A mixed frequency BVAR for the euro area labour market*†

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Abstract

We introduce a Bayesian Mixed-Frequency VAR model for the aggregate euro area labour market that features a structural identification via sign restrictions. The purpose of this paper is twofold: we aim at (i) providing reliable and timely forecasts of key labour market variables and (ii) enhancing the economic interpretation of the main movements in the labour market. We find satisfactory results in terms of nowcasting and forecasting, especially for employment growth. Furthermore, we look into the shocks that drove the labour market and macroeconomic dynamics from 2002 to early 2022, with an insight also on the COVID-19 recession. While domestic and foreign demand shocks were the main drivers during the Global Financial Crisis, technology and wage bargaining factors reflecting the degree of lockdown-related restrictions have been important drivers of key labour market variables during the pandemic.

Keywords: Labour market, Mixed Frequency Data, Bayesian VAR
JEL codes: J6, C53, C32, C11

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1 Introduction

Understanding labour market dynamics is of high importance for interpreting the macroeconomic developments in an economy. While there is a substantial literature to understand the dynamics of labour markets in the U.S. from a structural point of view (see, among many, Gertler et al. (2008), Mumtaz and Zanetti (2012), Christiano et al. (2016a)) and also for forecasting purposes (e.g. Montgomery et al. (1998), Askitas and Zimmermann (2009), and D'Amuri and Marcucci (2017)), not many studies are available to understand euro area labour market developments. The need to cover the euro area labour market is relevant because its structure is quite different from the US, in terms of regulations, composition of the labour force, as well as the dynamics of the ins and outs of unemployment (also known as the job market flows).

With this paper, we aim at filling this gap. We introduce an empirical model for the aggregate euro area labour market with the twofold purpose of providing reliable and timely forecasts of key labour market variables and enhancing the economic interpretation of the main movements in the labour market. An extensive literature is analysing the role of macroeconomic shocks, since the nature of the shocks is key to understand the economic consequences and to tailor monetary or fiscal policies in response. Standard demand and supply shocks can be accompanied in the analysis by shocks originated directly in the labour market. These types of shocks have been mostly analysed within general equilibrium models, and they are described as exogenous shifts in the dis-utility of supplying labour or as movements in wage mark-ups (see for example, see Galí (2011), Gali et al. (2007), Galí et al. (2012), and Phaneuf et al. (2018)). In this paper, we focus on the labour market from an empirical perspective, seeking to describe the role of different macroeconomic and labour market shocks in a semi-structural model. We develop a structural vector autoregression (SVAR) model, which includes mixed frequency data, and we identify shocks by means of sign restrictions. We are, in fact, interested in obtaining a "real-time" evaluation of the dynamics in the euro area labour market. Therefore, we face the fact that some variables are available at monthly frequency (such as the unemployment rate and survey measures), while other labour market indicators (such as employment and the job vacancy rate) are available only at quarterly frequency and with different publication delays. While the literature on mixed frequency techniques is vast by now, in this paper we follow the approach of Schorfheide and Song (2015) and use a mixed frequency Bayesian VAR (MF-BVAR). The choice of this method is driven by the purpose of our study: first, we want to have a set of variables depicting the labour market and macroeconomic dynamics; second, we want to be able to provide a reliable forecast of the main variables; and third, we want to have a structural interpretation in light of economic shocks, which are likely to explain the history of the time series, as well as the projected forecasts. A Bayesian VAR set up is, therefore, very convenient for us, given that it allows to focus on a relatively small and timely set of variables and to obtain economically interpretable results. As a methodological contribution, we merge two strands of literature, the mixed-frequency and the sign restrictions fields, and we augment the methodology of Schorfheide and Song (2015), by including a step that draws impact matrices that fulfil the imposed restrictions, with the methodology of Rubio-Ramirez et al. (2010). While there are few examples of structural mixed frequency VARs (see Foroni and Marcellino (2014) and Ghysels (2016)), to the best of our knowledge, however, no previous papers use sign restrictions in mixed frequency VARs and, therefore, we aim at closing a methodological gap. Moreover, our sign-restricted SVAR also provides a powerful policy tool for practitioners, given that it allows the interpretation of the drivers of nowcasts in terms of the structural shocks.

We evaluate the forecasting properties of the model in terms of a real-time exercise. We find satisfactory results in terms of nowcasting when looking at quarterly variables, such as employment growth and wage growth. These findings are aligned with most of the results available in the mixed frequency literature, which suggest that the content available in higher frequency data helps improve the forecasting accuracy of lower frequency variables. Additionally, we also find that our model produces suitable short-term forecasts for the unemployment rate and short- to medium-term forecasts for inflation and industrial production growth, in comparison to an AR model.

Further, we look into the shocks that drove the labour market and macroeconomic dynamics from 2002 to the early 2022. We find noteworthy insights. First, demand shocks were the main drivers during the past Global Financial Crisis. Second, shocks originating in the labour market play an important role in explaining the period of low inflation and low wage growth from 2013 onward. We further dig into the corona virus (COVID-19) period, in order to find an assessment of the shocks explaining this crisis. We find that, in contrast to the Global Financial Crisis, technology and wage bargaining shocks are important drivers of key labour market variables.

The remainder of paper is organised as follows. Section 2 describes the model we set up for interpreting the euro area labour market developments. Section 3 describes the methodology for the estimation of the SVAR model. Section 4 provides the main economic results, and a snapshot on the analysis of the economic developments during the COVID-19 crisis. Section 5 summarises the forecasting performance results. Section 6 concludes.

2 A model for the euro area labour market

We start our analysis by describing the empirical semi-structural approach to identify the main macroeconomic drivers behind the variables in our mixed-frequency BVAR model. Our model can exploit the information available at different frequencies to produce reliable forecasts and to derive a narrative based on the key structural shocks to them.

Our VAR model includes six variables. At the monthly frequency: industrial production growth rate (Δip_t), inflation (Δp_t), and unemployment rate (u_t); at the quarterly frequency: wage growth (Δw_t measured by compensation per employee), employment growth (Δe_t, measured by total persons employed), and the job vacancy rate (jvr_t). A detailed description of the variables and of their transformations can be found in Appendix A. The number of lags included in the estimation is equal to 12.[1]

With this set of variables, we aim at identifying six shocks. Specifically, an aggregate demand shock; two technology shocks, neutral and investment-specific; and three shocks originating in the labour market, a labour supply shock, a wage bargaining shock, and a mismatch shock. The identification is obtained by means of sign restrictions, following theoretical results from a class of DSGE models featuring labour market variables (see, for example, Smets and Wouters (2007); Christiano et al. (2016b); Mumtaz and Zanetti (2015); Foroni et al. (2018a)).

We consider the following identification scheme, where all the restrictions are imposed on impact:

Table 1: Identification scheme via sign restrictions - baseline model

	Supply		Demand	Labour Market		
	Neutral tech.	Investment-spec. tech.	Agg. Demand	Labour Supply	Wage Bargaining	Mismatch
u_t	-	+	-	+	-	-
Δip_t	+	+	+	+	+	+
Δp_t	-	///	+	-	-	-
Δw_t	+	///	///	-	-	-
Δe_t	///	-	///	+	+	+
jvr_t	///	///	///	///	+	-

The sign + indicates a positive response of the variable on impact for that specified shock. The sign - indicates a negative response. The sign /// indicates no restrictions. All shocks are normalised such that they have a contemporaneous positive effect on output.

An aggregate demand shock represents a shift in the demand curve, which pushes up output (in our case industrial production growth) and inflation, while it lowers the unem-

[1]As a robustness check, we estimate the model using 4, 6, and 12 lags. Results remained qualitatively robust. Given the mixture of monthly and quarterly variables, we choose a lag order of 12, in order to integrate the dynamics of a year for each variable.

ployment rate. These dynamics are consistent with the effects induced by monetary policy, government spending, discount factor, and most financial shocks.

Following Mumtaz and Zanetti (2012, 2015), we identify two types of technology shocks - neutral and investment-specific. A neutral technology shock represents an increase in productivity, which reduces the marginal costs for firms and, therefore, pushes inflation down. The production expansion creates incentives for increasing hiring and it makes firms more willing to keep their employees, therefore decreasing the unemployment rate. However, a positive technology shock also creates a positive shift in the labour demand curve, which increases output and wage growth. On the other hand, an investment-specific technology shock rises the productivity of capital, which also expands production. However, in contrast to neutral technology shocks, the higher productivity of capital creates incentives to firms to decrease hiring, therefore increasing unemployment. In fact, Mumtaz and Zanetti (2015) find that the key feature to distinguish between neutral and investment-specific technology shocks is the contrary reaction of unemployment. In this setup, we can also conceive an automation shock as an example of an the investment-specific technology shock.

Labour supply, wage bargaining, and mismatch shocks generate an inverse co-movement between output and real wages (see Foroni et al. (2018a)). A positive labour supply shock is an exogenous increase in labour supply, or a reduction in the disutility of working, which increases the number of participants in the labour market. An exogenous increase in labour supply leads to an increase in the number of job seekers and makes it easier for firms to fill vacancies and to reduce hiring costs. Thereby, leading to a decrease in wages and prices and to an increase in output. A negative wage bargaining shock captures a reduction of the negotiation power of workers and at the same time firms can benefit more from a larger share of the bargaining surplus. That leads to a reduction in wages and to an increase in firms' vacancy posting conditions and hiring. That ultimately leads to a decrease in the unemployment rate. Matching efficiency shocks refer to exogenous changes in the job-worker matching process and represent a wedge in the standard matching function. An exogenous increase of in the matching efficiency reduces the costs of firing workers, rises output and creates incentives for increasing employment. However, mismatch shocks can shift the Beveridge curve, which summarises the positive relationship between unemployment and the vacancies.

To distinguish between labour supply and the two additional labour market shocks, the response of unemployment is key. The new people entering the labour market won't automatically find a job in the same period of the shock. Therefore, a pool of the new workers will find a job contemporaneously, whereas another portion will transition through unemployment, at least temporarily. Hence, both employment and the unemployment rate rise when the labour supply shock hits the economy (see Foroni et al. (2018a)).

3 Methodology

Mixed-frequency vector autoregressions (MF-VARs) are well established models in the toolbox for macroeconomic analysis. While most of the studies with MF-VARs focus on forecasting (see Kuzin et al. (2011), Schorfheide and Song (2015), Brave et al. (2019), Cimadomo et al. (2020), among others), there are a few studies focusing on structural analysis with MF-VARs (see Foroni and Marcellino (2016) and Ghysels (2016)). In this chapter, we focus on a model that is jointly able to perform a structural analysis of the euro area labour market and, at the same time, has a good forecasting performance for main labour market variables. For this purpose, we take the Schorfheide and Song (2015) model as starting point and we extend their methodology to a structural VAR, where we identify key macroeconomic and labour market shocks by means of sign restrictions.

