.96	0.99	0.97	0.93	0.91	0.94	0.93	0.92
h2	1.06	0.99	1.07	1.01	0.97	1.04	0.98	1.00	1.01	0.99	1.07	1.01	1.07	1.03	1.01
h4	1.39	1.10	1.23	1.19	1.07	1.31	1.13	1.12	1.11	1.11	1.39	1.14	1.28	1.20	1.13
h8	1.63	1.11	1.22	1.20	1.13	1.63	1.15	1.12	1.07	1.17	1.77	1.11	1.30	1.17	1.17
FLOW-BVAR model: Pre-COVID period															
h1	1.08	1.03	1.08	1.05	1.01	1.04	0.97	1.03	1.02	0.98	1.08	1.02	1.08	1.05	1.02
h2	1.09	1.03	1.08	1.01	0.98	1.04	0.94	0.98	0.98	0.96	1.10	1.02	1.07	1.02	1.02
h4	1.13	1.06	1.05	1.00	1.00	1.15	1.00	0.94	1.00	1.04	1.15	1.02	1.02	1.00	1.06
h8	1.07	1.08	1.03	1.01	1.04	1.19	1.13	1.03	1.07	1.16	1.08	1.02	1.00	0.97	1.07
BVAR model: Pre-COVID period															
h1	1.00	0.99	1.01	1.00	0.99	1.00	0.98	0.97	1.01	0.99	1.03	1.02	1.02	1.02	1.02
h2	1.00	1.00	1.00	0.98	0.98	1.00	0.96	0.93	0.99	0.99	1.02	1.02	1.00	1.01	1.04
h4	1.08	1.05	1.01	1.00	1.03	1.14	1.05	0.94	1.03	1.09	1.10	1.05	1.00	1.03	1.11
h8	1.05	1.00	1.00	1.00	1.03	1.19	1.14	1.02	1.09	1.17	1.07	1.01	0.98	0.99	1.10

Notes: When the ratio is less than one the RMSFE of the flow-based model is smaller than the RMSFE of the model without flow rates. var1 refers to the number of people receiving the basic unemployment allowance; var2 to the number of people receiving the labour market subsidy; var3 to the number of people on earnings-related unemployment allowance; var4 to the number of furloughed; and var5 to number of vacancies. If several numbers are mentioned the model contains all these variables as explanatory variables. Otherwise, see notes for Table 1.

Table 16: RMSFE ratios for unemployment rate forecasting models with additional explanatory variables relative to benchmark model

