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DSGE Models and Machine Learning: An Application to Monetary Policy in the Euro Area*

By Daniel Stempel† and Johannes Zahner‡

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In the euro area, monetary policy is conducted by a single central bank for 19 member countries. However, countries are heterogeneous in their economic development, including their inflation rates. This paper combines a New Keynesian model and a neural network to assess whether the European Central Bank (ECB) conducted monetary policy between 2002 and 2022 according to the weighted average of the inflation rates within the European Monetary Union (EMU) or reacted more strongly to the inflation rate developments of certain EMU countries. The New Keynesian model first generates data which is used to train and evaluate several machine learning algorithms. We find that a neural network performs best out-of-sample. Thus, we use this algorithm to classify historical EMU data. Our findings suggest disproportional emphasis on the inflation rates experienced by southern EMU members for the vast majority of the time frame considered (80%). We argue that this result stems from a tendency of the ECB to react more strongly to countries whose inflation rates exhibit greater deviations from their long-term trend.

JEL: C45, C53, E58,
Keywords: New Keynesian Models, Monetary Policy, European Monetary Union, Neural Networks, Transfer Learning

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I. Introduction

In the European Monetary Union (EMU), monetary policy is conducted by a single central bank for its 19 member countries. The European Central Bank (ECB) aims to stabilize the union-wide price level. This setup harbors an obvious potential issue when countries are heterogeneous in their economic development, including the development of their inflation rates. In particular, we show the presence of a somewhat north-south divide between EMU members: northern countries exhibit below-average inflation rate volatility and southern countries display above-average volatility.

This naturally raises the question of whether the ECB conducts monetary policy in accordance with the weighted average of the inflation rates[1] within the EMU or reacts more strongly to potential deflationary or inflationary pressure in some member states. Since latent variables, such as the ECB's inflation weight, cannot be directly observed and may be subject to frequent changes, conventional empirical methods may fall short in its identification. To circumvent these issues, we simulate a New Keynesian model of a monetary union to generate a synthetic data set in which we control for variation in the latent variable. We then combine the New Keynesian model and a neural network to assess the ECB's historical inflation weight on southern and northern countries over the last two decades. We find that the ECB reacted disproportionally to the inflation rates experienced by southern EMU members (80% of periods).

Our analysis consists of four parts. First, we establish that inflation rate developments structurally differ between EMU countries. Second, we build a two-country New Keynesian model of a monetary union that replicates first and second moments of main macroeconomic variables in northern and southern EMU countries. In the model, the central bank is assumed to react to the union-wide inflation rate or more strongly to the inflation rate experienced by either the northern or the southern country respectively. By simulating a series of demand and supply shocks, we generate a data set of ten macroeconomic variables for each of the three monetary policy regimes. Third, we use this data set to train and evaluate a multitude of machine learning models. We find that a neural network performs best, accurately categorizing over 97% of the simulated data in an out-of-sample exercise. Fourth, using the trained neural network, we classify a historical EMU data set of the same ten variables between 2002 and 2022. The machine learning algorithm classifies 80% of the last two decades as periods during which the ECB reacted more strongly to the inflation rates of southern countries. We argue that this result might stem from a tendency of the ECB to react more vigorously to the countries whose inflation rates deviate more strongly from their long-term

[1] Specifically, the European Central Bank (2022) states that "the Harmonised Index of Consumer Prices (HICP) is used to measure consumer price inflation", which is "compiled by Eurostat". Eurostat (2022) calculates the European HICP "as the weighted average of the national HICPs, using the weights of the countries [...] concerned. The weight of a country is based on the share of the HFMCE [household final consumption expenditure that occurs in monetary transactions] in the total."

trend.

Our paper contributes to the literature in the following ways. The approach relates to the trade-off between the degree of theoretical coherence and empirical validity that central bankers face during the model selection process. Pagan (2003) proposes an illustration of this trade-off, known as the Pagan Frontier, in which Dynamic Stochastic General Equilibrium (DSGE) and vector autoregression (VAR) models are the corresponding specializations. Recently, Genberg and Karagedikli (2021) suggested an extension of the Pagan Frontier in conjunction with the growing trend of machine learning in macroeconomics and monetary policy (e.g., Chakraborty and Joseph, 2017; Athey, 2019; Tiffin, 2019; Hinterlang, 2020; Baumgärtner and Zahner, 2021; Doerr et al., 2021; Paranhos, 2021; Fouliard et al., 2021), where the black box algorithms are (at least) equivalent in terms of empirical coherence. Figure 1 is an illustration of this adjusted Pagan Frontier. The authors then pose the question of how machine learning *"can move towards the middle, and what modifications need to be introduced to enable them to do so"* (Genberg and Karagedikli, 2021, p. 4). In this paper, we propose such a modification by *combining* DSGE and machine learning models to study inflation dynamics in the EMU.

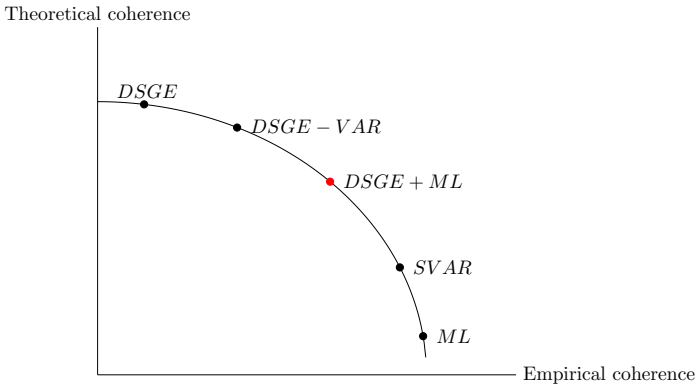

Figure 1 : The Pagan Frontier.

Notes: The illustration closely resembles Pagan's (2003) original frontier but was extended by Genberg and Karagedikli (2021) to take machine learning into account.

To the best of our knowledge, Hinterlang and Hollmayr (2020) are the only ones to use an approach similar to ours. They generate a time series from a DSGE model to identify monetary and fiscal dominance regimes in the United States. Their approach differs primarily in terms of the applied machine learning models. The authors focus on tree-based models, with the best performing model (AdaBoost) achieving 95% accuracy on a binary classification task with many input variables. We extend this approach by employing neural networks, which appear to outperform tree-based models (at least in our case). We demonstrate

that another advantage of neural networks appears to be their performance in environments with a limited number of variables, extending application of such classification tasks to the utilization of simple theoretical models.
Lastly, we add to the literature on the assessment of inflation differentials within New Keynesian models (such as Canzoneri et al., 2006; Angeloni and Ehrmann, 2007; Andrés et al., 2008; Duarte and Wolman, 2008; Rabanal, 2009; Neyer and Stempel, 2022).
The remainder of this paper is structured as follows. In Section II, we explain the motivation behind our research question and provide preliminary descriptive evidence. Section III introduces the DSGE model used for the data-generating process, before Section IV assesses first and second moments of the simulation. Section V introduces and evaluates the machine learning classifiers, which are subsequently applied to historical EMU data in Section VI. Section VII concludes this paper.

