Freie Universität Berlin

# Essays on Large Data Sets and Unbalanced Panels in Empirical Macroeconomics

INAUGURAL-DISSERTATION

zur Erlangung des akademischen Grades
eines Doktors der Wirtschaftswissenschaft
*doctor rerum politicarum*
(Dr. rer. pol.)

am Fachbereich Wirtschaftswissenschaft
der Freien Universität Berlin

vorgelegt von
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Berlin, 2021

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Tag der Disputation: 21. Juni 2021

*To Stefan, my lovely partner in life.*

# Acknowledgments

This dissertation is the goal at the end of a long road full of dreams and aspirations that started back in Mexico in the early years of my Licenciatura. It also closes my chapter living in Berlin, which I will always remember as a wonderful time that allowed me to learn a lot and to meet amazing people.

First of all, I want to thank Helmut Lütkepohl for being the best PhD supervisor one could wish for and for being an example of excellence in research, which I will try to follow in my career. I am grateful for his feedback, advice, and support throughout my research, applications to internships, and during the job market. I am also greatly indebted to my second supervisor, Lars Winkelmann, who gave me the opportunity to work at Freie Universität Berlin for almost three years. I really enjoyed being part of his team and I thank him for taking time to read my research and for encouraging me to continuously improve my work.

I thank Dieter Nautz, Alex Kriwoluzky, and Mathias Trabandt for giving me valuable feedback in workshops and seminars and for providing a strong net of support during my PhD. Also, I am grateful to all my PhD fellow students who participated in the Seminar of Empirical Macroeconomics at Freie Universität Berlin, as well as the participants of many research conferences for helpful comments and suggestions.

I had a *structural break* when Agostino Consolo offered me a Traineeship at the ECB. This experience was both personally and professionally outstanding. I thank Agostino for always having an open door for either discussing research or just for having a chat. Moreover, I am very grateful for his unconditional support throughout the job market. I also thank my co-author and friend Claudia Foroni, for having fun with me in the writing process of our paper and for teaching me a bit of Italian. During my stay at the ECB, I had the pleasure of meeting Matteo Ciccarelli. I am deeply indebted to him for his continuous advice and mentorship which are a great motivation for keeping on pursuing a career in research.

The two internships in my PhD allowed me to meet amazing people. First, I thank Enrique Martínez-García for selecting me as a summer fellow at the

Federal Reserve Bank of Dallas. I also thank Marc Giannoni and Karel Mertels, their suggestions helped me polish the research question of my job market paper. I am also grateful to Jesus Cañas, T.J. Davis, and Marcus Pestl for their support and friendship during my stay in Dallas. At the ECB, I thank Vasco Botelho and Lara Vivian for their joyful company on long working days.

I thank my colleagues at the DIW Graduate Center and at the FU, especially Daniel Bierbaumer, Max Diegel, Simon Jukartis, Martín Harding, Chi Hyun Kim, Tatsiana Kliatskova, Melanie Koch, Alejandro Sarmiento, Thore Schlaak, Marcel Stechert, and the whole GC cohort of 2015. It was a pleasure to share my PhD time with them. Moreover, I thank Juliane Metzner, Isabella Winter, and Bianka Zeglin; for friendly helping me solve day-to-day administrative issues. I thank Adam Lederer and Sigrid Pearson for correcting and improving my English.

The estimation of the models in my dissertation would not have been possible without the HPC-cluster Curta at Freie Universität Berlin. For this, I thank Loris Bennett and the Curta-team for their friendly help every time I was fighting with a code.

I thank my dear friends Pablo Anaya, Robin Braun, Flora Budianto, Patrick Burauel, Caterina Forti Grazzini, and Stefan Gebauer who happen to be economists as well. Through many calls, coffee breaks, dinners, and fun times, their support and friendship helped me keep my spirits high during my PhD.

I also thank my friends: Linda Bildau, Almita Delgadillo, Gaby R. Flores, Karina Rosales, Philip Schniedermeier, Lucía Terrazas, and many friends in Mexico for giving me moments of joy during stressful times.

I am always grateful to my parents and my Schwiegereltern for supporting and guiding me on my road toward the PhD. I also thank my family in Mexico and in Germany for all the love and support in the world.

Most importantly, I have no words to express my gratitude to my husband Stefan. Without his unconditional love and support, I would not have been able to complete this dissertation.

Berlin, April 2021 Catalina Martínez Hernández

# Declaration of Co-Authorship and Publications

This dissertation consists of three research papers. One paper was written in collaboration with two co-authors. My contribution in conception, implementation and drafting can be summarized as follows:

- **Disentangling the Effects of Multidimensional Monetary Policy on Inflation and Inflation Expectations in the Euro Area**
  Written by: Catalina Martínez Hernández
  An earlier version of this chapter was published as Freie Universität Berlin School of Business & Economics Discussion Paper 2020/18.
  Contribution: 100%

- **Improving US Inflation Forecasting: The Role of Unbalanced Factor Models**
  Written by: Catalina Martínez Hernández
  Contribution: 100%

- **A Mixed Frequency Model for the Euro Area Labor Market**
  Written by: Agostino Consolo, Claudia Foroni, and Catalina Martínez Hernández
  Disclaimer: This chapter should not be reported as representing the views of the European Central Bank (ECB). The views expressed are those of the authors and do not necessarily reflect those of the ECB.
  Contribution: 33.33%

# Contents

**Acknowledgments** **V**

**Declatation of Co-authorship and Publications** **VII**

**List of Figures** **X**

**List of Tables** **XIII**

**Summary** **XIX**

**Zusammenfassung** **XXI**

**Introduction and Overview** **XXV**

**1 Disentangling the Effects of Multidimensional Monetary Policy on Inflation and Inflation Expectations in the Euro Area** **1**

1.1 Introduction . . . . . 1

1.2 High-frequency identification of monetary policy shocks . . . . . 5

1.2.1 A comparison with the proxies of Altavilla et al (2019) . . . 15

1.3 Monetary policy in a data-rich environment . . . . . 16

1.3.1 The large Bayesian VAR . . . . . 17

1.3.2 The internal instrument approach . . . . . 20

1.4 Empirical assessment . . . . . 22

1.4.1 Data . . . . . 22

1.4.2 Results . . . . . 23

1.5 Conclusions . . . . . 28

Appendix 1.A Inflation and inflation expectations in the euro area . . 30

Appendix 1.B Target factors from two windows . . . . . 33

Appendix 1.C Monetary policy proxies and selected governing council meetings . . . . . 34

Appendix 1.D Data description . . . . . 36

Appendix 1.E Convergence test . . . . . 37

Appendix 1.F Further impulse responses . . . . . . . . . . . . . . . . . 39
Appendix 1.G Impulse responses without long-term expectations . . . 44

**2 Improving US Inflation Forecasting: The Role of Unbalanced Factor Models 49**
2.1 Introduction . . . . . . . . . . . . . . . . . . . . . . . . . . . . 49
2.2 Unbalanced factor models . . . . . . . . . . . . . . . . . . . . . . 52
2.2.1 The quasi-maximum likelihood estimation of Doz, Giannone and Reichlin (DGR) . . . . . . . . . . . . . . . . . . . 54
2.2.2 The maximum likelihood method of Bańbura and Modugno (BM) . . . . . . . . . . . . . . . . . . . . . . . . . . . 55
2.2.3 The interpolation method of Stock and Watson (SW) . . . . 56
2.2.4 The three-pass regression filter . . . . . . . . . . . . . . . . 57
2.3 Pseudo real-time forecasting analysis . . . . . . . . . . . . . . . . 59
2.3.1 Data . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 60
2.3.2 Results . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 62
2.4 Conclusion . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 76
Appendix 2.A Data description . . . . . . . . . . . . . . . . . . . . . 77

**3 A Mixed Frequency Model for the Euro Area Labor Market 83**
3.1 Introduction . . . . . . . . . . . . . . . . . . . . . . . . . . . . 83
3.2 Methodology . . . . . . . . . . . . . . . . . . . . . . . . . . . . 86
3.2.1 The mixed frequency Bayesian VAR of Schorfheide and Song (2015) . . . . . . . . . . . . . . . . . . . . . . . . . . . 86
3.2.2 Bayesian estimation . . . . . . . . . . . . . . . . . . . . . . 90
3.2.3 Shock identification with sign restrictions . . . . . . . . . . 92
3.3 A model for the euro area labor market . . . . . . . . . . . . . . . 93
3.3.1 Drivers of the euro area labor market . . . . . . . . . . . . . 96
3.3.2 An early assessment of the COVID-19 period . . . . . . . . 102
3.4 Forecasting performance . . . . . . . . . . . . . . . . . . . . . . 106
3.5 Conclusions . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 117
Appendix 3.A Data description . . . . . . . . . . . . . . . . . . . . . 118
3.A.1 Results from the MDD optimization . . . . . . . . . . . . . 118
Appendix 3.B Impulse responses of main macroeconomic and labor market shocks . . . . . . . . . . . . . . . . . . . . . . . . . . 119
Appendix 3.C Impulse responses of main macroeconomic and labor market shocks - COVID-19 sample . . . . . . . . . . . . . . . . . 122

# List of Figures


1.1 Scree plot (monetary policy event window) . . . . . . . . . . . . . . . 9
1.2 Loadings and the OIS term structure . . . . . . . . . . . . . . . . . . . . 12
1.3 Proxies for monetary policy shocks . . . . . . . . . . . . . . . . . . . . . 15
1.4 Responses of inflation and inflation expectations to monetary policy . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 26
1.5 Responses of inflation and short-term inflation expectations to monetary policy . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 27
1.6 Inflation in the euro area . . . . . . . . . . . . . . . . . . . . . . . . . . . 30
1.7 Inflation expectations of consumers in the euro area . . . . . . . 31
1.8 Inflation expectations of professional forecasters in the euro area 32
1.9 Target factors . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 33
1.10 Target factor and monetary policy decisions . . . . . . . . . . . . . 34
1.11 LTRO factor and monetary policy decisions . . . . . . . . . . . . . 35
1.12 QE factor and monetary policy decisions . . . . . . . . . . . . . . . 35
1.13 Geweke convergence test (p-values) . . . . . . . . . . . . . . . . . . 38
1.14 Responses of output variables to multi-dimensional monetary policy . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 39
1.15 Responses of the euro area yield curve and the spread between Italian and German sovereign bond yields to multi-dimensional monetary policy . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 40
1.16 Responses of euro area financial variables to multi-dimensional monetary policy . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 41
1.17 Responses of oil and commodity prices and further financial variables to multi-dimensional monetary policy . . . . . . . . . . . . 42
1.18 Responses of oil and commodity prices and further financial variables to multi-dimensional monetary policy . . . . . . . . . . . . 43
1.19 Responses of out[H]put variables to multi-dimensional monetary policy . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 44

1.20 Responses of the euro area yield curve and the spread between Italian and German sovereign bond yields to multi-dimensional monetary policy . . . . . 45
1.21 Responses of euro area financial variables to multi-dimensional monetary policy . . . . . 46
1.22 Responses of oil and commodity prices and further financial variables to multi-dimensional monetary policy . . . . . 47

2.1 Parameters in forecasting analysis . . . . . 63
2.2 RMSFE for the full evaluation period . . . . . 64
2.3 US CPI year-over-year inflation . . . . . 66
2.4 RMSFE during the Global Financial Crisis period . . . . . 66
2.5 RMSFE, $h = -1$, Global Financial Crisis period . . . . . 69
2.6 RMSFE, $h = 0$, Global Financial Crisis period . . . . . 69
2.7 RMSFE, $h = 1$, Global Financial Crisis period . . . . . 70
2.8 RMSFE, $h = 12$, Global Financial Crisis period . . . . . 70
2.9 US CPI inflation during the COVID-19 crisis . . . . . 73
2.10 RMSFE, $h = -1$, COVID-19 period . . . . . 74
2.11 RMSFE, $h = 0$, COVID-19 period . . . . . 74

3.1 Historical decomposition of the unemployment rate . . . . . 98
3.2 Historical decomposition of the employment growth rate . . . . . 99
3.3 Historical decomposition of the wage growth rate, measured by compensation per employee . . . . . 99
3.4 Historical decomposition of the job finding rate . . . . . 100
3.5 Historical decomposition of the job separation rate . . . . . 100
3.6 Historical decomposition of the industrial production growth rate 101
3.7 Historical decomposition of inflation . . . . . 101
3.8 Historical decomposition of key labor market and macroeconomic variables during the COVID-19 sample . . . . . 105
3.9 Cumulative impulse responses of an aggregate supply shock . . . 119
3.10 Cumulative impulse responses of an aggregate domestic demand shock . . . . . 119
3.11 Cumulative impulse responses of an aggregate foreign demand shock . . . . . 120
3.12 Cumulative impulse responses of a labor supply shock . . . . . 120
3.13 Cumulative impulse responses of a mismatch shock . . . . . 121
3.14 Cumulative impulse responses of a wage bargaining shock . . . . 121
3.15 Cumulative impulse responses of an aggregate supply shock . . . 122

3.16 Cumulative impulse responses of an aggregate domestic demand shock . . . . . 122
3.17 Cumulative impulse responses of an aggregate foreign demand shock . . . . . 123
3.18 Cumulative impulse responses of a labor supply shock . . . . . . 123
3.19 Cumulative impulse responses of a mismatch shock . . . . . . . . 124
3.20 Cumulative impulse responses of a wage bargaining shock . . . . 124

# List of Tables

1.1 Properties of monetary policy shocks . . . . . . . . . . . . . . . . . . 7
1.2 Orthogonal and normalized factor loadings . . . . . . . . . . . . . . 14
1.3 Correlation between my factors and Altavilla, Brugnolini, Gürkaynak, Motto, and Ragusa (2019)'s factors . . . . . . . . . . . . . . . . . . 16
1.4 The re-anchoring effect . . . . . . . . . . . . . . . . . . . . . . . . . 28
1.5 Data description VAR model . . . . . . . . . . . . . . . . . . . . . . 36

2.1 A comparison of unbalanced factor models . . . . . . . . . . . . . . 54
2.2 Forecasting models . . . . . . . . . . . . . . . . . . . . . . . . . . . 60
2.3 Missing values patterns . . . . . . . . . . . . . . . . . . . . . . . . . 61
2.4 RMSFE relative to a PCA forecast, full evaluation sample . . . . . 65
2.5 RMSFE relative to a PCA forecast, Global Financial Crisis . . . . . 67
2.6 RMSFE relative to a model with the full data set, Global Financial Crisis . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 71
2.7 AR model vs best performing models, Global Financial Crisis . . . 72
2.8 RMSFE relative to a PCA forecast, COVID-19 period . . . . . . . . 72
2.9 RMSFE relative to a model with the full data set, COVID-19 crisis 75
2.10 RMSFE of AR and best performing models, COVID-19 period . . . 75
2.11 Data description . . . . . . . . . . . . . . . . . . . . . . . . . . . . 77

3.1 Type of missing observations . . . . . . . . . . . . . . . . . . . . . . 88
3.2 Ragged-edges by February 28, 2020 . . . . . . . . . . . . . . . . . . 94
3.3 Identification scheme via sign restrictions . . . . . . . . . . . . . . 95
3.4 Ragged-edges by March 8, 2021 . . . . . . . . . . . . . . . . . . . . 102
3.5 Nowcasts of key macroeconomic and labor market variables . . . 104
3.6 Data flow within quarters . . . . . . . . . . . . . . . . . . . . . . . . 107
3.7 Forecasting performance: RMSFE relative to an AR benchmark - Full sample . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 109
3.8 Forecasting performance: RMSFE relative to an AR benchmark - Great Recession sample . . . . . . . . . . . . . . . . . . . . . . . . . . 111

3.9 Forecasting performance: RMSFE relative to an AR benchmark - Benchmark model without flows . . . . . . . . . . . . . . . . . . . . . . 112
3.10 Average log-predictive likelihood - AR vs benchmark model - Full sample . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 114
3.11 Forecasting performance: Average log-predictive likelihood - Benchmark model vs AR model - Great Recession sample . . . . . . . . . 115
3.12 Forecasting performance: Average log-predictive likelihood - Benchmark model without flows . . . . . . . . . . . . . . . . . . . . . . . . 116
3.13 Optimal hyperparameters . . . . . . . . . . . . . . . . . . . . . . . . 118

# List of Abbreviations

| | |
|---|---|
| **ABSPP** | Asset-Backed Securities Purchase Programme |
| **ALPL** | Average log-predictive likelihood |
| **APSA** | Automatic Proxy-Selection Algorithm |
| **AR** | Autoregressive |
| **BIC** | Bayesian Information Criterion |
| **BM** | Bańbura and Modugno (2014) |
| **CBPP3** | Third Covered Bond Purchase Programme |
| **CISS** | Composite Indicator of Systemic Stress |
| **COVID-19** | Corona Virus Disease 2019 |
| **CPI** | Consumer Price Index |
| **CSPP** | Corporate Sector Purchase Programme |
| **DE** | Germany |
| **DFM** | Dynamic Factor Model |
| **DFR** | Deposit Facility Rate |
| **DGR** | Doz, Giannone, and Reichlin (2012) |
| **EA-MPD** | Euro Area Monetary Policy Event-Study Database |
| **EM** | Expectation-Maximization |
| **EB** | Eurozone Barometer |
| **ECB** | European Central Bank |
| **EFSF** | European Financial Stability Facility |
| **EONIA** | Euro Overnight Index Average |
| **ES** | Spain |
| **ESI** | Economic Sentiment Index |
| **ESM** | European Stability Mechanism |
| **EURIBOR** | Euro Interbank Offered Rate |
| **Fed** | Federal Reserve System |
| **FG** | Forward Guidance |
| **FOMC** | Federal Open Market Committee |
| **FR** | France |
| **FRED** | Federal Reserve Economic Data |
| **GLP** | Giannone, Lenza, and Primiceri (2015) |

| | |
|---|---|
| **HH** | Households |
| **HLN** | Harvey, Leybourne, and Newbold (1997) |
| **IT** | Italy |
| **LASSO** | Least Absolute Shrinkage and Selection Operator |
| **LPD** | Log-predictive likelihood |
| **LTRO** | Longer-Term Refinancing Operations |
| **MP** | Monetary Policy |
| **NaN** | Not a Number |
| **NEER** | Nominal Effective Exchange Rate |
| **NFC** | Non-Financial Corporations |
| **MCMC** | Markov Chain Monte Carlo |
| **MDD** | Marginal Data Density |
| **MF-VAR** | Mixed-Frequency Vector Autoregression |
| **MF-BVAR** | Mixed-Frequency Bayesian Vector Autoregression |
| **MRO** | Main refinancing operations rate |
| **OECD** | Organisation for Economic Co-operation and Development |
| **OIS** | Overnight Indexed Swap |
| **OLS** | Ordinary Least Squares |
| **OMT** | Outright Monetary Transactions |
| **PCA** | Principal Components Analysis |
| **PCE** | Personal Consumption Expenditure |
| **PEPP** | Pandemic Emergency Purchase Programme |
| **PMI** | Purchasing Managers Index |
| **PSPP** | Public Sector Purchase Programme |
| **QE** | Quantitative Easing |
| **RMSFE** | Root Mean Squared Forecast Error |
| **SMP** | Securities Market Programme |
| **SPF** | Survey of Professional Forecasters |
| **SVAR** | Structural Vector Autoregression |
| **SW** | Stock and Watson (2002a) |
| **TLTRO** | Targeted Longer-Term Refinancing Operations |
| **TPRF** | Three-Pass Regression Filter |
| **US** | United States of America |
| **VAR** | Vector Autoregression |
| **VAT** | Value-Added Tax |
| **yoy** | year-over-year |

# Summary

Forecasting and the identification of structural shocks are two main purposes in empirical time series models. In this dissertation, I study both purposes in the context of two frequent empirical issues: the estimation of large data models and handling unbalanced panels. The first and third chapters focus on the estimation of vector autoregressions (VARs) for the euro area economy using large data sets and mixed frequencies, respectively. Although the identification of macroeconomic shocks in the context of VARs is well studied, the literature regarding large structural VARs and structural mixed frequency VARs is scarce. Therefore, with these two chapters, I contribute to the existing literature by integrating an identification strategy involving the use of external data and sign restrictions in the context of the aforementioned VARs. The second and third chapters deal with methodologies for unbalanced panels to estimate nowcasts and forecasts. Specifically, in the second chapter, I study different patterns of missing observations in forecasting US inflation with factor models. In the third chapter, I analyze the use of a mixed frequency data with distinct publication delays for the forecasting of key labor market variables using a VAR.

In the first chapter, I propose a novel identification approach based on a set of high frequency surprises and the estimation of a factor model. Since the Great Recession, the European Central Bank (ECB) is deploying a plethora of conventional and unconventional monetary policy tools, to provide an ample degree of accommodation. To summarize the ECB's monetary policy stance, I identify shocks capturing changes in the policy rates, the communication of the economic outlook, forward guidance, policies to ease lending conditions, and quantitative easing (QE). This differentiation is a key contribution to the literature assessing euro area monetary policy. To the best of my knowledge, this is the first paper to simultaneously identify five shocks capturing the multidimensionality of the ECB's policy toolkit. In a second step, I estimate a large Bayesian VAR to study the effectiveness of each of the considered tools for achieving the ECB's mandate of price stability. I find that most of the tools anchor the long-term inflation expectations of forecasters. However, only for-

ward guidance and QE raise inflation for about two years after the shocks. In an additional exercise, I re-estimate the model discarding long-term inflation expectations, where I find a muted response of inflation to forward guidance and QE shocks. These results highlight the relevance of the anchoring of inflation expectations for transmitting monetary policy to inflation.

The second chapter digs into the problem of missing observations in large data sets, where I evaluate US inflation forecasting based on factor models. To the best of my knowledge, no previous paper conducts an empirical comparison of the existing methodologies dealing with missing observations while simultaneously, concentrating on inflation forecasting. I find more accurate inflation forecasts when I select a large data set and a method that formally deals with unbalanced panels. Moreover, I find that variables related to interest rates and spreads are crucial for improving the accuracy of the forecasts during the Great Recession. In contrast, for the ongoing COVID-19 crisis, variables related to consumption, orders, and inventories are relevant for the construction of the forecasts. This is because these variables summarize both supply and demand elements, which are key components of the COVID-19 shock.

In the third chapter, joint work with Agostino Consolo and Claudia Foroni, we construct a structural mixed frequency Bayesian VAR for the euro area, where we identify macroeconomic and labor market shocks via sign restrictions. This model allows to assess the main drivers of both the nowcasts and the full history of the time series in the model. We find that aggregate demand governs the dynamics of most of the variables in the model during the Great Recession. Moreover, we find that shocks emerging in the labor market play a crucial role in explaining the low inflation and low wage dynamics after 2013. In an early assessment of the COVID-19 crisis, we find that aggregate supply and labor supply seem to be essential in explaining the developments in the labor market. Furthermore, we conduct a pseudo real-time forecasting analysis and find that our model produces suitable point-forecasts for the employment growth rate, the job flows, and the industrial production growth rate.

**Keywords:** Large data models, missing observations, structural vector autoregressions, factor models, Bayesian estimation, macroeconomic forecasting, monetary policy, the anchoring of inflation expectations, mixed frequency data

**JEL Classifications:** C11, C22, C32, C38, C53, C55, E24, E31, E37, E52, E58, J6

# Zusammenfassung

Prognosen und die Identifikation von strukturellen Schocks sind zwei Hauptanwendungsbereiche für empirische Zeitreihenmodelle. In dieser Dissertation untersuche ich beide Anwendungsbereiche vor dem Hintergrund von zwei häufigen empirischen Problemstellungen: Die Schätzung von Modellen mit großem Datensatz und dem Umgang mit fehlenden Beobachtungen. Das erste und dritte Kapitel konzentriert sich auf die Schätzung von vektorautoregressiven Modellen (VARs) für die Eurozone jeweils unter Heranziehung von großen Datensätzen und gemischten Frequenzen. Auch wenn die Identifikation von makroökonomischen Schocks in der Literatur bereits viel Beachtung gefunden hat, sind Arbeiten zu großen strukturellen VARs und strukturellen gemischten Frequenzen selten. Meine Arbeiten leisten daher einen Beitrag zur bestehenden Literatur, indem sie eine Identifikationsstrategie unter Heranziehung von externen Daten und Vorzeichenrestriktionen in den Kontext der oben genannten VARs einbinden. Das zweite und dritte Kapitel widmen sich Prognosen und Nowcasts, die auf Methoden zum Umgang mit fehlenden Beobachtungen aufbauen. Im Detail betrachte ich im zweiten Kapitel verschiedene Muster fehlender Beobachtungen bei US-Inflationsvorhersagen mit Faktorenmodellen. Im dritten Kapitel analysiere ich die Anwendung von Daten mit gemischten Frequenzen und unterschiedlichen Verzögerungen bei der Veröffentlichung für die Vorhersage von Kernvariablen des Arbeitsmarkts mit einem VAR.

Im ersten Kapitel schlage ich eine neue Identifikationsmethode basierend auf Hochfrequenzüberraschungen und der Schätzung eines Faktorenmodells vor. Seit der großen Rezession wendet die Europäische Zentralbank (EZB) eine Fülle von konventionellen und unkonventionellen Maßnahmen der Geldpolitik an, mit dem Ziel eine größtmögliche geldpolitische Lockerung zu erreichen. Um die geldpolitische Ausrichtung der EZB vollumfänglich zu erfassen, identifiziere ich Schocks, die Veränderungen in Leitzinsen, der Kommunikation von wirtschaftlichen Aussichten, Leitlinien für die zukünftige Leitzinsentwicklung (forward guidance), Maßnahmen zur Lockerung von Kreditbedingungen und quantitative Lockerungen (oder QE vom englischen Begriff Quantitative Easing) beachten. Soweit mir bekannt, ist diese Arbeit die erste ihrer Art, die gleichzeitig 5 Schocks identifiziert und so der Multidimensionalität der Maßnahmen der EZB Rechnung trägt. In einem zweiten Schritt schätze ich ein großes bayesianisches VAR, um die Effektivität jeder einzelnen Maßnameart zur Erreichung des Preisstabilitätziels der EZB zu untersuchen. Ich komme zu dem Ergebnis, dass die meisten Schocks die langfristigen Inflationserwartungen von professionellen Ökonomen verankern. Unabhängig davon erhöhen jedoch nur QE und forward guidance die Inflation in einem Zeitraum von etwas mehr als 2 Jahren nach den Schocks. Zusätzlich schätze ich das Model erneut ohne Berücksichtigung von langfristigen Inflationserwartungen und komme zu dem Ergebnis, dass sich in diesem Fall eine schwache Reaktion der Inflation als Antwort auf forward guidance und QE beobachten lässt.

Das zweite Kapitel, in dem ich US-Inflationsvorhersagen auf der Basis von Faktormodellen untersuche, widmet sich dem Problem von fehlenden Beobachtungen in großen Datensätzen. Nach meinem besten Wissen existiert bisher kein Beitrag, der einen empirischen Vergleich der existierenden Methoden zum Umgang mit fehlenden Beobachtungen durchführt und sich gleichzeitig auf Inflationsvorhersagen fokussiert. Ich erhalte akkuratere Inflationsvorhersagen durch die Verwendung eines großen Datensets und einer Methode, die formal mit fehlenden Beobachtungen umgeht. Darüber hinaus zeige ich, dass Variablen in Verbindung zu Zinssätzen und Zinsspreads die Genauigkeit von Vorhersagen während der großen Rezession wesentlich verbessern. Im Gegensatz dazu sind für die anhaltende COVID-19-Krise Variablen mit Bezug zu Nachfrage, Bestellungen und Inventaren wesentlich für die Erstellung von Vorhersagen. Dieser Umstand ist darauf zurückzuführen, dass diese Variablen Nachfrage- und Angebotselemente gleichermaßen betreffen, die wiederum zentrale Elemente des COVID-19 Schocks sind.

Im dritten Kapitel, welches in Zusammenarbeit mit Agostino Consolo und Claudia Foroni verfasst wurde, konstruieren wir ein strukturelles bayesianisches VAR mit gemischter Frequenz für den Euroraum, um makroökonomische- und Arbeitsmarkt-Schocks mit Hilfe von Vorzeichenrestriktionen zu identifizieren. Dieses Modell erlaubt es uns die Haupttreiber des Nowcasts und der gesamten Historie der Zeitreihe zu bemessen. Als Ergebnis lässt sich feststellen, dass die aggregierte Nachfrage die Dynamik der meisten Variablen während der großen Rezession bestimmt. Darüber hinaus stellen wir fest, dass Schocks auf dem Arbeitsmarkt eine zentrale Rolle bei der Erklärung der Dynamik aus geringer Inflation und geringem Lohn nach 2013 spielen. In einer vorläufigen Bewertung der COVID-19-Krise kommen wir zu dem Ergebnis, dass aggregiertes Angebot und Arbeitsangebot wesentlich für die Entwicklung auf dem Arbeitsmarkt scheinen. Zusätzlich führen wir eine Analyse einer pseudo-Echtzeit-Prognose durch. Unsere Ergebnisse zeigen, dass unser Modell geeignete Punktprognosen für Arbeitsmarktvariablen und die Wachstumsrate industrieller Produktion liefert.

# Introduction and Overview

Two representations of time series models - structural and reduced-form - are used in empirical macroeconomics for two main purposes: forecasting and the identification of key macroeconomic shocks. These practices are crucial for policy makers and central banks because they allow them to assess the early developments of variables strategically for the design of policy; as well as to understanding the key drivers governing such variables. However, problems in the estimation of time series models may already arise with the selection of the variables. Specifically, the availability of data is rapidly increasing and, at the same time, the burden of storing large data and use it in models has substantially decreased. Therefore, the use of large data sets has become an important pillar in empirical macroeconomics, both for forecasting and for conducting structural analysis (see among many, Bernanke, Boivin, and Eliasz (2005), Forni, Giannone, Lippi, and Reichlin (2009), De Mol, Giannone, and Reichlin (2008), Bańbura, Giannone, and Reichlin (2010), Korobilis (2013), and Giannone et al. (2015)).

The use of large data sets comes with a limitation known as the curse of dimensionality. This is because researchers may face the situation of having more variables than time series observations. For instance, in applications to the euro area economy, the researcher can choose among a large space of variables only available for about twenty years. In such cases, the estimation of classical models such as ordinary least squares and maximum likelihood is no longer feasible. Therefore, researchers rely on the implementation of shrinkage or dimension reduction techniques, in order to make the estimation of time series models possible. Examples of such models are regularization methods, Bayesian shrinkage techniques, and factor models. Although the idea of a large data set could be related to a couple of hundreds or thousands of variables, problems with a sizable reduction of the degrees of freedom can already emerge when dealing with few tens of variables, e.g., a quarterly euro area data base. However, from another perspective, we can interpret the large space of potential variables as the blessing of dimensionality. This is because the increase of data has also let researchers choose more suitable variables for conducting economic analysis. Moreover, this has also caused the emerging of new types of data sets, such as Google Trends, the high frequency posting of vacancies, and textual analysis. From an econometric point of view, Barigozzi (2019) highlights that the larger the number of variables, the better the asymptotic properties of some dimension reduction techniques, such as factor models.

Furthermore, a frequent empirical issue confronting researchers and practitioners is the problem of missing observations, especially in applications involving large data sets. Significant examples of this problem relate to the use of mixed frequencies (which can be interpreted as a missing value problem) and different publication lags of the variables in the data set (also known as ragged-edges). Due to the highly empirical relevance of these issues, in this dissertation, I concentrate on analyzing the gains of using large data models, addressing the problems that convey them. Specifically, this dissertation contains three different chapters independently focusing on forecasting and the identification of macroeconomic shocks. In the first and third chapters, I focus on the estimation of vector autoregressions (VARs) for the euro area economy, where I address the issues of large data sets and mixed frequencies, respectively. Although the identification of macroeconomic shocks in the context of VARs is well studied (Blanchard and Quah (1989), Bernanke and Blinder (1992), Faust (1998), Rigobon (2003), Bernanke et al. (2005), Gürkaynak, Sack, and Swanson (2005), Lanne and Lütkepohl (2010), Stock and Watson (2012), *inter alia*), the literature regarding structural large VARs and structural mixed frequency VARs remains scarce. Therefore, with these two chapters, I contribute to the existing literature by integrating a strategy involving the use of extraneous data and sign restrictions in the context of the aforementioned VARs. Furthermore, in the second and third chapters, I study the forecasting accuracy gains of considering models formally dealing with the issue of missing observations in macroeconomic data sets. The second chapter focuses on forecasting US inflation and the third chapter concentrates on the euro area labor market.

In the **first chapter**, *Disentangling the Effects of Multidimensional Monetary Policy on Inflation and Inflation Expectations in the Euro Area*, I propose a novel approach to identify five different types of monetary policy shocks. Since the Great Recession, the European Central Bank (ECB) is deploying a wide range of conventional and unconventional monetary policy tools, in order to maintain an ample degree of accommodation. Therefore, my identification approach summarizes the monetary policy stance of the ECB through shocks capturing changes in the policy rates, forward guidance, the communication of the current and future economic outlook, policies to ease lending conditions, and quantitative easing (QE). This differentiation of shocks is a fundamental contribution to the literature empirically assessing euro area monetary policy. To the best of my knowledge, this is the first paper to simultaneously identify five shocks capturing the multidimensionality of the ECB's policy toolkit. This paper is unique because, in addition to providing a meticulous identification, I narrow my research question to what worries the ECB the most: inflation. For this reason, I analyze the individual effectiveness of the mentioned tools for increasing inflation and their implications for the anchoring of inflation expectations. I rely on a two-step approach, where, in the first step, I estimate proxies for monetary policy shocks through a factor model based on the high frequency surprises of asset prices constructed by Altavilla et al. (2019). In a second step, I interpret the proxies as the underlying monetary policy shocks and integrate them in a large Bayesian VAR.