In this section, we summarise the main features of the Schorfheide and Song (2015) model, and the main ingredients of the Bayesian estimation.

Let us define N_m monthly variables denoted by $x_{m,t}$ and N_q quarterly variables represented by $y_{q,t}$, for $i = 1, \dots, T$ months. The block $y_{q,t}$ is a set of variables with missing observations and have available data only every third month. Further, we denote the latent monthly counterpart of the quarterly variables as $x_{q,t}$. We assume the economy evolves as a monthly frequency VAR with p lags:

$$x_t = c + A_1 x_{t-1} + \cdots + A_p x_{t-p} + u_t, \tag{1}$$

where $x_t = [x'_{m,t}, x'_{q,t}]$ of dimension $N = N_m + N_q$, which can be rewritten in a more compact way as

$$x_t = c + A_+ z_{t-1} + u_t. \tag{2}$$

where $A_+ = [A_1 \dots A_p]$ and $z_{t-1} = [x_{t-1} \dots x_{t-p}]'$. To address the volatility stemming from outliers occurring in crisis periods, e.g., the observations during the trough of the COVID-19 pandemic, we let the innovations in the VAR to marginally follow a t-distribution as in Chan (2020). To do so, he proposes a flexible covariance structure for the errors u_t and assumes the following:

$$\text{vec}(U) \sim N(0, (\Sigma \otimes \Omega)), \tag{3}$$

where vec is the vectorisation operator and $U = (u_1, \cdots, u_T)'$. The covariance has a kronecker structure including an $N \times N$ matrix Σ and a $T \times T$ matrix Ω, capturing the cross-sectional and serial correlation, respectively. Now, the errors u_t follow a marginal t-distribution by defining $\Omega = \text{diag}(\lambda_1, \cdots, \lambda_T)$. Given the degrees of freedom ν, $(\lambda_t|\nu) \sim$ inverse Gamma $(\nu/2, \nu/2)$, for $t = 1, \cdots, T$.

Since the VAR contains latent variables, we need to write the model in a state-space representation in order to obtain estimates of both the parameters and the states. To do this, let us denote T as the sample size which is defined as the last month for which we have at least one observation in the monthly block; T_{bq} is the time period at which we have a quarterly balanced set and finally T_b is the data point for which we have a balanced panel in the monthly block. Notice that, not all monthly variables might be available between T_b and T and in a similar fashion we can face ragged edges within the quarterly set. We could then have three types of missing observations: (i) mixed frequencies from $t = 1, \cdots, T_b$, (ii) ragged edges in the quarterly set and (iii) ragged edges in the monthly variables. Until time $t = T_b$ the state vector only corresponds to the quarterly block. However, due to the presence of missing monthly observations between T_b and T, a subset of the monthly block becomes a state for $t > T_b$.

The bridge between observable and latent observations (both quarterly and also monthly, whenever ragged edges are present) is given by the measurement equation (4).

$$y_t = M_t x_t \quad \text{for} \quad t = 1, ..., T. \tag{4}$$

The key component is the selection matrix M_t which selects the variables that are observed at time t and are part of the information set. This also means that the selection matrix M_t bridges the observable quarterly variables with their latent monthly counterpart through an accumulator, which in this case corresponds to the average. The state space representation is given by equations (1) and (4).

We follow the two-block Gibbs sampler developed by Schorfheide and Song (2015) in order to obtain draws from the conditional posterior distributions of the parameters and states of the model. Within the VAR block, we have two sub-blocks, $(\Phi = [c, A_+], \Sigma)$ and Ω, which are a priori independent (see Chan (2020). For the pair (Φ, Σ), we consider a standard Normal-inverse Wishart prior, i.e.

$$\text{vec}(\Phi)|\Sigma \sim \mathcal{N}(\text{vec}(\Phi_0), \Sigma \otimes V_0) \quad \text{and} \quad \Sigma \sim iW(S, d) \tag{5}$$

The moments of the normal distribution of the parameters follow a Minnesota structure (Litterman (1986), Sims and Zha (1998), Del Negro and Schorfheide (2011)). This means that all the elements in Φ_0 are zero and the diagonal covariance matrix V_0 has elements that induces shrinkage. Specifically, the diagonal elements are defined as $v_{\Phi,ii} = \kappa_2$ for the intercept and $v_{\Phi,ii} = \kappa_1/(p^2 s_j^2)$. The scale matrix S is diagonal, whose element s_j is defined as the standard deviation of an AR model estimated for a training sample. We set the degrees of freedom d to be $N + 2$ which is the minimum number such that the mean of an inverse Wishart distribution exists, see Kadiyala and Karlsson (1997). We follow Chan (2020) setting the hyperparameters $\kappa_1 = 0.2^2$, $\kappa_2 = 10^2$ and the degrees of freedom $\nu = 5$.

3.1 Shock identification with sign restrictions

In contrast to Schorfheide and Song (2015), we do not limit our study to forecasting but we use the MF-VAR for structural analysis. The literature on structural analysis with mixed frequency data is still scarce and relies on simple identification schemes, such as the Cholesky decomposition (see Foroni and Marcellino (2016)). With our paper, we further contribute to the literature by allowing identification of structural shocks through sigh restrictions in a mixed frequency Bayesian VAR framework.

We link the reduced-form VAR from equation (1) with the structural macroeconomic shocks, ε_t, as follows:

$$u_t = B\varepsilon_t, \ \varepsilon_t \overset{iid}{\sim} N(0, I_N) \tag{6}$$

where B is an $N \times N$ matrix of impact effects, such that $\Sigma = B'B$. The identification of the structural shocks driving the system hinges on identifying the columns of B. To do so, the sign restrictions approach relies on restricting the elements of the columns of B such that the impact of the shocks onto the variables in the VAR are backed by economic theory. To obtain draws of the posterior distribution of matrix B, we follow the methodology of Rubio-Ramirez et al. (2010). This approach draws a candidate matrix B^*, defined as

$$B^* = PQ,$$

where Q is a rotation matrix, $P = \text{chol}(\Sigma)$, and chol denotes the lower-triangular Cholesky decomposition. To generate draws of the rotation matrix, Rubio-Ramirez et al. (2010) propose an algorithm based on a QR decomposition, which translates to an independent Haar-uniform prior of the rotation matrix. In our framework, once we obtain a draw of the states and the parameters of the VAR, we draw B^* for up to 100,000 candidate matrices until we find a draw that fulfils the sign restrictions. In this paper, we consider a partially-identified model, therefore, we corroborate that the non-identified shocks have a different set of signs than the restricted elements of the shocks of interest.

4 Drivers of the euro area labour market

Through the lenses of our MF-BVAR model with sign restrictions, we aim at explaining the dynamics in the euro area labour market variables. We report the historical decomposition of the main labour market variables in Figures 1 to 4 (results for industrial production and inflation are also provided in Figures 5 and 6).

First, macroeconomic shocks such as aggregate demand and technology shocks are equally important to the shocks internally originated in the labour market to account for the business cycle fluctuations of unemployment, employment, wages and the job vacancy rate. In the trough of the Global Financial Crisis, the model points at demand shocks as the main factors explaining the dynamics of most of the variables, influencing both real and nominal variables. However, looking at the period starting in 2014 (typically identified as a period of low inflation), the role of shocks originated in the labour market, especially wage bargaining power and mismatch, become more important to explain low wage growth (and, consequently, low inflation). In particular, the wage bargaining shock plays an important role as a driver of the wage inflation, since it reflects the overall effects stemming from reforms in labour market institutions implemented in the euro area following the 2010 Sovereign Debt Crisis. This is consistent with the interpretation of the wage bargaining shock in our model, which captures both a change in the pure bargaining power of workers and a change in the workers' outside option. The latter indeed decreased both for the effect of the crisis and also for the increased flexibility of labour market institutions across some euro area countries (see Koenig et al. (2016)).

Furthermore, we also find that the mismatch shock complements the wage bargaining shock in explaining key labour market developments during the euro area Sovereign Debt Crisis, in line with a standard search and matching model à la Pissarides (2000). According to Consolo and Da Silva (2019), the degree of labour market mismatch has increased following the euro area Sovereign Debt Crisis, which is also visible in the outward shift of the euro area Beveridge curve as of 2011. In our model, this is reflected in the historical decomposition of the job vacancy rate and the unemployment rate, which co-move in the peak of the Sovereign Debt Crisis.

As in Elsby et al. (2013), the dynamics of the unemployment rate during the Sovereign Debt Crisis are also driven by the mismatch shock, which features an important cyclical component. Nevertheless, the dominant driver of the unemployment rate for the whole sample period corresponds to the wage bargaining shock.

As we detail in the next section, one advantage of our model is that it can provide an economic interpretation that goes beyond the historical data. In particular, we can derive a decomposition of the contribution of different shocks also for the nowcasting and forecasting period. Figures 1 – 6 show also the the nowcasts and forecasts up to three years ahead derived using the outcome of the mixed-frequency BVAR estimation. Therefore, our contribution of augmenting the model of Schorfheide and Song (2015) to an SVAR provides a key tool for policy work.

Impulse responses are reported in Figures 12-17 in Appendix B. In particular, we report the cumulative responses for the variables in growth rates. The shaded areas show the 68% point-wise credibility bands, whereas the blue line depicts the point-wise median. We choose the median as the central tendency of the impulse responses, since it is the optimal solution of the sum of the absolute loss of the impulse responses (see Baumeister and Hamilton (2015, 2018)). We find that investment-specific technology, aggregate demand, the wage bargaining, and mismatch shocks have the most persistent effects on employment and the unemployment rate. Moreover, wages react strongly to neutral technology, labour supply, and wage bargaining shocks. The most persistent shock to inflation is aggregate demand. Industrial production has a significant reaction to the six shocks in the model. Finally, the wage bargaining shock has the more persistent effect on the job vacancy rate.

4.1 An assessment of the COVID-19 period

The euro area labour market has been severely hit by the COVID-19 pandemic and associated containment measures. Employment and total hours worked declined at the sharpest rates on record. Unemployment increased more slowly and to a lesser extent, reflecting the high take-up rate of job retention schemes and transitions into inactivity. The labour market adjustment occurred primarily via a strong decline in average hours worked and labour force participation (see Anderton et al. (2021), for an overview).