	Shimer 1M					Shimer 3M					Elsby				
	var14	var24	var34	var15	var25	var14	var24	var34	var15	var25	var14	var24	var34	var15	var25
FLOW-BVAR model: Whole sample period															
h1	0.97	0.94	0.98	0.93	0.90	0.93	0.90	0.93	0.93	0.90	1.00	0.99	1.03	0.98	0.93
h2	1.22	1.17	1.23	1.24	1.11	1.12	1.06	1.13	1.15	1.07	1.37	1.32	1.39	1.38	1.19
h4	1.33	1.25	1.25	1.44	1.24	1.24	1.17	1.22	1.33	1.20	1.54	1.47	1.36	1.61	1.28
h8	1.13	1.08	1.12	1.42	1.22	1.13	1.05	1.11	1.47	1.21	1.29	1.24	1.14	1.64	1.21
BVAR model: Whole sample period															
h1	0.91	0.91	0.92	0.90	0.89	0.97	0.97	0.94	0.96	0.96	0.92	0.93	0.94	0.92	0.92
h2	1.05	1.02	1.04	1.04	0.99	1.02	1.00	1.01	1.02	1.00	1.09	1.06	1.08	1.07	1.02
h4	1.25	1.16	1.12	1.32	1.11	1.18	1.11	1.14	1.27	1.14	1.32	1.22	1.19	1.39	1.13
h8	1.16	1.06	1.05	1.45	1.10	1.16	1.03	1.06	1.57	1.16	1.25	1.15	1.07	1.62	1.10
FLOW-BVAR model: Pre-COVID period															
h1	1.07	1.07	1.09	1.06	1.04	1.05	1.03	1.04	1.03	0.99	1.07	1.05	1.08	1.07	1.03
h2	1.05	1.01	1.09	1.05	1.04	1.02	0.94	1.00	1.01	0.96	1.06	0.99	1.08	1.08	1.02
h4	1.08	0.99	1.09	1.10	1.08	1.06	0.95	0.96	1.10	1.01	1.06	0.96	1.06	1.12	1.03
h8	1.06	0.99	1.05	1.08	1.09	1.11	1.06	0.99	1.20	1.11	1.00	0.93	1.01	1.09	1.00
BVAR model: Pre-COVID period															
h1	1.01	1.00	1.02	1.00	1.00	1.02	1.01	0.99	0.99	1.00	1.04	1.03	1.04	1.02	1.02
h2	0.99	0.97	1.03	0.98	1.00	1.00	0.96	0.97	0.98	0.97	1.03	0.99	1.05	1.01	1.02
h4	1.01	0.98	1.04	1.05	1.07	1.07	1.00	0.97	1.10	1.06	1.04	0.99	1.07	1.08	1.05
h8	1.03	0.95	1.02	1.06	1.01	1.11	1.06	1.00	1.20	1.12	1.00	0.94	1.02	1.08	1.00
	v145	v245	v345	v35	v45	v145	v245	v345	v35	v45	v145	v245	v345	v35	v45
FLOW-BVAR model: Whole sample period															
h1	0.96	0.94	0.97	0.97	0.91	0.94	0.92	0.94	0.93	0.91	0.99	0.97	1.02	1.04	0.96
h2	1.21	1.19	1.23	1.27	1.12	1.13	1.10	1.15	1.15	1.07	1.34	1.30	1.38	1.51	1.25
h4	1.30	1.31	1.27	1.34	1.22	1.23	1.23	1.24	1.25	1.15	1.48	1.46	1.35	1.64	1.35
h8	1.10	1.15	1.15	1.23	1.09	1.15	1.14	1.15	1.20	1.06	1.28	1.27	1.16	1.48	1.18
BVAR model: Whole sample period															
h1	0.91	0.92	0.92	0.93	0.91	0.98	0.99	0.96	0.96	0.99	0.92	0.93	0.94	0.94	0.93
h2	1.04	1.04	1.04	1.06	0.99	1.02	1.03	1.02	1.02	1.01	1.05	1.04	1.06	1.06	1.02
h4	1.18	1.17	1.12	1.18	1.09	1.15	1.14	1.13	1.13	1.06	1.24	1.18	1.15	1.25	1.11
h8	1.10	1.09	1.06	1.13	1.03	1.18	1.10	1.09	1.12	1.00	1.21	1.13	1.07	1.25	1.05
FLOW-BVAR model: Pre-COVID period															
h1	1.06	1.07	1.08	1.08	1.03	1.03	1.03	1.04	1.02	1.01	1.06	1.06	1.08	1.08	1.03
h2	1.04	1.02	1.08	1.08	0.99	1.01	0.96	1.00	0.98	0.96	1.06	1.01	1.08	1.07	1.01
h4	1.06	1.05	1.09	1.09	0.96	1.03	1.00	0.97	0.96	0.96	1.06	1.00	1.06	1.04	0.96
h8	1.06	1.11	1.05	1.07	1.02	1.10	1.15	1.01	1.05	1.08	1.01	1.00	1.02	1.03	0.97
BVAR model: Pre-COVID period															
h1	1.00	1.01	1.01	1.02	1.00	1.02	1.03	0.99	0.97	1.01	1.03	1.04	1.03	1.02	1.02
h2	0.99	0.99	1.02	1.02	0.98	1.00	0.99	0.97	0.94	0.99	1.04	1.01	1.05	1.02	1.01
h4	1.02	1.03	1.05	1.06	0.99	1.04	1.05	0.98	0.96	1.00	1.04	1.02	1.07	1.03	1.00
h8	1.03	1.02	1.02	1.04	1.01	1.11	1.15	1.01	1.04	1.09	1.01	0.99	1.02	1.03	1.00

Notes: See notes for Table 15.

## E Impact of additional explanatory variables

This appendix reports the results for the FLOW-BVAR, BVAR and benchmark models which include explanatory variables compared to the corresponding model without any explanatory variables.

Table 17: RMSFE ratios for unemployment rate forecasting models: the benefits of additional labour market variables