The analysis conducted in chapter 1 is closely related to Altavilla et al. (2019). However, I address several limitations in their construction of the monetary policy proxies. First, I consider that, since 2016, the communication of both conventional and unconventional tools is first delivered in a press release, followed by further explanation in a press conference. For this reason, I consider the surprises spanning a window covering both events. This piece of information is key for achieving a sharper identification of the shocks and, in fact, it allows me to find an additional shock, not present in the study of Altavilla et al. (2019). Second, I distinguish the effects of Delphic and Odyssean forward guidance, whereas the former refers to the communication of the ECB's economic outlook and the latter is associated to the commitment to a particular policy, such as the communication of the future path of interest rates. Third, from an econometric point of view, I corroborate that the monetary policy proxies are orthogonal and that the assumption of standardized data holds, as usual, in factor models. I find that these issues have, in fact, implications for the estimation of the VAR.

My identification approach provides additional insights regarding the implications of the plethora of monetary policy tools available for achieving the ECB's mandate of price stability. In particular, I find that most monetary policy tools are effective in anchoring the long-term inflation expectations of professional forecasters. However, my results indicate that only forward guidance and QE contribute to achieving the mandate of price stability. This is because, after these shocks hit the economy, inflation rises and remains significant for approximately two years. Moreover, I find that these shocks are also effective in raising the short-term expectations of both consumers and professional forecasters. To test the role of the anchoring of expectations in the rise of inflation, I re-estimate the model discarding long-term inflation expectations. As a result, inflation remains muted, thus highlighting the anchoring of inflation expectations as a key intermediate step for successfully transmitting monetary policy to inflation.

In the **second chapter**, *Improving US Inflation Forecasting: The Role of Unbalanced Factor Models*, I study the properties of US inflation nowcasts and forecasts based on factor models, estimated with unbalanced panels. Although many authors find suitable forecasting properties of factor models (Bai and Ng (2008), Giannone, Reichlin, and Small (2008), Eickmeier and Ziegler (2008), and Boivin and Ng (2006), among many others), the forecasting gains of selecting an algorithm formally dealing with missing observations is not yet studied in the context of inflation forecasting. I consider a large data set covering standard categories of economic data. The data contains three types of missing observations stemming from: (i) different starting date; (ii) publication delays; and (iii) unsystematic patterns in the middle of the time series. Overall, I find that factor-based forecasts have superior accuracy when they are estimated using a methodology based on an Expectation-Maximization algorithm, thus formally dealing with missing data. Specifically, I find that the three-pass regression filter (Kelly and Pruitt (2015) and Hepenstrick and Marcellino (2019)) outperforms principal components, a model trivially dealing with the missing observations by filling them with zeros.

For the periods related to the Great Recession and the COVID-19 crisis, I further study the information gain of each considered data category. For the Great Recession sample, I find that the methodologies of Stock and Watson (2002b) and Bańbura and Modugno (2014) are superior in forecasting inflation, also in comparison to a univariate autoregressive (AR) model. Moreover, my results suggest that the information contained in interest rates and spreads is key for obtaining more accurate forecasts. Therefore, including variables capturing the monetary policy stance of the Fed appears to be crucial during the Great Recession. In contrast, discarding variables related to output and money seems to play a negligible role for improving the nowcasts and forecasts. On the other hand, for the COVID-19 crisis, my early assessment points to the importance of variables related to consumption, orders, and inventories for an accurate projection of US inflation. This result is in line with the interpretation of the COVID-19 shock as a mixture of supply and demand components. Therefore, variables related to consumption, orders, and inventories can capture both elements.

The **third chapter**, *A Mixed Frequency Model for the Euro Area Labor Market*, is joint work with Agostino Consolo and Claudia Foroni, and it was partially written during my time as a PhD trainee and as an external consultant at the ECB. In the previous two chapters, I independently deal with forecasting and the identification of macroeconomic shocks. However, in this chapter, we study both purposes of empirical time series models in a unified approach. To do so, we consider a mixed frequency data set including monthly and quarterly variables. This set summarizes the dynamics in the macroeconomy and the labor market of the euro area aggregate. Therefore, in this chapter, I also study a fourth type of missing observations, in conjunction to several publication delays. To conduct our analysis, we consider the mixed frequency Bayesian VAR proposed by Schorfheide and Song (2015). Despite a broad literature studying mixed frequency VAR models in the context of forecasting (Kuzin, Marcellino, and Schumacher (2011), Schorfheide and Song (2015), Foroni, Guérin, and Marcellino (2015), and Brave, Butters, and Justiniano (2019)), only few papers focus on a structural analysis, e.g., Foroni and Marcellino (2014) and Ghysels (2016). Therefore, we extend the methodology of Schorfheide and Song (2015) to a structural VAR by including a step that allows the identification of economic shocks via sign restrictions.

In the first part of the paper, we propose a sign restriction scheme for identifying supply, demand, and labor market shocks, where we incorporate information on the unemployment flows in order to disentangle shocks. We find that the key drivers of most of the variables during the past Great Recession are associated to aggregate demand, both domestic and foreign. However, the role of shocks originating in the labor market (labor supply, wage bargaining, and mismatch) becomes crucial for explaining the low inflation and low wage dynamics starting in 2013. It is important to note that, at this stage, the model produces nowcasts of the latest months and quarters for which data are not available due to publication delays. Moreover, the nowcasts can be also assessed in terms of the shocks that likely drive them. Therefore, our model also contributes with a useful policy tool for practitioners by the timely interpretation of the latest nowcasts through the lenses of a structural time series model.

In the second part of the paper, we study the forecasting properties of the model and find that it produces accurate point-forecasts, especially for quarterly variables. This result is in line with the literature of mixed frequency models, which finds that the information content of high frequency variables can improve the forecasting accuracy of low frequency variables. Additionally, the nowcasts and forecasts of industrial production growth from our model outperform those from a univariate AR model. Thus, for this case, the information content in quarterly variables is important for the forecasting of a monthly variable, as also found by Foroni, Guérin, and Marcellino (2018b).

In an early assessment, we additionally concentrate on the COVID-19 period and evaluate the main structural shocks stemming from this crisis. In contrast to the Great Recession, we find that aggregate supply and labor supply shocks seem to have a large weight in the dynamics governing most of the variables. Moreover, we find signs of a recovery in the labor market for the first quarter of 2021, mainly governed by aggregate supply and wage bargaining shocks. The latter shock captures the effects of short-term schemes for the wage of workers, i.e., they are working less hours but keeping the same wage rate. Furthermore, our model also predicts a rise in inflation mainly driven by foreign demand, wage bargaining, and labor supply shocks.

# Chapter 1

# Disentangling the Effects of Multidimensional Monetary Policy on Inflation and Inflation Expectations in the Euro Area*

## 1.1 Introduction

Under its mandate of price stability, the European Central Bank (ECB) conducts monetary policy with the goal of stabilizing inflation to levels "below, but close to 2% over the medium term" in the euro area. For most of the 2010s, inflation and inflation expectations have remained low, on average lower than the ECB's target.[1] Furthermore, the ECB is facing an era of low interest rates that is, in turn, limiting its space for steering short-term interest rates, its main policy tool. To provide an ample degree of accommodation, the ECB introduced several non-conventional tools. Although the rationale for deploying individual tools may differ, all share the ultimate goal of achieving price stability and anchoring inflation expectations to the ECB's target.

The effective lower bound has raised complications in identifying monetary policy shocks, owing to the fact that a plethora of instruments summarize the monetary policy stance of the ECB. Due to the challenges of disentangling these policies, a big strand of the literature identifies a unique unconventional monetary policy shock condensing the multidimensionality of the ECB's toolkit into a single shock. Under this strong assumption, all tools have the same impact, as in Corsetti, Duarte, and Mann (2020) and Hachula,

*This chapter is part of the DFG project "The Anchoring of Inflation Expectations" at Freie Universität Berlin.

[1]See the graphs in appendix 1.A, for an overview.

Piffer, and Rieth (2019). Another approach is the focus on a single tool or on a block of tools. For instance, communication shocks in the euro area are analyzed by Jarociński and Karadi (2020), Andrade and Ferroni (2021), and Kerssenfischer (2019). These papers identify information shocks, with the latter two also studying forward guidance shocks.[2] Overall, they find that an information (forward guidance) shock moves medium-term rates and stock market indices in the same (opposite) direction. Additionally, the authors find that inflation expectations also react in the same direction as interest rates in the case of information shocks. Concerning the effects of balance sheet tools, Boeckx, Dossche, and Peersman (2017) and Gambetti and Musso (2017) study expansionary Longer-Term Refinancing Operations (LTRO) and quantitative easing (QE) shocks, respectively. They find that these policies have a positive effect on output and prices. The work of Altavilla et al. (2019) is a prominent example that integrates the multidimensional feature of monetary policy in their analysis. Nevertheless, they only assess the impact of the different monetary policy shocks on asset prices and do not study their effects on the macroeconomy.

In this paper, I concentrate on the multidimensional feature of monetary policy in the euro area and study the effects of the ECB's conventional, unconventional, and communication tools. Specifically, this paper contributes to the existing literature by providing a taxonomy of the ECB's policy toolkit and by comparing the individual effectiveness of the tools to influence inflation and inflation expectations. To do so, my analysis is based on a two-step approach that combines a high-frequency identification strategy and the estimation of a large Bayesian vector autoregression (VAR). Based on the work of Gürkaynak et al. (2005), Swanson (2021), and Altavilla et al. (2019), I propose a novel high-frequency identification approach that considers three dimensions of monetary policy announcements: target, path, and the balance sheet. Through the estimation of a rotated factor model, I identify shocks related to the interest rate target, information, forward guidance, policies implemented to ease lending conditions, and QE.[3] I impose that the parameters of the factor model fulfill a set of economic restrictions mainly concerning short-term maturities of the Overnight Indexed Swap (OIS) term structure. In this way, I interpret the estimated factors as a measure of the underlying monetary policy shocks.

[2]Based on the terminology of Campbell et al. (2012), Delphic forward guidance or information shocks are related to announcements about the central bank's view on the current and future economic outlook, whereas (Odyssean) forward guidance refers to commitment to policy such as the future path of interest rates.

[3]An economic explanation of these shocks is provided in section 1.2.

This study is close to Altavilla et al. (2019), who construct the Euro Area Monetary Policy Event-Study Database (EA-MPD), a compendium of surprises of asset prices available for three different windows regarding the communication of ECB's monetary policy decisions: The press release, the press conference, and the full monetary policy event window.[4] Based on a data set exclusively containing surprises of the OIS term structure, Altavilla and co-authors find evidence of a target component in the press release window as well as timing, forward guidance, and QE components in the press conference window. The work and data set of Altavilla et al. (2019) are crucial for analyzing monetary policy in the euro area. However, their estimation of the proxies for monetary policy shocks has several limitations. First, they identify timing, forward guidance, and QE shocks uniquely using the surprises from the press conference window. The selection of this window could hamper the accuracy of the estimated shocks because, from 2016 onward, the ECB communicates decisions regarding unconventional monetary policy already in the press release. Therefore, omitting this piece of information could result in discarding surprises that occurred already in the first stage of the communication of the decisions. Second, Altavilla et al. (2019) disentangle timing and forward guidance effects, whereby the time series of these shocks start in 2002. This means that their forward guidance factor uniquely corresponds to information (Delphic forward guidance) shocks from 2002 to 2013 and a mixture of information and (Odyssean) forward guidance shocks after 2013. This is because the ECB only started to give guidance about the future path of interest rates from July 4, 2013, onward, abandoning its *no pre-commitment* policy.[5]

A main contribution of this paper is to approach the previously described limitations from Altavilla et al. (2019). In contrast to Altavilla and co-authors, I take the surprises of the EA-MPD from the whole monetary policy event window. This selection allows me to identify an additional shock that isolates the effects of policies implemented to provide funding and to ease lending condi-

[4]Monetary policy decisions from the Governing Council meeting are communicated in two phases. First, a press release is published at 13:45 CET containing policy decisions. Afterwards, from 14:30-15:30 CET, there is a press conference where the ECB's president reads the introductory statement explaining the rationale behind the decisions taken and communicating the ECB's view on current economic conditions. Afterwards, there is a Q&A session for the press. Consequently, the whole monetary policy event window spans from 13:45-15:30 CET.

[5]On this date the introductory statement included the following information: *"The Governing Council expects the key ECB interest rates to remain at present or lower levels for an extended period of time. This expectation is based on the overall subdued outlook for inflation extending into the medium term, given the broad-based weakness in the real economy and subdued monetary dynamics."* For further detailed information, see also Rostagno, Altavilla, Carboni, Lemke, Motto, Saint Guilhem, and Yiangou (2019).

tions in the aftermath of the Sovereign Debt Crisis.[6] Furthermore, since timing effects can be interpreted as short-term forward guidance (see Gürkaynak, Sack, and Swanson (2007)), I allow this shock to be included in the forward guidance shock. Therefore, all observations before 2013 correspond to the expectations of market participants about changes in the policy rates for the next couple of meetings. Moreover, I differentiate between information effects and forward guidance using their empirical relationship among interest rates and stock market indices. To the best of my knowledge, this is the first paper that simultaneously identifies five shocks capturing the multidimensional feature of monetary policy in the euro area.

Furthermore, this paper is unique because, in addition to providing a meticulous identification, I give further insights to the assessment of monetary policy transmission and the anchoring of inflation expectations. To do so, in a second step, I consider a monthly data set containing 22 macroeconomic and financial variables, which allows to have a comprehensive representation of the dynamics within the euro area economy. I follow the internal instrument approach (Ramey (2011), Noh (2017), Stock and Watson (2018), and Plagborg-Møller and Wolf (2021)) and integrate the estimated proxies for monetary policy shocks into the data set. I estimate five large Bayesian VARs based on the methodology proposed by Giannone et al. (2015). I further analyze the responses of inflation and inflation expectations of both consumers and professional forecasters to the five different types of monetary policy shocks.

My findings suggest that the long-term inflation expectation of professional forecasters anchors after forward guidance and QE shocks hit the economy. This is because the long-term expectation moves in the direction toward the ECB's target. Therefore, I interpret this rise as a re-anchoring effect given that expectations have decreased, especially after 2014. Specifically, the long-term inflation expectation of forecasters rises about 0.07 and 0.05 percentage points around a year after forward guidance and QE shocks, respectively. These shocks also have a positive impact on the short-term inflation expectations of consumers and professional forecasters, whereas QE appears to be more persistent than forward guidance. In addition, I find that these policies are successful in moving inflation upwards. My results point to an increase in inflation of about 0.9 percentage points for forward guidance and about 0.58 percentage points for QE.

Overall, my results stress the importance of inflation expectations for the

[6]The finding of a similar factor is also obtained by Wright (2019). However, he does not implement restrictions in order to interpret it economically and does not assess its effects on the macroeconomy.

transmission of monetary policy. I test the anchoring of inflation expectations channel by re-estimating the VAR models with the long-term inflation expectation of forecasters excluded from the model. I obtain a weaker response of inflation and short-term inflation expectations to forward guidance and QE shocks. This means that the anchoring of inflation expectations is a crucial intermediate step for achieving a stronger transmission of monetary policy to inflation.

This chapter proceeds as follows. In section 1.2, I present my identification strategy, while I explain the internal instrument approach and the estimation of large Bayesian VARs in section 1.3. Section 1.4 provides an overview of the data and the main results of the paper. Finally, section 1.5 concludes.

## 1.2 High-frequency identification of monetary policy shocks

The influential analyses of Cook and Hahn (1989) and Kuttner (2001) triggered a rising literature on the estimation of monetary policy shocks based on high-frequency data sets (e.g. Cochrane and Piazzesi (2002), Gürkaynak et al. (2005), Nakamura and Steinsson (2018), Rogers, Scotti, and Wright (2018), Altavilla et al. (2019), and Swanson (2021), among many others). This is due to the availability of asset prices at intra-daily and daily frequencies, whereby it is possible to exploit the rich information contained in futures and swap rates for identifying monetary policy shocks. In this section, I further contribute to this literature by constructing a taxonomy of the monetary policy tools used by the ECB in order to achieve its mandate of price stability. In detail, I concentrate my analysis on the estimation of the following monetary policy proxies:

*Target.* Before the zero lower bound was reached, the main policy tool of the ECB was the change in its official rates (deposit facility, main refinancing operations, and marginal lending facility rates). This shock captures the surprises of an unexpected change in the official rates, and therefore, it corresponds to a conventional monetary policy shock.

*Information.* This shock represents the markets' response to the communication of the ECB's view on the current and future economic outlook. It is also known as Delphic forward guidance (see Campbell et al. (2012)).

*Forward guidance (FG).* This captures the markets' reactions to statements referring to the ECB's commitment to particular monetary policy actions, such as the future path of interest rates. In the terminology of Campbell et al. (2012), this shock is labeled as Odyssean forward guidance. Moreover, this shock also captures timing components, which correspond to revisions of policy expectations regarding the following two meetings. Therefore, timing effects are also interpreted as short-term forward guidance (see Gürkaynak et al. (2007) and Altavilla et al. (2019)).

*LTRO*. This shock covers the surprises to announcements regarding policies implemented to reassure funding and to ease lending conditions, especially in the aftermath of the Sovereign Debt Crisis. Examples of such policies include the Securities Purchase Programme (SMP), the announcements of Outright Monetary Transactions (OMT), and Longer-Term Refinancing Operations (LTRO).

*Quantitative easing (QE)*. Since 2015, the ECB conducts large purchases of assets. Their goal is to supply more liquidity to the banking system, in order to address downward risks for medium-term inflation.[7] This shock contains the reaction of markets regarding announcements about the introduction and implementation of such programs.

The policies above are a mixture of conventional, unconventional, and communication tools. Their deployment aims at influencing different segments of the term structure of interest rates. Specifically, conventional monetary policy targets short-term maturities; communication tools, such as information and forward guidance, move medium- to long-term horizons; whereas QE affects the long end of the yield curve. In contrast, policies to ease lending conditions are effective in reducing spreads. In table 1.1, I summarize the previous properties. Moreover, based on the evidence found in the literature, the table also shows my hypothesis regarding their individual effect on inflation ($\pi_t^*$) and inflation expectations ($\pi_t^{e*}$), when the monetary policy shocks are expansionary. I will study these responses in section 1.4.

I base the construction of the monetary policy proxies on the EA-MPD. This data set contains the surprises of a wide range of asset and bond prices, where a surprise is defined as the difference between the median quote 10 minutes before and 10 minutes after a specified time window. Altavilla et al. (2019) provide the surprises for three windows: the press release, the press conference, and the whole monetary policy event. The time dimension of these data sets is $T^*$, which corresponds to the frequency of the ECB's governing council

[7]The ECB's Asset Purchase Programmes are the following: Corporate Sector Purchase Programme (CSPP), Public Sector Purchase Programme (PSPP), asset-backed securities Purchase Programme (ABSPP), the third Covered Bond Purchase Programme (CBPP3), and the Pandemic Emergency Purchase Programme (PEPP)).

Table 1.1: Properties of monetary policy shocks

| Shock | MP type | Yield curve | $\pi_t$* | $\pi_t^e$* |
|---|---|---|---|---|
| Target | conventional | short | + | + |
| Information | communication | medium-long | / | / |
| FG | unc. & comm. | medium-long | + | + |
| LTRO | unconventional | spreads | / | / |
| QE | unconventional | long-end | + | + |

Note: $\pi_t^*$ and $\pi_t^{e*}$ represent the prior hypothesis regarding the responses of inflation and inflation expectations to the individual expansionary monetary policy shocks. The symbol "/" represents an agnostic belief.

meetings, i.e., every six weeks. Following Rogers et al. (2018) and Altavilla et al. (2019), I define the target factor, $F_t^{Target}$, as the surprises of the OIS at one month maturity during the press release window. The rationale behind this measure is that the main reaction to conventional monetary policy occurs at the press release, given that in the press conference a larger emphasis is given to explaining changes in unconventional monetary policy.

To identify the proxies related to the ECB's communication and unconventional tools, I consider a subset of the EA-MPD covering the surprises of 34 asset and bond prices over the whole monetary policy event window,[8] spanning from January 2002 to February 2020. This means that I consider a total of 199 governing council meetings. Specifically, I use a data set including the following surprises: the OIS at several maturities ranging between one month, three months, six months, and one to twenty years; German sovereign bond yields at the maturities of three and six months as well as one, two, five, and ten years; the two, five and ten years maturities of French, Italian, and Spanish sovereign bond yields;[9] the STOXX50 and SX7 indices;[10] and exchange rates against the dollar, the pound sterling, and the yen. Unlike Altavilla et al. (2019), I do not estimate the second block of proxies exclusively using the surprises from the press conference window. This is because, from March 2016 onward, changes in unconventional policies are communicated in the press release. Moreover, starting in July 2016, an official forward guid-

[8]This monetary policy event window covers the difference between the surprises of the median quote for the time 13:25-13:35 and 15:40-15:50, i.e. 10 minutes before the publication of the press release and 10 minutes after the end of the press conference (see Altavilla et al. (2019)). Following Altavilla et al. (2019), I consider the surprises from the governing council meetings on October 8, 2008 and November 26, 2008 as outliers.

[9]To denote the bond surprises of the several countries, I follow standard European notation, i.e., Germany (DE), France (FR), Italy (IT), and Spain (ES).

[10]The STOXX50 is a stock market index covering the largest fifty firms in the euro area, whereas SX7 is an index composed by the prices of the stocks of the largest banks in the euro area.

ance statement is also included in the press release. Therefore, considering the whole monetary policy event window yields a more precise identification. In fact, as highlighted by Wright (2019), considering this window allows for distinguishing an additional proxy that does not appear in the other two windows, which captures policies implemented in the aftermath of the Sovereign Debt Crisis. These policies seek to reassure funding, especially in periphery countries. For this reason, Wright (2019) calls it the *save the euro* factor. In contrast to Wright (2019), I develop a formal identification of this factor and further use it to analyze its impact on price stability and the anchoring of inflation expectations. In this study, I name this factor as *LTRO*.

I collect the surprises in the $34 \times 1$ vector, $Z_t$, for $t = 1, \ldots, 199$, and assume it evolves as the following static factor model with $r$ factors:

$$Z_t = \Lambda F_t + \xi_t \quad \xi_t \sim \mathcal{N}(0, R), \tag{1.1}$$

where $F_t$ is a vector of latent factors of dimension $r \times 1$, $\Lambda$ is a $34 \times r$ loading matrix, and $\xi_t$ is a $34 \times 1$ vector of idiosyncratic components with unrestricted covariance matrix $R$. I standardize the matrix of surprises to have mean zero and unit variance, common in the estimation of factor models. As shown in figure 1.1, four factors explain 86.7% of the variance and each of them contribute with more than 5%. Moreover, the criterion of Alessi, Barigozzi, and Capasso (2010) selects four factors when the maximum number of factors is 5, therefore I set $r = 4$. From these four factors, I aim at constructing five monetary policy proxies. I detail how I achieve this below.

The first part of the right-hand-side of equation (1.1) is called the common component, $\chi_t = \Lambda F_t$, where the factors and loadings can be rotated freely. Therefore, to pin down the surprises concerning the different types of monetary policy tools, I must find a unique rotation matrix such that the parameters of the factor model fulfill a set of economic restrictions.

Since the monetary policy event window integrates the communication of the complete set of monetary policy tools, I consider again a target factor, in order to clean the effects of conventional monetary policy on the remaining factors. Nevertheless, for my final assessment, I consider the target factor from the press release window, given that the surprises stemming from conventional monetary policy mainly occur in this window.[11] I concatenate the four factors in the $199 \times 4$ matrix $F$ and split the factors into two blocks, as denoted in equation (1.2). The first block, $F^{TC}$, includes the target and

[11] In appendix 1.B, I present a figure depicting both factors. We can see that the factor from the whole monetary policy event window is noisier, however both factors co-move. In fact, they have a correlation of 0.6.

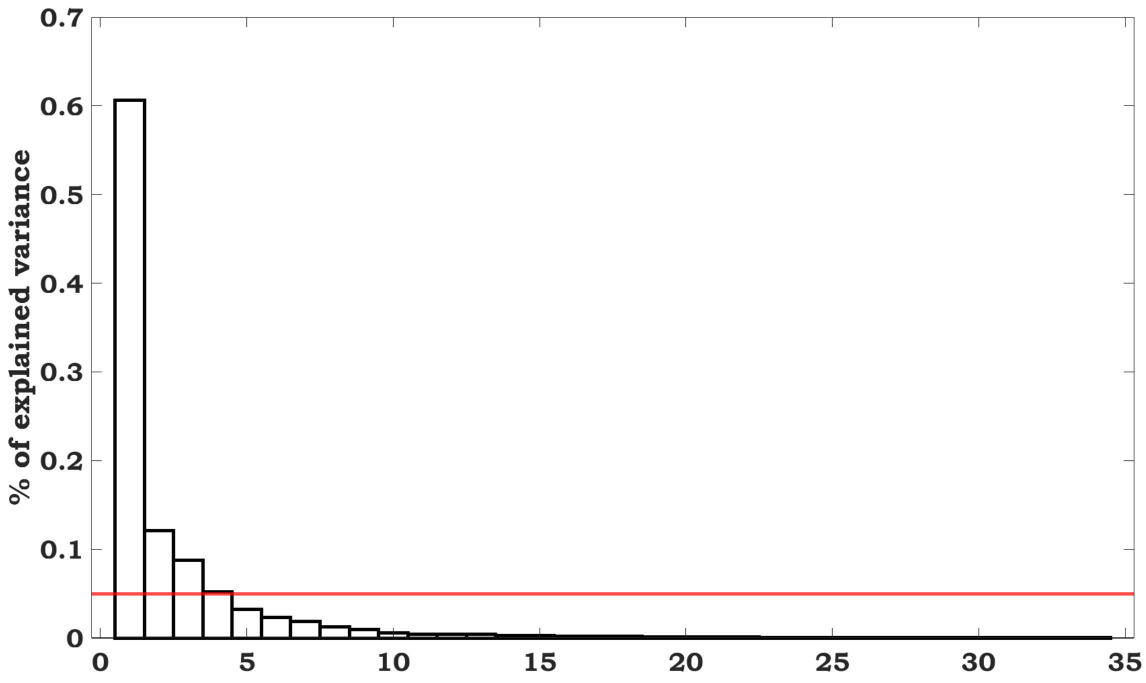


Figure 1.1: Scree plot (monetary policy event window)

communication (path) factors, whereas the second block, $F^{BS}$, contains two factors related to balance sheet tools, specifically to policies implemented to ease lending conditions (LTRO) and QE.

$$F = [F^{TC}\ F^{BS}] \tag{1.2}$$

The policies related to the factors in sub-matrix $F^{BS}$ were initially introduced during and after the Great Recession. Therefore, I impose the first restriction such that the LTRO and QE factors explain the least percentage of explained variance for the period before the crisis (Jan 2002-August 2008), in the spirit of Swanson (2021). Furthermore, following Gürkaynak et al. (2005), Altavilla et al. (2019), and Andrade and Ferroni (2021), I restrict the one-month OIS loadings to zero for the communication and balance sheet factors. The rationale behind these restrictions is that forward guidance and QE are implemented with the goal of influencing medium-term and long-term rates, respectively. Moreover, there is broad evidence that the implementation of LTROs reduced a wide range of spreads, where the majority of the analyses focus on horizons larger than six months. In contrast, the target factor can affect the shortest maturity of the OIS.

The previous set of restrictions does not guarantee the identification between the LTRO and QE factors. Given that QE aims at influencing the long end of the yield curve, and not short-maturities, I additionally restrict the loading of the OIS at the six-months maturity to zero. Moreover, it is important to highlight that the identification among the communication and LTRO factors is achieved. This is because the latter is included in the block of factors that have more explanatory power only after the Great Recession.

I denote the rotated factors as $F^* = FQ$, such that $Q$ is a rotation matrix. The subset of $F^*$ containing the balance sheet factors is characterized by $F^{BS^*}$. Now we must find a rotation matrix, $Q^*$, that incorporates the restrictions above. To do so, I consider the following optimization problem for the pre-crisis period:

$$
\begin{aligned}
Q^* = \arg\min \frac{1}{T^*} \, &\text{trace}(F^{BS^{*\prime}} F^{BS^*}) \\
&\text{s.t.} \\
&Q'Q = I_r \\
\Lambda_{OIS1M,\bullet} Q_{\bullet,2} = 0, \quad &\Lambda_{OIS1M,\bullet} Q_{\bullet,3} = 0 \quad \Lambda_{OIS1M,\bullet} Q_{\bullet,4} = 0 \\
\Lambda_{OIS3M,\bullet} Q_{\bullet,5} = 0 &
\end{aligned} \tag{1.3}
$$

The syntax $\Lambda_{i,\bullet}$ denotes the $i$-th row of the loading matrix, whereas $Q_{\bullet,i}$ is the $i$-th column of the orthogonal matrix. Therefore, the rotated matrix of factor loadings has the following structure:

$$
\Lambda^* = \left[\begin{array}{cccc} \text{Target} & \text{Path} & \text{LTRO} & \text{QE} \\ * & 0 & 0 & 0 \\ * & * & * & 0 \\ * & * & * & * \\ \vdots & \vdots & \vdots & \vdots \\ * & * & * & * \end{array}\right] \begin{array}{c} \\ \text{OIS1M} \\ \text{OIS3M} \\ \text{OIS6M} \\ \vdots \\ \\ \end{array}
$$

where the character "*" denotes an unrestricted value.

As a second step, I disaggregate the path factor into information and forward guidance. To do so, I follow the literature on Delphic (information) and Odyssean forward guidance. Several studies find that the stock market and medium-term interest rates have a positive correlation for the former and a negative for the latter in the euro area (see Kerssenfischer (2019), Jarociński and Karadi (2020), Andrade and Ferroni (2021)). I define the information factor to the observations in the path factor such that the surprises of the STOXX50 and the two-year OIS move in the same direction. Within a similar reasoning, when these surprises move in opposite directions, the observation of the communication factor is related to forward guidance.

Summarizing, we now have a target factor from the press release window and a set of four unconventional factors from the whole monetary policy event window. To properly capture the effects of QE, I follow Altavilla et al. (2019) and set observations before June 2014 to zero. This is the date when former President Mario Draghi announced the preparatory work for starting the purchase of asset-backed securities. Due to the use of different data sets, the zeros in the QE factor, and the dis-aggregation of the path factor, the factors are not necessarily orthogonal. In the next step, I construct the rotated factors, denoted by $\tilde{F}_{k,t}$, through the recursive estimation of the following linear regressions:

$$F_{k,t} = \beta_k F_t^{Target} + \sum_{j=1}^{k-1} \gamma_j \tilde{F}_{j,t} + e_{k,t}, \quad e_{k,t} \sim \mathcal{N}(0, \sigma_k^2), \tag{1.4}$$

for $k = \{\text{information, forward guidance, LTRO, QE}\}$. I obtain the orthogonal factors by defining them as the residual of each regression, i.e., $\tilde{F}_{k,t} = F_{k,t} - \hat{\beta}_k F_t^{Target} - \sum_{j=1}^{k-1} \hat{\gamma}_j \tilde{F}_{j,t}$. In order to have a monthly version of the orthogonal factors, I set the months with no governing council meeting to zero. For the isolated cases where two meetings took place in one month, the sum of the surprises corresponds to the observation in that particular month.[12]

I compute the orthogonal loadings, $\tilde{\Lambda}$, based on the individual regressions:

$$Z_{i,t} = \tilde{\Lambda}_i \tilde{F}_t + v_{i,t}, \quad v_{i,t} \sim \mathcal{N}(0, \omega_i^2), \tag{1.5}$$

for $i = 1, \cdots, 34$. Since the factors and loadings are identified up to sign, I normalize the factors and each of the columns of the loadings matrix such that the target and the QE factors have a unit effect on the one-month and the twenty-year OIS, respectively. Both the information and the forward guidance factors are normalized to a unit effect on the two-year maturity OIS. Moreover, I normalize the LTRO factor such that it has a unit effect on the five-year German sovereign bond yield.

Figure 1.2 depicts the normalized, orthogonal loadings corresponding to the OIS term structure, where the shaded areas cover the 95% confidence intervals. Given that the static factor model from equation (1.1) works as a descriptive tool for the underlying monetary policy shocks, some variables may still feature some degree of heteroskedasticity. In fact, I reject the null of non-autocorrelated residuals of the Ljung-Box Q-test for some variables.

[12]This aggregation technique induces serial correlation in the proxies. Previously to the inclusion of the proxies in the VAR models studied in section 1.4, I eliminate the serial correlation by fitting an autoregressive model to each proxy.

Therefore, to properly conduct inference, I compute the confidence intervals through a heteroskedasticity-and-autocorrelation consistent estimation (Andrews (1991), Andrews and Monahan (1992)). The maximum impact on the target factor corresponds to the one-month rate and the relevance of farther rates decreases the longer the maturity. The loadings associated to the information factor reach a plateau between the two and the ten-years maturities. Similarly, the forward guidance factor loadings peak at the five-year horizon and the relevance of longer maturities decreases along the end of the yield curve. The importance of longer-term maturities is greater for the loadings linked to the balance sheet factors.