The MF-BVAR model interprets the decline in the employment rate observed during the crisis as being induced primarily by a combination of technology and demand shocks. This reflects the impact of lockdown and containment measures introduced by national governments during the pandemic, which forced many shops and firms to temporarily close or reduce their operations. Demand shocks reflect constraints on the demand for services as a consequence of the lockdown measures, as well as other factors, such as an increase in uncertainty during the pandemic, which restrained consumption. Investment-specific technology shocks capture the decline in employment due to the accelerated digitalisation that many firms undertook (see OECD (2020), Consolo et al. (2021), Bergholt et al. (Fort)).

The small response of euro area unemployment to the decline in activity (which stayed well below the euro area average, as shown by the negative numbers in the figure) can be attributed to the job retention schemes that aimed to protect employment and limit unemployment, as well as to a large number of workers transitioning into inactivity, rather than into unemployment. As shown in Figure 3, technology, aggregate demand, and mismatch shocks contributed positively to the dynamics in unemployment. However, the large share explained by the wage bargaining shocks strongly pulled the unemployment rate downwards. In fact, wage bargaining shocks also capture exogenous variations in unemployment benefits including job retention schemes.

Shocks originated in the labour market play a lower role in explaining nominal variables (in particular, wages and, consequently, inflation), whereas aggregate demand and technology shocks explain their strong decay.

Now turning to an econometric issue, we further test the robustness of including the observations during the pandemic. We re-estimate the model using the same vintage from January 10, 2022. However, we cut the estimation sample until February 2020. We find that the composition of the shocks throughout the history of the time series before the COVID-19 outbreak remains quite stable. These results are available upon request.

5 Real-time forecasting performance

To further validate the model in Section 2, we conduct a real-time forecasting evaluation, with a particular focus on the labour market variables. We split the analysis into two blocks - quarterly and monthly variables - and compute up to one year ahead forecasts. For the quarterly block, we additionally evaluate the temporal evolution of the nowcasts in subsection 5.1.

We consider real-time data vintages updated every 10th and 25th day of each month spanning from January 2010 - January 2022.[2] The selection of these days allows us to have the latest figures of the unemployment rate and industrial production, which are typically available before the 10th and 25th day of each month, respectively.[3] Table 7 in appendix A shows a "general" pattern of publication delays for each variable, to give an impression on when data become available (irregularities in the release are nevertheless taken into account in our proper real-time evaluation).

We construct the forecasts based on an expansive window approach. For each date in

[2]The vintages were constructed based on the information available in the ECB's Statistical Data Warehouse (SDW). We are grateful to Katalin Bódnar for making these vintages available to us.

[3]In addition, the Purchasing Managers' Index (PMI) employment of the present month is also available by the 25th day of each month.

the evaluation sample, we estimate the model based on 10000 draws using the initial 5000 as burn-in sample. We compute each h-step ahead prediction through an iterative forecasting equation, based on the reduced-form parameters of the VAR from equation (1). As evaluation sample, we consider the period between January 2010 and January 2022.

To evaluate the forecasts, we compute the root mean squared forecast error (RMSFE), defined as:

$$RMSFE(i,h) = \sqrt{\frac{\sum_{t=\tau_0}^{\tau_1-h}\left(\hat{y}_{i,t+h|t} - y^o_{i,t+h}\right)^2}{\tau_1 - h - \tau_0 + 1}}, \tag{7}$$

where $y^o_{i,t+h}$ denotes the realised value of variable i and $\hat{y}_{i,t+h|t}$ is the h-step ahead forecast of variable i, τ_0 and τ_1 are the extremes of the evaluation sample.

The computation of equation (7) changes depending the frequency of the variable. For monthly variables, the time index t and the horizon h denote months, where the forecasts are computed up to twelve-months ahead. For quarterly variables, the indices and the horizons are in terms of quarters and the maximum forecast horizon is four quarters ahead. We construct two versions of the RMSFE, depending on the realised value of the target variable. Specifically, we evaluate the forecasts with respect to the first release and the latest release which corresponds to the data available in January 10, 2022.

As a benchmark model we consider a univariate Bayesian autoregressive model. Similar as for the MF-BVAR, we allow the errors of the AR to marginally follow a t-distribution (as in Chan (2014), Chapter 3). We estimate the autoregressive parameters and the variance of the AR based on standard Normal-inverse Gamma priors taking the same number of draws/burn-in sample as in the MF-BVAR.[4] In order to have a stable comparison, we include information up to one year in the AR, i.e., the number of lags for monthly variables is 12, whereas for quarterly variables is 4. For both the MF-BVAR and the AR, we consider the point forecast based on the mean of the posterior distribution of the forecasts.

We divide the forecasting evaluation in three groups- M1, M2, and M3 - depending on the information set available in each month of the quarter when the forecast is computed. The first group corresponds to the first month of the quarter, i.e., January, April, July, and October; the second to the months of February, May, July, and November; and the third, to March, June, September, and December. We split each group into two blocks, depending whether the forecast is computed on the 10th or the 25th day of the month.

[4]Another natural benchmark would be a standard BVAR in a quarterly frequency. However, the job vacancy rate starts only in 2005, allowing few observations to estimate the model starting in 2010. This highlights another advantage of our MF-BVAR model, which is suitable to deal with longer time series, when missing values are present.

Forecasting horizons change according to the group. In addition, we also report the RMSFE based on all months. We consider the same groups for the monthly variables, given that also in this case the flows of both the monthly and quarterly variables are relevant for the forecasts. Therefore, we can evaluate whether the lower-frequency variables help forecasting the higher-frequency variables and vice-versa.

In Table 2 and Table 3 we report the results for quarterly and monthly variables, respectively, when the forecasts are compared to the first release. On the other hand, Table 4 and Table 5 report the results compared against the vintage of January 10, 2022, the last available release. In all tables, we show the RMSFE of our model relative to the RMSFE of the AR process. Therefore, whenever the number reported is smaller than one, it indicates a superior performance of the model relative to the AR.

We obtain substantial gains when predicting the quarterly labour market variables (see tables 2 and 4). This is consistent with most of the evidence concerning mixed frequency models, in which the higher frequency information typically helps improve the forecasting performance of low frequency variables. The results are particularly satisfactory for employment growth. For the job vacancy rate, we find relevant gains for the medium- to long-term horizons. Further, we find a relatively higher accuracy of wage growth and the job vacancy rate when we compare the forecasts against the last release.

In Table 3 and Table 5, we report the results for the monthly variables. Although less commonly applied, it is also possible to include quarterly information to predict monthly variables, if the content contained in the lower frequency information carries important information (see Foroni et al. (2018b)). In this case, we find a higher accuracy of the MF-BVAR relative to the AR for short-term forecasts of industrial production growth and the one-year-ahead forecasts of the unemployment rate.

The COVID-19 pandemic caused an unprecedented decline in key macroeconomic and the labour market variables. However, despite these extreme observations, we find that our model still provides a better alternative than forecasts based on the AR.

To further investigate this good performance, we also consider two sub-samples, (i) excluding the pandemic observations and (ii) isolating the pandemic observations, i.e., considering evaluation samples from January 2010 - December 2019 and January 2020 - January 2022, respectively. Overall, we find that the accuracy of the MF-BVAR further improves during the pandemic in comparison to the AR. Our results hold for the evaluation period exclusively covering the pandemic. For the pre-pandemic period, we find that the MF-BVAR is still superior for the short-term forecasts of employment growth and wage growth. These results are available upon request.

5.1 Nowcasting the labour market

In this section, we conduct an analysis of the temporal evolution of the nowcasts of employment growth and wage growth, since they are core in monitoring the euro area labour market. In the previous section, we defined the forecast horizons in terms of future months or quarters. In contrast, we now fix each quarter to be analysed and define the forecast horizon with respect to the distance of the current vintage and the end of the reference quarter. We start computing the nowcast in the first month of the current quarter until the first release of the same quarter is published. As an example, let us take the evaluation of the nowcast of employment in 2021-Q1. We define the forecast horizon $h = 0M$ as the nowcast estimated at the end of the reference quarter, i.e., on March 25, 2021. Therefore, the first forecast horizon, $h = +2.5M$, corresponds to the estimation done in January 10, 2021. The last forecast horizon is $h = -1.5M$, related to the estimation of employment in 2010-Q1 in May 10, 2010, i.e., a backcast. We stop the estimation in horizon $h = -1.5M$ since the flash of employment was published by May 25, 2010. Taking this information together, we evaluate the estimation of each quarter for 9 forecasting horizons. In a similar fashion, for compensation per employee (our measurement of wages), we consider 10 forecasting horizons.[5]

Similar as in the previous section, we consider the AR model as benchmark and a baseline evaluation sample including the pandemic, i.e., we evaluate the quarters from 2010-Q1 to 2021-Q3. The RMSFE is computed in the same fashion as in equation (7). In addition, we consider four additional models in order to study the relevance of soft indicators and the labour market flows. Specifically, we augment our baseline MF-BVAR by (i) the job finding rate and the job separation rate (the labour market flows); (ii) PMI Employment; (iii) PMI Manufacturing and PMI Services; and (iv) the European Commission's Economic Sentiment Indicator (ESI) for the unemployment rate.

We report the temporal evolution of RMSFEs compared to the first release in figures 7 and 8, for employment growth and wage growth, respectively. Similarly, the RMSFEs based on the last release are reported in figures 9 and 10. We find that all specifications of the MF-BVAR have better nowcasting properties than the AR for both variables and both releases.

The flow of information available within the months of the quarters improves the nowcasts of employment growth. We find that the information content of PMI employment, PMI

[5] It is important to note that, in November 14, 2018 Eurostat introduced a flash release for employment. Before this date, the first release of employment was published 75 days after the end of the reference quarter, i.e., 11 horizons to evaluate. For the sake of exposition, we do not report the last two forecasting horizons, $h = -2M, -2.5M$, since they are not uniform across all points of the evaluation sample. The releases of compensation per employee follow a similar pattern. However, after 2018 the first release has been published only 60 days after the reference quarter. Therefore, we do not report the horizon, $h = -2.5M$.

Manufacturing, and PMI Services helps improving the nowcasting accuracy for the horizons before the end of the reference quarter. However, this advantage is weaker the closer we get to the last forecasting horizon. In contrast, the ESI unemployment marginally has the least information advantage among the MF-BVAR class of nowcasts.

The evolution of the RMSFE of wage growth nowcasts is more variant than the chart for employment growth. In fact, for the horizons after the end of the quarter, the inflow of new data seems to deteriorate the accuracy of the nowcasts. Moreover, in contrast to employment growth, the advantage of including PMIs is only present in the first three horizons.