	Shimer 1M					Shimer 3M					Elsby				
	var1	var2	var3	var4	var5	var1	var2	var3	var4	var5	var1	var2	var3	var4	var5
FLOW-BVAR model: Whole sample period															
h1	0.93	0.99	0.94	0.95	0.97	0.95	0.99	0.92	0.97	1.00	0.96	0.99	1.00	0.98	0.98
h2	0.95	1.00	0.99	0.93	0.96	0.94	0.99	0.94	0.95	0.98	1.00	0.99	1.11	1.00	0.97
h4	1.09	1.01	1.08	1.03	0.96	1.04	1.00	0.99	0.99	0.96	1.16	1.00	1.24	1.10	0.96
h8	1.35	1.04	1.16	1.26	0.96	1.36	1.05	1.06	1.17	0.96	1.54	1.03	1.33	1.32	0.97
BVAR model: Whole sample period															
h1	0.89	0.98	0.90	0.96	0.99	0.91	0.99	0.88	0.98	1.00	0.91	0.99	0.91	0.96	1.00
h2	0.90	0.99	0.92	0.92	0.95	0.88	0.98	0.86	0.93	0.98	0.87	0.98	0.89	0.92	0.96
h4	1.14	1.01	1.06	1.05	0.94	1.04	1.00	0.93	0.95	0.95	1.08	0.98	1.04	1.00	0.95
h8	1.53	1.03	1.17	1.34	0.94	1.50	1.05	1.04	1.16	0.95	1.62	1.01	1.21	1.28	0.95
FLOW-BVAR model: Pre-COVID period															
h1	0.99	1.01	1.00	1.00	0.99	0.99	0.99	0.99	1.01	1.00	0.99	0.99	1.00	0.99	1.00
h2	0.96	1.03	1.04	0.94	0.97	0.96	0.97	0.98	0.96	0.99	0.95	0.99	1.00	0.94	0.98
h4	0.92	1.06	1.14	0.87	0.92	0.92	0.99	1.01	0.86	0.94	0.90	0.99	1.07	0.84	0.94
h8	0.95	1.13	1.16	0.95	0.93	0.95	1.08	1.04	0.91	0.95	0.94	1.05	1.09	0.89	0.95
BVAR model: Pre-COVID period															
h1	0.95	0.99	0.96	0.98	1.00	0.94	0.98	0.92	0.99	1.00	0.94	0.99	0.94	0.97	1.00
h2	0.89	1.00	0.97	0.93	0.98	0.89	0.96	0.90	0.94	0.98	0.88	0.98	0.93	0.91	0.99
h4	0.85	1.03	1.07	0.84	0.93	0.87	0.99	0.96	0.84	0.94	0.82	0.97	1.00	0.82	0.94
h8	0.93	1.06	1.12	0.95	0.94	0.94	1.07	1.02	0.91	0.94	0.91	1.01	1.06	0.90	0.95
Benchmark model: Whole sample period						Benchmark model: Pre-COVID period									
h1	0.90	1.00	0.88	0.94	0.98	0.95	1.00	0.95	0.98	1.02					
h2	0.83	0.99	0.85	0.90	0.97	0.90	1.01	0.98	0.95	1.00					
h4	0.89	0.99	0.93	0.95	0.95	0.82	1.02	1.11	0.88	0.94					
h8	1.06	1.04	1.07	1.25	0.94	0.92	1.10	1.17	0.98	0.94					

Notes: When the ratio is less than one the RMSFE of the model with additional explanatory variables is smaller than the RMSFE of the model without additional explanatory variables. Benchmark refers to the BVAR model without flows. Otherwise, see notes for Table 15.

Table 18: RMSFE ratios for unemployment rate forecasting models: the benefits of additional labour market variables

	Shimer 1M					Shimer 3M					Elsby				
	var14	var24	var34	var15	var25	var14	var24	var34	var15	var25	var14	var24	var34	var15	var25
FLOW-BVAR model: Whole sample period															
h1	0.99	0.96	0.96	0.92	0.96	0.97	0.95	0.94	0.95	0.98	1.02	1.01	1.00	0.97	0.98
h2	0.96	0.94	0.94	0.92	0.94	0.96	0.93	0.94	0.93	0.97	1.04	1.03	1.03	0.99	0.96
h4	1.08	1.04	0.94	1.06	0.96	1.04	1.00	0.96	1.02	0.96	1.19	1.15	0.97	1.12	0.94
h8	1.35	1.20	0.98	1.29	1.00	1.38	1.20	0.99	1.37	1.02	1.52	1.36	0.98	1.47	0.98
BVAR model: Whole sample period															
h1	0.94	0.94	0.91	0.90	0.95	0.95	0.95	0.89	0.91	0.97	0.94	0.95	0.92	0.91	0.97
h2	0.94	0.94	0.91	0.88	0.94	0.91	0.92	0.88	0.87	0.95	0.94	0.94	0.92	0.87	0.94
h4	1.13	1.07	0.94	1.09	0.96	1.03	0.99	0.92	1.01	0.95	1.12	1.07	0.94	1.07	0.92
h8	1.52	1.28	1.00	1.44	0.99	1.49	1.22	0.99	1.52	1.02	1.59	1.37	1.00	1.57	0.96
FLOW-BVAR model: Pre-COVID period															
h1	1.00	0.98	1.02	0.99	1.00	1.01	0.98	1.01	1.00	0.99	0.99	0.97	1.01	0.99	0.99
h2	0.97	0.94	1.05	0.95	1.00	0.97	0.90	1.00	0.95	0.96	0.95	0.90	1.02	0.95	0.96
h4	0.92	0.86	1.14	0.88	0.99	0.89	0.81	0.99	0.87	0.92	0.88	0.80	1.07	0.87	0.91
h8	0.99	0.98	1.21	0.92	1.13	0.93	0.94	1.04	0.92	1.04	0.92	0.91	1.15	0.91	1.02
BVAR model: Pre-COVID period															
h1	0.96	0.95	0.97	0.96	0.99	0.97	0.96	0.95	0.95	0.99	0.96	0.94	0.97	0.95	0.98
h2	0.91	0.91	0.99	0.89	0.97	0.93	0.90	0.93	0.89	0.94	0.91	0.89	0.97	0.88	0.94
h4	0.84	0.83	1.07	0.82	0.96	0.85	0.82	0.95	0.83	0.91	0.81	0.79	1.03	0.80	0.89
h8	0.96	0.95	1.19	0.91	1.05	0.92	0.94	1.03	0.91	1.03	0.89	0.89	1.14	0.89	0.99
Benchmark model: Whole sample period								Benchmark model: Pre-COVID period							
h1	0.93	0.94	0.89	0.90	0.97	0.96	0.95	0.96	0.96	0.99					
h2	0.88	0.91	0.86	0.83	0.94	0.93	0.94	0.97	0.92	0.98					
h4	0.98	1.00	0.91	0.89	0.93	0.87	0.88	1.07	0.82	0.93					
h8	1.47	1.36	1.07	1.11	1.01	0.97	1.03	1.21	0.89	1.08					