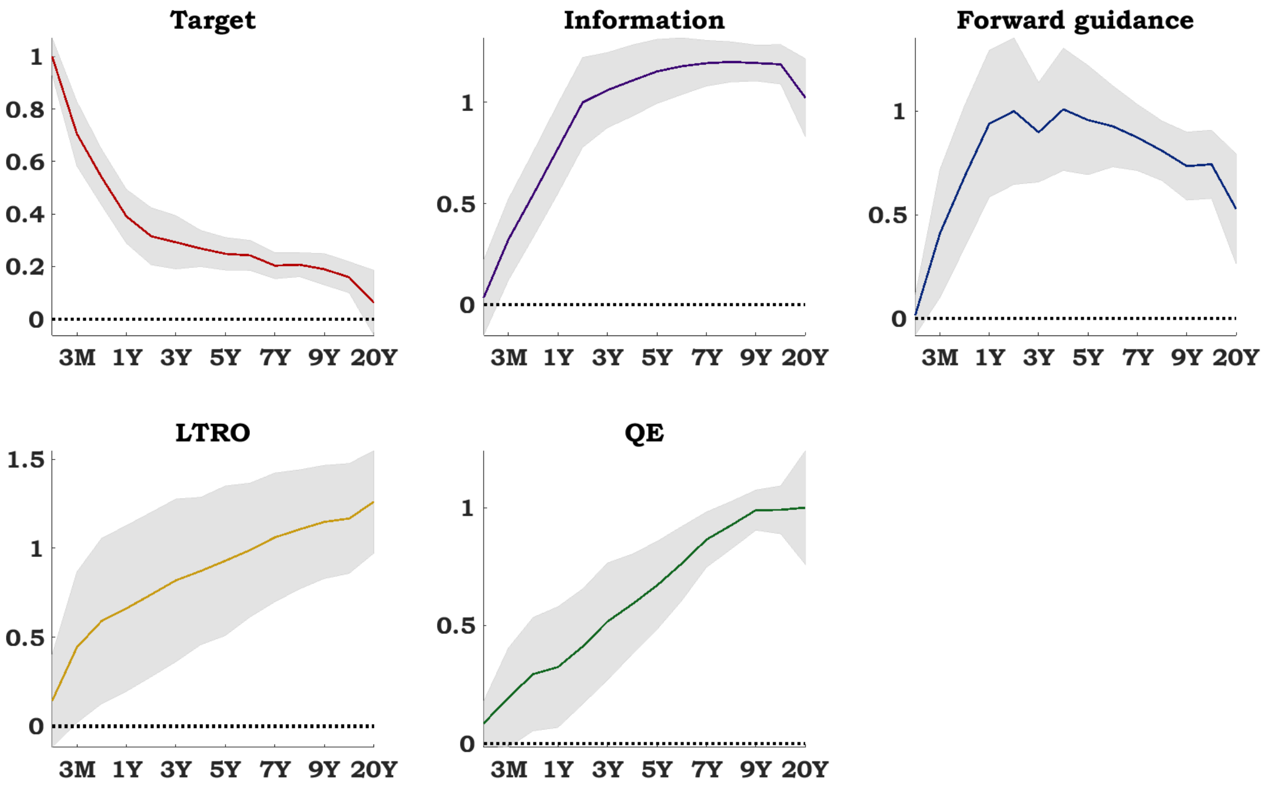


Figure 1.2: Loadings and the OIS term structure

Note: The shaded areas correspond to the 95% confidence intervals.

In Table 1.2, I show the full set of orthogonal and normalized loadings. Numbers with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively. As expected from macro-finance theory, a conventional monetary policy shock (measured by the target factor) moves short-term interest rates and stock market price indices in opposite directions. This is because higher rates increase the discount factor that translates to a lower present value of returns. When the shock is contractionary (expansionary), the euro appreciates (depreciates) meaning that domestic assets become more attractive to foreign investors, therefore increasing the demand for them. Furthermore, a rise in the short-term rate also has a contractionary effect in the four largest countries of the euro area, because the sovereign bond yields increase. For the case of the information factor, I find a positive and significant relationship between medium- to long-term maturities of the OIS and stock market price indices. Moreover, I find a significant depreciation of the euro against the US dollar and the pound sterling. For the case of forward guidance, I find that the STOXX50 and the SX7 respond in opposite directions to medium-term rates, both variables are significant at 5% level.

Following the terminology in the Economic Bulletin ECB (2015), the LTRO and QE factors are proxies for active balance sheet shocks.[13] In this bulletin, the authors differentiate between two types of active balance sheets policies: Credit easing measures and quantitative easing. In fact, one feature that can distinguish between them is that one of the goals of credit easing policies is to influence spreads. As pointed out by Altavilla, Giannone, and Lenza (2016) (for OMT announcements), Rogers, Scotti, and Wright (2014) (for LTROs), and Wright (2019), the introduction of credit easing policies moves the German government bond yields and the yields of crisis countries in opposite directions. I find evidence of this characteristic and it is highlighted by the bold numbers in Table 1.2. This means that the LTRO factor increases the OIS and government bonds yields of core countries. At the same time, it reduces the government bond yields of Italy and Spain. Therefore, my identification achieves the differentiation between credit and quantitative easing policies.

Lastly, figure 1.3, I present the plots of the five rotated and normalized factors. The impact of target shocks decreases significantly after the beginning of the Sovereign Debt Crisis. This coincides with the ECB's decision to set the deposit facility rate and the main refinancing operations rate to zero in July 2012 and March 2016, respectively. The LTRO shock has a strong concentration during the period of the Sovereign Debt Crisis. The small movements in this factor before 2007 reflect other type of market operations that were implemented for correcting malfunctions in the financial market. Finally, the large spikes of the QE factor coincide with main announcements regarding the different large-asset purchasing programmes introduced by the ECB.[14]

[13]A passive balance sheet corresponds to transactions that the ECB conducts to supply liquidity for restoring the appropriate transmission of monetary policy in malfunctioning markets (see the Monthly Bulletin ECB (2010)). On the other hand, an active balance sheet concerns transactions having the goal of providing additional monetary policy accommodation.

[14]In appendix 1.C, I associate spikes of some of the factors to selected policy announcements.

Table 1.2: Orthogonal and normalized factor loadings

| | | Target | Info | FG | LTRO | QE |
|---|---|---|---|---|---|---|
| **OIS** | 1M | 1.00*** | 0.03 | 0.01 | 0.14* | 0.08 |
| | 3M | 0.71*** | 0.32*** | 0.41*** | 0.44*** | 0.19 |
| | 6M | 0.54*** | 0.54*** | 0.68*** | 0.59*** | 0.29*** |
| | 1Y | 0.39*** | 0.77*** | 0.94*** | 0.66*** | 0.32*** |
| | 2Y | 0.32*** | 1.00*** | 1.00*** | 0.74*** | 0.41*** |
| | 3Y | 0.29*** | 1.06*** | 0.90*** | 0.82*** | 0.52*** |
| | 4Y | 0.27*** | 1.11*** | 1.01*** | 0.87*** | 0.59*** |
| | 5Y | 0.25*** | 1.15*** | 0.96*** | 0.93*** | 0.67*** |
| | 6Y | 0.24*** | 1.18*** | 0.93*** | 0.99*** | 0.76*** |
| | 7Y | 0.20*** | 1.19*** | 0.87*** | 1.06*** | 0.86*** |
| | 8Y | 0.21*** | 1.20*** | 0.81*** | 1.11*** | 0.93*** |
| | 9Y | 0.19*** | 1.19*** | 0.73*** | 1.15*** | 0.99*** |
| | 10Y | 0.16*** | 1.19*** | 0.74*** | 1.17*** | 0.99*** |
| | 20Y | 0.06 | 1.02*** | 0.53*** | 1.26*** | 1.00*** |
| **Government bond yields** | DE3M | 0.37*** | -0.15 | 0.12 | -0.06 | 0.11 |
| | DE6M | 0.32*** | 0.24* | 0.61*** | 0.45*** | 0.29* |
| | DE1Y | 0.40*** | 0.60*** | 0.91*** | 0.66*** | 0.33*** |
| | DE2Y | 0.28*** | 0.91*** | 1.06*** | 0.77*** | 0.45*** |
| | DE5Y | 0.22*** | 1.08*** | 0.93*** | 1.00*** | 0.70*** |
| | DE10Y | 0.12*** | 1.07*** | 0.64*** | 1.22*** | 1.20*** |
| | FR2Y | 0.38*** | 0.89*** | 0.99*** | 0.70*** | 0.49*** |
| | FR5Y | 0.38*** | 1.02*** | 0.89*** | 0.60*** | 0.87*** |
| | FR10Y | 0.30*** | 1.02*** | 0.60*** | 0.53*** | 1.45*** |
| | IT2Y | 0.27*** | 0.65*** | 0.89*** | **-0.85***** | 0.91*** |
| | IT5Y | 0.29*** | 0.64*** | 0.75*** | **-1.06***** | 1.12*** |
| | IT10Y | 0.27*** | 0.53*** | 0.45*** | **-1.08***** | 1.44*** |
| | ES2Y | 0.23*** | 0.77*** | 1.03*** | **-0.34***** | 0.66*** |
| | ES5Y | 0.21*** | 0.87*** | 0.87*** | **-0.72***** | 1.03*** |
| | ES10Y | 0.18*** | 0.69*** | 0.57*** | **-0.89***** | 1.35*** |
| **Stock Market** | STOXX50 | -0.31*** | 0.87*** | -0.20** | 0.88*** | -1.25*** |
| | SX7E | -0.23*** | 0.57*** | -0.21** | 1.40*** | -0.77*** |
| **Exchange rates** | EURUSD | 0.18*** | -0.48*** | 0.03 | 1.22*** | 1.07*** |
| | EURGBP | 0.15*** | -0.28** | 0.00 | 1.15*** | 1.05*** |
| | EURJPY | 0.20*** | -0.09 | 0.06 | 1.28*** | 1.13*** |

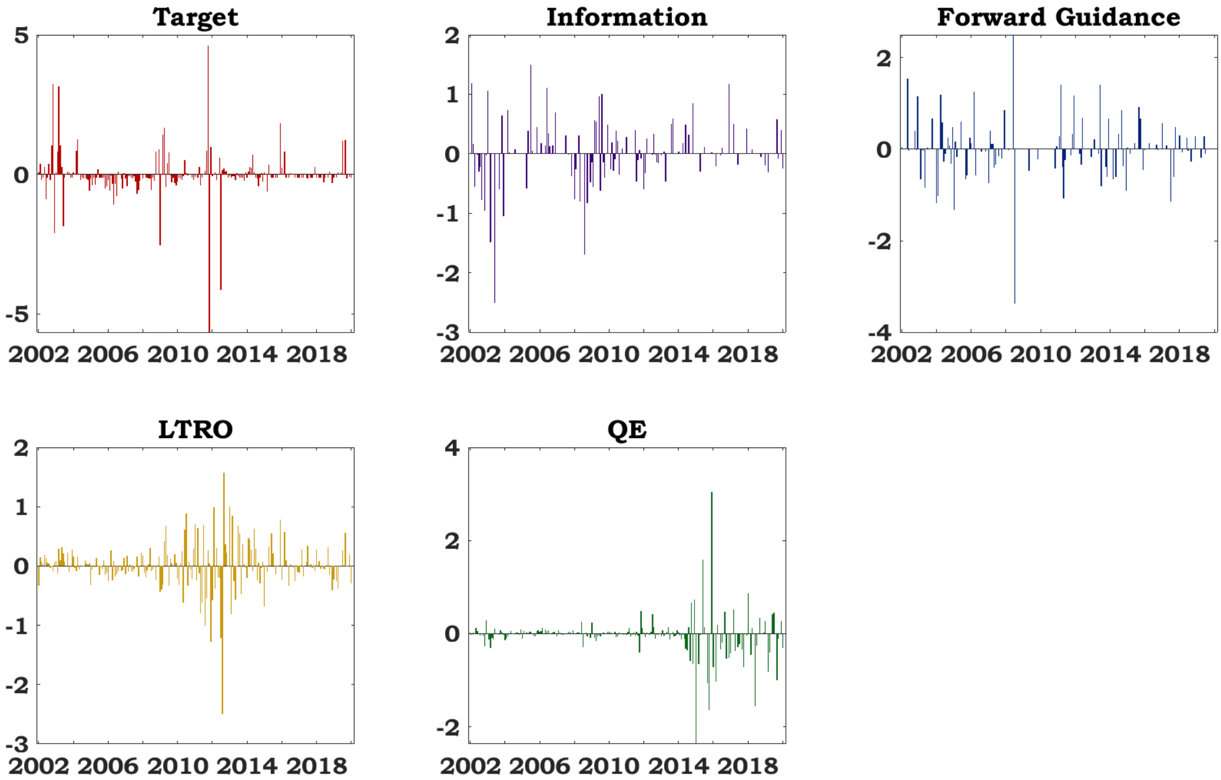


Figure 1.3: Proxies for conventional and unconventional monetary policy shocks

### 1.2.1 A comparison with the proxies of Altavilla et al (2019)

This paper is closely related to Altavilla et al. (2019). These authors identify target, timing, forward guidance, and QE proxies based on the surprises of seven maturities of the OIS term structure. They estimate the target factor from the press release window and the remaining factors from the press conference window. As previously stated, the selection of these windows could have implications for the identification of the factors, given that, starting in 2016, the ECB already communicates decisions regarding unconventional monetary policy in the press release.

In table 1.3, I show the correlation between the shocks in this paper (columns) and those obtained by Altavilla et al. (2019) (rows). It is no surprise that the target factors are perfectly correlated, given that I exactly follow their approach. It is important to note, however, that the timing, forward guidance, and QE factors of Altavilla et al. (2019) have some correlation with their target factor. This stems from the non-orthogonality property of their shocks. As previously stressed, the forward guidance factor of Altavilla et al. (2019)

is most likely a combination of information and forward guidance. In fact, their forward guidance factor has the highest correlation with my information and forward guidance factors. Moreover, the timing, forward guidance, and QE factors from Altavilla et al. (2019) share some components with the LTRO factor, since they have a correlation between 0.2 and 0.32.

Table 1.3: Correlation between my factors and Altavilla et al. (2019)'s factors

| | Target | Info | FG | LTRO | QE |
|---|---|---|---|---|---|
| Target | 1 | 0 | 0 | 0 | 0 |
| Timing | -0.04 | 0.07 | 0.13 | 0.22 | 0.08 |
| FG | 0.13 | 0.41 | 0.49 | 0.20 | 0.05 |
| QE | 0.02 | 0.08 | -0.02 | 0.32 | 0.57 |

Note: numbers represent the correlation between my factors (columns) and Altavilla et al. (2019)'s factors (rows).

I want to highlight further differences in the estimation of Altavilla et al. (2019)'s factors in comparison with those estimated in this paper. First, I specifically corroborate that the factors are orthogonal to each other. This step is crucial, given that the factors are proxies for structural monetary policy shocks and, therefore, they should not be correlated. Second, the factor model in Altavilla et al. (2019) is based on raw surprises. In contrast, I base my estimation on standardized data, a frequent assumption in factor models. The standardization step is important because it brings the data to the same levels. When the data is not standardized, variables with larger variance can have a larger weight in the estimation of the factors. I recognized that this step indeed has implications for the identification of the shocks. In fact, impulse responses of shocks based on raw surprises tend to have higher uncertainty.

## 1.3 Monetary policy in a data-rich environment

The conduct of monetary policy in the euro area requires monitoring a large set of variables. To have a comprehensive representation of the full dynamics in the euro area economy, I consider a wide range of macroeconomic and financial variables. However, due to a high degree of parametrization in large systems, the estimation of VARs is not feasible under conventional methods. Therefore, we must apply a dimension reduction (sparse) or a shrinkage (dense) technique.[15] A popular approach to cope with the curse of dimensionality is to set up a factor-based model like a Factor Augmented VAR (Bernanke and Boivin (2003), Bernanke et al. (2005)) or a structural factor model (Forni et al. (2009)). This type of dense models summarizes the common information of a large number of variables into a strictly smaller number of factors. A second frequent approach is the set up of a large Bayesian VAR, where the econometrician relies on the implementation of Bayesian shrinkage. In this paper, I consider the second approach since it neither relies on stationary transformations of the variables nor on the normalization of the factors for analyzing the results of the model.[16] Moreover, I integrate the factors from the previous section into a large Bayesian VAR, in order to analyze the effects of multidimensional monetary policy in the euro area economy. I describe the methodology in the following subsections.

### 1.3.1 The large Bayesian VAR

Let us consider a large vector of endogenous variables, $y_t$, of dimension $N \times 1$. I jointly model its dynamics through a VAR with $p$ lags described in equation (1.6):

$$y_t = c + A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t, \tag{1.6}$$

where $A_1, \cdots, A_p$ are $N \times N$ matrices of autoregressive coefficients, $c$ is a vector of constant terms, and $u_t \sim \mathcal{N}(0, \Sigma)$ is a vector of reduced-form errors. The VAR can also be written in compact form:

$$y_t = A_+ x_t + u_t, \tag{1.7}$$

where $x_t = [y'_{t-1}, \ldots, y'_{t-p}, 1]'$ is an $(Np+1) \times 1$ vector containing all the lagged values of $y_t$ and the constant term, the matrix $A_+ = [A_1, \cdots, A_p, c]$ has all stacked coefficients and it has a dimension of $N \times (Np+1)$. Additionally, the VAR has the following matrix form:

$$Y = XA'_+ + U, \tag{1.8}$$

[15]See Giannone, Lenza, and Primiceri (forthcoming) for an assessment of dense and sparse models in a forecasting framework.

[16]Other possible approaches are Panel VAR (see Canova and Ciccarelli (2013) for a survey), Global VAR (Pesaran and Smith (2006), Dees, Mauro, Pesaran, and Smith (2007)), Stochastic Search Variable Selection (George and McCulloch (1995)), LASSO (Tibshirani (1996), Park and Casella (2008)), among others.

where $Y$ is a $T \times N$ matrix of data, $X = [x_1, \ldots, x_T]'$ is a $T \times (Np + 1)$ matrix of lagged endogenous variables, and $U$ is a $T \times N$ matrix of stacked reduced-form errors.

The literature on large VARs tracks back to the articles of Litterman (1986) and Doan, Litterman, and Sims (1984), who introduced Bayesian methods in the framework of VAR analysis. They propose an informative prior distribution - popularly known as the Minnesota prior- for the estimation of a ten-variable VAR. A proposal for selecting the degree of shrinkage for larger models is made by Bańbura et al. (2010). The authors propose selecting the shrinkage parameter over a grid in a data-driven approach for a set of 131 variables. In more detail, they estimate a large Bayesian VAR, selecting the hyperparameter governing the overall degree of shrinkage such that it has the best in-sample fit. This approach takes into consideration the cross-sectional dimension of the data, i.e., the larger the number of time series, the larger the tightness of the prior. Nevertheless, when Bańbura et al. (2010) additionally consider a sum of coefficients prior (see below), they arbitrarily set the hyperparameter ruling this prior.

Subsequently, Giannone, Lenza, and Primiceri (2015) (GLP, henceforth) propose a hierarchical model treating the hyperparameters as an additional vector to estimate. In particular, the authors consider priors taking the Normal-inverse Wishart form as follows:

$$\Sigma \sim iW(\Psi, d) \tag{1.9}$$

$$\alpha|\Sigma \sim \mathcal{N}(a, (\Sigma \otimes \underline{V})), \tag{1.10}$$

where $\alpha = \text{vec}(A'_+)$ and the inverse Wishart distribution is parameterized with degrees of freedom $d = N + 2$ such that the mean of $\Sigma$ exists, see Kadiyala and Karlsson (1997). The authors also set the scale matrix to be a diagonal matrix, i.e., $\Psi = \text{diag}(\psi_1, \cdots, \psi_N)$. Typically, the diagonal elements are constructed with the variances resulting from fitting an autoregressive (AR) model to each variable. The matrices $\underline{A}$ and $\underline{V}$ correspond to the prior mean and variance of the VAR parameters, where $a = \text{vec}(\underline{A})$ is an $N(Np + 1) \times 1$ vector. These parameters are functions of a vector of hyperparameters $\theta$ (which I define below). Assuming a Gaussian likelihood, the great computational advantage of considering Normal-inverse Wishart priors is that the posterior distribution is from the same distributional family as the prior, i.e., the priors are Natural conjugate.

I consider two types of priors: The Minnesota prior and the sum of coefficients prior. The Minnesota prior is initially proposed by Litterman (1986) and its broad idea is to set up the prior as if the variables in the VAR follow independent random walks, by setting the diagonal elements of $\underline{A}_1$ to one and the off-diagonal elements to zero. Furthermore, GLP assume that the more distant lags have a smaller weight in the equation of $y_{i,t}$, for $i = 1, \cdots, N$. Following the notation in GLP, the Minnesota structure sets the prior belief that the matrices of coefficients are independent and follow a Normal distribution with the following moments:

$$\underline{A}_{\ell,ij} := \mathbb{E}[A_{\ell,ij}|\Sigma] = \begin{cases} \delta_i, & i = j \quad \& \quad \ell = 1 \\ 0 & \text{otherwise} \end{cases} \tag{1.11}$$

$$\text{cov}\left(A_{\ell,ij}, A_{k,rs}|\Sigma\right) = \begin{cases} \frac{\theta_1^2}{\ell^{\theta_2}} \frac{\Sigma_{i,r}}{\psi_j/(d-N-1)} & j = s \quad \& \quad \ell = k \\ 0 & \text{otherwise;} \end{cases} \tag{1.12}$$

where $\underline{A}_{\ell,ij}$ denotes the $(i,j)$-th element of the prior mean matrix and the prior covariance matrix can be cast in the diagonal matrix $\underline{V}$, for lags $\ell, k = 1, \ldots, p$, and $i, j, r, s = 1, \ldots, N$. Furthermore, I set a diffuse prior for the intercept term.

This version of the Minnesota prior is more flexible than the traditional set up, since it allows for a mixture of stationary and non-stationary variables. Specifically, the parameter $\delta_i$ equals one when variable $y_i$ is not stationary and zero otherwise. The crucial hyperparameter of the prior is $\theta_1$, because it governs the overall degree of shrinkage. When $\theta_1 = 0$, the data is not informative enough and the posterior perfectly coincides with the prior distribution. At the other extreme, as $\theta_1 \to \infty$ the posterior mean draws converge to Least Squares estimates. For lags $\ell > 1$, the hyperparameter $\theta_2$ penalizes stronger the more distant lags.

The last prior is a refinement of the Minnesota prior and is implemented by adding artificial or dummy observations to the original data.[17] The sum-of-coefficients prior (also known as inexact-differencing or no-cointegration-prior) is proposed by Doan et al. (1984). To understand this extension, let us rewrite the VAR from equation (1.6) in an error-correction form:

$$\Delta y_t = c - (I_N - A_1 - \cdots - A_p) y_{t-1} + \Gamma_1 \Delta y_{t-1} + \ldots + \Gamma_{p-1} \Delta y_{t-p} + u_t. \tag{1.13}$$

The combination of the Minnesota prior with the sum-of-coefficients prior shrinks the term $(I_N - A_1 - \cdots - A_p)$ to zero. The shrinkage of this relationship is ruled by hyperparameter $\theta_3$. When $\theta_3$ is zero, the VAR is set in first differences, which implies no cointegration relationships among the variables. At the other extreme, if $\theta_3 \to \infty$, the prior is diffuse and no additional shrinkage

[17] For a detailed explanation of the construction of the dummies, see Del Negro and Schorfheide (2011).

is imposed.

We now embed the sum-of-coefficients prior in form of $T_d$ artificial observations, denoted as $Y^*$ and $X^*$. They are constructed as follows:

$$Y^* = \text{diag}(\bar{y}_1, \cdots, \bar{y}_N)/\theta_3 \qquad X^* = \left[ \begin{array}{cc} (1_{1\times p} \otimes \text{diag}(\bar{y}_1, \cdots, \bar{y}_N)/\theta_3) & 0_{N\times 1} \end{array} \right],$$

where the last block of zeros in $X^*$ corresponds to the prior for the constant term. We concatenate the original data with the artificial (dummy) observations in the matrices $\tilde{Y} = [Y', Y^{*\prime}]'$ and $\tilde{X} = [X', X^{*\prime}]'$, whose time dimension equals $\tilde{T} = T + T_d$. Since the priors are conjugate, the posterior distributions of the VAR parameters and the error covariance matrix take the following form:

$$\alpha|\Sigma, Y \sim \mathcal{N}\left(\tilde{\alpha}, \tilde{V}_\alpha\right) \tag{1.14}$$

$$\Sigma|Y \sim iW\left(\Psi + \tilde{u}'\tilde{u} + (\tilde{A} - \underline{A})'V_a^{-1}(\tilde{A} - \underline{A}), \tilde{T} - p + d\right) \tag{1.15}$$

with

$$\tilde{A} = \left(\tilde{X}'\tilde{X} + V_a^{-1}\right)^{-1}\left(\tilde{X}'\tilde{Y} + \tilde{V}_a^{-1}\underline{A}\right) \quad \text{and} \quad \tilde{V}_\alpha = \Sigma \otimes \left(\tilde{X}'\tilde{X} + V_a^{-1}\right)^{-1},$$

and $\tilde{\alpha} = \text{vec}(\tilde{A}')$ and $\tilde{u} = \tilde{Y} - \tilde{X}\tilde{A}'$.

GLP estimate the parameters based on the optimization of the marginal data density $p(Y|\theta)$, which is a function depending on the hyperparameters governing the priors, $\theta = [\theta_1, \theta_2, \theta_3]$. The direct optimization of the marginal likelihood is possible since the authors provide a closed-form solution. The simulation of the posterior parameters is carried out in two parts. First, they numerically optimize the marginal data density, which is equivalent to maximizing the one-step-ahead forecast likelihood. GLP use the results from the likelihood optimization to draw the hyperparameters' vector from gamma distributions in a Metropolis-Hastings step.[18] Secondly, given the hyperparameters, they draw the parameters of the VAR based on (1.14) and (1.15).

### 1.3.2 The internal instrument approach

Thus far, I describe the reduced-form representation of the VAR. However, I am interested in analyzing the effects of a set of monetary policy shocks on the euro area economy. To do so, we can bridge the reduced-form with the

[18]For further detail about the functional form of the marginal data density and the MCMC algorithm, see the web appendices of Giannone et al. (2015).

structural representation of the VAR as follows:

$$u_t = H\varepsilon_t, \tag{1.16}$$

where $\varepsilon_t \sim \mathcal{N}(0, I_N)$ is a vector of structural shocks and $H$ is a non-singular matrix capturing the impact effects of structural shocks on the endogenous variables $y_t$. Therefore, the identification of macroeconomic shocks hinges on identifying the columns of $H$.

The literature studying large Bayesian structural VARs relies on identifying macroeconomic shocks through a recursive approach.[19] Nevertheless, justifying the order of the variables in a data-rich environment can be cumbersome, since the ordering needs to be backed up with economic theory. In this paper, I use the proxies (or instruments) computed in section 1.2 as the observed shocks (see Stock and Watson (2018)), given that they are estimated in a tight window when only monetary policy announcements occur. I jointly model them with the endogenous variables $y_t$ through the internal instrument approach. This methodology consists of augmenting the proxies $m_{k,t}$ one-by-one onto a VAR based on equation (1.6). Therefore, I rely on the estimation of the following models:

$$\begin{bmatrix} m_{k,t} \\ y_t \end{bmatrix} = \begin{bmatrix} 0 \\ c_k \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ \Gamma_{k,1} & A_{k,1} \end{bmatrix} \begin{bmatrix} m_{k,t-1} \\ y_{t-1} \end{bmatrix} + \cdots + \begin{bmatrix} 0 & 0 \\ \Gamma_{k,p} & A_{k,p} \end{bmatrix} \begin{bmatrix} m_{k,t-p} \\ y_{t-p} \end{bmatrix} + \begin{bmatrix} w_{k,t} \\ u_{k,t}, \end{bmatrix}, \tag{1.17}$$

for $k = 1, \cdots, 5$. I define the vector of errors $\tilde{u}_{k,t}$ as follows:

$$\tilde{u}_{k,t} = \begin{bmatrix} w_{k,t} \\ u_{k,t} \end{bmatrix} \sim \mathcal{N}(0, \Omega),$$

where $w_{k,t}$ corresponds to the $k$-th monetary policy shock. Given that the proxies are embedded in the VAR, this model is also known as hybrid VAR.

The matrix of impact effects is obtained by decomposing the covariance matrix as $\Omega = HH'$ through a Cholesky decomposition. However, it is important to note that we are only interested in the first column of $H$, which is associated with the monetary policy shock measured by proxy $m_{k,t}$.

The hybrid VAR in equation (1.17) is a restricted case of a large Bayesian VAR. Therefore, I carry out its estimation through the technique proposed by Giannone et al. (2015), described in subsection 1.3.1.

[19] An exception is the paper by Korobilis (2020), who proposes a methodology based on sign restrictions.

Finally, I must stress that other techniques are also possible for the estimation of the impulse responses, such as a Proxy-VAR model (Stock and Watson (2012) and Mertens and Ravn (2013); and Caldara and Herbst (2019), Arias, Rubio-Ramírez, and Waggoner (2021), Drautzburg (2020), for a Bayesian approach). In fact, Noh (2017) and Paul (2020) develop the conditions under which the internal instrument approach and the Proxy-VAR are equivalent. These conditions are the following: (i) invertibility of the shocks of interest must hold; (ii) the proxies must be serially uncorrelated; and (iii) $\Gamma_{k,i} = 0$, for $i = 1, \ldots, p$. In this paper, I choose the internal instrument approach since estimating the models and conducting inference is particularly simpler.

## 1.4 Empirical assessment

### 1.4.1 Data

I consider a medium-scale monthly data set containing 22 variables spanning from January 2007 to February 2020.[20] The data set contains information about industrial production, the unemployment rate, the economic sentiment index (ESI), the harmonized index of consumer prices, the Euro Over-Night Index Average (EONIA), the six months Euro Interbank Offered Rate (EURIBOR), euro area yields at the two and the twenty years maturities, the stock market index EUROSTOXX50, corporate and banks spreads from Gilchrist and Mojon (2018), the spread between the 10-year government bond yields of Italy and Germany, loans to non-financial corporations (NFC) and households (HH), an indicator of the cost of borrowing for NFCs, the composite indicator of sovereign stress (CISS), and the nominal effective exchange rate (NEER).[21] To capture downward risks in global inflation, I also incorporate oil and commodity price indices (see Ciccarelli and Osbat (2017)). From the side of short-term (one year ahead) expectations, I consider the expectations of consumers and professional forecasters. To measure the former, I take the balance index from the consumers' survey collected by the European Commission. This variable measures the qualitative expectations, where the consumers are asked about the trend of prices in the next twelve months, see figure 1.7 in appendix 1.A. The expectations of professional forecasters are measured by the consensus median of the short-term (one year ahead) inflation forecasts from the Eurozone Barometer (EB), gathered by MJEconomics. Additionally, I include the

[20] I do not consider the period of extreme observations stemming from the COVID-19 pandemic, since its size can compromise the inference of the large VAR. For a methodology handling such episodes, see the work of Lenza and Primiceri (2020).

[21] For detailed information about the data set see appendix 1.D.

long-term (five years ahead) inflation forecast from the ECB's survey of professional forecasters. The latter data set is available at a quarterly frequency, which I transform into a monthly time series through a Chow-Lin decomposition (Chow and Lin (1971, 1976)).[22] I use monthly short-term expectations and monthly perceptions from EB as bridge variables.[23]

### 1.4.2 Results

This subsection presents results from the estimation of the five models based on the hybrid Bayesian VAR in equation (1.17).[24] For all models, I use the same variables and six lags. I simulate 50000 draws of the posterior distribution of the parameters and keep the last 25000 for inference.[25] In all figures, I present the median of the posterior distribution of the impulse responses, together with 68% point-wise credibility intervals.

I normalize all the shocks such that they are expansionary. In detail, I normalize the target shock to a 20 basis points decrease in the EONIA; the information and forward guidance shocks are associated to a 20 basis points decrease in the two-year yield; the LTRO shock is normalized to a 20 basis points decrease in the spreads between Italian and German sovereign bond yields; and the QE shock is linked to a 20 basis points decrease in the twenty-years yield.

In figure 1.4, I depict the responses of year-on-year (yoy) inflation ($\pi$) and the inflation expectations of consumers ($\pi^{e,short,c}$) and professional forecasters ($\pi^{e,short,f}$ and $\pi^{e,long,f}$) to expansionary monetary policy shocks in the euro area. Furthermore, figures 1.14-1.18 in appendix 1.F show the results from the remaining variables in the VAR, which are also important to analyze for identification purposes.

In line with macroeconomic theory, I find evidence that a target shock raises output and decreases unemployment (see figure 1.14). However, this shock only mildly increases the long-term inflation expectations of professional forecasters five to nine months after the shock. The responses of in-

[22]Another possible dis-aggregation method is studied in Chapter 3. However, I do not implement such methodology in the present chapter, given that the complexity of the large model combined with mixed frequencies would substantially increase the computational burden of the model.