As in the previous section, we consider two additional evaluation samples covering (i) 2010-Q1 to 2019-Q4 and (ii) 2020-Q1 to 2021-Q3. In general, the MF-BVAR class holds to be more accurate than the AR. However, this property is weakened for wage growth before the pandemic. Furthermore, we find that the relevance of soft indicators were less relevant for the period before the COVID-19 outbreak. These results are available upon request.

As a final analysis, we take a closer look to the evolution of the nowcast of employment growth for 2020-Q3. This is a quarter of interest since employment took a turning recovery from -2.97% in 2020-Q2 to 0.93% in 2020-Q3 (based on the flash releases). In Figure 11 we show the nowcasts based on our baseline MF-BVAR in the blue line and those from the AR in the red line. The nowcasts are estimated starting at the beginning of the quarter until the release of the flash. An crucial result is that the nowcasts based on the MF-BVAR did not plummeted as those from the AR.

6 Conclusions

In this paper, we proposed a Bayesian mixed-frequency VAR model, with the twofold purpose of interpreting the main movements in the labour market variables through the lenses of structural shocks, and at the same time, being able to produce reliable and economically interpretable forecasts. Moreover, we shifted our focus to the euro area labour market and we did it from an empirical perspective, seeking to describe the role of different macroeconomic and labour market shocks in a signed-identified SVAR. We found satisfactory results in terms of forecasting, especially when nowcasting quarterly labour market variables, such as employment growth and wage growth. Further, we looked into the shocks that drove the labour market and macroeconomic dynamics from 2002 to early 2022, with an insight on the COVID-19 recession. First, demand shocks were the main drivers during the past Global Financial Crisis. In contrast, technology and wage bargaining shocks shocks are important drivers of key labour market variables during the quarters affected by the COVID-pandemic.

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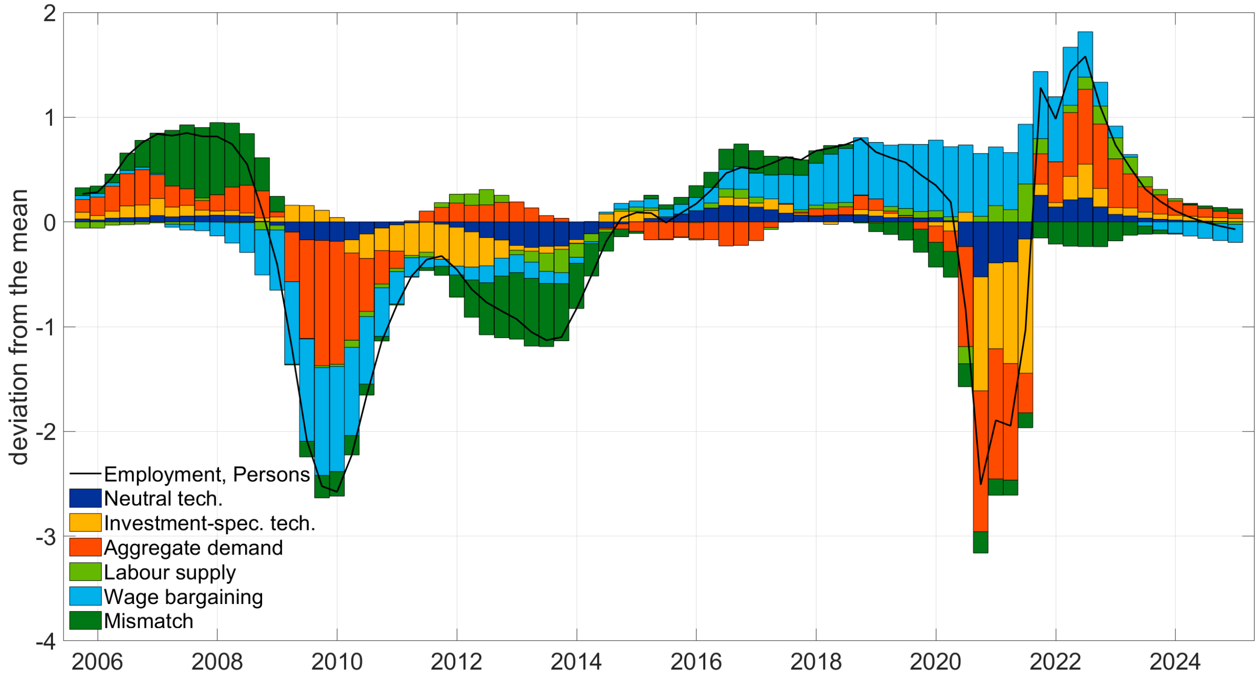

Figure 1: Historical decomposition of employment growth (annual % change)

Note: The graph shows the point-wise median of the posterior distribution of the historical decomposition of the variables in deviation from their initial conditions.

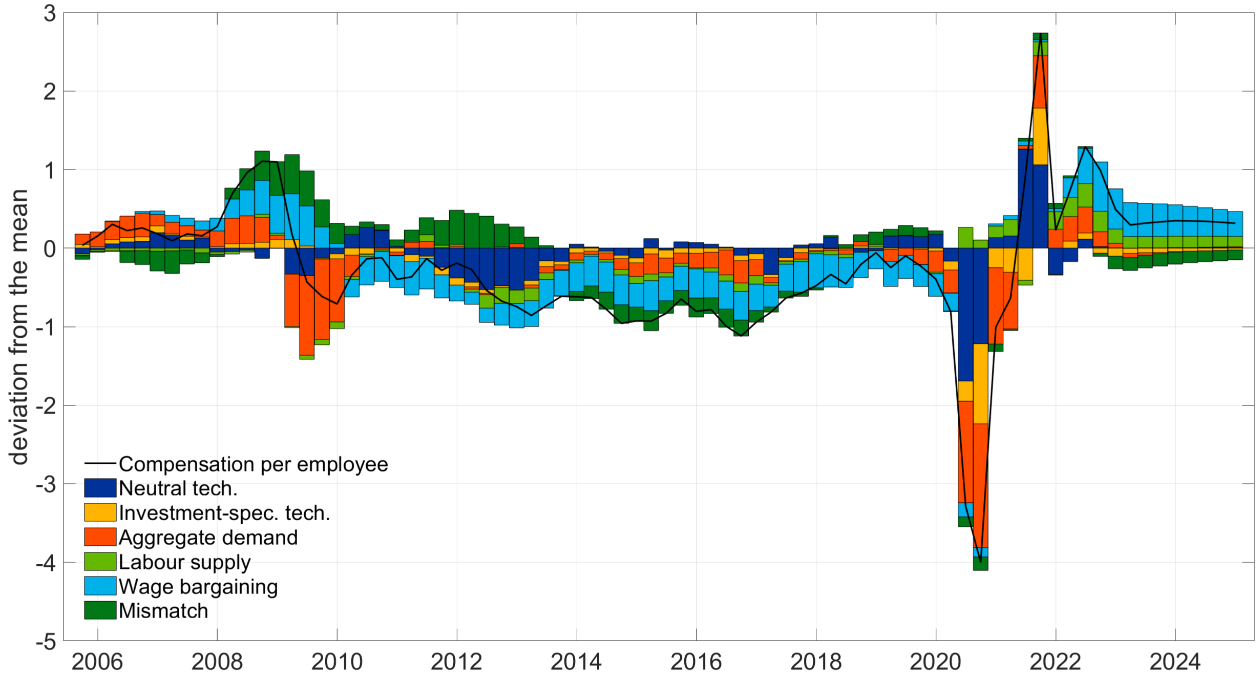

Figure 2: Historical decomposition of wage growth (annual % change, measured by compensation per employee)

Note: The graph shows the point-wise median of the posterior distribution of the historical decomposition of the variables in deviation from their initial conditions.

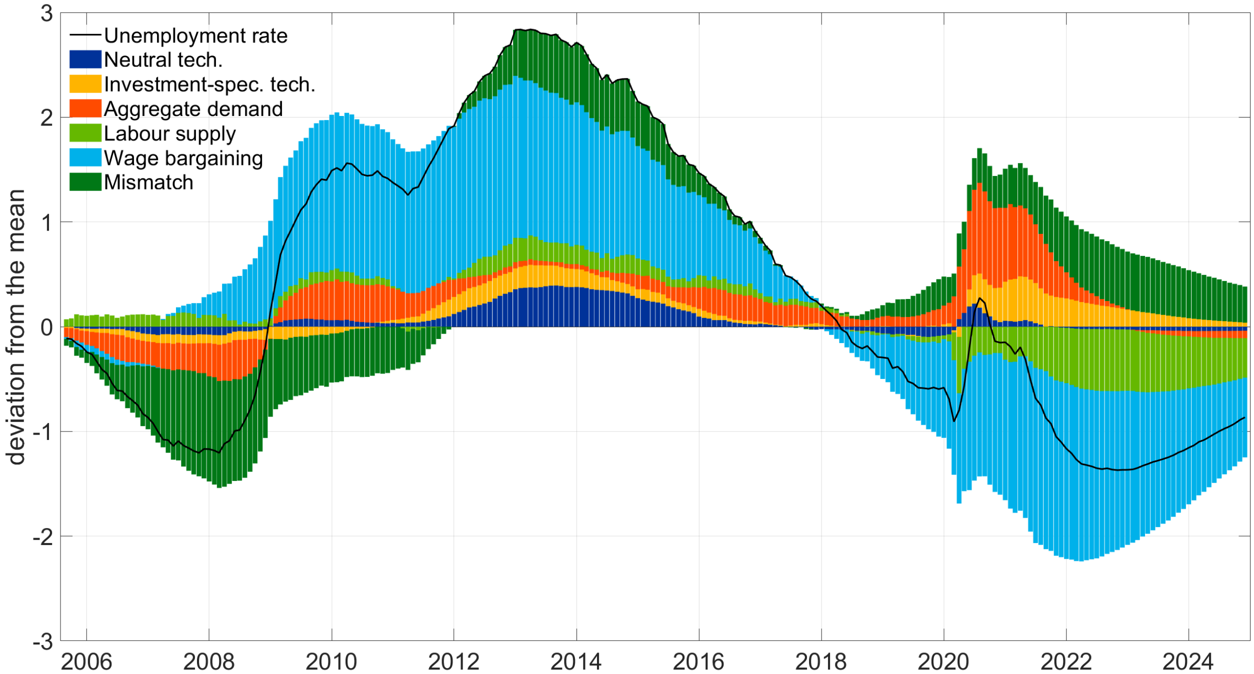

Figure 3: Historical decomposition of unemployment rate

Note: The graph shows the point-wise median of the posterior distribution of the historical decomposition of the variables in deviation from their initial conditions.

