A mixed frequency model for the euro area labour market*

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Abstract

In this paper we analyse labour market dynamics, with a 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 economic interpretable forecasts. Further, we want to exploit the relevant information contained in the labour market flows. To do so, we use a mixed-frequency Bayesian VAR, which can incorporate the latest information and take into account monthly and quarterly data. We obtain satisfactory results in forecasting quarterly variables. From an economic perspective, we disentangle the shocks that explained the behaviour of the main economic variables, and, among other findings, we show the relevance of shocks originated in the labour market.

Keywords: Job flows, Nowcasting, Mixed Frequency Data, Bayesian VAR
JEL codes: J6, C53, C32, C11

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Non-technical summary

The importance of labour market dynamics is crucial for understanding the macroeconomic developments in the economy. While there is a substantial literature for the U.S. economy from both a structural and forecasting points of view, there is a scarce number of studies focusing on the euro area. With this paper, therefore, we aim at filling this gap, and we introduce a model for the euro area labour market 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 economic interpretable forecasts. Following the established work of Shimer (2007), Barnichon (2012) and Barnichon and Nekarda (2012), we consider labour market flows for understanding and predicting unemployment fluctuations. The relative importance and the rate at which workers flow into and out of the unemployment pool are crucial for determining the unemployment dynamics.

To address data availability issues we choose to set up a mixed-frequency model, a natural framework to take into account data at different frequencies and publication lags. In particular, we follow the approach of Schorfheide and Song (2015), and use a mixed-frequency Bayesian VAR. The choice of this method is driven by the purpose of our study of having a set of variables which depicts the labour market dynamics and at the same time to be able to provide reliable forecasts and give a structural interpretation of the projected path of the main variables. Our methodological contribution hinges in the extension of the model of Schorfheide and Song (2015) into the literature of Structural VARs. To do so, we augment their algorithm in order to identify key macroeconomic shocks by means of sign restrictions. Specifically, we identify supply, domestic and foreign demand, labour supply, wage-bargaining, and mismatch shocks.

What we find is that satisfactory results are obtained in terms of forecasting, especially when looking at quarterly variables, as employment growth and compensation per employee. These findings are aligned with most of the results available in the mixed-frequency literature. Further, we look into the shocks which drove the labour market dynamics and we find interesting insights. First, demand shocks were the main drivers during the past Great Recession. Second, shocks originated in the labour markets play an important role in explaining the period of low inflation from 2014 onward, highlighting the crucial role played by labour markets in the economic analysis. Finally, from a practitioner's point of view, it is possible to use our model also to provide an economic interpretation to the generated forecasts in order to understand what are the drivers behind the projected path.

1 Introduction

Understanding the 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. (2016)) and also for forecasting purposes (e.g. Montgomery et al. (1998), Askitas and Zimmermann (2009), D'Amuri and Marcucci (2017)), not many studies are available to understand the euro area labour markets developments. The need of covering the euro area labour market is relevant, because the labour market structure is quite different from the U.S., in terms of regulations, composition of the labour force and the dynamics of the ins and outs of unemployment. With this paper, therefore, we aim at filling this gap, and we introduce a model for the euro area labour market 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 economic interpretable forecasts.

In order to reach our goal, we develop a Structural VAR model, which includes mixed-frequency data and it is identified by sign restrictions. We are, in fact, interested in getting a "real-time" evaluation of the labour market for the euro area. Therefore, we face the fact that some variables are available at monthly frequency (as unemployment rate and survey measures), while other labour market indicators (as employment and labour market flows) are available only at quarterly frequency, and with different publication lags. To address data availability issues we choose to set up a mixed-frequency model, a natural framework to take into account data at different frequencies and publication lags. While the literature in mixed-frequency techniques is vast by now, in this paper we follow the approach by Schorfheide and Song (2015) and use a mixed-frequency Bayesian VAR. The choice of this method is driven by the purpose of our study: first, we want to have a set of variables which depicts the labour market dynamics; second, we want to be able to provide a reliable forecast of the main variables; third, we want to have a structural interpretation of the projected path in light of economic shocks which are likely to generate the forecast. A VAR set up is therefore very convenient for us, given that it allows to identify shocks in a straightforward manner. While there are few examples of structural mixed-frequency VARs (see Foroni and Marcellino (2014) as a reference), to the best of our knowledge, however, no previous papers use sign restrictions in mixed-frequency VARs and we therefore aim at closing a methodological gap.

What we find is that satisfactory results are obtained in terms of forecasting, especially when looking at quarterly variables, as employment growth and compensation per employee. These findings are aligned with most of the results available in the mixed-frequency literature.

Unemployment rate is more difficult to predict, given that the information contained in its own lags is often already sufficient to provide a good forecast. Further, we look into the shocks which drove the labour market dynamics and we find interesting insights. First, demand shocks were the main drivers during the past Great recession. Second, shocks originating in the labour markets play an important role in explaining the period of low inflation from 2014 onward, highlighting the crucial role played by labour markets in the economic analysis. Finally, from a practitioner's point of view, it is possible to use our model also to provide an economic interpretation to the generated forecasts in order to understand what are the drivers behind a projected path.

In addition to the results just mentioned, another contribution in our analysis stays in considering labour market flows, and not only the more standard employment and unemployment rate. The role of labour market flows in understanding and predicting unemployment fluctuations is well established in the literature. The relative importance and the rate at which workers flow into and out of the unemployment pool are crucial for determining unemployment dynamics in various countries. Starting with the milestone contribution of Shimer (2007), various papers in the literature looked at establishing methods to derive appropriate measures of flows (see, among others, Elsby et al. (2013) and Barnichon (2012)). The information contained in the labour market flows can be helpful in predicting the dynamics of other labour market variables, and of the economy more in general. The paper by Barnichon and Nekarda (2012) shows that the inflow and outflow rates of unemployment convey useful information for the unemployment level in the U.S. economy. Promising results for predicting quarterly unemployment are obtained also for the OECD countries (see Barnichon and Garda (2016)). With our analysis, we confirm that the inclusion of flows in the set of variables helps the prediction of employment growth and wage growth. The inclusion of flows also improves the forecasts of unemployment rate, consistently with the findings in the literature, but still the information on those is not enough to predict monthly developments in the unemployment rate.

The remainder of the paper is organized as follows: Section 2 describes in detail the notation and the algorithms which allow us to estimate the model and to include sign restrictions on it. Section 3 provides a detailed description of our baseline model and the main results. Section 4 concludes.

2 Mixed-frequency Bayesian Vector Autoregression with sign restrictions

One of the main contributions of this paper its to include sign restrictions in a mixed frequency VAR setup. As we describe in the rest of the section, we follow the model by Schorfheide and Song (2015) and extend their methodology to a Structural VAR where we identify key macroeconomic shocks by means of sign restrictions.

2.1 The Schorfheide and Song (2015) model

Following Schorfheide and Song (2015), let us assume we have a group of N_m monthly variables denoted by $x_{m,t}$ and N_q quarterly variables represented by $y_{q,t}$, for $i = 1, \cdots, T$ months. The block $y_{q,t}$ is a set of variables with missing observations and have available data only every third month. We are interested in modelling the joint dynamics of these two groups of variables as a vector autoregression (VAR). To achieve this, we consider the latent monthly counterpart of the quarterly variables which we denote as $x_{q,t}$.[1] We gather the monthly information sets in the time series vector $x_t = [x'_{m,t}, x'_{q,t}]$ of dimension $N = N_m + N_q$ and we assume it evolves as a VAR with p lags in the following way:

$$x_t = c + A_1 x_{t-1} + \cdots + A_p x_{t-p} + u_t, \quad \text{where} \quad u_t \overset{iid}{\sim} N(0, \Sigma), \tag{1}$$

where A_i are matrices of reduced-form parameters, for $i = 1, \cdots, p$, $u_t = [u'_{m,t}, u'_{q,t}]'$ is a vector of reduced-form errors and $c = [c'_m, c'_q]'$ is a vector of constants.

Now, let us rewrite the VAR in compact form by stacking all lags of x_t in vector z_{t-1} as follows:

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

The $Np \times 1$ vector $z_{t-1} = [z'_{m,t-1}, z'_{q,t-1}]'$ is decomposed in two parts. The first block corresponds to the $N_m p \times 1$ vector $z_{m,t-1} = [x'_{m,t-1}, x'_{m,t-2}, \cdots, x'_{m,t-p+1}]'$ which contains all the lags of monthly variables. The second block stacks the lags of the quarterly set in the $N_q p \times 1$ vector $z_{q,t-1} = [x'_{q,t-1}, x'_{q,t-2}, \cdots, x'_{q,t-p+1}]'$. The $N \times Np$ matrix A_+ stacks matrices A_i. In equation (3), we rewrite the compact VAR in terms of the blocks of monthly and quarterly variables. We divide the matrix of parameters into four sub-matrices: A_{mm} which

[1] Notice that from now on, the letter x will represent a variable in monthly terms. Here we have two cases: (i) $x_{m,t}$ which is originally available at this frequency and (ii) $x_{q,t}$ which is a latent monthly counterpart of the quarterly (and observable) variable $y_{q,t}$.

is a $N_m \times N_m p$ matrix of parameters governing the relationship among monthly variables; A_{mq}, a $N_m \times N_q p$ matrix containing the impact of quarterly variables into monthly equations; similarly, A_{qm} is a $N_q \times N_m p$ matrix representing the impact of monthly variables into quarterly equations and A_{qq} is a $N_q \times N_q p$ matrix with the interactions among quarterly variables. The blocks of constants c_q and c_m are of dimension $N_q \times 1$ and $N_m \times 1$, respectively. The same dimensions apply for the blocks of error terms $u_{q,t}$ and $u_{m,t}$.

$$\begin{bmatrix} x_{m,t} \\ x_{q,t} \end{bmatrix} = \begin{bmatrix} c_m \\ c_q \end{bmatrix} + \begin{bmatrix} A_{mm} & A_{mq} \\ A_{qm} & A_{qq} \end{bmatrix} \begin{bmatrix} z_{m,t-1} \\ z_{q,t-1} \end{bmatrix} + \begin{bmatrix} u_{m,t} \\ u_{q,t} \end{bmatrix}, \tag{3}$$

In a similar way, we partition the covariance matrix into four blocks:

$$\Sigma = \begin{bmatrix} \Sigma_{mm} & \Sigma_{mq} \\ \Sigma_{qm} & \Sigma_{qq} \end{bmatrix}. \tag{4}$$

Since the block 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. Summarising, we could 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. As an illustration of these problems, we consider the case of a data set with two monthly and three quarterly variables that have the following missing observations pattern:

Table 1: Type of missing observations

Jun 19	$x_{m1,1}$	$x_{m2,1}$	$y_{q1,1}$	$y_{q2,1}$	$y_{q3,1}$	$t = T_{bq}$
Jul 19	$x_{m1,2}$	$x_{m2,2}$	NaN	NaN	NaN	
Aug 19	$x_{m1,3}$	$x_{m2,3}$	NaN	NaN	NaN	
Sep 19	$x_{m1,9}$	$x_{m2,9}$	$y_{q1,9}$	$y_{q2,9}$	NaN	
Oct 19	$x_{m1,10}$	$x_{m2,10}$	NaN	NaN	NaN	
Nov 19	$x_{m1,11}$	$x_{m2,11}$	NaN	NaN	NaN	
Dec 19	$x_{m1,12}$	$x_{m2,12}$	$y_{q1,12}$	NaN	NaN	$t = T_b$
Jan 20	$x_{m1,13}$	$x_{m2,13}$	NaN	NaN	NaN	
Feb 20	$x_{m1,14}$	NaN	NaN	NaN	NaN	$t = T$

Taking a look at this example, we can recognize that 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 $t > T_b$. For this reason, we split our problem into two state-space representations.

The first state-space model copes with the problem of having two frequencies and the fact that we are interested in obtaining an estimate of $x_{q,t}$, the monthly counterpart of quarterly variables. Additionally, we might encounter the problem of ragged edges within the observed quarterly variables, $y_{q,t}$. The starting point is to recognize that we observe T_b observations for at least one quarterly variable from the set $y_{q,t}$ and up to this period we observe all monthly variables $x_{m,t}$. A second time period to consider is $T_{b,q}$ which is the point at which the quarterly set is balanced. First, let us define the state and measurement equations for the mixed frequency set, which is defined for $t = 1, \cdots, T_{b,q}$. To do this, we partition the block VAR of equation (3) in two parts: the observable part (monthly variables) and the latent part which is contained in the second equation. We define the state vector, S_t, as follows:

$$S_t = \begin{bmatrix} x_{q,t} \\ z_{q,t-1} \end{bmatrix} = \begin{bmatrix} x_{q,t} \\ x_{q,t-1} \\ \vdots \\ x_{q,t-p+1} \end{bmatrix}.$$

S_t stacks present and past values of the quarterly set with dimension $N_s = N_q(p+1) \times 1$. Disentangling the parts associated to the states in equation (3), the state equation in companion form is the following:

$$\underbrace{\begin{bmatrix} x_{q,t} \\ x_{q,t-1} \\ \vdots \\ x_{q,t-p+1} \end{bmatrix}}_{S_t} = \underbrace{\begin{bmatrix} c_q \\ 0_{(N_q \times p) \times 1} \end{bmatrix}}_{\Gamma_c} + \underbrace{\begin{bmatrix} A_{qm} \\ 0_{(N_q \times p) \times (N_m \times p)} \end{bmatrix}}_{\Gamma_z} \underbrace{\begin{bmatrix} A_{qq} & 0_{N_q} \\ I_{(N_q \times p)} & 0_{(N_q \times p) \times N_q} \end{bmatrix}}_{\Gamma_s} \begin{bmatrix} z_{m,t-1} \\ S_{t-1} \end{bmatrix}$$
$$+ \underbrace{\begin{bmatrix} I_{N_q} \\ 0_{(N_q \times p) \times N_q} \end{bmatrix}}_{\Gamma_u} u_{q,t}$$

The dimensions of state matrices Γ_c, Γ_z, Γ_s and Γ_u are $N_s \times 1$, $N_s \times N_m p$, $N_s \times N_s$ and

$N_s \times N_q$, respectively. Therefore, we compress the state equation as follows:

$$S_t = \Gamma_c + \Gamma_z z_{m,t-1} + \Gamma_s S_{t-1} + \Gamma_u u_{q,t} \tag{5}$$

Now, we need to link the observable variables in $y_{q,t}$ with the latent set $x_{q,t}$. Assuming that the length of the VAR is larger than three lags, we make a bridge between these variables through $\tilde{y}_{q,t}$ which is the latent monthly average of $x_{q,t}$ if the quarterly variable is a stock or the sum if it is a flow. Without loss of generality, we position the stock variables first, therefore the relationship between $\tilde{y}_{q,t}$ and the states is summarised by equation (6).

$$\begin{aligned} \tilde{y}_{q,t} &= \begin{bmatrix} \frac{1}{3} I_{N_q^{stock}} & 0_{N_q^{stock}} & \frac{1}{3} I_{N_q^{stock}} & 0_{N_q^{stock}} & \frac{1}{3} I_{N_q^{stock}} & 0_{N_q^{stock}} & 0_{N_q^{stock} \times (N_s - N_q)} \\ 0_{N_q^{flow}} & I_{N_q^{flow}} & 0_{N_q^{flow}} & I_{N_q^{flow}} & 0_{N_q^{flow}} & I_{N_q^{flow}} & 0_{N_q^{flow} \times (N_s - N_q)} \end{bmatrix} S_t \\ &= \Lambda_s S_t, \end{aligned} \tag{6}$$

where N_q^{stock} and N_q^{flow} are the number of stock and flow variables, respectively, and $N_q = N_q^{stock} + N_q^{flow}$. Now, let us remember that every three months we observe the quarterly counterpart of this average/sum in the vector $y_{q,t}$. Therefore, the bridge between observables and latent observation is given by equation (7).

$$y_{q,t} = M_{q,t} \tilde{y}_{q,t}. \tag{7}$$

The key component is matrix $M_{q,t}$ which is a $N_q \times N_q$ selection matrix that will be empty for the months between the quarter and an identity for the month where we observe the quarterly variable. Therefore, for periods where we observe quarterly variables, i.e. March, June, September, December, the measurement equation is the following:

$$\begin{aligned} \underbrace{\begin{bmatrix} x_{m,t} \\ y_{q,t} \end{bmatrix}}_{y_t} &= \left[\underbrace{\begin{matrix} A_{mm} \\ 0_{N_q \times N_m p} \end{matrix}}_{\Lambda_z} \; \underbrace{\begin{matrix} 0_{N_m \times N_q} \quad A_{mq} \\ M_{q,t} \Lambda_s \end{matrix}}_{\Lambda_{y,s}} \right] \begin{bmatrix} z_{m,t-1} \\ \left. \begin{matrix} x_{q,t} \\ z_{q,t-1} \end{matrix} \right\} = S_t \end{bmatrix} \\ &+ \underbrace{\begin{bmatrix} c_m \\ 0_{N_s \times 1} \end{bmatrix}}_{\Lambda_c} + \underbrace{\begin{bmatrix} I_{N_m} \\ 0_{N_q \times N_m} \end{bmatrix}}_{\Lambda_u} u_{m,t} \end{aligned} \tag{8}$$

Since we observe $x_{m,t}$, the first line in the measurement equation corresponds to the first equation of the block VAR of equation (3). Notice that we define $y_t = [x'_{m,t}, y'_{q,t}]'$ as the vector of data that we actually observe. We now write equation (8) into two measurement equations regarding monthly and quarterly variables, separately:

$$x_{m,t} = A_{mm} z_{m,t-1} + A_{mq} S_t + c_m + u_{m,t} \tag{9}$$

$$y_{q,t} = M_{q,t} \Lambda_s S_t \tag{10}$$

If t corresponds to a month between quarters, i.e. January, February, April, May, July, August, October or November, we exclusively have one measurement equation which corresponds to equation (9). This is because the selection matrix $M_{q,t}$ will be empty.