[23]I use the toolbox on temporal dis-aggregation written by Enrique M. Quilis and available at https://www.mathworks.com/matlabcentral/fileexchange/69800-temporal-disaggregation.

[24]I carry out the estimation of the large Bayesian Hybrid VARs through modifications to the MATLAB files from Giannone et al. (2015) and available at Giorgio Primiceri's website: http://faculty.wcas.northwestern.edu/~gep575/GLPreplicationWeb.zip.

[25]Appendix 1.E presents a convergence test of the MCMC algorithm.

flation and short-term expectations remain muted. The previous result can be explained by the zero lower bound. This is because, after 2012, the policy stance of the ECB has been mainly summarized by a mixture of conventional and unconventional tools.

I find that an expansionary information shock contemporaneously decreases the yoy rate of the EUROSTOXX50 and increases corporate spreads ten months after the shock (see figures 1.17 and 1.16). This means that when the ECB's president gives information with respect to a negative outlook for the economy, market participants become more pessimistic. Nevertheless, in response to the information provided by the ECB, professional forecasters revise their long-term expectations upward and inflation has a short-lived increase one month after the shock. It is usual that the ECB communicates its economic outlook together with guidance about policy. Therefore, I interpret the increase in expectations as an anchoring effect, given that professional forecasters revise their expectations in the direction of the ECB's target. Despite the communication of a negative outlook for the economy, forecasters believe that the central bank will conduct monetary policy reflecting its price stability mandate. This interpretation can be further corroborated with the responses of inflation and expectations to a forward guidance shock. An expansionary forward guidance shock increases inflation and all considered measures of inflation expectations. In particular, consumers' expectations decrease contemporaneously but pick up three months after the shock and remain significant for almost two years after the shock. Professional forecasters revise their short- and long-term expectations in a range of 0.07-0.58 and 0.03-0.17 percentage points around one year after the shock, respectively. Moreover, for around the same horizon, inflation rises in the interval of 0.38 to 2.1 percentage points.

Turning to balance sheet shocks, one of the effects of policies implemented to ease lending conditions after the Sovereign Debt Crisis was the reduction of spreads (see Wright (2019)). However, there is no consensus in the literature regarding their effects on inflation and inflation expectations. In this paper, these policies are summarized by the LTRO shock. Nonetheless, I do not find evidence that the LTRO shock moves inflation and inflation expectations significantly. On the other hand, I find that an expansionary QE shock increases the long-term inflation expectation of forecasters contemporaneously between 0.01 and 0.02 percentage points, then reaches a maximum increase between 0.03 and 0.1 percentage points nine months after the shock. This shock has a persistent effect on short-term expectations of consumers and forecasters since it lasts for almost two years after occurrence. Most importantly, I find evidence that, together with the stabilization in expectations, inflation increases, having its greatest impact at the eleven months horizon between 0.26-1.13 percentage points. In addition, I find that QE is effective at increasing output and the loans to households and NFCs, as well as at reducing unemployment and risk premia (see graphs 1.14 and 1.16).

In summary, I obtain a re-anchoring of long-term inflation expectations conditional on target, information, forward guidance, and QE shocks. However, only forward guidance and QE shocks produce a persistent response of inflation. To gain a better understanding of the role of inflation expectations for the transmission of monetary policy to inflation, I re-estimate the same hybrid VARs with the difference of eliminating the long-run inflation expectation of forecasters from the data. The impulse responses of inflation and the short-term inflation expectations are depicted in figure 1.5. The responses of the remaining variables in the VAR are included in the graphs 1.19 to 1.22 in appendix 1.G. The key result from this experiment is the lower response of inflation for both a forward guidance and a QE shock. Therefore, I find evidence of the *re-anchoring of inflation expectations channel*, as in Andrade, Breckenfelder, De Fiore, Karadi, and Tristani (2016) and Gambetti and Musso (2017).

In table 1.4, I summarize the maximum responses of inflation and inflation expectations to forward guidance and QE shocks, from the benchmark model and a model discarding long-term expectations. The values in parenthesis correspond to the $16^{\text{th}}$, $50^{\text{th}}$, and $84^{\text{th}}$ percentiles of the posterior distribution of the impulse response function. We can see a substantial decrease of the response of inflation to forward guidance and QE shocks. In fact, once I discard the re-anchoring effect of long-term inflation expectations, the highest (median) response of inflation decreases by 0.31 and 0.24 percentage points for forward guidance and QE shocks, respectively. Therefore, the anchoring of long-term inflation expectations is a crucial intermediate channel for achieving a stronger response of inflation, in the particular cases of forward guidance and QE.

Furthermore, the effectiveness of forward guidance and QE stresses the relevance of the “combined arms” strategy of the ECB (see Rostagno et al. (2019)). This is because between 2016-2018, forward guidance was mainly composed by state- and time-contingent statements regarding the implementation of the Asset Purchasing Programmes. Therefore, my results shed light on the importance of inflation expectations for achieving the transmission of these policies to inflation.

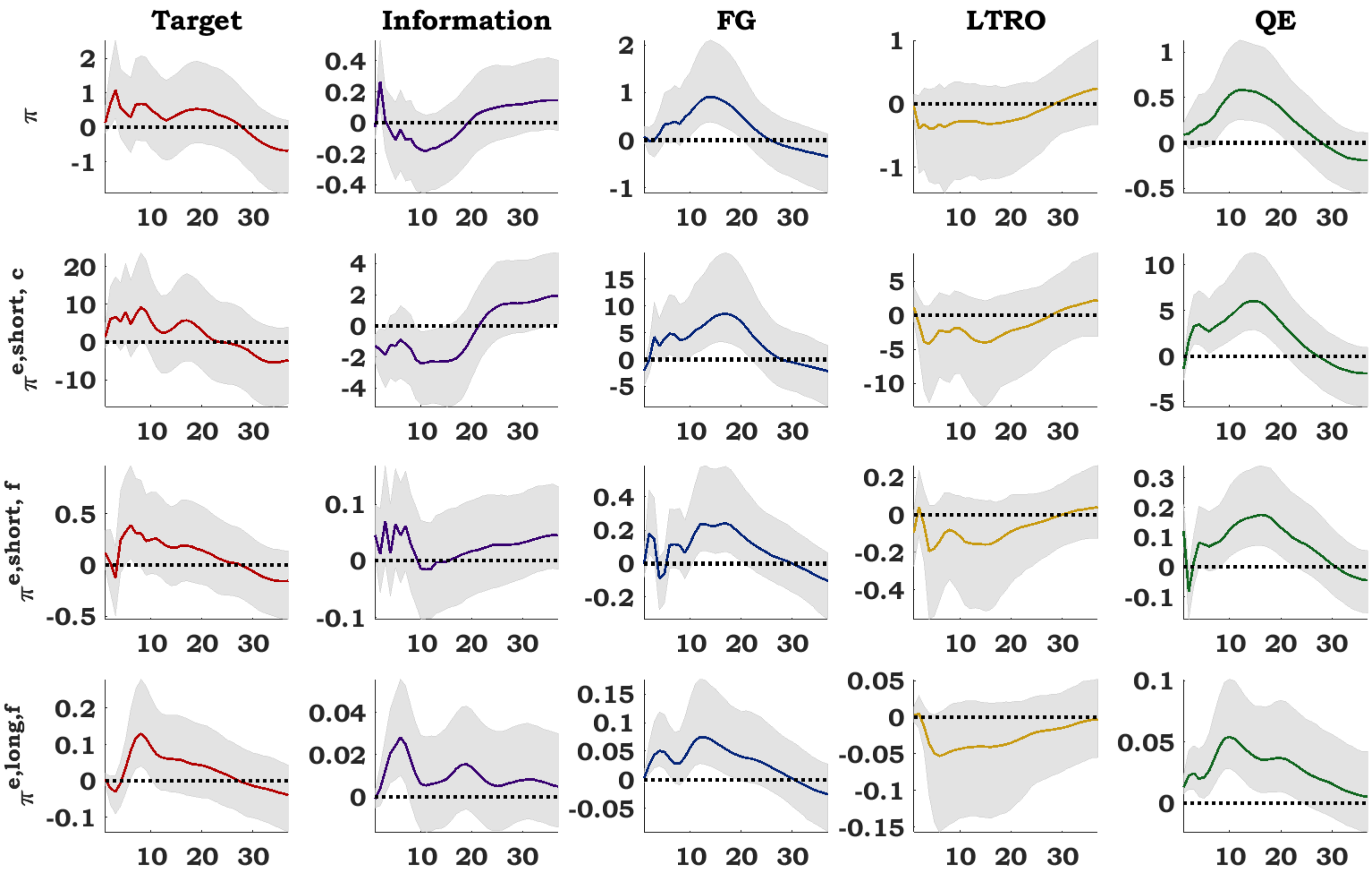


Figure 1.4: Responses of euro area inflation and inflation expectations to multi-dimensional monetary policy

Note: This figure shows the impulse responses of expansionary target (red), information (purple), forward guidance (blue), and QE (green) shocks, normalized to a decrease of 20 basis points in the EONIA, the two-years yield, and the twenty-years yield, respectively. The LTRO shock (yellow) is normalized to a 20 basis point decrease in the spread between Italian and German Government bond yields at the ten-years maturity. Bands represent the 68% point-wise credibility sets.

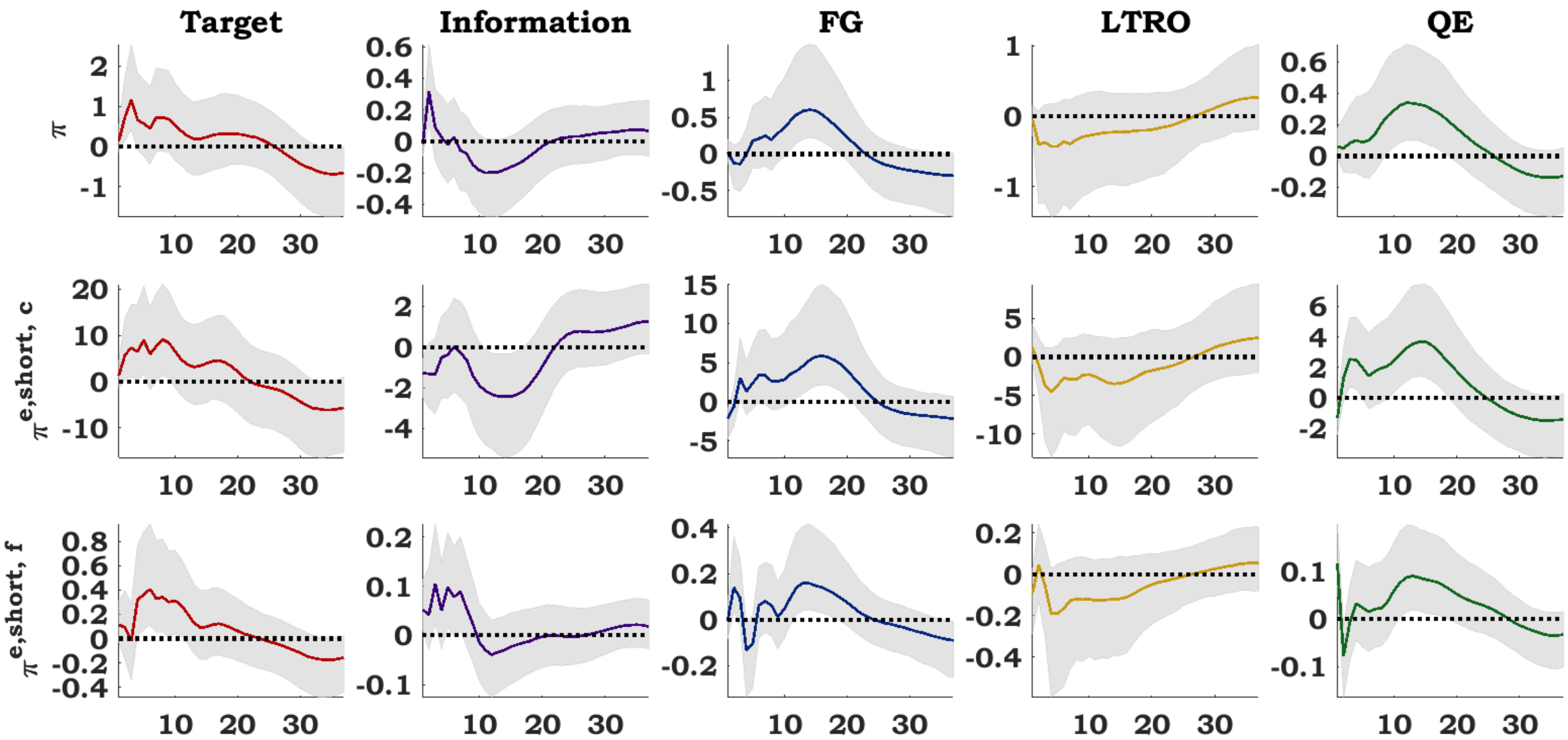


Figure 1.5: Responses of euro area inflation and short-term expectations of consumers and forecasters to multi-dimensional monetary policy.

Note: See note in figure 1.4.

Table 1.4: The re-anchoring effect

| | FG | | QE | |
|---|---|---|---|---|
| | Benchmark | no expec. | Benchmark | no expec. |
| $\pi$ | (0.38, 0.91, 2.10) | (0.22, 0.6, 1.5) | (0.26, 0.58, 1.13) | (0.10, 0.34, 0.71) |
| | h=13 | | h=11 | |
| $\pi^{short,c}$ | (3.20, 8.55, 19.93) | (2.20, 5.91, 15.03) | (2.87, 6.04, 11.32) | (1.36, 3.7, 7.45) |
| | h=16 | h=15 | h=14 | |
| $\pi^{short,f}$ | (0.07, 0.24, 0.58) | (0.04, 0.16, 0.40) | (0.07, 0.17, 0.34) | (0.02, 0.09, 0.20) |
| | h=16 | h=12 | h=15 | h=12 |
| $\pi^{long,c}$ | (0.03, 0.07, 0.17) | — | (0.03, 0.05, 0.10) | — |
| | h=11 | | h=9 | |

Note: The numbers in parenthesis show the 16$^{th}$, 50$^{th}$, and 84$^{th}$ percentiles of the maximum response of inflation and inflation expectations to forward guidance and QE shocks, for the benchmark and a model without long-term expectations.

## 1.5 Conclusions

In response to the Great Recession and the Sovereign Debt Crisis, the ECB implemented a series of unconventional monetary policy tools, in order to address the undershooting of inflation and inflation expectations. Despite the high degree of policy accommodation, inflation remained low. In this study, I propose a novel identification approach of monetary policy shocks and analyze the effectiveness of conventional, communication and unconventional tools for pushing up inflation and expectations of consumers and forecasters. To the best of my knowledge, this is the first paper to jointly assess empirically the implications of multidimensional monetary policy onto what worries the ECB the most: inflation.

The main result of this paper is that the long-term inflation expectations of professional forecasters anchor for most of the shocks. Moreover, inflation increases and remains significant for about a year after forward guidance and QE shocks. To test the importance of the re-anchoring effect for monetary policy transmission, I re-estimated the VAR models excluding long-term inflation expectations of professional forecasters from the model. I find a weaker response of inflation after forward guidance and QE shocks. This result has strong policy implications because it means that the anchoring of inflation expectations could imply a (median) difference of 0.3 and 0.24 percentage points in inflation, for forward guidance and QE, respectively. In addition, I also find that, despite the communication of a negative economic outlook, professional forecasters increase their long-term inflation expectations. Together with the strong results of forward guidance, the main message I extract is that agents listen. This means that how the ECB communicates monetary policy decisions and the economic outlook is crucial for the transmission of monetary policy via the expectations channel. Therefore, the ECB has still enough space in the design of more transparent communication tools.

Whilst this paper distinguishes between several types of unconventional monetary policies, there is still room for a deeper analysis. For instance, studying the transmission of negative interest policy rates and by further differentiating out the effects of the Targeted Longer-Term Refinancing Operations (TLTROs).

Although the results of this paper exclusively isolate the effects of monetary policy, there are other structural factors contributing to the low-inflation-low-expectations environment. Examples include the impact of digitalization, demographic conditions, and climate change on the economy. The evaluation of the interaction of these factors with monetary policy is key for the design and development of further monetary policy tools. However, this topic is left for future research.

## 1.A Inflation and inflation expectations in the euro area

Figure 1.6 shows the evolution of the yoy inflation rate for the euro area aggregate. One of the main lessons from this graph is that inflation remained low. On average, it reached a level of 1.5% in the period between January 2007 and February 2020, the considered estimation period in the VAR from equation (1.17).

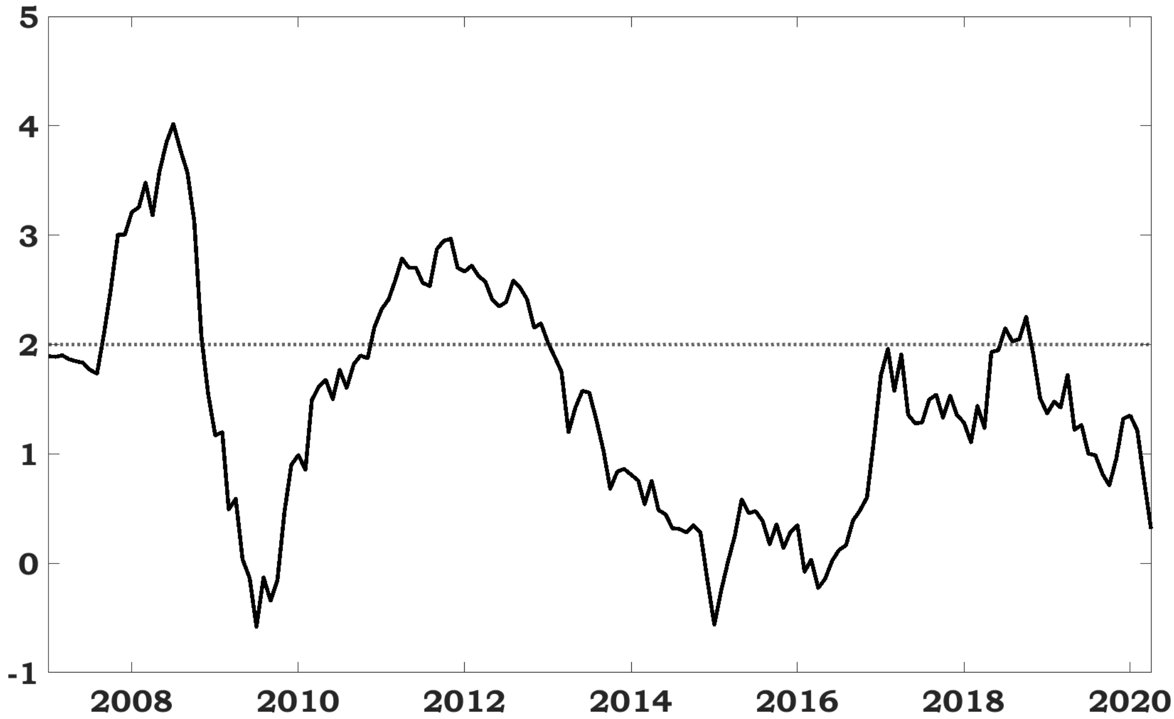


Figure 1.6: Inflation in the euro area

The short-term expectations of consumers are depicted in figure 1.7. This time series refers to the balance index based on the consumer's survey conducted by the European Commission. In detail, consumers respond the question: *By comparison with the past 12 months, how do you expect that consumer prices will develop in the next 12 months?* They have the following available answers: increase more rapidly, increase at the same rate, increase at a slower rate, stay about the same, fall, and don't know. Therefore, the balance index captures the overall expectations about the evolution of the trend in inflation.[26]

[26]For detailed information about the construction of the balance index see https://ec.europa.eu/info/sites/info/files/bcs_user_guide_2021_02_en.pdf.

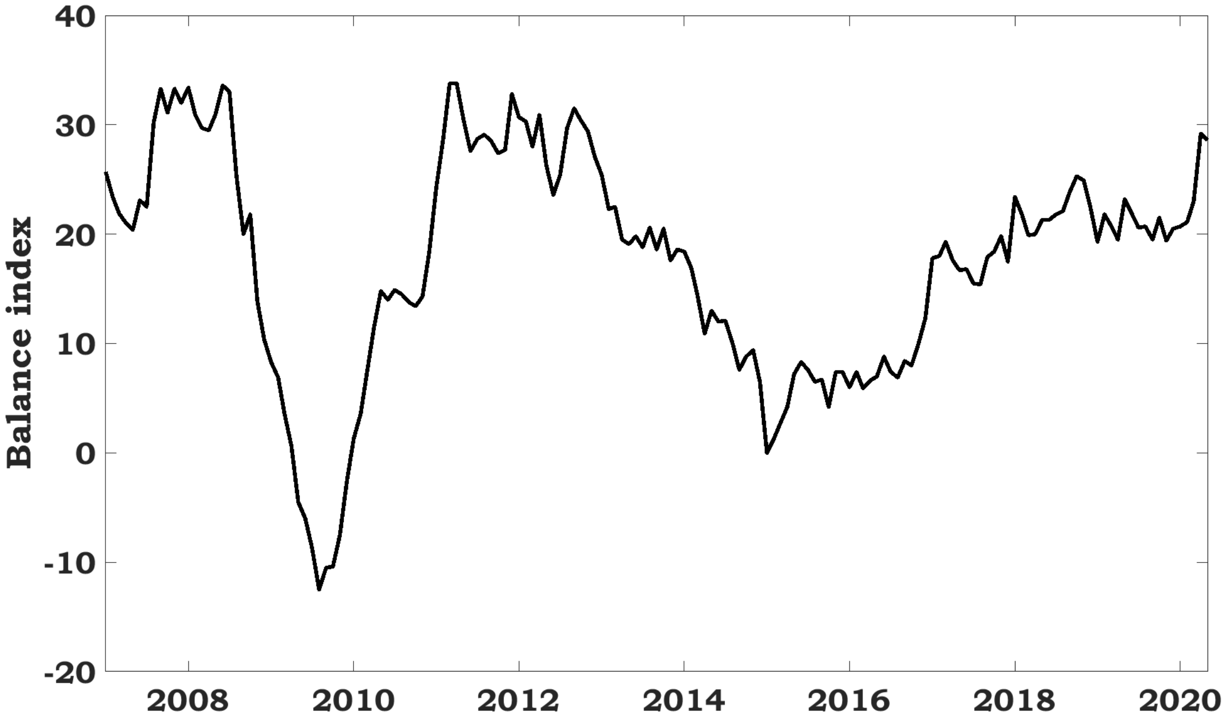


Figure 1.7: Inflation expectations of consumers in the euro area

Note: The chart depicts the short-term (one-year-ahead) expectations of consumers based on the qualitative balance index computed by the European Commission.

Figure 1.8 depicts the short-term and the long-term inflation expectations of professional forecasters. The black line shows the median response of one-year ahead expectations from the Eurozone Barometer (EB), gathered by MJEconomics. The green line represents the average response of the ECB's survey of professional forecasters (SPF) at the five-years horizon. This data is originally available in a quarterly frequency and I transformed it to a monthly variable through a Chow-Lin decomposition.

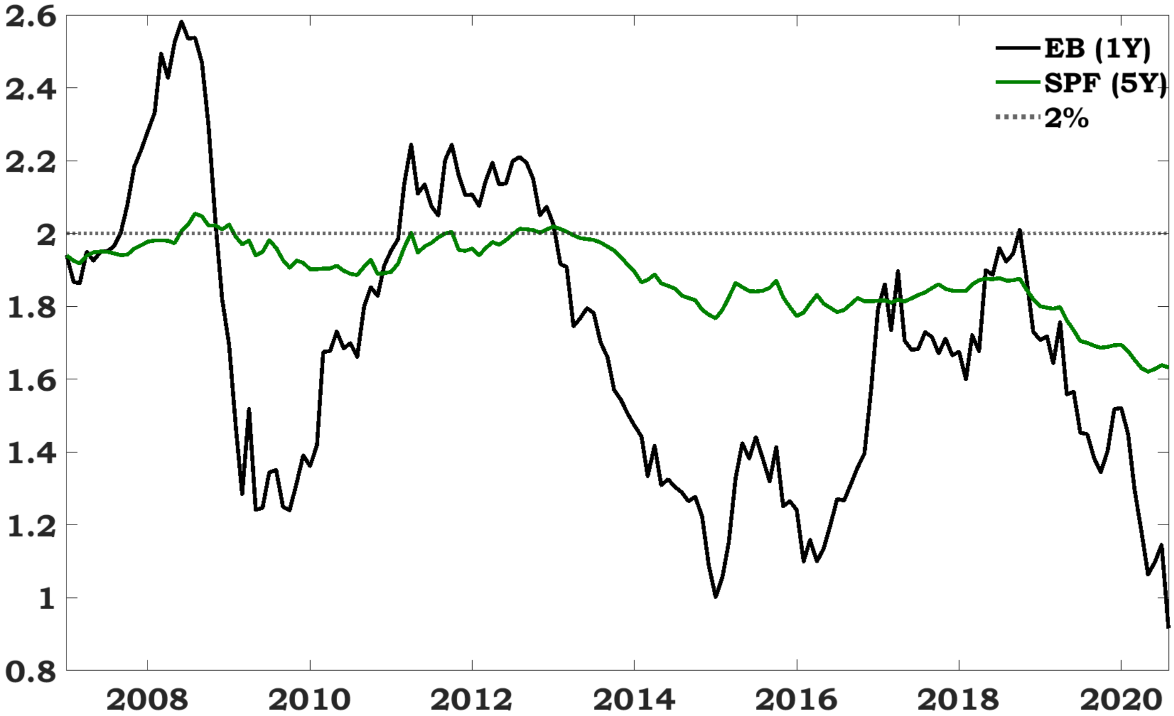


Figure 1.8: Inflation expectations of professional forecasters in the euro area

Note: The black line shows the short-term expectations (one-year-ahead) of professional forecasters taken from the Eurozone barometer of MJEconomics. The green line depicts the long-term expectations (five-year-ahead) from the ECB's survey of professional forecasters.

## 1.B Target factors from two windows

Figure 1.9 shows the bar plot of the target factors from the press release window (red) and from the monetary policy event window (gray). These factors co-move and have a correlation of 0.6.

