

Large datasets for the euro area and its member countries and the dynamic effects of the common monetary policy

Matteo Barigozzi*

Claudio Lissona*

Lorenzo Tonni†

This version: November 21, 2025

Abstract

We introduce EA-MD-QD, a new publicly available dataset comprising 1136 macroeconomic time series for the euro area (EA) and its ten largest member countries observed at monthly or quarterly frequency. Since January 2024, EA-MD-QD has been updated monthly and continuously revised, providing a valuable resource for policy analysis in the EA. Using EA-MD-QD, we study country-specific impulse responses to an EA-wide monetary policy shock. Results reveal moderate yet significant cross-country heterogeneity, with a core–periphery pattern in prices and interest rates and meaningful differences in real activity, while stock price responses are relatively homogeneous. Evidence points to homeownership and saving behavior as potential drivers of the observed cross-country differences.

*Department of Economics, University of Bologna, Italy.

†Department of Economics, Management and Quantitative Methods, University of Milan, Italy.

All authors gratefully acknowledge financial support from the Italian Ministry of Education, University and Research (PRIN 2020, Grant 2020N9YFFE_003).

1 Introduction

The recent and ongoing “data revolution” has enabled researchers to collect and process large amounts of information, thereby broadening the scope of macroeconomic research. The availability of high-dimensional datasets—where the number of series, N , can be comparable to or even exceed the time dimension, T —allows researchers to exploit the rich information contained in large sets of macroeconomic and financial indicators. This, in turn, facilitates addressing relevant policy questions using econometric methods specifically designed to handle, and in some cases benefit from, such large datasets.

In this paper, we present and document a new large-scale dataset for macroeconomic analysis, denoted as EA-MD-QD. The dataset comprises time series for both the euro area (EA) as a whole and its ten largest member countries, providing an accessible and comprehensive resource for policy analysis of EA-wide outcomes. It also enables comparisons across data vintages and empirical studies. Overall, EA-MD-QD includes 1136 time series, at either monthly or quarterly frequency depending on data availability. The first available vintage spans the period January 2000-January 2024. After that date the data has been and is updated every month. The countries covered are Austria, Belgium, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, and Spain. All the series are retrieved from institutional sources, namely Eurostat, ECB, OECD and FRED. The EA-MD-QD is made publicly available online and updated every month and come jointly with Matlab and Python codes for data transformation, missing-value imputation, and the treatment of outliers and the COVID period.¹

Although the cost of data collection has substantially decreased in recent years, several sunk costs still hinder data availability and, consequently, the reproducibility of economic research. First, the manual updating of time series becomes increasingly burdensome as the dimensionality of the dataset grows, highlighting the need for systematic procedures to facilitate data acquisition. Second, once collected, data are often not immediately suitable for analysis due to issues such as seasonality, non-stationarity, and missing values, which require additional pre-processing. In this work, we aim to reduce, if not entirely eliminate, these costs by providing a dataset that is periodically updated and accompanied by codes enabling users to generate, within seconds, a research-ready dataset.

Given that data are updated on a monthly basis, then real-time monthly vintages are available.

¹<https://zenodo.org/doi/10.5281/zenodo.10514667>

Specifically, updates occur at the end of each calendar month, either on the last working day or on the day when all updates scheduled for that month by the data providers have been released. Making vintages publicly available serves two main purposes. First, it enables users to account for the effects of data revisions across different periods, which have been shown to matter in many macroeconomic applications (see, e.g., Orphanides and Norden, 2002). Second, it fosters the reproducibility of research findings, as users can identify and retrieve the exact data vintage employed in a given analysis.

Building on the seminal contribution of Stock and Watson (1996), several large-scale datasets have been developed to foster macroeconomic research. Among the most prominent examples are FRED-MD and FRED-QD by McCracken and Ng (2016, 2020), two publicly available collections of monthly and quarterly macroeconomic and financial time series for the United States. Similarly, Fortin-Gagnon et al. (2022) constructed a large macroeconomic dataset for Canada.

To the best of our knowledge, this is the first attempt to provide a comprehensive dataset for macroeconomic research that encompasses both the EA as a whole and its largest member countries. The closest reference to our work using EA data is the real-time database developed by Giannone et al. (2012), which relies on the information contained in the ECB’s Monthly Bulletins, i.e., the rawest information set available to policymakers on the data of the ECB governing council. Our dataset differs from theirs along several dimensions. First, the relatively short amount of vintages of our data prevents a fully real-time analysis. Second, both the timing of data collection and the information content of our dataset do not correspond to any specific policy meeting or information set available to policymakers. Instead, we provide a snapshot of macroeconomic conditions in the EA and its largest member countries at a given point in time. Hence, the purpose and scope of the two datasets is different. Finally, unlike Giannone et al. (2012), our dataset also covers the largest EA countries, with the aim of offering comparable information at both the national and EA aggregate levels. Moreover, we also provide practitioners with all the codes needed to make the dataset readily usable for empirical macroeconomic research.

As a second contribution, we employ EA-MD-QD to study the Impulse Response Functions (IRF) of a common monetary policy shock in the EA and, particularly, across individual EA member countries. The availability of country-level data enables policymakers to account for cross-country heterogeneity, which may ultimately influence both the effectiveness and the transmission of the common monetary policy. In this context, understanding whether, and to what extent,

heterogeneous dynamics arise across countries is essential for designing and implementing more effective EA-level policies.

To this end, we employ the recently proposed Common Component Vector Autoregression (CC-VAR) methodology by Forni et al. (2025), which relies on the natural assumption of an underlying factor structure in the data. In a first step, standard Principal Component Analysis (PCA) is employed to extract the common factors and compute the common components of all variables. In a second step, a VAR model is estimated on some selected common components of interest along with other observables. Intuitively, this allows to study IRFs to common shocks, as the EA monetary policy one, without any contamination from idiosyncratic dynamics. More precisely, provided we include in the VAR step at least as many variables as common factors, we can fully identify the space spanned by the common shocks, by focussing on their common components only. This implies that the IRFs to common shocks for the variables considered in the VAR step do not change, even if some variables are substituted by others. Such an invariance property motivates our preference for the CC-VAR over more classical alternatives as, e.g., a standard VAR or a FAVAR (Bernanke et al., 2005).

In our baseline specification we identify an EA-wide common monetary policy shock using monthly data and the Instrumental Variables (IV) approach proposed by Stock and Watson (2012) and Mertens and Ravn (2013), in combination with the High-Frequency Identification (HFI) strategy of Gertler and Karadi (2015). We test several instruments from the pool provided by Altavilla et al. (2019) and select the 1-year overnight index swap (OIS), which is associated with the highest first-stage F -statistic.

We find four key results. First, looking at the share of variance explained by the common factors, we uncover non-negligible cross-country heterogeneity, particularly in unemployment and interest rate dynamics, whereas industrial production, stock prices, and prices display a higher degree of homogeneity. These findings provide a preliminary assessment of the degree of comovement among EA countries across different economic dimensions.

Second, the IRFs are consistent with standard economic theory. In particular, we observe a decline in the IRFs of prices in all EA economies following a contractionary monetary policy shock—although with different magnitudes, while at the EA level their magnitude aligns with other results in the literature (Jarociński and Karadi, 2020).

Third, we find evidence of a moderate yet meaningful heterogeneity in impulse responses across

countries for several key variables. In particular, our estimates point to a core-periphery pattern in price and interest rate dynamics. For prices, core countries' responses are on average aligned with—or even more pronounced than—the EA aggregate, whereas peripheral countries appear less affected. Symmetrically, interest rates responses in peripheral countries display stronger medium-term effects on average. No clear pattern emerges for real indicators, though some countries—such as Italy and Greece—show notable deviations from the aggregate. By contrast, stock prices exhibit a relatively homogeneous behavior across countries. On average, Germany's responses closely mirror the EA aggregate, while Greece shows the most pronounced deviations.

Finally, to explore potential drivers of this heterogeneity, we examine the correlations between the peak country-level IRFs and selected structural characteristics related to labor markets, households, firms, and national economic structures (Corsetti et al., 2022). While no causal inference is implied, the evidence suggests that monetary policy transmission is strongly related to several economic channels—including homeownership rates and savings behavior—that either dampen or amplify the effects of common shocks across countries.

Over the years, a large body of literature has studied the effects of common monetary policy in the EA (Jarociński and Karadi, 2020; Andrade and Ferroni, 2021). In this paper, we also analyse potential asymmetries in the transmission mechanism of monetary policy shocks across EA member countries. In particular, by employing a novel large-dimensional dataset, more recent data vintages, and a novel econometric framework, we extend and update the previous studies by Barigozzi et al. (2014), Georgiadis (2015), Burriel and Galesi (2018), Corsetti et al. (2022), Mandler et al. (2022).

Despite differences in sample coverage, our results broadly align with those of Barigozzi et al. (2014), who document similar cross-country patterns in prices and unemployment rates, partly driven by a core–periphery dynamic within the EA. Differently from our results, Corsetti et al. (2022) report price increases for several countries in response to monetary tightening. Nevertheless, despite this difference in sign, the relative cross-country patterns we identify are broadly consistent with their findings. Conversely, Mandler et al. (2022) obtain an inverted cross-country ranking in price responses compared with our results.

Section 2 describes the EA-MD-QD dataset. Section 3 introduces the baseline specification adopted for the empirical application. Section 4 discusses the factor analysis, while Section 5 examines the comovements across variables and countries explained by the factors. Section 6

describes the estimation and identification of the EA and country-specific IRFs to a common monetary policy shock. Section 7 reports the estimated IRFs, as well as the analysis of cross-country heterogeneity and its potential drivers. Section 8 concludes. In a Supplementary Appendix we provide a detailed description of the data, a step-by-step guide to data preparation and estimation of the comovements, and additional empirical results, based on different data and identification approaches, showing the robustness of our results.

2 The EA-MD-QD dataset

2.1 Data description

The dataset is constructed according to three guiding principles: (i) *accessibility*: all series are sourced from public, institutional databases; (ii) *timeliness*: the dataset is fully web-scraped, enabling monthly updates of all series in the panel according to their respective release calendars; and (iii) *coverage*: it includes variables representing the most relevant sources for modern macro-financial analysis. Importantly, the monthly updates provide practitioners with a new vintage of the dataset each month, incorporating all data releases and revisions to previously published series, if any. All monthly vintages are available from the initial release of EA-MD-QD in January 2024.

Euro area. The dataset for the EA comprises $N = 118$ series, of which $N_M = 47$ are monthly and $N_Q = 71$ are quarterly. All series span from 2000:M1 (2000:Q1) to the most recent available observation. The selection of variables follows established datasets for the US (McCracken and Ng, 2016, 2020) and covers: (1) National Accounts, (2) Labor Market Indicators, (3) Credit Aggregates, (4) Labor Costs, (5) Exchange Rates, (6) Financial Markets, (7) Industrial Production and Turnover, (8) Prices, (9) Confidence Indicators, and (10) Monetary Aggregates. Among the 118 series, 104 are sourced from Eurostat, 10 from the ECB Data Warehouse, 3 from the OECD Statistical Database, and 1 from the FRED portal.

Countries. In addition to the EA dataset, we provide datasets for the ten largest EA countries: Austria, Belgium, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, and Spain. Each country-specific dataset is constructed according to the same principles used for the EA data, with a few exceptions. For instance, variables related to Monetary Aggregates are not included at the country level, as they cannot be straightforwardly attributed to individual countries. Other groups of variables (e.g., Credit Aggregates or Industrial Production and Turnover) are smaller

for some countries, such as Ireland, due to data unavailability. The country specific variables are sourced from the same providers as those of the EA dataset.

Table 1 provides a summary of the series included in the dataset, along with a brief description, their frequency (column F), and provider (column P). For each series, the last columns of Table 1 indicate the countries for which the series is available. A checkmark denotes availability, while a dash indicates that the series is not available for that country. A more detailed description of the series, with additional informations, is in Table A2 in Appendix A.

Table 2 provides a detailed breakdown of the numerosity of series by country, organized according to the ten macro-categories included in the dataset. Broadly, each category is similarly represented across countries, and the frequency of individual series is generally uniform across countries. Specifically, for both the EA and each individual country, approximately 60% of the series are quarterly, while the remaining 40% are monthly. There are two notable exceptions: indicators of Industrial Production and Turnover are unavailable for Ireland, and Producer Prices are missing for both Ireland and Portugal.

Due to their mixed-frequency nature, the dataset is inherently unbalanced, with quarterly series recorded in the first month of each corresponding quarter and missing values in the remaining months. The provided codes allow users to handle this unbalanced structure. Practitioners can choose to: (i) retain the mixed-frequency format; (ii) subset the dataset to include only monthly or only quarterly variables; or (iii) aggregate the monthly data to the quarterly frequency. In the latter case, monthly series are aggregated to the quarterly level by summing the values of monthly *flow* variables and taking the mean of monthly *stock* variables.²

Besides its mixed frequency nature, the dataset is unbalanced also because of both data availability and ragged edges arising from the asynchronous release of different series. Regarding data availability, while most series begin at or before 2000:Q1 (2000:M1), some start few periods later (see Appendix A for details). As for release timing, the series are updated at different intervals across categories: some variables (e.g., National Accounts) are published roughly one to two months after the end of the reference quarter, while others (e.g., Credit Aggregates) may be released up to four months later. The companion codes allow practitioners to impute these missing values by means of two different procedures described in Section 2.3.

²Alternatively, one could take the value from the last month of the reference quarter as the quarterly observation. However, this approach would overlook intra-quarter dynamics that may be informative. For instance, if 2020:Q2 were represented solely by June 2020 data, much of the COVID-19 shock observed in April 2020 would be disregarded.

Table 1: Data Description by country

N	ID	Series	F	P	EA	AT	BE	DE	EL	ES	FR	IE	IT	NL	PT
(1) National Accounts															
1	GDP	Real Gross Domestic Product	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
2	EXPGS	Real Export Goods and services	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
3	IMPGS	Real Import Goods and services	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
4	GFCE	Real Government Final consumption expenditure	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
5	HFCE	Real Households consumption expenditure	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
6	CONSD	Real Households consumption expenditure: Durable Goods	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
7	CONSSD	Real Households consumption expenditure: Semi-Durable Goods	Q	EUR	-	✓	-	✓	-	-	✓	✓	✓	✓	-
8	CONSSV	Real Households consumption expenditure: Services	Q	EUR	-	✓	-	✓	-	-	✓	✓	✓	✓	-
9	CONSND	Real Households consumption expenditure: Non-Durable Goods	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	-
10	GCF	Real Gross capital formation	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
11	GCFC	Real Gross fixed capital formation	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
12	GFACON	Real Gross Fixed Capital Formation: Construction	Q	EUR	✓	✓	-	✓	✓	✓	✓	✓	✓	✓	✓
13	GFAMG	Real Gross Fixed Capital Formation: Machinery and Equipment	Q	EUR	✓	✓	-	✓	✓	✓	✓	✓	✓	✓	✓
14	AHRDI	Adjusted Household Real Disposable Income	Q	EUR	✓	-	-	-	-	-	-	-	-	-	-
15	AHFCE	Actual Final Consumption Expenditure of Households	Q	EUR	✓	-	-	-	-	-	-	-	-	-	-
16	GNFCPS	Gross Profit Share of Non-Financial Corporations	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
17	GNFCIR	Gross Investment Share of Non-Financial Corporations	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
18	GHIR	Gross Investment Rate of Households	Q	EUR	✓	✓	-	✓	✓	✓	✓	✓	✓	✓	✓
19	GHSR	Gross Households Savings Rate	Q	EUR	✓	✓	✓	✓	-	✓	✓	✓	✓	✓	✓
(2) Labor Market Indicators															
20	TEMP	Total Employment (domestic concept)	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
21	EMP	Employees (domestic concept)	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
22	SEMP	Self Employment (domestic concept)	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
23	THOURS	Hours Worked: Total	Q	EUR	✓	✓	-	✓	✓	✓	✓	✓	✓	✓	✓
24	EMPAG	Quarterly Employment: Agriculture, Forestry, Fishing	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
25	EMPIN	Quarterly Employment: Industry	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
26	EMPMN	Quarterly Employment: Manufacturing	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
27	EMPCON	Quarterly Employment: Construction	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
28	EMPRT	Quarterly Employment: Wholesale/Retail trade, transport, food	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
29	EMPIT	Quarterly Employment: Information and Communication	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
30	EMPFC	Quarterly Employment: Financial and Insurance activities	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
31	EMPRE	Quarterly Employment: Real Estate	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
32	EMPPR	Quarterly Employment: Professional, Scientific, Technical activities	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
33	EMPPA	Quarterly Employment: PA, education, health ad social services	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
34	EMPENT	Quarterly Employment: Arts and recreational activities	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
35	UNETOT	Unemployment: Total (% active population)	M	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
36	UNEO25	Unemployment: Over 25 years (% active population)	M	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
37	UNEU25	Unemployment: Under 25 years (% active population)	M	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
38	RPRP	Real Labour Productivity (person)	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
39	WS	Wages and salaries	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
40	ESC	Employers' Social Contributions	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
(3) Credit Aggregates															
41	TASS.SDB	Total Economy - Assets: Short-Term Debt Securities	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
42	TASS.LDB	Total Economy - Assets: Long-Term Debt Securities	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
43	TASS.SLN	Total Economy - Assets: Short-Term Loans	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
44	TASS.LLN	Total Economy - Assets: Long-Term Loans	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
45	TLB.SDB	Total Economy - Liabilities: Short-Term Debt Securities	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
46	TLB.LDB	Total Economy - Liabilities: Long-Term Debt Securities	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
47	TLB.SLN	Total Economy - Liabilities: Short-Term Loans	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
48	TLB.LLN	Total Economy - Liabilities: Long-Term Loans	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
49	NFCASS	Non-Financial Corporations: Total Financial Assets	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
50	NFCASS.SLN	Non-Financial Corporations - Assets: Short-Term Loans	Q	EUR	✓	✓	✓	✓	✓	✓	-	✓	✓	✓	✓
51	NFCASS.LLN	Non-Financial Corporations - Assets: Long-Term Loans	Q	EUR	✓	✓	✓	✓	✓	✓	-	✓	✓	✓	✓
52	NFCLB	Non-Financial Corporations: Total Financial Liabilities	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
53	NFCLB.SLN	Non-Financial Corporations - Liabilities: Short-Term Loans	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	-	✓	✓
54	NFCLB.LLN	Non-Financial Corporations - Liabilities: Long-Term Loans	Q	EUR	✓	✓	✓	✓	✓	✓	✓	-	✓	✓	✓
55	GGASS	General Government: Total Financial Assets	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
56	GGASS.SLN	General Government - Assets: Short-Term Loans	Q	EUR	✓	✓	✓	-	-	-	-	-	-	-	-
57	GGASS.LLN	General Government - Assets: Short-Term Loans	Q	EUR	✓	✓	-	✓	-	-	✓	-	-	-	✓
58	GGLB	General Government: Total Financial Liabilities	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
59	GGLB.SLN	General Government - Liabilities: Short-Term Loans	Q	EUR	✓	✓	✓	✓	✓	✓	-	✓	✓	✓	✓
60	GGLB.LLN	General Government - Liabilities: Long-Term Loans	Q	EUR	✓	✓	✓	✓	✓	✓	-	✓	✓	✓	✓
61	HHASS	Households: Total Financial Assets	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
62	HHASS.SLN	Households - Assets: Short-Term Loans	Q	EUR	✓	-	-	-	-	-	✓	-	-	-	-
63	HHASS.LLN	Households - Assets: Long-Term Loans	Q	EUR	✓	-	-	-	-	-	✓	-	-	-	✓
64	HHLB	Households: Total Financial Liabilities	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
65	HHLB.SLN	Households - Liabilities: Short-Term Loans	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	-	✓	✓
66	HHLB.LLN	Households - Liabilities: Long-Term Loans	Q	EUR	✓	✓	✓	✓	✓	✓	✓	-	✓	✓	✓
(4) Labor Costs															
67	ULCIN	Nominal Unit Labor Costs: Industry	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
68	ULCMQ	Nominal Unit Labor Costs: Mining and Quarrying	Q	EUR	✓	✓	✓	-	✓	-	✓	✓	-	✓	✓
69	ULCMN	Nominal Unit Labor Costs: Manufacturing	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
70	ULCCON	Nominal Unit Labor Costs: Construction	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	-	✓	✓
71	ULCRT	Nominal Unit Labor Costs: Wholesale/Retail Trade, Transport, Food, IT	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
72	ULCFC	Nominal Unit Labor Costs: Financial Activities	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
73	ULCRE	Nominal Unit Labor Costs: Real Estate	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	-	✓	✓
74	ULCPR	Nominal Unit Labor Costs: Professional, Scientific, Technical activities	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
(5) Financial Markets															
75	REER42	Real Exchange Rate (42 main industrial countries)	M	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
76	ERUS	Exchange Rate (US dollar)	M	EUR	✓	-	-	-	-	-	-	-	-	-	-
77	SHIX	Stock Price Index	M	OECD	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
(6) Interest Rates															
79	IRT3M	3-Months Interest Rates	M	EUR	✓	-	-	-	-	-	-	-	-	-	-
79	IRT6M	6-Months Interest Rates	M	EUR	✓	-	-	-	-	-	-	-	-	-	-
80	LTIRT	Long-Term Interest Rates (EMU Criterion)	M	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 1: Data Description by country

N	ID	Series	F	P	EA	AT	BE	DE	EL	ES	FR	IE	IT	NL	PT
(7) Industrial Production and Turnover															
81	IPMN	Industrial Production Index: Manufacturing	M	EUR	✓	✓	✓	✓	✓	✓	✓	-	✓	✓	✓
82	IPCAG	Industrial Production Index: Capital Goods	M	EUR	✓	✓	✓	✓	✓	✓	✓	-	✓	✓	✓
83	IPCOG	Industrial Production Index: Consumer Goods	M	EUR	✓	✓	✓	✓	✓	✓	✓	-	✓	-	-
84	IPDCOG	Industrial Production Index: Durable Consumer Goods	M	EUR	✓	✓	✓	✓	✓	✓	✓	-	✓	✓	✓
85	IPNDCOG	Industrial Production Index: Non Durable Consumer Goods	M	EUR	✓	✓	✓	✓	✓	✓	✓	-	✓	✓	✓
86	IPING	Industrial Production Index: Intermediate Goods	M	EUR	✓	✓	✓	✓	✓	✓	✓	-	✓	✓	✓
87	IPNRG	Industrial Production Index: Energy	M	EUR	✓	✓	✓	✓	✓	✓	✓	-	✓	✓	✓
88	TRNMN	Turnover Index: Manufacturing	M	EUR	✓	✓	✓	✓	✓	✓	✓	-	-	✓	✓
89	TRNCAG	Turnover Index: Capital Goods	M	EUR	✓	✓	✓	✓	✓	✓	✓	-	✓	✓	✓
90	TRNCOG	Turnover Index: Consumer Goods	M	EUR	✓	✓	✓	✓	✓	✓	✓	-	✓	✓	✓
91	TRNDCOG	Turnover Index: Durable Consumer Goods	M	EUR	✓	✓	✓	✓	✓	✓	✓	-	✓	✓	✓
92	TRNNDCOG	Turnover Index: Non Durable Consumer Goods	M	EUR	✓	✓	✓	✓	✓	✓	✓	-	✓	✓	✓
93	TRNING	Turnover Index: Intermediate Goods	M	EUR	✓	✓	✓	✓	✓	✓	✓	-	✓	✓	✓
94	TRNNRG	Turnover Index: Energy	M	EUR	✓	✓	✓	✓	✓	✓	✓	-	✓	-	✓
95	CAREG	Passenger's Cars Registrations	M	ECB	✓	-	-	-	-	-	-	-	-	-	-
(8) Prices															
96	PPICAG	Producer Price Index: Capital Goods	M	EUR	✓	✓	✓	✓	✓	✓	✓	-	✓	✓	-
97	PPICOG	Producer Price Index: Consumer Goods	M	EUR	✓	✓	✓	✓	✓	✓	✓	-	✓	✓	-
98	PPIDCOG	Producer Price Index: Durable Consumer Goods	M	EUR	✓	✓	✓	✓	✓	✓	✓	-	✓	✓	-
99	PPINDCOG	Producer Price Index: Non Durable Consumer Goods	M	EUR	✓	✓	✓	✓	✓	✓	✓	-	✓	✓	-
100	PPIING	Producer Price Index: Intermediate Goods	M	EUR	✓	✓	✓	✓	✓	✓	✓	-	✓	✓	-
101	PPINRG	Producer Price Index: Energy	M	EUR	✓	✓	✓	✓	✓	✓	✓	-	✓	✓	-
102	HICPOV	Harmonized Index of Consumer Prices: Overall Index	M	ECB	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
103	HICPNEF	Harmonized Index of Consumer Prices: All Items, no Energy&Food	M	ECB	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
104	HICPG	Harmonized Index of Consumer Prices: Goods	M	ECB	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
105	HICPIN	Harmonized Index of Consumer Prices: Industrial Goods	M	ECB	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
106	HICPSV	Harmonized Index of Consumer Prices: Services	M	ECB	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
107	HICPNG	Harmonized Index of Consumer Prices: Energy	M	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
108	DFGDP	Real Gross Domestic Product Deflator	Q	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
109	HPRC	Residential Property Prices (BIS)	Q	FRED	✓	✓	✓	✓	-	✓	✓	✓	✓	✓	-
(9) Confidence Indicators															
110	ICONFIX	Industrial Confidence Indicator	M	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
111	CCONFIX	Consumer Confidence Index	M	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
112	ESENTIX	Economic Sentiment Indicator	M	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
113	KCONFIK	Construction Sentiment Indicator	M	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
114	RTCONFIX	Retail Confidence Indicator	M	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
115	SCONFIX	Services Confidence Indicator	M	EUR	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
116	BCI	Business Confidence Index	M	OECD	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
117	CCI	Consumer Confidence Index	M	OECD	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
(10) Monetary Aggregates															
118	CURR	Money Stock: Currency	M	ECB	✓	-	-	-	-	-	-	-	-	-	-
119	M1	Money Stock: M1	M	ECB	✓	-	-	-	-	-	-	-	-	-	-
120	M2	Money Stock: M2	M	ECB	✓	-	-	-	-	-	-	-	-	-	-

Table 2: Number of series: EA and individual countries

	EA	AT	BE	DE	EL	ES	FR	IE	IT	NL	PT	TOTAL
(1) National Accounts	17	17	11	17	12	14	17	17	17	14	14	161
(2) Labor Market Indicators	21	21	20	21	21	21	21	21	21	21	21	229
(3) Credit Aggregates	26	24	22	23	17	22	25	18	22	25	24	248
(4) Labor Costs	8	8	8	7	8	7	8	6	7	8	8	85
(5) Financial Markets	3	2	2	2	2	2	2	2	2	2	2	23
(6) Interest Rates	3	1	1	1	1	1	1	1	1	1	1	12
(7) Production and Turnover	14	14	14	14	14	14	14	0	13	12	13	136
(8) Prices	14	14	14	14	13	14	14	8	14	14	7	140
(9) Confidence Indicators	8	8	8	8	8	8	8	8	8	8	8	88
(10) Monetary Aggregates	3	0	0	0	0	0	0	0	0	0	0	3
(1)-(10) TOTAL	118	109	100	107	96	103	110	81	105	108	99	1136

Finally, while most series are already seasonally adjusted at the source, some are only available in raw form. For these, we retrieve the unadjusted series and apply seasonal adjustment *ex post*. In particular, we employ standard seasonal filtering methods (Findley et al., 1998) for monthly variables, while quarterly variables are adjusted using a simple dummy-variable approach.³ Only

³It is well known that filtering techniques can suffer from end-of-sample issues, requiring many observations to obtain reliable estimates of the trend component. Given the limited time span at the quarterly frequency, end-of-period estimates for seasonally adjusted quarterly variables obtained with these filters are therefore unreliable.