II. Inflation Development in the Euro Area

Figure 2 illustrates the inflation rate development of selected EMU countries between 2002 and 2022. It suggests that EMU members structurally differ in the volatility of their inflation rates over the last two decades. The inflation rates of countries like Greece (EL), Ireland (IE), Italy (IT), Portugal (PT), and Spain (ES) display higher volatility (~ 1.52 on average, shown in panel a) than the average inflation rate of all EMU members (~ 1.26). In particular, they (on average) deviate negatively from the EMU-wide inflation rate in times of low inflation (i.e., when the EMU-wide inflation rate is below the 2% target) and vice versa (panel b).[2]
Conversely, the inflation rates of Austria (AT), Germany (DE), and the Netherlands (NL) display lower volatility (~ 0.88 on average) than the EMU-wide rate. This implies that, on average, their inflation rates deviate positively from the EMU-wide rate in times of low inflation and vice versa (panel b).
More generally, the evidence presented displays somewhat of a north-south divide. Inflation rates fluctuate more in southern countries than in northern countries. This difference is significant at the 5% level. For simplicity, we refer in the following to EMU members that exhibit high inflation volatility as southern countries, while referring to EMU countries with low inflation volatility as northern countries. This descriptive evidence naturally raises the question whether the ECB conducts monetary policy in accordance with the weighted average of the inflation rates within the EMU (see Footnote 1) or reacts more strongly to potential deflationary/inflationary pressure in some EMU member states.

[2]While the focus of our work is on inflation differentials across countries, we recognize the possibility of heterogeneous inflation developments within countries. However, a recent ECB working paper by Consolo et al. (2021) suggests that inflation variation across countries in the EMU is more substantial than inflation variation within countries. We therefore focus on the former.

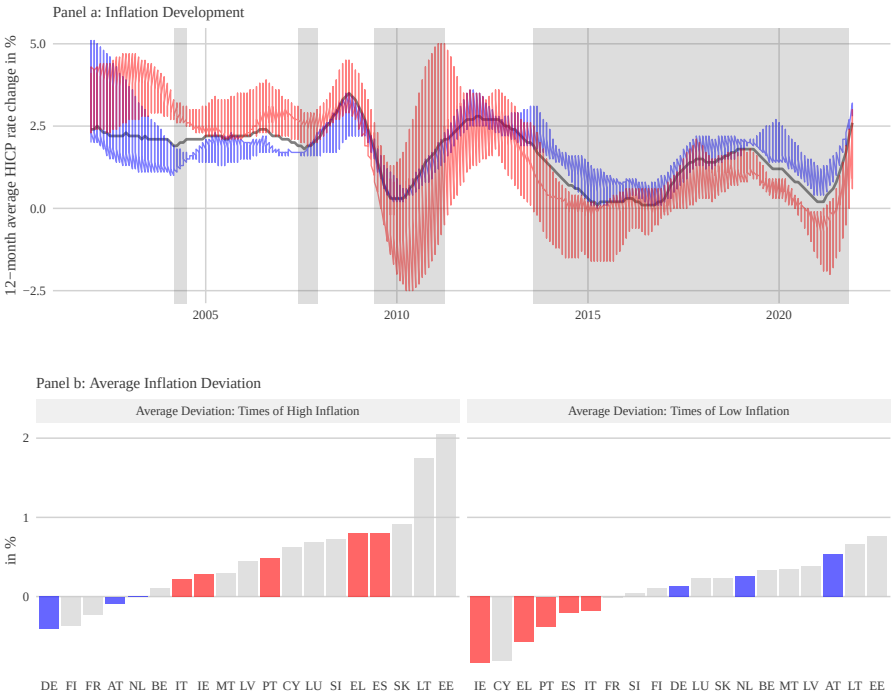

Figure 2 : Inflation Rate Developments and Average Inflation Deviations.

Notes: Panel a: Moving 12-month average inflation rate development of selected high-volatility (red) and low-volatility (blue) countries. Grey-shaded areas indicate periods in which the EMU-wide inflation rate was below 2%. Panel b: Average deviation of the inflation rate of EMU members in periods where the EMU-wide inflation rate was below 2% and where the EMU-wide inflation rate was above 2%. BE: Belgium, CY: Cyprus, EE: Estonia, FI: Finland, FR: France, LV: Latvia, LT: Lithuania, LU: Luxembourg, MT: Malta, SK: Slovakia, SI: Slovenia. Own calculation, based on years in which countries were members of the EMU. Data source: Eurostat.

III. Model

This section presents the model that generates the synthetic data set used to train and evaluate the machine learning mechanisms described in Section V. The model consists of two countries, $k = N, S$, with $-k$ being the respective other country, in a monetary union. Each country consists of a household and a firm sector. Monetary policy is conducted on the union level.

A. Households

The utility function of a representative household in country k (household k, for simplicity) is given by

$$U_t^k = Z_t^k log\left(C_t^k - \Psi_k C_{t-1}^k\right) - \frac{\left(L_t^k\right)^{1+\varphi_k}}{1+\varphi_k}, \tag{1}$$

with Z_t^k being defined as an AR(1) preference shock, Ψ_k as a habit parameter, L_t^k as labor, φ_k as the inverse Frisch elasticity of labor supply, and C_t^k as a constant elasticity of substitution (CES) index of consumption. Preferences change individually by country:

$$ln\left(Z_t^k\right) = \rho_Z ln\left(Z_{t-1}^k\right) + \eta_Z^k \epsilon_{Z,t},$$

where ρ_Z denotes the persistence, η_Z^k is a scaling parameter that determines the strength of the shock, and $\epsilon_{Z,t} \sim \mathcal{N}\left(0, \sigma_Z^2\right)$ is a normally distributed shock with mean 0 and variance σ_Z^2. The CES consumption index is given by:

$$C_t^k \equiv \left(\gamma_k^{\frac{1}{\vartheta_C^k}} \left(C_{k,t}^k\right)^{\frac{\vartheta_C^k - 1}{\vartheta_C^k}} + (1-\gamma_k)^{\frac{1}{\vartheta_C^k}} \left(C_{-k,t}^k\right)^{\frac{\vartheta_C^k - 1}{\vartheta_C^k}} \right)^{\frac{\vartheta_C^k}{\vartheta_C^k - 1}}. \tag{2}$$