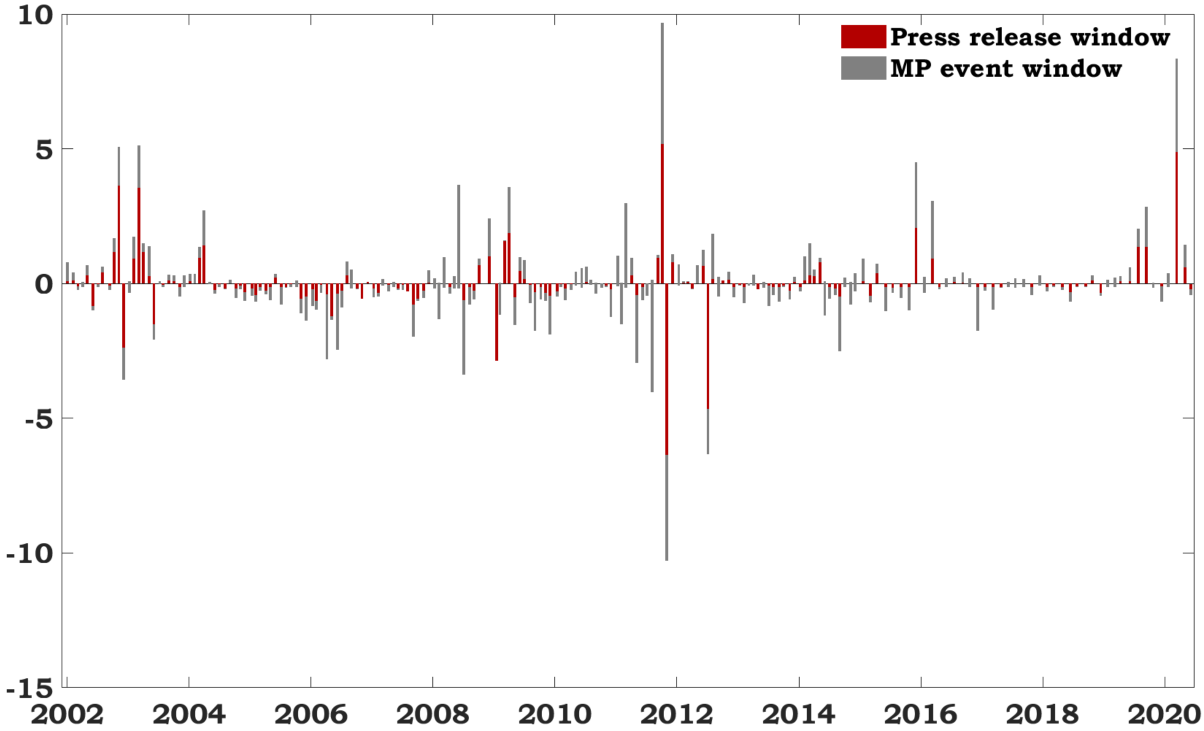


Figure 1.9: Target factors

## 1.C Monetary policy proxies and selected governing council meetings

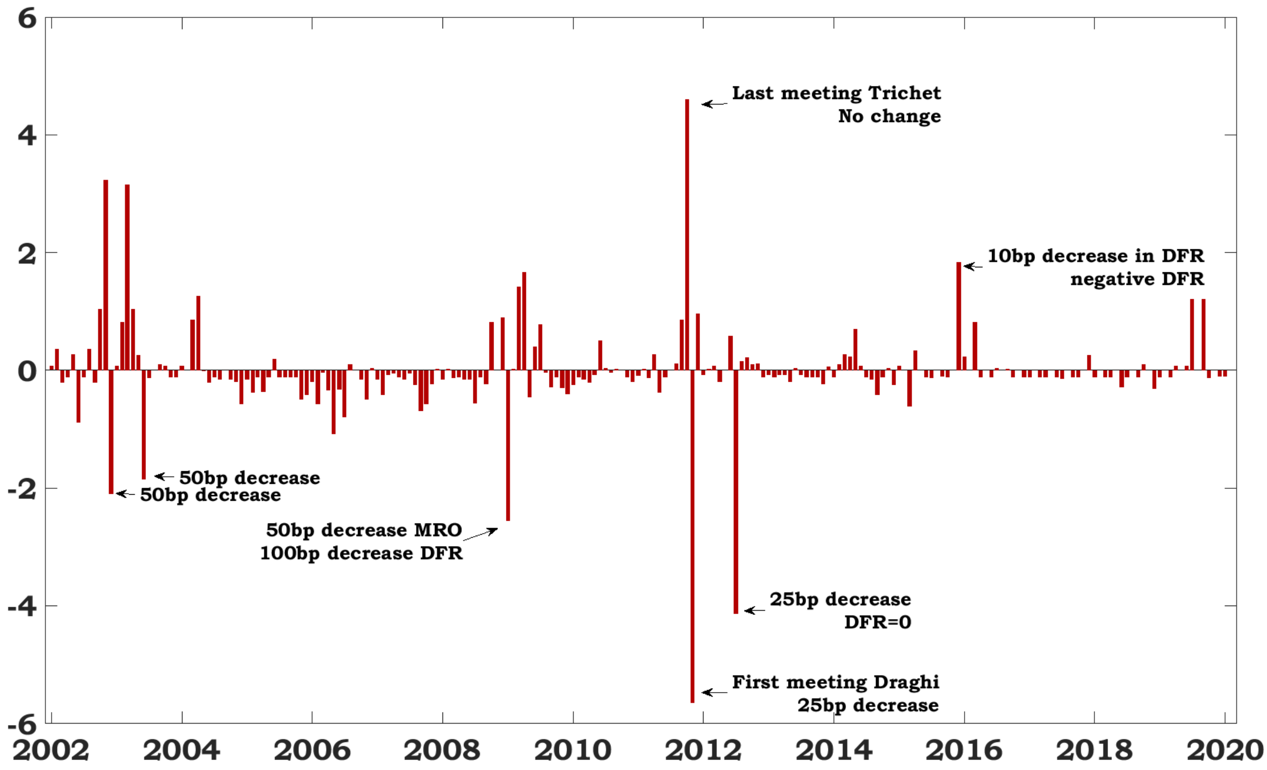


Figure 1.10: Target factor and selected policy decision dates

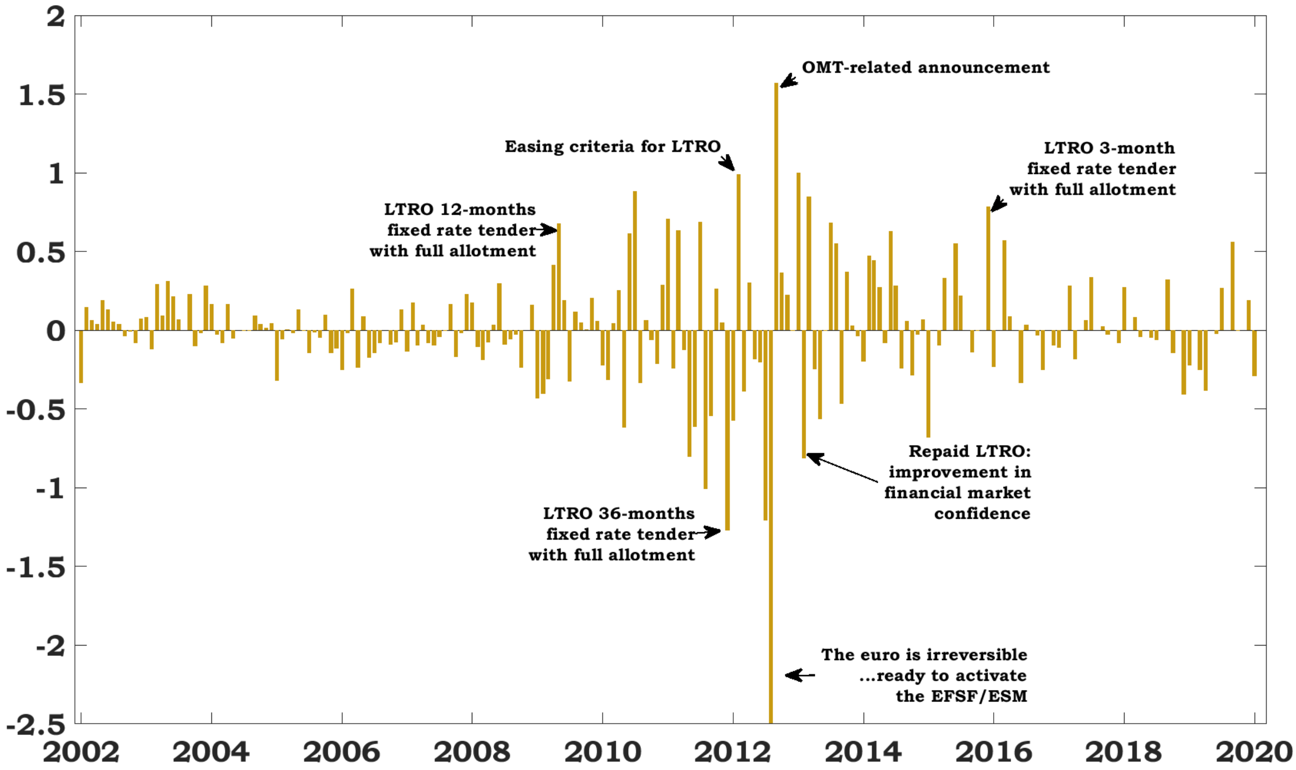


Figure 1.11: LTRO factor and selected policy decision dates

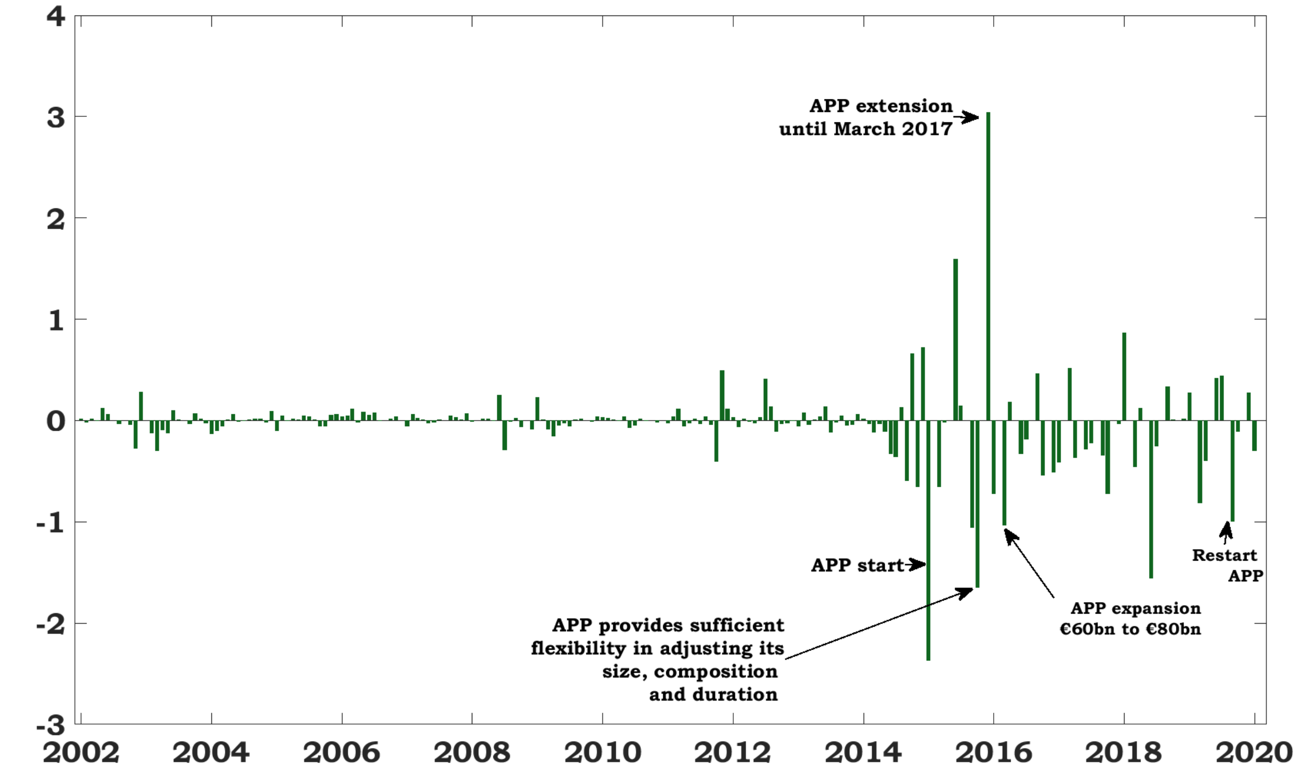


Figure 1.12: QE factor and selected policy decision dates

## 1.D Data description

Table 1.5 shows the description of the macroeconomic and financial data used in the large hybrid VARs as endogenous variables. The majority of variables are transformed to the yoy rate, i.e.,

$$y_{i,t}^{yoy} = 100 \times ((\ln(y_{i,t}) - \ln(y_{i,t-12}))).$$

I select this transformation for two reasons. First, the ECB designs monetary policy in order to achieve its mandate of price stability, which concerns the yoy inflation rate of the euro area aggregate. Second, the surveys of short-term inflation expectations are normally conducted based on this transformation. I leave interest rates, spreads, and variables already expressed as annualized rates in levels.

The column RW equals one when the variable is shrunken towards a random walk and 0 when the variable is considered stationary. In other words, this is the indicator $\delta_i$ in equation (1.11).

Table 1.5: Data description VAR model

| Variable | Description | Source | Trans. | RW |
|---|---|---|---|---|
| IP | Volume index of production; Mining and quarrying; manufacturing; electricity, gas, steam and air conditioning supply; Seasonally and calendar adjusted data; Index, 2015=100 | Eurostat | yoy | 0 |
| UR | Percentage of active population; Seasonally adjusted data, not calendar adjusted data | Eurostat | levels | 1 |
| ESI | Economic sentiment indicator (EA) | Eurostat | yoy | 0 |
| HIPC | All-items HICP; Index, 2015=100 | Eurostat | yoy | 0 |
| CONSEXP | Price trends over the next 12 months, Seasonally adjusted data, not calendar adjusted data, Balance index | Eurostat | levels | 1 |
| PROFEXP | Consensus mean of one-year ahead inflation forecast (eurozone barometer) | MjEconomics | levels | 1 |
| SPF | Euro area - HICP Inflation - Average of Point forecasts - Long term | ECB-SDW | levels | 1 |
| OILPRICE | Brent crude oil 1-month Forward - fob (free on board) per barrel - Historical close, average of observations through period | ECB-SDW | yoy | 0 |
| COMPRICE | ECB Commodity Price index, import weighted | ECB-SDW | yoy | 0 |
| EONIA | Eonia rate - Historical close, average of observations through period | ECB-SDW | levels | 1 |
| YLD2Y | Yield curve spot rate, 2-year maturity - Government bond, nominal, all issuers all ratings included - | ECB-SDW | levels | 1 |

| | | | | |
|---|---|---|---|---|
| | Euro area (changing composition) | | | |
| YLD20Y | Yield curve spot rate, 20-year maturity - Government bond, nominal, all issuers all ratings included - | ECB-SDW | levels | 1 |
| SOVSPR | Euro area (changing composition) yield and 10-year German sovereign bond yield (own calculations) | Eurostat | levels | 1 |
| SPNFCEA | Spread of euro area NFC with respect to Bund | BdF | levels | 1 |
| SPBKEA | Spread of euro area banks with respect to Bund | BdF | levels | 1 |
| NEER | ECB Nominal effective exch. rate of the Euro against, EER-19 group of trading partners excluding the Euro; Average of observations through period | ECB-SDW | yoy | 1 |
| EUROSTOXX50 | Dow Jones Euro Stoxx 50 Price Index, source: DataStream | ECB-SDW | yoy | 0 |
| LOANS | Loans vis-a-vis euro area NFC reported by MFI excluding ESCB in the euro area (stock) | ECB-SDW | yoy | 0 |
| LOANSHH | Loans vis-a-vis euro area households reported by MFI excluding ESCB in the euro area (stock) | ECB-SDW | yoy | 0 |
| CISSEA | Composite Indicator of Sovereign Stress Euro area, correlation and equal-country weights | ECB-SDW | yoy | 0 |
| COST | Cost of borrowing for corporations - euro area | ECB-SDW | levels | 1 |

## 1.E Convergence test

The estimation of the hybrid Bayesian VARs from equation (1.17) is based on 50000 draws, whereby I use the last 25000 draws for inference. In order to assess the convergence of the MCMC algorithm, I compute the $\chi^2$-test proposed by Geweke (1992).[27] The idea is to carry out a test of equal mean between the initial 20% and the last 60% of the draws. Given the fact that we have a total of 23 variables (including the proxy in the VAR), six lags, and an intercept, I test a total of 3726 parameters (3197 from the reduced-form matrices and 529 from the covariance matrix).

As standard in Bayesian estimation, I consider every tenth draw for inference, in order to reduce the chances of autocorrelated draws. In figure 1.13, I show the histograms of the $\chi^2$ test p-value, for each VAR. I highlight in red the proportion of parameters that do not converge based on a 5% significance level. Since this group only corresponds to 4%-5% of the total parameters, we accept the results.

[27] I conduct the convergence check through the build-in functions of the Econometrics toolbox of James P. LeSage, available in https://www.spatial-econometrics.com/

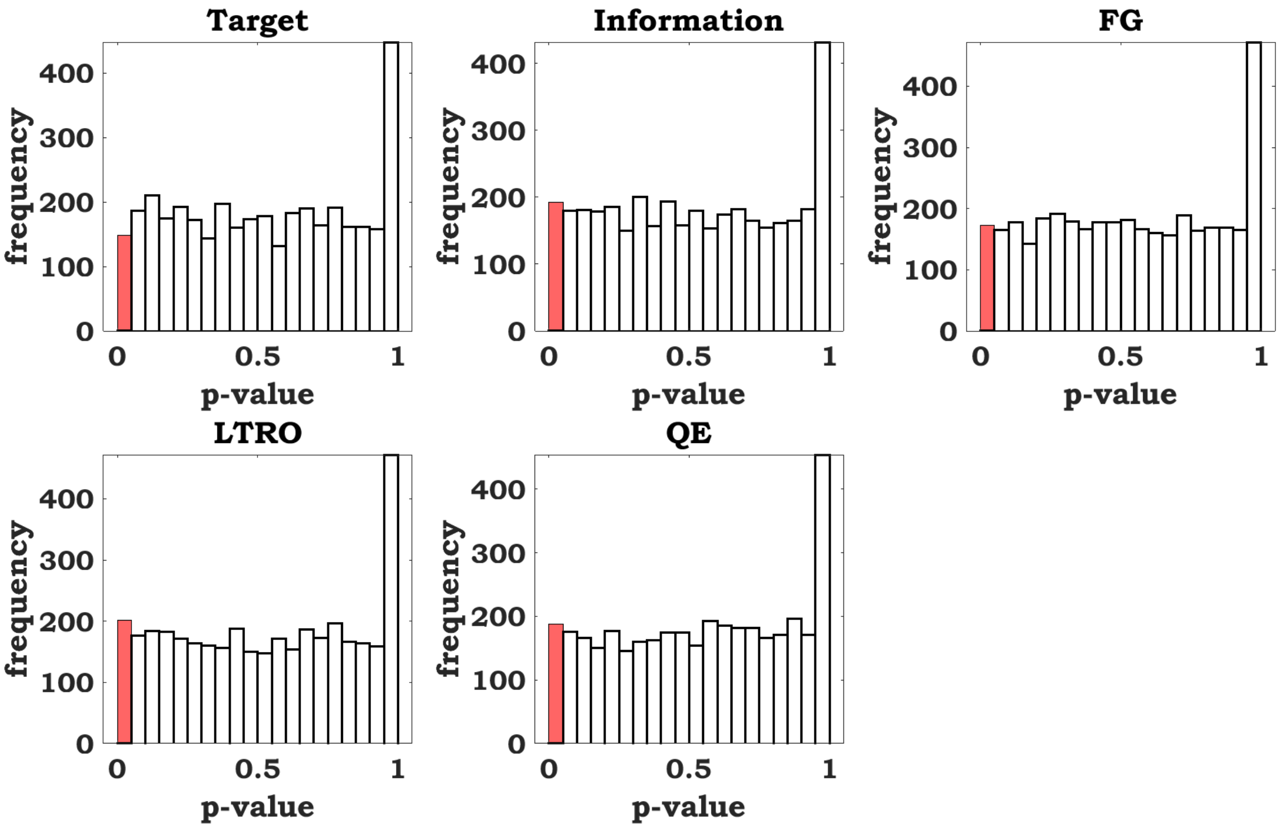


Figure 1.13: Geweke convergence test (p-values)

Note: This figure shows the histogram of the p-values from the $\chi^2$-test of Geweke (1992).

## 1.F Further impulse responses

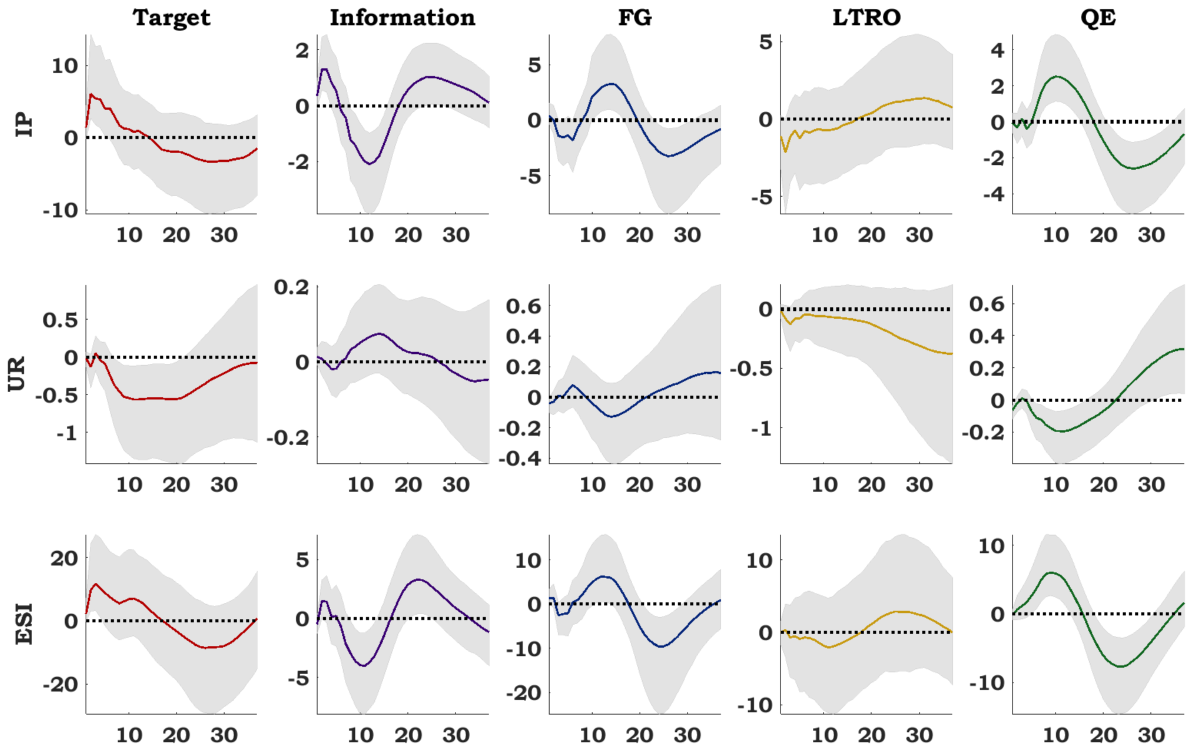


Figure 1.14: Responses of output variables to multi-dimensional monetary policy

Note: This figure shows the impulse responses of expansionary target (red), information (purple), forward guidance (blue), and QE (green) shocks, normalized to a decrease of 20 basis points in the EONIA, the two-years yield, and the twenty-years yield, respectively. The LTRO shock (yellow) is normalized to a 20 basis point decrease in the spread between Italian and German Government bond yields at the ten-years maturity. Bands represent the 68% pointwise credibility sets.

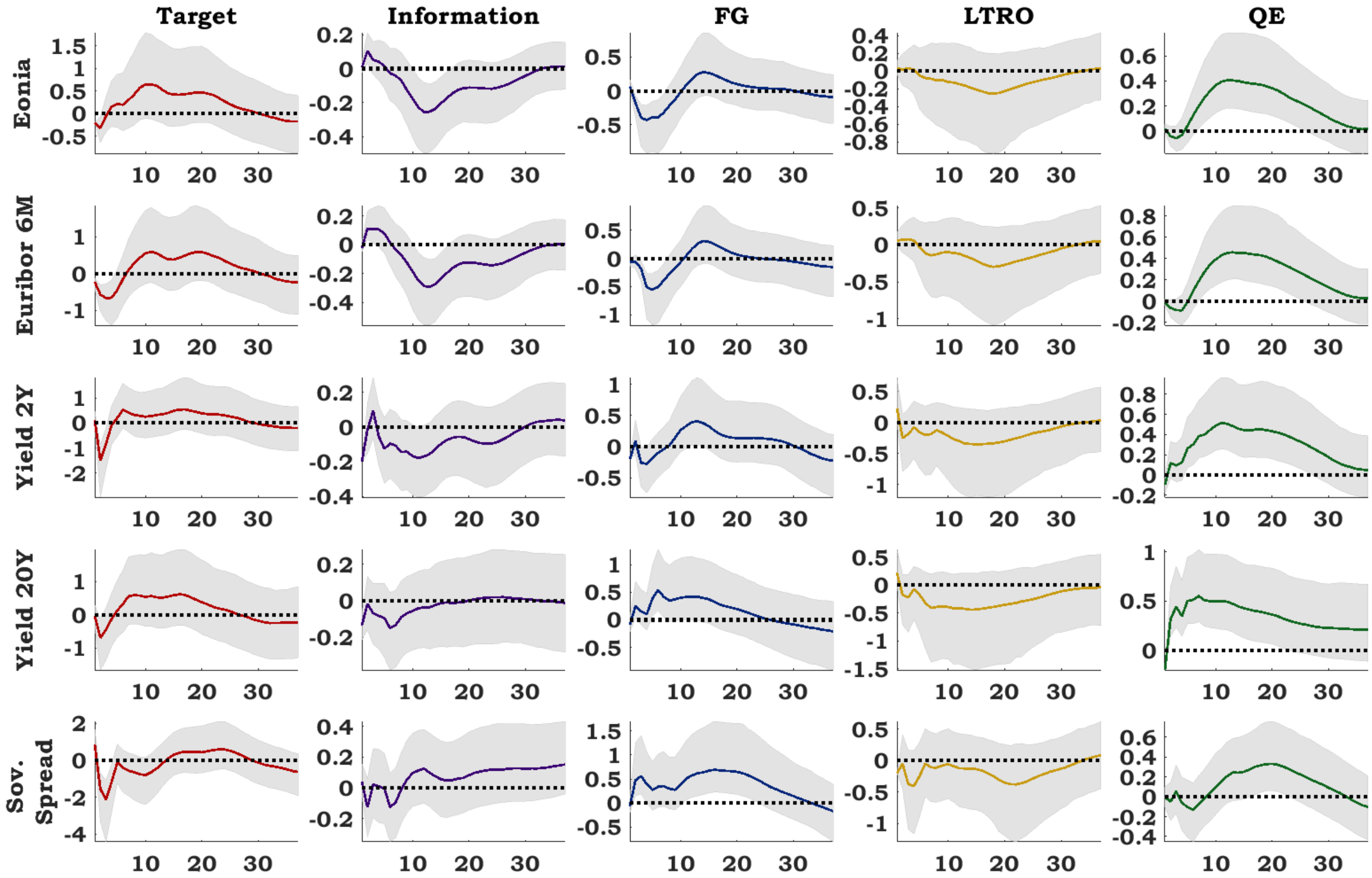


Figure 1.15: Responses of the euro area yield curve and the spread between Italian and German sovereign bond yields to multi-dimensional monetary policy

Note: See note in figure 1.14.

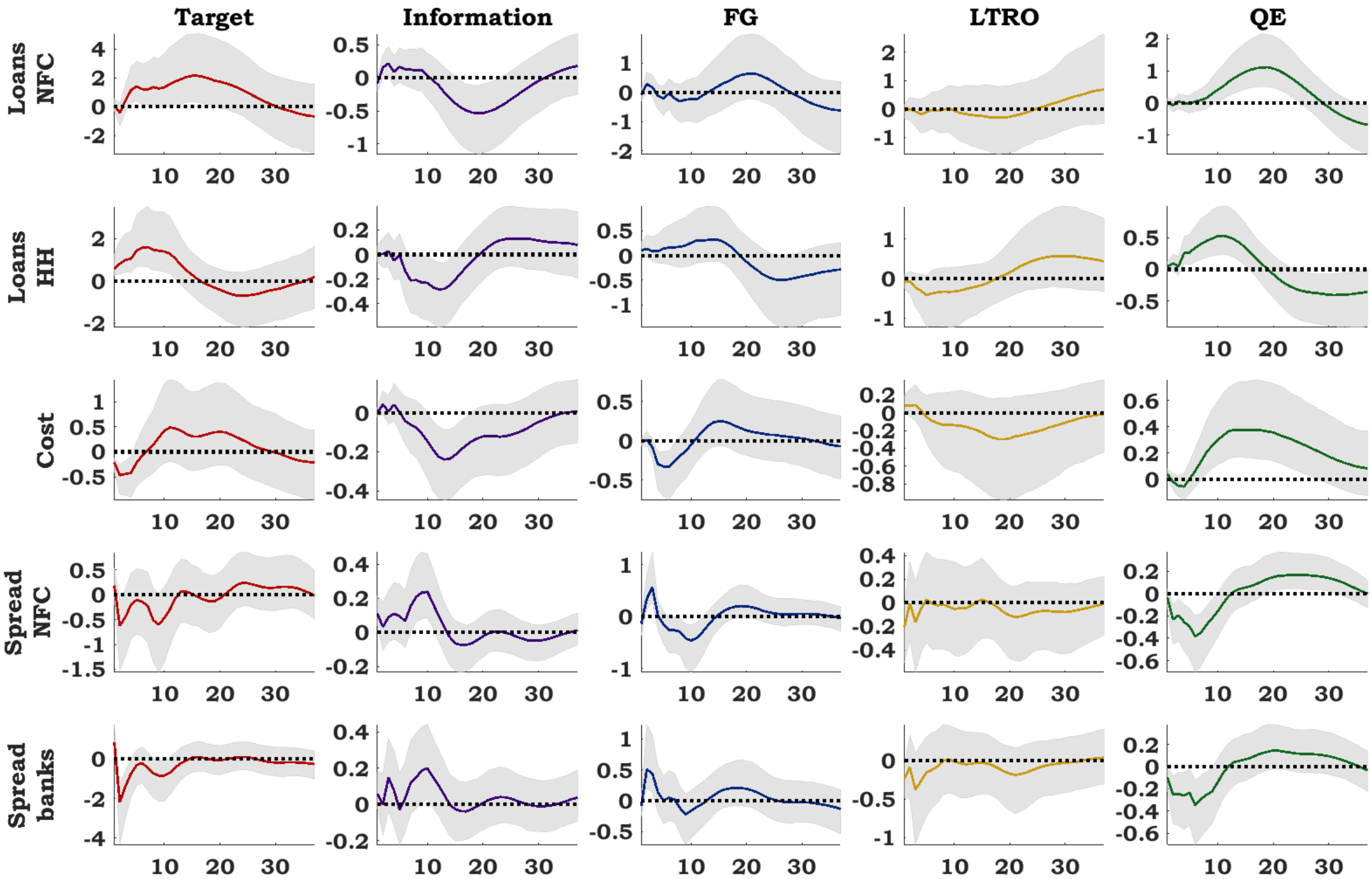


Figure 1.16: Responses of euro area financial variables to multi-dimensional monetary policy

Note: See note in figure 1.14.

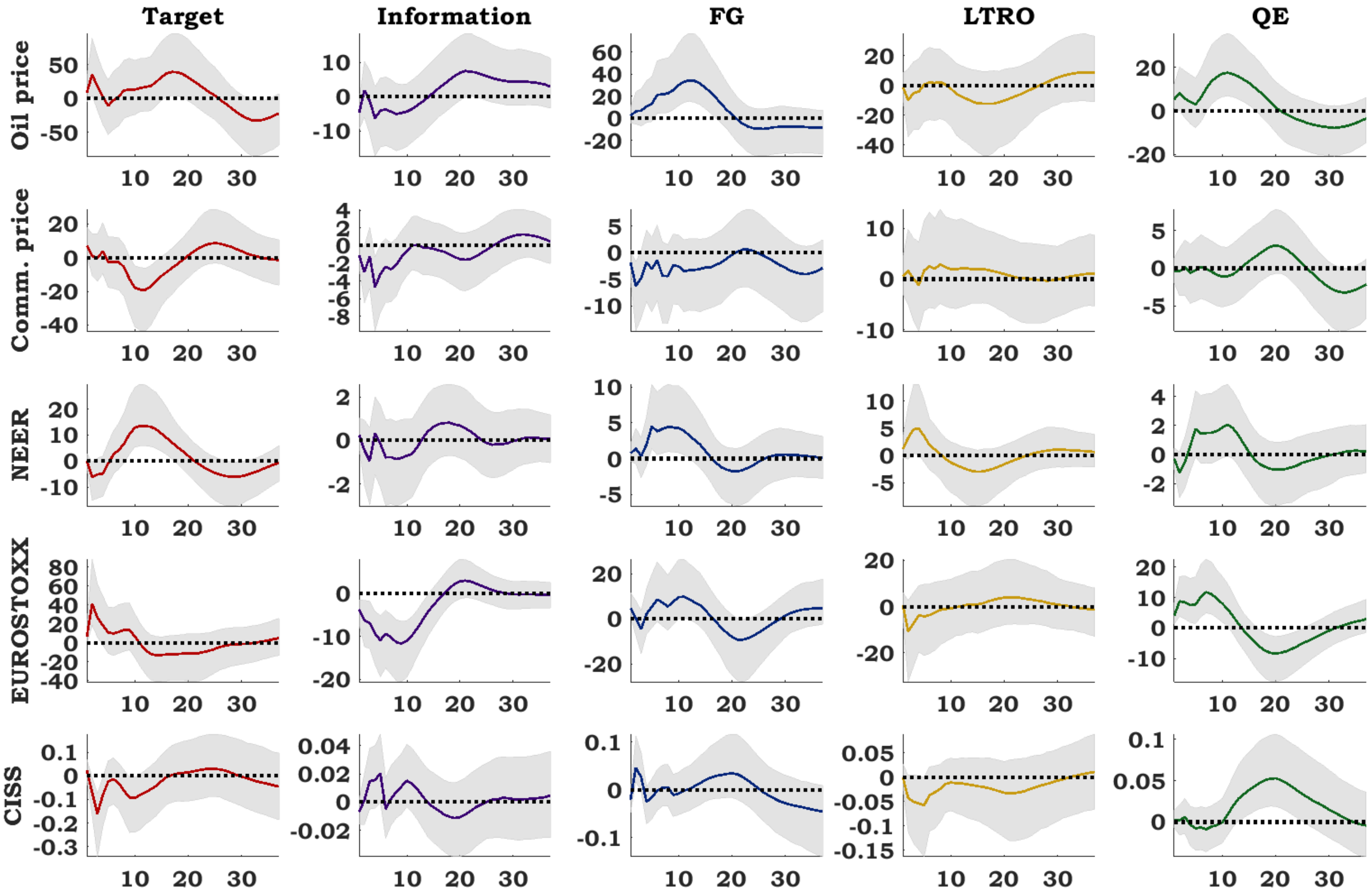


Figure 1.17: Responses of oil and commodity prices and further financial variables to multi-dimensional monetary policy

Note: See note in figure 1.14.

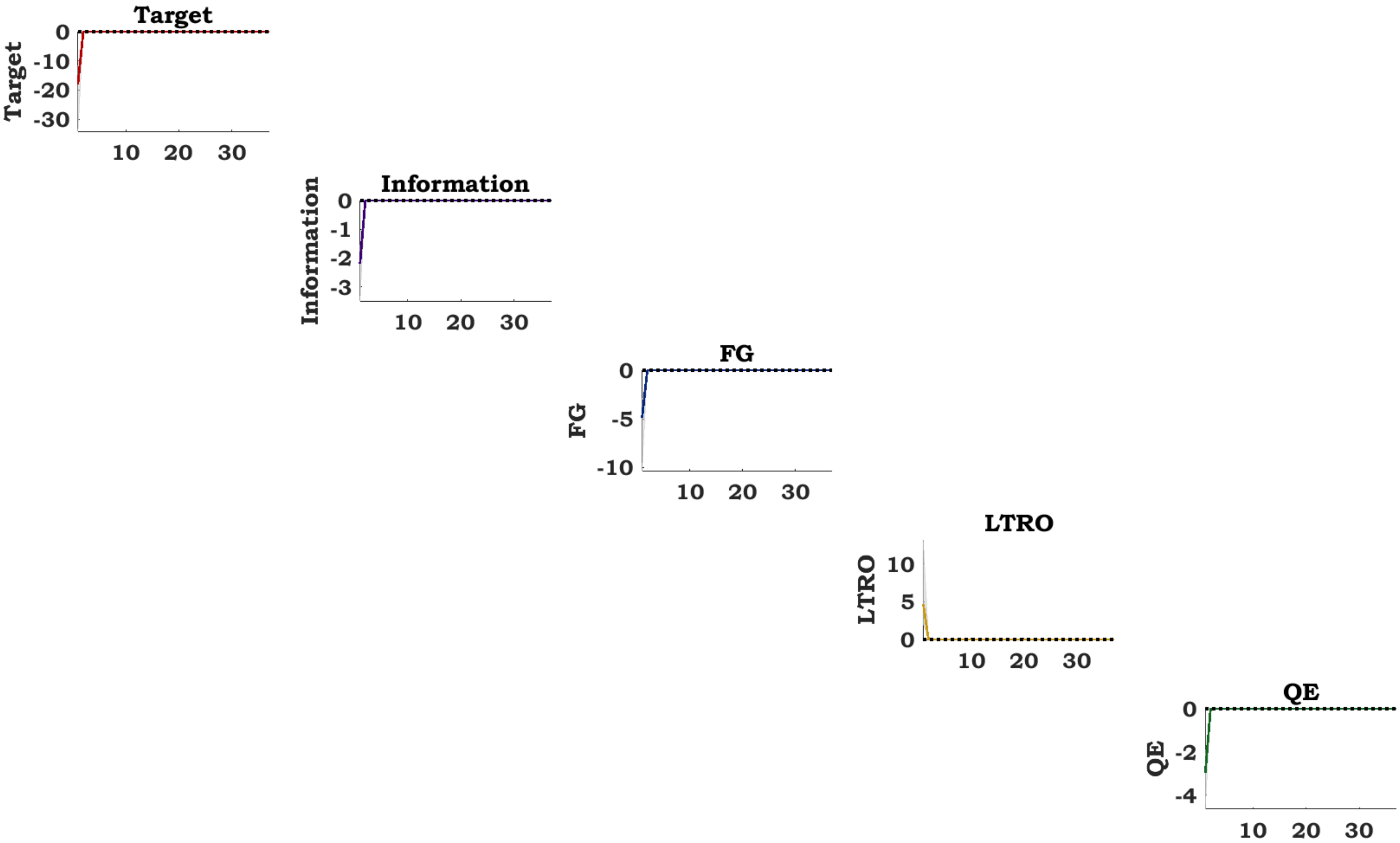


Figure 1.18: Responses of oil and commodity prices and further financial variables to multi-dimensional monetary policy

Note: See note in figure 1.14.