The second type of missing observations in this representation is ragged edges within quarterly variables, which may occur for $t = T_{b,q} + 1, \cdots, T_b$. In this instance, we need to slightly modify the state-space model. We follow the approach of Durbin and Koopman (2012) who set the model depending on the observations available at each period of time. This means that the size of the vector of observables is time varying. To illustrate this, lets return to the example in table 1. By June 2019 (which in this example corresponds to $t = T_{bq}$), we have no missing observations, therefore the size of y_t in the measurement equation (8) is 5×1. On the other hand, by September 2019 we do not have the information of the last quarter available for the last quarterly variable, henceforth the size of y_t is 4×1. Finally, by December 2019 we only have information for the first variable within the quarterly set, and hence the dimension of y_t is 3×1, respectively. The matrices in the measurement equation will differ because the row corresponding to the variable missing is suppressed. We denote N_{q^*} as the number of quarterly variables available at time t. For this case, equation (11) denotes the measurement equation in terms of the available information which is captured in the $(N_m + N_q^*) \times 1$ vector $y_t^* = [x'_{m,t}, y^{*'}_{q,t}]'$.

$$\begin{aligned} \underbrace{\begin{bmatrix} x_{m,t} \\ y^*_{q,t} \end{bmatrix}}_{y_t^*} &= \begin{bmatrix} \underbrace{\begin{matrix} A_{mm} \\ 0_{N_q^* \times (N_m \times p)} \end{matrix}}_{\Lambda_z^*} & \underbrace{\begin{matrix} 0_{N_m \times N_q} \quad A_{mq} \\ \Lambda_s^* \end{matrix}}_{\Lambda_{y,s}^*} \end{bmatrix} \begin{bmatrix} z_{m,t-1} \\ S_t \end{bmatrix} \\ &+ \underbrace{\begin{bmatrix} c_m \\ 0_{N_s^* \times 1} \end{bmatrix}}_{\Lambda_c^*} + \underbrace{\begin{bmatrix} I_{N_m} \\ 0_{N_q^* \times N_m} \end{bmatrix}}_{\Lambda_u^*} u_{m,t}. \end{aligned} \tag{11}$$

The matrices Λ_z^*, $\Lambda_{y,s}^*$, Λ_c^* and Λ_u^* have the dimensions $(N_m + N_q^*) \times (N_m(1 + p))$, $(N_m + N_q^* \times (N_q(p + 1))$, $(N_m + N_q^*) \times 1$ and $(N_m + N_q^*) \times N_m$, respectively. Finally, notice that this representation is valid only when the month at time t corresponds to the last month of the corresponding quarter, otherwise equation (9) is the single measurement equation.

The second state-space model considers the case of ragged edges in the monthly block.

Even though we also could have the same problem in the quarterly set, the approach we took at the end of the previous subsection does not apply for the monthly variables. Notice that the quarterly variables have always been considered states and therefore the ragged edge problem is solved by modifying the matrices depending on the information available. Now, a subset of monthly variables change their status from being observed to become a state. We define the new state vector as $\tilde{z}_t = [z_t', x_{t-p}']$ which is of dimension $N_{\tilde{z}} \times 1$ with $N_{\tilde{z}} = Np + N$. This state vector is only defined for $t = T_b + 1, \cdots, T$ for which only monthly variables are available. The state equation in companion form is represented in equation (12) and it is based on the compact VAR from equation (2):

$$\tilde{z}_t = \underbrace{\begin{bmatrix} c \\ 0_{Np\times 1} \end{bmatrix}}_{\tilde{c}} + \underbrace{\begin{bmatrix} A_+ & 0_{N\times N} \\ I_{Np} & 0_{Np\times N} \end{bmatrix}}_{\tilde{\Phi}} \tilde{z}_{t-1} + \underbrace{\begin{bmatrix} u_t \\ 0_{Np\times 1} \end{bmatrix}}_{\tilde{u}_t}. \tag{12}$$

The companion form matrices $\tilde{c}$, $\tilde{\Phi}$ and $\tilde{u}_t$ are of dimension $N_{\tilde{z}} \times 1$, $N_{\tilde{z}} \times N_{\tilde{z}}$ and $N_{\tilde{z}} \times 1$, respectively. In a similar way, we denote $\Sigma_{\tilde{z}} = \begin{bmatrix} \Sigma & 0_{Np\times N} \\ 0_{N\times Np} & 0_{N\times N} \end{bmatrix}$ as the variance covariance matrix of $\tilde{u}_t$.

The measurement equation depends exclusively on monthly variables that we observe from $t = T_b + 1, \cdots, T$. We define $N_{\tilde{m}}$ as the number of monthly variables available after T_b, then the measurement equation is the following:

$$\tilde{y}_t = M_{\tilde{z}} \tilde{z}_t, \tag{13}$$

where $M_{\tilde{z}}$ is a $N_{\tilde{m}} \times N_{\tilde{z}}$ selection matrix picking only those variables with observations after T_b.

2.2 Bayesian estimation

Schorfheide and Song (2015) develop a two-block Gibbs sampler in order to obtain draws from the conditional posterior distributions of the parameters and states of the model. Specifically, they start by sampling the state vector following the Carter-Kohn algorithm (see Carter and Kohn (1994)), which is the Bayesian counterpart of the Kalman filter. Given the states, it is easy to sample from the conditional distribution of the parameters $\Phi = [c, A_+]$ and the reduced-form covariance matrix Σ when the prior is conjugate, i.e. the posterior distribution belongs to the same distributional family as the prior, assuming a Gaussian likelihood. In particular, we consider a Normal-inverse Wishart prior, i.e.

$$\text{vec}(\Phi)|\Sigma \sim \mathcal{N}\left(\text{vec}(\Phi_0), \Sigma \otimes V_0\right) \quad \text{and} \quad \Sigma \sim iW\left(S, d\right) \tag{14}$$

where the moments of the normal distribution of the parameters follow a Minnesota structure (Litterman (1980), Litterman (1986)). The scale covariance matrix $S = diag(s_1, \cdots, s_N)$ correspond to the standard deviation of each variable in the 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).

Following the set up of the Minnesota prior as in Del Negro and Schorfheide (2011), we shrink the autoregressive parameters towards a random walk. Therefore, the diagonal elements of parameter matrix A_1 are equal to one and the off-diagonal elements are zero. Moreover, all matrices related to a lag larger then one are set to zero. For the case of the covariance, we assume a diagonal matrix where we impose that the more distant lags and the coefficients from variable k have a smaller weight in the equation of $x_{j,t}$, for $j \neq k$ and $j, k = 1, \cdots, N$. These ideas are summarised by the following moments:

$$\begin{aligned}
\mathbb{E}\left[\left(A_i\right)_{jk}|\Sigma\right] &= \begin{cases} 1 \quad \text{if} \quad j = k \quad \text{and} \quad i = 1 \\ \qquad 0 \quad \text{otherwise} \end{cases} \\
\text{cov}\left(\left(A_i\right)_{jk}, \left(A_l\right)_{mr}|\Sigma\right) &= \begin{cases} \frac{\Sigma_{jm}}{\left(\lambda_1 i^{\lambda_2}\right)s_j^2} \quad \text{if} \quad i = l \quad \& \quad r = j \\ \qquad 0 \quad \text{otherwise} \end{cases}
\end{aligned} \tag{15}$$

The overall shrinkage of the parameters is ruled by λ_1 and the hyperparameter λ_2 rules the shrinkage of higher-order lags. In general the larger the hyperparameters, the stronger the shrinkage.

Since the influential paper of Sims and Zha (1998) the implementation of the Minnesota prior has been commonly adopted through the use of dummy or artificial observations.[2] The popularity of this approach is due to the simplicity of implementing additional priors for modelling further relationships among parameters. Similar as in Schorfheide and Song (2015), we consider the sum-of-coefficients prior (also known as “inexact-differencing” or “no-cointegration-prior”) which was proposed by Doan et al. (1984). To understand this extension, let us rewrite the VAR from equation (1) in an error-correction form:

$$\Delta x_t = c - (I_N - A_1 - \cdots - A_p)x_{t-1} + \Gamma_1 \Delta x_{t-1} + \ldots + \Gamma_{p-1}\Delta x_{t-p} + u_t. \tag{16}$$

[2]Many researchers also implement the Minnesota prior through dummy observations as in Bańbura et al. (2010). For detailed explanation of how this works, see also Del Negro and Schorfheide (2011).

The combination of the Minnesota with the sum-of-coefficients prior shrinks the parameter $\Pi = (I_N - A_1 - \cdots - A_p)$ to zero. This prior introduces an additional shrinkage parameter, λ_3, on the relationship $(I_N - A_1 - \cdots - A_p)$. When λ_3 is zero the VAR is set in first differences which implies a unit root equation for each variable and therefore there are no cointegration relationships among the variables. If $\lambda_3 \to \infty$ the prior is diffuse and no additional shrinkage is imposed. Sims and Zha (1998) propose the implementation of the previous priors by augmenting the model's data with artificial data also called dummy observations as follows:

$$x_d = \begin{bmatrix} \lambda_1 \mathrm{diag}(s_1^2, \cdots, s_N^2) \\ 0_{N(p-1)\times N} \\ \cdots \\ \mathrm{diag}(s_1^2, \cdots, s_N^2) \\ \cdots \\ \lambda_3 \mathrm{diag}(\bar{y}_{0,1}, \cdots, \bar{y}_{0,N}) \end{bmatrix} \qquad z_d = \begin{bmatrix} J^{\lambda_2} \otimes \lambda_1 \mathrm{diag}(s_1^2, \cdots, s_N^2) & 0_{Np\times 1} \\ \cdots & \\ 0_{N\times Np} & 0_{N\times 1} \\ \cdots & \\ (1_{1\times p} \otimes \lambda_3 \mathrm{diag}(\bar{y}_{0,1}, \cdots, \bar{y}_{0,N})) & \lambda_3 \end{bmatrix}$$

where $J = \mathrm{diag}(1, \cdots, p)$. In summary, the artificial observations consists of three blocks. The first one implements the moments of autoregressive coefficients following the Minnesota prior, as in equation (15). The second block corresponds to the prior for the covariance matrix Σ and the last block corresponds to the sum-of-coefficients prior.

The augmented data is defined as $X^* = [X', x_d']'$, $Z^* = [Z', z_d']'$, where X and Z come from the matrix form of the compact VAR (2). Henceforth, we now have $T^* = T + T_d$ observations. Accordingly to Kadiyala and Karlsson (1997), we consider the following augmented VAR:

$$X^* = Z^* \Phi^* + U^*, \tag{17}$$

where $U^* = [U', u_d']'$. In intuitive words, the augmented model combines the prior and the likelihood of the data, therefore the posterior distribution will have the following form:

$$\begin{aligned} \mathrm{vec}(\Phi^*)|X, \Sigma &\sim \mathcal{N}\left(\hat{\Phi}, \Sigma \otimes \left(X^{*\prime} X^*\right)^{-1}\right) \\ \Sigma|X &\sim iW(\hat{\Sigma}, T^* + 1 - Np), \end{aligned} \tag{18}$$

where $\hat{\Phi} = \left(Z^{*\prime} Z^*\right)^{-1} \left(Z^{*\prime} X^*\right)$ and $\hat{\Sigma} = (Y^* - X^*\Phi^*)' (Y^* - X^*\Phi^*)$.

As we can see from the artificial observations, the vector of hyperparameters, $\Lambda = [\lambda_1, \lambda_2, \lambda_3]$ rules the behaviour of the prior, therefore an important issue to consider is its estimation. Due to the nature of states and observable time series in the VAR, the marginal data density (MDD) does not have a closed-form solution and therefore the methodologies for its optimisation are not available, e.g. Giannone et al. (2015), Chan et al. (2019). Schorfheide and Song (2015) propose to approximate the MDD through the harmonic mean estimator of Geweke (1999). Once they obtain the approximation, the optimal parameters can be estimated over a grid. In this paper, we follow their approach. We show the considered grid and the selected hyperparameters for the models considered here in appendix A.3.

2.3 Shock identification with sign restrictions

Our methodological contribution lies in the extension of the mixed-frequency BVAR of Schorfheide and Song (2015) to a Structural model. Specifically, we link the reduced-form model of equation (1) with the structural shocks, ε_t, as follows:

$$u_t = B\varepsilon_t, \tag{19}$$

where B corresponds to the matrix of impact effects such that $\Sigma = BB'$. The identification of structural shocks hinges in identifying the columns of matrix B. To do this, we rely on an identification strategy based on sign restrictions. Specifically, we augment the Gibbs Sampler algorithm of Schorfheide and Song (2015) and include a third block where we obtain rotation matrices Q based on the methodology of Arias et al. (2018). We generate a draw of the impact matrix as $B = \text{chol}(\Sigma)Q$ and retain the draw that fulfils the sign restrictions.

3 A SVAR model for understanding the euro area labour market

In this section we describe our baseline model, in which we include a set of variables with the twofold purpose of (i) providing timely information for predicting future developments of labour market variables and (ii) interpreting the developments according to economically meaningful shocks. As we will describe in the next subsections, we exploit the role of labour market flows to refine the shock identification and to disentangle the nature of more shocks originating the labour market. Further, we will show that flows also help forecasting some of the labour market variables.

3.1 Baseline model

We set up a BVAR model with the following variables: industrial production growth rate (Δip_t), an index to identify the relative strength of the manufacturing relative to the service sector (which for simplicity we will call as MS index (ms_t))[3], inflation (Δp_t), wage growth (Δw_t measured by compensation per employee), unemployment rate (u_t), employment growth (Δe_t), and job flows, specifically job finding (f_t) and job separation rates (s_t). A detailed description of the variables and of the transformations can be found in Appendix A.1. The number of lags included in the estimation is equal to 4.

With this set of variables we aim at identifying six shocks, in particular two demand shocks, domestic and foreign, a technology shock, and three shocks originated 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.

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

Table 2: Identification scheme via sign restrictions - baseline model

	Demand		Supply	Labour Market		
	Domestic	Foreign	Technology	Labour Supply	Mismatch	Wage Bargaining
u_t	-	-	-	-	-	-
Δip_t	+	+	+	-	+	+
Δp_t	+	+	-	+	///	-
Δw_t	///	///	+	+	+	-
Δe_t	///	///	///	///	///	///
ms_t	-	+	///	///	///	///
f_t	+	+	+	///	+	///
s_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.

A demand shock represents a shift in the demand curve, which pushes up output (in our case industrial production) and inflation, while it lowers the unemployment rate. These dynamics are consistent with the effects induced by monetary policy, government spending, marginal efficiency of investment, discount factor and most financial shocks. The MS index helps us distinguishing between domestic and foreign demand shocks because when the former hits the economy, the demand for non-tradable goods (services sector) is more affected than the one of tradable goods (manufacturing) and hence MS<0. In the case of a foreign demand shock, manufacturing is more affected than services and henceforth MS>0.

[3]The MS index is defined as the difference between the growth rates of the Purchasing Managers' Index (PMI) in Manufacturing and Services: $MS = \Delta \ln PMI_t^M - \Delta \ln PMI_t^S$. We consider surveys instead of the gross-value-added in both sectors since the former detects the impact of shocks in a more promptly than the latter.

Therefore, a domestic demand shock moves the MS index positively, while a global demand shock negatively.

Following Mumtaz and Zanetti (2015), we further use the information of labour market flows for the identification of neutral technology shocks. 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 which translates into a rise in job finding rate. Moreover, the rise in productivity makes firms more willing to keep their employees which decreases the job separation rate. As a consequence, the unemployment rate decreases. However, a positive technology shock also creates a positive shift in the labour demand curve, which increases output and wage growth.