$C_{k,t}^k$ is defined as the consumption of domestically produced goods, $C_{-k,t}^k$ represents foreign consumption. The parameter γ_k indicates the relative weight of domestic goods, ϑ_C^k denotes the elasticity of substitution between the goods. $C_{k,t}^k$ and $C_{-k,t}^k$ are symmetric CES functions given by

$$C_{k,t}^k \equiv \left(\int_0^1 C_{k,t}^k(i)^{\frac{\epsilon-1}{\epsilon}} di \right)^{\frac{\epsilon}{\epsilon-1}}, \tag{3}$$

$$C_{-k,t}^k \equiv \left(\int_0^1 C_{-k,t}^k(i)^{\frac{\epsilon-1}{\epsilon}} di \right)^{\frac{\epsilon}{\epsilon-1}}, \tag{4}$$

with ϵ denoting the elasticity of substitution between domestic and foreign varieties respectively.
Expenditure minimization with respect to the varieties yields

$$C_{k,t}^k(i) = \left(\frac{P_{k,t}(i)}{P_{k,t}} \right)^{-\epsilon} C_{k,t}^k, \tag{5}$$

$$C_{-k,t}^k(i) = \left(\frac{P_{-k,t}(i)}{P_{-k,t}} \right)^{-\epsilon} C_{-k,t}^k, \tag{6}$$

with $P_{k,t} \equiv \left(\int_0^1 P_{k,t}(i)^{1-\epsilon} di \right)^{\frac{1}{1-\epsilon}}$ and $P_{-k,t} \equiv \left(\int_0^1 P_{-k,t}(i)^{1-\epsilon} di \right)^{\frac{1}{1-\epsilon}}$ being the overall price indices of domestic and foreign goods respectively.

Expenditure minimization with respect to the level of domestic and foreign consumption gives

$$C_{k,t}^k = \left(\frac{P_{k,t}}{P_t^{C,k}}\right)^{-\vartheta_C^k} \gamma_k C_t^k, \tag{7}$$

$$C_{-k,t}^k = \left(\frac{P_{-k,t}}{P_t^{C,k}}\right)^{-\vartheta_C^k} (1-\gamma_k) C_t^k, \tag{8}$$

with $P_t^{C,k} \equiv \left(\gamma_k P_{k,t}^{1-\vartheta_C^k} + (1-\gamma_k) P_{-k,t}^{1-\vartheta_C^k}\right)^{\frac{1}{1-\vartheta_C^k}}$ being defined as the consumer price index of household k. The household maximizes its expected discounted lifetime utility given by

$$\mathbb{E}_t \left[\sum_{\iota=0}^{\infty} \beta^\iota U_{t+\iota}^k\right], \tag{9}$$

subject to the budget constraint

$$P_t^{C,k} C_t^k + Q_t B_t^k = B_{t-1}^k + W_t^k L_t^k + D_t^k, \tag{10}$$

where B_t^k is defined as one-period, nominally risk-free bonds purchased at price Q_t, W_t^k as the nominal wage, and D_t^k as exogenous dividends from the ownership of firms. The optimality conditions are given by

$$\left(L_t^k\right)^{\varphi_k} = w_{k,t} U_{c,t}^k, \tag{11}$$

$$Q_t = \beta\, \mathbb{E}_t \left[\Lambda_{t,t+1}^k \frac{1}{\Pi_{t+1}^{C,k}}\right] \tag{12}$$

with $U_{c,t}^k \equiv \frac{Z_t}{C_t^k - \Psi_k C_{t-1}^k} - \frac{\mathbb{E}_t[Z_{t+1}]\Psi_k \beta}{\mathbb{E}_t\left[C_{t+1}^k\right] - \Psi_k C_t^k}$ being defined as the marginal utility of consumption, $w_t^k \equiv \frac{W_t^k}{P_t^{C,k}}$ as the real wage, $\beta \Lambda_{t,t+1}^k \equiv \beta\, \mathbb{E}_t \left[\frac{U_{c,t+1}^k}{U_{c,t}^k}\right]$ as the stochastic discount factor, and $\Pi_{t+1}^{C,k} \equiv \frac{P_{t+1}^{C,k}}{P_t^{C,k}}$ as CPI inflation. Due to the shared bond market, we can obtain the following risk sharing condition between the two households by combining the Euler equations for each household:

$$U_{c,t}^{k} = U_{c,t}^{-k}\Phi^{k}\frac{P_{t}^{C,k}}{P_{t}^{C,-k}}, \tag{13}$$

with $\Phi^{k}\equiv\frac{U_{c,SS}^{k}}{U_{c,SS}^{-k}}$, where the subscript SS denotes the zero inflation steady state of a variable.

B. Firms

In each country, a representative firm k produces one variety i of goods. The production function is given by

$$Y_{k,t}(i) = \left(L_{t}^{k}(i)\right)^{1-\alpha_{k}}, \tag{14}$$

where $1-\alpha_{k}$ is the partial factor elasticity of labor. The real cost function is given by

$$TC_{k,t}(i) = A_{t}^{k}w_{t}^{k}L_{t}^{k}(i), \tag{15}$$

where A_{t}^{k} is a cost-push shock given by

$$ln\left(A_{t}^{k}\right) = \rho_{A}ln\left(A_{t-1}^{k}\right) + \eta_{A}^{k}\epsilon_{A,t},$$

where ρ_{A} denotes the persistence, η_{A}^{k} determines the strength of the shock, and $\epsilon_{A,t}\sim\mathcal{N}\left(0,\sigma_{A}^{2}\right)$ is a normally distributed shock with mean 0 and variance σ_{A}^{2}. The firm maximizes its expected stream of current and future profits given by

$$\mathbb{E}_{t}\left[\sum_{\iota=0}^{\infty}\beta^{\iota}\Lambda_{t,t+\iota}^{k}\lambda_{k}^{\iota}\left(\frac{P_{k,t}(i)}{P_{t+\iota}^{C,k}}Y_{k,t+\iota|t}(i) - TC\left(Y_{k,t+\iota|t}(i)\right)\right)\right], \tag{16}$$

subject to

$$Y_{k,t+\iota|t}(i) = \left(\frac{P_{k,t}(i)}{P_{k,t+\iota}}\right)^{-\epsilon}Y_{k,t+\iota}, \tag{17}$$

with λ_{k} being defined as the probability of a firm not being able to reset its price (as in Calvo, 1983), $Y_{k,t+\iota|t}(i)$ as the output of firm i in period $t+\iota$ for a price set in t, and $Y_{k,t+\iota}$ as the overall output produced in country k. Dropping index i due to symmetry, the optimal price is given by

$$\left(p_{k,t}^{*}\right)^{1+\frac{\epsilon\alpha_{k}}{1-\alpha_{k}}} = \mu\left(\frac{P_{k,t}}{P_{t}^{C,k}}\right)^{-1}\frac{x_{1,t}^{k}}{x_{2,t}^{k}}, \tag{18}$$

where the auxiliary variables are defined as

$$x_{1,t}^k \equiv U_{c,t}^k Y_{k,t} mc_{k,t} + \beta \lambda_k \mathbb{E}_t \left[\Pi_{k,t+1}^{\frac{\epsilon}{1-\alpha_k}} x_{1,t+1}^k \right],$$

$$x_{2,t}^k \equiv U_{c,t}^k Y_{k,t} + \beta \lambda_k \mathbb{E}_t \left[\Pi_{k,t+1}^{\epsilon} \left(\Pi_{t+1}^{C,k} \right)^{-1} x_{2,t+1}^k \right],$$

and $p_{k,t}^* \equiv \frac{P_{k,t}^*}{P_{k,t}}$. The variable $mc_{k,t} = \frac{1}{1-\alpha_k} w_t^k Y_{k,t}^{\frac{\alpha_k}{1-\alpha_k}} A_t^k$ denotes the economy-wide real marginal costs of the good produced in country k and $\Pi_{k,t+1} \equiv \frac{P_{k,t+1}}{P_{k,t}}$ is defined as inflation of domestic goods. Aggregate price dynamics are given by:

$$1 = (1-\lambda_k) \left(p_{k,t}^* \right)^{1-\epsilon} + \lambda_k \left(\frac{1}{\Pi_{k,t}} \right)^{1-\epsilon}. \tag{19}$$