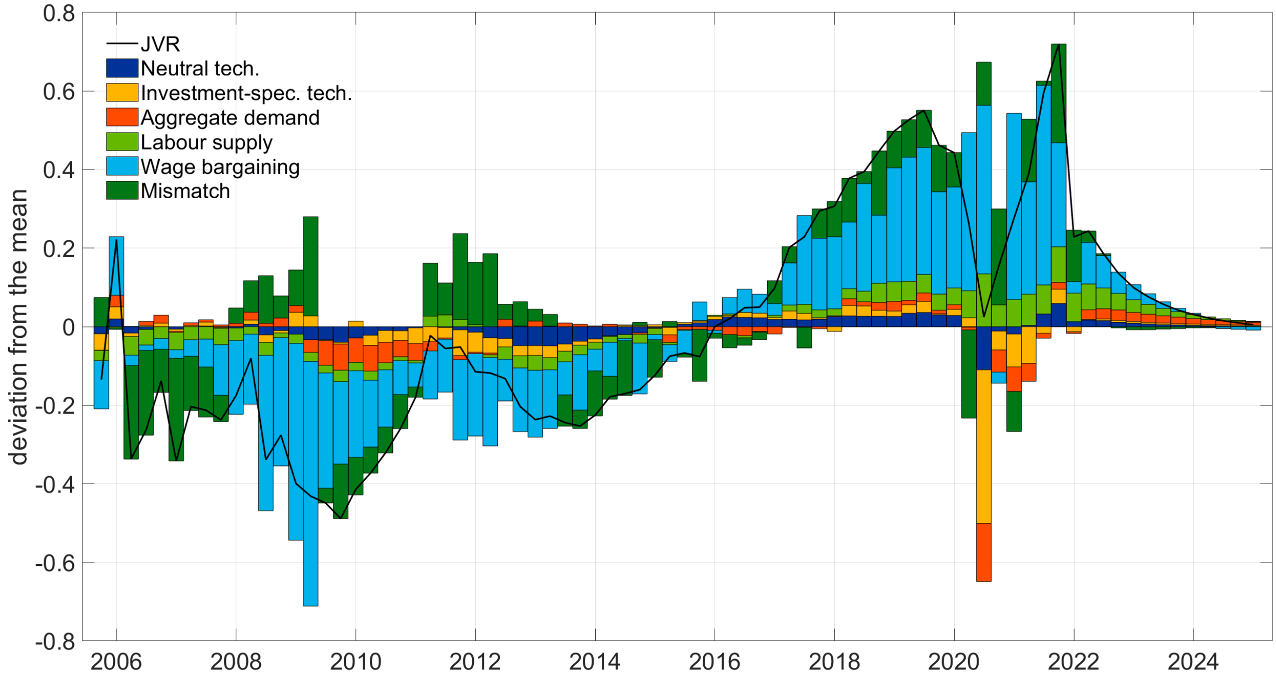

Figure 4: Historical decomposition of job vacancy rate

Note: The graph shows the point-wise median of the posterior distribution of the historical decomposition of the variables in deviation from their initial conditions.

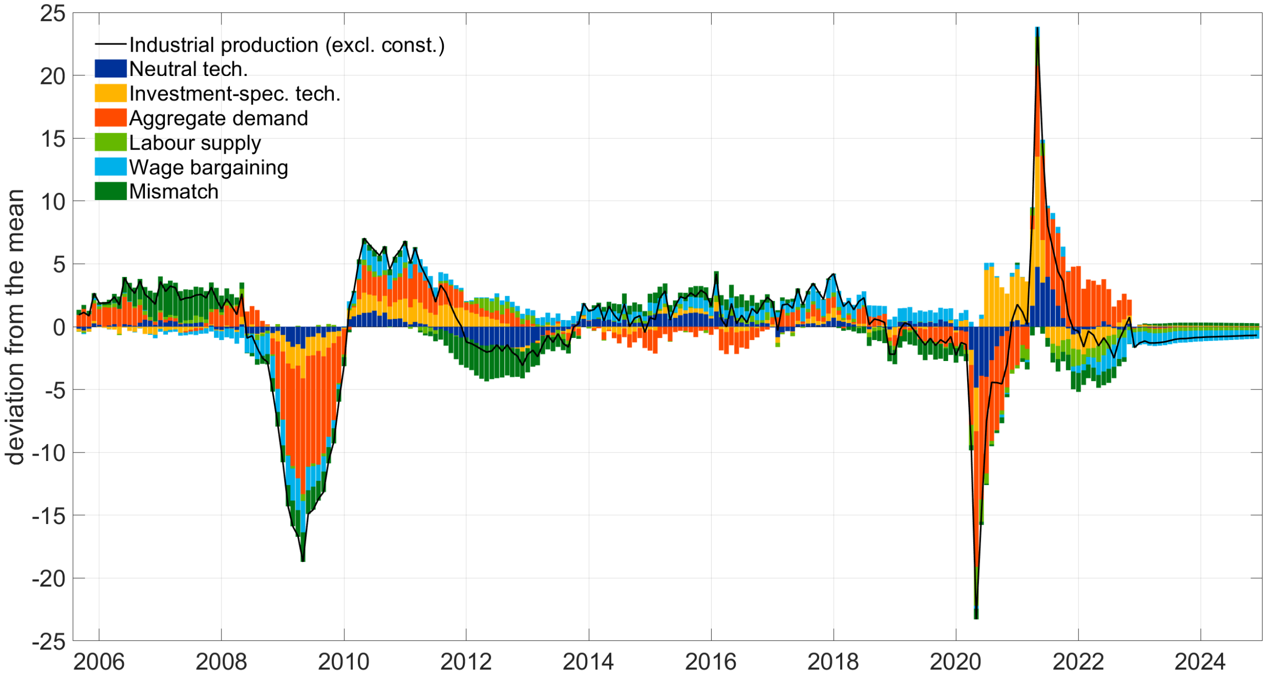

Figure 5: Historical decomposition of industrial production growth (annual % change)

Note: The graph shows the point-wise median of the posterior distribution of the historical decomposition of the variables in deviation from their initial conditions.

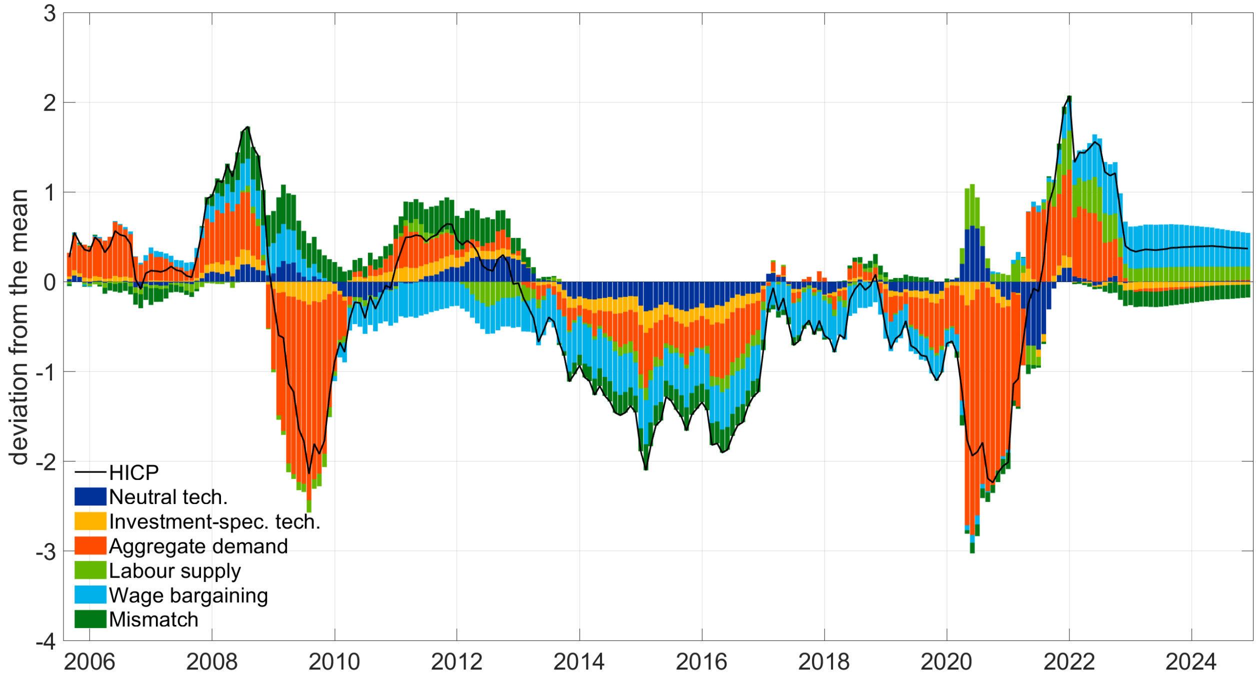

Figure 6: Historical decomposition of HICP (annual % change)

Note: The graph shows the point-wise median of the posterior distribution of the historical decomposition of the variables in deviation from their initial conditions.

Table 2: Quarterly variables. RMSFE in comparison to the first release

	All	M1-10	M1-25	M2-10	M2-25	M3-10	M3-25
				Employment growth			
Q(-1)	**0.67**	**0.59**	**0.74**	**0.68**	**0.77**	**0.74**	
Q(0)	**0.65**	**0.71**	**0.71**	**0.68**	**0.58**	**0.63**	**0.55**
Q(+1)	**0.78**	**0.83**	**0.86**	**0.84**	**0.72**	**0.69**	**0.78**
Q(+2)	**0.83**	**0.80**	**0.85**	**0.79**	**0.85**	**0.84**	**0.87**
Q(+3)	**0.81**	**0.81**	**0.84**	**0.81**	**0.79**	**0.79**	**0.81**
Q(+4)	**0.89**	1.03	1.02	1.03	**0.79**	**0.78**	**0.84**
				Wage growth			
Q(-1)	**0.93**	**0.85**	**0.96**	**0.95**	**0.97**	**0.95**	
Q(0)	**0.92**	**0.98**	**0.97**	**0.96**	**0.91**	**0.85**	**0.83**
Q(+1)	1.00	**0.99**	**0.99**	1.00	1.01	**0.99**	1.03
Q(+2)	**0.99**	**0.99**	**0.99**	**0.99**	**0.99**	**0.99**	**0.98**
Q(+3)	**0.98**	**0.98**	**0.98**	**0.98**	**0.97**	**0.99**	**0.99**
Q(+4)	**0.99**	**0.99**	**0.99**	**0.99**	**0.99**	**0.98**	**0.99**
				Job vacancy rate			
Q(-2)	1.24	1.31	1.12	1.13	1.87	2.52	3.32
Q(-1)	1.13	1.15	1.12	1.12	1.06	1.09	1.26
Q(0)	1.09	1.10	1.09	1.07	1.05	1.08	1.12
Q(+1)	**0.95**	**0.96**	**0.95**	**0.94**	**0.91**	**0.94**	**0.99**
Q(+2)	**0.95**	**0.90**	**0.91**	**0.91**	1.00	1.03	1.00
Q(+3)	**0.85**	**0.64**	**0.84**	**0.85**	**0.99**	1.04	**0.97**
Q(+4)	**0.62**	**0.33**	**0.72**	**0.79**	1.04	1.06	1.06

Note: The table shows the RMSFE of the MF-BVAR relative to the RMSFE of an AR. The RMSFE are computed in terms of the first release of the quarterly variables. The evaluation sample spans the vintages from January 2010 - January 2022. Bold numbers represent a value where the MF-BVAR is more accurate than the AR.