Both labour supply and wage bargaining shocks generate an inverse co-movement between output and real wages (see Foroni et al. (2018a)). In the first case, an exogenous increase in labour supply leads to an increase in the number of job seekers, makes it easier for firms to fill vacancies and decreases hiring costs, thereby leading to a decrease in wages and prices and to an increase in output and employment. In the second case, a reduction in the bargaining power of workers has a direct negative effect on wages, thus contributing to lower marginal costs and prices. Since firms now capture a larger share of the surplus associated with employment relationships, they post more vacancies and increase employment. 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. It is reasonable to assume that at least some of the new participants will transit through unemployment for the first quarter.

A negative wage bargaining (or wage mark-up) shock leads firms to capture a larger share of the bargaining surplus. A reduction in the bargaining power of workers leads to a decline in wages. It is now a very good moment for firms to hire and vacancy posting increases, leading to a decrease in unemployment. Matching efficiency shocks can be interpreted as reallocation shocks. In line with search and matching models with endogenous job destruction (see Pissarides (2000)), an exogenous increase in mismatch efficiency shifts the job creation curve outwards increasing the labour market tightness which pushes wages upwards. The increase in efficiency makes it easier for workers to find a job and therefore the job finding rate increases. The lower mismatch reduces the costs of firing people in order to get a better match for the job which increases the job separation rate. Additionally, this shock shifts the Beveridge curve inwards which translates into lower unemployment. For further detail see Consolo and Da Silva (2019).

3.2 Forecasting results

We evaluate the forecasting properties of the mixed-frequency BVAR for the labour market in the euro area. In particular, we evaluate forecasts up to a year ahead for the real and nominal labour market quarterly variables: compensation per employee growth, employment growth rate and the in- and out-flows of unemployment[4].

We estimate our model over the sample spanning from January 1998 to December 2019 and we carry out a pseudo real time forecasting exercise for the period from January 2010 to the end of the sample.[5] At each forecasting step, we obtain 20000 draws and discard the initial 10000. The dataset we consider is mixed-frequency and with ragged edges, given that the series have different publication delays. For this exercise, we assume that we update our data set on the tenth day of the month, such that we have the latest released figure of the unemployment rate. Table 3 shows an example of the ragged-edge pattern within the months of the quarter, where “x” means that the information is available whereas NaN represent that the corresponding observation is missing. We split the flow of data into three blocks: Beginning, middle and end. This is because for the case of the quarterly variables, we divide the forecast evaluation into these groups, based 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 (January, April, July, October, “beginning” later on), the second to the months of February, May, July, November (“middle”) and the third, to March, June, September and December (“end”). Forecasting horizons change according to the group. As a clarifying example, if we are at the beginning of January, the forecast of the first quarter corresponds to a 2 months ahead horizon, while if we are at the beginning of February, the forecast of the first quarter corresponds to a 1 month ahead forecast and when we are in March, the nowcast (horizon=0) correspond to the forecast of the first quarter.

[4]Additionally we include results for industrial production growth rate and inflation rate in appendix A.2.

[5]Given the ragged edge structure of the dataset, the last available realised values for the quarterly series as dowloaded in May 2020 correspond to December 2019.

Table 3: Data flow within quarters

		Monthly variables				Quarterly variables			
		u_t	Δip_t	Δp_t	ms_t	Δw_t	Δe_t	f_t	s_t
Beginning	Sep/Q3	x	x	x	x	x	x	x	x
	Oct	x	x	x	x	NaN	NaN	NaN	NaN
	Nov	x	NaN	x	x	NaN	NaN	NaN	NaN
	Dec/Q4	NaN	NaN	NaN	x	NaN	NaN	NaN	NaN
	Jan	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Middle	Oct	x	x	x	x	x	x	x	x
	Nov	x	x	x	x	NaN	NaN	NaN	NaN
	Dec/Q4	x	NaN	x	x	NaN	NaN	NaN	NaN
	Jan	NaN	NaN	NaN	x	NaN	NaN	NaN	NaN
	Feb	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
End	Nov	x	x	x	x	x	x	x	x
	Dec/Q4	x	x	x	x	x	x	NaN	NaN
	Jan	x	NaN	x	x	NaN	NaN	NaN	NaN
	Feb	NaN	NaN	NaN	x	NaN	NaN	NaN	NaN
	Mar	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

Results are reported in Table 4 and 5. In order to assess the importance of job flows for forecasting we compute estimates from the benchmark model and a model without the flows. In both tables we report the root mean square forecast error (RMSFE) of the model indicated relative to the RMSFE of an AR process with the lag length selected according to the BIC criterion. Therefore, whenever the number reported is smaller than one it indicates a superior performance of the model relative to the AR. We additionally tested if the MFBVAR models are significantly different against the AR model through a HLN test (Harvey et al. (1997)). The numbers with (***) means that the null hypothesis of equal accuracy is rejected at 1%, with (**) and (*) the null is rejected at 5% and 10% levels, respectively.

What we can see is that we obtain significant gains when predicting quarterly variables. This is consistent with most of the evidence concerning mixed-frequency models. In particular, in the case of compensation per employee, the results show improvements at all horizons, while for employment growth bigger gains are shown for the outer horizons. Further, in Table 4 we find some evidence that the more we obtain information during the quarter (moving from "beginning" to "middle" and "end") the better we are able to take advantage of this information and the improve over the benchmark.

We report results of the job finding and job separation rates in Table 5. The MFBVAR model is more effective in forecasting the job separation rate, since their numbers are smaller than the AR. However, for the job finding rate, considering the mixed frequency model improve forecasts when we are in the last month of the quarter.

For completeness we report also the forecasting performance for the monthly unemployment rate. Although less commonly applied, it is 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 the case of unemployment rate however, we do not obtain any gain in predicting it with mixed frequency information (See table 6), relative to using a simple AR process. The reason lays most likely in the fact that the unemployment rate is very persistent, therefore the information contained in the last month available is dominating over the information included in other series which are released with a bigger delay. In general though, we confirm the evidence in the literature that the inclusion of flows improves the accuracy of short- and medium-term forecasts for unemployment rate.

3.3 Economic interpretation

The advantage of our model is that it allows us to complement the nowcasting of labour market variables with a timely interpretation of the underlying structural shocks. In this way, we can extend the historical decomposition of labour market variables over the forecast horizon and – from a nowcasting perspective – we can also better understand how our model processes the marginal information from high-frequency data. In Figures 1 to 7 we report the historical decomposition of the variables in our benchmark model, in deviations from their mean.[6]

We summarize here the main economic findings. First, the model points at demand shocks (internal and foreign) as the main factors explaining the dynamics of most of the variables in the period of the Great Recession. In particular, the demand shocks were the drivers of the large fall in industrial production and in inflation. In the labour markets, they also contributed strongly to explain the developments in employment and unemployment rate. During the period of the Great Recession, the role of foreign originated shocks is consistent with the fact that this recession originates in the US first, and then spilled over to the euro area. Second, looking at the period of low inflation starting in 2014, the role of shocks

[6]All figures report the mean of the posterior distribution of the historical decomposition. We do not show the historical decomposition for the MS index, since this variable is included for identification purposes only.

originated in the labour markets (labour supply, bargaining power and mismatch) become very important to explain both low inflation and low wage growth. In particular, the wage bargaining and the mismatch shock play an important role for the labour market and inflation dynamics. The wage bargaining shock reflects the overall effects on the labour market stemming from reforms in labour market institutions implemented in the euro area following the 2010 sovereign debt crisis. In our model, the wage bargaining shock captures both the pure bargaining power of workers and their outside option. The latter has 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)). 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 and that also visible in the outward shift of the euro area Beveridge curve as of 2011. In our model, this is evident in the historical decomposition of the job finding rate in Figure 14, which suggests a negative contribution from job matching efficiency starting from 2011. Consistent with the search and matching framework, higher mismatch in the labour market has led to lower wage growth over the same period as visible in Figure 12. Our model thus provides additional evidence on the drivers of low inflation in the euro area which is related to a shift in the wage bargaining power of workers and an increase in labour market mismatch. As in Elsby et al. (2008), the short-term dynamics of the unemployment rate is also driven by mismatch shock which feature an important cyclical component.

3.4 Alternative model specifications

As a robustness to our results presented in Section 2 and 3, we explore potential richer alternatives to the baseline model. First in the view of improving the forecasting performance, we add the PMI employment in the set of variables, with no additional restrictions to the model. Second, we expand the identification scheme, by adding a monetary policy shock. The identification is achieved by adding a measure of interest rate, in our case the 2 year interest rate. Third, we identify a risk shock in the block of demand shocks, by adding a variable of spread, defined as the difference between the ten-year and the two-year yield.

In general, these alternative models confirm the results described in the previous sections. Identifying more shocks do not penalize the forecasting performance, so it can be an important way forward to get more economic insights. The inclusion of the PMI survey data tends to be beneficial in terms of forecasts, confirming the importance of timely high-frequency information contained in the surveys. Identification schemes and detailed results are available in an Online Appendix.

4 Conclusions

In this paper we developed a mixed-frequency structural VAR model, identified by sign restrictions, with the purpose to understand the dynamics of the euro area labour market. We obtain satisfactory results in terms of forecasting performance, especially for quarterly variables as the employment and wage growth. For the monthly unemployment rate, it is difficult to be an AR benchmark. All the results are aligned with the findings in the mixed-frequency literature. In terms of economic interpretation, we find that demand shocks were the main drivers during the past Great recession. Second, shocks originating in the labour markets played an important role in explaining the period of low inflation from 2014 onward. Finally, we exploited the information available in the labour market flows, and we found that they contain useful information for the forecasts, and to provide a more detailed picture of the euro area labour market.

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Table 4: Forecast evaluation: Quarterly variables

Compensation per employee (growth rate)						
	Benchmark			No Flows		
Horizon	Beginning	Middle	End	Beginning	Middle	End
Q(-1)	**0.63****	0.69*		0.73	**0.57****	
Q(0)	0.71**	0.69*	0.70	**0.63****	**0.61****	**0.65***
Q(+1)	0.81	**0.75****	**0.75****	**0.79**	0.80**	0.76**
Q(+2)	**0.82***	1.09	0.92	0.85*	**0.97**	**0.83**
Q(+3)	0.81	**0.71***	0.97	**0.74**	0.85	**0.80***

Employment (growth rate)						
	Benchmark			No Flows		
Horizon	Beginning	Middle	End	Beginning	Middle	End
Q(-1)	1.88***	1.45***−		**1.64*****	**1.37****	
Q(0)	1.47**	1.28*	1.81***	**1.34***	**1.23**	**1.67*****
Q(+1)	**0.85**	1.03	1.57**	1.13	**1.02**	**1.44***
Q(+2)	**0.73**	**0.75**	**1.02**	1.40	1.10	1.51*
Q(+3)	**0.72**	**0.74**	**0.88**	1.29	1.17	1.33

Note: The numbers in the table report the root mean square forecast error (RMSFE) relative to an AR(p) model where the optimal number of lags was selected through the BIC criterion. The bold number represent the best model between the benchmark and the model with no flows. We test the corresponding MFBVAR against the AR(p) model through a HLN test, the significance is presented as follows: 1% (***), 5% (**) and 10% (*).

Table 5: Forecast evaluation: Job flows

	Job Finding Rate			Job Separation Rate		
Horizon	Beginning	Middle	End	Beginning	Middle	End
Q(-1)	1.36**	1.34	0.83	1.06	0.80	0.82
Q(0)	0.95	0.78	0.66**	0.72	0.59**	0.61**
Q(+1)	0.98	0.85	0.61***	0.75	0.52**	0.53**
Q(+2)	1.12	1.25	0.82	0.89	0.90	0.71
Q(+3)	1.14	1.21	0.85	0.78	0.87	0.67

Note: The numbers in the table report the root mean square forecast error (RMSFE) relative to an AR(p) model where the optimal number of lags was selected through the BIC criterion. We test the corresponding MFBVAR against the AR(p) model through a HLN test, the significance is presented as follows: 1% (***), 5% (**) and 10% (*).

Table 6: Forecast evaluation: Unemployment rate

	Benchmark			No Flows		
Horizon	Beginning	Middle	End	Beginning	Middle	End
-1	1.60**	1.81***	2.03***	**1.55****	**1.76** ***	**2.02*****
0	1.57**	2.04***	1.44***	**1.50****	**1.94*****	**1.39*****
1	**1.93*****	**2.66*****	**1.65*****	2.12***	2.97 ***	1.83***
2	**1.92*****	**2.21*****	**1.64*****	2.13 ***	2.44 ***	1.78***
3	1.76***	**2.07*****	**1.53*****	**1.74*****	2.09 ***	1.72***
4	**1.64*****	**1.98*****	**1.48*****	1.65***	2.01***	1.62***
5	**1.57*****	**1.85*****	**1.38****	1.63***	1.88***	1.55***
6	**1.47*****	1.77***	**1.39***	1.50***	**1.71*****	1.48**
7	**1.37****	**1.59*****	**1.32**	1.44**	1.61 ***	1.36
8	**1.33***	**1.46****	**1.26**	1.35*	1.54***	1.28
9	**1.27**	**1.40***	1.21	1.30	1.43***	**1.19**
10	1.22	**1.31**	**1.16**	**1.21**	1.34*	1.16
11	**1.15**	**1.23**	1.13	1.15	1.34	**1.11**
12	**1.09**	**1.20**	1.09	1.16	1.27	**1.04**

Note: The numbers in the table report the root mean square forecast error (RMSFE) relative to an AR(p) model where the optimal number of lags was selected through the BIC criterion. The bold number represent the best model between the benchmark and the model with no flows. We test the corresponding MFBVAR against the AR(p) model through a HLN test, the significance is presented as follows: 1% (***), 5% (**) and 10% (*).

Figure 1: Historical decomposition of unemployment rate (deviation from its mean)

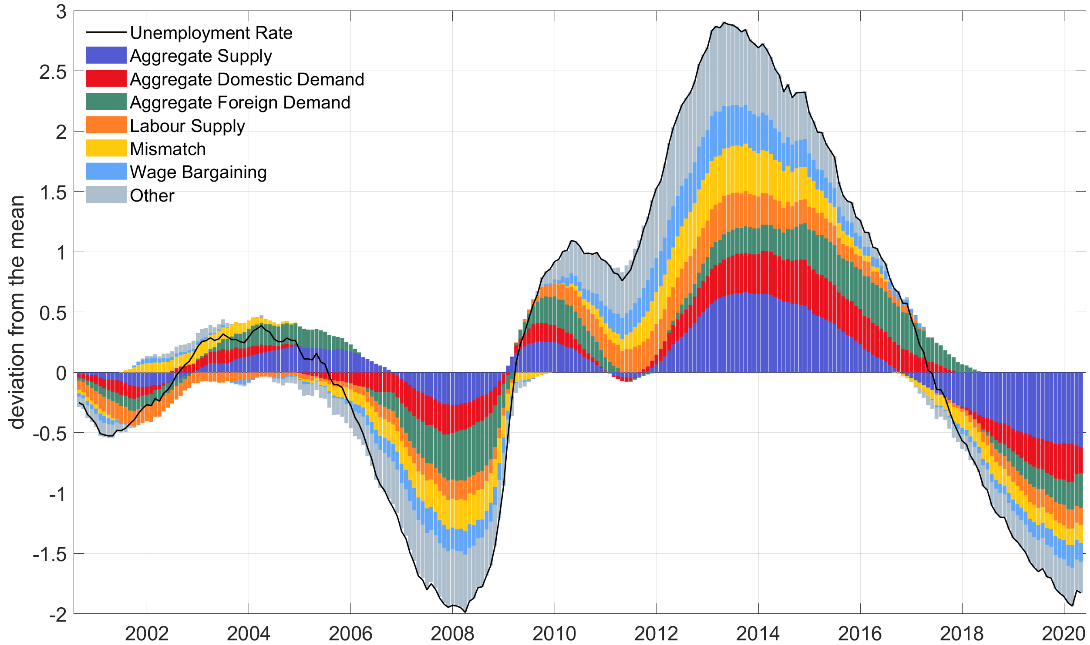


Figure 2: Historical decomposition of Industrial Production (y-o-y rate, deviation from its mean)