C. Central Bank

The central bank follows a Taylor rule given by

$$i_t = \rho + \phi_\pi \left(\omega_{\pi,t} \pi_t^{C,S} + (1-\omega_{\pi,t}) \pi_t^{C,N} \right), \tag{20}$$

where $i_t \equiv log\left(1/Q_t\right)$, $\rho \equiv log\left(1/\beta\right)$, and $\pi_t^{C,k} \equiv log\left(\Pi_t^{C,k}\right)$. The parameter $\phi_\pi > 1$ denotes the standard reaction coefficient of the central bank to the weighted CPI inflation rates of households from countries S and N. If $\omega_\pi = C_t^S/(C_t^S + C_t^N)$, the central bank reacts to the average (as measured by the ECB, see Footnote 1), economy-wide CPI inflation rate given by:

$$\pi_t^C = \frac{C_t^S}{C_t^S + C_t^N} \pi_t^{C,S} + \left(1 - \frac{C_t^S}{C_t^S + C_t^N} \right) \pi_t^{C,N}. \tag{21}$$

However, if $\omega_{\pi,t} \neq C_t^S/(C_t^S + C_t^N)$, the central bank reacts more strongly to the CPI inflation rate of either country S ($\omega_{\pi,t} > C_t^S/(C_t^S + C_t^N)$) or N ($\omega_{\pi,t} < C_t^S/(C_t^S + C_t^N)$) than suggested by the economy-wide inflation rate.
The Fisher equation holds for each household:

$$i_t = r_t^k + \mathbb{E}_t \left[\pi_{t+1}^{C,k} \right]. \tag{22}$$

D. Market Clearing

Bond market, labor markets, and goods markets clear:

$$B_t^k = -B_t^{-k}, \tag{23}$$

$$L_t^k = \int_0^1 L_t^k(i) di, \tag{24}$$

$$Y_{k,t} = C_{k,t}^k + C_{k,t}^{-k}. \tag{25}$$

Union-wide output is defined as:

$$Y_t = Y_{k,t} + Y_{-k,t}. \tag{26}$$

E. Calibration

The calibration of the model draws from a multitude of sources. In order to realistically capture the north-south divide reported in Section II, we calibrate country S to represent the southern EMU members, which exhibit high inflation volatility (in particular, EL, IE, IT, PT, ES) and N according to the EMU members which exhibit low inflation volatility (i.e., AT, DE, and NL). Note that these eight countries account for more than 70% of EMU GDP. For the calibration, we utilize studies that estimate the structural parameters for the countries that we use in our model. In particular, for N we use Breuss and Rabitsch (2008) for AT, Albonico et al. (2019) for DE, and Garcia et al. (2021) for NL. For S we use Papageorgiou (2014) (EL), Garcia et al. (2021) (IE), Albonico et al. (2019) (ES, IT), and Almeida (2009) (PT).

Table 1: Calibration.

	Description	Value	
	Households		
		S	N
Ψ_k	Habit parameter	0.77	0.71
φ_k	Inverse Frisch elasticity	2.01	2.73
η_Z^k	Preference shock strength	1	0.5
γ_k	Weight of domestic goods	0.75	0.75
ϑ_C^k	Elasticity of substitution between domestic and foreign goods	1.42	1.50
ϵ	Price elasticity of demand	6	6
β	Discount rate	0.995	0.995
	Firms		
		S	N
α_k	Output elasticity labor	0.33	0.33
η_A^k	Cost-push shock strength	1	0.5
λ_k	Calvo parameter	0.737	0.852
	Central Bank		
ϕ_π	Taylor rule coefficient	1.5; 2.5	
ω_π	CPI inflation weight	$\frac{C_t^S}{C_t^S+C_t^N}$; 0.2; 0.8	

We then continue by weighting each country-specific parameter with the country-specific share of GDP in order to calculate the parameter value for S and N.[3] For instance, the habit parameter for country N is calculated in the following

[3]Note that weighting with consumption shares delivers similar results.

way: the values for Germany (0.73), the Netherlands (0.65), and Austria (0.67) are weighted with their relative GDP, leading to an overall value of 0.71 for N. The corresponding calibration is shown in Table 1.
We observe that southern EMU members exhibit structurally higher habit formation and a higher Frisch elasticity of labor supply. Interestingly, S and N display a similar level of home bias in consumption as well as a comparable elasticity of substitution between domestic and foreign goods. Importantly, prices are stickier in northern EMU member states, which will play an important role when determining the volatility of the inflation rates of S and N. Note that we assume the preference and the cost-push shock to differ in their impact between the countries. The validity of this assumption is discussed in Section IV. Lastly, we simulate model responses for a variety of different Taylor rule specifications. In particular, three baseline models are simulated: one in which the central bank reacts to the union-wide inflation rate ($\omega_\pi = C_t^S/(C_t^S + C_t^N)$), one where the central bank reacts more strongly to country S ($\omega_\pi = 0.8$), and one in which the central bank reacts more strongly to country N ($\omega_\pi = 0.2$).[4] The reaction coefficient is set to 1.5 in all cases. In total, we therefore simulate the model for 3 different versions of the Taylor rule, which are then used to train and evaluate a multitude of machine learning mechanisms.

IV. Historical Data

In order to properly classify monetary policy in EMU, the New Keynesian model must accurately match the statistical properties of historical EMU data, as we use the simulated data to train the machine learning mechanisms. We briefly describe the historical EMU data in the following.

A. Description

We collect data on consumption, employment, price levels, interest rates, output, and population. Detailed information on data availability, frequency, and sources can be found in Table 2.
Using population data, consumption, employment, and output values are converted into per capita values.[5] Measures for northern and southern EMU members are constructed as follows.

Consumption: In order to aggregate the country-specific values into a measure for consumption of northern and southern EMU members, we calculate the (consumption-)weighted average per capita consumption of the three northern and five southern countries.