Credit Aggregates and Producer Prices are not seasonally adjusted at the source, accounting on average for about 30% of the total series. Starting from the October 2025 release, we also provide users with raw data, where these series remain unadjusted.

2.2 Transformations to stationarity

Being composed of variables that capture a wide range of economic and financial aggregates, the EA-MD-QD includes both stationary and non-stationary series. Although recent advances in econometric methods allow for the presence of non-stationarity in large-dimensional settings (Barigozzi et al., 2021), many empirical applications still require stationary data. For this reason, together with the raw data, we provide users with transformation codes designed to achieve stationarity.

We consider three possible sets of transformations. First, *statistical* transformations which remove any $I(1)$ or $I(2)$ according to standard unit root tests (Dickey and Fuller, 1979; Phillips and Perron, 1988). Overall, both across variable categories and countries, only a small number of series exhibit $I(2)$ dynamics. Most of these belong to the group of Credit Aggregates, distributed relatively evenly across countries, with a few notable exceptions related to Unit Labor Costs and Labor Market Indicators. Conversely, the majority of the series in the panel are $I(1)$. A smaller subset of variables is instead $I(0)$, primarily concentrated among confidence indicators and, for some countries, national accounts variables. The transformations are applied uniformly across countries, with only minor deviations reflecting country-specific idiosyncrasies that generate dynamics differing from those of the corresponding EA series. We refer to Table A2 in Appendix A for details.

Second, we consider the statistical set of transformations described above with the exception of interest rates which are kept in levels. This choice is in line with the literature on EA monetary policy transmission which is also the focus of the second part of the paper (Corsetti et al., 2022). Third, we consider the statistical set of transformations described above with the exception of interest rates and unemployment rates in order to keep all rates in levels.

The companion codes allow the users either to keep the data in levels or to apply either of the three set of transformations described above.

2.3 Treatment of missing values

As discussed above, regardless of the dataset frequency, missing values remain due to ragged edges arising from data availability, the asynchronous timing of data releases, as well as from removals of outliers. Moreover, the transformations applied to the series, as described in Section 2.2, introduce additional missing values because of observation losses due to differencing. While the untreated data are always provided, the companion codes to the dataset allow practitioners to choose among two different strategies for imputing missing values.

Specifically, missing values can be imputed using either the Expectation Maximization (EM) algorithm proposed by Stock and Watson (2002b) and also employed by McCracken and Ng (2016), or the one by Ba  bura and Modugno (2014). The former represents the most straightforward approach commonly used in the literature for imputing both outliers and missing values, though not necessarily the most sophisticated. The latter is particularly suitable when the data exhibit a factor structure with autocorrelated factors.

2.4 Treatment of outliers and COVID

Following McCracken and Ng (2020), an observation is considered an outlier if it deviates from the sample median by more than ten interquartile ranges. Once outliers are detected and removed we can impute the corresponding missing values by either of the methods described in Section 2.3. This applies to all sample except the Covid period.

Unlike “standard” outliers, the COVID shock is pervasive, affecting most series in the panel—particularly those representing the real economy—with substantial heterogeneity even within these series. Moreover, it is unclear how much of the COVID shock should be attributed to economic versus exogenous forces (Ng, 2021). In light of these considerations, treating the COVID period as composed of sporadic outliers would result in the loss of potentially important economic information relevant for understanding the current economic stance.

In the companion codes, we provide users with two alternatives related to the treatment of the COVID period. In the first option, data for variables representing the real side of the economy, as, e.g., Industrial Production, are treated as missing in 2020-2021 and imputed via the Kalman smoother using information from financial and nominal variables, as, e.g., the Stock Price Index and Prices. Alternatively, users can retain the transformed data without any specific treatment for COVID.

3 Baseline specification

As discussed above the user has many possible choices about the data to be analysed and their treatment treating. Clearly, the specific choices depend on the aim of the empirical analysis. In the rest of the paper, we exploit the EA-MD-QD database to study the transmission of EA monetary policy across countries, with the goal of highlighting the advantages the database offers for structural macroeconomic analysis. To this end, hereafter, we adopt the following baseline specification.

1. We consider only monthly data. Results for quarterly or monthly data plus GDP, i.e., mixed frequency data, are in Appendices I and J, respectively.
2. All variables are differenced according to the statistical transformations, except for interest rates, which are kept in levels. Results based on the two other sets of transformations discussed in Section 2.2 are in Appendices F and G.
3. Missing values are imputed according to the method by Stock and Watson (2002b) as discussed in Section 2.3. Results based using the imputation method by Ba  nbara and Modugno (2014) are virtually identical and thus omitted.
4. Outliers are detected as in McCracken and Ng (2020) as discussed in Section 2.4, with the exception of COVID period, which is not treated as an outlier, but it is explicitly accounted for in the empirical analysis. Results based on a sample ending in 2019:M12, thus excluding COVID, are in Appendix D.

Specifically, we construct a balanced panel $\mathbf{x} = \{x_{it}, i = 1, \dots, N; t = 1, \dots, T\}$ consisting of 47 EA-wide monthly variables and 200 national series, all transformed as described above, for a total of $N = 247$ time series, and covering the period 2002:M1-2023:M10, corresponding to $T = 263$ monthly observations.

These choices are based on a series of practical considerations. First, regarding the chosen sample, we begin the analysis in 2002:M1, following the literature on the identification of EA monetary policy shocks via instrumental variables (IV) (Altavilla et al., 2019; Andrade and Ferroni, 2021), since liquidity in the Overnight Index Swap (OIS) market was limited before then, hindering identification. The sample ends in 2023:M10, which is the latest date for which monetary policy surprises from Altavilla et al. (2019)—used to identify the shocks—are currently available.

Second, when the goal is extracting common factors, as in our empirical analysis, it is well documented that adding more series to the dataset does not necessarily help in recovering the factors (Boivin and Ng, 2006). Indeed, one should retain only those series that are most likely to be driven by the same common shocks. Not surprisingly these are the most aggregated series. Hence our choice of appending to the EA monthly dataset the following national variables: Industrial Production Indexes (IPMN, IPCAG, IPCOG, IPDCOG, IPNDCOG, IPING, IPNRG), Harmonized Indexes of Consumer Prices (HICPOV, HICPNEF, HICPG, HICPIN, HICPSV, HICPNG), Producer Price Indexes (PPICAG, PPICOG, PPINDCOG, PPIDCOG, PPIING, PPINRG), 10-years Interest Rates (LTIRT), Stock Price Indexes (SHIX), and Unemployment Rates (UNETOT).⁴

Third, although for consistent estimation of the factors we do not require any constraint between the cross-sectional dimension N and the sample size T , still it is advisable to have a panel where these quantities have a comparable value. As pointed out by Onatski (2010) if N is much larger than T it is harder to recover consistently the number of factors by studying the behavior of sample eigenvalues. Since the considered time span is relatively short, then we prefer working with just a subset of the whole EA-MD-QD data.

A step-by-step description of the procedure adopted in this section and Sections 4 and 5 to prepare and analyze the data through a factor model is given in Appendix B.

4 Factor analysis

We assume that the N -dimensional vector of observed data at time t , \mathbf{x}_t , follows a factor model:

$$\mathbf{x}_t = \boldsymbol{\mu} + \boldsymbol{\Lambda}\mathbf{f}_t + \boldsymbol{\xi}_t = \boldsymbol{\chi}_t + \boldsymbol{\xi}_t \quad t = 1, \dots, T, \quad (1)$$

where $\boldsymbol{\Lambda}$ is the $N \times r$ vector of loadings associated to the r -dimensional vector of zero-mean common factors \mathbf{f}_t , $\boldsymbol{\xi}_t$ is a $N \times 1$ vector of zero-mean idiosyncratic components, and $\boldsymbol{\mu}$ is a $N \times 1$ vector of constants, hence $\mathbb{E}[\mathbf{x}_t] = \boldsymbol{\mu}$.

Both the factors and the idiosyncratic components are allowed to be serially correlated. Moreover, when N is large is reasonable to allow the idiosyncratic components to be also (weakly) cross-sectionally correlated, and, in this case, we say that (1) is an approximate factor model. We

⁴Indeed, when including all the monthly variables in the dataset, the variance of the idiosyncratic components of the most relevant variables included in our analysis grows by 20% on average.

refer to Bai (2003) for the formal assumptions.

The loadings and the factors in (1) are not identified, since the factor model can equivalently be expressed with $\Lambda \mathbf{H}$ as the loadings matrix and $\mathbf{H}^{-1} \mathbf{f}_t$ as the factors vector, for some invertible $r \times r$ matrix \mathbf{H} . To identify the factors additional assumptions would be needed (Bai and Ng, 2013), but since in this paper our interest is only in estimating the common component $\chi_t = \mu + \Lambda \mathbf{f}_t$, we do not explore this path further. Indeed, χ_t is always identified once we determine the number of factors r , so that we can disentangle it from the idiosyncratic component.

The factors and loadings are estimated via the classical PCA approach. So we estimate the loadings, denoted as $\hat{\Lambda}$, as \sqrt{N} times the r normalized eigenvectors corresponding to the r -largest eigenvalues of the sample covariance matrix of the standardized data \mathbf{x}_t , i.e., of $T^{-1} \sum_{t=1}^T \hat{\Omega}^{-1/2} (\mathbf{x}_t - \hat{\mu}) (\mathbf{x}_t - \hat{\mu})' \hat{\Omega}^{-1/2}$, where $\hat{\mu}$ and $\hat{\Omega}$ are, respectively, the N dimensional vector of sample means and a diagonal $N \times N$ matrix with entries the N sample variances of each element of \mathbf{x}_t . Then, the factors, $\hat{\mathbf{f}}_t$, are obtained by projecting the estimated loadings onto the data, i.e., $\hat{\mathbf{f}}_t = (\hat{\Lambda}' \hat{\Lambda})^{-1} \hat{\Lambda}' \hat{\Omega}^{-1/2} (\mathbf{x}_t - \hat{\mu}) = N^{-1} \hat{\Lambda}' \hat{\Omega}^{-1/2} (\mathbf{x}_t - \hat{\mu})$ (due normalization of the eigenvectors). The estimated common components are then de-standardized and de-centered by multiplying them by the standard deviation of the original series and adding the corresponding mean. The resulting common component N -dimensional vector is denoted as $\hat{\chi}_t = \hat{\mu} + \hat{\Omega}^{1/2} \hat{\Lambda} \hat{\mathbf{f}}_t$.

From the results in Stock and Watson (2002a) and Bai (2003), it immediately follows that $\hat{\chi}_t$ is a consistent estimator of χ_t , as $N, T \rightarrow \infty$. This in practice shows the necessity of working with a high-dimensional panel in order to consistently disentangle the common components capturing all main comovements from the idiosyncratic ones.

In Table 3 we report the number of common factors obtained by employing the following standard methods: (i) the log-information criterion (IC2) of Bai and Ng (2002), implemented also when (ii) tuning the penalty as suggested by Alessi et al. (2010), (iii) the eigenvalue-ratio criterion by Ahn and Horenstein (2013), and (iv) the test by Onatski (2010).⁵ Hereafter, we set $r = 6$.

5 Comovements across EA countries

For a given variable, the share of total variance explained by the common component offers a straightforward measure of cross-country comovement. Specifically, for a given country and vari-

⁵For those methods requiring it, we set the maximum number of factors to $r_{\max} = 15$.

Table 3: Estimated number of factors

Method	Number of factors r
Bai and Ng (2002)	8
Alessi et al. (2010)	6
Onatski (2010)	2
Ahm and Horenstein (2013)	2

Table 4: Share of Explained Variance by the common factors

Country	IP: Manufacturing (IPMN)	HICP: Overall (HICPOV)	10-years Interest Rate (LTIRT)	Stock Price Index (SHIX)	Unemployment Rate (UNETOT)
EA	0.88 (0.83-0.91)	0.82 (0.77-0.86)	0.93 (0.87-0.95)	0.90 (0.86-0.92)	0.64 (0.53-0.68)
AT	0.63 (0.52-0.70)	0.68 (0.61-0.73)	0.93 (0.86-0.94)	0.78 (0.73-0.80)	0.10 (0.08-0.15)
BE	0.18 (0.12-0.26)	0.50 (0.43-0.58)	0.94 (0.88-0.95)	0.81 (0.77-0.84)	0.11 (0.08-0.17)
DE	0.72 (0.63-0.78)	0.58 (0.51-0.65)	0.91 (0.82-0.91)	0.81 (0.77-0.84)	0.14 (0.11-0.28)
EL	0.15 (0.11-0.22)	0.42 (0.34-0.49)	0.13 (0.12-0.39)	0.61 (0.55-0.65)	0.12 (0.10-0.21)
ES	0.81 (0.72-0.86)	0.64 (0.56-0.70)	0.79 (0.74-0.86)	0.77 (0.72-0.79)	0.55 (0.49-0.64)
FR	0.86 (0.79-0.89)	0.65 (0.60-0.73)	0.94 (0.86-0.94)	0.88 (0.84-0.90)	0.17 (0.12-0.22)
IE	- (-)	0.57 (0.51-0.67)	0.65 (0.59-0.77)	0.71 (0.66-0.75)	0.29 (0.22-0.40)
IT	0.77 (0.69-0.82)	0.52 (0.46-0.61)	0.81 (0.77-0.86)	0.85 (0.81-0.86)	0.41 (0.32-0.48)
NL	0.29 (0.21-0.36)	0.37 (0.30-0.46)	0.92 (0.84-0.92)	0.83 (0.78-0.85)	0.27 (0.20-0.34)
PT	0.52 (0.39-0.61)	0.47 (0.39-0.55)	0.41 (0.35-0.61)	0.67 (0.62-0.70)	0.32 (0.26-0.40)

NOTES: Each entry in the table corresponds to the share of variability within each variable (in the columns) for each country (in the rows) explained by the common component, $\hat{\chi}_{i,t}$. Numbers in parentheses indicate the lower and upper bounds of the 68% confidence interval, computed using the bootstrap procedure described in Appendix B.

able, a high proportion of variance explained by the common component indicates that the variable is primarily driven by EA-wide common factors rather than by country-specific idiosyncratic dynamics. To provide an intuition of the explanatory power of the common factors, Table 4 reports the share of variance explained by the common component for selected key variables. This analysis offers a preliminary assessment of the degree of synchronization across EA countries. Indeed, if country dynamics were perfectly aligned, we would expect relatively similar levels of comovement across countries for each variable. Confidence intervals for the explained variance are obtained using 1000 replications of the bootstrap procedure by Barigozzi et al. (2018) and described in Appendix B.

Comovement across variables is relatively high at the EA level. At the country level, however, some heterogeneity emerges across indicators. For industrial production, Belgium, Greece, the Netherlands, and, to a lesser extent, Portugal, deviate from the high commonality observed at the EA level. Hence, larger industrial economies are more closely aligned with the EA, whereas smaller economies exhibit a higher degree of idiosyncratic variation in production. In contrast,

prices display a relatively more homogeneous pattern across countries, but the average share of variance explained is lower than for industrial production. Indeed, nominal variables have been shown to comove less than real variables in standard large macroeconomic datasets (Ahn and Luciani, 2025; Lissona and Ruiz, 2025). The degree of commonality for interest rates exhibits a clear core-periphery pattern: Northern European countries display a high level of commonality, whereas interest rate dynamics in Southern countries appear more driven by country-specific factors. However, even within this group, the extent of idiosyncrasy varies considerably: Italy and Spain comove more strongly with the EA, while Greece is almost entirely idiosyncratic. Stock prices show a relatively high and homogeneous degree of commonality across countries, with the exceptions of Greece and Portugal.

The variable exhibiting the highest degree of heterogeneity is the unemployment rate. Recall that this variable is taken in first difference under our baseline specification. As such its degree of comovement is not very large, but still there are considerable differences across countries and these are unaffected by the chosen transformation.⁶

Overall, these results provide preliminary insights into the degree of heterogeneity across variables and EA countries. While no structural claims can be made at this stage, they motivate a deeper analysis to determine whether this heterogeneity persists conditional on a monetary policy shock (see Section 7.4).

Finally, we acknowledge that a more rigorous analysis of comovements across EA variables would require explicitly accounting for lag and lead relationships both across variables and countries, as in D’Agostino et al. (2016) and Cascaldi-Garcia et al. (2024). However, given the large dimensionality of our data—both within and across countries—such an approach would require modifications of the employed methodology which are beyond the scope of this paper.

6 Estimation and identification of IRFs

6.1 Common Component VAR

It is widely acknowledged that by using large datasets we can retrieve structural shocks via factor analysis (see, e.g., the theoretical and empirical findings by Giannone and Reichlin, 2006; Forni

⁶If the unemployment rate were taken in levels, then its high-persistence would result in an anomalously large explained variance of its common component. The choice of taking first differences is precisely made to avoid such “overfitting” phenomenon.

et al., 2009, 2014). In this spirit, here we adopt the CC-VAR by Forni et al. (2025) in order to estimate and identify the IRFs to the EA monetary policy shock. This approach simply consists in fitting a VAR on a vector \mathbf{Y}_t of n endogenous variables with $n \ll N$, and containing n^* estimated common components of selected variables, $\hat{\mathbf{x}}_t$, with $r \leq n^* \leq n$, along with any possible additional observable of interest.

The CC-VAR has three main advantages. First, since the common components are always identified, identification of the shocks can be achieved by means of any existing method borrowed by the traditional structural VAR literature. Second, if, in presence of r latent factors, we include $n^* = r$ common components in the VAR, then the space spanned by the structural shocks driving all N common components coincides with the space spanned by the reduced form shocks, i.e., the VAR innovations. This is because all common components are generated by the same underlying shocks through the factors, which are common to all N considered variables. It follows that, third, when considering a VAR for the common components and substituting one of these with another, the IRFs of the retained variables do not change, i.e., they are invariant with respect to the choice of the other variables included in the model.

Given the above described properties and our task of identifying the common EA monetary policy shock, the CC-VAR then seems to be a more suitable choice than the FAVAR (Bernanke et al., 2005). Indeed, while by augmenting a classical VAR with latent factors, the FAVAR allows us to recover the space spanned by structural shocks, this space is also contaminated by idiosyncratic dynamics. Hence, we cannot guarantee the invariance of the IRFs which characterizes the CC-VAR. This is because in the FAVAR we use the observed variables and not their common components.⁷ Moreover, since the factors are not identified (see Section 4), including them in the VAR makes identification less straightforward. Clearly, a classical VAR is also inferior to the CC-VAR since, not only it lacks the invariance property of IRFs, but also it does not guarantee that we can recover the space of the structural shocks (Alessi et al., 2011).

Our specification of the vector \mathbf{Y}_t is given in Table 5. First, we include the observed EA 2-years Interest Rate R_t , which is also our policy rate (see Section 6.2 for its motivation). Then, we include the common component for five key EA variables: the Industrial Production growth in manufacturing (IPMN), the Overall Harmonized Consumer Price Index inflation (HICPOV), the

⁷Note that if we augmented the CC-VAR with factors, as for example in the original application by Forni et al. (2025), the invariance of the IRFs would obviously still be preserved, and we could think of it as a FAVAR for common components.

Table 5: Components of \mathbf{Y}_t in the CC-VAR

Notation	ID	name
R_t	-	EA 2-years Interest Rate
$\hat{\chi}_{\text{IPMN EA},t}$	IPMN	EA IP: Manufacturing (common component)
$\hat{\chi}_{\text{HICPOV EA},t}$	HICPOV	EA HICP: Overall (common component)
$\hat{\chi}_{\text{LTIRT EA},t}$	LTIRT	EA 10-years Interest Rate (common component)
$\hat{\chi}_{\text{SHIX EA},t}$	SHIX	EA Stock Price Index (common component)
$\hat{\chi}_{\text{UNETOT EA},t}$	UNETOT	EA Unemployment Rate (common component)
$\hat{\chi}_{\text{nat.},t}$	-	National variable (common component)

10-years Interest Rate (LTIRT), the Stock Price Index growth (SHIX), and the monthly change in the Unemployment Rate (UNETOT). Finally, we include, one at a time, the common components of various national variables of interest, for which we aim to study the IRF. In particular, we consider a total of 49 different national variables resulting in 49 possible choices for \mathbf{Y}_t .⁸ For any of those choices, \mathbf{Y}_t has always dimension $n = 7$ and $n^* = n - 1 = 6$ so that $n^* = r$, and, as a consequence, the IRFs for the first six variables in \mathbf{Y}_t are unchanged in all 49 VARs (see the results in Section 7.1).

Specifically, for any choice of \mathbf{Y}_t , we estimate the following reduced-form VAR:

$$\mathbf{Y}_t = \mathbf{c} + \sum_{i=1}^p \mathbf{B}_i \mathbf{Y}_{t-i} + \sigma_t \mathbf{u}_t, \quad t = 1, \dots, T, \quad (2)$$

where \mathbf{c} is a $n \times 1$ vector of reduced-form constants, \mathbf{B}_i , $i = 1, \dots, p$, are $n \times n$ matrices of reduced-form coefficients and \mathbf{u}_t is the $n \times 1$ zero-mean vector of reduced-form errors, with zero mean and covariance matrix Σ .

The scaling factor σ_t is included to address the significant fluctuations observed during the Covid period by adjusting the model residual volatility, as suggested by Lenza and Primiceri (2022). In particular, σ_t , takes a value of 1 for all periods preceding the Covid onset period, while from 2020:M3 until the end of the sample, at $T = 2023:\text{M10}$, σ_t is estimated in each period by maximum likelihood.⁹

⁸The five key variables (IPMN, HICPOV, LTIRT, SHIX, UNETOT) for the ten countries covered by the EA-MD-QD, and recalling that Industrial Production for Ireland is unavailable.

⁹Our approach differs slightly from the approach of Lenza and Primiceri (2022) as their approach is based on US data. Nevertheless, the variations introduced do not significantly affect our results. Moreover, adjusting the IRFs for Covid introduces slight deviations from this invariance due to changes in the volatility parameter σ_t , leading to unwanted dispersion in the EA IRFs. To address this and preserve the invariance property of the CC-VAR, we first estimate σ_t for each specification differing only in the last variable. We then take the median of the estimated σ_t vectors across specifications to obtain an average volatility, which is subsequently used to compute the national IRFs as described.

Estimation of the VAR in (2) gives the estimated coefficients $\hat{\mathbf{B}}_i$ and by VAR inversion we obtain the estimated reduced form IRFs. Throughout, we choose $p = 8$ lags in the VAR. Consistency, as $N, T \rightarrow \infty$, is proved in Forni et al. (2025) (see also Forni et al., 2009, and Bai and Ng, 2006, for similar results).

6.2 Identification of the monetary policy shock

The structural counterpart of (2) is:

$$\mathbf{A}_0 \mathbf{Y}_t = \mathbf{c}^* + \sum_{i=1}^p \mathbf{A}_i \mathbf{Y}_{t-i} + \sigma_t \boldsymbol{\varepsilon}_t, \quad t = 1, \dots, T, \quad (3)$$

where the reduced-form errors \mathbf{u}_t are related to the structural errors $\boldsymbol{\varepsilon}_t$ through the following relationship:

$$\mathbf{u}_t = \mathbf{A}_0^{-1} \boldsymbol{\varepsilon}_t, \quad t = 1, \dots, T. \quad (4)$$

Hereafter, let $\mathbf{S} \equiv \mathbf{A}_0^{-1}$ for simplicity of notation.

As is well known in the VAR literature, the matrix \mathbf{S} is unobserved and we need an identification strategy to estimate it and give an economic interpretation to the elements of $\boldsymbol{\varepsilon}_t$. For our application, focused on the monetary policy shock only, it is sufficient to identify the associated elements in the column of the matrix \mathbf{S} . We denote such column as \mathbf{s} and the corresponding monetary policy shock as ε_t^p , while all other structural shocks are collected into the vector $\boldsymbol{\varepsilon}_t^q$. The entry of \mathbf{s} corresponding to ε_t^p , which is the contemporaneous impact of the monetary policy shock on the policy rate, is denoted as s^p , while all other entries are collected into the vector \mathbf{s}^q . Once the EA wide monetary policy shock is identified the corresponding IRFs are then computed from the, truncated, VMA(∞) representation of the estimated structural VAR defined in (3).