# 1.G Impulse responses without long-term expectations

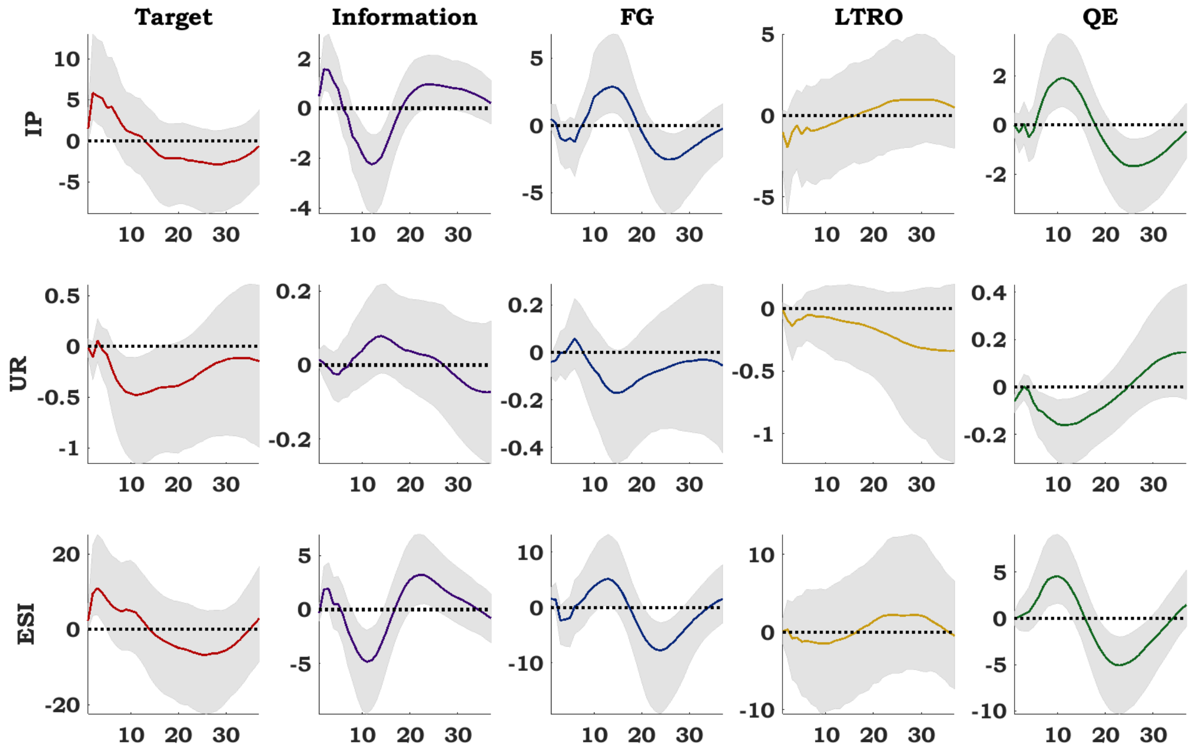


Figure 1.19: Responses of out[H]put variables to multi-dimensional monetary policy

Note: This figure shows the impulse responses of expansionary target (red), information (purple), forward guidance (blue), and QE (green) shocks, normalized to a decrease of 20 basis points in the EONIA, the two-years yield, and the twenty-years yield, respectively. The LTRO shock (yellow) is normalized to a 20 basis point decrease in the spread between Italian and German Government bond yield at the ten-years maturity. Bands represent the 68% pointwise credibility sets.

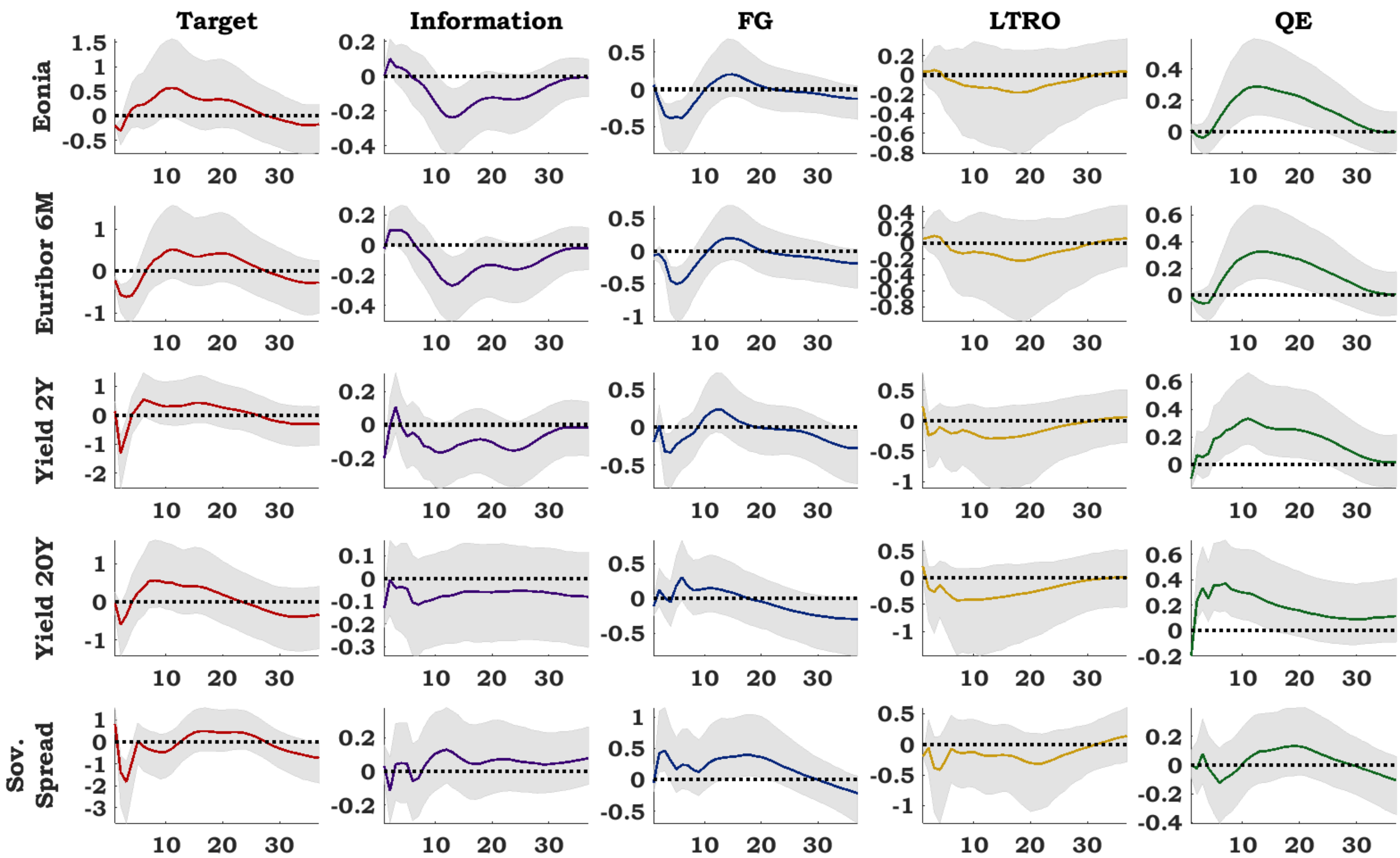


Figure 1.20: Responses of the euro area yield curve and the spread between Italian and German sovereign bond yields to multi-dimensional monetary policy

Note: See note in figure 1.19.

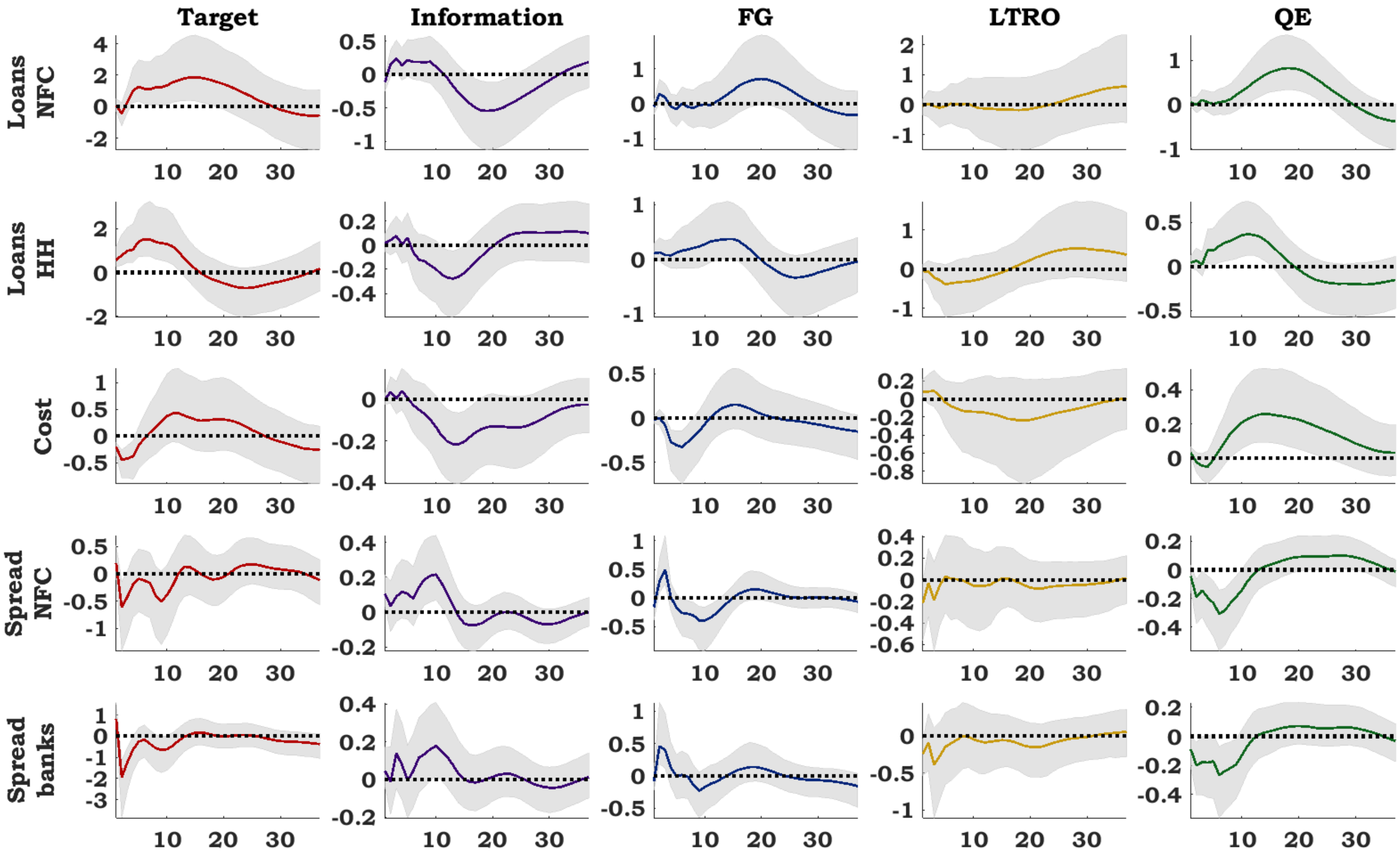


Figure 1.21: Responses of euro area financial variables to multi-dimensional monetary policy

Note: See note in figure 1.19.

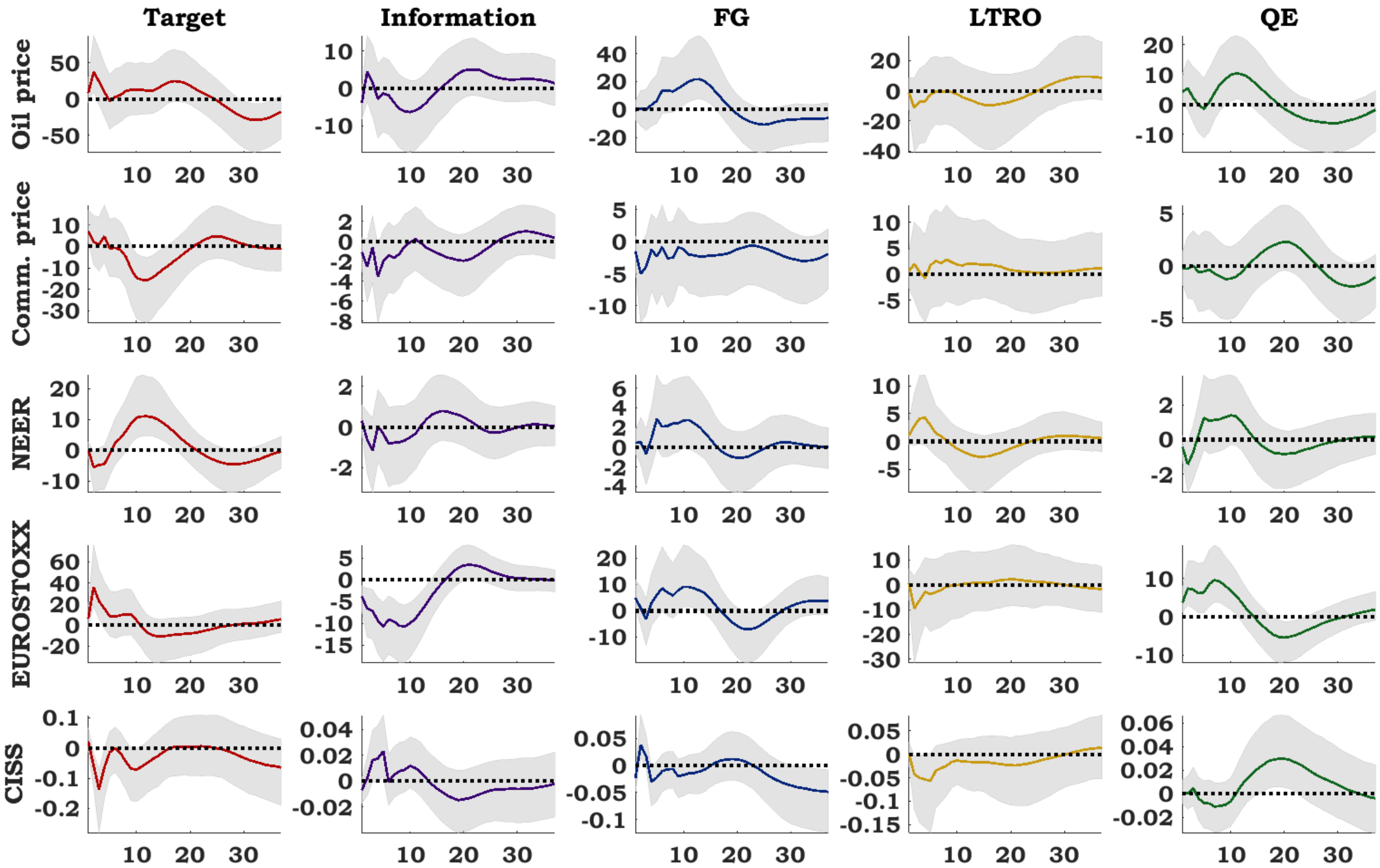


Figure 1.22: Responses of oil and commodity prices and further financial variables to multi-dimensional monetary policy

Note: See note in figure 1.19.

# Chapter 2

# Improving US Inflation Forecasting: The Role of Unbalanced Factor Models

## 2.1 Introduction

A key element underpinning the design of monetary policy is the analysis of a wide range of macroeconomic forecasts. In particular, inflation forecasting is relevant for policy makers and central banks since it provides an indicator of the future evolution of inflation, an important component in the decisions of households and firms regarding consumption, savings, and investment. Moreover, the majority of central banks in developed economies have the objective to stabilize prices, therefore, the analysis of inflation forecasts from different types of agents is crucial for assessing the anchoring of inflation expectations.

A part of the literature studying inflation forecasting focuses on obtaining predictions based on univariate and multivariate models using a handful of variables (Ang, Bekaert, and Wei (2007), Atkeson and Ohanian (2001), Chan, Koop, and Potter (2013, 2016), Chan, Clark, and Koop (2018), and Stock and Watson (1999, 2003, 2007), among many others). Examples of these models are the Autoregressive (AR) model, the Phillips curve, the unobserved components model, a small-scale vector autoregression (VAR), and random walks. Another branch of the literature focuses on models using large data sets. This is because the availability of data that can be used to construct a forecast is rapidly increasing and, simultaneously, the burden of storing large data has substantially decreased. Consequently, a variety of sparse and dense models are feasible techniques to forecast inflation (De Mol et al. (2008), Bańbura et al. (2010), Giannone et al. (forthcoming), Koop and Korobilis (2012), Korobilis (2013), Nakamura (2005), Stock and Watson (2002a,b), and Wright (2009), among many others). These include, for instance, factor models, the least absolute shrinkage and selection operator (LASSO), Ridge regressions, large Bayesian VARs, neural networks, and Bayesian moving average, among many others. In particular, factor models are popular in macroeconomics and finance due to their parsimonious way of shrinking the cross-sectional dimension of the data into a strictly smaller number of factors. Moreover, several authors find that factor models are particularly good for forecasting macroeconomic variables (see among many, Banerjee and Marcellino (2006), Boivin and Ng (2005, 2006), D' Agostino and Giannone (2012), Eickmeier and Ziegler (2008), Forni, Hallin, Lippi, and Reichlin (2003, 2005), Giannone et al. (2008), Schumacher and Breitung (2008), and Stock and Watson (2002a,b)).

In this paper, I analyze the accuracy of US inflation nowcasts and forecasts based on factor models. I concentrate on studying issues with unbalanced panels, a frequent empirical problem in dealing with big data models. I investigate three different types of missing observations: (i) Differences in the starting point of the time series; (ii) publication lags (also known as ragged-edges); and (iii) unsystematic missing observations in the middle of the time series (such as generated missing observations when dealing with outliers).[1] Problems with missing observations are sometimes trivially solved by trimming the data. This practice is likely to result in a loss of relevant information and, hence, decreases forecasting accuracy. Since the influential work of Rubin and Thayer (1982), Shumway and Stoffer (1982), and Watson and Engle (1983), missing observations in factor models are popularly approached through an Expectation-Maximization (EM) algorithm. Several authors propose extensions of these methodologies. For instance, Stock and Watson (2002b) develop an iterative interpolation procedure based on principal components analysis (PCA). Doz et al. (2012) rely on a quasi-maximum likelihood approach, where they fill the missing observations via the Kalman filter and estimate the parameters of the factor model through PCA and Ordinary Least Squares (OLS). Bańbura and Modugno (2014) further generalize the work of Shumway and Stoffer (1982), Engle and Watson (1983), and Doz et al. (2012). Their main contribution lies on a closed-form solution of an EM-algorithm based on maximum likelihood and the Kalman filter.

Despite the extensive literature on inflation forecasting, few papers analyze

[1]Mixed-frequencies are the fourth type of missing observations and they lie outside the scope of this chapter. However, I further study this issue in chapter 3.

unbalanced factor models.[2,3] In fact, to the best of my knowledge, there is no paper assessing the nowcasting and forecasting properties of the different unbalanced factor models for US inflation. For this reason, I contribute to the existing literature by closing this gap through a broad empirical comparison among the available algorithms for estimating an unbalanced factor model. Specifically, I evaluate the methodologies of Stock and Watson (2002b), Doz et al. (2012), and Bańbura and Modugno (2014). I additionally study the properties of the three-pass regression filter (Kelly and Pruitt (2015) and Hepenstrick and Marcellino (2019)), in order to capture a methodology that considers the forecasting variable in the computation of the factors. I analyze nowcasts and forecasts up to twelve months ahead for US Consumer Price Index (CPI) inflation. To do this, I conduct a pseudo real-time forecasting analysis, where I simulate the pattern of ragged-edges by February 1, 2021, for each estimated forecast. First, I analyze the forecasting accuracy of the models during an evaluation sample covering the 2000s until the period before the COVID-19 outbreak. In a second and third phase, I further focus on the periods covering the Global Financial Crisis and the ongoing COVID-19 crisis. As the benchmark model, I consider a forecast estimated by principal components, where I trivially fill the missing observations with zeros. This allows me to evaluate the gains of using a model that formally approaches unbalanced panels. Furthermore, I also compare factor-based forecasts to an AR model, in order to assess the forecasting gains of large data sets. Overall, I find that unbalanced factor models outperform the two considered benchmarks for the one- to twelve-months ahead horizons. Nonetheless, my results suggest that the best nowcasting model is the AR.

In a further exercise, I isolate the relevance of different data categories (output, consumption, prices, the financial market, the labor market, inflation expectations, housing, money, and interest rates) for improving inflation nowcasting and forecasting during the considered crises. I estimate the models eliminating each category one-by-one. Generally, I find that variables related to inflation expectations, money, and interest rates are crucial for obtaining more accurate inflation nowcasts during the Global Financial Crisis. Additionally, the consumption and the labor market categories seem to be important for the one-year ahead horizon. In contrast, for the COVID-19 period, I find that including interest rates and spreads in the data set significantly worsens the nowcasts.

[2] In this text, I refer to an unbalanced factor model when the estimation of a factor model is based on a data set with missing observations.

[3] An example is the nowcasting and forecasting study of Modugno (2013). However, he uniquely considers the methodology of Bańbura and Modugno (2014).

As a general result, I find that once I eliminate variables related to the housing market, the three-pass regression filter significantly outperforms the nowcast based on the AR during the Global Financial Crisis. Moreover, for the COVID-19 crisis, eliminating interest rates and spreads lets the methodologies of Bańbura and Modugno (2014) and Stock and Watson (2002b) improve the nowcasts with respect to the AR. My results highlight the forecasting gains of considering large information sets, as well as of choosing models that formally deal with the problem of missing observations.

This paper is organized as follows. Section 2.2 explains the considered algorithms for estimating an unbalanced factor model. Section 2.3 presents the main results of the pseudo real-time forecasting analysis. Finally, I conclude in section 2.4.

## 2.2 Unbalanced factor models

Factor models are popular for forecasting macroeconomic variables because they parsimoniously shrink the cross-sectional dimension of the data into a strictly smaller number of latent factors, $F_t$. Letting $X_t$ denote an $N \times 1$ vector of data, a dynamic factor model with $r$ factors is described by the following state-space representation:

$$X_t = \Lambda F_t + \epsilon_t, \quad \epsilon_t \overset{iid}{\sim} (0, R), \tag{2.1}$$

$$F_t = A_1 F_{t-1} + \ldots + A_p F_{t-p} + u_t, \quad u_t \overset{iid}{\sim} (0, Q), \tag{2.2}$$

where $\Lambda$ is an $N \times r$ matrix of loadings, $F_t$ is an $r \times 1$ vector of common factors, and $\epsilon_t$ is an $N \times 1$ vector of idiosyncratic terms. $A_1, \ldots, A_p$ are $r \times r$ matrices of parameters for up to $p$ lags; $R$ and $Q$ are the covariance matrices of $\epsilon_t$ and $u_t$, respectively. When the number of lags is set to zero, the model condenses to a static factor model. It is important to note that one of the assumptions of factor models is that the variables in $X_t$ are standardized to have zero mean and unit variance. Moreover, in this paper, I transform the data such that it is stationary, a standard assumption in factor models. For methodologies allowing for non-stationarity, long-memory, and cointegration, see Peña and Poncela (2004), Eichler, Motta, and Von Sachs (2011), Banerjee, Marcellino, and Masten (2014), Luciani and Veredas (2015), Barigozzi, Lippi, and Luciani (2016), and Corona, Poncela, and Ruiz (2020).

Equation (2.1) shows that the data can be decomposed into a common component and an idiosyncratic component. The common component is represented by $\chi_t = \Lambda F_t$, such that cov$(\chi_t, \epsilon_t) = 0$. The common component summarizes all shared information among the $N$ variables of the data set; while the idiosyncratic component, $\epsilon_t$, contains specific characteristics of the variables and measurement errors. In this paper, I assume that the data follows an approximate factor model (Chamberlain and Rothschild (1983) and Connor and Korajczyk (1986)), which allows for a small degree of cross-sectional dependence, i.e., the covariance matrix $R$ is not necessarily diagonal.

Unbalanced panels are a frequent empirical problem in the estimation of factor models. To assess this issue, Rubin and Thayer (1982), Shumway and Stoffer (1982), and Watson and Engle (1983) initially propose an Expectation-Maximization (EM) algorithm.[4] Since the 2000s, several authors have extended and refined these algorithms, thus allowing for more flexibility in the model and in the patterns of missing observations. Specifically, in this paper, I assess the methodologies of Doz et al. (2012), Bańbura and Modugno (2014), Stock and Watson (2002b), and Hepenstrick and Marcellino (2019). Although these methods deal with the problem of missing observations in different ways, they all are initiated by principal components. However, to achieve the full estimation of a factor model, Doz et al. (2012) rely on quasi-maximum likelihood; Bańbura and Modugno (2014) estimate the parameters through a maximum likelihood approach; Stock and Watson (2002b) focus on a PCA framework; and Hepenstrick and Marcellino (2019) extend the three-pass regression filter of Kelly and Pruitt (2015), which is based on the estimation of three equations via OLS. Moreover, whereas the methodologies of Doz et al. (2012) and Bańbura and Modugno (2014) address missing observations through the Kalman filter and smoother, Stock and Watson (2002b) and Hepenstrick and Marcellino (2019) consider a method that interpolates the missing data points. An overview of these properties is summarized in table 2.1. In the following subsections, I give a further explanation of each of the considered methods for estimating an unbalanced factor model.

[4]An EM algorithm is an iterative procedure to obtain solutions of a model when the likelihood is difficult to estimate. This method is based on two steps: for iteration $(j)$, the expectation step (E) consists of computing the expected value of the likelihood conditional on the data and on the estimated parameters from iteration $(j-1)$. The maximization step (M) optimizes the likelihood given the parameters from the E-step (for a detailed explanation, see Bańbura and Modugno (2014)).

Table 2.1: A comparison of unbalanced factor models

| Method | Estimation | Missing observations |
|---|---|---|
| Doz et al. (2012) | quasi-maximum likelihood | Kalman filter |
| Bańbura and Modugno (2014) | maximum likelihood | Kalman filter |
| Stock and Watson (2002b) | PCA | Interpolation |
| Hepenstrick and Marcellino (2019) | OLS | Interpolation |

### 2.2.1 The quasi-maximum likelihood estimation of Doz, Giannone and Reichlin (DGR)

Doz et al. (2012) develop a quasi-maximum likelihood approach for estimating a dynamic factor model characterized by equations (2.1) and (2.2). We define $\theta$ as the vector containing the parameters of the factor model, i.e., $\Lambda, R, A_1, \ldots, A_p$, and $Q$. For iteration $(j)$, the EM algorithm of Doz et al. (2012) consists of the following steps:

**E-step**: The common factors are approximated by their mean conditional on the data and the estimated parameters from the previous iteration:

$$F_t^{(j)} = E[F_t | X_t, \theta^{(j-1)}]. \tag{2.3}$$

This conditional moment is available via the Kalman filter and smoother.

**M-Step:** The updated factors from the E-step are treated as the real factors and the estimation of the parameters in $\theta^{(j)}$ is carried out by OLS.

Doz et al. (2012) highlight that this EM-algorithm converges to the local maximum of the likelihood. For further details about the asymptotic behavior of this procedure, I refer the reader to the appendices of Doz, Giannone, and Reichlin (2011); Doz et al. (2012).

Although the original paper of Doz et al. (2012) does not directly address missing observations, a straightforward extension allowing for unbalanced panels is available by integrating the methodology of Durbin and Koopman (2012) in their algorithm. The intuition behind this approach is that, for each $t = 1, \ldots, T$, the parameters of the model are uniquely estimated using the available data. As a clarifying example, let us assume that we consider a data set with 10 variables. At time $t = 1$, the observations of the first two variables are missing. Therefore, the size of the vector with available data is $8 \times 1$. For this particular case, the first two rows of the loading matrix $\Lambda$ and the corresponding rows and columns of the covariance matrix $R$ are discarded in the estimation of the factor and the parameters.

The initial values of the factors, loadings, and the covariance matrix $R$ are set to principal components estimates, i.e., $F_t^{(0)} = \hat{F}_t^{PCA}$, $\Lambda^{(0)} = \hat{\Lambda}^{PCA}$, and $R^{(0)} = \hat{R}^{PCA}$. To obtain the PCA estimates, one can set the missing observations to zero, given that for standardized data, this is the unconditional mean of the variables. The parameters of the VAR of the factors are initialized by OLS, i.e., $A_i^{(0)} = \hat{A}_i^{OLS}$, for $i = 1, \ldots, p$; and $Q^{(0)} = \hat{Q}^{OLS}$.

The algorithm of Doz et al. (2012) is assumed to converge when the likelihood increments between two consecutive iterations is small. Specifically, the authors follow the rule:

$$\frac{\mathcal{L}(X; F_t^{(j)}, \theta^{(j)}) - \mathcal{L}(X; F_t^{(j-1)},\ \theta^{(j-1)})}{(\mathcal{L}(X; F_t^{(j)}, \theta^{(j)}) + \mathcal{L}(X; F_t^{(j-1)},\ \theta^{(j-1)}))/2} < 10^{-4},$$

where $X$ is the data available until observation $T$, $\mathcal{L}(X; F_t^{(j)}, \theta^{(j)})$ is the log-likelihood given the factors and the parameters from iteration $(j)$.

### 2.2.2 The maximum likelihood method of Bańbura and Modugno (BM)

Bańbura and Modugno (2014) extend the EM-algorithm of Doz et al. (2012) based on the work of Shumway and Stoffer (1982) and Engle and Watson (1983). Their method allows for general patterns of missing data and serially correlated idiosyncratic components.[5]

The E-step from the EM algorithm of Bańbura and Modugno (2014) coincides with the E-step of Doz et al. (2012). However, they conduct the M-step based on a maximum likelihood estimation. Their novelty boils down to providing a closed-form solution for the estimation of the parameters as follows:[6]

$$A^{(j)} = \left(\sum_{t=1}^{T} E[F_t F_{t-1}' | X, \theta^{(j-1)}]\right) \left(\sum_{t=1}^{T} E[F_{t-1} F_{t-1}' | X, \theta^{(j-1)}]\right)^{-1} \tag{2.4}$$

$$Q^{(j)} = \frac{1}{T} \left(\sum_{t=1}^{T} E[F_t F_t' | X, \theta^{(j-1)}] - A^{(j)} \sum_{t=1}^{T} E[F_{t-1} F_t' | X, \theta^{(j-1)}]\right) \tag{2.5}$$

[5]In an early version of this chapter, I estimate dynamic factor models with serially correlated idiosyncratic terms. However, I do not obtain forecasting gains due to the substantial increase of the parameters of the model. In this case, the idiosyncratic component becomes an $N$-dimensional vector of states. Therefore, the model is far from being parsimonious.

[6]I refer the reader to Bańbura and Modugno (2014) and its working paper version to obtain further details of how these formulas are obtained.

$$\text{vec}\left(\Lambda^{(j)}\right) = \left(\sum_{t=1}^{T} E[F_t F_t' | X, \theta^{(j-1)}] \otimes W_t\right)^{-1} \text{vec}\left(\sum_{i=1}^{T} W_t X_t E[F_t' | X, \theta^{(j-1)}]\right) \tag{2.6}$$

$$R^{(j)} = \text{diag}\left(\frac{1}{T}\left(\sum_{t=1}^{T} E[X_t X_t' | X, \theta^{(j-1)}] - \Lambda^{(j)} \sum_{t=1}^{T} E[F_t X_t' | X, \theta^{(j-1)}]\right)\right) \tag{2.7}$$

To deal with missing observations, they introduce the $N \times N$ diagonal selection matrix $W_t$, whose elements equal 0 when there is a missing observation and 1 otherwise. In other words, the updating formulas only take into consideration the available observations at time $t$. The moments $E[F_t'|X, \theta^{(j-1)}]$, $E[F_t F_{t-1}'|X, \theta^{(j-1)}]$, $E[F_t F_t'|X, \theta^{(j-1)}]$, and $E[F_{t-1} F_{t-1}'|X, \theta^{(j-1)}]$ are computed in the E-step through the Kalman filter and smoother following the approach in Durbin and Koopman (2012).

With the same intuition and notation as in the method of Doz et al. (2012), Bańbura and Modugno (2014) assume their algorithm converges according to the following rule:

$$\frac{\mathcal{L}(X; F_t^{(j)}, \theta^{(j)}) - \mathcal{L}(X; F_t^{(j-1)},\ \theta^{(j-1)})}{(|\mathcal{L}(X; F_t^{(j)}, \theta^{(j)})| + |\mathcal{L}(X; F_t^{(j-1)}, \theta^{(j-1)})|)/2} < 10^{-4},$$

### 2.2.3 The interpolation method of Stock and Watson (SW)

Stock and Watson (2002b) propose an EM-algorithm that interpolates missing observations based on a static factor model. This procedure minimizes the following function:

$$V^{\star}(F, \Lambda) = \sum_{i=i}^{N} \sum_{t=1}^{T} I_{i,t}(X_{i,t} - \lambda_i' F_t)^2, \tag{2.8}$$

where variable $I_{i,t}$ takes the value of 1 when $X_{i,t}$ is available and 0 otherwise, while $\lambda_i$ corresponds to the $i$-th row of the loading matrix $\Lambda$. When the data set is balanced, $I_{i,t}$ is omitted from the optimization problem and it reduces to a principal components estimation. Stock and Watson (2002b) clarify that, under the assumption $X_{i,t} \overset{iid}{\sim} \mathcal{N}(\lambda_i X_{i,t}, 1)$, the sum of squared idiosyncratic terms is proportional to the log-likelihood. Hence, equation (2.8) can be estimated in an iterative way through an EM-algorithm.

For iteration $(j)$, the raw stationary data is denoted by $\tilde{X}_t^{(j)}$. The algorithm starts by computing its mean, $\mu^{(j)}$, and its standard deviation, $\sigma^{(j)}$. The data $\tilde{X}_t^{(j)}$ is standardized to have mean zero and unit variance, in order to compute the factors $F_t^{(j)}$ and the loadings $\Lambda^{(j)}$ by principal components. Thus, the common component equals $\hat{\chi}_t^{(j)} = \hat{\Lambda}^{(j)} \hat{F}_t^{(j)}$. A particular data point missing in the original data is replaced by $\mu_i^{(j)} + \sigma_i^{(j)} \times \hat{\chi}_{i,t}$, which allows to construct the raw data at iteration $(j+1)$, $\tilde{X}^{(j+1)}$. This procedure is carried out until the factors and loadings converge.