Table 3: Monthly variables. RMSFE in comparison to the first release

	All	M1-10	M1-25	M2-10	M2-25	M3-10	M3-25
				Unemployment rate			
M(-1)	1.08	1.00	1.18	**0.87**	1.07	1.15	1.40
M(0)	1.03	1.02	1.14	**0.91**	1.05	1.02	1.00
M(+1)	1.02	**0.98**	1.13	**0.99**	**0.96**	1.01	1.03
M(+6)	1.00	1.01	1.04	**0.94**	**0.92**	**0.94**	1.11
M(+12)	**0.32**	**0.46**	**0.55**	**0.45**	**0.37**	**0.17**	**0.42**
				IP growth rate			
M(-2)	**0.87**	1.22		**0.90**		**0.79**	
M(-1)	**0.90**	**0.92**	**0.90**	**0.84**	**0.77**	1.08	1.34
M(0)	**0.94**	**0.90**	**0.86**	1.04	1.13	**0.93**	**0.97**
M(+1)	**0.98**	1.01	1.00	1.01	**0.98**	**0.98**	**0.94**
M(+6)	1.00	**0.99**	1.00	1.01	1.00	1.02	1.00
M(+12)	1.02	1.01	1.01	1.04	1.05	1.02	1.02
				Inflation			
M(-1)	**0.99**	1.03	1.05	**0.96**	**0.95**	**0.89**	1.05
M(0)	**0.99**	**0.96**	**1.03**	**0.96**	**0.96**	1.01	1.03
M(+1)	**0.99**	**0.95**	**0.98**	1.03	1.07	**0.96**	**0.93**
M(+6)	**0.99**	**0.99**	1.00	1.04	1.04	**0.95**	**0.96**
M(+12)	1.05	1.05	1.07	1.11	1.12	**0.99**	1.01

Note: The table shows the RMSFE of the MF-BVAR relative to the RMSFE of an AR. The RMSFE are computed in terms of the first release of the monthly variables. The evaluation sample spans the vintages from January 2010 - January 2022. Bold numbers represent a value where the MF-BVAR is more accurate than the AR.

Table 4: Quarterly variables. RMSFE in comparison to the last vintage

	All	M1-10	M1-25	M2-10	M2-25	M3-10	M3-25
				Employment growth			
Q(-1)	**0.68**	**0.60**	**0.75**	**0.69**	**0.72**	**0.69**	
Q(0)	**0.66**	**0.73**	**0.72**	**0.69**	**0.60**	**0.64**	**0.56**
Q(+1)	**0.78**	**0.81**	**0.83**	**0.82**	**0.74**	**0.71**	**0.79**
Q(+2)	**0.81**	**0.78**	**0.81**	**0.77**	**0.82**	**0.81**	**0.84**
Q(+3)	**0.79**	**0.80**	**0.83**	**0.80**	**0.77**	**0.77**	**0.79**
Q(+4)	**0.89**	1.01	1.00	1.01	**0.79**	**0.78**	**0.83**
				Wage growth			
Q(-1)	**0.92**	**0.83**	**0.94**	**0.94**	**0.96**	1.00	
Q(0)	**0.90**	**0.97**	**0.95**	**0.95**	**0.90**	**0.84**	**0.82**
Q(+1)	**0.99**	**0.98**	**0.98**	**0.99**	1.00	**0.98**	1.02
Q(+2)	1.00	1.01	1.01	1.01	1.01	**0.98**	**0.97**
Q(+3)	**0.99**	**0.98**	**0.98**	**0.98**	**0.97**	1.00	1.01
Q(+4)	**0.99**	**0.99**	**0.99**	**0.99**	**0.99**	**0.98**	**0.98**
				Job vacancy rate			
Q(-2)	1.66	1.85	1.45	1.44	1.65	2.38	2.82
Q(-1)	1.32	1.31	1.27	1.26	1.20	1.27	1.68
Q(0)	1.12	1.10	1.09	1.07	1.13	1.16	1.23
Q(+1)	**0.87**	**0.85**	**0.86**	**0.84**	**0.86**	**0.89**	**0.94**
Q(+2)	**0.91**	**0.87**	**0.90**	**0.90**	**0.94**	**0.97**	**0.92**
Q(+3)	**0.81**	**0.57**	**0.79**	**0.81**	1.02	1.09	0.98
Q(+4)	**0.55**	**0.28**	**0.65**	**0.73**	1.12	1.12	1.13

Note: The table shows the RMSFE of the MF-BVAR relative to the RMSFE of an AR. The RMSFE are computed in terms of the last release of the quarterly variables. The evaluation sample spans the vintages from January 2010 - January 2022.

Table 5: Monthly variables. RMSFE in comparison to the last vintage

	All	M1-10	M1-25	M2-10	M2-25	M3-10	M3-25
				Unemployment rate			
M(-1)	1.07	1.05	1.12	1.02	1.03	1.09	1.13
M(0)	1.05	1.04	1.16	0.99	1.00	1.07	1.03
M(+1)	1.02	1.02	1.14	1.01	**0.95**	1.00	**0.95**
M(+6)	1.02	1.02	1.06	**0.98**	**0.96**	**0.97**	1.13
M(+12)	**0.35**	**0.49**	**0.59**	**0.50**	**0.40**	**0.18**	**0.45**
				IP growth rate			
M(-2)	**0.88**	1.18		**0.89**		**0.82**	
M(-1)	**0.91**	**0.90**	**0.89**	**0.87**	**0.80**	1.08	1.30
M(0)	**0.95**	**0.92**	**0.89**	1.04	1.13	**0.93**	**0.96**
M(+1)	**0.98**	1.02	1.00	1.01	**0.98**	**0.98**	**0.95**
M(+6)	1.00	1.00	1.00	1.00	1.00	1.00	**0.99**
M(+12)	1.01	1.00	1.01	1.03	1.03	1.02	1.02
				Inflation			
M(-1)	**0.99**	1.02	1.04	**0.96**	**0.97**	**0.90**	1.09
M(0)	1.00	**0.96**	1.02	**0.97**	**0.98**	1.01	1.04
M(+1)	**0.99**	**0.96**	**0.99**	1.02	1.06	**0.96**	**0.92**
M(+6)	**0.98**	**0.99**	1.01	1.03	1.02	**0.95**	**0.95**
M(+12)	1.05	1.05	1.06	1.11	1.12	**0.99**	1.01

Note: The table shows the RMSFE of the MF-BVAR relative to the RMSFE of an AR. The RMSFE are computed in terms of the last release of the monthly variables. The evaluation sample spans the vintages from January 2010 - January 2022.

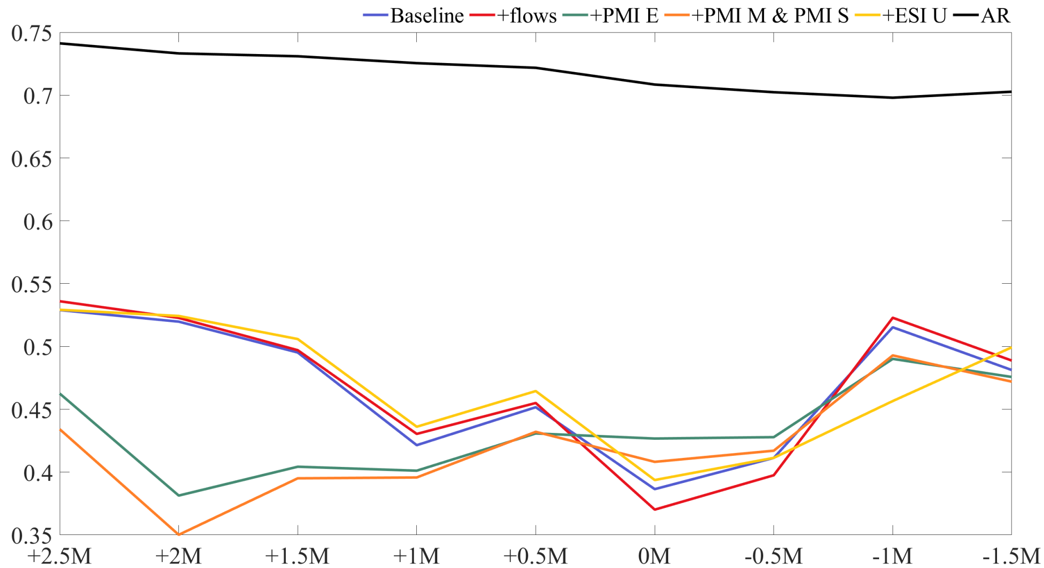

Figure 7: Evolution of employment growth nowcasts

Note: The lines show the RMSFE compared to the first release of employment. The forecasting horizons are defined with respect to the distance in months to the end of the reference quarter. The evaluation sample spans 2010-Q1 to 2021-Q3.