To identify \mathbf{s} and ε_t^p , we employ the high-frequency Proxy-SVAR method from Gertler and Karadi (2015).¹⁰ This approach requires jointly specifying two types of variables: a policy indicator and a monetary policy instrument. The policy indicator, denoted as R_t , is a variable capturing the central bank's monetary policy stance, it is included in \mathbf{Y}_t and thus enters directly into the CC-VAR model. The monetary policy instrument, denoted as Z_t , must satisfy two characteristics.

¹⁰In Appendix H we consider also sign restrictions as an alternative identification strategy.

First, it must be correlated with the monetary policy shock:

$$E[Z_t \varepsilon_t^p] > 0. \quad (5)$$

Second, it must be exogenous to all other shocks, collected in the vector $\boldsymbol{\varepsilon}_t^q$, i.e.,

$$E[Z_t \boldsymbol{\varepsilon}_t^q] = \mathbf{0}. \quad (6)$$

For a given choice of R_t and Z_t , after estimating the reduced-form VAR in (2), and its vector of estimated reduced-form residuals $\hat{\mathbf{u}}_t$, we identify \mathbf{s} using a two-step procedure. First, we project the residual of the policy indicator R_t , which we denote as \hat{u}_t^p , on the instrument Z_t . That is, we estimate the linear regression:

$$\hat{u}_t^p = \alpha + \beta Z_t + \zeta_t, \quad t = 1, \dots, T. \quad (7)$$

Then, letting $\hat{\alpha}$ and $\hat{\beta}$ be the OLS estimates of α and β and letting $\hat{u}_t^p = \hat{\alpha} + \hat{\beta} Z_t$, we estimate the linear regression,

$$\hat{\mathbf{u}}_t^q = \boldsymbol{\gamma} \hat{u}_t^p + \boldsymbol{\delta}_t, \quad t = 1, \dots, T, \quad (8)$$

where $\hat{\mathbf{u}}_t^q$ contains all other reduced-form residuals. The OLS estimate of $\boldsymbol{\gamma}$, denoted as $\hat{\boldsymbol{\gamma}}$, is then an estimate of \mathbf{s}^q / s^p . This identifies \mathbf{s} up to a scaling factor. To fully identify \mathbf{s} , we normalize the impact of the monetary policy shock on the interest rate to one, i.e., we set $s^p = 1$, so that $\hat{\boldsymbol{\gamma}} = \hat{\mathbf{s}}^q$. This results into an identified monetary policy shock which increases at impact the policy rate R_t of one percentage point.

As in Gertler and Karadi (2015), we test different combinations of instrument-policy indicators. Specifically, our selection of policy indicator R_t candidates includes EA the 1-, 2-, and 3-years rates interest rates downloaded from the Eurostat database, and our choice for the pool of instrument candidates is drawn from the work of Altavilla et al. (2019).¹¹ We then select the pair (R_t, Z_t) that exhibits the highest F -statistic related to Equation 7. The F -statistic is used to test the null hypothesis of instrument irrelevance (low F -statistic) against the alternative hypothesis of instrument relevance (high F -statistic), with a threshold of 10 commonly used to distinguish

¹¹To convert high-frequency data into monthly frequency, daily observations are cumulated over the last 30 days and then averaged over the corresponding month, following Gertler and Karadi (2015). This procedure substantially mitigates the temporal aggregation bias (Kilian, 2024).

between strong and weak instruments (Stock et al., 2002). Based on this test we choose R_t as the EA 2-years interest rate, while for Z_t we choose the 1-year OIS. This choice gives a standard F -statistic equal to 16.6 and a robust F -statistic, computed following Olea and Pflueger (2013), equal to 11.3.¹²

The OIS price is measured immediately before and after both the ECB’s press statement and press conference. The policy surprise measure is derived by summing these two price differences. The rationale is that, before the ECB policy announcements, the swap price incorporates market expectations regarding the future path of the OIS. Therefore, any adjustment in the price immediately after the policy announcements is interpreted as a recalibration of market expectations in response to an unforeseen monetary policy surprise. This satisfies the correlation requirement in (5). Regarding the exogeneity condition in (6), we assume that no other significant macroeconomic shock occurs in the time span between the press statement and the press conference. Additionally, we distinguish conventional monetary policy shocks from information shocks (Jarociński and Karadi, 2020; Andrade and Ferroni, 2021) by retaining only those high-frequency observations for the OIS price that are associated with a simultaneous movement of opposite sign in the swap price on the Euro Stoxx 50 index.

Finally, to quantify uncertainty around the estimated IRFs, we employ a standard Wild bootstrap (Gonçalves and Kilian, 2004) with 1000 bootstrap repetitions, also accounting for the well-known bias due to the estimation of the VAR in finite samples (Kilian, 1998).

7 The dynamic effects of the EA monetary policy

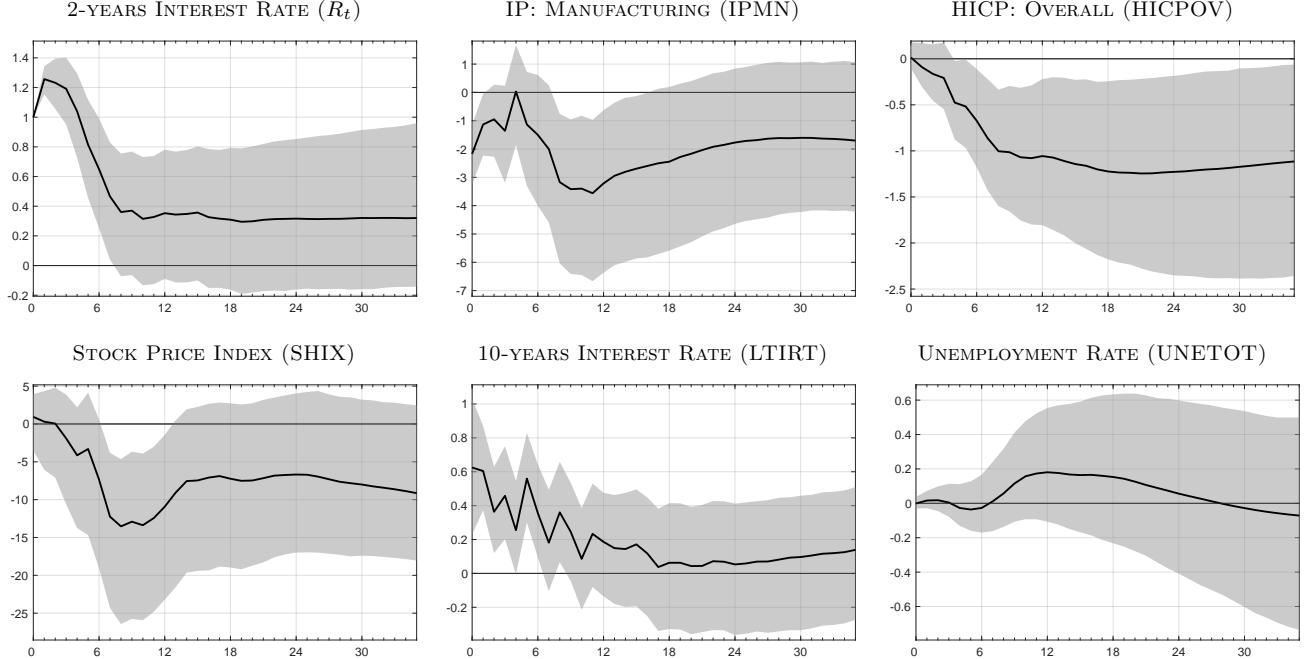
7.1 EA IRFs

Figure 1 presents the estimated IRFs of the EA variables included in the CC-SVAR in (2) in response to a 100 basis-point (bps) shock to the 2-years interest rate, along with their one-standard-deviation, i.e., 68%, confidence intervals. As already highlighted in Section 6.1, we notice that the same EA IRFs are obtained for any of the 49 VARs considered, each with a different national common component included. When comparing these results with classical VAR or FAVAR models

¹²We obtained similar results using other instrument-policy variable combinations. Specifically, we also tested the 1-year OIS together with the 1-year interest rate (F -statistic 13.9), the 1-year OIS together with the 3-year interest rate (F -statistic 12.0) and the 2-year OIS together with the 2-year interest rate (F -statistic 12.8). All these specifications yielded similar results.

(see Figures E1 and E2 in Appendix E), we see that neither of those approaches gives EA IRFs which are invariant with respect to the use of different national variables. Indeed, both for the VAR and the FAVAR we obtain 49 different IRFs for each of the six EA variables. This is what motivates our choice of the CC-VAR.

Figure 1: EA IRFs



NOTES: Each sub-figure plots the impulse response of one EA variable to a 100bps contractionary monetary policy shock. The black solid line is the point estimate in our baseline setting, while the gray shaded area is the corresponding 68% confidence interval.

A contractionary monetary policy shock leads to an increase in both short-term and long-term interest rates, with the latter rising to roughly half the magnitude of the former at impact. This pattern is expected, as monetary policy shocks typically have a stronger effect on shorter maturities than on the upper end of the yield curve (Altavilla et al., 2019). As anticipated, industrial production, prices, and the stock price in the EA decline. In contrast, the unemployment rate rises with a lag of a few months, although the response is not statistically significant.

The magnitudes of the responses of prices and the stock price are comparable to those reported by Jarociński and Karadi (2020) (after rescaling the interest rate increase to 100 basis points therein), but contrasts with Corsetti et al. (2022), who document a muted reaction of prices. This difference is likely to reflect our explicit control for so-called *information shocks* when constructing the instruments, consistently with the findings of Andrade and Ferroni (2021) and Jarociński and Karadi (2020). The pointwise response of the unemployment rate is similar in magnitude to the

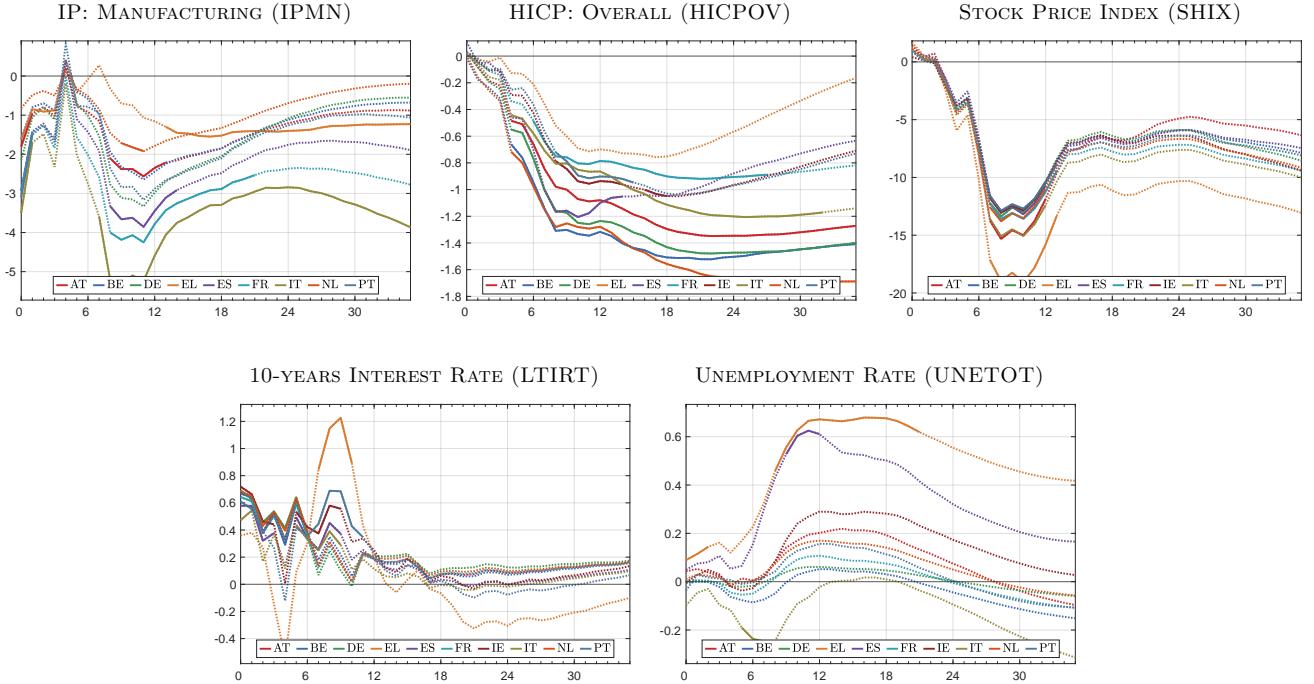
one reported by Corsetti et al. (2022).

These results, and those in the next sections, are coherent with those obtained using alternative sets of transformations (Appendices F and G), monthly or quarterly data and sign restrictions (Appendices H and I), as well as when augmenting the monthly data considered so far with quarterly EA and national GDPs (Appendix J).

7.2 Country-level IRFs

Figure 2 presents the IRFs for the national variables. At each horizon, responses that are significant at the one-standard-deviation, i.e., 68%, confidence level are shown with solid lines, while non-significant responses are depicted with dotted lines. Individual responses with their confidence intervals can be found in Appendix C.

Figure 2: Country-level IRFs



NOTES: Each sub-figure plots the impulse responses, for all countries, of one variable to a 100bps contractionary monetary policy shock. Within each sub-figure, at each horizon $h = 0, \dots, 36$ the country-level impulse responses are denoted with a solid line if the IRF is statistically significant at the 68% level at that horizon, and with a dotted line otherwise.

As with the EA IRFs, the direction of the IRFs for each country is consistent with standard economic theory. Moreover, the IRFs exhibit broadly similar dynamics across countries, with the main differences appearing in the magnitude of the response. For industrial production, the peak

decline in the IRFs ranges from approximately 6% for Italy to around 2% for Greece, which stands out both in terms of magnitude and the shape of its response relative to other countries. These results highlight how the largest manufacturing economies in the EA are more strongly affected by the adverse effects of a contractionary shock. Price responses are particularly homogeneous across countries, with a slightly more muted reaction in Greece. The maximum difference between the IRFs is approximately 1.5 percentage points, indicating only minor misalignments across countries.

Similar patterns are observed for stock prices, although Greece exhibits a particularly strong response to the contractionary shock, with its stock price declining by roughly 20%.

On the interest rate side, Greece again stands out with an exceptionally strong response, peaking at around 120 bps. More generally, interest rates increase more in other peripheral countries (i.e., Portugal, Ireland, Italy, and Spain) compared to core countries. This core-periphery distinction is less clear for the unemployment rate. While Greece and Spain experience notably higher responses, Italy shows a counterintuitive, though mostly non-significant, effect. Overall, most unemployment responses are borderline significant at best.

These results suggest only moderate heterogeneity across countries, which is mostly concentrated in a few selected cases. However, this analysis alone does not allow us to fully assess this claim, as these observed differences may be entirely obscured by estimation uncertainty.

7.3 Assessing cross-country heterogeneity

To quantify heterogeneity across EA countries, for each variable of interest we compute the difference between the national IRFs and the corresponding EA IRF. This procedure allows for a direct comparison across individual countries. Specifically, at each horizon, a positive (negative) value indicates that the national response lies above (below) the corresponding EA response. Importantly, this relative positioning does not necessarily imply a stronger or weaker response in absolute terms, as it depends on the sign and magnitude of both IRFs. For instance, a positive difference may arise either when both IRFs are positive and the national response is larger, or when both are negative and the national response is smaller. By repeating this procedure for each bootstrap repetition, we can also quantify the uncertainty around these point estimates.

Figure 3 presents these differences along with one-standard-deviation, i.e., 68%, confidence intervals. For industrial production, France and Italy stand out from the other countries, as they are the only ones exhibiting a stronger downward response relative to the EA aggregate. This

pattern differs for Germany, which, despite being one of the main manufacturing economies in the EA like Italy and France, shows no substantial deviation from the EA aggregate response. All other countries display weaker responses compared with the EA, particularly core economies such as Austria, Belgium, and the Netherlands.

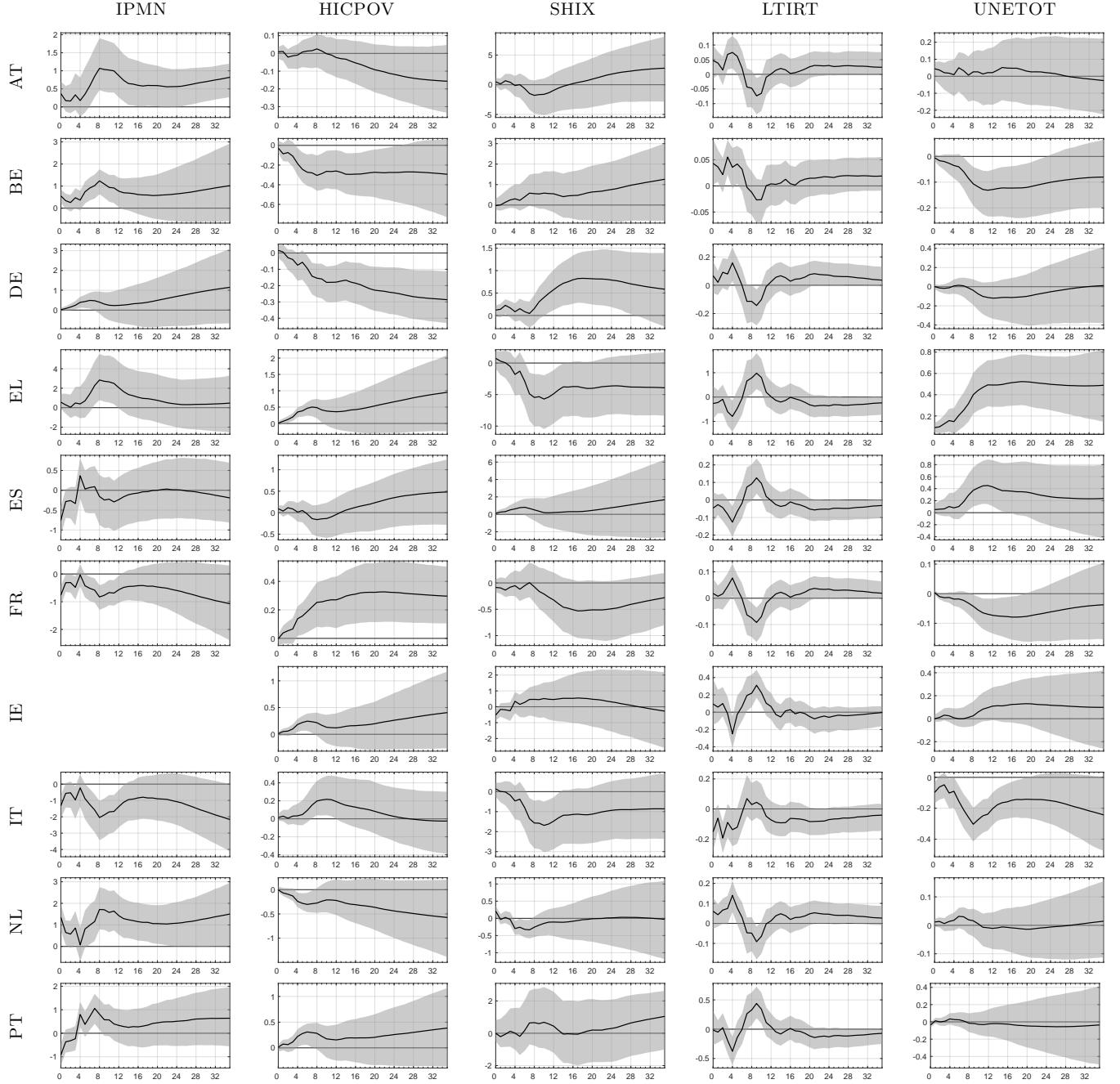
In contrast, for prices, some differences emerge between core and peripheral countries. Core countries are either closely aligned with the EA aggregate (e.g., Austria) or exhibit a stronger response (e.g., Germany), whereas peripheral countries generally show a more muted reaction, with the exception of Spain, where the difference is not statistically significant. This pattern seems to suggests that the transmission of monetary policy to prices differs between core and peripheral countries (Barigozzi et al., 2014).

Stock prices present a relatively homogeneous picture, with only Germany, Italy, and Greece showing statistically significant deviations from the EA aggregate. However, the magnitude of these differences varies markedly: Germany and Italy deviate by at most approximately 2%, whereas Greece exhibits a substantially stronger response, with a difference exceeding 5% compared to the EA counterpart.

An interesting pattern emerges for interest rates. First, for nearly all countries, the peak differences relative to the EA occur between 6 and 8 months, coinciding with the horizon at which most responses are statistically significant. Second, there is a hint of a core-periphery pattern: responses in peripheral countries tend to lie above the EA aggregate at medium horizons, whereas those of core countries peak below the EA at the same horizons. Notably, the magnitude of the response for Greece is particularly strong. On the labor market side, the most pronounced differences are observed for Greece and Spain, whose responses exceed the EA aggregate, and for Italy and France, whose responses are comparatively lower. These pattern is coherent with the one observed by Barigozzi et al. (2014), despite the different samples considered.

Overall, our results indicate the presence of moderate, yet non-negligible, heterogeneity across EA countries. The estimates point to a core-periphery pattern in price and interest rate dynamics. In terms of prices, core economies react broadly in line with—or somewhat more strongly than—the EA aggregate, whereas the responses of peripheral countries are more muted. Conversely, interest rates in peripheral countries tend to display comparatively stronger effects over the medium term. No systematic pattern emerges for real variables, although some countries, such as Italy and Greece, deviate more visibly from the aggregate dynamics. In contrast, stock prices behave in a largely

Figure 3: Difference between country-level and EA IRFs



NOTES: Each sub-figure plots the difference between the country-level IRF and the corresponding EA counterpart for one variable and one country. Each column of the graph represents a variable, while each row represents a country. The variables considered are: Industrial Production: Manufacturing (IPMN), HICP: Overall (HICPOV), Stock Price Index (SHIX), 10-years Interest Rates (LTIRT) and Unemployment Rate (UNETOT). The black solid line is the point estimate in our baseline setting, while the gray shaded area is the corresponding 68% confidence interval. The scale in the vertical axis differs across variables and countries.

uniform manner. Among all members, Germany’s reactions most closely match the EA aggregate, while Greece exhibits the largest departures.

These results do not signal major concerns for the conduct and transmission of monetary policy in the EA. However, they highlight the importance of closely monitoring within-country dynamics to further smooth policy transmission and mitigate adverse effects on domestic production, labor market outcomes, and—most importantly—financing costs, particularly in light of the recent post-Covid surge in public spending.

7.4 Cross-country characteristics and IRF dynamics

To investigate cross-country differences in responses to monetary policy shocks, we follow the methodology outlined in Corsetti et al. (2022). For each country, we compile data on selected institutional characteristics, including—but not limited to—labor market features, the financial conditions of firms and households, wage and price dynamics, and other country-specific factors. Whenever possible, these variables are averaged over the sample period; otherwise, we use data up to the most recent available period. We then compute the correlation between each explanatory variable and the peak response of the country-specific IRFs. The results of this analysis are reported in Table 6.

We begin by examining labor market indicators, including wage flexibility and job security. For wages, we consider three levels of wage adjustment frequency: more than once a year, once a year, and less than once a year. We find no statistically significant relationship between downward wage rigidity and heterogeneous responses across countries. Nevertheless, the signs of the correlations suggest that higher wage rigidity is associated with a stronger response in real activity and a more muted response in prices, consistent with a flatter aggregate demand curve (Christiano et al., 2005). Results for the employment protection index are weaker: as expected, higher employment protection corresponds to a smaller increase in unemployment, but its effect on other variables is relatively muted.

Turning to firm characteristics, lower price stickiness is associated with a stronger transmission of monetary policy to prices, along with a more muted response in real activity (see, e.g. Alvarez et al., 2016). Regarding the financial structure of firms, the results suggest that a higher leverage ratio of non-financial corporations relative to GDP is linked to a weaker response in real activity and stock prices, but a stronger response in prices. Similar findings are reported by Dedola and Lippi

(2005), as higher leverage proxies for borrowing capacity and, consequently, firm performance.

For households, we focus on their housing situation and consumption behavior. Our results indicate that homeownership per se provides little information on cross-country heterogeneity. In contrast, the method of financing housing appears more relevant. Countries with a higher share of homeowners with a mortgage experience a stronger impact on prices (and a weaker impact on stock prices), whereas the opposite holds for homeowners without a mortgage. This finding is consistent with recent literature, which, building on rational inattention models, shows that households with mortgages are more attentive to central bank communication and interest rate decisions, thereby enhancing monetary policy transmission (Ahn et al., 2024). We do not find any meaningful relationship between the type of mortgages (i.e., fixed versus floating) and country-specific responses. However, in countries where households have higher loan-to-value ratios on their mortgages, the impact on stock prices is smaller, further reinforcing the mechanism described in Dedola and Lippi (2005). Unlike Corsetti et al. (2022), we do not find any statistically significant results related to households' consumption habits. However, the direction of our findings is consistent with theirs. Specifically, hand-to-mouth households tend to dampen the transmission of monetary policy to prices, production, and the labor market, while increasing its impact on interest rates and having no effect on stock prices. Similar patterns are observed for wealthy hand-to-mouth consumers.

From a broader perspective, higher saving rates are associated with a stronger impact on prices. In contrast, long-term interest rates exhibit a less pronounced increase, while the negative effects on stock prices are mitigated.