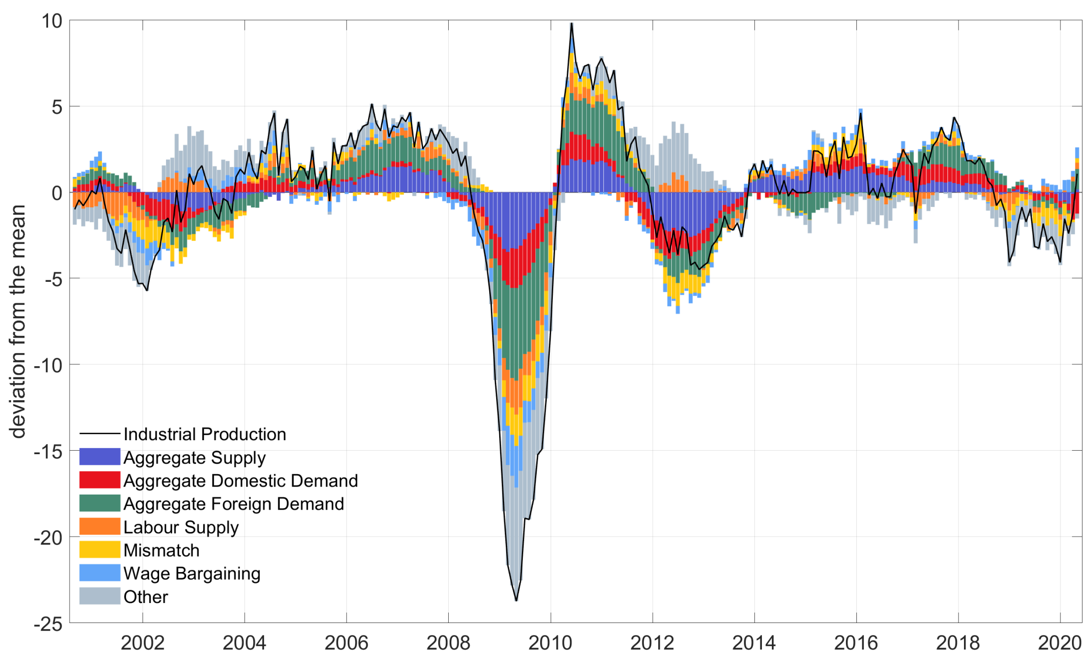


Figure 3: Historical decomposition of Inflation (y-o-y rate, deviation from its mean)

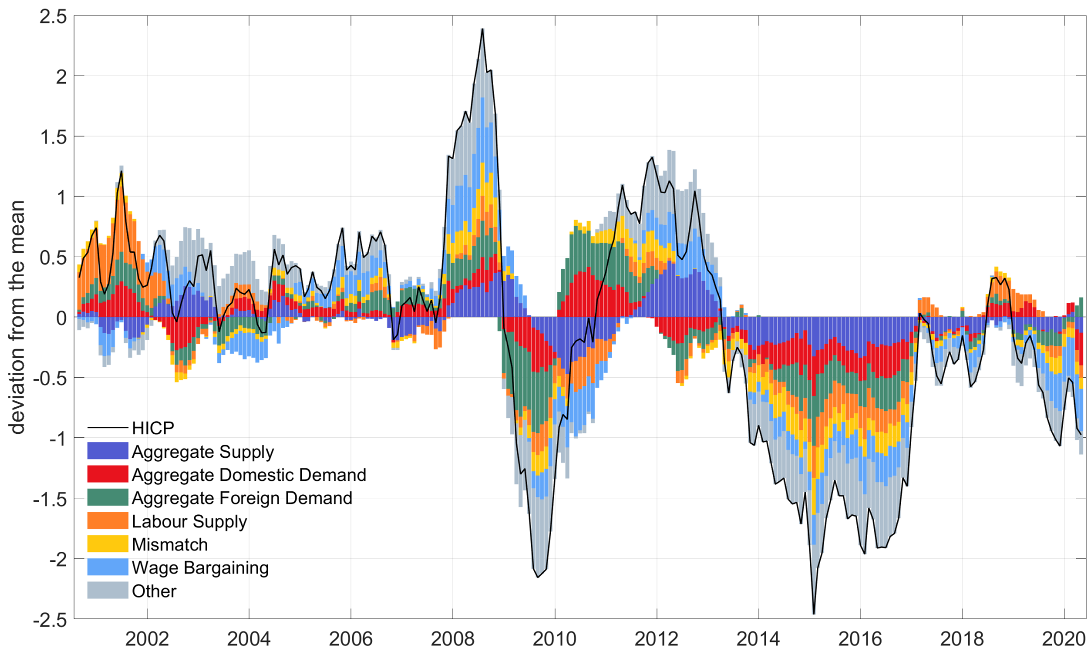


Figure 4: Historical decomposition of Compensation per employee (y-o-y rate, deviation from its mean)

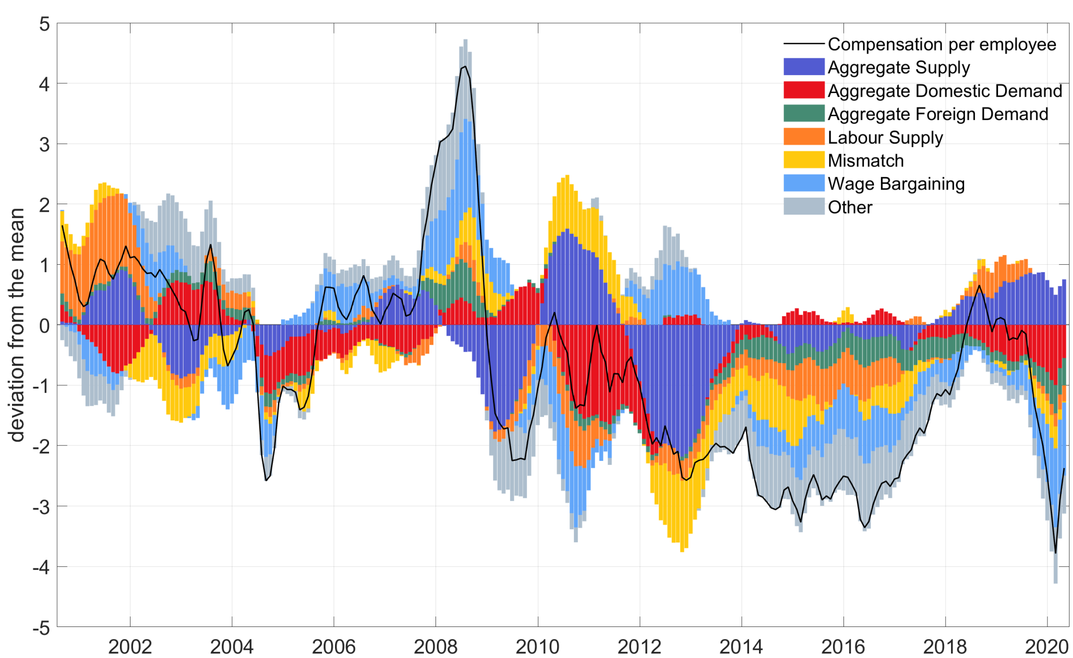


Figure 5: Historical decomposition of Employment (y-o-y rate, deviation from its mean)

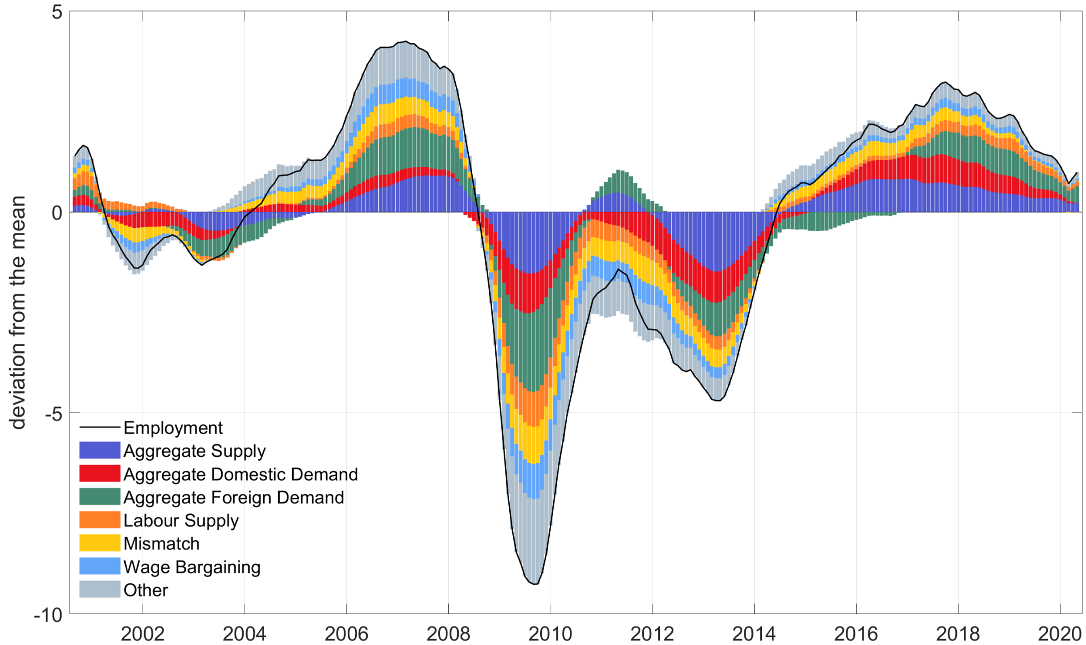


Figure 6: Historical decomposition of job finding rate (deviation from its mean)

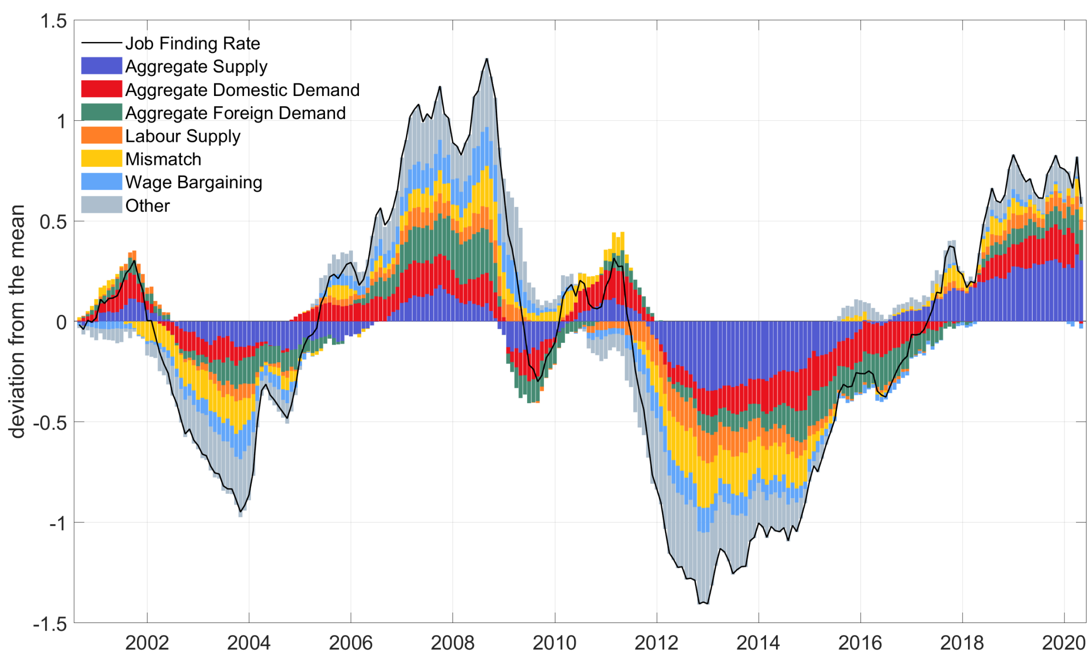
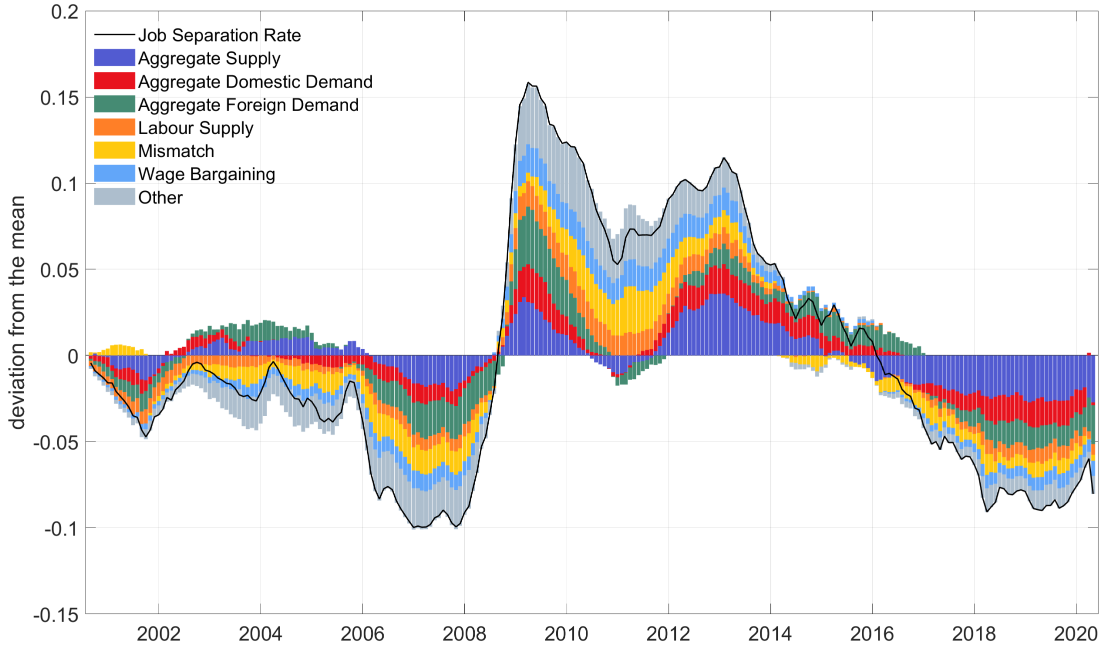


Figure 7: Historical decomposition of job separation rate (deviation from its mean)



A Appendix

A.1 Data description

Name	Description	Transformation	Frequency
u	Unemployment rate (as a % of labour force)	Levels	M
IP	Industrial production for the euro area	Δln(IP)	M
HICP	HICP - Overall index	Δln(HICP)	M
PMIm	Purchasing Managers' Index: Manufacturing	Δln(PMIm)	M
PMIs	Purchasing Managers' Index: Services	Δln(PMIs)	M
r	Euro area 1-year Government Benchmark bond yield - Yield	Levels	M
slope	Slope of the yield curve $r_{t,10Y} - r_{t,2Y}$	Levels	M
w	Compensation per employee	Δ ln(w)	Q
e	Employment (in thousands of persons)	ln(e)	Q
f	Job finding rate	Levels	Q
s	Job separation rate	Levels	Q

A.2 Forecast results for non-labour market variables

Table 7: Forecast evaluation: Industrial Production (growth rate)

	Benchmark			No Flows		
Horizon	Beginning	Middle	End	Beginning	Middle	End
-2	**1.04**	**1.11**	**1.13****	1.06	1.14	1.18**
-1	1.13	1.04	**1.02**	**1.12**	**1.01**	1.04
0	**1.09**	**1.02**	**1.23**	1.12	1.04	1.29**
+1	**1.07**	**1.20****	1.14**	1.15	1.32***	**1.13****
+2	**1.47****	**1.00**	1.05	1.65***	1.14	**1.04**
+3	**1.23****	**1.09**	**1.24**	1.30***	1.24**	1.36*
+4	**1.17**	**1.29*****	**1.10**	1.38***	1.38**	1.14
+5	**1.38***	**1.13***	**1.11**	1.49***	1.17	1.16***
+6	**1.19*****	**1.19**	**1.36**	1.37*	1.26***	1.53*
+7	**1.19**	**1.20**	**1.15**	1.45***	1.46	1.37**
+8	**1.34****	**1.00**	1.07	1.40***	1.21	**1.04**
+9	**1.28***	**1.10**	**1.36**	1.35	1.36***	1.53
+10	**1.10**	**1.30****	**1.29****	1.22	1.78**	1.37*
+11	**1.25**	**1.07**	**1.10***	1.66***	1.37*	1.27**
+12	**1.30*****	**1.11**	**1.07**	1.63***	1.49**	1.41

Note: The numbers in the table report the root mean square forecast error (RMSFE) relative to an AR(p) model where the optimal number of lags was selected through the BIC criterion. The bold number represent the best model between the benchmark and the model with no flows. We test the corresponding MFBVAR against the AR(p) model through a HLN test, the significance is presented as follows: 1% (***), 5% (**) and 10% (*).