[4]Note that countries S and N are roughly equal in size. Therefore, the unbiased inflation weight in the steady state is close to parity, i.e., ≈ 0.49.

[5]We use population data from 2021 for the first quarter of 2022, as population data for 2022 is not yet available.

Table 2: Data Sources.

Data	Countries/Regions	Years	Frequency	Source
Consumption	AT, DE, EL, ES, IE, IT, NL, PT	2002–2022	Quarterly	Eurostat: GDP and main components
Employment	AT, EL, ES, IE, IT, NL, PT	2002–2022	Quarterly	Eurostat: Employment by sex, age, and citizenship
Price levels	AT, DE, EL, ES, IE, IT, NL, PT	2002–2022	Monthly	Eurostat: HICP - monthly data (index)
Interest rates	EA	2002–2022	Monthly	Bundesbank: ECB interest rates for main refinancing operations, shadow rates as in Wu and Xia (2020)
Output	AT, DE, EA, EL, ES, IE, IT, NL, PT	2002–2022	Quarterly	Eurostat: GDP and main components
Population	AT, DE, EA, EL, ES, IE, IT, NL, PT	2002–2021	Annually	Eurostat: Population on 1 January by age and sex

Employment: We weight the per capita employment values with relative GDP in order to calculate the aggregate measures for the northern and southern countries. As data for DE is not available for the entire time period, the employment data for the northern countries is based on AT and NL.

Price levels: We use the monthly HICP index at the beginning of each quarter for each country. Following the ECB, we calculate the aggregate price level of the North and South by weighting the country-specific price levels with the relative consumption of each country respectively (see Footnote 1).

Interest rates: Interest rates apply EMU-wide and are reported on a monthly basis. We use the interest rate at the beginning of each quarter. Until 2004Q3, we use the ECB's interest rate for main refinancing operations (MRO rate) as the policy rate. Starting in 2004Q4 (due to data availability), we utilize the shadow rate, as in Wu and Xia (2020). The shadow rate is useful as it accounts for unconventional monetary policy measures, specifically for quantitative easing. Hence, including the shadow rate allows us to study an uninterrupted time series. Furthermore, it ensures a comparable measure for monetary policy in the data as well as in the simulated model results.

Output: We calculate the aggregate output measure for the northern and southern countries by weighting their individual GDP per capita with their relative total GDP. In addition, we use EMU-wide GDP per capita in our analysis.

The entire data set (except for the interest rates) are transformed into logs. Our New Keynesian model reports percentage deviations from steady state. As the data generated from this model is used to train the machine learning algorithms, it is necessary to transform the EMU data set into percentage deviations from steady state as well. Therefore, we utilize a Hamilton (2018) filter (lag length $p = 4$, forecast horizon $h = 8$) in order to extract the cyclical component of each variable in our data set. Figure 3 provides an overview of the transformed macroeconomic variables. As expected, the macroeconomic indicators show greater variance in

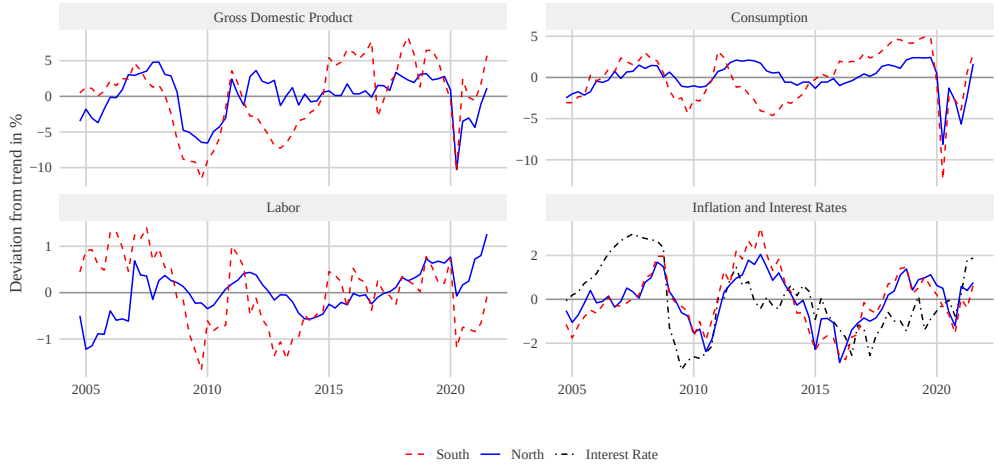

Figure 3 : Hamilton-Filtered Data of Aggregated Northern, Southern, and Euro Area Variables.

the southern countries than in the northern ones. In particular, the aggregated inflation rate in the southern countries deviates more strongly from its trend than its northern counterpart, as expected from the examination of the descriptive data presented in Section II.[6]

B. Model Fit

We simulate 10,000 periods with random demand (preference, Z_t^k) and supply (cost-push, A_t^k) shocks, corresponding to 2,500 years of observation. In order to create perfect counterfactual data, we draw the identical shocks for each of our three baseline models, thus generating a synthetic data set in which only the latent inflation weight varies. Table 3 reports the simulated moments generated by the model compared to the respective moments calculated from the historical data.

Overall, all model specifications match the moments of the actual data reasonably well. While our model understates (steady state) inequality in consumption and GDP, it replicates the fact that northern countries produce and consume more than southern countries do. Furthermore, the model replicates higher volatility across all variables in the southern countries compared to their northern coun-

[6]Note that we use deviations from the trend inflation rate instead of deviations from the 2% target of the ECB for the following reasons: a) the policy rule in the New Keynesian model is defined in deviations from its trend/steady state, b) uncertainty remains regarding the exact magnitude of the ECB's inflation target (at least until the clarification of the inflation target in July 2021), c) it would be difficult to justify a 2% target for each individual country, and d) it is unlikely to make a difference since the trend is very close to 2%.

Table 3: Comparison of Simulated Moments with Data.