Finally, we examine how the degree of cross-sectional comovement for each variable, as quantified in Section 5, influences dynamic responses across countries. We find that countries whose industrial production is more closely aligned with the rest of the panel are notably more affected by the contractionary shock. This finding is consistent with Table 4, which shows the largest comovements in industrial production among the main manufacturing countries in the EA. In contrast, the impact on long-term interest rates is smaller for countries that are more aligned with the panel. This reflects the fact that countries with more idiosyncratic dynamics experience the strongest transmission of monetary policy to sovereign yield movements.

Overall, the results highlight several interesting channels through which a common monetary policy is transmitted across countries. However, these findings should be interpreted with caution, as they are based on variability across a relatively small cross-section of countries and should be

Table 6: Cross-country characteristics and IRFs dynamics: correlation analysis

ID	Variable	IPMN	HICPOV	LTIRT	SHIX	UNETOT
1	Employment Protection	-0.03 (0.38)	-0.20 (0.35)	-0.03 (0.35)	-0.10 (0.35)	-0.32 (0.34)
2	Wage Adj. Frequency: more than once a year	0.28 (0.43)	-0.28 (0.39)	0.31 (0.39)	0.33 (0.39)	-0.46 (0.36)
3	Wage Adj. Frequency: once a year	0.55 (0.37)	-0.08 (0.41)	0.32 (0.39)	-0.06 (0.41)	0.35 (0.38)
4	Wage Adj. Frequency: less than once a year	-0.61 (0.35)	0.01 (0.41)	-0.54 (0.34)	-0.35 (0.38)	-0.46 (0.36)
5	Price Flexibility	0.17 (0.44)	-0.39 (0.41)	-0.21 (0.44)	0.65 (0.34)	-0.02 (0.45)
6	NFC Leverage	0.22 (0.37)	-0.38 (0.33)	-0.33 (0.33)	0.62* (0.28)	-0.21 (0.35)
7	Homeownership	-0.06 (0.38)	0.37 (0.33)	0.14 (0.35)	-0.07 (0.35)	0.44 (0.32)
8	Homeownership with mortgage	0.35 (0.35)	-0.66** (0.27)	-0.33 (0.33)	0.60* (0.28)	-0.26 (0.34)
9	Homeownership without mortgage	-0.33 (0.36)	0.76** (0.23)	0.35 (0.33)	-0.54 (0.30)	0.47 (0.31)
10	Fixed-Rate Mortgages	-0.07 (0.38)	-0.59* (0.28)	-0.34 (0.33)	0.37 (0.33)	-0.63* (0.28)
11	Loan to Value	-0.17 (0.40)	-0.27 (0.36)	-0.37 (0.35)	0.61* (0.30)	-0.20 (0.37)
12	Share of HtM	0.33 (0.36)	0.41 (0.32)	0.39 (0.33)	0.06 (0.35)	0.38 (0.33)
13	Share of WHtM	0.26 (0.37)	0.53 (0.30)	0.50 (0.31)	-0.10 (0.35)	0.53 (0.30)
14	Saving Rate	-0.08 (0.38)	-0.78*** (0.22)	-0.65** (0.27)	0.63* (0.28)	-0.44 (0.32)
15	Explained Variance	-0.82*** (0.22)	0.12 (0.35)	-0.78*** (0.22)	0.47 (0.31)	0.25 (0.34)

NOTES: Each entry of the table corresponds to the correlation between each indicator (in the row) and the peak of the impulse response for a specific variable (in the columns). The variables considered are: Industrial Production: Manufacturing (IPMN), HICP: Overall (HICPOV), Stock Price Index (SHIX), 10-years Interest Rates (LTIRT) and Unemployment Rate (UNETOT). Standard errors in parentheses, asterisks denote statistical significance at 99% (**), 95% (**), and 90% (*). The first row reports the Employment Protection Index (OECD). Rows 2–4 show the frequency of wage adjustments by firms (Brantén et al., 2018), while row 1 reports the frequency with which firms adjust output prices (Gautier et al., 2024). Row 6 shows the leverage of non-financial corporations relative to GDP (Eurostat). Row 7 reports the homeownership rate as a share of the population (Eurostat). Rows 8 and 9 indicate, respectively, the shares of residential properties with and without an outstanding mortgage (Eurostat). Row 10 reports the share of fixed-rate mortgages (De Stefani and Mano, 2025). Row 11 shows the average household loan-to-value ratio from the Eurosystem Household Finance and Consumption Survey (HFCS). Rows 12 and 13 display, respectively, the shares of “wealthy hand-to-mouth” and “poor hand-to-mouth” households, constructed as in Slacalek et al. (2020) based on HFCS data. Row 14 reports the household saving rate as a percentage of GDP (OECD). Finally, row 15 corresponds to the share of variance explained by the common factors for each variable in the columns, as reported in Table 4.

regarded primarily as descriptive.

8 Conclusions

We introduce a new high-dimensional dataset, EA-MD-QD, covering both the euro area (EA) and its ten largest member countries. The dataset, including all its vintages, is publicly available online and offers a freely accessible, continuously updated resource for macroeconomic analysis. We employ this novel dataset to study the effects of a monetary policy shock on EA- and country-level variables using a Common Component SVAR. We then examine the presence and magnitude of cross-country heterogeneity in the dynamic responses to a common monetary policy shock.

Our analysis reveals moderate but meaningful heterogeneity in the transmission of monetary policy across EA countries. Price and interest rate dynamics display a core-periphery pattern, while real variables exhibit less systematic cross-country variation, and stock prices, by contrast, behave relatively uniformly across countries.

Finally, an exploratory analysis relating peak country-level impulse responses to country-specific characteristics suggests that heterogeneity in the transmission of monetary policy may be linked to factors like homeownership and saving behavior. While these correlations should not be interpreted causally, they indicate that domestic economic factors can affect the strength of common monetary shocks across EA countries.

References

- H. J. Ahn and M. Luciani. Common and idiosyncratic inflation. *Journal of Applied Econometrics*, 2025.
- H. J. Ahn, S. Xie, and C. Yang. Effects of monetary policy on household expectations: The role of homeownership. *Journal of Monetary Economics*, 147:103599, 2024.
- S. C. Ahn and A. R. Horenstein. Eigenvalue ratio test for the number of factors. *Econometrica*, 81(3):1203–1227, 2013.
- L. Alessi, M. Barigozzi, and M. Capasso. Improved penalization for determining the number

- of factors in approximate factor models. *Statistics & Probability Letters*, 80(23-24):1806–1813, 2010.
- L. Alessi, M. Barigozzi, and M. Capasso. Non-fundamentalness in structural econometric models: A review. *International Statistical Review*, 79(1):16–47, 2011.
- C. Altavilla, L. Brugnolini, R. S. Gürkaynak, R. Motto, and G. Ragusa. Measuring euro area monetary policy. *Journal of Monetary Economics*, 108:162–179, 2019.
- F. Alvarez, H. Le Bihan, and F. Lippi. The real effects of monetary shocks in sticky price models: a sufficient statistic approach. *American Economic Review*, 106(10):2817–2851, 2016.
- P. Andrade and F. Ferroni. Delphic and odyssean monetary policy shocks: Evidence from the euro area. *Journal of Monetary Economics*, 117:816–832, 2021.
- J. Bai. Inferential theory for factor models of large dimensions. *Econometrica*, 71(1):135–171, 2003.
- J. Bai and S. Ng. Determining the number of factors in approximate factor models. *Econometrica*, 70(1):191–221, 2002.
- J. Bai and S. Ng. Confidence intervals for diffusion index forecasts and inference for factor-augmented regressions. *Econometrica*, 74(4):1133–1150, 2006.
- J. Bai and S. Ng. Principal components estimation and identification of static factors. *Journal of Econometrics*, 176(1):18–29, 2013.
- M. Bańbura and M. Modugno. Maximum likelihood estimation of factor models on datasets with arbitrary pattern of missing data. *Journal of Applied Econometrics*, 29(1):133–160, 2014.
- M. Bańbura, D. Giannone, and L. Reichlin. Nowcasting. In M. P. Clements and D. F. Hendry, editors, *The Oxford Handbook of Economic Forecasting*, pages 193–224. Oxford University Press, 2011.
- M. Barigozzi, A. M. Conti, and M. Luciani. Do euro area countries respond asymmetrically to the common monetary policy? *Oxford Bulletin of Economics and Statistics*, 76(5):693–714, 2014.
- M. Barigozzi, H. Cho, and P. Fryzlewicz. Simultaneous multiple change-point and factor analysis for high-dimensional time series. *Journal of Econometrics*, 206(1):187–225, 2018.

- M. Barigozzi, M. Lippi, and M. Luciani. Large-dimensional Dynamic Factor Models: Estimation of Impulse–Response Functions with I(1) cointegrated factors. *Journal of Econometrics*, 221(2):455–482, Apr. 2021.
- B. S. Bernanke, J. Boivin, and P. Eliasz. Measuring the effects of monetary policy: a factor-augmented vector autoregressive (favar) approach. *The Quarterly Journal of Economics*, 120(1):387–422, 2005.
- J. Boivin and S. Ng. Are more data always better for factor analysis? *Journal of Econometrics*, 132(1):169–194, 2006.
- E. Branten, A. Lamo, and T. Rööm. Nominal wage rigidity in the eu countries before and after the great recession: Evidence from the wdn surveys. ECB Working Paper 2159, European Central Bank, 2018.
- P. Burriel and A. Galesi. Uncovering the heterogeneous effects of ecb unconventional monetary policies across euro area countries. *European Economic Review*, 101:210–229, 2018.
- D. Cascaldi-Garcia, T. R. Ferreira, D. Giannone, and M. Modugno. Back to the present: Learning about the euro area through a now-casting model. *International Journal of Forecasting*, 40(2):661–686, 2024.
- L. J. Christiano, M. Eichenbaum, and C. L. Evans. Nominal rigidities and the dynamic effects of a shock to monetary policy. *Journal of Political Economy*, 113(1):1–45, 2005.
- G. Corsetti, J. B. Duarte, and S. Mann. One money, many markets. *Journal of the European Economic Association*, 20(1):513–548, 2022.
- A. De Stefani and R. C. Mano. Long-term debt and short-term rates: Fixed-rate mortgages and monetary transmission. Technical report, International Monetary Fund, 2025.
- L. Dedola and F. Lippi. The monetary transmission mechanism: evidence from the industries of five OECD countries. *European Economic Review*, 49(6):1543–1569, 2005.
- D. A. Dickey and W. A. Fuller. Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, 74(366a):427–431, 1979.

- A. D'Agostino, D. Giannone, M. Lenza, and M. Modugno. Nowcasting business cycles: A bayesian approach to dynamic heterogeneous factor models. In *Dynamic Factor Models*, pages 569–594. Emerald Group Publishing Limited, 2016.
- D. F. Findley, B. C. Monsell, W. R. Bell, M. C. Otto, and B.-C. Chen. New capabilities and methods of the X-12-ARIMA seasonal-adjustment program. *Journal of Business & Economic Statistics*, 16(2):127–152, 1998.
- M. Forni, D. Giannone, M. Lippi, and L. Reichlin. Opening the black box: Structural factor models with large cross sections. *Econometric Theory*, 25(5):1319–1347, 2009.
- M. Forni, L. Gambetti, and L. Sala. No news in business cycles. *The Economic Journal*, 124(581):1168–1191, 2014.
- M. Forni, L. Gambetti, M. Lippi, and L. Sala. Common components structural VARs. *Journal of Business & Economic Statistics*, pages 1–24, 2025. available online.
- O. Fortin-Gagnon, M. Leroux, D. Stevanovic, and S. Surprenant. A large Canadian database for macroeconomic analysis. *Canadian Journal of Economics*, 55(4):1799–1833, 2022.
- R. Fry and A. Pagan. Sign restrictions in structural vector autoregressions: A critical review. *Journal of Economic Literature*, 49(4):938–960, 2011.
- E. Gautier, C. Conflitti, R. P. Faber, B. Fabo, L. Fadejeva, V. Jouvanceau, J.-O. Menz, T. Messner, P. Petroulas, P. Roldan-Blanco, et al. New facts on consumer price rigidity in the euro area. *American Economic Journal: Macroeconomics*, 16(4):386–431, 2024.
- G. Georgiadis. Examining asymmetries in the transmission of monetary policy in the euro area: Evidence from a mixed cross-section global VAR model. *European Economic Review*, 75:195–215, 2015.
- M. Gertler and P. Karadi. Monetary policy surprises, credit costs, and economic activity. *American Economic Journal: Macroeconomics*, 7(1):44–76, 2015.
- D. Giannone and L. Reichlin. Does information help in recovering structural shocks from past observations? *Journal of the European Economic Association*, 4(2-3):455–465, 2006.

- D. Giannone, J. Henry, M. Lalik, and M. Modugno. An area-wide real-time database for the euro area. *The Review of Economics and Statistics*, 94(4):1000–1013, 2012.
- S. Gonçalves and L. Kilian. Bootstrapping autoregressions with conditional heteroskedasticity of unknown form. *Journal of Econometrics*, 123(1):89–120, 2004.
- M. Jarociński and P. Karadi. Deconstructing monetary policy surprises—the role of information shocks. *American Economic Journal: Macroeconomics*, 12(2):1–43, 2020.
- L. Kilian. Small-sample confidence intervals for impulse response functions. *Review of economics and statistics*, 80(2):218–230, 1998.
- L. Kilian. How to construct monthly VAR proxies based on daily surprises in futures markets. *Journal of Economic Dynamics and Control*, 168:104966, 2024.
- M. Lenza and G. E. Primiceri. How to estimate a vector autoregression after march 2020. *Journal of Applied Econometrics*, 37(4):688–699, 2022.
- C. Lissona and E. Ruiz. Heterogeneous economic growth vulnerability across euro area countries under stressed scenarios. *arXiv preprint arXiv:2506.14321*, 2025.
- M. Mandler, M. Scharnagl, and U. Volz. Heterogeneity in euro area monetary policy transmission: Results from a large multicountry BVAR model. *Journal of Money, Credit and Banking*, 54(2-3):627–649, 2022.
- M. McCracken and S. Ng. FRED-QD: A Quarterly Database for Macroeconomic Research, Mar. 2020.
- M. W. McCracken and S. Ng. FRED-MD: A Monthly Database for Macroeconomic Research. *Journal of Business & Economic Statistics*, 34(4):574–589, 2016.
- K. Mertens and M. O. Ravn. The dynamic effects of personal and corporate income tax changes in the united states. *The American Economic Review*, 103(4):1212–1247, 2013.
- S. Ng. Modeling macroeconomic variations after COVID-19. Technical report, National Bureau of Economic Research, 2021.
- J. L. M. Olea and C. Pflueger. A robust test for weak instruments. *Journal of Business & Economic Statistics*, 31(3):358–369, 2013.

- A. Onatski. Determining the number of factors from empirical distribution of eigenvalues. *The Review of Economics and Statistics*, 92(4):1004–1016, 2010.
- A. Orphanides and S. v. Norden. The unreliability of output-gap estimates in real time. *The Review of Economics and Statistics*, 84(4):569–583, 2002.
- G. Peersman. What caused the early millennium slowdown? Evidence based on vector autoregressions. *Journal of Applied Econometrics*, 20(2):185–207, 2005.
- P. C. Phillips and P. Perron. Testing for a unit root in time series regression. *Biometrika*, 75(2):335–346, 1988.
- J. F. Rubio-Ramirez, D. F. Waggoner, and T. Zha. Structural vector autoregressions: Theory of identification and algorithms for inference. *The Review of Economic Studies*, 77(2):665–696, 2010.
- J. Slacalek, O. Tristani, and G. L. Violante. Household balance sheet channels of monetary policy: A back of the envelope calculation for the euro area. *Journal of Economic Dynamics and Control*, 115:103879, 2020.
- H. Stock, James and M. W. Watson. Evidence on structural instability in macroeconomic time series relations. *Journal of Business & Economic Statistics*, 14(1):11, 1996.
- J. H. Stock and M. W. Watson. Forecasting using principal components from a large number of predictors. *Journal of the American Statistical Association*, 97(460):1167–1179, 2002a.
- J. H. Stock and M. W. Watson. Macroeconomic forecasting using diffusion indexes. *Journal of Business & Economic Statistics*, 20(2):147–162, 2002b.
- J. H. Stock and M. W. Watson. Disentangling the channels of the 2007–09 recession. *Brookings Papers on Economic Activity*, 2012(1):81–135, 2012.
- J. H. Stock, J. H. Wright, and M. Yogo. A survey of weak instruments and weak identification in generalized method of moments. *Journal of Business & Economic Statistics*, 20(4):518–529, 2002.
- J. C. Wu and F. D. Xia. Measuring the macroeconomic impact of monetary policy at the zero lower bound. *Journal of Money, Credit and Banking*, 48(2-3):253–291, 2016.

Large datasets for the euro area and its member countries and the
dynamic effects of the common monetary policy
Supplementary Appendix

Matteo Barigozzi

Claudio Lissone

Lorenzo Tonni

A Data description

This appendix provides a detailed description of the dataset for the EA and its ten largest member countries. All series are retrieved from institutional sources. For each series, we provide a brief description, the data source, the measurement unit, the seasonal adjustment procedure, and the transformation (if any) applied. Table A1 presents a glossary to facilitate the interpretation of the data description reported in Table A2.

The first eight columns of Table A2 contain several identifiers for each series, namely: a numeric indicator (N), an alphabetical identifier (ID), a short description (Series), the unit of measure (Unit), any information about seasonal adjustment (SA), the frequency (F), the data provider (P), and the class (C) to which each variable belongs (Real, Nominal, or Financial). The remaining columns list all countries included in the dataset, starting with the EA aggregate, followed by individual countries in alphabetical order. Each entry in the country columns denotes the transformation applied to the corresponding series for that country. These *statistical transformations* ensure stationarity for each series, and are based on standard unit root tests (Dickey and Fuller, 1979; Phillips and Perron, 1988). Two alternative sets of transformations are described in Section 2.2, and require minor changes to the transformations described in Table A2. Throughout the table, when a series is unavailable for a given country, the corresponding entry is marked with a “_”.

The dataset for the EA and individual countries is constructed with the objective of ensuring consistency across countries in terms of time coverage, number of indicators, and treatment of variables. Due to data limitations, full harmonization is not always possible. Specifically, the main differences across countries are as follows:

1. Labor Market Indicators are seasonally and calendar adjusted for all countries, except for France, Portugal, and Greece, where they are only seasonally adjusted.
2. Credit Aggregates are available from 2000:Q1 for all countries, except for Ireland, for which they start in 2002:Q1.
3. Labor Costs are available from 2000:Q1 for all countries, except for the EA, where they are available from 2001:Q1.
4. Turnover Indicators are available from 2000:M1 for all countries, except for France, where data start in 2002:M1.
5. The Harmonized Index of Consumer Prices (HICP) is available for all countries from 2000:M1, except for Spain (2000:M12), Ireland (2002:M1), and Belgium (2001:M1).

Table A1: Glossary

Source	Unit	
EUR = Eurostat OECD = Organization for Economic Co-operation and Development ECB = European Central Bank FRED = Federal Reserve Economic Data	CLV15 = Chain-linked volumes (2015=100) CP = Current Prices (Million€) 1000p = Thousands of persons 1000U = Thousands of Units I_{xx} = Index, $20_{xx} = 100$	
Seasonal Adjustment	Frequency	Transformation
NSA = No Seasonal Adjustment SA = Seasonal Adjustment SCA = Seasonal and Calendar Adjustment MSA = Manual adjustment	Q = Quarterly M = Monthly	1 = $100 \times \log(x_t)$ 2 = $100 \times \Delta \log(x_t)$ 3 = $100 \times \Delta^2 \log(x_t)$ 4 = x_t (No Transformation) 5 = Δx_t

Table A2: Data Description and Transformation by country

Table A2: Data Description and Transformation by country

N	ID	Series	Unit	SA	F	P	C	EA	AT	BE	DE	EL	ES	FR	IE	IT	NL	PT
(7) Industrial Production and Turnover																		
81	IPMN	Industrial Production Index: Manufacturing	I21	SCA	M	EUR	R	2	2	2	2	2	2	2	-	2	2	2
82	IPCGAG	Industrial Production Index: Capital Goods	I21	SCA	M	EUR	R	2	2	2	2	2	2	2	-	2	2	2
83	IPCOG	Industrial Production Index: Consumer Goods	I21	SCA	M	EUR	R	2	2	2	2	2	2	2	-	2	-	-
84	IPDCOG	Industrial Production Index: Durable Consumer Goods	I21	SCA	M	EUR	R	2	2	2	2	2	2	2	-	2	2	2
85	IPNDCOG	Industrial Production Index: Non Durable Consumer Goods	I21	SCA	M	EUR	R	2	2	2	2	2	2	2	-	2	2	2
86	IPING	Industrial Production Index: Intermediate Goods	I21	SCA	M	EUR	R	2	2	2	2	2	2	2	-	2	2	2
87	IPNRG	Industrial Production Index: Energy	I21	SCA	M	EUR	R	2	2	2	2	2	2	2	-	2	2	2
88	TRNMM	Turnover Index: Manufacturing	I21	SCA	M	EUR	R	2	2	2	2	2	2	2	-	-	2	2
89	TRNCAG	Turnover Index: Capital Goods	I21	SCA	M	EUR	R	2	2	2	2	2	2	2	-	2	2	2
90	TRNCOG	Turnover Index: Consumer Goods	I15	SCA	M	EUR	R	2	2	2	2	2	2	2	-	2	2	2
91	TRNDCOG	Turnover Index: Durable Consumer Goods	I21	SCA	M	EUR	R	2	2	2	2	2	2	2	-	2	2	2
92	TRNNDCOG	Turnover Index: Non Durable Consumer Goods	I21	SCA	M	EUR	R	2	2	2	2	2	2	2	-	2	2	2
93	TRNING	Turnover Index: Intermediate Goods	I21	SCA	M	EUR	R	2	2	2	2	2	2	2	-	2	2	2
94	TRNNRG	Turnover Index: Energy	I21	SCA	M	EUR	R	2	2	2	2	2	2	2	-	2	-	2
95	CAREG	Passenger's Cars Registrations	1000U	SCA	M	ECB	R	2	-	-	-	-	-	-	-	-	-	-
(8) Prices																		
96	PPICAG	Producer Price Index: Capital Goods	I21	MSA	M	EUR	N	2	2	2	2	2	2	2	-	2	2	-
97	PPICOG	Producer Price Index: Consumer Goods	I21	MSA	M	EUR	N	2	2	2	2	2	2	2	-	2	2	-
98	PPIDCOG	Producer Price Index: Durable Consumer Goods	I21	MSA	M	EUR	N	2	2	2	2	2	2	2	-	2	2	-
99	PPINDCOG	Producer Price Index: Non Durable Consumer Goods	I21	MSA	M	EUR	N	2	2	2	2	2	2	2	-	2	2	-
100	PPING	Producer Price Index: Intermediate Goods	I21	MSA	M	EUR	N	2	2	2	2	2	2	2	-	2	2	-
101	PPINRG	Producer Price Index: Energy	I21	MSA	M	EUR	N	2	2	2	2	2	2	2	-	2	2	-
102	HICPOV	Harmonized Index of Consumer Prices: Overall Index	I10	SCA	M	ECB	N	2	2	2	2	2	2	2	2	2	2	2
103	HICPNEF	Harmonized Index of Consumer Prices: All Items, no Energy&Food	I10	SCA	M	ECB	N	2	2	2	2	2	2	2	2	2	2	2
104	HICPG	Harmonized Index of Consumer Prices: Goods	I10	SCA	M	ECB	N	2	2	2	2	2	2	2	2	2	2	2
105	HICPIN	Harmonized Index of Consumer Prices: Industrial Goods	I10	SCA	M	ECB	N	2	2	2	2	2	2	2	2	2	2	2
106	HICPSV	Harmonized Index of Consumer Prices: Services	I10	SCA	M	ECB	N	2	2	2	2	2	2	2	2	2	2	2
107	HICPN	Harmonized Index of Consumer Prices: Energy	I10	MSA	M	EUR	N	2	2	2	2	2	2	2	2	2	2	2
108	DFGDP	Real Gross Domestic Product Deflator	I15	SCA	Q	EUR	N	2	2	2	2	2	2	2	2	2	2	2
109	HPRC	Residential Property Prices (BIS)	MLN€	SCA	Q	FRED	N	2	2	2	2	-	2	2	2	2	-	-
(9) Confidence Indicators																		
110	ICONFIX	Industrial Confidence Indicator	Index	SA	M	EUR	C	4	4	4	4	4	4	4	4	4	4	4
111	CCONFIX	Consumer Confidence Index	Index	SA	M	EUR	C	4	4	4	4	5	5	5	5	5	4	5
112	ESENTIX	Economic Sentiment Indicator	Index	SA	M	EUR	C	4	4	4	4	5	5	5	4	5	5	5
113	KCONFIX	Construction Sentiment Indicator	Index	SA	M	EUR	C	4	5	4	4	5	5	5	4	5	5	5
114	RTCONFIX	Retail Confidence Indicator	Index	SA	M	EUR	C	4	4	4	4	4	4	4	4	4	4	4
115	SCONFIX	Services Confidence Indicator	Index	SA	M	EUR	C	4	4	4	4	4	4	4	4	4	4	4
116	BCI	Business Confidence Index	2010=100	SA	M	OECD	C	4	4	4	4	5	4	4	4	4	4	4
117	CCI	Consumer Confidence Index	2010=100	SA	M	OECD	C	4	4	4	4	5	5	5	5	4	5	5
(10) Monetary Aggregates																		
118	CURR	Money Stock: Currency	CP	SCA	M	ECB	F	2	-	-	-	-	-	-	-	-	-	-
119	M1	Money Stock: M1	CP	SCA	M	ECB	F	2	-	-	-	-	-	-	-	-	-	-
120	M2	Money Stock: M2	CP	SCA	M	ECB	F	2	-	-	-	-	-	-	-	-	-	-

B Pseudo-code for replicating Sections 2.2-2.4

[1] Data processing

Input: De-seasonalized EA-MD-QD data from 2000:M1 to 2025:M3 → \mathbf{Y} of size $T_1 \times N_1$.