Notes: See notes for Table 17.

Table 19: RMSFE ratios for unemployment rate forecasting models: the benefits of additional labour market variables

	Shimer 1M					Shimer 3M					Elsby				
	var145	var245	var345	var35	var45	v145	v245	v345	v35	v45	v145	v245	v345	v35	v45
FLOW-BVAR model: Whole sample period															
h1	0.98	0.96	0.95	0.93	0.94	0.98	0.96	0.94	0.92	0.97	1.00	0.98	0.99	1.00	0.99
h2	0.95	0.93	0.94	0.95	0.91	0.96	0.94	0.95	0.94	0.95	1.01	0.99	1.01	1.09	0.98
h4	1.04	1.02	0.94	1.01	0.99	1.03	0.99	0.96	0.98	0.97	1.13	1.08	0.95	1.18	1.04
h8	1.27	1.19	0.96	1.03	1.16	1.37	1.20	0.99	1.03	1.16	1.47	1.29	0.95	1.23	1.25
BVAR model: Whole sample period															
h1	0.94	0.95	0.91	0.90	0.96	0.96	0.96	0.90	0.88	0.99	0.94	0.95	0.92	0.90	0.96
h2	0.92	0.92	0.89	0.90	0.92	0.91	0.92	0.88	0.87	0.93	0.91	0.89	0.89	0.87	0.92
h4	1.06	1.03	0.93	1.00	0.99	1.00	0.97	0.91	0.92	0.93	1.04	0.97	0.90	0.99	0.95
h8	1.39	1.22	0.97	1.04	1.20	1.46	1.21	0.97	1.01	1.14	1.49	1.24	0.95	1.12	1.19
FLOW-BVAR model: Pre-COVID period															
h1	1.01	0.99	1.02	1.01	1.00	1.02	0.99	1.01	0.99	1.01	1.00	0.97	1.01	1.00	1.00
h2	0.98	0.94	1.04	1.03	0.96	0.98	0.91	1.00	0.97	0.97	0.97	0.90	1.02	1.00	0.95
h4	0.91	0.84	1.10	1.11	0.86	0.87	0.79	0.97	0.96	0.84	0.87	0.77	1.04	1.02	0.83
h8	0.97	1.00	1.16	1.15	0.93	0.91	0.93	1.01	1.02	0.89	0.90	0.88	1.10	1.08	0.87
BVAR model: Pre-COVID period															
h1	0.97	0.96	0.97	0.97	1.00	0.99	0.98	0.96	0.94	1.01	0.98	0.96	0.97	0.95	0.99
h2	0.93	0.91	0.99	0.98	0.96	0.94	0.92	0.94	0.90	0.96	0.93	0.89	0.98	0.93	0.94
h4	0.85	0.80	1.03	1.05	0.85	0.83	0.79	0.93	0.91	0.83	0.82	0.75	1.00	0.96	0.82
h8	0.95	0.92	1.14	1.12	0.93	0.90	0.92	1.00	1.00	0.89	0.88	0.85	1.08	1.05	0.88
Benchmark model: Whole sample period															
h1	0.93	0.93	0.89	0.88	0.95	0.98	0.95	0.97	0.96	1.00					
h2	0.88	0.88	0.85	0.84	0.91	0.95	0.93	0.98	0.97	0.98					
h4	0.97	0.94	0.90	0.91	0.98	0.87	0.81	1.03	1.03	0.90					
h8	1.42	1.26	1.02	1.03	1.31	0.95	0.94	1.15	1.12	0.95					
Benchmark model: Pre-COVID period															

Notes: See notes for Table 17.



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