Variable	Description	$\omega_{\pi,t}=\frac{C_t^S}{C_t^S+C_t^N}$	$\omega_{\pi,t}=0.8$	$\omega_{\pi,t}=0.2$	Data
C_{SS}^S/C_{SS}^N	Relative consumption per capita	0.962	0.962	0.962	0.805
$Y_{S,SS}/Y_{N,SS}$	Relative GDP per capita	0.980	0.980	0.980	0.773
$\sigma\left(\hat{y}_{N,t}\right)/\sigma\left(\hat{y}_{S,t}\right)$	Relative volatility GDP	0.816	0.810	0.821	0.587
$\sigma\left(\hat{y}_t\right)/\sigma\left(\hat{y}_{S,t}\right)$	Relative volatility union-wide GDP, S	0.879	0.867	0.883	0.671
$\sigma\left(\hat{y}_t\right)/\sigma\left(\hat{y}_{N,t}\right)$	Relative volatility union-wide GDP, N	1.076	1.072	1.076	1.144
$\sigma\left(\hat{c}_t^N\right)/\sigma\left(\hat{c}_t^S\right)$	Relative volatility consumption	0.196	0.190	0.204	0.559
$\sigma\left(\hat{n}_t^N\right)/\sigma\left(\hat{n}_t^S\right)$	Relative volatility labor	0.816	0.810	0.821	0.718
$\sigma\left(\hat{\pi}_t^{C,N}\right)/\sigma\left(\hat{\pi}_t^{C,S}\right)$	Relative volatility inflation	0.919	0.926	0.912	0.842
$\rho\left(\hat{y}_{S,t},\hat{y}_{N,t}\right)$	Correlation GDP S, N	0.875	0.864	0.885	0.591
$\rho\left(\hat{c}_t^S,\hat{c}_t^N\right)$	Correlation consumption S, N	0.804	0.773	0.818	0.636
$\rho\left(\hat{n}_t^S,\hat{n}_t^N\right)$	Correlation labor S, N	0.875	0.864	0.885	0.132
$\rho\left(\hat{n}_t^S,\hat{c}_t^S\right)$	Correlation labor, consumption S	0.949	0.948	0.950	0.627
$\rho\left(\hat{n}_t^N,\hat{c}_t^N\right)$	Correlation labor, consumption N	0.711	0.689	0.724	0.466

Note: $\hat{x}_t$ denotes the deviation of a variable X from its zero inflation steady state.

terparts, i.e., the relative volatility of all model variables is smaller than one. This property can particularly be ascribed to the differences in the impact of the shocks ($\eta_Z^S > \eta_Z^N$ and $\eta_A^S > \eta_A^N$), implying that the assumption with respect to the values of these parameters seem reasonable. Furthermore, despite focusing on only eight EMU countries, the model replicates the fact that EMU-wide output fluctuates more (less) than the output of northern (southern) members. Finally, we find that the correlations between variables in EMU data and our model are both qualitatively and quantitatively similar. Thus, our model appears to fit both the direction and magnitude of correlations between macroeconomic variables in the EMU. In particular, it replicates the stronger correlation between labor and consumption in southern states. Naturally, the model overstates the strength of this relationship as we abstract from other sources of income apart from work as well as from additional inputs in production (such as capital).
In most cases, the model that includes a higher weight on the inflation rate experienced by country S ($\omega_{\pi,t} = 0.8$) matches the historical data more closely than the other two models. This provides a preliminary indication that the ECB might respond to southern economies' inflation rates more strongly.

V. Machine Learning Methodology

This section introduces the algorithms used in our analysis for the classification task. Specifically, we compare the performance of twelve algorithms in a horserace-style assessment, subsequently choosing the one with the greatest out-of-sample prediction performance.[7] All models adhere to the following structure

$$y_t = h_\beta(X_t) + \epsilon_t, \tag{27}$$

[7]Note that none of the variables and parameters used in this section coincide with the ones defined in Section III.

where $y \in (S, N, C)$ are the categorical inflation weights for north (N), south (S) and consumption-weighted (C), $h(.)$ is a function with coefficients β that maps the simulated macroeconomic variables X to these weights, and ϵ the residual. This section only provides a brief overview of the models, as well as their most essential parameterization. A more comprehensive review can be found in Chakraborty and Joseph (2017).

A. (Quasi-) Linear Model

Multinomial logistic regression: We set a benchmark using a simple linear multinomial logistic regression (MLR) model. MLRs are logistic regressions for a categorical dependent variable with $k \in K$ categories. Explicitly, the following probabilities are being estimated:

$$P(Y_t = k) = \frac{exp(\beta_k \times X_t)}{1 + \sum_{k=1}^{K-1} exp(\beta_k \times X_t)}. \tag{28}$$

Penalized linear regression: We complement the MLR model with penalized linear regressions, which (in linear models) are primarily used to reduce dimensionality. Although our data set does not contain many dimensions (we have 10 independent variables), introducing constraints to the complexity of the linear model through regularization may nevertheless improve predictive performance. The general form can be described as follows

$$L = \sum_{t=1}^{T} (y_t - f(x_t))^2 + \lambda \sum_{j=1}^{n} \left[(1-\alpha)|\beta_j| + \alpha|\beta_j|^2 \right], \tag{29}$$

where L is a loss function that is optimized, λ represents intensity, and α determines the type of regularization. In particular, we employ a Lasso regression model ($\alpha = 0$), an elastic net ($0 < \alpha < 1$) and a ridge regression model ($\alpha = 1$). For all three regularized regression methods, we optimize $\lambda \in [10^{-2}, 10^{-4}]$ using cross fold validation.

KNN: The K-Nearest-Neighbor (KNN) algorithm is a non-parametric supervised classifier that classifies the dependent variable based on a plurality vote of its nearest neighbors with respect to the independent variables. In the most basic instance (k = 1), the inflation weight at time t predicted is simply the inflation weight of the single nearest neighbor. We optimize KNN over $k \in [1, 100]$.

B. Tree-Based Model

Tree: Tree-based algorithms are non-parametric supervised machine learning methods that divide data into subsets using a series of *if-else* rules. Each addi-

tional layer increases the complexity of these classification models, allowing for more precise and distinct predictions. In practice, tree-based models perform well out-of-box (e.g., Boehmke and Greenwell, 2019) and are easy to interpret due to the possibility to illustrate a schematic representation of a given tree model. With T being the number of nodes in a tree, we optimize the tree using the following loss-function

$$L_\gamma = \sum_{m=1}^{|T|} \left[(y_t - f(x_t))^2 + \gamma |T| \right], \tag{30}$$

where γ controls the regularization in a similar fashion to how λ did for penalized regressions. Following the literature, we specify a range of cut-of losses, used to determine the complexity of the tree.

Prune tree: As trees tend to overfit, pruning a tree is a good method of improving the predictive performance. Pruning a tree is equivalent to optimizing L_γ over γ.

Random forest: A random forest is a classification algorithm that uses r decision trees to classify data. All decision trees are randomly generated and produce one prediction for the classification task. The random forest's final classification is determined by the class with the most votes. We set $r = 1000$ in our setup.