Step 1: Subset \mathbf{Y} to monthly data → \mathbf{Z} of size $T_1 \times N_0$.

Step 2: Apply to \mathbf{Z} statistical transformations + interest rates in levels → $\mathbf{Z}^{(0)}$ of size $T_0 \times N_0$.

Step 3: Impute missing values as in Stock and Watson (2002b):

3.1: Standardize using univariate sample moments from available sample → $\check{\mathbf{Z}}^{(0)} = \{\mathbf{Z}^{(0)} - \hat{\boldsymbol{\mu}}_Z^{(0)}\} \otimes \hat{\boldsymbol{\sigma}}_Z^{(0)}$;

3.2: Impute missing values with 0 (sample mean of $\check{\mathbf{Z}}^{(0)}$) → $\tilde{\mathbf{Z}}^{(0)}$;

3.3: Determine the number of factors → r ;

3.4: Estimate factor model by first r PCs of $\tilde{\mathbf{Z}}^{(0)}$ → $\hat{\boldsymbol{\chi}}^{(0)} = \hat{\mathbf{F}}^{(0)} \hat{\boldsymbol{\Lambda}}^{(0)'} = (\hat{\boldsymbol{\chi}}_1^{(0)} \cdots \hat{\boldsymbol{\chi}}_{T_0}^{(0)})'$ of size $T_0 \times N_0$;

3.5: For a given threshold ϵ and maximum number of iterations I (e.g., $\epsilon = 10^{-6}$, $I = 1000$), let $i = 1$:

while $i < I$ **do**

3.5.1: Impute missing values with $\hat{\boldsymbol{\chi}}^{(i-1)}$ and de-standardize → $\mathbf{Z}^{(i)} = \hat{\boldsymbol{\chi}}^{(i-1)} \odot \hat{\boldsymbol{\sigma}}_Z^{(i-1)} + \hat{\boldsymbol{\mu}}_Z^{(i-1)}$;

3.5.2: Repeat steps 3.1–3.4 → $\hat{\boldsymbol{\chi}}^{(i)} = \hat{\mathbf{F}}^{(i)} \hat{\boldsymbol{\Lambda}}^{(i)'} = (\hat{\boldsymbol{\chi}}_1^{(i)} \cdots \hat{\boldsymbol{\chi}}_{T_0}^{(i)})'$ of size $T_0 \times N_0$;

3.5.3: Impute missing values with $\hat{\boldsymbol{\chi}}^{(i)}$ and de-standardize → $\mathbf{Z}^{(i+1)} = \hat{\boldsymbol{\chi}}^{(i)} \odot \hat{\boldsymbol{\sigma}}_Z^{(i)} + \hat{\boldsymbol{\mu}}_Z^{(i)}$;

3.5.4: Compute MSE = $\sum_{t=1}^{T_0} \|\hat{\boldsymbol{\chi}}_t^{(i)} - \hat{\boldsymbol{\chi}}_t^{(i-1)}\|^2 / \sum_{t=1}^T \|\hat{\boldsymbol{\chi}}_t^{(i-1)}\|^2$;

if MSE < ϵ ; $i^* = i + 1$; **break**;

else $i = i + 1$.

end

end

Output: $\mathbf{X}^{(0)} = \mathbf{Z}^{(i^*)}$ of size $T_0 \times N_0$.

[2] Estimation of the common components

Input: Processed data from [1] from 2002:M1 to 2023:M10 → $\mathbf{X}^{(0)}$ of size $T \times N_0$.

Step 1: Subset $\mathbf{X}^{(0)}$ to data for empirical analysis → \mathbf{X} of size $T \times N$.

Step 2: Standardize → $\tilde{\mathbf{X}} = \{\mathbf{X} - \hat{\boldsymbol{\mu}}_X\} \otimes \hat{\boldsymbol{\sigma}}_X$.

Step 3: Determine the number of factors → r .

Step 4: Estimate factor model by first r PCs of $\tilde{\mathbf{X}}$ → $\hat{\boldsymbol{\chi}} = \hat{\mathbf{F}} \hat{\boldsymbol{\Lambda}}' = (\hat{\boldsymbol{\chi}}_1 \cdots \hat{\boldsymbol{\chi}}_T)'$ of size $T \times N$.

Step 5: Run the block bootstrap of Barigozzi et al. (2018):

for $b = 1 : B$ **do**

5.1: For the factors, resample rows of $\hat{\mathbf{F}}$ → $\mathbf{F}^{(b)}$ of size $T \times r$;

5.3: Generate bootstrap data → $\tilde{\mathbf{X}}^{(b)} = \mathbf{X} + (\mathbf{F}^{(b)} - \hat{\mathbf{F}}) \hat{\boldsymbol{\Lambda}}'$ of size $T \times N$;

5.4: Estimate factor model by first r PCs of $\tilde{\mathbf{X}}^{(b)}$ → $\hat{\boldsymbol{\chi}}^{(b)} = \hat{\mathbf{F}}^{(b)} \hat{\boldsymbol{\Lambda}}^{(b)} = (\hat{\boldsymbol{\chi}}_1^{(b)} \cdots \hat{\boldsymbol{\chi}}_T^{(b)})'$ of size $T \times N$.

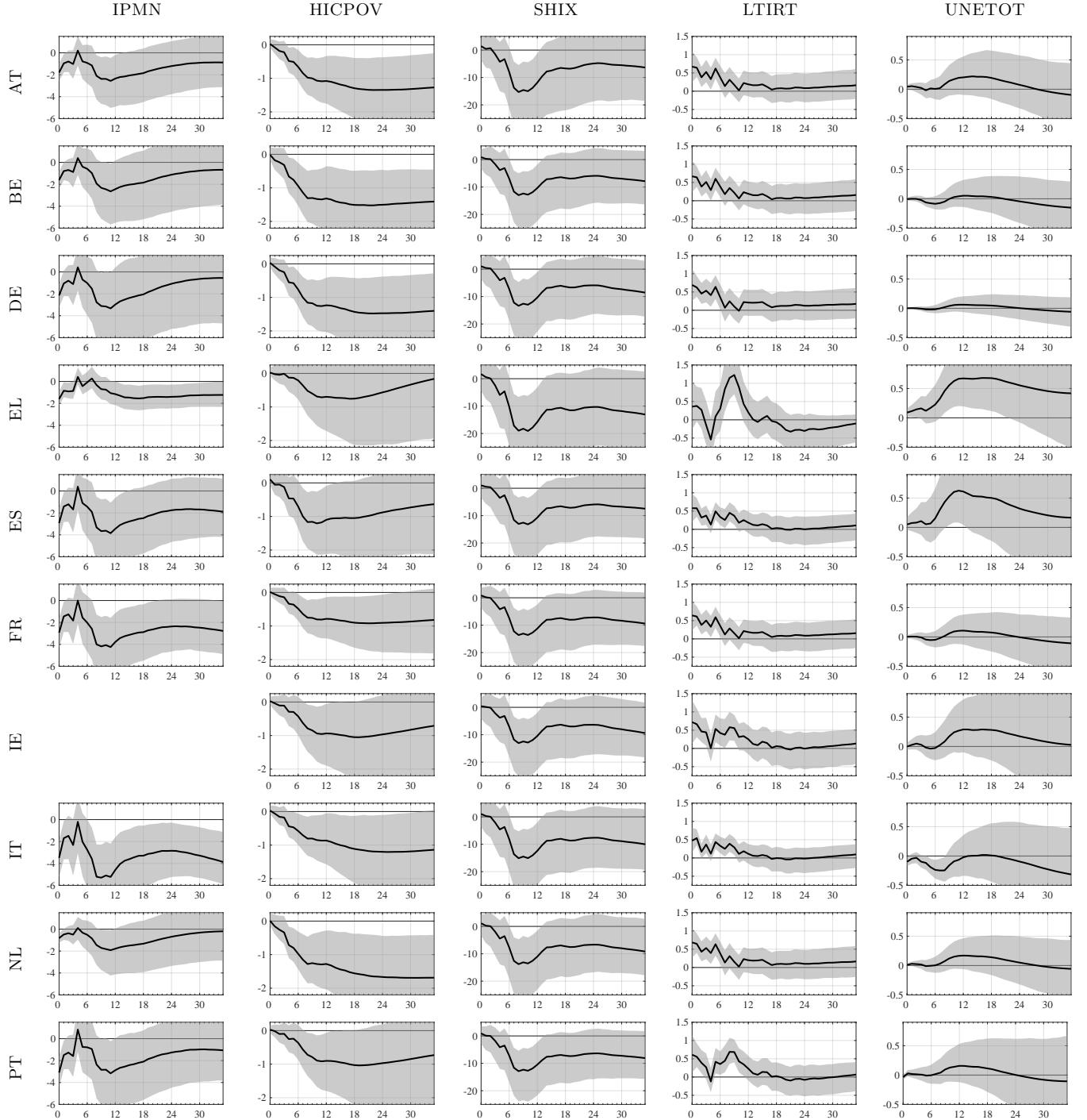
end

Step 6: Compute the quantiles of $(\hat{\boldsymbol{\chi}}_{it}^{(1)} \cdots \hat{\boldsymbol{\chi}}_{it}^{(B)})'$ → $\hat{q}_{it,\alpha/2}$, $\hat{q}_{it,1-\alpha/2}$, $i = 1, \dots, N$, $t = 1, \dots, T$.

Output: $\hat{\boldsymbol{\chi}}_{it}$ and $[\hat{\boldsymbol{\chi}}_{it} - \hat{q}_{it,\alpha/2}, \hat{\boldsymbol{\chi}}_{it} + \hat{q}_{it,1-\alpha/2}]$, $i = 1, \dots, N$, $t = 1, \dots, T$.

C Country-level IRFs: baseline specification

Figure C1: Country-level IRFs

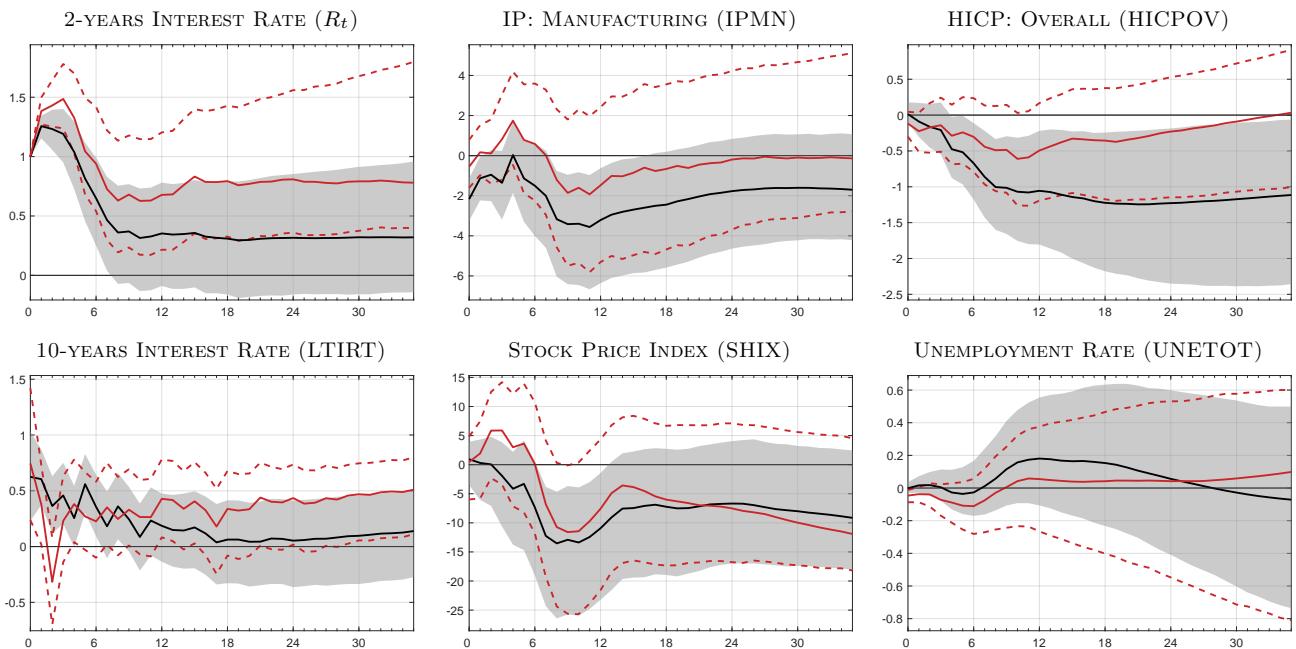


NOTES: Each sub-figure plots the impulse response to a 100bps contractionary monetary policy shock for one variable and one country . Each column of the graph represents a variable, while each row represents a country. The variables considered are: Industrial Production: Manufacturing (IPMN), HICP: Overall (HICPOV), Stock Price Index (SHIX), 10-years Interest Rates (LTIRT) and Unemployment Rate (UNETOT). The black solid line is the point estimate in our baseline setting, while the gray shaded area is the corresponding 68% confidence interval. The scale in the vertical axis has been fixed to be the same across countries, to allow for a one-to-one comparison with Figure 2 in the main text.

D Comparison with pre-Covid estimates

D.1 EA IRFs

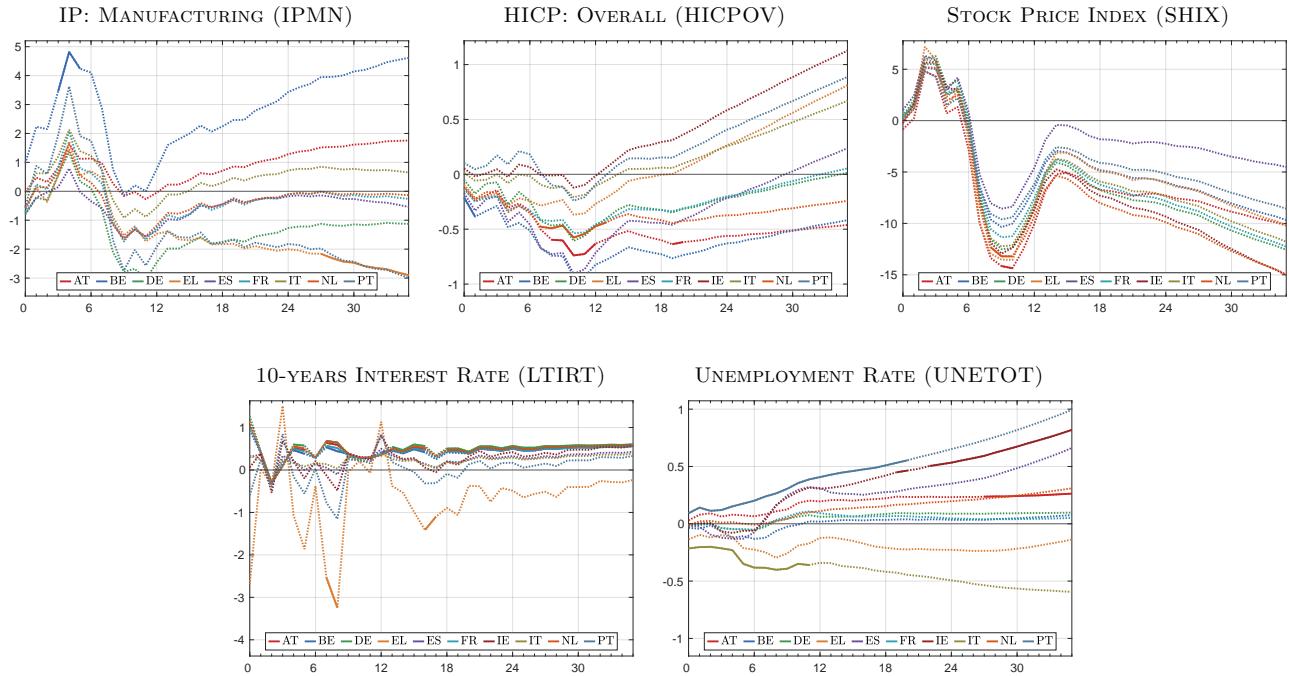
Figure D1: EA IRFs: full sample vs 2019:M12



NOTES: Each sub-figure plots the impulse response of one EA variable to a 100bps contractionary monetary policy shock. The black solid line is the point estimate in our baseline setting, while the red solid line is the point estimate obtained with data truncated in 2019:M12. The gray shaded area and red dotted lines are the corresponding 68% confidence intervals.

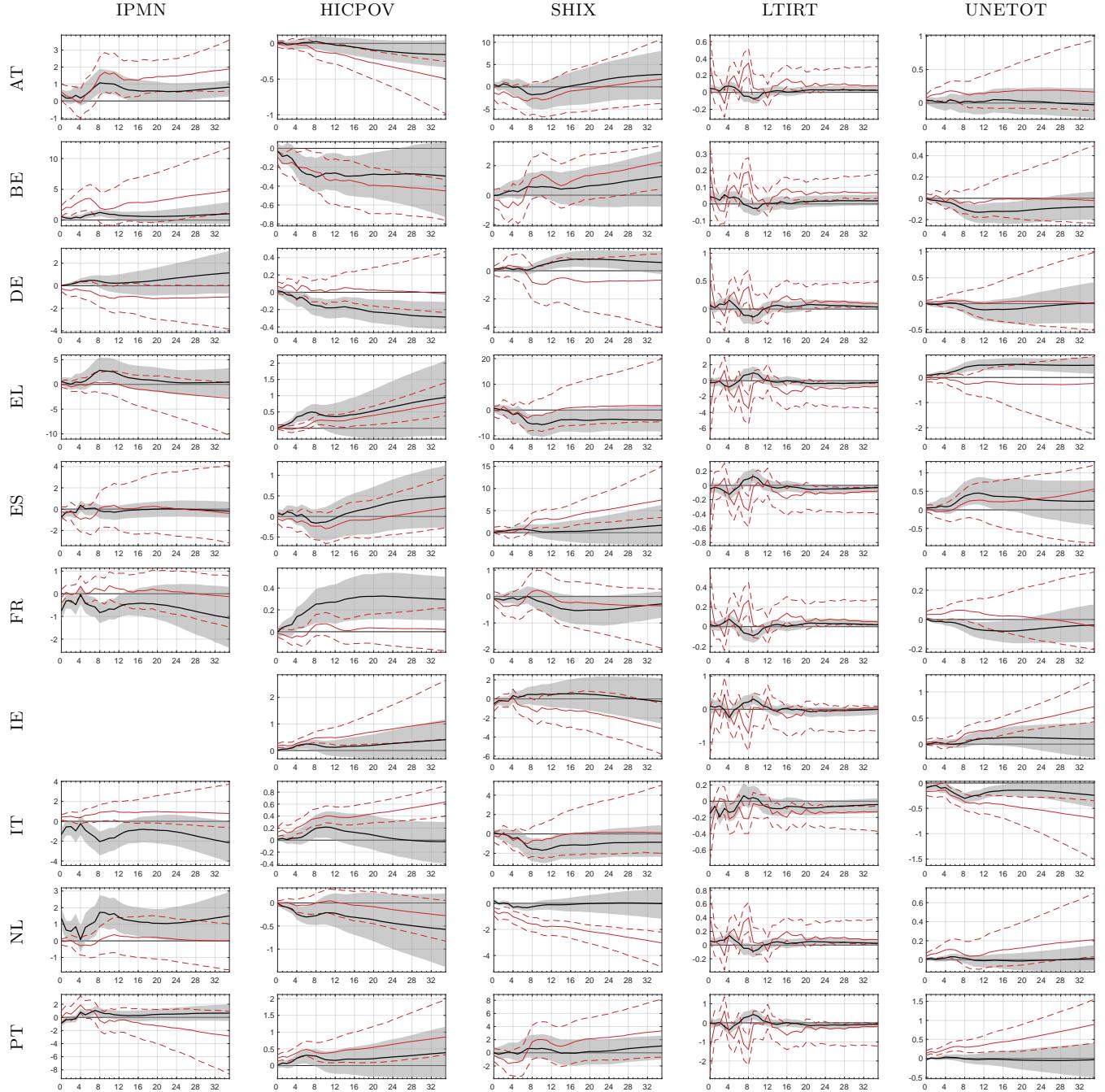
D.2 Country-level IRFs

Figure D2: Country-level IRFs: statistical transformations



NOTES: Each sub-figure plots the impulse responses, for all countries, of one variable to a 100bps contractionary monetary policy shock. Within each sub-figure, at each horizon $h = 0, \dots, 36$ the country-level impulse responses are denoted with a solid line if the IRF is statistically significant at the 68% level at that horizon, and with a dotted line otherwise.

Figure D3: Difference between EA and country-level IRFs: full sample vs 2019:M12



NOTES: Each sub-figure plots the difference between the country-level IRF and the corresponding EA counterpart for one variable and one country. Each column of the graph represents a variable, while each row represents a country. The variables considered are: Industrial Production: Manufacturing (IPMN), HICP: Overall (HICPOV), Stock Price Index (SHIX), 10-years Interest Rates (LTIRT) and Unemployment Rate (UNETOT). The black solid line is the point estimate in our baseline setting, while the red solid line is the point estimate obtained with data truncated in 2019:M12. The gray shaded area and red dotted lines are the corresponding 68% confidence intervals. The scale in the vertical axis differs across variables and countries.

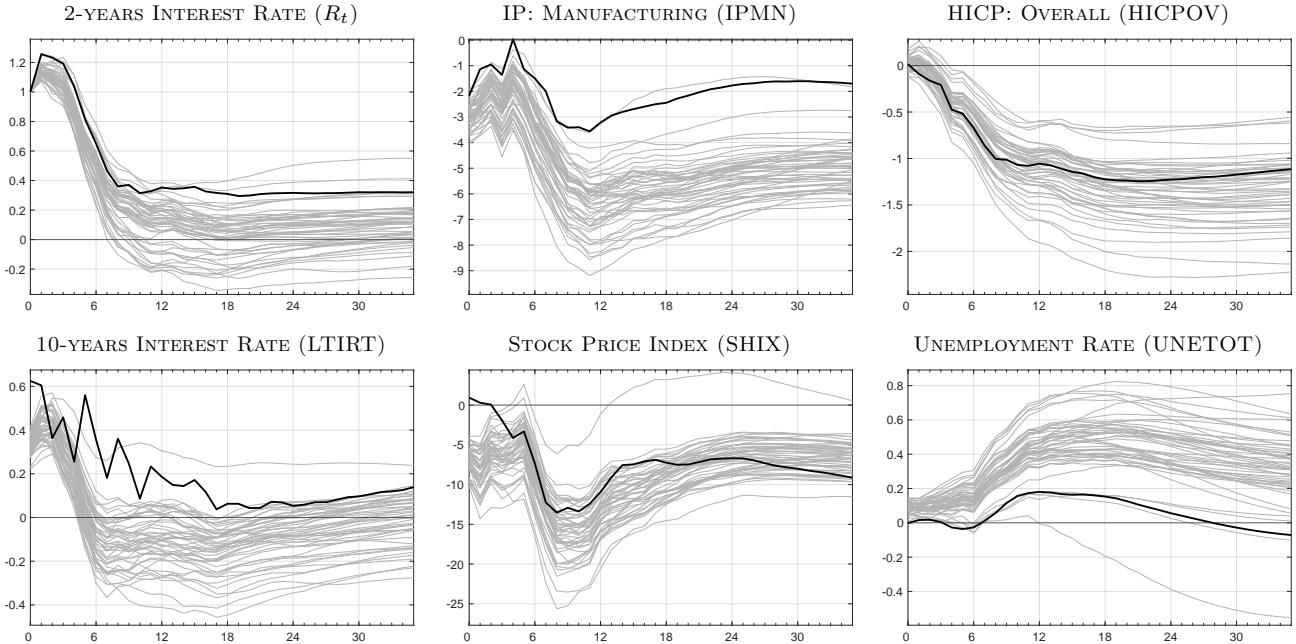
E Comparison with alternative estimation approaches

E.1 VAR

Table E1: Components of \mathbf{Y}_t in the VAR

notation	ID	name
R_t	-	EA 2-years Interest Rate
$x_{IPMN EA,t}$	IPMN	EA IP: Manufacturing
$x_{HICPOV EA,t}$	HICPOV	EA HICP: Overall
$x_{LTIRT EA,t}$	LTIRT	EA 10-years Interest Rate
$x_{SHIX EA,t}$	SHIX	EA Stock Price Index
$x_{UNETOT EA,t}$	UNETOT	EA Unemployment Rate
$x_{nat.,t}$	-	National variable

Figure E1: EA IRFs: CC-VAR vs VAR



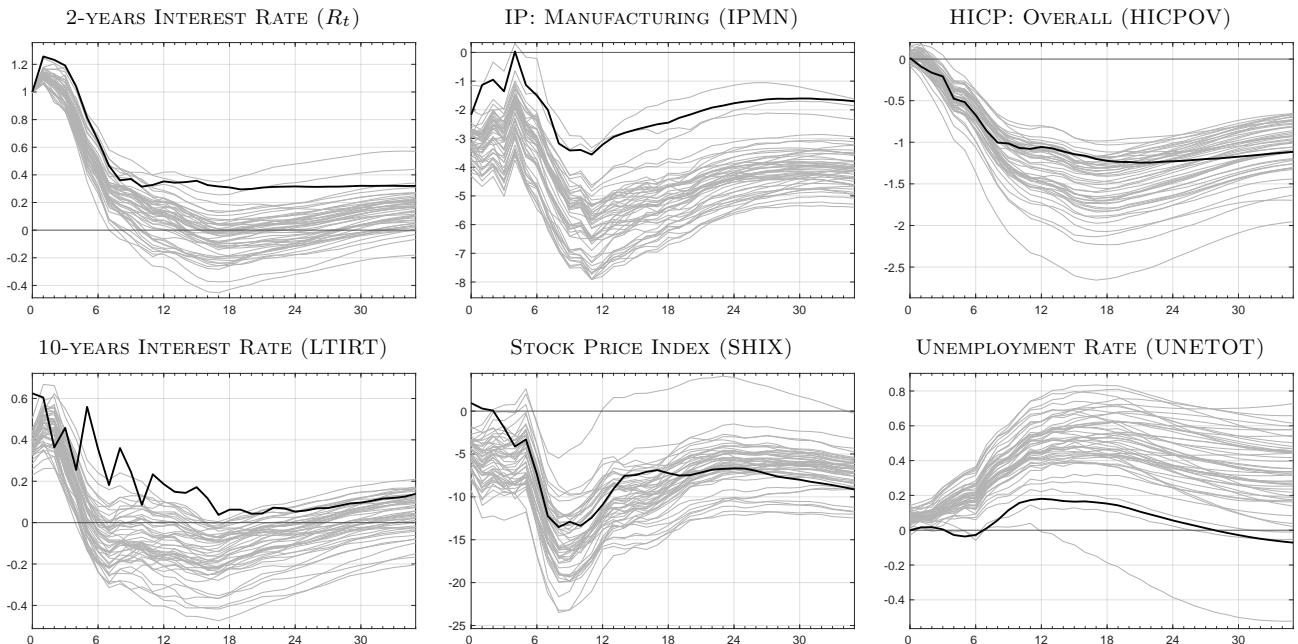
NOTES: Each sub-figure plots the impulse response of one EA variable to a 100bps contractionary monetary policy shock. The black solid line is the point estimate obtained with the CC-VAR, which is the same regardless of the set of common components included in the model. The thin gray lines are the point estimates obtained with the 49 considered VAR models differing only for the national variable included.