Table 8: Forecast evaluation: Inflation (m-o-m rate)

	Benchmark			No Flows		
Horizon	Beginning	Middle	End	Beginning	Middle	End
-1	1.07	1.10*	0.97	**1.06**	**1.08**	**0.95**
0	1.04	1.07***	1.04	**1.00**	**1.04** **	**1.00**
+1	1.08	**1.05**	0.98	**1.01**	1.05*	**0.94**
+2	**1.03**	**0.92**	**1.06**	1.03	1.11**	1.11
+3	1.07	1.09*	**1.03**	**1.01**	**0.97**	1.11
+4	1.01	1.04	1.01	**0.95**	**1.00**	**0.98**
+5	**1.02**	**0.99**	**1.11****	1.11	1.11	1.20
+6	1.10*	**1.00**	**1.02**	**0.98**	1.04	1.15**
+7	**1.11****	**1.01**	**1.02**	1.17**	1.12	1.14***
+8	1.16*	**0.98**	**1.07**	**1.09**	1.19	1.21
+9	1.13	**1.10****	**1.16***	**1.07**	1.14*	1.16
+10	1.12	**1.07**	**1.12***	**1.09**	1.18	1.15
+11	**1.03**	**1.07**	1.07	1.21	1.23***	**0.99**
+12	1.12	**1.00**	**1.11***	**0.93**	1.10*	1.23

Note: The numbers in the table report the root mean square forecast error (RMSFE) relative to an AR(p) model where the optimal number of lags was selected through the BIC criterion. The bold number represent the best model between the benchmark and the model with no flows. We test the corresponding MFBVAR against the AR(p) model through a HLN test, the significance is presented as follows: 1% (***), 5% (**) and 10% (*).

Table 9: Forecast evaluation: Industrial Production (all models)

	Benchmark			PMI			MP			Risk			No Flows		
	Beginning	Middle	End	Beginning	Middle	End	Beginning	Middle	End	Beginning	Middle	End	Beginning	Middle	End
	Benchmark			PMI			MP			Risk			No Flows		
	Beginning	Middle	End	Beginning	Middle	End	Beginning	Middle	End	Beginning	Middle	End	Beginning	Middle	End
-2	1.04***	1.11***	1.13***	1.03***	1.07***	1.08***	**1.01*****	**1.04*****	**1.08*****	1.04***	1.18***	1.09***	1.06***	1.14***	1.18***
-1	1.13	1.04	1.02*	1.09	0.99	1.05	**1.08**	**0.97**	**1.02**	1.27	1.03	1.03	1.12	1.01	1.04**
0	1.09	1.02	1.23	1.09	1.01	**1.19**	1.06	1.04	1.22	**1.06***	**0.98**	1.28	1.12	1.04	1.29
1	1.07	1.20	1.14	1.10	1.20	**1.02**	1.18	**1.17**	1.07	**0.98**	1.26	1.02**	1.15	1.32	1.13
2	1.47	1.00**	1.05**	1.46**	1.08*	1.11	1.54*	**0.92****	1.04	**1.45**	1.07***	1.10	1.65	1.14***	**1.04****
3	1.23**	1.09	1.24	1.24*	1.06	1.26	1.16***	1.07	**1.22**	**1.15*****	**0.99**	1.24*	1.30***	1.24	1.36
4	1.17**	1.29	1.10	1.16*	1.35	1.10	1.17	1.30	**1.03**	**1.13****	1.36	1.08***	1.38***	1.38**	1.14
5	**1.38**	1.13***	1.11	1.57	1.14***	1.20	1.46	1.06**	1.09	1.43	1.04***	**1.01***	1.49***	**1.17****	1.16
6	1.19*	1.19	1.36	1.22***	1.15*	**1.18**	1.20**	1.08	1.29**	**1.15*****	**1.06**	1.26	1.37***	1.26	1.53***
7	1.19***	1.20	1.15	1.18***	1.32	1.22	1.20	**1.11**	**1.07****	**1.09*****	1.39	1.12***	1.45*	1.46***	1.37*
8	**1.34**	**1.00**	1.07	1.44	1.05*	1.07**	1.46	1.19	1.06	1.37	1.24***	1.10**	1.40***	1.21	**1.04****
9	**1.28*****	1.10	1.36	1.55**	1.23	1.25	1.36***	1.12**	1.31	1.30***	**1.05*****	**1.17**	1.35***	1.36	1.53
10	**1.10*****	1.30	1.29	1.19***	1.30***	**1.15****	1.14***	**1.28**	1.18*	1.11***	1.28	1.17***	1.22	1.78***	1.37
11	**1.25**	**1.07*****	1.10**	1.36	1.24*	1.18	1.47	1.11	1.05	1.34	1.27*	**1.01***	1.66	1.37**	1.27*
12	1.30	1.11	**1.07****	1.43*	1.10**	1.35**	1.32**	1.09	1.30	**1.26****	**1.03*****	1.16	1.63***	1.49*	1.41**

Note: The numbers in the table report the root mean square forecast error (RMSFE) relative to an AR(p) model where the optimal number of lags was selected through the BIC criterion. The bold number represent the best model between the benchmark and the model with no flows. We test the corresponding MFBVAR against the AR(p) model through a HLN test, the significance is presented as follows: 1% (***), 5% (**) and 10% (*).

Table 10: Forecast evaluation: Inflation (m-o-m rate, all models)

	Benchmark			PMI			MP			Risk			No Flows		
	Beginning	Middle	End	Beginning	Middle	End	Beginning	Middle	End	Beginning	Middle	End	Beginning	Middle	End
-1	1.07***	1.10***	0.97***	1.06***	1.11***	0.98***	1.10***	**1.05*****	0.96***	1.09***	1.07***	0.98***	**1.06*****	1.08***	**0.95*****
0	1.04	1.07 **	1.04	1.03	1.08**	1.05	1.03*	1.05	1.04	1.01*	1.07	1.06	**1.00**	**1.04***	**1.00**
1	1.08	1.05***	0.98	1.07	**1.01*****	0.99	1.09	1.05***	0.98	1.13	1.03**	0.99	**1.01**	1.05**	**0.94**
2	1.03	**0.92**	**1.06**	**1.01**	0.94	1.09	1.02*	0.99	1.16	1.03**	0.94	1.23	1.03	1.11	1.11
3	1.07	1.09	1.03	1.01	1.06	1.10**	0.98	1.11	**1.00*****	**0.97**	1.18	1.10***	1.01	**0.97****	1.11
4	1.01	1.04*	1.01	0.96	1.07	1.06	0.96	1.10*	1.03	1.05	1.14***	1.06	**0.95**	**1.00**	**0.98**
5	1.02	**0.99**	1.11	**0.93**	1.04	1.14	1.00	1.05	**1.06**	1.01	1.10*	1.19	1.11	1.11	1.20
6	1.10	1.00	**1.02***	1.05	**0.96**	1.09***	0.99	1.09	1.07	1.04	1.06	1.03**	**0.98**	1.04	1.15
7	1.11*	1.01	**1.02**	1.10	1.05	1.12	**1.04**	1.09	1.09	1.09	1.10	1.13	1.17	1.12	1.14**
8	1.16**	0.98	1.07	1.08	**0.93**	1.08	1.08	1.08	**1.06**	**0.99**	1.02	1.11	1.09	1.19**	1.21***
9	1.13***	**1.10**	1.16	**0.98**	1.22	1.19	1.05	1.23	**1.12**	1.04	1.15	1.22	1.07	1.14	1.16
10	1.12	**1.07****	1.12*	1.03	1.16*	1.19	0.99	1.07***	**1.12**	**0.91**	1.08	1.19***	1.09	1.18*	1.15
11	1.03	**1.07**	1.07*	**1.03**	1.09	1.11*	1.07	1.10	1.11	1.06	1.15	1.21	1.21	1.23	**0.99**
12	1.12	1.00	**1.11**	1.02	1.10	1.16	1.05	0.99***	1.14	1.02	**0.96**	1.31**	**0.93**	1.10***	1.23

Note: The numbers in the table report the root mean square forecast error (RMSFE) relative to an AR(p) model where the optimal number of lags was selected through the BIC criterion. The bold number represent the best model between the benchmark and the model with no flows. We test the corresponding MFBVAR against the AR(p) model through a HLN test, the significance is presented as follows: 1% (***), 5% (**) and 10% (*).

A.3 Results from MDD-hyperparameters optimisation

Following Schorfheide and Song (2015), we select the hyperparameters over a grid. We consider the following grids:

$$\Lambda_1 = [0.010 \quad 1.12 \quad 2.23 \quad 3.34 \quad 4.45 \quad 5.56 \quad 6.67 \quad 7.78 \quad 8.89 \quad 10]$$
$$\Lambda_2 = [0.010 \quad 1.12 \quad 2.23 \quad 3.34 \quad 4.45 \quad 5.56 \quad 6.67 \quad 7.78 \quad 8.89 \quad 10]$$
$$\Lambda_3 = [0.1 \quad 0.977 \quad 1.855 \quad 2.73 \quad 3.61 \quad 4.48 \quad 5.36 \quad 6.24 \quad 7.12 \quad 8]$$

Table 11 shows the constellation of hyperparameters that yield the maximum MDD for each of the models considered.

Table 11: Optimal hyperparameters

Hyperparameters	Benchmark	+PMI	+MP	+Slope	No flows
λ_1	5.56	4.45	6.67	6.67	3.34
λ_2	5.56	5.56	5.56	5.56	2.23
λ_3	3.61	1.85	1.85	6.24	1.85

B Online Appendix

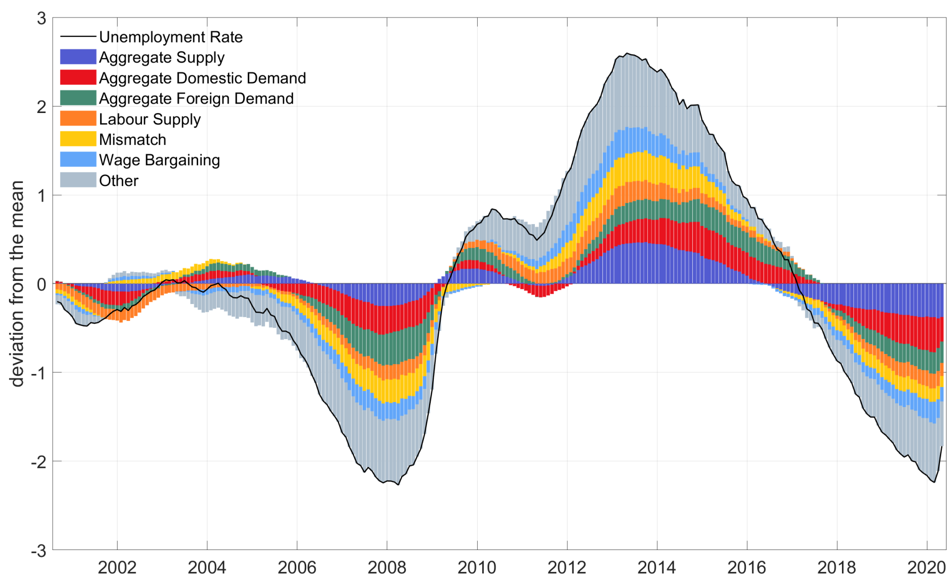
B.1 Results of benchmark model plus PMI

Table 12: Identification scheme via sign restrictions - including survey model

	Demand		Supply	Labour Market		
	Domestic	Foreign	Technology	Labour Supply	Mismatch	Wage Bargaining
u_t	-	-	-	-	-	-
Δip_t	+	+	+	-	+	+
Δp_t	+	+	-	+	///	-
Δw_t	///	///	+	+	+	-
Δe_t	///	///	///	///	///	///
ms_t	-	+	///	///	///	///
f_t	+	+	+	///	+	///
s_t	-	-	-	///	+	///
Δpmi_t	///	///	///	///	///	///

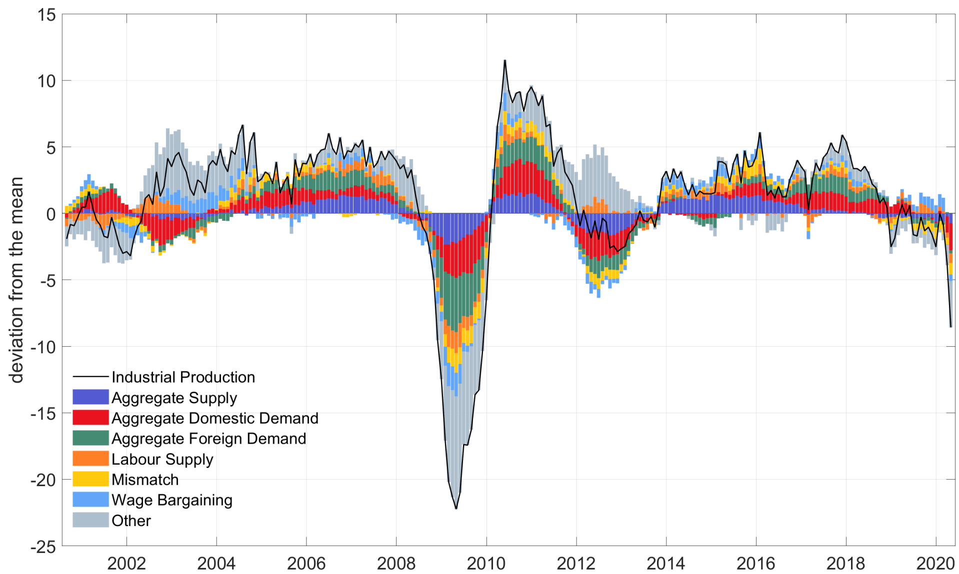
The sign + indicates a positive response of the variable on impact for that specified shock. The sign - indicates a negative response. The sign /// indicates no restrictions.

Figure 8: Historical decomposition of unemployment rate (deviation from its mean)



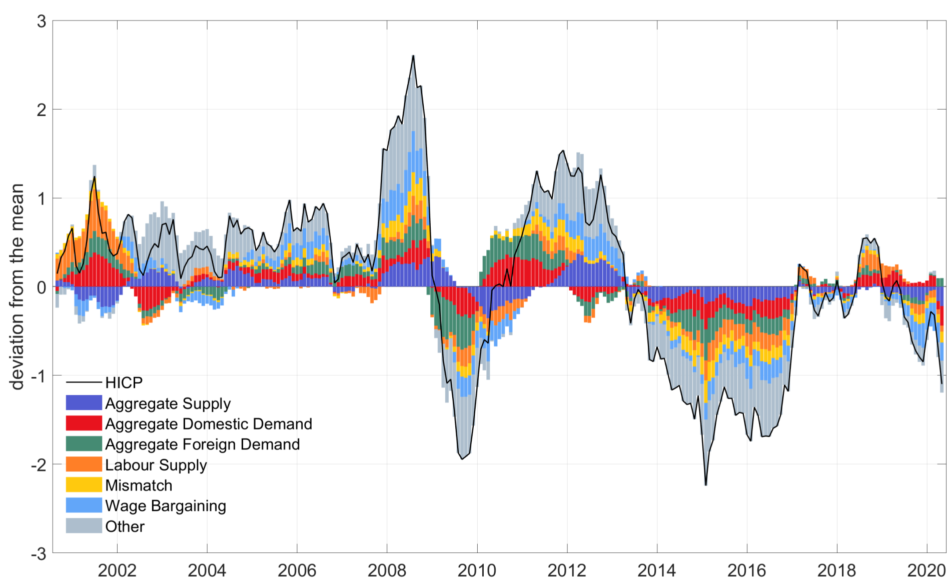
Note: This graph shows the mean of the posterior distribution of the historical decomposition. This model includes PMI-employment in the specification of the MFBVAR.

Figure 9: Historical decomposition of Industrial Production (y-o-y rate, deviation from its mean)



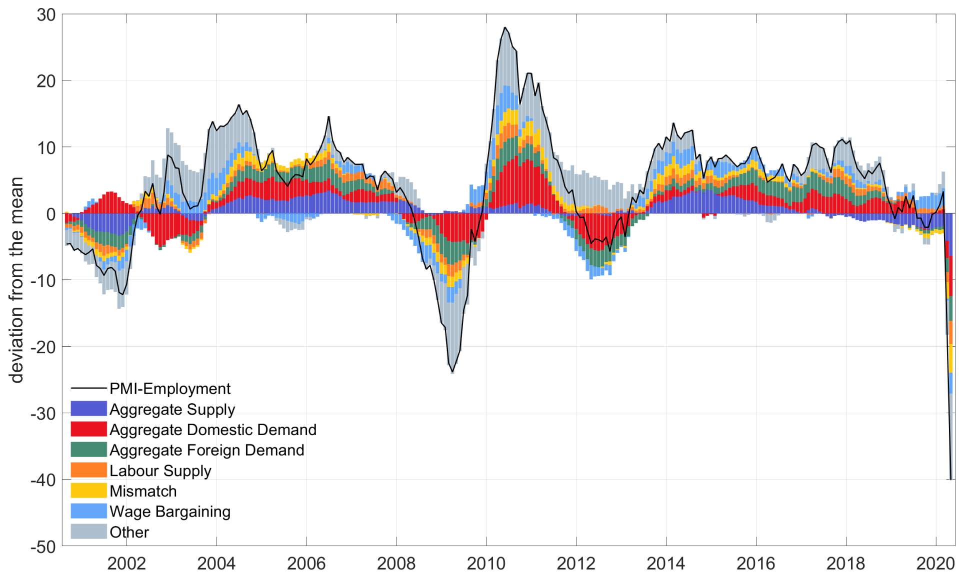
Note: See Fig. 8.