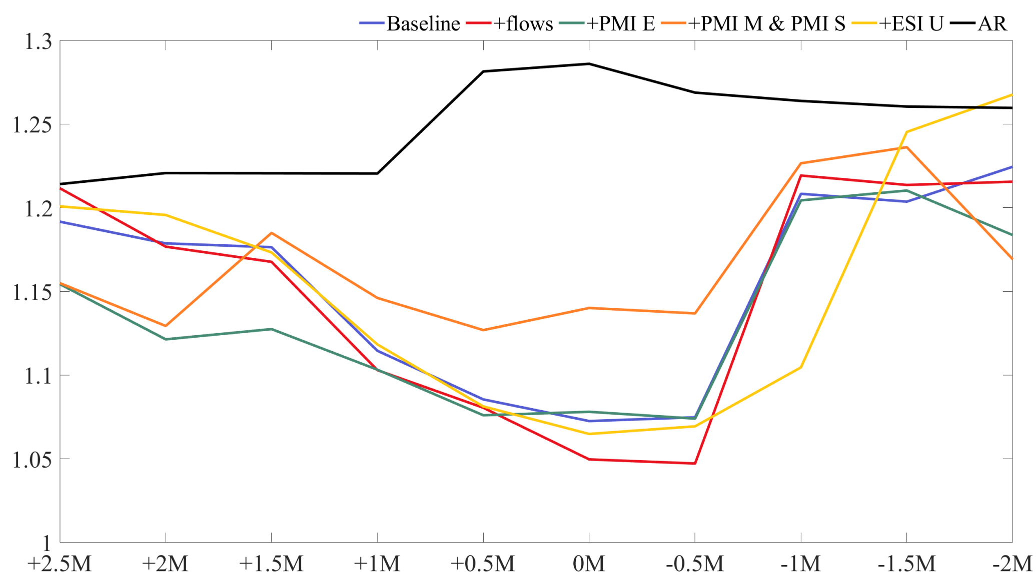

Figure 8: Evolution of wage growth nowcasts

Note: The lines show the RMSFE compared to the first release of compensation per employee. The forecasting horizons are defined with respect to the distance in months to the end of the reference quarter. The evaluation sample spans 2010-Q1 to 2021-Q3.

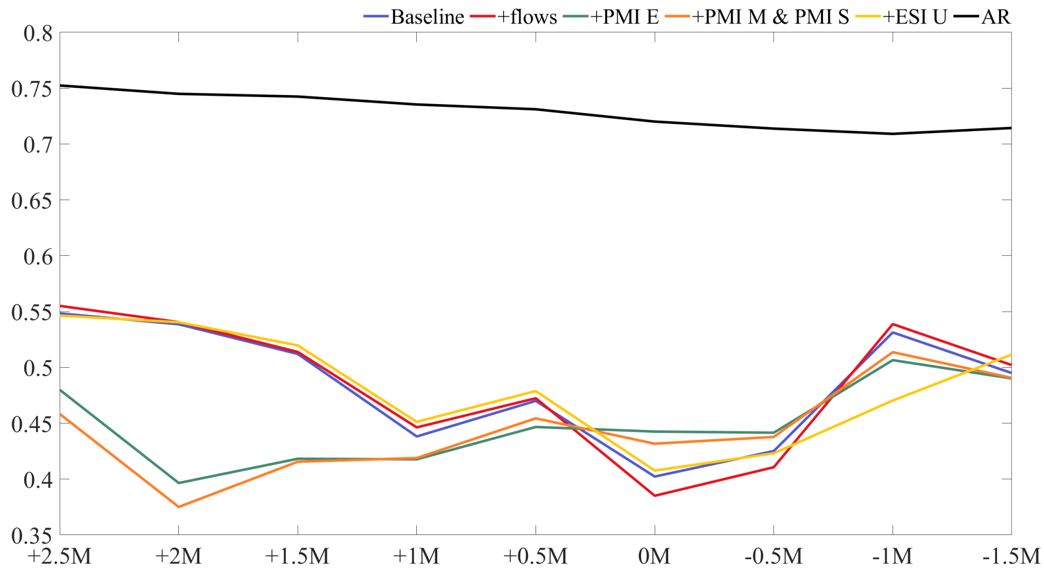

Figure 9: Evolution of employment growth nowcasts

Note: The lines show the RMSFE compared to the last release of employment. The forecasting horizons are defined with respect to the distance in months to the end of the reference quarter. The evaluation sample spans 2010-Q1 to 2019-Q4.

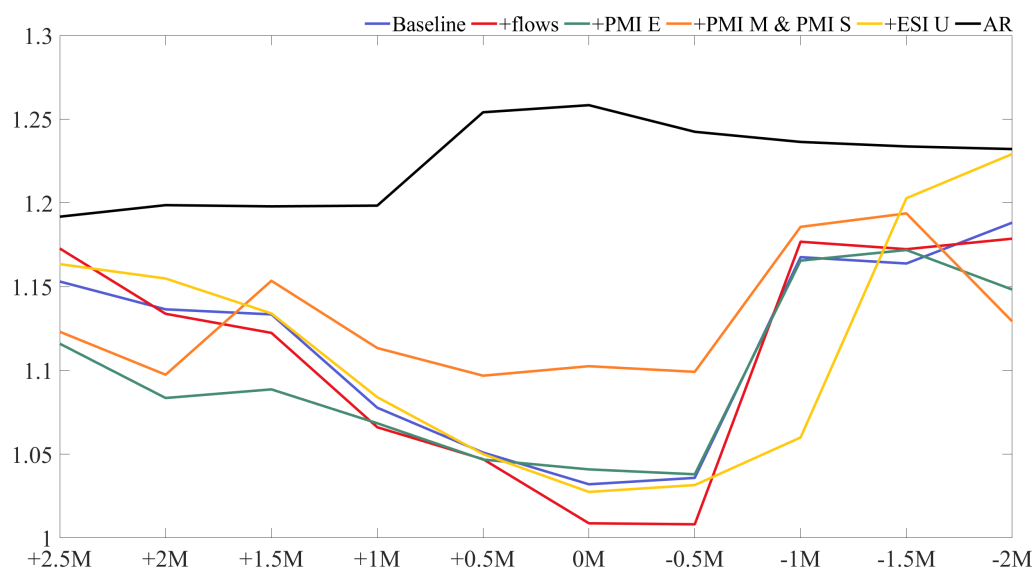

Figure 10: Evolution of wage growth nowcasts

Note: The lines show the RMSFE compared to the last release of compensation per employee. The forecasting horizons are defined with respect to the distance in months to the end of the reference quarter. The evaluation sample spans 2010-Q1 to 2019-Q4.

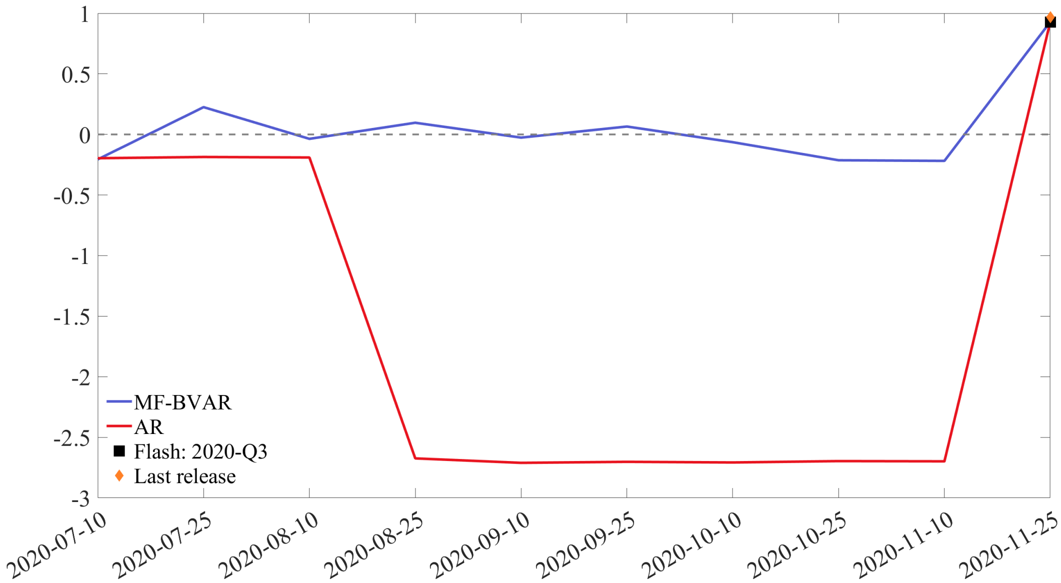

Figure 11: Evolution of employment growth nowcast for 2020-Q3

Note: The blue (red) line represent the evolution of the MF-BVAR (AR) nowcasts for 2020-Q3. The data point represented by the black square shows the flash release, whereas the diamond correspond to the revision as of January 10, 2022.

A Data description

Table 6: Data description

Name	Description	Transformation	Frequency	Source
Unemployment	Unemployment rate (as a \% of labour force), SA	Levels	M	Eurostat
IP	Industrial production for the euro area excl. Construction, SA	Log-diff	M	Eurostat
HICP	HICP - Overall index, SA	Log-diff	M	Eurostat
PMI M	Purchasing Managers' Index: Manufacturing, SA	Levels	M	IHS Markit
PMI S	Purchasing Managers' Index: Services, SA	Levels	M	IHS Markit
PMI E	Purchasing Managers' Index: Employment, SA	Levels	M	IHS Markit
ESI U	Economic Sentiment Indicator, SA	Levels	M	EC
Compensation	Compensation per employee - All activities, SA	Log-diff	Q	Eurostat
Employment	Total employment - All activities, SA	Log-diff	Q	Eurostat
JVR	Industry, construction and services (except activities of households as employers and extra-territorial organisations and bodies)	Levels	Q	Eurostat
JFR*	Job finding rate	Levels	Q	Eurostat
JSR*	Job separation rate	Levels	Q	Eurostat

*ECB staff calculations

Table 7: Stylised publication delay pattern

	M1-10	M1-25	M2-10	M2-25	M3-10	M3-25
Unemployment	2 M	2 M	2 M	2 M	2 M	2 M
IP	3 M	2 M	3 M	2 M	3 M	2 M
HICP	1 M	1 M	1 M	1 M	1 M	1 M
PMI E	1 M		1 M		1 M	
PMI M	1 M	1 M	1 M	1 M	1 M	1 M
PMI S	1 M	1 M	1 M	1 M	1 M	1 M
ESI U	1 M	1 M	1 M	1 M	1 M	1 M
Compensation	2 Q	2 Q	2 Q	2 Q	2 Q	1 Q
Employment	2 Q	2 Q	2 Q	2 Q	2 Q	1 Q
JVR	3 Q	3 Q	3 Q	2 Q	2 Q	2 Q
JFR	3 Q	3 Q	3 Q	3 Q	3 Q	3 Q
JSR	3 Q	3 Q	3 Q	3 Q	3 Q	3 Q

The notation "x M"/ "x Q" represents the number of months/quarters missing including the present month/quarter. Therefore, "1 M" means that only the present month is missing. Same notation applied to quarterly variables.