The algorithm is assumed to achieve convergence when the change in the common component from two consecutive iterations is small. This is reflected by the following stopping rule:

$$\frac{\text{vec}(\hat{\chi}^{(j)} - \hat{\chi}^{(j-1)})'\text{vec}(\hat{\chi}^{(j)} - \hat{\chi}^{(j-1)})}{\text{vec}(\hat{\chi}^{(j-1)})'\text{vec}(\hat{\chi}^{(j-1)})} < 10^{-4}.$$

This method can be easily extended to a dynamic specification through augmenting the algorithm by a step that updates the factors through the Kalman filter and smoother. As in the previously explained methods, this algorithm is initialized using principal components and OLS estimates, setting the missing observations to zero.

### 2.2.4 The three-pass regression filter

A potential drawback of standard factor models is that the factors are computed without considering the forecasting variable in their estimation. To tackle this issue, Kelly and Pruitt (2015) propose the three-pass regression filter (TPRF), which is key in the idea that not all the factors that drive the data $X_t$ are actually relevant for forecasting the target variable $y_t$. Therefore, one of the main differences between the TPRF and a standard factor model is that the former identifies relevant factors to forecast the target variable; while the latter computes a series of factors that may be irrelevant for the target variable. To identify the relevant factors, the authors rely on a $T \times r$ matrix of proxies $Z$, which contains the common variation with the target variable. This method is parsimonious since it is based on the estimation of the following three regressions, estimated by OLS:[7]

**Pass 1:** For each variable $i = 1, \ldots, N$, I run the following time series regressions of the $T \times 1$ vector $X_i$ onto the proxies $Z$ and a constant:

$$X_i = \phi_{0,i} + Z\phi_i + \epsilon_t, \tag{2.9}$$

where $\phi_i$ is an $r \times 1$ vector of parameters and $\phi_{0,i}$ is the intercept term.

**Pass 2:** For each time period $t = 1, \ldots, T$, we use the $N \times r$ matrix $\hat{\phi}$ from

[7]For details about the asymptotic properties of this model, see Kelly and Pruitt (2015).

pass 1 as regressor in the following cross-sectional regressions:

$$X_t = \delta_{0,t} + \hat{\phi} F_t + \varepsilon_t, \tag{2.10}$$

where $X_t$ is an $N \times 1$ vector of data, $F_t$ is an $r \times 1$ vector of factors, and $\delta_{0,t}$ is the intercept.

**Pass 3:** A one-step ahead forecast of the target variable is computed through the regression:

$$y_{t+1} = \alpha + \beta \hat{F}_t' + \nu_{t+1}. \tag{2.11}$$

The idea of the TPRF is that the target variable is driven by a $T \times r$ matrix of factors $F$, which can be estimated through the proxies Z. Such proxies can be either chosen by the econometrician using economic theory or estimated through the Automatic Proxy-Selection Algorithm (APSA), which I review below. Thus, the first pass consists of regressing $X_i$ onto the proxies $Z$ and a constant, for each variable $i = 1, \ldots, N$. Pass 1 provides an estimate $\widehat{\phi_i}$ captures the level of sensitivity of variable $X_i$ to the proxies, as highlighted by Kelly and Pruitt (2015). In other words, this parameter is equivalent to the loadings matrix in standard factor models. Pass 2 is carried out by regressing $X_t$ onto the estimated sensitivity parameter matrix $\widehat{\phi}$ and a constant, for each time period $t = 1, \ldots, T$. As a result, we obtain an estimate of the relevant factors. Finally, in pass 3, a forecast is estimated following a direct equation.

The estimation of the proxies $Z$ is crucial, given that they are assumed to share common forces with the target variable $y_t$. Moreover, they are used in pass 1 for obtaining the sensitivity matrix. As previously stated, the computation of the proxies $Z$ can be done automatically through the APSA. We define the automatic proxy as $\omega_k$, for $k = 1, \ldots, r$. For the initial iteration, this algorithm sets the automatic proxy to the target variable, i.e., $\omega_0 = y_t$. The algorithm is built on the following steps:

1. For $k < r$, we define the proxy $\omega_k = \omega_{k-1}$,
2. The TPRF is carried out using $Z_k = \omega_k$, and
3. Proxy $\omega_k$ is constructed as $y_{t+1} - \hat{y}_{t+1|t}$, where $\hat{y}_{t+1|t}$ is the forecast computed by the third equation of TPRF.

Once the proxies are computed, a final run of the TPRF is carried out.

Hepenstrick and Marcellino (2019) modify the TPRF to the case of mixed frequency data and missing observations. This method initializes the parameters by principal components and interpolate the missing observations in the same fashion as in Stock and Watson (2002b). The difference is that, for iterations $j > 0$, the parameters are estimated through the TPRF instead of PCA. Dynamic versions of this methodology are trivially extended by updating the factors via the Kalman filter and smoother.

## 2.3 Pseudo real-time forecasting analysis

In this section, I analyze the empirical nowcasting and forecasting properties of the considered methods for estimating an unbalanced factor model. I carry out a pseudo real-time forecasting analysis, where I concentrate on forecasts of CPI inflation. Given that decisions regarding monetary policy are conducted based on a year-on-year (yoy) rate, I transform the target variable accordingly.

I analyze forecasts up to the one-year-ahead horizon and compute the $h$-step ahead forecasts based on the following direct equation:[8]

$$y_{t+h} = \alpha_i^{(h)} + \beta_i^{(h)} \widehat{F}_{i,t} + \nu_{i,t+h} \tag{2.12}$$

where $y_{t+h}$ is the yoy CPI inflation, $\widehat{F}_{i,t}$ are the factors estimated by model $i$, and $\nu_{i,t+h}$ is the forecast error. Thus, a forecast at horizon $h$ based on model $i$ is constructed as follows:

$$\hat{y}_{i,T+h|T} = \hat{\alpha}_i^{(h)} + \hat{\beta}_i^{(h)} \hat{F}_{i,T}, \tag{2.13}$$

where $T$ is the last available observation. It is important to note that, although the variables used to estimate the factors are standardized, the target variable does not follow any particular standardization.

I consider the constellation of models presented in table 2.2. To assess the accuracy gains of the unbalanced factor models from section 2.2, I take a forecast based on principal components as the benchmark. This is because, for constructing PCA-based forecasts, I trivially set the missing observations to zero, given that it is the unconditional mean of the variables. Additionally, I also include an AR model as a second benchmark, in order to assess the gains of using large data sets. Furthermore, I estimate factor-based forecasts allowing for lags of the target variable in the forecasting equation (2.12). As a result, I obtain highly correlated forecasts with the AR model. Therefore, I exclude them from the results of this paper, given their strong similarity to

[8]Other popular forecasting equations are based on sequential, unrestricted, and non-parametric approaches, see Boivin and Ng (2005) for a comparison.

the AR forecasts.

Table 2.2: Forecasting models

| Model | Description |
|---|---|
| BM | Dynamic factor model à la Bańbura and Modugno (2014) |
| SW | Dynamic factor model à la Stock and Watson (2002b) |
| TPRF | Dynamic three-pass regression filter à la Hepenstrick and Marcellino (2019) |
| DGR | Dynamic factor model à la Doz et al. (2012) |
| SW-S | Static factor model à la Stock and Watson (2002b) |
| TPRF-S | Static three-pass regression filter à la Hepenstrick and Marcellino (2019) |
| PCA | Principal components |
| AR | Autoregressive model |

### 2.3.1 Data

I estimate the forecasting models based on the FRED-MD, a data set gathered by the Federal Reserve Bank of St. Louis and frequently updated given new releases of the variables. A full description of this data set is found in appendix 2.A and for further details see McCracken and Ng (2016).[9] To capture the inflation expectations of market participants and consumers, I augment the data set with two more variables. Specifically, I include the 5-year-5-year forward inflation expectation rate and the median one-year-ahead inflation expectation from the Surveys of Consumers, collected by the University of Michigan.[10] In total, the data set has 130 variables divided in the categories: Output and income; consumption, orders and inventories; the labor market; housing; money and credit; interest rates and spreads; prices; the financial market; and inflation expectations. Following the standard assumptions in factor models, I transform the data such that each time series is stationary and standardized to have zero mean and unit variance.

I consider a sample spanning from January 1960 to February 2021 based on the vintage from February 1, 2021. Within this range, the data set contains three types of missing observations. I show examples of these patterns in

[9] This data set can be found in https://research.stlouisfed.org/econ/mccracken/fred-databases/.

[10] The 5-year-5-year forward inflation expectation rate measures the expected inflation of market participants in the long-term. Specifically, it summarizes the expectations over five years starting five years from today.

table 2.3, where the character "x" denotes available data and "NaN" depicts a missing value.

Table 2.3: Missing values patterns

| Date | CPIAUCSL | UMCSENT | FEDFUNDS | CP3M | EXUSUK | T5YIFR |
|---|---|---|---|---|---|---|
| Jan 1960 | x | NaN | x | x | x | NaN |
| Feb 1960 | x | x | x | x | x | NaN |
| Mar 1960 | x | NaN | x | x | x | NaN |
| Apr 1960 | x | NaN | x | x | x | NaN |
| May 1960 | x | x | x | x | x | NaN |
| Jun 1960 | x | NaN | x | x | x | NaN |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| Jan 1978 | x | x | x | x | x | NaN |
| Feb 1978 | x | x | x | x | x | NaN |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| Nov 2002 | x | x | x | x | x | NaN |
| Dec 2002 | x | x | x | x | x | NaN |
| Jan 2003 | x | x | x | x | x | x |
| Feb 2003 | x | x | x | x | x | x |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| Mar 2020 | x | x | x | x | x | x |
| Apr 2020 | x | x | x | NaN | x | x |
| May 2020 | x | x | x | x | x | x |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| Oct 2020 | x | x | x | x | x | x |
| Nov 2020 | x | x | x | x | x | x |
| Dec 2020 | x | x | x | x | x | x |
| Jan 2021 | NaN | NaN | x | x | x | x |
| Feb 2021 | NaN | NaN | x | x | NaN | x |

Note: the character "x" denotes an available observation and "NaN" depicts a missing value.

The first type of missing observations is due to different starting dates of the variables. For instance, the 5-year-5-year forward inflation expectation rate (T5Y1FR) is only available from 2003 onward. The second pattern of missing values corresponds to different release dates of the time series. This pattern is typically known in the forecasting literature as ragged-edges. For example, assuming it is February 1, 2021, the CPI (CPIAUCSL) and the Consumer Sentiment Index (UMCSENT) have a publication delay of one month, i.e., the data from January 2021 and the ongoing month are missing. Although the exchange rate between the dollar and the British pound (EXUSUK) is typically available at daily and intra-daily frequencies, I update it with respect to the updating frequency of the FRED website, which is weekly. By February 1, 2021, the latest available data point of the target variable (CPIAUCSL) is December 2020. Therefore, in addition to the twelve-step ahead forecasts, I also evaluate the nowcasts for the past and current months. Finally, the third pattern is due to unsystematic missing values in the middle of the time series. To depict this case, I show two examples. The UMCSENT was initially gathered as a quarterly variable and, in January 1978, it started being available at a monthly frequency. Another example is the missing observation of the 3-Month Commercial Paper Rate (CP3M) in April 2020. This is due to a generated missing observation as a result of a change in the filtering technique used by the Fed.[11]

### 2.3.2 Results

To conduct the pseudo real-time forecasting analysis, I simulate the pattern of ragged edges assuming that we forecast inflation on the first day of the month.[12] I carry out the analysis through an extended window approach based on a full evaluation sample spanning from January 2000 to December 2019. I choose the last month of the evaluation sample, because this is the last possible date for evaluating the twelve-step ahead forecast, i.e., December 2020.

For each date of the evaluation sample, I estimate the optimal number of factors based on the criterion proposed by Ahn and Horenstein (2013); as well as the number of lags in the dynamic factor models and in the AR model through the Bayesian Information Criterion (BIC). Figure 2.1 shows these selected parameters for each date of the evaluation sample. The number of factors ranges between two and ten, where fewer factors are selected between 2009 and 2016. The number of lags in the state equation of the dynamic factor models remains relatively stable at six lags. Finally, the number of lags in the AR-based forecasts ranges between two and eleven, selecting fewer lags in the period after the Global Financial Crisis.

[11]See announcement on May 7, 2020 in https://www.federalreserve.gov/feeds/cp.html

[12]Another interesting study is a real-time forecasting analysis, i.e., updating the data vintage with respect to the data release. Given that my goal is to compare the forecasting accuracy across methods, a more stable pattern of missing observations is more suitable. Therefore, I leave a real-time forecasting analysis for future research.


Figure 2.1: Parameters in forecasting analysis

Note: The upper left panel shows the selected number of factors by the criterion of Ahn and Horenstein (2013). The upper right panel corresponds to the selected lags in the dynamic factor models and the bottom panel presents the number of lags in the AR model, both selected by the BIC criterion.

To evaluate the forecasts, I construct the root mean squared forecast error (RMSFE) as follows:

$$RMSFE = \sqrt{\frac{\sum_{t=\tau_0}^{\tau_1-h}\left(\hat{y}_{i,t+h|t} - y_{t+h}\right)^2}{\tau_1 - h - \tau_0 + 1}}, \tag{2.14}$$

where $\tau_0$ and $\tau_1$ are the indices of the full sample representing the last available observation before the start of the evaluation sample and the end of the evaluation sample, respectively. This means that $\tau_0$ is December 1999 and $\tau_1$ is December 2019. The RMSFE is frequently used for evaluating point forecasts, where a larger number represents a less accurate forecast.

Figure 2.2 shows the RMSFE of the eight considered models for four different forecasting horizons: the nowcast of the previous month ($h = -1$), the nowcast of the present month ($h = 0$), the one-month ahead forecast ($h = 1$), and the twelve-months ahead forecast ($h = 12$). With the exception of the methodology of Doz et al. (2012), unbalanced factor models outperform forecasts based on PCA. These results suggest that using a model that formally deals with the problem of missing values produces more accurate inflation forecasts. Nevertheless, only forecasts based on the three-pass regression filter have small gains at the one-year ahead horizon, with respect to a univariate AR model.

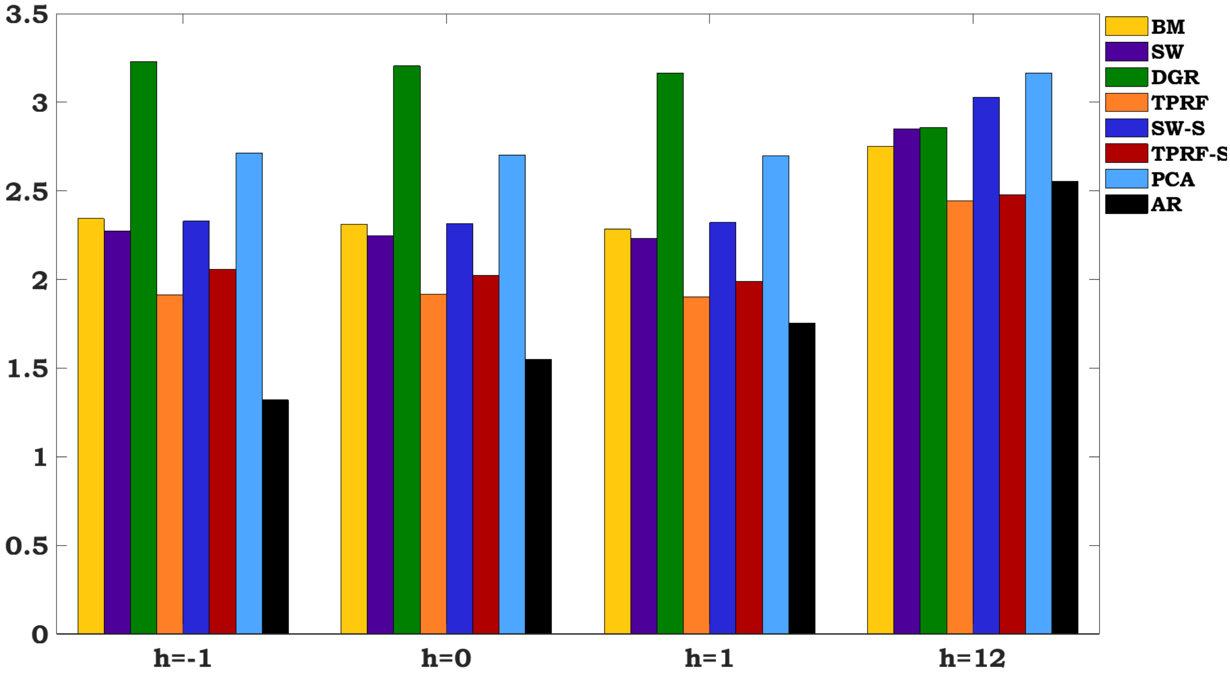


Figure 2.2: RMSFE for the full evaluation period

Additionally, in table 2.4, I show the RMSFE relative to a forecast based on principal components, for horizons $h = -1, 0, 1, \ldots, 12$. Thus, a number smaller than 1 represents a higher accuracy of the particular model in comparison to the benchmark model. To test if factor-based and AR-based forecasts have the same accuracy as the benchmark model, I conduct the test proposed by Harvey, Leybourne, and Newbold (1997) (HLN, henceforth). I find that all models outperform PCA forecasts, with the exception of the DGR model for short horizons. Although the AR model is superior for nowcasting and forecasting one-month ahead inflation, I find that the dynamic three-pass regression filter outperforms all models for horizons longer than one month. Moreover, these forecasts are significantly different than PCA forecasts up to horizon seven. A possible explanation of the good performance of the TPRF is that this methodology considers the target variable for the construction of the factors. In contrast, for the remaining factor models, the estimation of the factors is carried out regardless of the target variable. In this study, I find that the importance of large data sets for forecasting US inflation increases the longer the forecasting horizon.

Table 2.4: RMSFE relative to a PCA forecast, full evaluation sample

| | BM | SW | DGR | TPRF | SW-S | TPRF-S | AR |
|---|---|---|---|---|---|---|---|
| -1 | 0.87*** | 0.84*** | 1.19*** | 0.71*** | 0.87** | 0.76*** | **0.48***** |
| 0 | 0.86** | 0.84** | 1.18*** | 0.71*** | 0.86** | 0.75*** | **0.57***** |
| +1 | 0.85** | 0.83** | 1.17** | 0.71*** | 0.87** | 0.74** | **0.65**** |
| +2 | 0.84** | 0.83** | 1.13** | **0.69***** | 0.87** | 0.72** | 0.71** |
| +3 | 0.82** | 0.84** | 1.11 | **0.69**** | 0.88* | 0.71** | 0.76* |
| +4 | 0.81** | 0.84** | 1.05 | **0.68**** | 0.88* | 0.71** | 0.81 |
| +5 | 0.81** | 0.85** | 0.99 | **0.71**** | 0.89* | 0.72** | 0.84 |
| +6 | 0.81* | 0.86* | 0.92 | **0.74**** | 0.90 | 0.74** | 0.86 |
| +7 | 0.83* | 0.87* | 0.91* | **0.78*** | 0.91 | 0.79* | 0.89 |
| +8 | 0.84* | 0.89* | 0.90 | **0.80** | 0.92 | 0.82 | 0.92 |
| +9 | 0.85 | 0.90 | 0.90 | **0.81** | 0.94 | 0.82 | 0.92 |
| +10 | 0.86 | 0.91 | 0.90 | **0.78** | 0.95 | 0.80* | 0.88 |
| +11 | 0.87 | 0.91 | 0.90 | **0.77** | 0.96 | 0.79* | 0.83 |
| +12 | 0.88 | 0.91 | 0.91 | **0.76** | 0.97 | 0.78* | 0.80* |

Note: based on the HLN test of equal accuracy, numbers with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively. Bold numbers represent the best model.

### Assessing the Global Financial Crisis

The Global Financial Crisis triggered the lowest level of inflation observed since the 1960s and the highest level since the 2000s, see figure 2.3. Given that the crisis was defined by a high level of volatility in inflation, I additionally assess the accuracy of the forecasts during this period. Specifically, I consider the evaluation sample from December 2007 to June 2009, the official duration of the crisis accordingly to the National Bureau of Economic Research. Figure 2.4 shows the RMSFE of all considered models for the nowcasts, the one-month ahead forecasting horizon, and twelve-months ahead forecasting horizon, during the crisis period. Contrary to the results based on the full evaluation sample, I find that the accuracy of the AR model decreases. Overall, I also find that unbalanced factor models have a higher accuracy than the benchmark. These results reflect the importance of large information sets for forecasting inflation during the crisis.

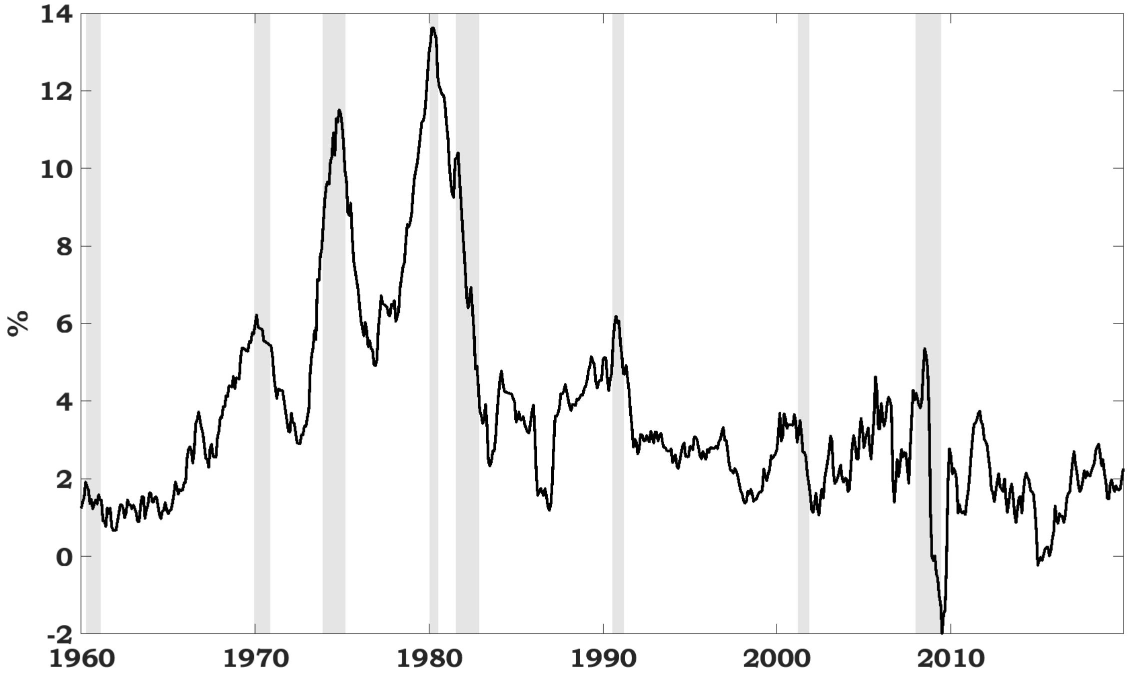


Figure 2.3: US CPI year-over-year inflation

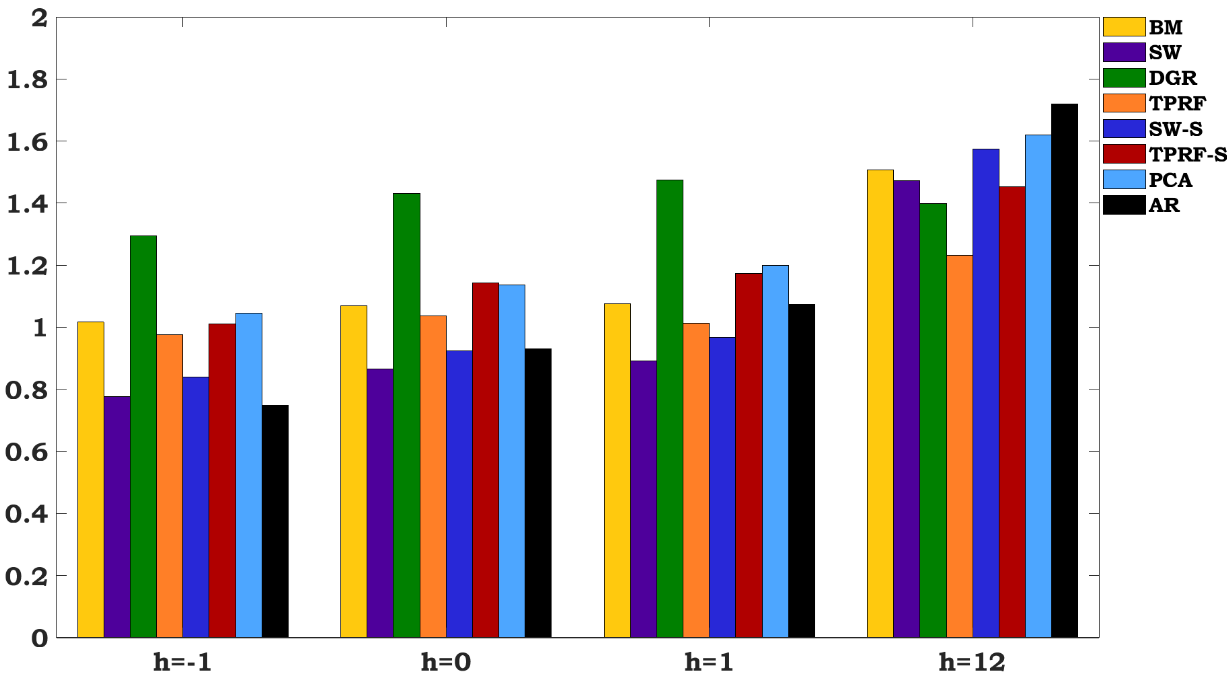


Figure 2.4: RMSFE during the Global Financial Crisis period

In table 2.5, I present the relative RMSFE of the models with respect to the benchmark model up to the twelve-month forecasting horizon. For this period, the AR model only outperforms factor-based nowcasts for the previous month. Moreover, I find that the EM-algorithms of Stock and Watson (2002b) and Bańbura and Modugno (2014) are the best methods for horizons 0-4 months and 5-9 months, respectively. For the ten- to twelve-months ahead horizons, the dynamic three-pass regression filter gives the most accurate forecasts. It is also important to note that, with the exception of the DGR model, forecasts based on PCA have a lower accuracy than unbalanced factor models.

Table 2.5: RMSFE relative to a PCA forecast, Global Financial Crisis

| | BM | SW | DGR | TPRF | SW-S | TPRF-S | AR |
|---|---|---|---|---|---|---|---|
| -1 | 0.97 | 0.74$^{***}$ | 1.24$^{***}$ | 0.93 | 0.80$^{***}$ | 0.97 | **0.72** |
| 0 | 0.94$^{*}$ | **0.76**$^{***}$ | 1.26$^{***}$ | 0.91 | 0.81$^{***}$ | 1.01 | 0.82$^{**}$ |
| +1 | 0.90$^{***}$ | **0.74**$^{***}$ | 1.23$^{***}$ | 0.84$^{*}$ | 0.81$^{***}$ | 0.98 | 0.90 |
| +2 | 0.85$^{***}$ | **0.72**$^{***}$ | 1.21$^{***}$ | 0.81$^{**}$ | 0.79$^{***}$ | 0.94 | 0.94 |
| +3 | 0.80$^{***}$ | **0.71**$^{***}$ | 1.28$^{***}$ | 0.78$^{**}$ | 0.78$^{***}$ | 0.90 | 1.01 |
| +4 | 0.71$^{***}$ | **0.70**$^{***}$ | 1.12$^{***}$ | 0.77$^{**}$ | 0.77$^{***}$ | 0.89$^{*}$ | 1.14 |
| +5 | **0.65**$^{***}$ | 0.73$^{***}$ | 1.07$^{***}$ | 0.85$^{**}$ | 0.80$^{***}$ | 0.92$^{*}$ | 1.28 |
| +6 | **0.64**$^{***}$ | 0.78$^{***}$ | 0.88$^{***}$ | 0.94 | 0.83$^{***}$ | 0.96$^{**}$ | 1.38$^{***}$ |
| +7 | **0.69**$^{***}$ | 0.83$^{***}$ | 0.84$^{***}$ | 0.97 | 0.87$^{***}$ | 1.03 | 1.41$^{***}$ |
| +8 | **0.74**$^{***}$ | 0.89$^{***}$ | 0.85$^{***}$ | 0.94 | 0.93$^{***}$ | 1.04 | 1.39$^{***}$ |
| +9 | **0.79**$^{***}$ | 0.94$^{**}$ | 0.87$^{***}$ | 0.86 | 0.98 | 0.97 | 1.31$^{***}$ |
| +10 | 0.85$^{***}$ | 0.94$^{**}$ | 0.86$^{***}$ | **0.79**$^{*}$ | 0.99 | 0.93 | 1.20$^{***}$ |
| +11 | 0.90$^{**}$ | 0.92$^{***}$ | 0.86$^{***}$ | **0.78**$^{*}$ | 0.98 | 0.92 | 1.11$^{***}$ |
| +12 | 0.93 | 0.91$^{***}$ | 0.86$^{***}$ | **0.76**$^{**}$ | 0.97$^{*}$ | 0.90$^{*}$ | 1.06$^{**}$ |

Note: see note in table 2.4.

As next step, I assess the importance of each data category for improving inflation forecasts based on unbalanced factor models. To do so, I re-estimate the models eliminating each data category one-by-one. The heatmaps in figures 2.5-2.8 depict the RMSFE of the nowcast for the previous month, the nowcast for the current month, the one-month ahead forecast, and the twelve-months ahead forecast, respectively. The rows in the heatmaps denote models where a particular category is eliminated. For example, row *-Cons.* means that the models are estimated without the variables in the category of consumption, orders, and inventories. The numbers in the heatmaps should be first compared column-by-column. For instance, column one shows the RMSFE of forecasts based on the model of Bańbura and Modugno (2014). Therefore, the goal is to compare each row of a column with respect to the first row (*All*), which contains the full data set. In this way, we are able to assess what we can gain or loose by excluding a particular category of data. As summarized by the scale on the right-hand side of the heatmaps, a number with a darker cell represents a less accurate model, since the RMSFE is higher. A second layer of comparison is the heatmap as a whole, where the best performing models are characterized by a cell with a lighter color.

In table 2.6, I show the RMSFE relative to the particular model using the full data set. This means that each row in the heatmaps is divided by the first row. I carry out the HLN test of equal accuracy for each of the models. A common result among horizons is that eliminating the variables related to interest rates and spreads seems to worsen the forecast for the majority of the models. The exceptions are the TPRF-S and the BM. This result means that including variables reflecting the monetary policy stance of the Fed is crucial for the accuracy of inflation nowcasts and forecasts during the Global Financial Crisis. Moreover, inflation expectations play an important role for improving the nowcast for the past and current months. This is because eliminating this category worsens the nowcasts, with the exception of the method of Doz et al. (2012). It is interesting to note that the category of inflation expectations only contains two variables: Consumers' and market participants' inflation expectations. Therefore, these two variables are an important pillar for the construction of the factors using the whole data set. Furthermore, including the category of money seems to be relevant for the nowcast of the current month and the one-month ahead horizon, with the exception of the TPRF. Finally, for the one-year ahead horizon, eliminating the variables related to the financial and the labor markets appears to deteriorate the forecast.