Figure 10: Historical decomposition of Inflation (y-o-y rate, deviation from its mean)



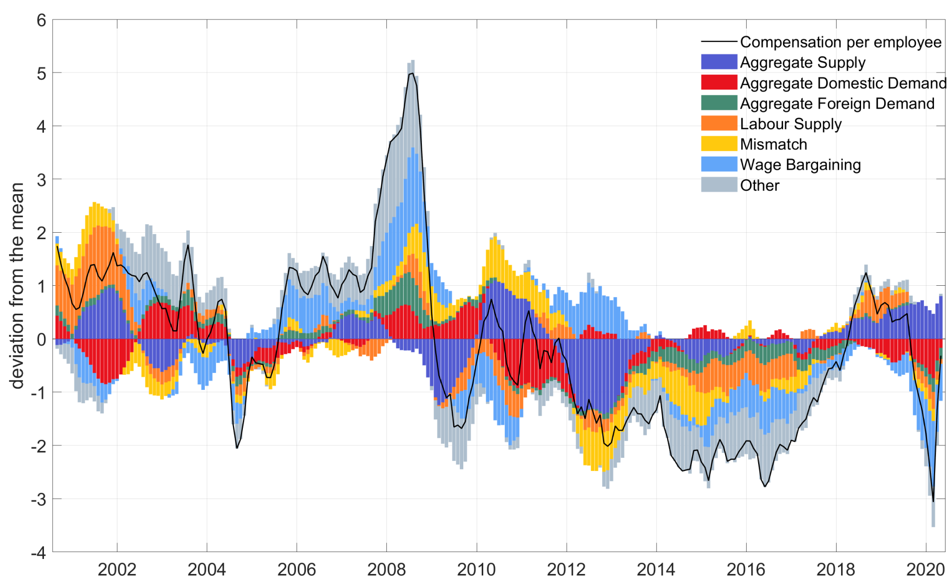
Note: See Fig. 8.

Figure 11: Historical decomposition of PMI-employment (y-o-y rate, deviation from its mean)



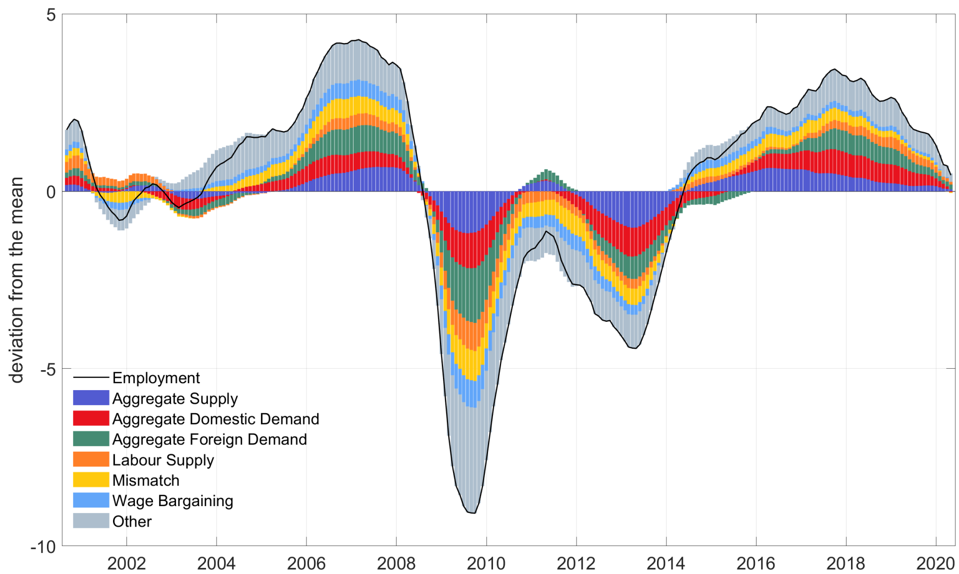
Note: See Fig. 8.

Figure 12: Historical decomposition of Compensation per employee (y-o-y rate, deviation from its mean)



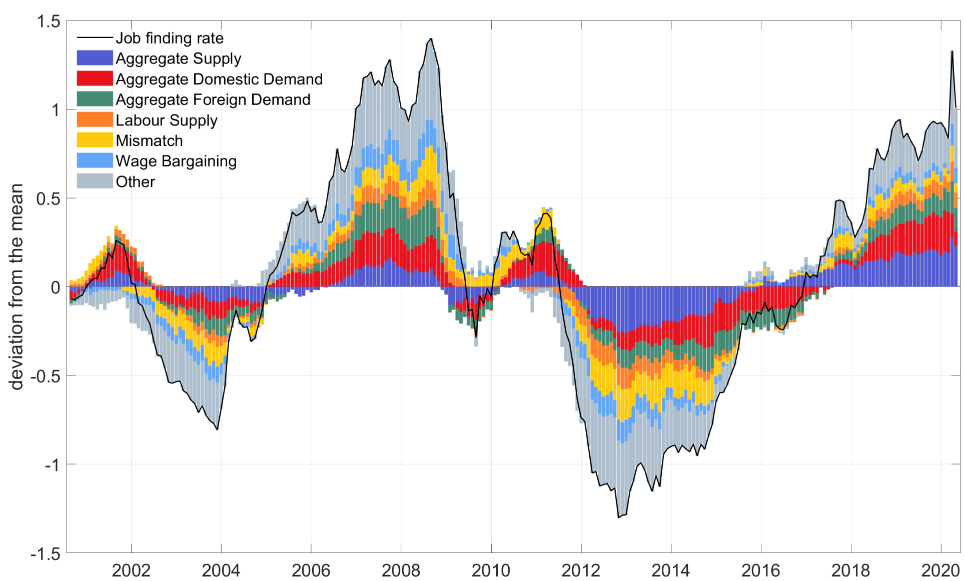
Note: See Fig. 8.

Figure 13: Historical decomposition of Employment (y-o-y rate, deviation from its mean)



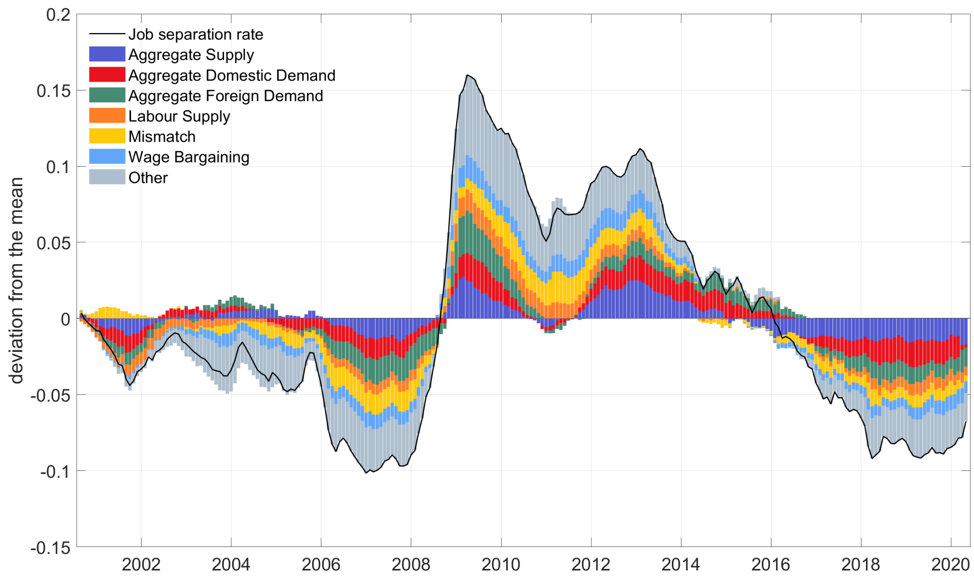
Note: See Fig. 8.

Figure 14: Historical decomposition of Job Finding Rate (y-o-y rate, deviation from its mean)



Note: See Fig. 8.

Figure 15: Historical decomposition of Job Separation Rate (y-o-y rate, deviation from its mean)



Note: See Fig. 8.

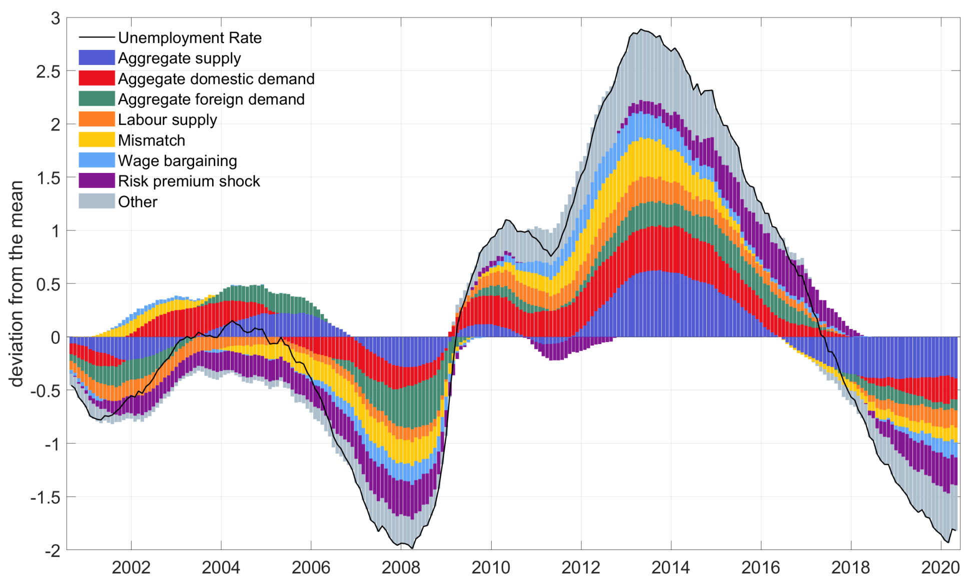
B.2 Results from the model with a monetary policy shock

Table 13: Identification scheme via sign restrictions - with Monetary and Fiscal Policies

	Demand			Supply	Labour Market		
	Fiscal Policy	Monetary Policy	Foreign	Technology	Labour Supply	Mismatch	Wage Bargaining
u_t	-	-	-	-	-	-	-
Δip_t	+	+	+	+	-	+	+
Δp_t	+	+	+	-	+	///	-
Δw_t	///	///	///	+	+	+	-
Δe_t	///	///	///	///	///	///	///
ms_t	-	-	+	///	///	///	///
f_t	+	+	+	+	///	+	///
s_t	-	-	-	-	///	+	///
r_t	+	-	///	///	///	///	///

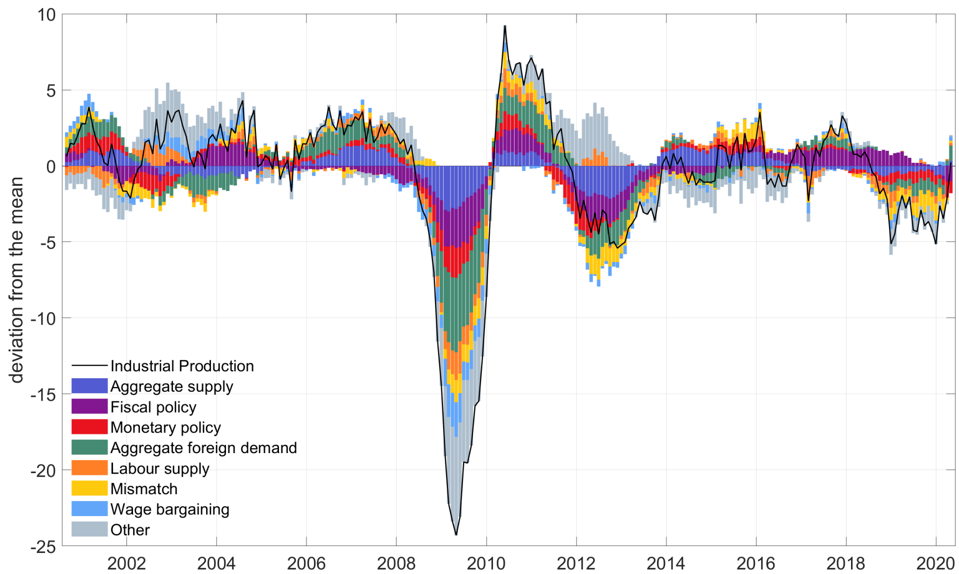
The sign + indicates a positive response of the variable on impact for that specified shock. The sign - indicates a negative response. The sign /// indicates no restrictions.

Figure 16: Historical decomposition of unemployment rate (deviation from its mean)



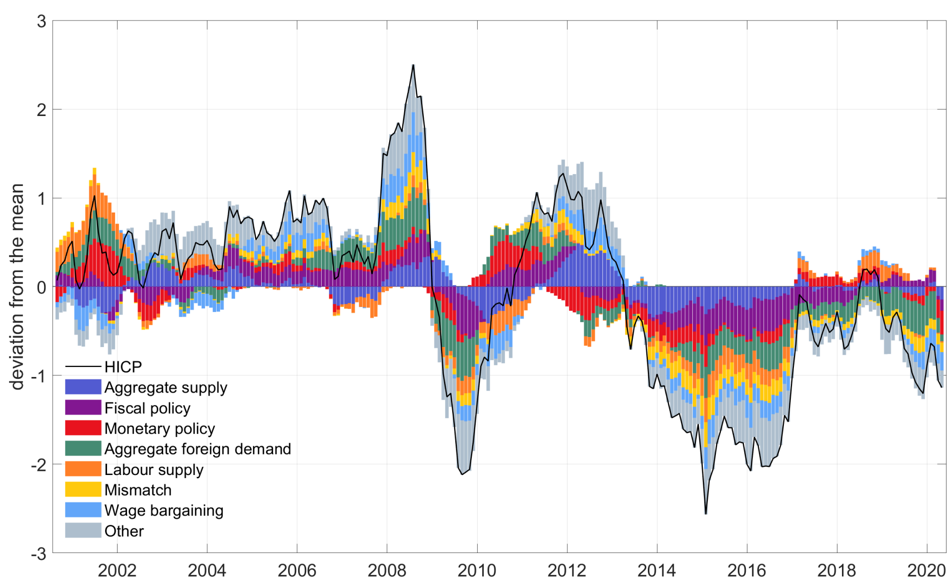
Note: This graph shows the mean of the posterior distribution of the historical decomposition. This model includes a monetary policy shock in the identification of the MFBVAR.

Figure 17: Historical decomposition of Industrial Production (y-o-y rate, deviation from its mean)



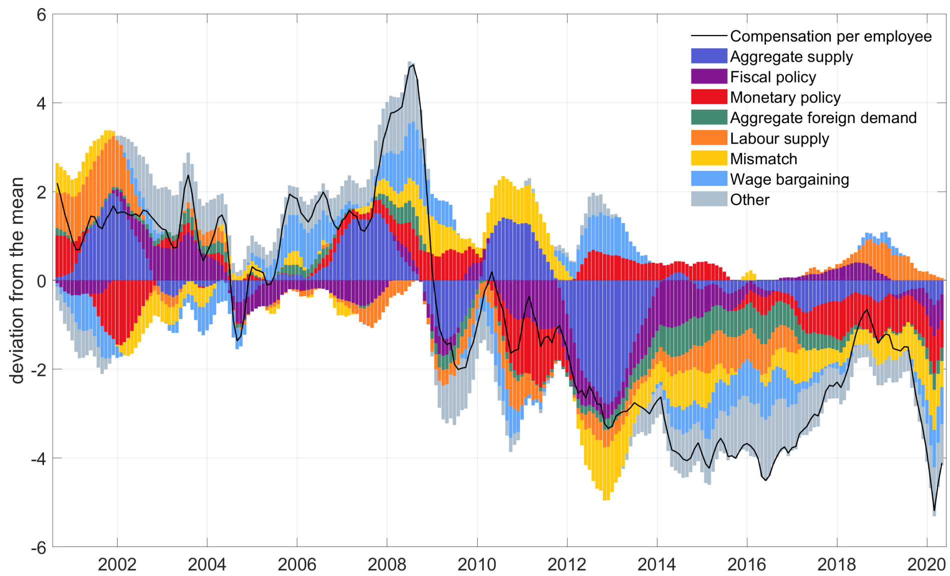
Note: See Fig. 16.