E.2 FAVAR

Table E2: Components of \mathbf{Y}_t in the FAVAR

notation	ID	name
R_t	-	EA 2-years Interest Rate
$x_{IPMN EA,t}$	IPMN	EA IP: Manufacturing
$x_{HICPOV EA,t}$	HICPOV	EA HICP: Overall
$x_{LTIRT EA,t}$	LTIRT	EA 10-years Interest Rate
$x_{SHIX EA,t}$	SHIX	EA Stock Price Index
$x_{UNETOT EA,t}$	UNETOT	EA Unemployment Rate
\hat{f}_{1t}	-	First estimated factor
$x_{nat.,t}$	-	National variable

Figure E2: EA IRFs: CC-VAR vs FAVAR

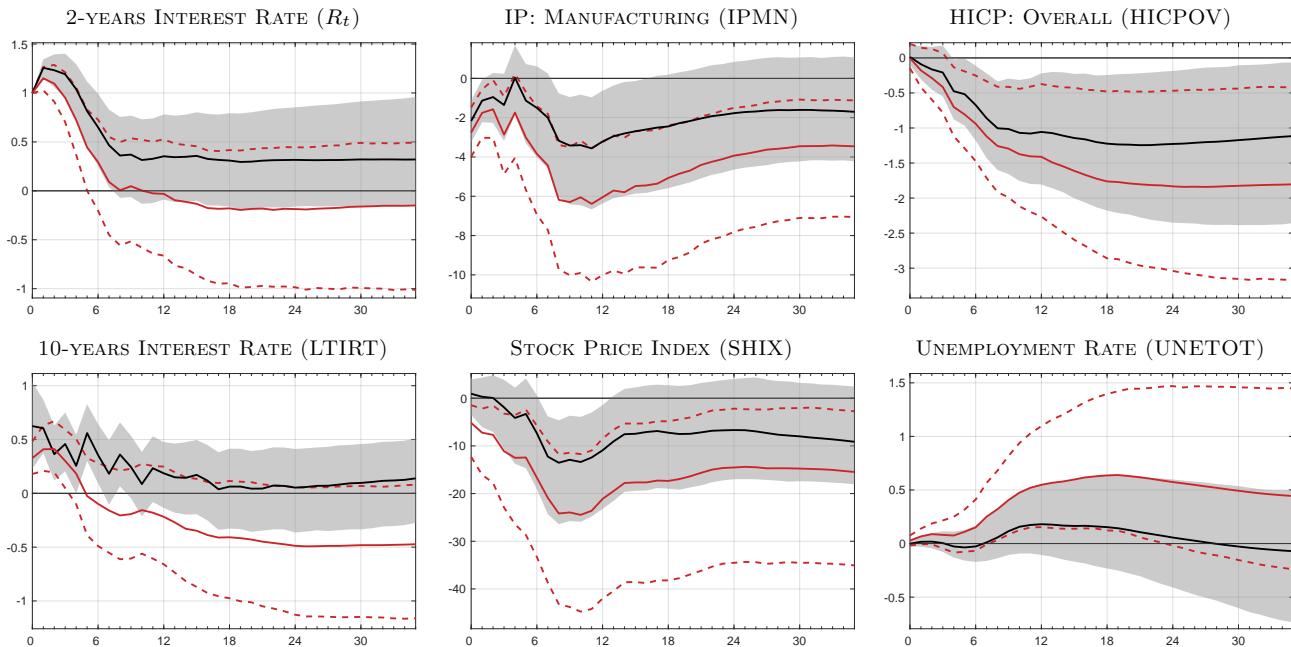


NOTES: Each sub-figure plots the impulse response of one EA variable to a 100bps contractionary monetary policy shock. The black solid line is the point estimate obtained with the CC-VAR, which is the same regardless of the set of common components included in the model. The thin gray lines are the point estimates obtained with the 49 considered FAVAR models differing only for the national variable included.

F Alternative transformations: statistical transformations

F.1 EA IRFs

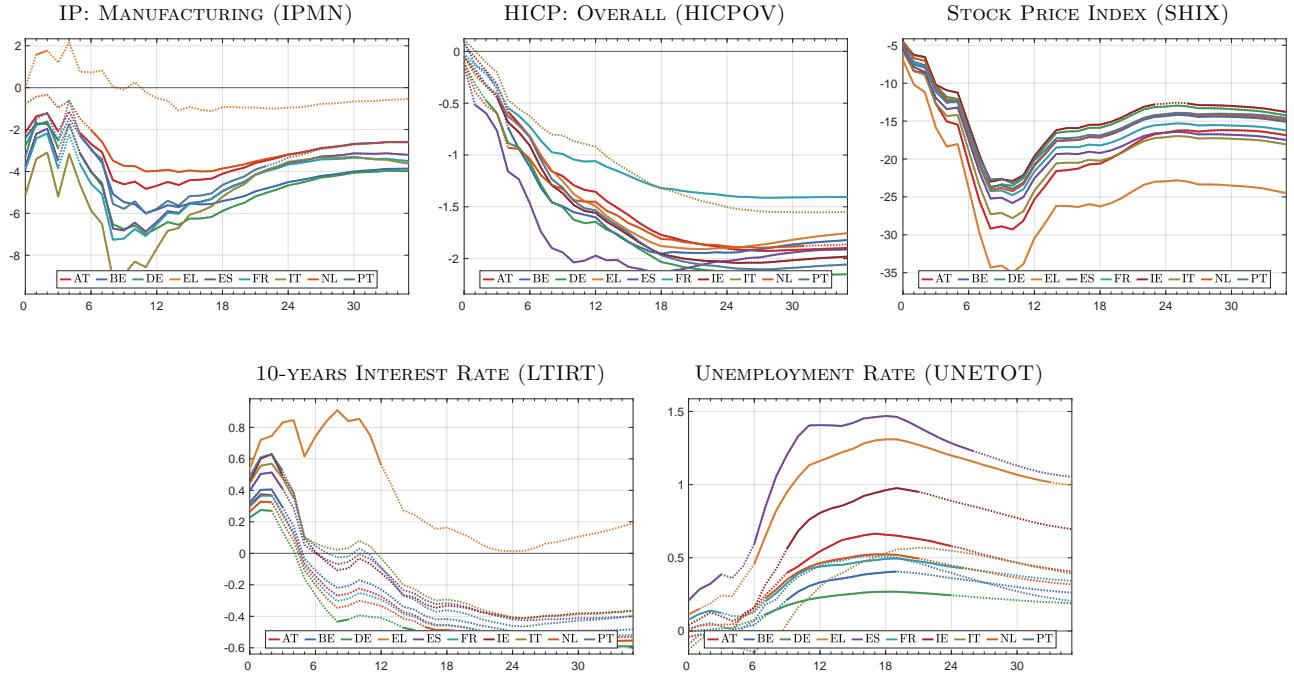
Figure F1: EA IRFs: baseline vs alternative set of transformations



NOTES: Each sub-figure plots the impulse response of one EA variable to a 100bps contractionary monetary policy shock. The black solid line is the point estimate in our baseline setting, while the red solid line is the point estimate obtained with the alternative set of transformations based on statistical criteria. The gray shaded area and red dotted lines are the corresponding 68% confidence intervals.

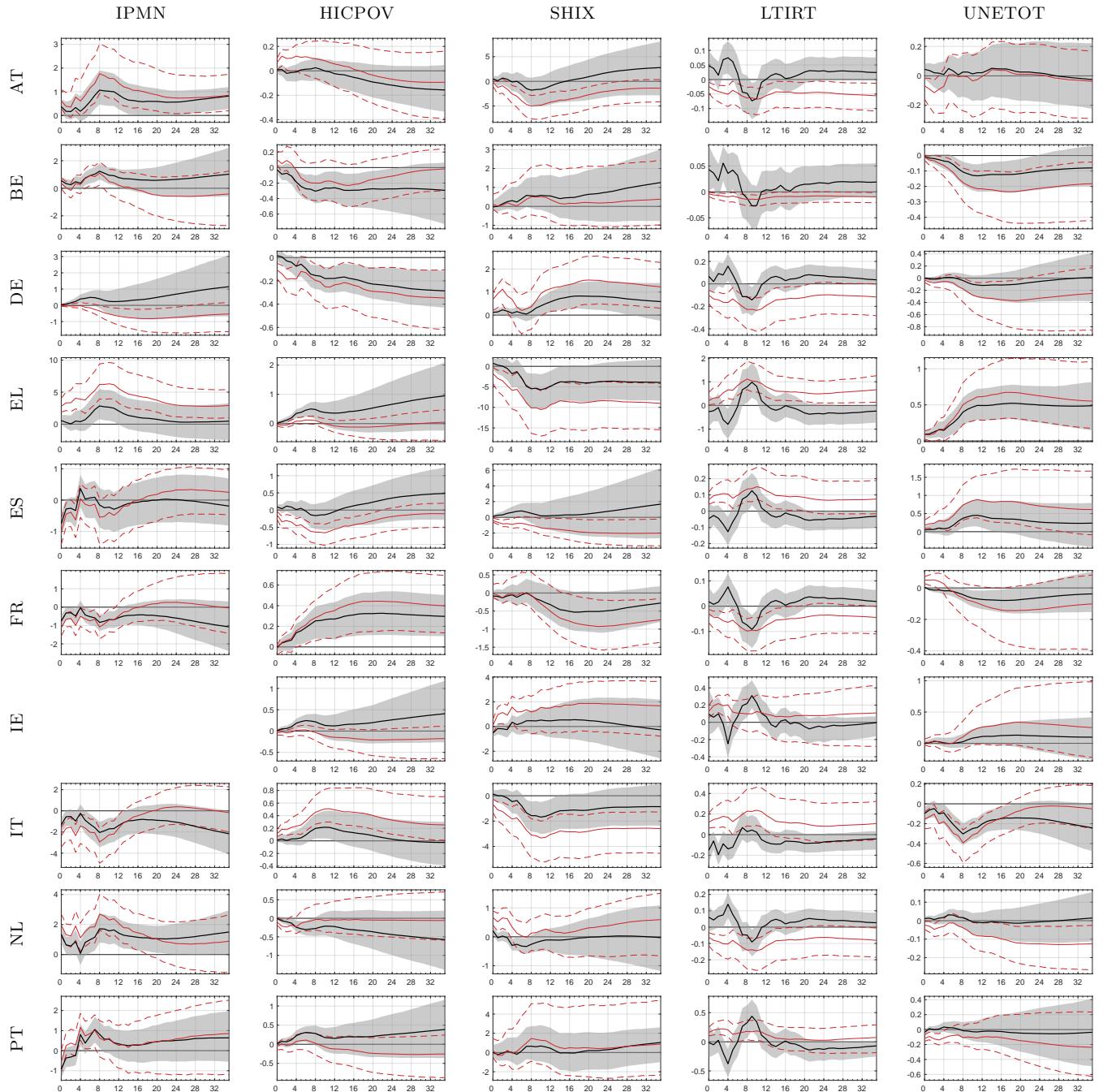
F.2 Country-level IRFs

Figure F2: Country-level IRFs: statistical transformations



NOTES: Each sub-figure plots the impulse responses, for all countries, of one variable to a 100bps contractionary monetary policy shock. Within each sub-figure, at each horizon $h = 0, \dots, 36$ the country-level impulse responses are denoted with a solid line if the IRF is statistically significant at the 68% level at that horizon, and with a dotted line otherwise.

Figure F3: Difference between country-level and EA IRFs: baseline vs. statistical transformations



NOTES: Each sub-figure plots the difference between the country-level IRF and the corresponding EA counterpart for one variable and one country. Each column of the graph represents a variable, while each row represents a country. The variables considered are: Industrial Production: Manufacturing (IPMN), HICP: Overall (HICPOV), Stock Price Index (SHIX), 10-years Interest Rates (LTIRT) and Unemployment Rate (UNETOT). The black solid line is the point estimate in our baseline setting, while the red solid line is the point estimate obtained with the statistical transformations. The gray shaded area and red dotted lines are the corresponding 68% confidence intervals. The scale in the vertical axis differs across variables and countries.

F.3 Cross-country characteristics and IRF dynamics

Table F1: Cross-country characteristics and IRFs dynamics: statistical transformations

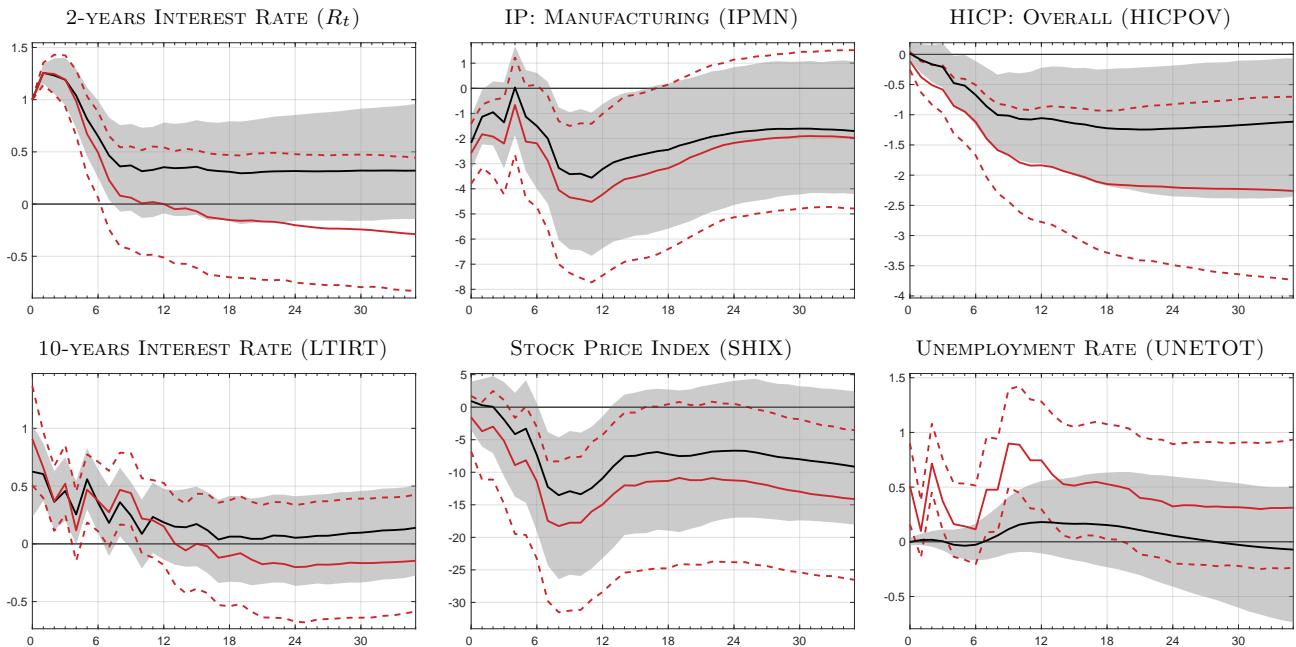
ID	Variable	IPMN	HICPOV	LTIRT	SHIX	UNETOT
1	Employment Protection	-0.05 (0.38)	0.17 (0.35)	-0.09 (0.35)	-0.05 (0.35)	-0.44 (0.32)
2	Wage Adj. Frequency: more than once a year	0.16 (0.44)	0.28 (0.39)	-0.52 (0.35)	0.38 (0.38)	-0.51 (0.35)
3	Wage Adj. Frequency: once a year	0.65 (0.34)	-0.15 (0.40)	-0.61 (0.32)	-0.22 (0.40)	0.11 (0.41)
4	Wage Adj. Frequency: less than once a year	-0.65 (0.34)	0.38 (0.38)	0.42 (0.37)	-0.16 (0.40)	-0.22 (0.40)
5	Price Flexibility	-0.09 (0.45)	-0.39 (0.41)	-0.39 (0.41)	0.64 (0.34)	-0.07 (0.45)
6	NFC Leverage	0.00 (0.38)	-0.06 (0.35)	-0.36 (0.33)	0.68** (0.26)	-0.15 (0.35)
7	Homeownership	0.09 (0.38)	-0.02 (0.35)	0.67** (0.26)	-0.09 (0.35)	0.57* (0.29)
8	Homeownership with mortgage	0.07 (0.38)	-0.21 (0.35)	-0.52 (0.30)	0.65** (0.27)	-0.30 (0.34)
9	Homeownership without mortgage	-0.01 (0.38)	0.17 (0.35)	0.81*** (0.21)	-0.59* (0.28)	0.57* (0.29)
10	Fixed-Rate Mortgages	-0.28 (0.36)	0.33 (0.33)	-0.77*** (0.23)	0.43 (0.32)	-0.63** (0.27)
11	Loan to Value	-0.32 (0.39)	-0.26 (0.36)	-0.11 (0.38)	0.71** (0.27)	-0.07 (0.38)
12	Share of HtM	0.39 (0.35)	-0.53 (0.30)	0.49 (0.31)	0.17 (0.35)	0.35 (0.33)
13	Share of WHtM	0.40 (0.35)	-0.48 (0.31)	0.70** (0.25)	-0.02 (0.35)	0.51 (0.30)
14	Saving Rate	-0.37 (0.35)	-0.12 (0.35)	-0.85*** (0.19)	0.60* (0.28)	-0.37 (0.33)
15	Explained Variance	-0.75** (0.25)	0.13 (0.35)	-0.95*** (0.11)	0.37 (0.33)	0.37 (0.33)

NOTES: Each entry of the table corresponds to the correlation between each indicator (in the row) and the peak of the impulse response for a specific variable (in the columns). The variables considered are: Industrial Production: Manufacturing (IPMN), HICP: Overall (HICPOV), Stock Price Index (SHIX), 10-years Interest Rates (LTIRT) and Unemployment Rate (UNETOT). Standard errors in parentheses, asterisks denote statistical significance at 99% (***) , 95% (**), and 90% (*). The first row reports the Employment Protection Index (OECD). Rows 2-4 show the frequency of wage adjustments by firms (Branten et al., 2018), while row 1 reports the frequency with which firms adjust output prices (Gautier et al., 2024). Row 6 shows the leverage of non-financial corporations relative to GDP (Eurostat). Row 7 reports the homeownership rate as a share of the population (Eurostat). Rows 8 and 9 indicate, respectively, the shares of residential properties with and without an outstanding mortgage (Eurostat). Row 10 reports the share of fixed-rate mortgages (De Stefani and Mano, 2025). Row 11 shows the average household loan-to-value ratio from the Eurosystem Household Finance and Consumption Survey (HFCS). Rows 12 and 13 display, respectively, the shares of “wealthy hand-to-mouth” and “poor hand-to-mouth” households, constructed as in Slacalek et al. (2020) based on HFCS data. Row 14 reports the household saving rate as a percentage of GDP (OECD). Finally, row 15 corresponds to the share of variance explained by the common factors for each variable in the columns.

G Alternative transformations: all rates in levels

G.1 EA IRFs

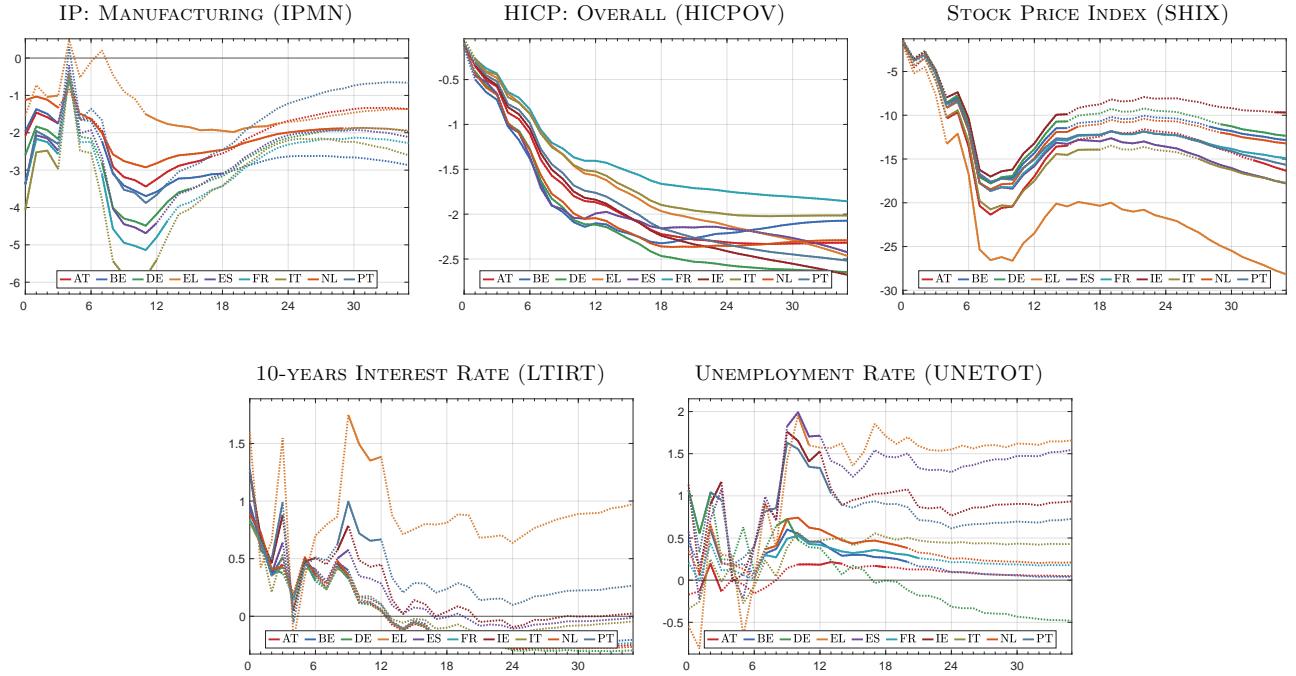
Figure G1: EA IRFs: baseline vs all rates in levels



NOTES: Each sub-figure plots the impulse response of one EA variable to a 100bps contractionary monetary policy shock. The black solid line is the point estimate in our baseline setting, while the red solid line is the point estimate obtained with the alternative set of transformations keeping all rates in levels. The gray shaded area and red dotted lines are the corresponding 68% confidence intervals.