C. Neural Networks

Neural networks (NNs) are supervised machine learning algorithms that are capable of achieving strong performance in classification tasks. A NN consists of – at least – three layers (i): an input layer (the independent variables), a hidden layer, and an output layer (the prediction of the network). An illustrative example is provided in Figure 4. With the exception of the first layer, the inputs Z for each layer are the dot product of a weighting matrix W_i and the previous output X_{i-1}:

$$Z_i = W_i \times X_{i-1} \tag{31}$$

This layer's output – the next layer's input – is then generated using an activation function $f(.)$:

$$X_i = f(Z_i) \tag{32}$$

The two functional forms of $f(.)$ applied in this paper are rectified linear unit (ReLU) activation for the hidden layers and softmax activation for the output layer:

$$f(x) = max(0, x) \qquad \text{ReLu}$$

$$f(x) = \frac{exp(x_k)}{\sum_{k=1}^{K} exp(x_k)} \qquad \text{Softmax}$$

During the training process, the NN optimizes W_i, in order to perform well on a given classification task using an iterative optimization algorithm called stochastic gradient descent (see, e.g., Athey, 2019). We initiate our training with a simple

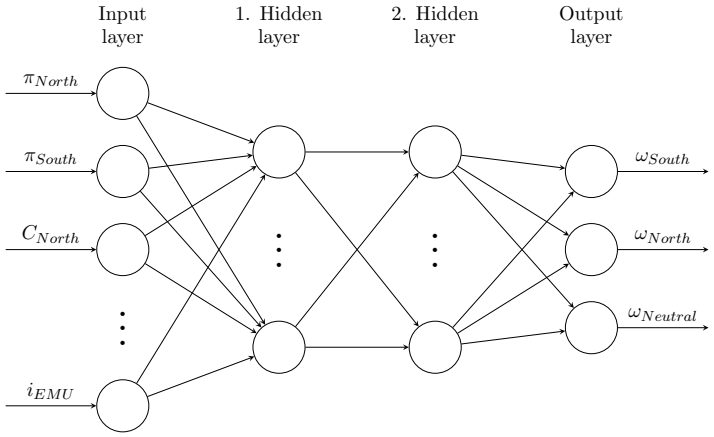

Figure 4 : Illustration of NN.

Notes: This figure illustrates the model architecture of a feed-forward NN with four layers: One input layer, two hidden layers, and an output layer. The connections between the layers represent the weighting matrix W_i and are adjusted during the training process.

four-layer NN, as shown in Figure 4. With the exception of the output layer where a softmax function is used to obtain a probabilistic distribution over the classification task, we rely on ReLu activation functions, as does much of the literature. Finally, we train our network in 500 iterations, with 20% of the data set serving as validation.[8]

D. Evaluation

In this subsection, we apply the machine learning models introduced in the previous subsection to our training data set to evaluate their relative performance. The aim is to determine the algorithm that best predicts the underlying inflation weight provided by the DSGE model. In order to do so, we simulate the DSGE model from Section III for three specifications, namely $\omega_\pi = C_t^S/(C_t^S + C_t^N)$ (C), $\omega_\pi = 0.8$ (S), and $\omega_\pi = 0.2$ (N) for 10,000 periods each. In the next step, we split this data set into a training set (80%) and a test set (20%). The training data is used to parameterize the machine learning algorithms and the test set is used to evaluate the models out-of-sample. The results are presented in Table 4.

[8]We choose 32 nodes per hidden layer, which in itself is a relatively small number. It is worth noting that even a simple model like this has over 1500 trainable parameters. In an unreported test, we increase the depth, width, and number of iterations. While we notice a slight improvement, we refrain from evaluating more complicated models due to the strong relative performance of this simple NN.

Table 4: Evaluation on Test Set

	Accuracy
Uninformed performance	0.33
MLR	0.34
Ridge regression	0.33
Lasso regression	0.33
Elastic net	0.33
K-nearest-neighbor	0.38
Tree	0.48
Complex tree	0.48
Prune tree	0.48
Prune complex tree	0.48
Random forest	0.39
Simple neural network	**0.97**

Note: Accuracy of the machine learning algorithms introduced in Section V in classifying the true inflation weight $\omega_{\pi,t}$ from the simulated data set introduced in section III. Accuracy can be calculated by the fraction of correct predictions over all predictions.

There are several noteworthy observations. First, in the prediction task presented, linear models do not perform particularly well. Whereas the linear model still has a slight advantage out-of-sample over a naive guess, penalized regressions actually perform marginally worse than guessing. While it is the best performing linear model, the KNN model with an accuracy of 38% does not fare much better. Second, using tree-based models does yield an improvement in performance. However, with an accuracy of below 50%, tree-based models still perform rather poorly. Interestingly, the random forest – the most complex tree-based model – performs worse out-of-sample. Finally, the NN – despite its simple structure – performs best by a huge margin. With an accuracy of $> 97\%$, its performance is more than twice as good as the second best performing algorithm. Therefore, we decide to use the NN as our primary predictor.

Using accuracy as a metric for evaluation can have drawbacks if the data is highly unbalanced, and it may not be informative with regard to a model's shortcomings. For example, our model may predict S disproportionately often, revealing a bias that may not be detected in an assessment based only on the accuracy metric. Despite the fact that we have a balanced data set by design, we assess whether our model suffers from biased predictions, which might invalidate the identification of the latent ω_π. As a result, we exhibit the NN's performance throughout a confusion matrix in Table 5. Each row in the table represents the networks' prediction of ω_π, while the columns reflect the true ω_π. For example, the NN predicted N 2499 times. This forecast was correct 2442 times, while C (S) would have been the appropriate prediction in 48 (9) cases. Table 5 provides no evidence of bias, which can be further mitigated using alternative performance

Table 5: Confusion Matrix of Out-of-Sample Prediction by NN

		True label		
		Neutral	North	South
Prediction	Consumption	2405	50	39
	North	48	2442	9
	South	47	7	2452

metrics such as $Recall = 0.97$ and $Precision = 0.97$.[9] As a result, we are confident in the unbiased predictive performance of our NN.

VI. Results

This section presents the results of our machine learning algorithm, applied to historical EMU data. We choose the NN for this classification task, based on its performance to retrieve the latent inflation weight ($\omega_{\pi,t}$) from the simulated data set of the New Keynesian model. Due to the constraint imposed by the Hamilton filter, the historical inflation weight is classified on a quarterly basis between 2004Q4 and 2022Q1.

Figure 5 shows the retrieved inflation weight and the development of several macroeconomic variables in the EMU.[10]

There are several interesting results. First, our findings do not indicate a systematic focus of the ECB on the union-wide inflation rate. In fact, we find a disproportional emphasis on inflation rates experienced by southern EMU members (i.e., $\omega_{\pi,t} = 0.8$), in 80% of the periods, whereas we find evidence of a balanced stance in only five quarters ($\sim 7\%$).

Second, one possible explanation is that the ECB is reacting more strongly to greater deviations of inflation rates from their long-term trend, which would imply a predominant inflation weight on S.[11] This interpretation tallies with the fact that a higher weight on northern countries occurs at times when northern inflation rates exhibit stronger deviations from their long-term trend, particularly when considering the regime switches around 2010 and 2018. The fact that the (rare) C classification occurs at times when the inflation rate deviations of northern and southern countries are almost identical supports our interpretation. The period following the EMU debt crisis in 2012 provides further evidence. The southern economies first experienced a relatively higher trend-adjusted inflation deviation, which prompted the central bank to implement tighter monetary policy. Around

[9] For this multi-label case, we define the two metrics in the following way: $Recall = \frac{1}{n}\sum_{i=1}^{n} \frac{TP_i}{TP_i+FP_i}$ and $Precision = \frac{1}{n}\sum_{i=1}^{n} \frac{TP_i}{TP_i+FN_i}$

[10] We follow Hinterlang (2020) by incorporating a regime change only if it occurs over n quarters, choosing $n = 2$.