Figure 18: Historical decomposition of Inflation (y-o-y rate, deviation from its mean)



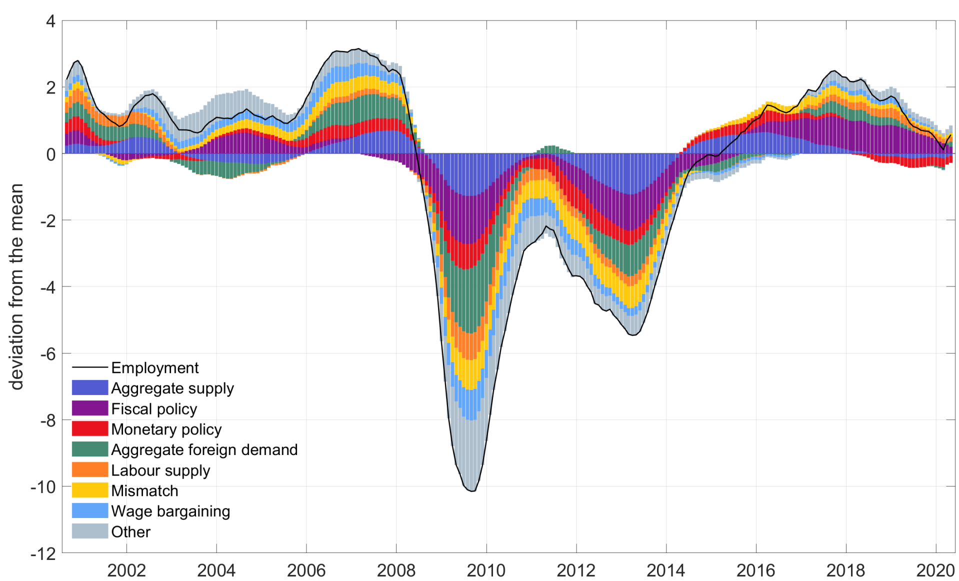
Note: See Fig. 16.

Figure 19: Historical decomposition of Compensation per employee (y-o-y rate, deviation from its mean)



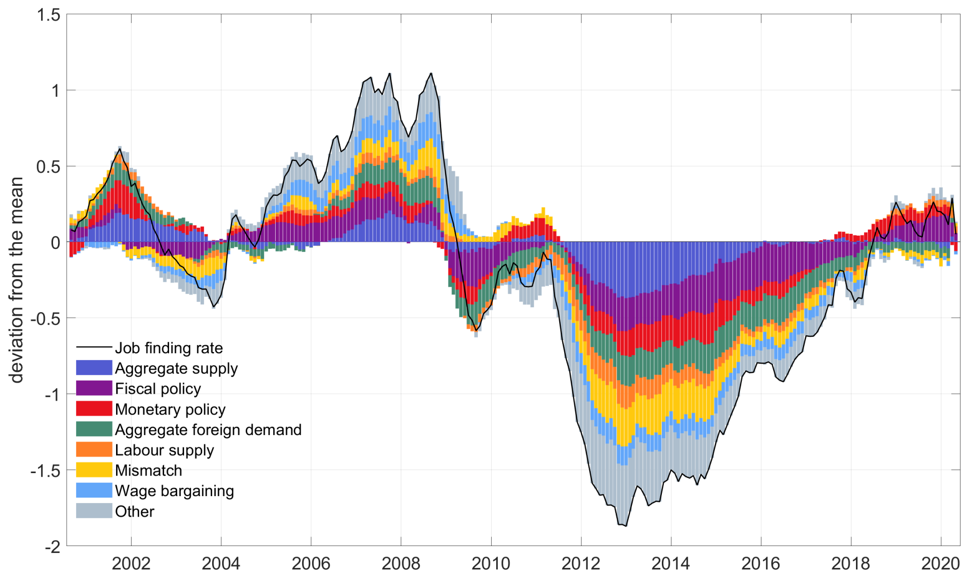
Note: See Fig. 16.

Figure 20: Historical decomposition of Employment (y-o-y rate, deviation from its mean)



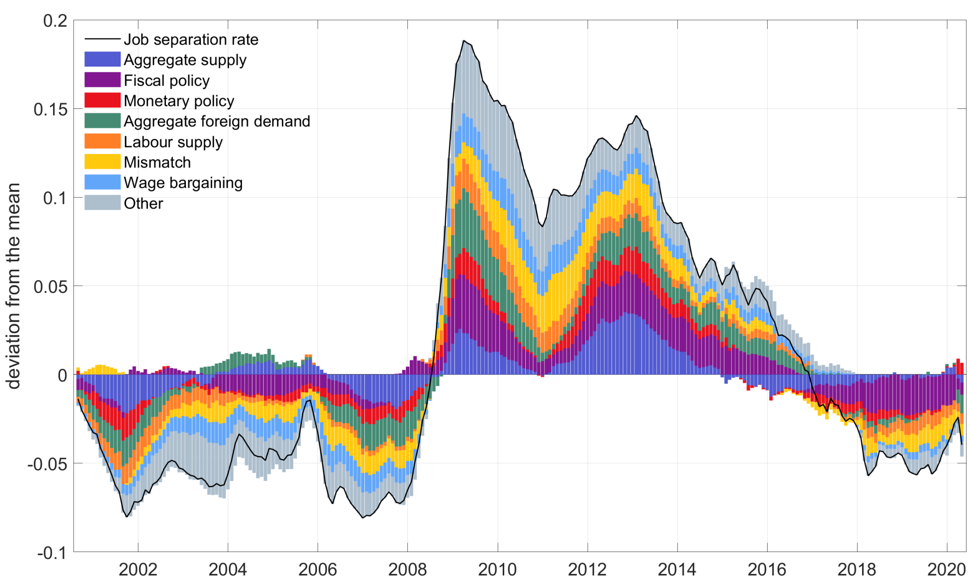
Note: See Fig. 16.

Figure 21: Historical decomposition of job finding rate (deviation from its mean)



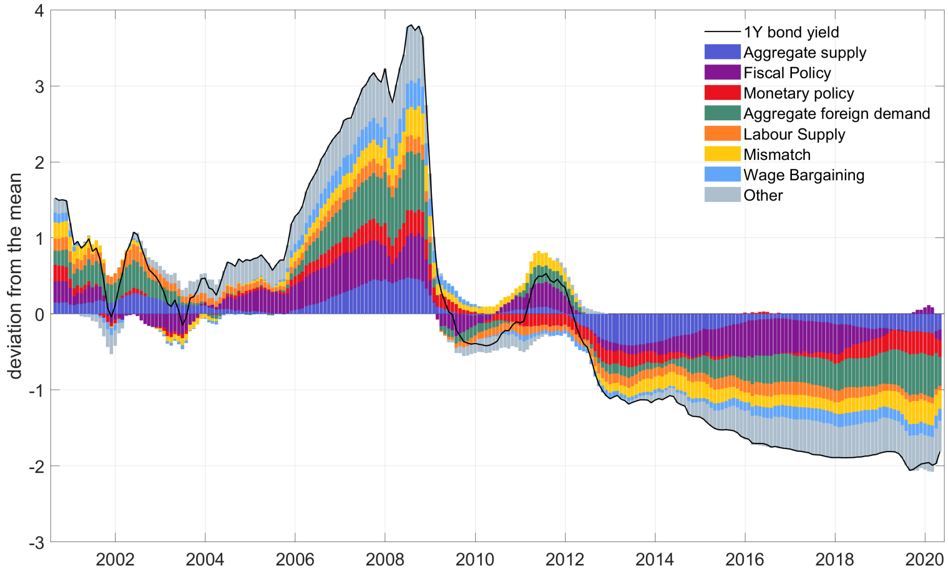
Note: See Fig. 16.

Figure 22: Historical decomposition of job separation rate (deviation from its mean)



Note: See Fig. 16.

Figure 23: Historical decomposition of the slope of the yield curve (deviation from its mean)



Note: See Fig. 16.

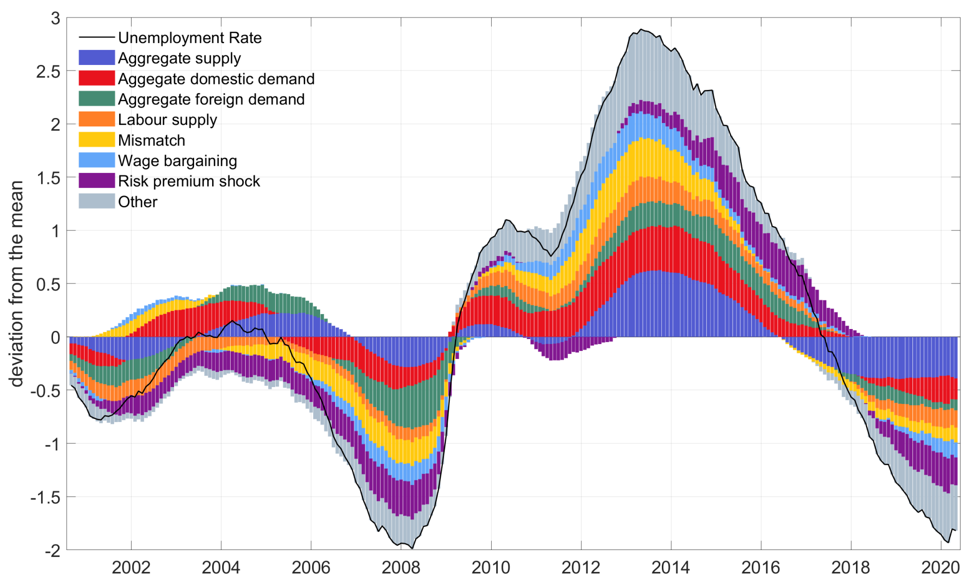
B.3 Results from a model with a risk premium shock

Table 14: Identification scheme via sign restrictions - with a Risk shock

	Demand			Supply	Labour Market		
	Domestic	Risk	Foreign	Technology	Labour Supply	Mismatch	Wage Bargaining
u_t	-	-	-	-	-	-	-
Δip_t	+	+	+	+	-	+	+
Δp_t	+	+	+	-	+	///	-
Δw_t	///	///	///	+	+	+	-
Δe_t	///	///	///	///	///	///	///
ms_t	-	-	+	///	///	///	///
f_t	+	+	+	+	///	+	///
s_t	-	-	-	-	///	+	///
$slope_t$	-	+	///	///	///	///	///

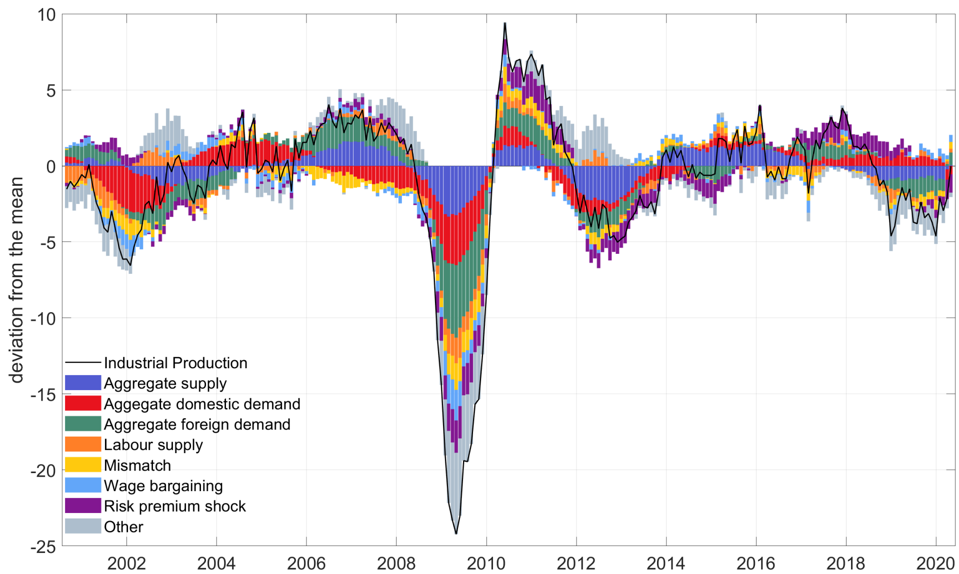
The sign + indicates a positive response of the variable on impact for that specified shock. The sign - indicates a negative response. The sign /// indicates no restrictions.

Figure 24: Historical decomposition of unemployment rate (deviation from its mean)



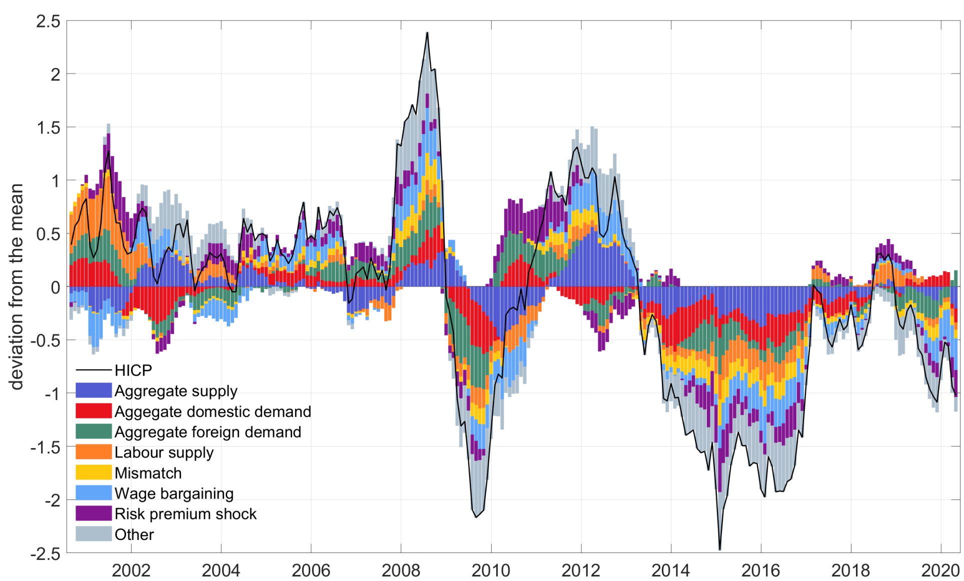
Note: this graph shows the mean of the posterior distribution of the historical decomposition. This model includes a risk premium shock in the identification of the MFBVAR.

Figure 25: Historical decomposition of Industrial Production (y-o-y rate, deviation from its mean)



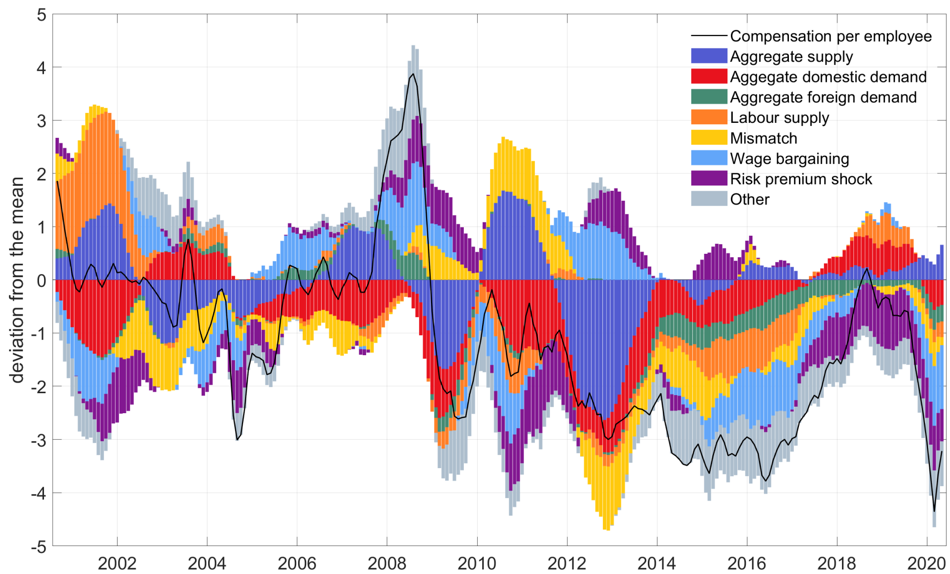
Note: See Fig. 24.