B Impulse responses of main macroeconomic and labour market shocks

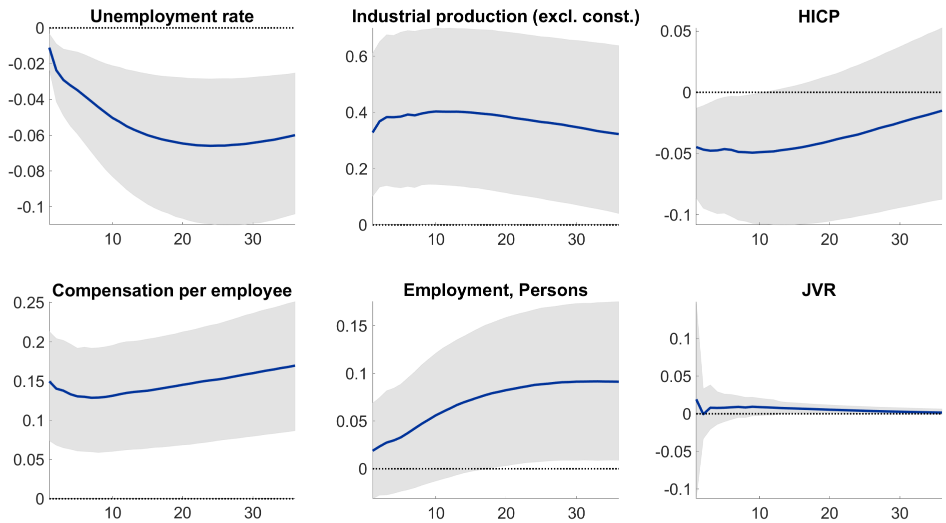

Figure 12: Responses to a neutral technology shock

Note: Shaded areas show the 68% point-wise credibility bands, whereas the blue line shows the point-wise median.

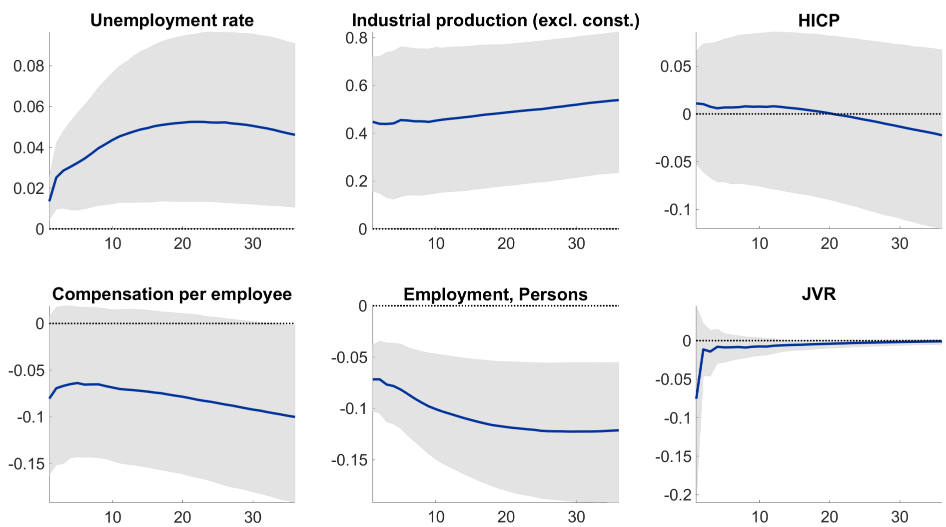

Figure 13: Responses to an investment-specific technology shock

Note: Shaded areas show the 68% point-wise credibility bands, whereas the blue line shows the point-wise median.

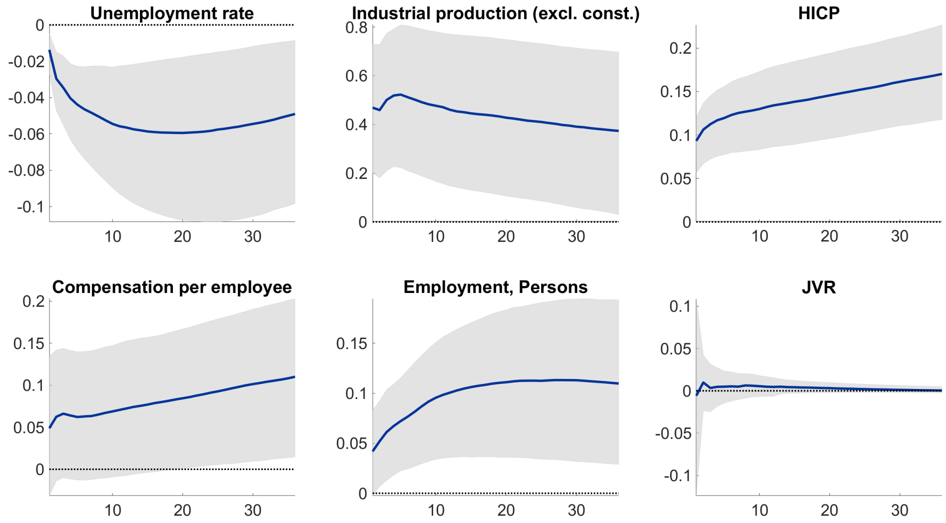

Figure 14: Responses to an aggregate demand shock

Note: Shaded areas show the 68% point-wise credibility bands, whereas the blue line shows the point-wise median.

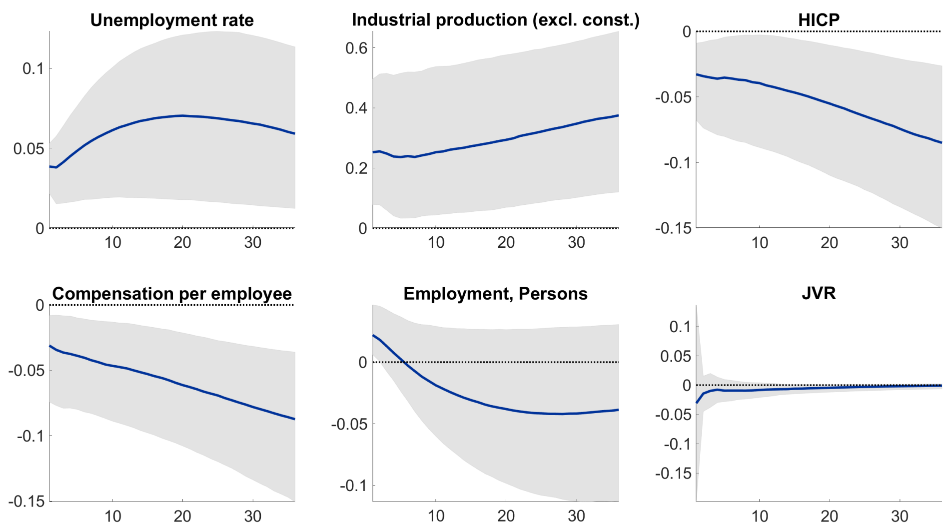

Figure 15: Responses to a labour supply shock

Note: Shaded areas show the 68% point-wise credibility bands, whereas the blue line shows the point-wise median.

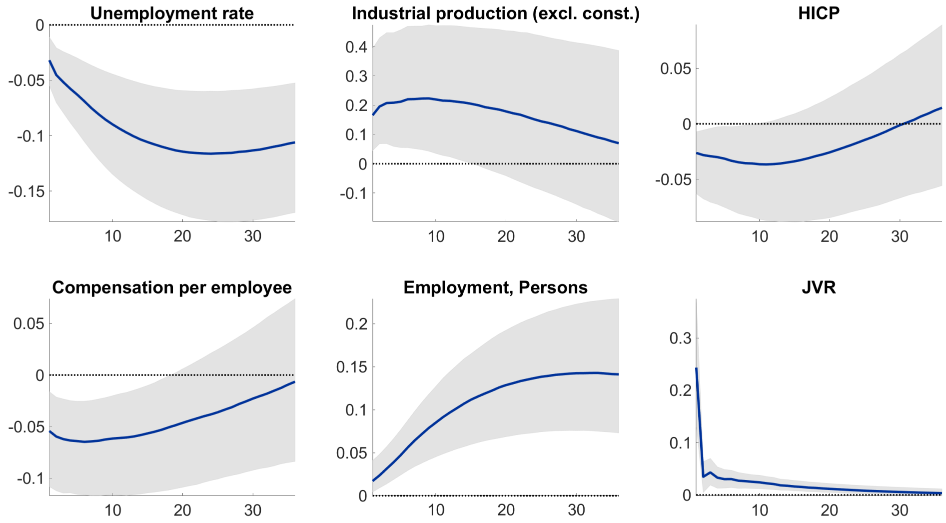

Figure 16: Responses to a wage bargaining shock

Note: Shaded areas show the 68% point-wise credibility bands, whereas the blue line shows the point-wise median.

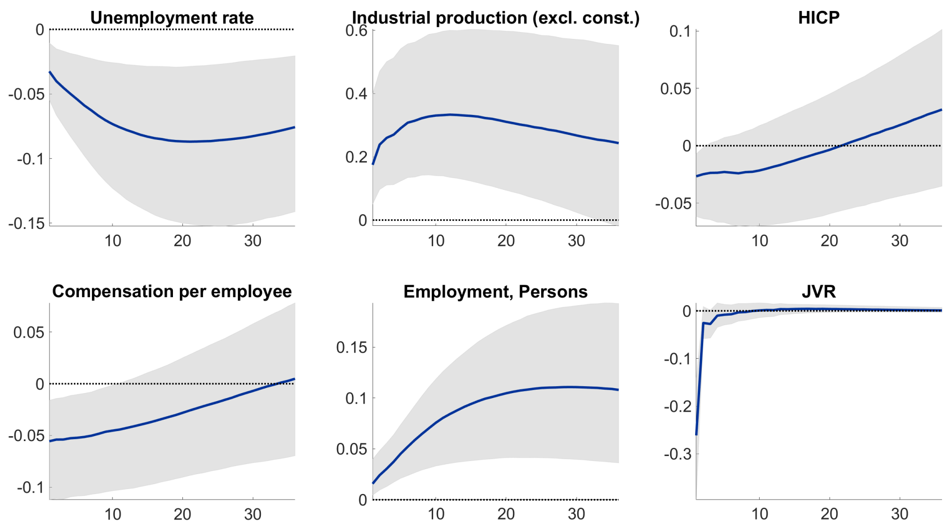

Figure 17: Responses to a mismatch shock

Note: Shaded areas show the 68% point-wise credibility bands, whereas the blue line shows the point-wise median.