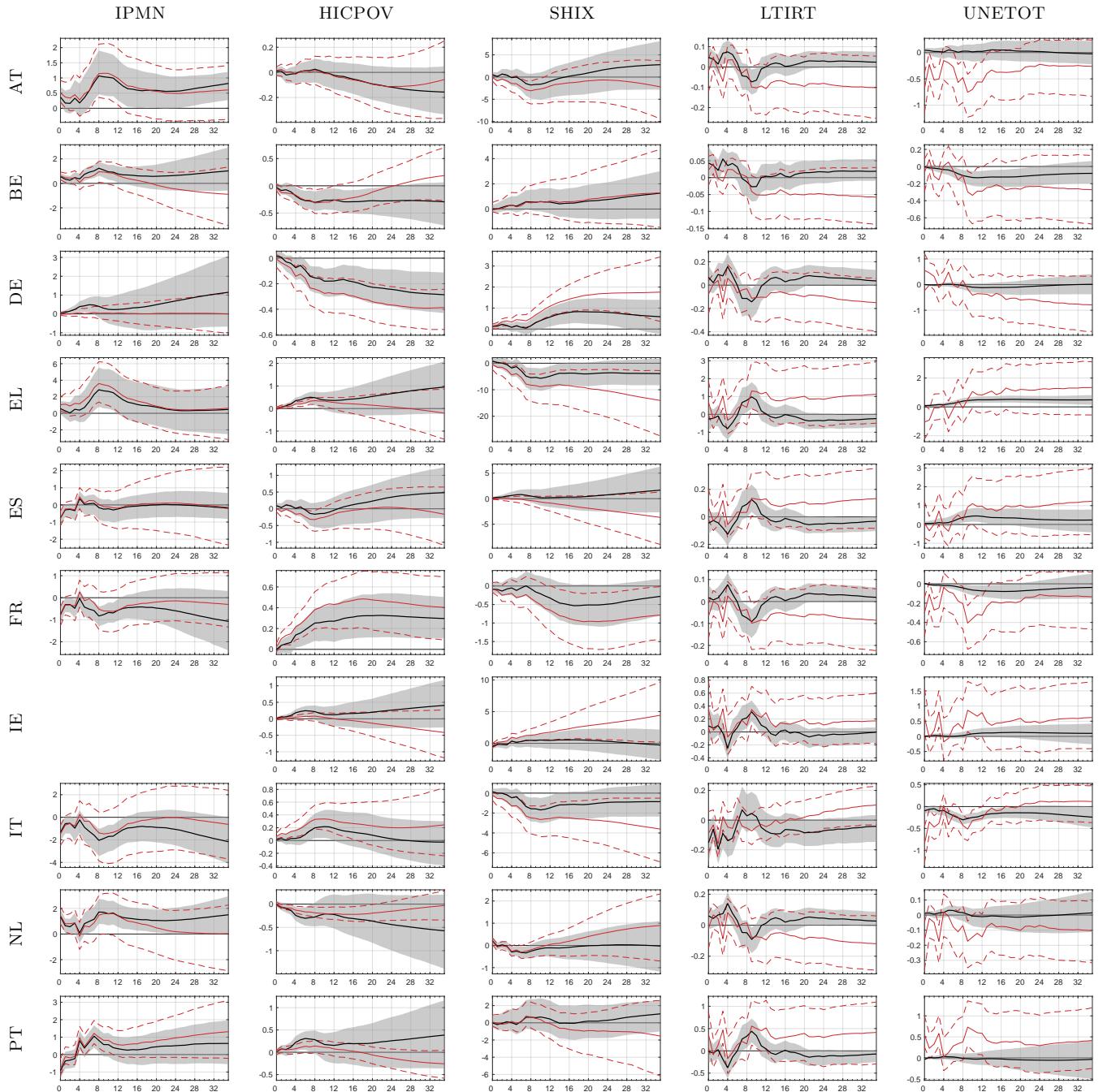
G.2 Country-level IRFs

Figure G2: Country-level IRFs: all rates in levels



NOTES: Each sub-figure plots the impulse responses, for all countries, of one variable to a 100bps contractionary monetary policy shock. Within each sub-figure, at each horizon $h = 0, \dots, 36$ the country-level impulse responses are denoted with a solid line if the IRF is statistically significant at the 68% level at that horizon, and with a dotted line otherwise.

Figure G3: Difference between country-level and EA IRFs: baseline vs. all rates in levels



NOTES: Each sub-figure plots the difference between the country-level IRF and the corresponding EA counterpart for one variable and one country. Each column of the graph represents a variable, while each row represents a country. The variables considered are: Industrial Production: Manufacturing (IPMN), HICP: Overall (HICPOV), Stock Price Index (SHIX), 10-years Interest Rates (LTIRT) and Unemployment Rate (UNETOT). The black solid line is the point estimate in our baseline setting, while the red solid line is the point estimate obtained with the alternative set of transformation leaving all rates in levels. The gray shaded area and red dotted lines are the corresponding 68% confidence intervals. The scale in the vertical axis differs across variables and countries.

G.3 Cross-country characteristics and IRF dynamics

Table G1: Cross-country characteristics and IRFs dynamics: all rates in level

ID	Variable	IPMN	HICPOV	LTIRT	SHIX	UNETOT
1	Employment Protection	-0.05 (0.38)	0.17 (0.35)	-0.09 (0.35)	-0.05 (0.35)	-0.44 (0.32)
2	Wage Adj. Frequency: more than once a year	0.16 (0.44)	0.28 (0.39)	-0.52 (0.35)	0.38 (0.38)	-0.51 (0.35)
3	Wage Adj. Frequency: once a year	0.65 (0.34)	-0.15 (0.40)	-0.61 (0.32)	-0.22 (0.40)	0.11 (0.41)
4	Wage Adj. Frequency: less than once a year	-0.65 (0.34)	0.38 (0.38)	0.42 (0.37)	-0.16 (0.40)	-0.22 (0.40)
5	Price Flexibility	-0.09 (0.45)	-0.39 (0.41)	-0.39 (0.41)	0.64 (0.34)	-0.07 (0.45)
6	NFC Leverage	0.00 (0.38)	-0.06 (0.35)	-0.36 (0.33)	0.68** (0.26)	-0.15 (0.35)
7	Homeownership	0.09 (0.38)	-0.02 (0.35)	0.67** (0.26)	-0.09 (0.35)	0.57* (0.29)
8	Homeownership with mortgage	0.07 (0.38)	-0.21 (0.35)	-0.52 (0.30)	0.65** (0.27)	-0.30 (0.34)
9	Homeownership without mortgage	-0.01 (0.38)	0.17 (0.35)	0.81*** (0.21)	-0.59* (0.28)	0.57* (0.29)
10	Fixed-Rate Mortgages	-0.28 (0.36)	0.33 (0.33)	-0.77*** (0.23)	0.43 (0.32)	-0.63** (0.27)
11	Loan to Value	-0.32 (0.39)	-0.26 (0.36)	-0.11 (0.38)	0.71** (0.27)	-0.07 (0.38)
12	Share of HtM	0.39 (0.35)	-0.53 (0.30)	0.49 (0.31)	0.17 (0.35)	0.35 (0.33)
13	Share of WHtM	0.40 (0.35)	-0.48 (0.31)	0.70** (0.25)	-0.02 (0.35)	0.51 (0.30)
14	Saving Rate	-0.37 (0.35)	-0.12 (0.35)	-0.85*** (0.19)	0.60* (0.28)	-0.37 (0.33)
15	Explained Variance	-0.75** (0.25)	0.13 (0.35)	-0.95*** (0.11)	0.37 (0.33)	0.37 (0.33)

NOTES: Each entry of the table corresponds to the correlation between each indicator (in the row) and the peak of the impulse response for a specific variable (in the columns). The variables considered are: Industrial Production: Manufacturing (IPMN), HICP: Overall (HICPOV), Stock Price Index (SHIX), 10-years Interest Rates (LTIRT) and Unemployment Rate (UNETOT). Standard errors in parentheses, asterisks denote statistical significance at 99% (***) , 95% (**), and 90% (*). The first row reports the Employment Protection Index (OECD). Rows 2-4 show the frequency of wage adjustments by firms (Branten et al., 2018), while row 1 reports the frequency with which firms adjust output prices (Gautier et al., 2024). Row 6 shows the leverage of non-financial corporations relative to GDP (Eurostat). Row 7 reports the homeownership rate as a share of the population (Eurostat). Rows 8 and 9 indicate, respectively, the shares of residential properties with and without an outstanding mortgage (Eurostat). Row 10 reports the share of fixed-rate mortgages (De Stefani and Mano, 2025). Row 11 shows the average household loan-to-value ratio from the Eurosystem Household Finance and Consumption Survey (HFCS). Rows 12 and 13 display, respectively, the shares of “wealthy hand-to-mouth” and “poor hand-to-mouth” households, constructed as in Slacalek et al. (2020) based on HFCS data. Row 14 reports the household saving rate as a percentage of GDP (OECD). Finally, row 15 corresponds to the share of variance explained by the common factors for each variable in the columns.

H Monthly data: identification via sign restrictions

Sign restrictions are imposed as summarized in Table H1. For the policy rate, R_t , we use the shadow rate of Wu and Xia (2016), as it is common in the literature on identification with sign restrictions to use a very short-term interest rate. Specifically, we impose a positive response of short- and long-term EA Interest Rates in the first two periods following the shock. For Industrial Production, Overall HICP, and the Stock Price Index, we impose a negative response in the second and third periods. Finally, for the Unemployment Rate, we impose a positive response in the second and third periods. This specification accommodates nominal rigidities and delayed real adjustments, allowing for a gradual transmission of monetary policy effects. Restrictions on Industrial Production, the Unemployment Rate, Overall HICP, and Interest Rates are consistent with the predictions of a standard New Keynesian DSGE model and with the conventional sign restrictions typically imposed to identify a monetary policy shock (e.g., Peersman, 2005; Barigozzi et al., 2014). The restriction on the Stock Price Index is consistent with the Jarociński and Karadi (2020) approach used to disentangle a standard monetary policy shock from an information shock.

Table H1: Sign restrictions: monthly data

Horizon	R_t	$\widehat{\chi}_{IPMN\ EA,t}$	$\widehat{\chi}_{HICPOV\ EA,t}$	$\widehat{\chi}_{LTIRT\ EA,t}$	$\widehat{\chi}_{SHIX\ EA,t}$	$\widehat{\chi}_{UNETOT\ EA,t}$
0	+			+		
1	+	-	-	+	-	+
2		-	-		-	+

Notes: Each column of the table represents the common component of one variable, except for the EA Shadow Rate (R_t). The EA variables considered are: Industrial Production: Manufacturing (IPMN), HICP: Overall (HICPOV), Stock Price Index (SHIX), 10-years Interest Rates (LTIRT) and Unemployment Rate (UNETOT).

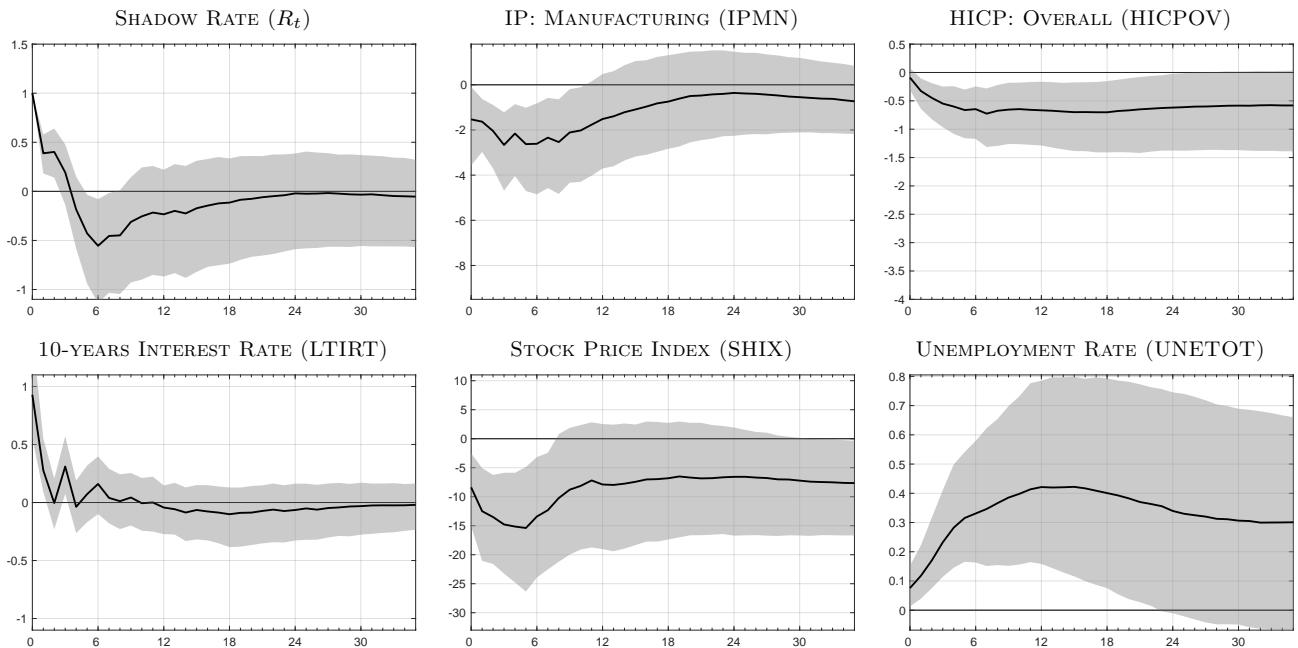
Confidence intervals and point estimates are obtained using a bootstrap procedure with 10,000 replications. For each iteration, we proceed as follows. We draw an $n \times n$ matrix \mathbf{W} whose rows are independently sampled from a $\mathcal{N}(\mathbf{0}, \mathbf{I}_n)$ distribution. We then compute the QR decomposition $\mathbf{W} = \mathbf{QR}$, where \mathbf{Q} is orthogonal and \mathbf{R} is upper triangular (Rubio-Ramirez et al., 2010). The candidate structural impact matrix is given by $\mathbf{S} = \mathbf{L}\mathbf{Q}'$, where \mathbf{L} denotes the lower triangular Cholesky factor of the reduced-form innovation covariance matrix Σ .

If the resulting impulse responses satisfy the sign restrictions in Table H1, the draw is accepted; otherwise, it is discarded. Within each bootstrap replication, we continue this process until K

admissible draws are obtained. Following Fry and Pagan (2011), we retain only the IRF that is closest to the median across the K accepted draws. Here we set $K = 30$. The same procedure is applied to the observed data. This yields 10,000+1 admissible IRFs, from which we construct the empirical distribution of responses. We take the median of this distribution as the point estimate, while the 16th and 84th percentiles serve as the lower and upper bounds of the confidence interval, respectively.

H.1 EA IRFs

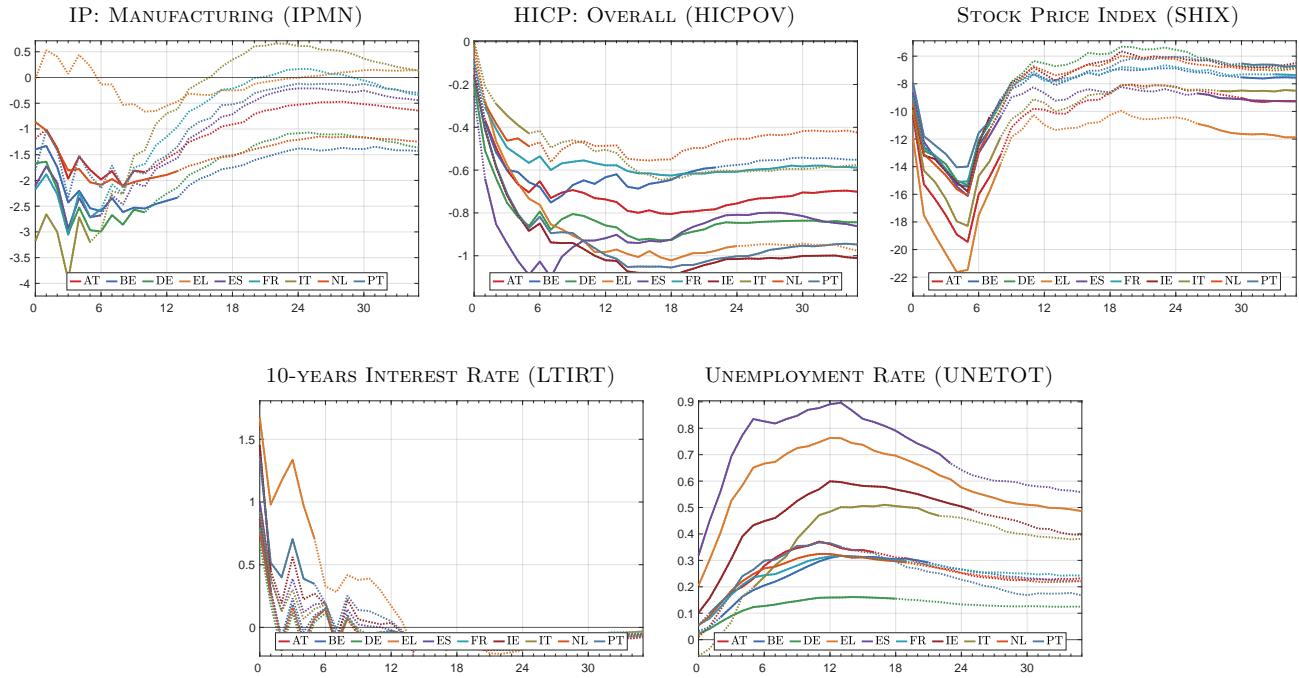
Figure H1: EA IRF: monthly data and sign restrictions



NOTES: Each sub-figure plots the impulse response of one EA variable to a 100bps contractionary monetary policy shock. The black solid line is the point estimate in our baseline setting, while the gray shaded area is the corresponding 68% confidence interval.

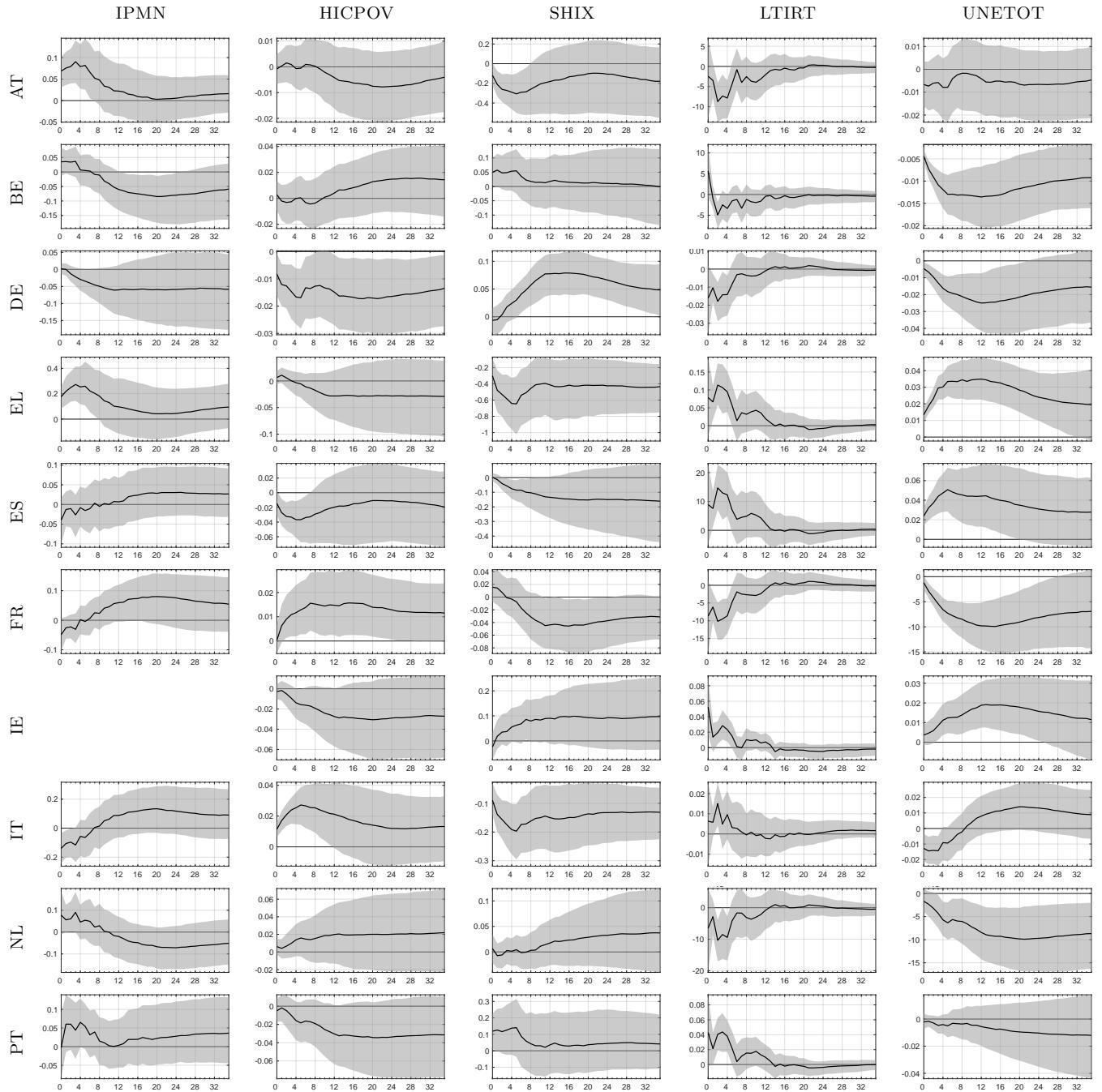
H.2 Country-level IRFs

Figure H2: Country-level IRFs: monthly data and sign restrictions



NOTES: Each sub-figure plots the impulse responses, for all countries, of one variable to a 100bps contractionary monetary policy shock. Within each sub-figure, at each horizon $h = 0, \dots, 36$ the country-level impulse responses are denoted with a solid line if the IRF is statistically significant at the 68% level at that horizon, and with a dotted line otherwise.

Figure H3: Difference between country-specific and EA IRFs: monthly data and restrictions



NOTES: Each sub-figure plots the impulse response of one variable for each country to a 100bps contractionary monetary policy shock. Each column of the graph represents a variable, while each row represents a country. The variables considered are: Industrial Production: Manufacturing (IPMN), HICP: Overall (HICPOV), Stock Price Index (SHIX), 10-years Interest Rates (LTIRT) and Unemployment Rate (UNETOT). The black solid line is the point estimate obtained identifying the monetary policy shock via sign restrictions, while gray shaded area are the corresponding 68% confidence intervals. The scale in the vertical axis differs across variables and countries.

I Quarterly data: identification via sign restrictions

I.1 Factor analysis and comovements across EA countries

In this section, we present the results obtained using quarterly data. Throughout, use $r = 6$ factors, according to the results of the results presented in Table I1.

Table I1: Estimated number of factors

Method	Number of factors r
Bai and Ng (2002)	8
Alessi et al. (2010)	6
Onatski (2010)	9
Ahn and Horenstein (2013)	1

Table I2 reports the share of variance for each variable explained by the common factors extracted using quarterly data.

Table I2: Share of Explained Variance by the common factors: quarterly data

Country	GDP (GDP)	HICP: Overall (HICPOV)	10-years Interest Rate (LTIRT)	Stock Price Index (SHIX)	Unemployment Rate (UNETOT)
EA	0.98 (0.97-0.99)	0.93 (0.90-0.95)	0.87 (0.84-0.93)	0.87 (0.81-0.89)	0.88 (0.84-0.92)
AT	0.90 (0.85-0.92)	0.89 (0.85-0.92)	0.92 (0.89-0.94)	0.84 (0.77-0.86)	0.50 (0.42-0.62)
BE	0.95 (0.93-0.96)	0.82 (0.77-0.86)	0.91 (0.88-0.94)	0.84 (0.77-0.86)	0.19 (0.16-0.31)
DE	0.88 (0.84-0.91)	0.85 (0.81-0.90)	0.92 (0.88-0.93)	0.77 (0.71-0.82)	0.13 (0.19-0.43)
EL	0.63 (0.56-0.74)	0.73 (0.67-0.80)	0.27 (0.26-0.57)	0.60 (0.52-0.69)	0.62 (0.57-0.75)
ES	0.95 (0.93-0.97)	0.83 (0.78-0.87)	0.73 (0.70-0.85)	0.75 (0.67-0.79)	0.75 (0.69-0.81)
FR	0.95 (0.93-0.96)	0.84 (0.80-0.89)	0.92 (0.89-0.94)	0.87 (0.80-0.89)	0.60 (0.54-0.69)
IE	0.27 (0.22-0.39)	0.79 (0.74-0.85)	0.64 (0.61-0.79)	0.79 (0.72-0.82)	0.41 (0.37-0.58)
IT	0.94 (0.92-0.96)	0.77 (0.71-0.83)	0.76 (0.74-0.86)	0.85 (0.78-0.88)	0.65 (0.58-0.71)
NL	0.91 (0.87-0.94)	0.66 (0.58-0.75)	0.92 (0.88-0.93)	0.83 (0.76-0.85)	0.47 (0.41-0.59)
PT	0.91 (0.87-0.93)	0.81 (0.76-0.86)	0.44 (0.43-0.68)	0.63 (0.55-0.70)	0.52 (0.46-0.64)

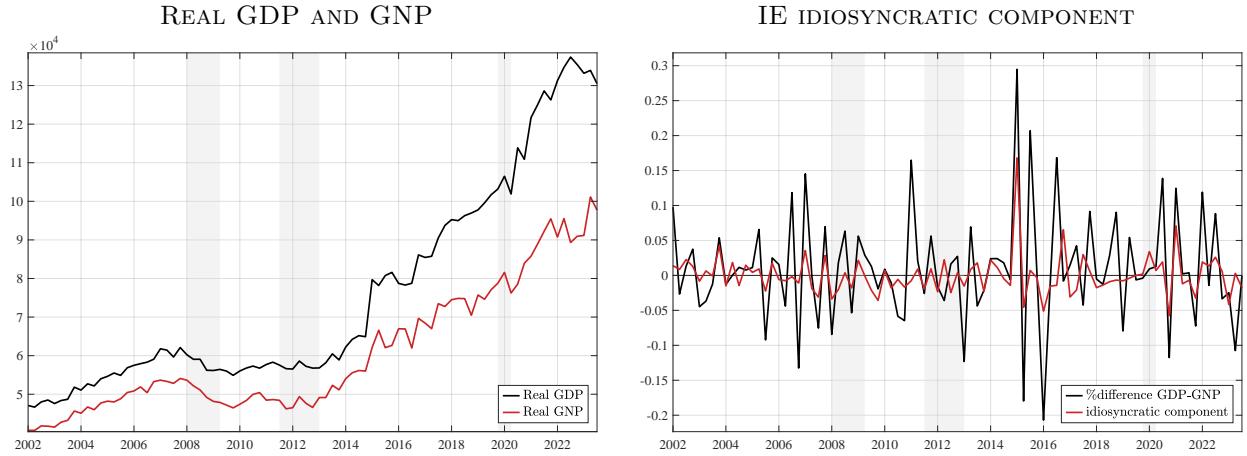
NOTES: Each entry in the table corresponds to the share of variability within each variable (in the columns) for each country (in the rows) explained by the common component, $\widehat{\chi}_{i,t}$. Numbers in parentheses indicate the lower and upper bounds of the 68% confidence interval, computed using the bootstrap procedure described in Appendix B.