Figure 26: Historical decomposition of Inflation (y-o-y rate, deviation from its mean)



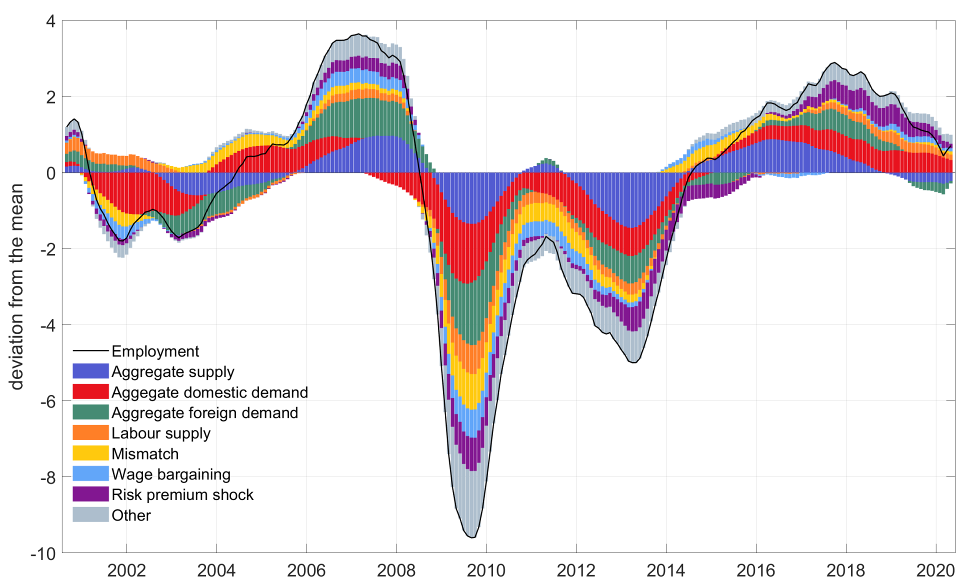
Note: See Fig. 24.

Figure 27: Historical decomposition of Compensation per employee (y-o-y rate, deviation from its mean)



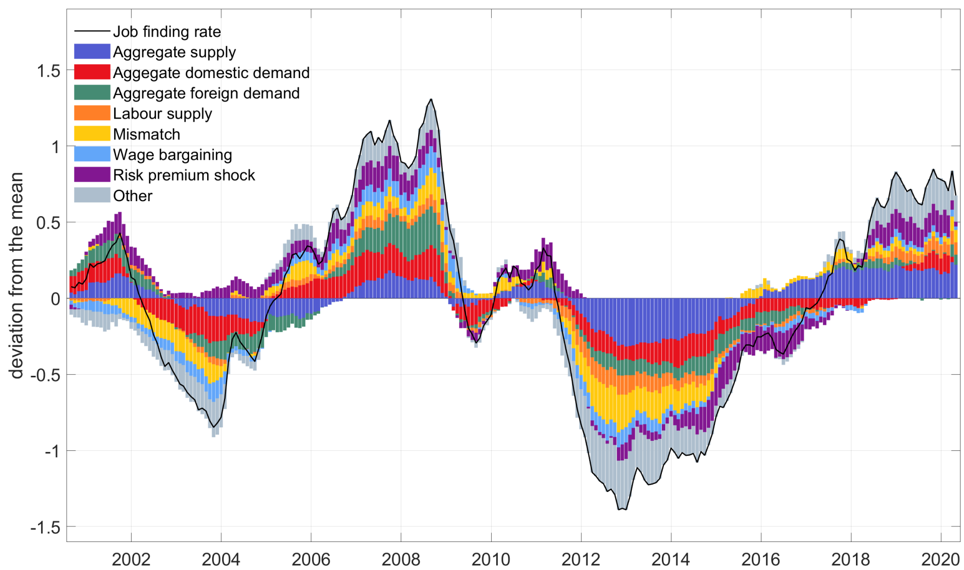
Note: See Fig. 24.

Figure 28: Historical decomposition of Employment (y-o-y rate, deviation from its mean)



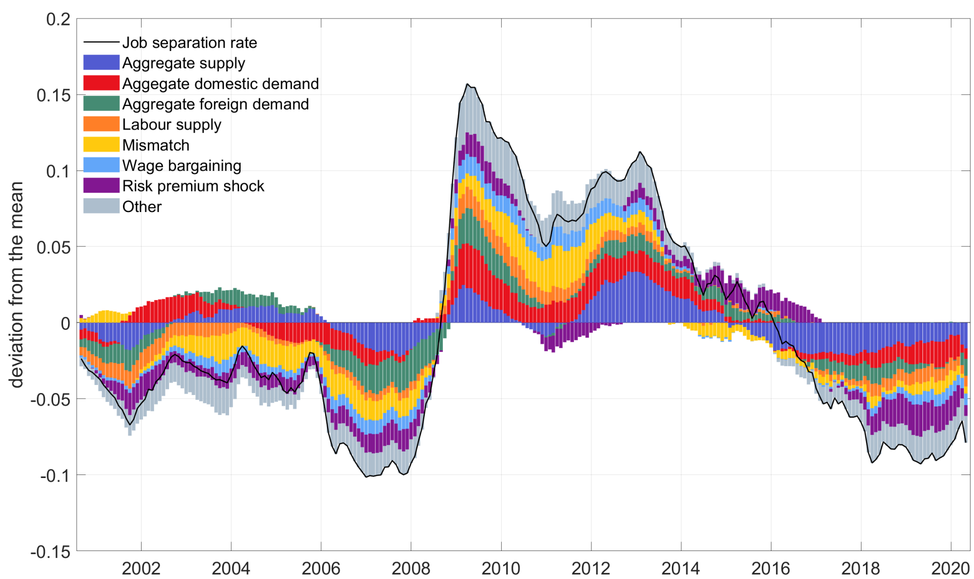
Note: See Fig. 24.

Figure 29: Historical decomposition of job finding rate (deviation from its mean)



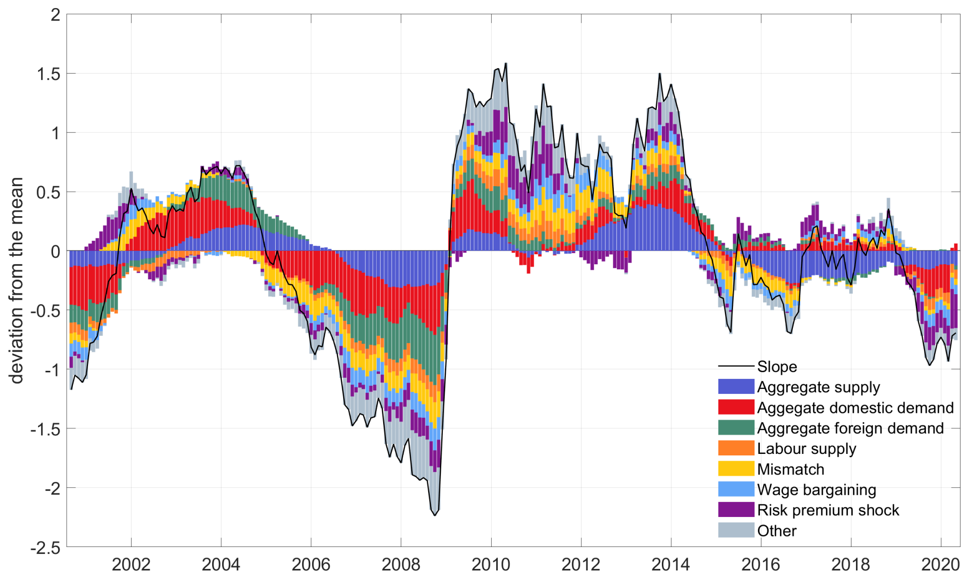
Note: See Fig. 24.

Figure 30: Historical decomposition of job separation rate (deviation from its mean)



Note: See Fig. 24.

Figure 31: Historical decomposition of the slope of the yield curve (deviation from its mean)



Note: See Fig. 24.

B.4 Forecasting results from alternative models

Table 15: Data flow within quarters

		Monthly variables							Quarterly variables			
		u_t	Δip_t	Δp_t	ms_t	PMI_t	r_t	$slope_t$	Δw_t	Δe_t	f_t	s_t
Beginning	Sep/Q3	x	x	x	x	x	x	x	x	x	x	x
	Oct	x	x	x	x	x	x	x	NaN	NaN	NaN	NaN
	Nov	x	NaN	x	x	x	x	x	NaN	NaN	NaN	NaN
	Dec/Q4	NaN	NaN	NaN	x	x	x	x	NaN	NaN	NaN	NaN
	Jan	NaN	NaN	NaN	NaN	NaN	x	x	NaN	NaN	NaN	NaN
Middle	Oct	x	x	x	x	x	x	x	x	x	x	x
	Nov	x	x	x	x	x	x	x	NaN	NaN	NaN	NaN
	Dec/Q4	x	NaN	x	x	x	x	x	NaN	NaN	NaN	NaN
	Jan	NaN	NaN	NaN	x	x	x	x	NaN	NaN	NaN	NaN
	Feb	NaN	NaN	NaN	NaN	NaN	x	x	NaN	NaN	NaN	NaN
End	Nov	x	x	x	x	x	x	x	x	x	x	x
	Dec/Q4	x	x	x	x	x	x	x	x	x	NaN	NaN
	Jan	x	NaN	x	x	x	x	x	NaN	NaN	NaN	NaN
	Feb	NaN	NaN	NaN	x	x	x	x	NaN	NaN	NaN	NaN
	Mar	NaN	NaN	NaN	NaN	NaN	x	x	NaN	NaN	NaN	NaN

We stack the RMSFE for all models in table 16 for labour market quarterly variables (including flows) and table 17 shows the results for the monthly variables.

Table 16: Forecast evaluation: Quarterly variables (all models)

Compensation per employee

	Benchmark			PMI			MP			Risk			No Flows		
	Beginning	Middle	End	Beginning	Middle	End	Beginning	Middle	End	Beginning	Middle	End	Beginning	Middle	End
Q(-1)	**0.63****	0.69*		0.64**	0.58**		0.74	0.83		0.81	0.91		0.73	**0.57****	
Q(0)	0.71**	0.69*	0.70	0.68*	0.66**	0.80	0.80	0.77	0.84	0.91	0.84	0.89	**0.63****	**0.61****	**0.65***
Q(+1)	0.80	0.75**	**0.75****	0.81	**0.71*****	0.78*	0.95	0.86	0.96	0.83	0.87	0.94	**0.79**	0.80**	0.76**
Q(+2)	**0.82***	1.09	0.92	0.86	**0.91**	0.99	0.97	1.08	0.92	0.87	1.22	1.06	0.85	0.97	**0.83**
Q(+3)	0.81	0.71*	0.97	0.75	**0.65****	0.91	0.95	0.88	0.88	0.79	0.75	1.01	**0.74**	0.85	**0.80***

Employment

	Benchmark			PMI			MP			Risk			No Flows		
	Beginning	Middle	End	Beginning	Middle	End	Beginning	Middle	End	Beginning	Middle	End	Beginning	Middle	End
Q(-1)	1.88***	1.45***		1.71***	1.39**		1.70***	1.37**		2.15***	1.68***		**1.64*****	**1.37****	
Q(0)	1.47**	1.28*	1.81***	1.45**	1.30*	1.70***	**1.33***	**1.16**	1.72***	1.71**	1.46***	2.14***	1.34*	1.23	**1.67*****
Q(+1)	0.85	1.03	1.57**	0.82	1.04	1.53 **	**0.79**	**0.92**	1.47 *	1.02	1.13	1.81**	1.13	1.02	**1.44***
Q(+2)	**0.73**	**0.75**	1.02	0.73	0.84	**0.91**	0.74	0.77	0.96	0.86	0.90	1.05	1.40	1.10	1.51*
Q(+3)	0.72	**0.74**	0.88	**0.69**	0.81	**0.84**	0.75	0.76	0.85	0.82	0.90	0.89	1.29	1.17	1.33

Job Finding Rate

	Benchmark			PMI			MP			Risk		
	Beginning	Middle	End	Beginning	Middle	End	Beginning	Middle	End	Beginning	Middle	End
Q(-1)	**1.36****	**1.34**	**0.83**	1.56***	1.38	0.91	1.58***	1.83	0.98	1.55**	1.98	0.96
Q(0)	**0.95**	**0.78**	**0.66****	1.05	0.84	0.71**	1.05	0.92	0.76*	1.07	0.92	0.76*
Q(+1)	0.98	0.85	**0.61*****	**0.96**	**0.75****	0.62***	1.16	0.78	0.67**	0.97	0.95	0.71**
Q(+2)	1.12	1.25	**0.82**	0.98	**0.89**	0.99	1.26	0.89	0.98	**0.98**	1.26	1.12
Q(+3)	1.14	1.21	**0.85**	0.98	0.93	0.96	1.20	**0.86**	0.97	**0.93**	1.24	1.01

Job Separation Rate

	Benchmark			PMI			MP			Risk		
	Beginning	Middle	End	Beginning	Middle	End	Beginning	Middle	End	Beginning	Middle	End
Q(-1)	**1.06**	**0.80**	0.82	1.20	0.87	**0.76**	1.24	0.88	0.89	1.23	0.92	0.99
Q(0)	**0.72**	**0.59****	0.61**	0.81	0.67*	**0.59****	0.82	0.64**	0.66*	0.86	0.62**	0.73
Q(+1)	0.75	0.52**	**0.53****	0.77	0.53**	0.53**	**0.63****	**0.43*****	0.57**	1.01	0.50**	0.64**
Q(+2)	0.89	0.90	**0.71**	0.87	0.76	0.79	**0.80**	**0.73**	0.90	1.13	0.80	0.83
Q(+3)	0.78	0.87	**0.67**	0.81	0.68	0.75	**0.73**	**0.68**	0.81	0.96	0.74	0.76

Note: The numbers in the table report the root mean square forecast error (RMSFE) relative to an AR(p) model where the optimal number of lags was selected through the BIC criterion. The bold number represent the best model between the benchmark and the model with no flows. We test the corresponding MFBVAR against the AR(p) model through a HLN test, the significance is presented as follows: 1% (***), 5% (**) and 10% (*).

Table 17: Forecast evaluation: Unemployment rate (all models)

	Benchmark			PMI			MP			Risk			No Flows		
	Beginning	Middle	End	Beginning	Middle	End	Beginning	Middle	End	Beginning	Middle	End	Beginning	Middle	End
-1	1.60***	1.81***	2.03***	1.55***	1.77***	1.93***	**1.36*****	**1.67*****	**1.92*****	1.84***	1.84***	2.04***	1.55***	1.76***	2.02***
0	1.57*	2.04***	1.44***	1.54*	2.03***	1.39***	**1.34*****	**1.85*****	**1.30*****	1.76***	2.04***	1.46***	1.50*	1.94***	1.39***
1	1.93*	2.66***	**1.65*****	2.18***	2.64***	1.82***	**1.88**	**2.33*****	1.68	1.94**	2.84***	2.11**	2.12**	2.97***	1.83***
2	1.92***	2.21***	**1.64*****	2.19***	2.24***	1.71***	**1.83*****	**1.91*****	1.69**	1.76***	2.33***	1.94***	2.13***	2.44***	1.78***
3	1.76***	2.07***	**1.53*****	1.92***	2.03***	1.58***	1.74***	**1.75*****	1.55***	**1.62*****	2.01***	1.75***	1.74***	2.09***	1.72***
4	1.64***	1.98***	**1.48*****	1.74***	1.90***	1.58***	1.65***	**1.76*****	1.51***	**1.59*****	1.89***	1.67***	1.65***	2.01***	1.62***
5	1.57***	1.85***	**1.38*****	1.63***	1.79***	1.46***	1.56***	**1.72*****	1.43***	**1.52*****	1.81***	1.56***	1.63***	1.88***	1.55***
6	1.47***	1.77***	1.39*	1.53***	1.65***	**1.37*****	**1.46*****	**1.58*****	1.40**	1.48***	1.71***	1.54***	1.50***	1.71***	1.48***
7	**1.37*****	1.59***	1.32*	1.41**	1.52***	**1.29****	1.38**	**1.46****	1.31***	1.41**	1.57***	1.42***	1.44***	1.61***	1.36*
8	1.33*	1.46**	1.26	1.34	1.42**	**1.23***	**1.28***	**1.37***	1.28*	1.29**	1.47*	1.34*	1.35**	1.54***	1.28
9	1.27	1.40**	1.21	1.30	1.35	**1.17**	**1.22**	**1.32**	1.24	1.29	1.43	1.26	1.30	1.43***	1.19
10	1.22	1.31	1.16	1.24	1.28	**1.12**	**1.14**	**1.25**	1.20	1.24	1.35	1.20	1.21	1.34***	1.16
11	1.15	1.23	1.13	1.18	1.22	**1.08**	**1.09**	**1.20**	1.17	1.20	1.29	1.18	1.15	1.34	1.11
12	1.09	1.20	1.09	1.16	1.18	1.05	**1.08**	**1.16**	1.12	1.18	1.22	1.13	1.16	1.27	**1.04**

Note: The numbers in the table report the root mean square forecast error (RMSFE) relative to an AR(p) model where the optimal number of lags was selected through the BIC criterion. The bold number represent the best model between the benchmark and the model with no flows. We test the corresponding MFBVAR against the AR(p) model through a HLN test, the significance is presented as follows: 1% (***), 5% (**) and 10% (*).