[11] Note that a convex loss function that separately includes the inflation variations of each member would imply such a reaction.

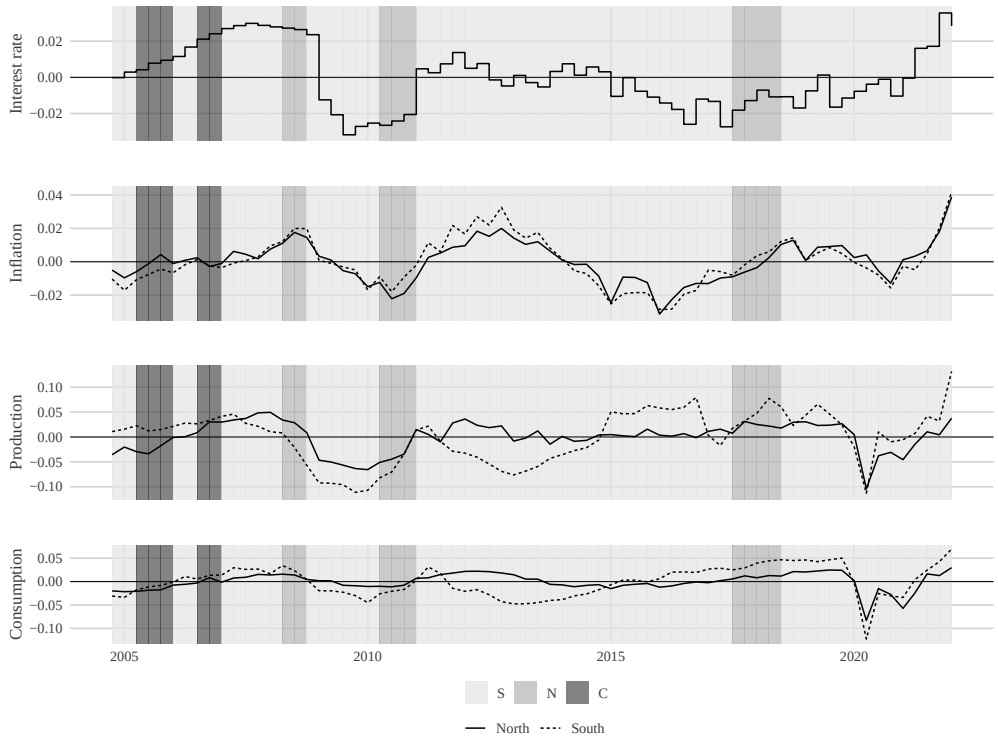

Figure 5 : S, N, C Classification and Macroeconomic Indicators.

2015, the relationship reverses: southern countries experienced a stronger drop in inflation rates than northern countries at a time when the monetary policy rate decreased substantially.

Third, we find that changes in the inflation weight may be associated with changes in the composition of the ECB's executive board. To investigate this further, we plot the NN's classification together with changes in the executive board in Figure 6. The solid line reflects the inflation weight, the vertical dashed lines represent the start of a new president's term and the horizontal dotted line is the relative share of members from S countries compared to N countries in the executive board.

We believe that the low variation in presidents as well as the vastly different economic circumstances during the presidencies make it difficult to derive reasonable conclusions. However, using the relative weight of ECB's board members from southern over northern countries provides far more variation and appears to be somewhat closely related to our inflation weight classification. For instance, the northern share in the board composition increases in May 2005. At the same time, we observe a corresponding change in the inflation weight. Throughout our

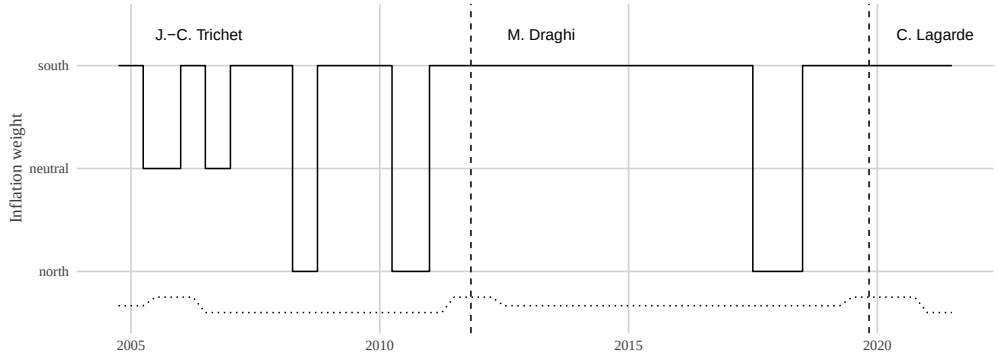

Figure 6 : Predicted ECB Inflation Weights 2004Q4 – 2022Q1

time series, there are several instances where the change in composition and the change in inflation weight occurred roughly at the same time. Two noteworthy examples are May 2011 and December 2020. These findings, while far from conclusive, suggest that the ECB's decision-making process may be collegian (e.g., Ehrmann and Fratzscher, 2007) as well as driven by board members who follow national objectives (e.g., Hayo and Méon, 2013).

VII. Conclusion

Combining DSGE models with machine learning methods facilitates the examination of various classification exercises. In particular, this paper investigates whether the ECB conducted monetary policy according to the EMU-wide inflation rate between 2002 and 2022. We first show that the inflation rate development of northern and southern EMU members differs substantially over time, with southern countries exhibiting greater volatility in their inflation rates than northern countries.

In order to classify whether the ECB reacted to the EMU-wide inflation rate or more strongly to northern/southern members, we generate data utilizing a New Keynesian model of a monetary union. We simulate a series of random demand and supply shocks for three different monetary policy rules of the union-wide central bank: one where the central bank reacts to the average union-wide inflation rate, and one where it reacts more strongly to the rate experienced in northern or southern countries respectively. The data set generated is then used to train and evaluate several machine learning algorithms. We find that a neural network performs best out-of-sample, with an accuracy of 97%.

Using the neural network, we classify historical EMU data between 2002 and 2022. Our findings suggest a disproportional emphasis on the inflation rates experienced by southern EMU members for the vast majority of the time frame

considered (80%). However, we find that there are several instances where a regime switch (from an emphasis on southern countries to the weighted average or to northern countries) takes place, especially in periods when southern inflation rates have already moved back to their long-term trend while northern inflation rates still exhibit deviations from theirs. We argue that these regime switches might be related to a potential tendency of the ECB to react more strongly to the countries whose inflation rates deviate more strongly from their long-term trend. This interpretation implies a higher weight on southern countries for a majority of periods (due to the higher volatility of southern inflation rates) and tallies with the fact that a higher weight on northern countries occurs at times when northern inflation rates exhibit stronger deviations from their long-term trend.

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