I.2 Ireland GDP

From Table I2 we notice that the explained variance for Ireland's GDP is particularly low. This, is due to Ireland being the legal domicile of many foreign large firms, creating remarkable distortions in Irish national accounts. To corroborate this finding, we computed the correlation between the

idiosyncratic component of Ireland's real GDP growth and the difference between the growth rates of real GDP and real GNP. Due to the strong presence of foreign-owned multinational corporations, a sizable portion of domestic income generated in Ireland is repatriated abroad, creating a persistent wedge between GDP and GNP. As a result, other countries' variables may comove more closely with Ireland's GNP than with its GDP. If this is the case, the idiosyncratic component of Ireland's GDP should correlate with the GDP-GNP growth differential. Figure I1 reports the results of this exercise. The left panel confirms a sizable and persistent wedge between Ireland's real GDP and GNP, as expected. The right panel compares the log-difference of this wedge with the idiosyncratic component of real GDP growth from our model. The two series are positively and strongly correlated, with a correlation of approximately 0.6 over the full sample. This result suggests that the distortion in Ireland's national accounts—arising from the repatriation of income by multinational firms—is indeed one of the main determinants of Ireland's idiosyncratic behaviour in our model.

Figure I1: Ireland's idiosyncratic dynamics vs. real GDP and GNP



NOTES: The left panel plots the real GDP and GNP for Ireland in millions of euros (black and red lines, respectively). The right panel compares the log-difference of real GDP and GNP (black line) with the idiosyncratic component of Ireland's GDP obtained in our setting using quarterly data.

I.3 Identification via sign restrictions

In the IRF analysis, we use the same sets of EA common component as in the monthly case, with the exception of Industrial Production which is substituted with GDP (see Table I3). Following the same procedure described in Appendix H, we impose the sign restrictions summarized in Table

Table I3: Components of \mathbf{Y}_t in the CC-VAR with quarterly data

notation	ID	name
R_t	-	EA 2-years Interest Rate
$\hat{\chi}_{\text{GDP EA},t}$	GDP	EA GDP
$\hat{\chi}_{\text{HICPOV EA},t}$	HICPOV	EA HICP: Overall
$\hat{\chi}_{\text{LTIRT EA},t}$	LTIRT	EA 10-years Interest Rate
$\hat{\chi}_{\text{SHIX EA},t}$	SHIX	EA Stock Price Index
$\hat{\chi}_{\text{UNETOT EA},t}$	UNETOT	EA Unemployment Rate
$\hat{\chi}_{\text{nat.,}t}$	-	National variable

I4. Specifically, we require a positive response of short- and long-term EA Interest Rates during the first two periods after the shock. For GDP, the Overall HICP, and the Stock Price Index, we impose a negative response in the second and third periods. Finally, for the Unemployment Rate, we impose a positive response in the second and third periods. Confidence intervals and point estimates are obtained using the same procedure described in Appendix H.

We do not report results based on identification via instrumental variables, which are unreliable due to the extremely low explanatory power of the instrument at the quarterly frequency. As noted by Kilian (2024), time aggregation of high-frequency instruments can become problematic as the sampling frequency decreases.

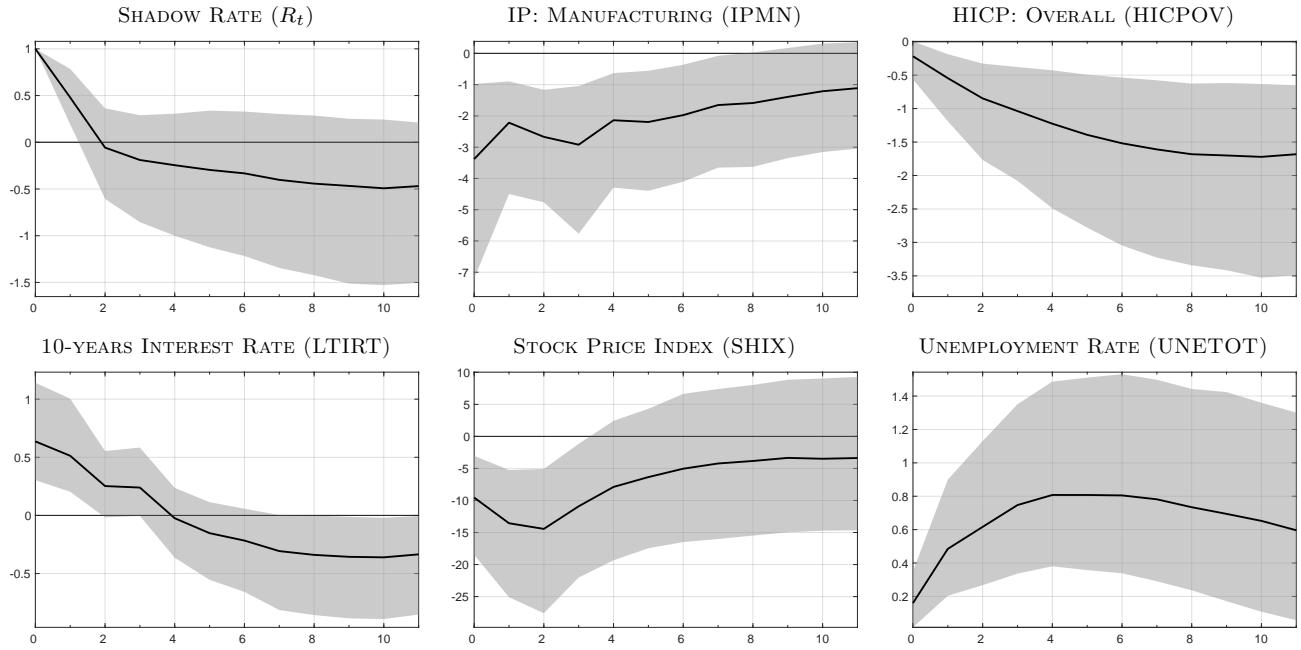
Table I4: Sign restrictions: quarterly data

Horizon	R_t	$\hat{\chi}_{\text{GDP EA},t}$	$\hat{\chi}_{\text{HICPOV EA},t}$	$\hat{\chi}_{\text{LTIRT EA},t}$	$\hat{\chi}_{\text{SHIX EA},t}$	$\hat{\chi}_{\text{UNETOT EA},t}$
0	+			+		
1	+	-	-	+	-	+
2		-	-		-	+

Notes: Each column of the table represents the common component of one variable, except for the EA Shadow Rate (R_t). The EA variables considered are: GDP, HICP: Overall (HICPOV), Stock Price Index (SHIX), 10-years Interest Rates (LTIRT) and Unemployment Rate (UNETOT).

I.4 EA IRFs

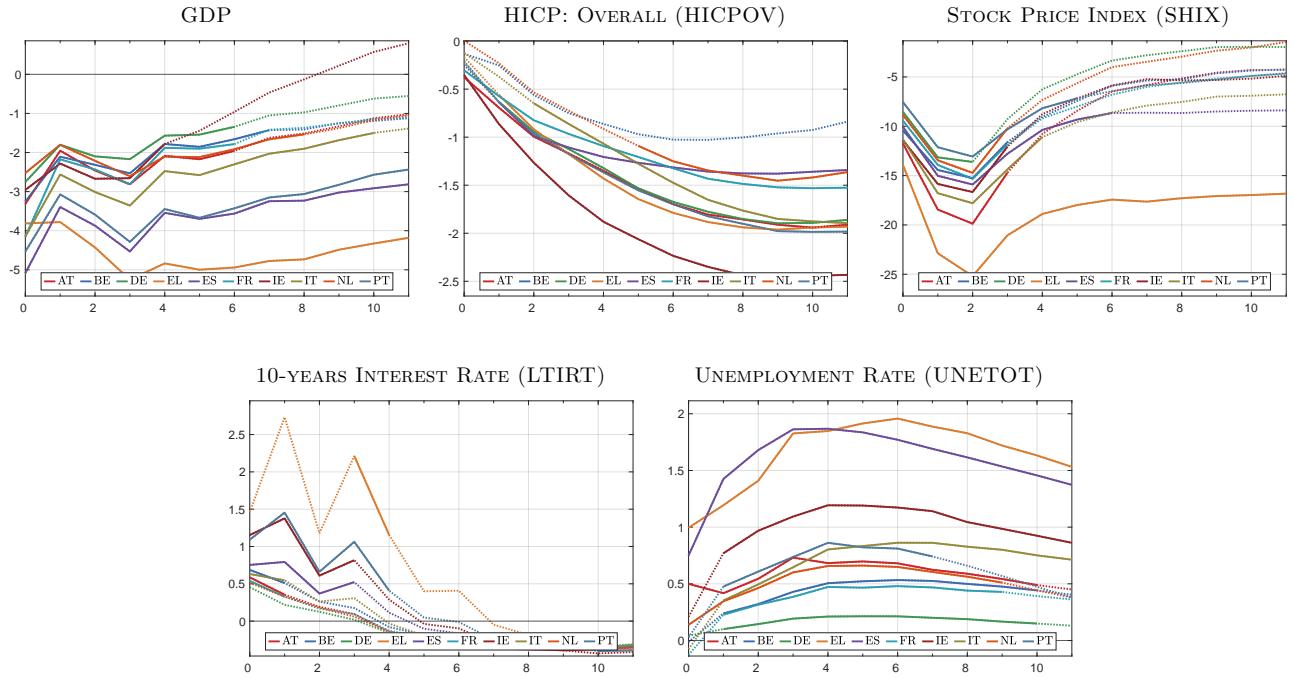
Figure I2: EA IRFs: quarterly data and sign restrictions



NOTES: Each sub-figure plots the impulse response of one EA variable to a 100bps contractionary monetary policy shock. The black solid line is the point estimate in our baseline setting, while the gray shaded area is the corresponding 68% confidence interval.

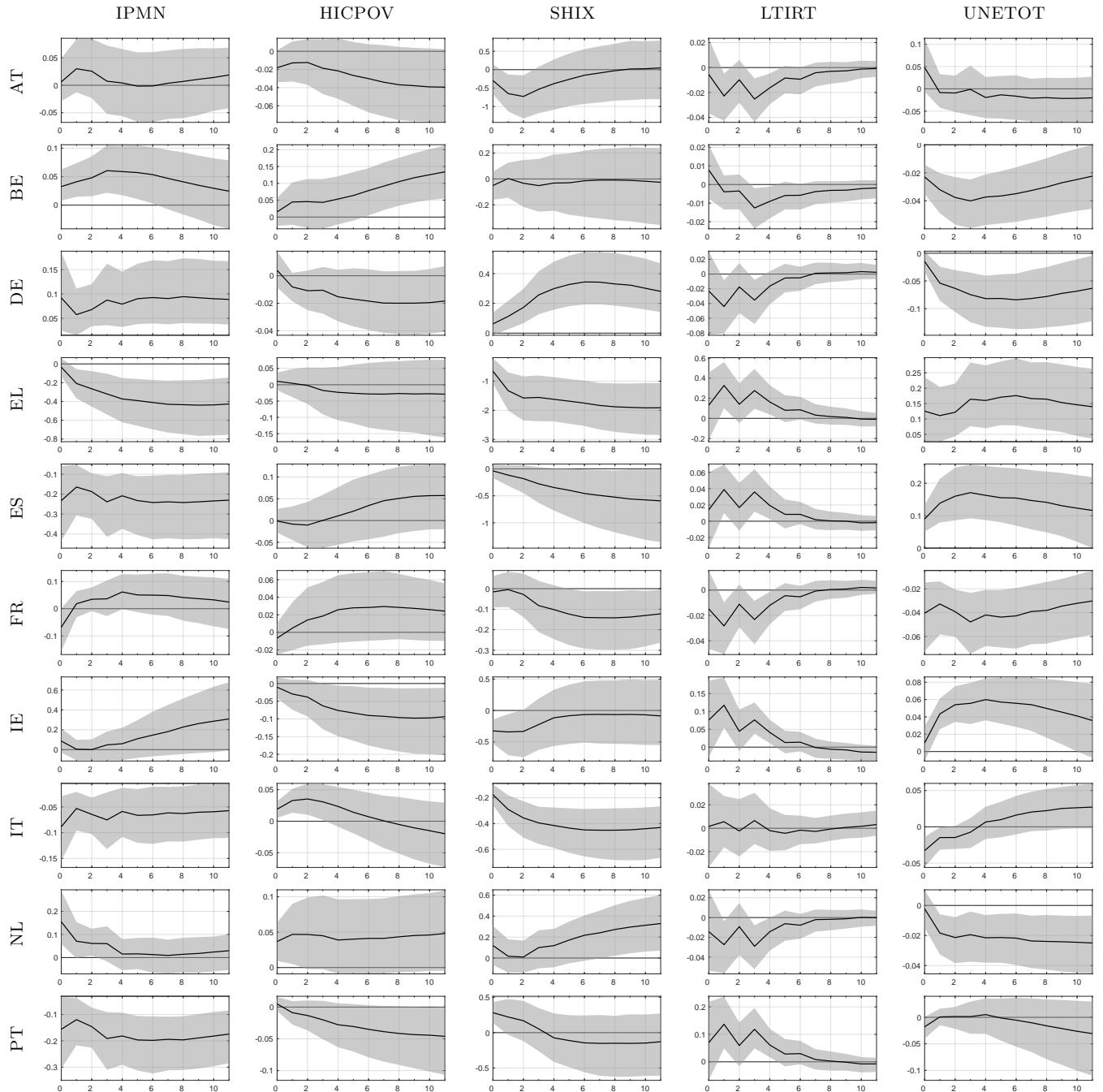
I.5 Country-level IRFs

Figure I3: Country-level IRFs: quarterly data and sign restrictions



NOTES: Each sub-figure plots the impulse responses, for all countries, of one variable to a 100bps contractionary monetary policy shock. Within each sub-figure, at each horizon $h = 0, \dots, 36$ the country-level impulse responses are denoted with a solid line if the IRF is statistically significant at the 68% level at that horizon, and with a dotted line otherwise.

Figure I4: Difference between country-specific and EA IRFs: quarterly data and sign restrictions



NOTES: Each sub-figure plots the difference between the country-level IRF and the corresponding EA counterpart for one variable and one country. Each column of the graph represents a variable, while each row represents a country. The variables considered are: GDP, HICP: Overall (HICPOV), Stock Price Index (SHIX), 10-years Interest Rates (LTIRT) and Unemployment Rate (UNETOT). The black solid line is the point estimate in our baseline setting, while the gray shaded area is the corresponding 68% confidence interval. The scale in the vertical axis differs across variables and countries.

J Mixed frequency data: identification via Instrumental Variables

J.1 Estimation

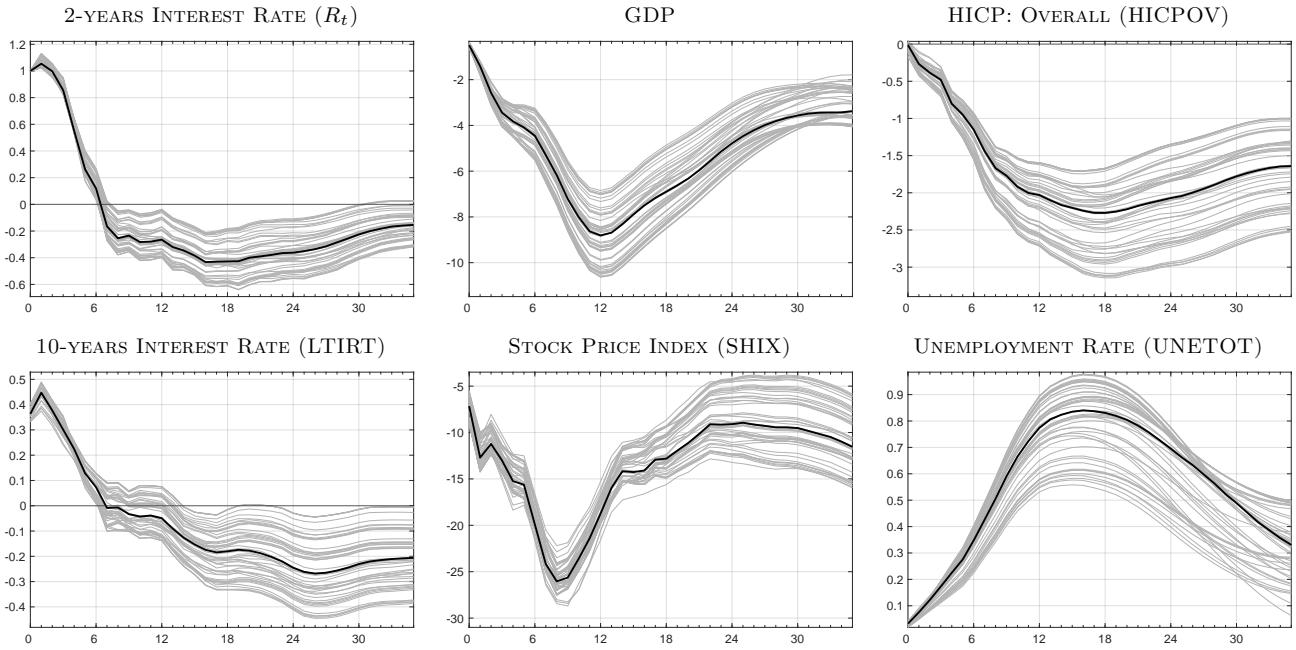
In order to handle mixed frequency data (monthly data as in the baseline specification plus EA and national quarterly GDPs) estimation of the factor model is via the EM algorithm by Ba  bura et al. (2011). The estimated common components are all at the monthly frequency. The variable used in the CC-VAR are listed in Table J1. Identification is via Instrumental Variables.

Table J1: Components of \mathbf{Y}_t in the CC-VAR with quarterly data

notation	ID	name
R_t	-	EA 2-years Interest Rate - monthly
$\hat{\chi}_{\text{GDP EA},t}$	GDP	EA GDP
$\hat{\chi}_{\text{HICPOV EA},t}$	HICPOV	EA HICP: Overall
$\hat{\chi}_{\text{LTIRT EA},t}$	LTIRT	EA 10-years Interest Rate
$\hat{\chi}_{\text{SHIX EA},t}$	SHIX	EA Stock Price Index
$\hat{\chi}_{\text{UNETOT EA},t}$	UNETOT	EA Unemployment Rate
$\hat{\chi}_{\text{nat.},t}$	-	National variable

J.2 EA IRFs

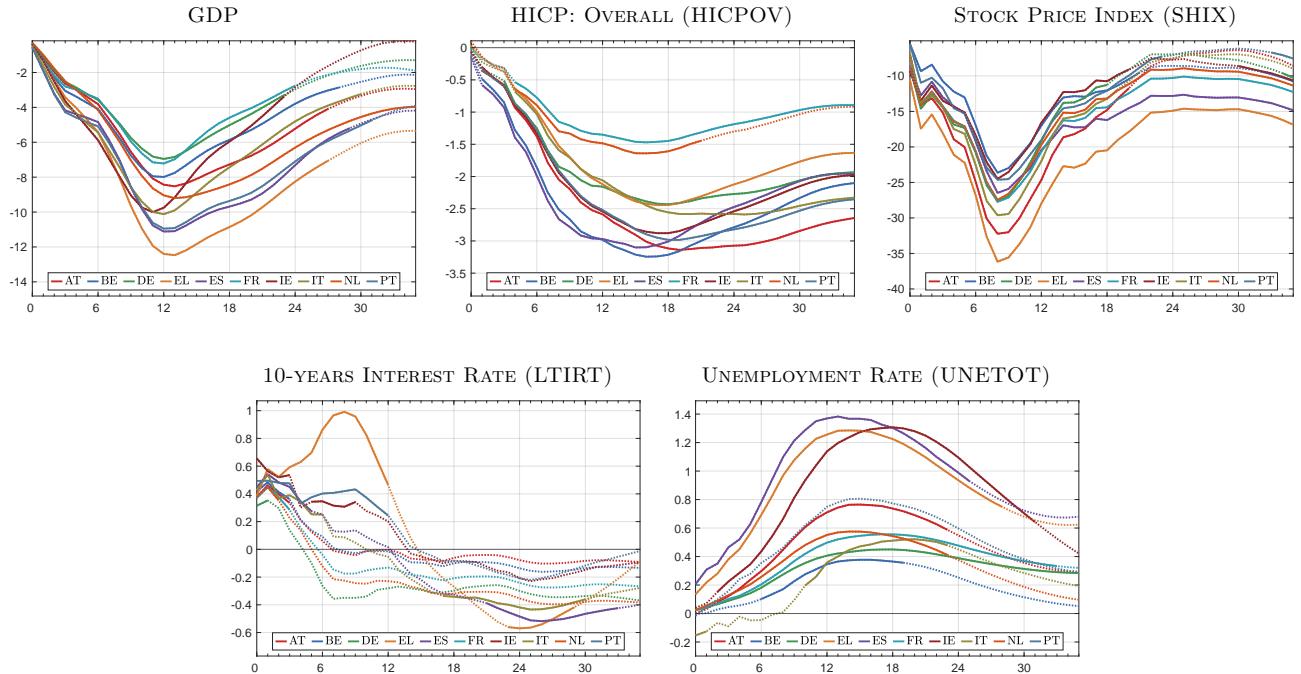
Figure J1: EA IRFs: mixed-frequency data



NOTES: Each sub-figure plots the impulse response of one EA variable to a 100bps contractionary monetary policy shock. The thin gray lines are the point estimates obtained with the 50 considered CC-VAR models differing only for the national variable included. The black solid line is the median estimate.

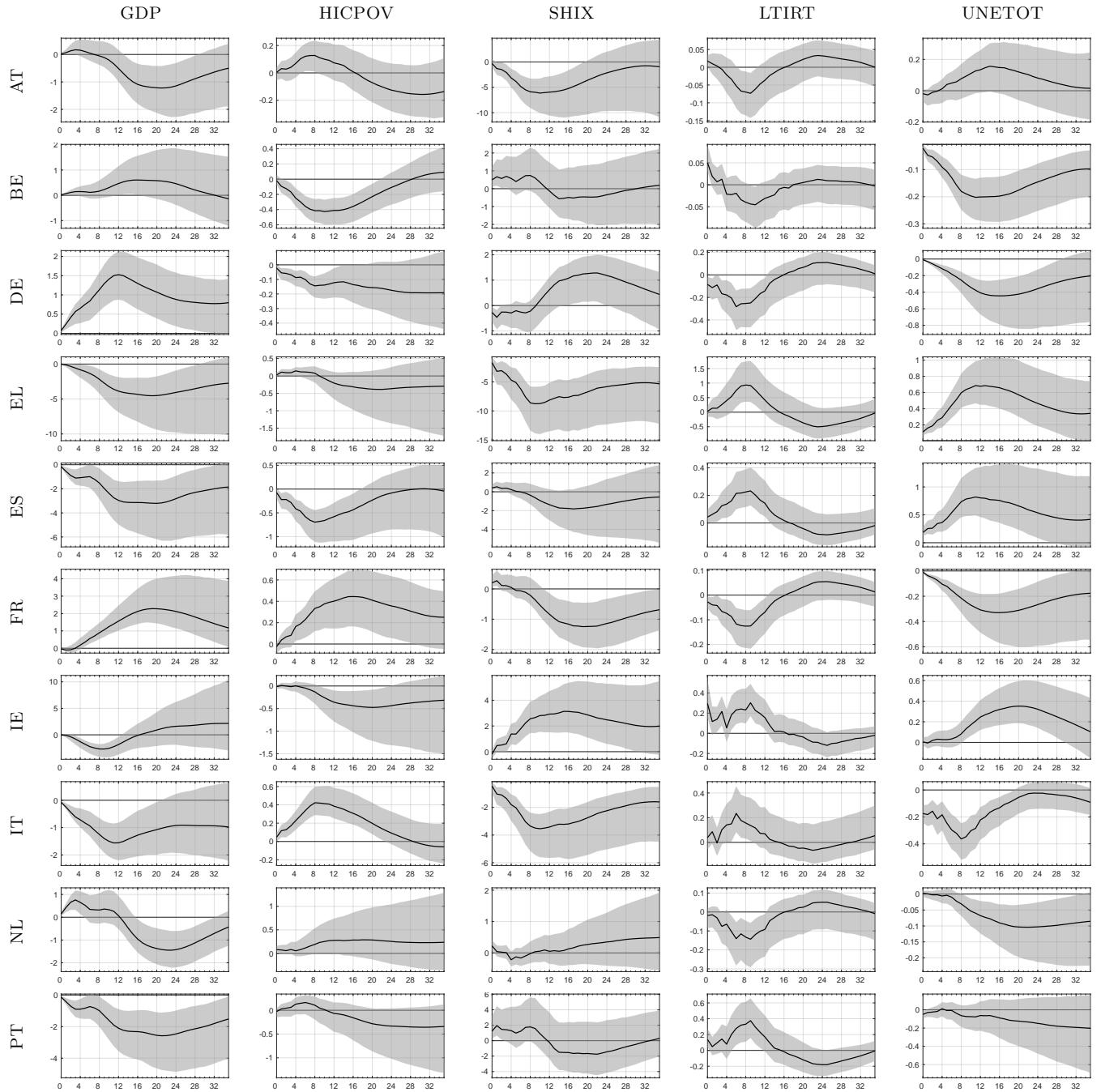
J.3 Country-level IRFs

Figure J2: Country-level IRFs: mixed-frequency data



NOTES: Each sub-figure plots the impulse responses, for all countries, of one variable to a 100bps contractionary monetary policy shock. Within each sub-figure, at each horizon $h = 0, \dots, 36$ the country-level impulse responses are denoted with a solid line if the IRF is statistically significant at the 68% level at that horizon, and with a dotted line otherwise.

Figure J3: Difference between country-level and EA IRFs: mixed-frequency data



NOTES: Each sub-figure plots the difference between the country-level IRF and the corresponding EA counterpart for one variable and one country. Each column of the graph represents a variable, while each row represents a country. The variables considered are: GDP, HICP: Overall (HICPOV), Stock Price Index (SHIX), 10-years Interest Rates (LTIRT) and Unemployment Rate (UNETOT). The black solid line is the point estimate in our baseline setting, while the gray shaded area is the corresponding 68% confidence interval. The scale in the vertical axis differs across variables and countries.