Taking a view to the whole heatmap, I find that the best model for all horizons corresponds to the TPRF. Specifically, the improvement relates to eliminating housing market variables for the nowcast of the previous month; discarding the category of output for the nowcast of the current month and the one-month ahead forecast; as well as erasing variables corresponding to the category of money for the one-year horizon. Although the models for the nowcasts and the one-month ahead horizons are significant at 1% level, there is not enough evidence to state that the TRPF without money variables has a different accuracy than the same model using the full data set. Nevertheless, the static version of the TPRF without the same category is the second-best performing model. Moreover, I can reject the null of equal accuracy with respect to the model using the full data set at the 1% level.

| | BM | SW | DGR | TPRF | SW-S | TPRF-S | PCA |
|---|---|---|---|---|---|---|---|
| All | 1.02 | 0.78 | 1.29 | 0.98 | 0.84 | 1.01 | 1.05 |
| -Cons. | 1.16 | 1.13 | 1.35 | 0.83 | 1.05 | 1.03 | 0.98 |
| -Expec. | 1.10 | 1.06 | 1.17 | 1.01 | 0.98 | 1.19 | 1.08 |
| -Finan. | 0.83 | 1.43 | 1.39 | 0.87 | 1.10 | 0.89 | 0.76 |
| -House | 1.04 | 1.15 | 1.34 | 0.67 | 1.07 | 0.86 | 1.01 |
| -Labor | 0.96 | 1.07 | 1.27 | 0.99 | 1.03 | 0.94 | 0.80 |
| -Money | 1.10 | 0.92 | 1.26 | 0.85 | 0.89 | 1.25 | 1.08 |
| -Ouput | 1.02 | 0.77 | 1.14 | 0.69 | 0.80 | 1.11 | 1.02 |
| -Price | 0.92 | 1.03 | 1.38 | 0.86 | 0.91 | 0.90 | 0.79 |
| -Rates | 1.71 | 1.03 | 1.55 | 0.98 | 1.02 | 0.91 | 1.21 |

Figure 2.5: RMSFE, $h = -1$, Global Financial Crisis period

Note: The heatmap depicts the RMSFE of the factor-based forecasts. The right-hand side scale shows that a cell with darker color represents a less accurate model, given that the RMSFE is higher. For the purpose of comparison, the RMSFE of an AR model equals 0.75.

| | BM | SW | DGR | TPRF | SW-S | TPRF-S | PCA |
|---|---|---|---|---|---|---|---|
| All | 1.07 | 0.87 | 1.43 | 1.04 | 0.92 | 1.14 | 1.14 |
| -Cons. | 1.20 | 1.21 | 1.53 | 0.88 | 1.12 | 1.09 | 1.06 |
| -Expec. | 1.15 | 1.17 | 1.35 | 1.04 | 1.06 | 1.26 | 1.17 |
| -Finan. | 0.86 | 1.46 | 1.47 | 0.93 | 1.15 | 0.94 | 0.86 |
| -House | 1.06 | 1.22 | 1.51 | 0.79 | 1.13 | 1.04 | 1.10 |
| -Labor | 0.96 | 1.13 | 1.37 | 1.03 | 1.11 | 1.06 | 0.88 |
| -Money | 1.16 | 1.00 | 1.43 | 0.89 | 0.98 | 1.29 | 1.17 |
| -Ouput | 1.07 | 0.84 | 1.35 | 0.73 | 0.87 | 1.16 | 1.11 |
| -Price | 0.90 | 1.08 | 1.38 | 0.90 | 0.97 | 0.96 | 0.88 |
| -Rates | 1.77 | 1.16 | 1.65 | 1.05 | 1.14 | 1.03 | 1.35 |

Figure 2.6: RMSFE, $h = 0$, Global Financial Crisis period

Note: See note in heatmap 2.5. For the purpose of comparison, the RMSFE of an AR model equals 0.93.

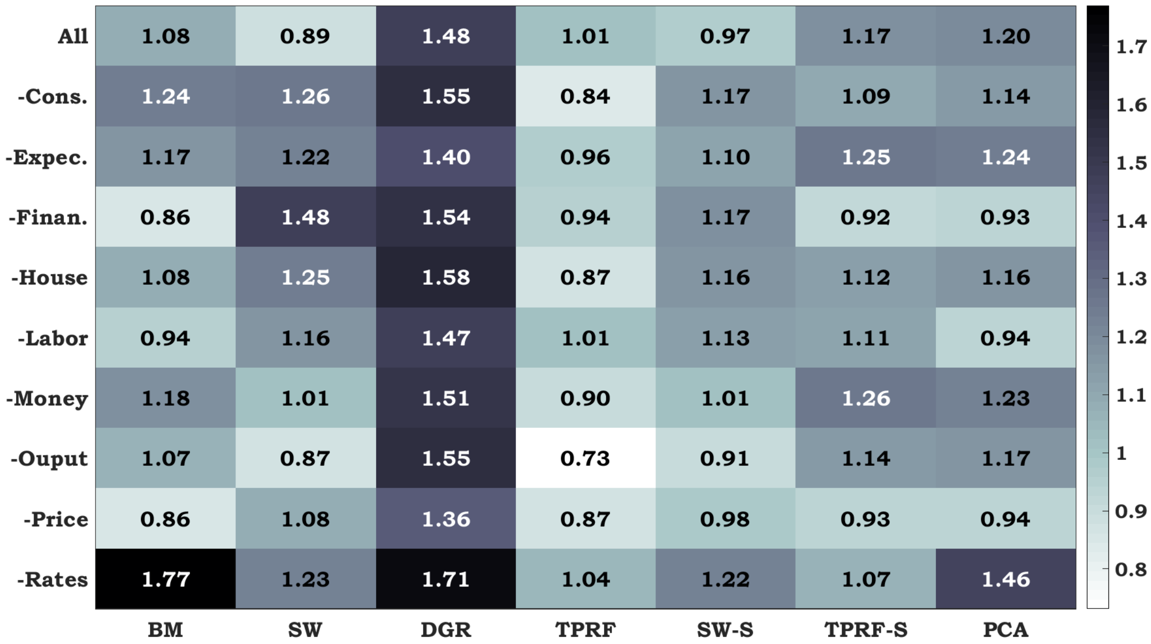


Figure 2.7: RMSFE, $h = 1$, Global Financial Crisis period

Note: See note in heatmap 2.5. For the purpose of comparison, the RMSFE of an AR model equals 1.07.

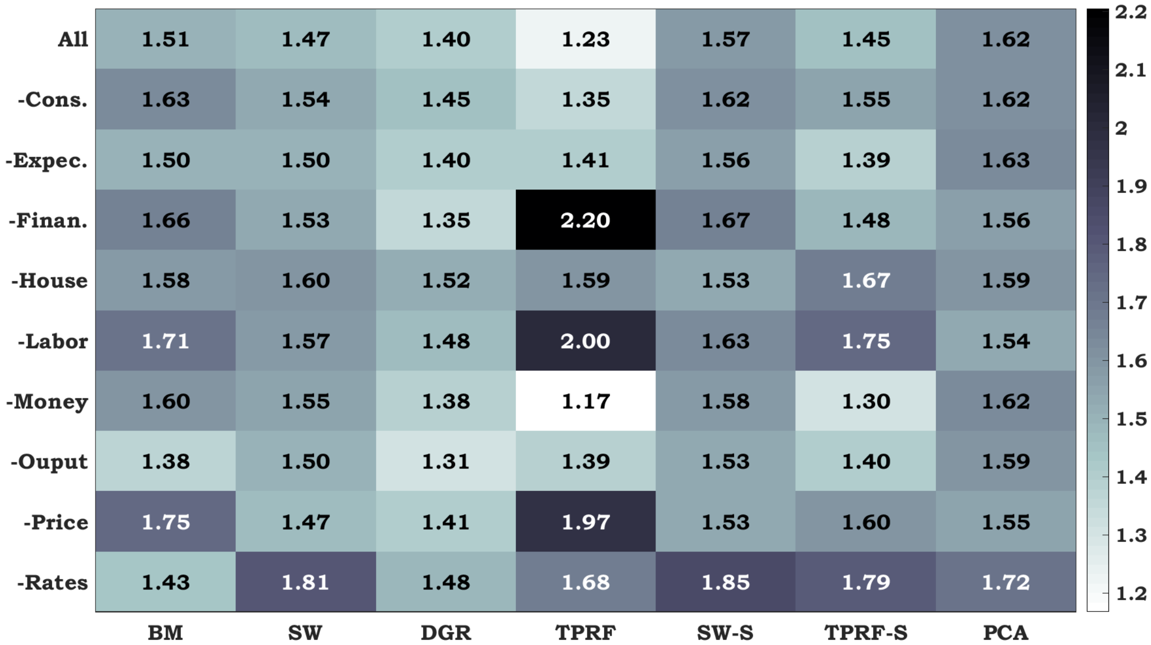


Figure 2.8: RMSFE, $h = 12$, Global Financial Crisis period

Note: See note in heatmap 2.5. For the purpose of comparison, the RMSFE of an AR model equals 1.72.

Table 2.6: RMSFE relative to a model with the full data set, Global Financial Crisis

| | BM | SW | DGR | TPRF | SW-S | TPRF-S | PCA | BM | SW | DGR | TPRF | SW-S | TPRF-S | PCA |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $h=-1$ | | | | | | | $h=0$ | | | | | | |
| -Cons. | 1.14$^{**}$ | 1.45$^{***}$ | 1.04 | 0.85$^{***}$ | 1.25$^{***}$ | 1.02$^{***}$ | 0.94 | 1.12$^{**}$ | 1.39$^{***}$ | 1.07$^{*}$ | 0.84$^{***}$ | 1.21$^{***}$ | 0.95$^{***}$ | 0.94 |
| -Expec. | 1.08$^{***}$ | 1.37$^{***}$ | 0.90$^{***}$ | 1.04$^{***}$ | 1.16$^{***}$ | 1.18$^{*}$ | 1.03$^{***}$ | 1.07$^{***}$ | 1.35$^{***}$ | 0.94$^{**}$ | 1.01$^{***}$ | 1.14$^{***}$ | 1.10 | 1.03$^{**}$ |
| -Finan. | **0.82**$^{**}$ | 1.84$^{***}$ | 1.08$^{**}$ | 0.89$^{***}$ | 1.31$^{***}$ | **0.88**$^{**}$ | **0.73**$^{**}$ | **0.80**$^{**}$ | 1.68$^{***}$ | 1.03 | 0.89$^{***}$ | 1.24$^{***}$ | **0.82**$^{**}$ | **0.76**$^{***}$ |
| -House | 1.02 | 1.48$^{***}$ | 1.04$^{**}$ | **0.69**$^{***}$ | 1.28$^{***}$ | 0.85$^{***}$ | 0.97$^{***}$ | 1.00 | 1.41$^{***}$ | 1.06$^{***}$ | 0.76$^{***}$ | 1.22$^{***}$ | 0.91$^{***}$ | 0.97$^{**}$ |
| -Labor | 0.95$^{*}$ | 1.37$^{***}$ | 0.98 | 1.02$^{***}$ | 1.23$^{***}$ | 0.93 | 0.76 | 0.90$^{**}$ | 1.31$^{***}$ | 0.95 | 1.00$^{***}$ | 1.20$^{***}$ | 0.93 | 0.78 |
| -Money | 1.09$^{***}$ | 1.19$^{***}$ | 0.98 | 0.87$^{***}$ | 1.06$^{***}$ | 1.23$^{***}$ | 1.03$^{***}$ | 1.08$^{***}$ | 1.16$^{***}$ | 1.00 | 0.86$^{***}$ | 1.06$^{***}$ | 1.13$^{**}$ | 1.03$^{***}$ |
| -Output | 1.00 | **0.99** | **0.88**$^{***}$ | 0.70$^{***}$ | **0.96**$^{***}$ | 1.09$^{**}$ | 0.97$^{**}$ | 1.00 | **0.97**$^{*}$ | **0.94** | **0.71**$^{***}$ | **0.94**$^{***}$ | 1.01$^{***}$ | 0.98 |
| -Price | 0.90$^{*}$ | 1.33$^{***}$ | 1.07$^{**}$ | 0.88$^{***}$ | 1.09$^{***}$ | 0.89$^{**}$ | 0.76$^{**}$ | 0.85$^{**}$ | 1.24$^{***}$ | 0.96 | 0.86$^{**}$ | 1.04$^{***}$ | 0.84$^{**}$ | 0.77$^{***}$ |
| -Rates | 1.68$^{***}$ | 1.33$^{***}$ | 1.19$^{***}$ | 1.01$^{***}$ | 1.22$^{***}$ | 0.90$^{***}$ | 1.16$^{***}$ | 1.65$^{***}$ | 1.34$^{***}$ | 1.15$^{***}$ | 1.01$^{***}$ | 1.23$^{***}$ | 0.90 | 1.19$^{***}$ |
| | $h=1$ | | | | | | | $h=12$ | | | | | | |
| -Cons. | 1.15$^{**}$ | 1.42$^{***}$ | 1.05 | 0.83$^{***}$ | 1.20$^{***}$ | 0.93$^{***}$ | 0.95$^{**}$ | 1.08$^{***}$ | 1.04$^{***}$ | 1.04$^{***}$ | 1.10$^{***}$ | 1.03 | 1.06$^{***}$ | 1.00$^{***}$ |
| -Expec. | 1.08$^{***}$ | 1.37$^{***}$ | 0.95$^{**}$ | 0.95$^{***}$ | 1.14$^{***}$ | 1.07$^{**}$ | 1.03 | 1.00 | 1.02 | 1.00 | 1.14 | 0.99$^{***}$ | 0.96$^{***}$ | 1.01$^{**}$ |
| -Finan. | **0.79**$^{**}$ | 1.65$^{***}$ | 1.04 | 0.93$^{***}$ | 1.21$^{***}$ | **0.78** | **0.78**$^{***}$ | 1.10$^{***}$ | 1.04$^{***}$ | 0.96$^{***}$ | 1.79$^{***}$ | 1.06$^{***}$ | 1.02$^{***}$ | 0.96 |
| -House | 1.00 | 1.40$^{***}$ | 1.07$^{***}$ | 0.86$^{***}$ | 1.20$^{***}$ | 0.96$^{*}$ | 0.97 | 1.05$^{**}$ | 1.09$^{***}$ | 1.09$^{***}$ | 1.29$^{***}$ | **0.97**$^{***}$ | 1.15$^{***}$ | 0.98$^{***}$ |
| -Labor | 0.88$^{***}$ | 1.30$^{***}$ | 1.00 | 1.00$^{***}$ | 1.16$^{***}$ | 0.94 | 0.78 | 1.14$^{***}$ | 1.07$^{***}$ | 1.05$^{***}$ | 1.62$^{***}$ | 1.03$^{***}$ | 1.20$^{***}$ | **0.95**$^{***}$ |
| -Money | 1.10$^{***}$ | 1.14$^{***}$ | 1.02$^{*}$ | 0.89$^{***}$ | 1.05$^{***}$ | 1.08$^{**}$ | 1.03$^{*}$ | 1.06$^{***}$ | 1.05$^{***}$ | 0.99$^{**}$ | **0.95** | 1.00 | **0.89**$^{**}$ | 1.00$^{***}$ |
| -Output | 0.99 | **0.98**$^{*}$ | 1.05 | **0.72**$^{***}$ | **0.94**$^{***}$ | 0.97$^{***}$ | 0.97 | **0.91**$^{***}$ | 1.02$^{**}$ | **0.93**$^{***}$ | 1.13$^{***}$ | 0.97$^{***}$ | 0.96$^{***}$ | 0.98$^{*}$ |
| Price | 0.80$^{**}$ | 1.21$^{***}$ | **0.92**$^{**}$ | 0.86 | 1.01$^{***}$ | 0.79$^{**}$ | 0.78$^{***}$ | 1.16$^{***}$ | **1.00** | 1.01 | 1.60$^{***}$ | 0.97$^{***}$ | 1.10$^{***}$ | 0.96$^{**}$ |
| Rates | 1.64$^{***}$ | 1.38$^{***}$ | 1.16$^{***}$ | 1.03$^{***}$ | 1.26$^{***}$ | 0.91 | 1.22$^{**}$ | 0.95 | 1.23$^{***}$ | 1.06$^{**}$ | 1.36$^{***}$ | 1.17$^{***}$ | 1.23$^{***}$ | 1.06$^{***}$ |

Note: Numbers show the RMSFE relative to each model using a full data set. Based on the HLN test of equal accuracy, numbers with $^{***}$, $^{**}$, and $^{*}$ are significant at the 1%, 5%, and 10% levels, respectively. Bold numbers represent the best model column wise.

To compare the best performing methods with respect to a univariate AR model, I summarize their RMSFEs in table 2.7. I further test if the best performing models have the same forecasting accuracy as the AR. I find that the nowcast of the previous month and the one-year ahead forecasts are significantly better models for forecasting inflation, in comparison to an AR.

Table 2.7: AR model vs best performing models, Global Financial Crisis

| Horizon | AR | Best model | |
|---|---|---|---|
| -1 | 0.75 | **0.67**$^{***}$ | TPRF(-House) |
| 0 | 0.93 | **0.73** | TPRF(-Output) |
| 1 | 1.07 | **0.73** | TPRF(-Output) |
| 12 | 1.72 | **1.30**$^{***}$ | TPRF-S(-Money) |

Note: numbers show the RMSFE of the AR and the best performing unbalanced factor models. Based on the HLN test of equal accuracy, numbers with ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively. Bold numbers represent the best model.

### Evaluating the COVID-19 period

The novel coronavirus outbreak triggered a substantial decrease in CPI inflation, reaching levels lower than 1.5%, see graph 2.9. Therefore, I consider the COVID-19 period as a second sub-sample to evaluate, i.e., March 2020 - December 2020. Given that the COVID-19 crisis is still ongoing, I uniquely concentrate on a nowcasting analysis.

Similar to the previous cases, table 2.8 shows the RMSFE relative to a PCA model. I find that no factor-based model has a better forecasting performance than the AR model. Within the unbalanced factor models, results show that the methodologies of Bańbura and Modugno (2014) and Stock and Watson (2002b) significantly outperform the PCA model for the nowcast of the previous month and only the latter for the nowcast of the current month.

Table 2.8: RMSFE relative to a PCA forecast, COVID-19 period

| | BM | SW | DGR | TPRF | SW-S | TPRF-S | AR |
|---|---|---|---|---|---|---|---|
| -1 | 0.87$^{***}$ | 0.95$^{***}$ | 1.12$^{***}$ | 1.07 | 1.06$^{***}$ | 0.94 | **0.46**$^{***}$ |
| 0 | 0.99 | 0.93$^{***}$ | 1.14$^{***}$ | 1.48$^{***}$ | 1.04$^{***}$ | 1.58$^{***}$ | **0.51**$^{***}$ |

Note: see note in table 2.4.

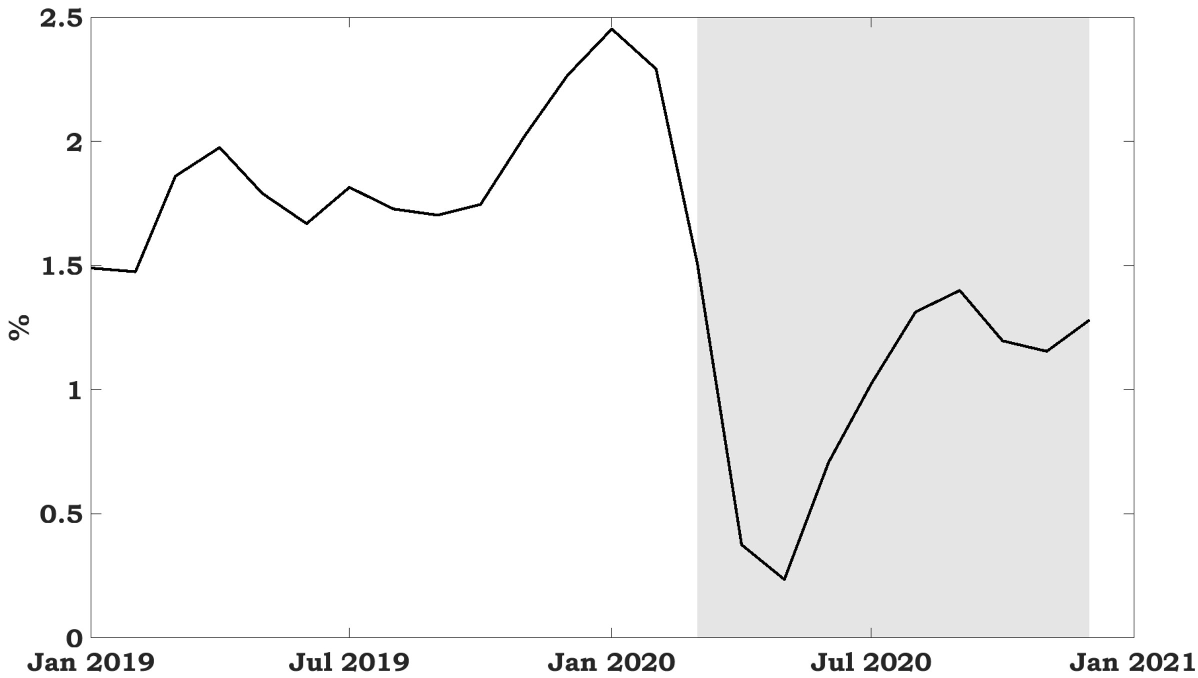


Figure 2.9: US CPI inflation during the COVID-19 crisis

To assess the relevance of the different categories of data, I conduct the same exercise that I did for the Global Financial Crisis period. The heatmaps in figures 2.10 and 2.11 show the RMSFE of all models for the two nowcasts, i.e., $h = -1$ and $h = 0$, respectively. Table 2.9 shows the relative RMSFE of all models with respect to a model using the full data set. It turns out that eliminating variables in the category of consumption, orders, and inventories worsens the nowcasts, with the exception of the TPRF and the SW-S. Moreover, the category of inflation expectations seems to be important for the nowcast of the past month. The result regarding the category of consumption, orders, and inventories comes at no surprise. This is because the COVID-19 shock comprises a mixture of supply and demand components. Therefore, the variables related to consumption, orders, and inventories are crucial for capturing these effects. In contrast to the previous crisis, I find no evidence of a strong importance of variables related to interest rates and spreads. Additionally, for all models, I find that eliminating variables in the labor market category gives more accurate forecasts. This means that the labor market variables do not seem to play a crucial role for nowcasting inflation during the COVID-19 crisis.

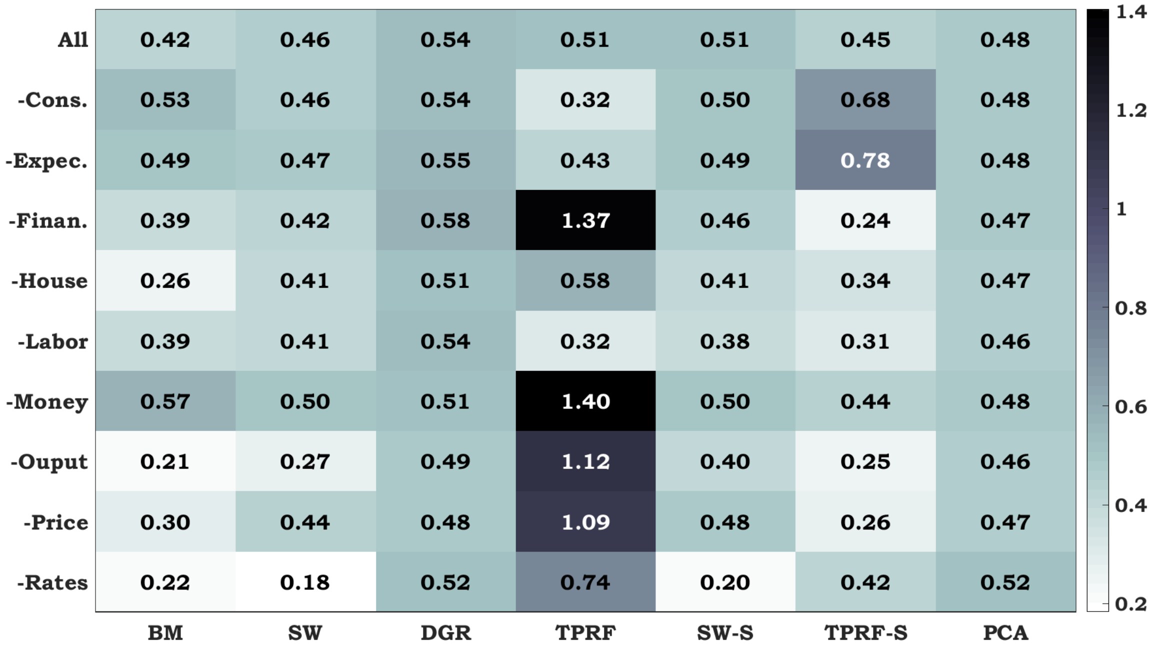


Figure 2.10: RMSFE, $h = -1$, COVID-19 period

Note: See note in heatmap 2.5. For the purpose of comparison, the RMSFE of an AR model equals 0.22.

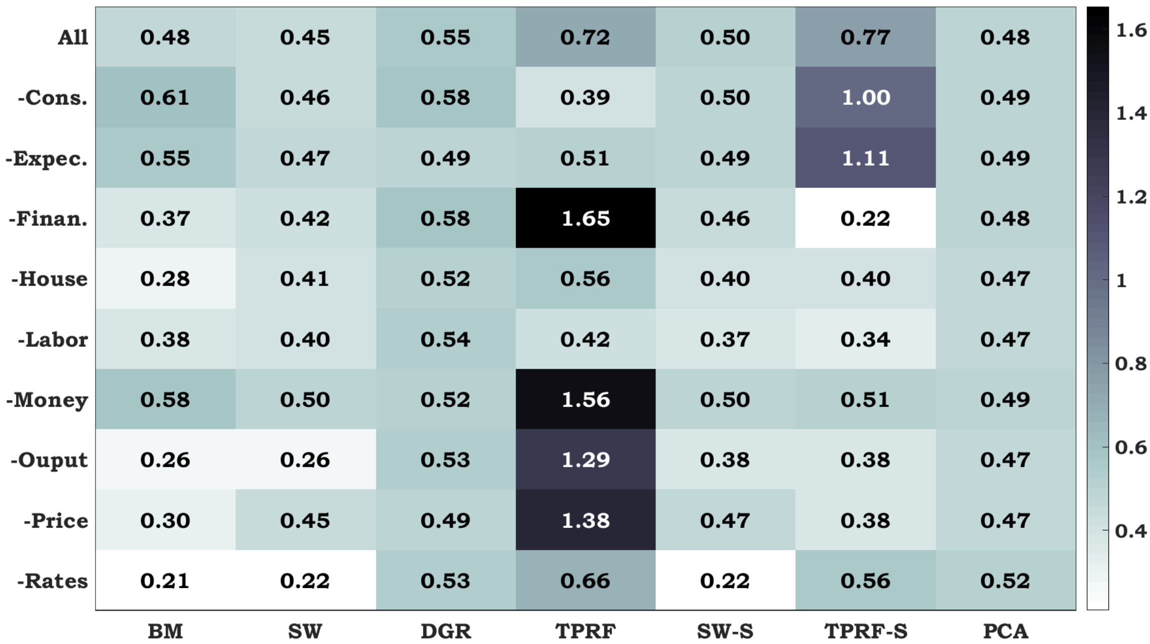


Figure 2.11: RMSFE, $h = 0$, COVID-19 period

Note: See note in heatmap 2.5. For the purpose of comparison, the RMSFE of an AR model equals 0.24.

Table 2.9: RMSFE relative to a model with the full data set, COVID-19 crisis

| | BM | SW | DGR | TPRF | SW-S | TPRF-S | PCA |
|---|---|---|---|---|---|---|---|
| | | | | $h = -1$ | | | |
| Cons. | 1.28*** | 1.01* | 1.01** | 0.63*** | 0.98*** | 1.52*** | 1.01*** |
| Expec. | 1.18*** | 1.04*** | 1.03*** | 0.84*** | 0.96*** | 1.73** | 1.01*** |
| Finan. | 0.93*** | 0.92*** | 1.08*** | 2.68*** | 0.90*** | **0.54***** | 0.98*** |
| House | 0.62*** | 0.90*** | 0.96*** | 1.13*** | 0.80*** | 0.76*** | 0.97*** |
| Labor | 0.93*** | 0.89*** | 0.99 | **0.62***** | 0.75*** | 0.68*** | **0.97***** |
| Money | 1.37*** | 1.09*** | 0.95*** | 2.75* | 0.98* | 0.98*** | 1.01 |
| Output | **0.50***** | 0.60*** | 0.91*** | 2.19*** | 0.79*** | 0.56*** | 0.97*** |
| Price | 0.71*** | 0.96*** | **0.89***** | 2.13*** | 0.94*** | 0.59*** | 0.98*** |
| Rates | 0.53*** | **0.40***** | 0.97*** | 1.46*** | **0.40***** | 0.94*** | 1.08*** |
| | | | | $h = 0$ | | | |
| Cons. | 1.27*** | 1.01** | 1.05*** | **0.54***** | 0.98*** | 1.31*** | 1.01*** |
| Expec. | 1.16*** | 1.05*** | 0.89*** | 0.72*** | 0.97*** | 1.45*** | 1.01*** |
| Finan. | 0.77*** | 0.92*** | 1.05*** | 2.31*** | 0.91*** | **0.28***** | 0.99*** |
| House | 0.59*** | 0.90*** | 0.93*** | 0.78*** | 0.79*** | 0.53*** | 0.98*** |
| Labor | 0.80*** | 0.89*** | 0.98*** | 0.58*** | 0.74*** | 0.45*** | 0.97*** |
| Money | 1.21*** | 1.10*** | 0.93*** | 2.18 | 0.99* | 0.67*** | 1.01*** |
| Output | 0.54*** | 0.57*** | 0.95*** | 1.80*** | 0.76*** | 0.49*** | **0.97***** |
| Price | 0.63*** | 0.99 | **0.88***** | 1.93*** | 0.94*** | 0.50*** | 0.98*** |
| Rates | **0.44***** | **0.48***** | 0.96*** | 0.92*** | **0.43***** | 0.73*** | 1.08*** |

Note: see note in table 2.6.

Overall, I find that the best performing models are those proposed by Stock and Watson (2002b) and Bańbura and Modugno (2014) without interest rates and spreads for $h = -1$ and $h = 0$, respectively. To compare their accuracy with respect to the AR model, I present their RMSFEs in table 2.10. I find that both unbalanced factor models outperform the nowcasts based on an AR and are significant at the 1% level.

Table 2.10: RMSFE of AR and best performing models, COVID-19 period

| Horizon | AR | Best model | |
|---|---|---|---|
| -1 | 0.22 | **0.18***** | SW(-Rates) |
| 0 | 0.24 | **0.21***** | BM(-Rates) |

Note: see note in table 2.7.

## 2.4 Conclusion

Although several approaches are now available to deal with missing data in the context of factor models, the benefit of using such methods for inflation forecasting is not previously studied. Therefore, this paper closes this gap in the literature by providing an empirical assessment of the most popular Expectation-Maximization algorithms for estimating an unbalanced factor model. I carry out a pseudo real-time nowcasting and forecasting analysis for the US inflation rate. I evaluate the models in three different periods: a sample from 2000-2019, the Global Financial Crisis, and the ongoing COVID-19 Crisis. Overall, my results point to the importance of two things. First, I find that the use of large data sets has significant forecasting improvements, especially during crises periods. Second, models formally dealing with unbalanced panels outperform forecasts based on principal components, where missing observations are trivially filled with zeros. For the full evaluation sample, results show that the AR model has better nowcasting properties, whereas the three-pass regression filter outperforms all models for horizons longer than one month. However, for crisis periods, I find that the three-pass regression filter and the methodologies of Bańbura and Modugno (2014) and Stock and Watson (2002b) outperform the AR nowcasts and forecasts.

To assess the variables driving an accurate inflation forecast during crises periods, I estimate the models eliminating each of the considered data categories one-by-one. I find that variables related to inflation expectations, money, and interest rates are crucial for nowcasting inflation during the Global Financial Crisis. Moreover, the categories of consumption, the labor market, and interest rates are important for the one-year ahead forecast. In contrast, for the COVID-19 crisis, I find that interest rates are irrelevant for the nowcasts. Moreover, my results point to the importance of variables in the field of consumption, orders, and inventories. This category captures movements in both aggregate supply and aggregate demand: a mixture of these two components characterizes the COVID-19 crisis.

Although the pseudo real-time forecasting analysis is suitable for a fair comparison among models, a real-time forecasting analysis is more realistic for studying the role of data revisions. Moreover, I narrow my analysis to factor models, given their popularity in macroeconomic forecasting. However, the issue of unbalanced panels is not limited to factor models. Therefore, the assessment of missing observations in the context of other types of big data models is key for empirical work. These issues are left for future research.

## 2.A Data description

Table 2.11 provides a detailed description of the data used to estimate the factor models in section 2.2. The column *Trans.* shows the transformation used such that the time series $X_i$ is stationary. The numbers in this column denote the following transformations: (1) no transformation, (2) first difference, (3) second difference, (4) logarithm, (5) log first difference, and (6) log second differences. The column *Release* shows the publication date for the latest available information shown in column *Figure*, accordingly to the vintage of February 1, 2021.

Table 2.11: Data description

| Mnemonics | Description | Category | Trans. | Release | Figure |
|---|---|---|---|---|---|
| RPI | Real Personal Income | Output | 5 | Jan 29, 21 | Dec 20 |
| W875RX1 | Real personal income excluding current transfer receipts | Output | 5 | Jan 29, 21 | Dec 20 |
| DPCERA3M086SBEA | Real personal consumption expenditures (chain-type quantity index) | Cons. | 5 | Jan 29, 21 | Dec 20 |
| CMRMTSPL | Real Manufacturing and Trade Industries Sales | Cons. | 5 | Jan 29, 21 | Dec 20 |
| RETAIL | Retail and Food Services Sales | Cons. | 5 | Jan 15, 21 | Dec 20 |
| INDPRO | Industrial Production: Total Index | Output | 5 | Jan 15, 21 | Dec 20 |
| IPFPNSS | Industrial Production: Final Products and Nonindustrial Supplies | Output | 5 | Jan 15, 21 | Dec 20 |
| IPFINAL | Industrial Production: Final Products | Output | 5 | Jan 15, 21 | Dec 20 |
| IPCONGD | Industrial Production: Consumer Goods | Output | 5 | Jan 15, 21 | Dec 20 |
| IPDCONGD | Industrial Production: Durable Consumer Goods | Output | 5 | Jan 15, 21 | Dec 20 |
| IPNCONGD | Industrial Production: Non-Durable Consumer Goods | Output | 5 | Jan 15, 21 | Dec 20 |
| IPBUSEQ | Industrial Production: Equipment: Business Equipment | Output | 5 | Jan 15, 21 | Dec 20 |
| IPMAT | Industrial Production: Materials | Output | 5 | Jan 15, 21 | Dec 20 |
| IPDMAT | Industrial Production: Durable Goods Materials | Output | 5 | Jan 15, 21 | Dec 20 |
| IPNMAT | Industrial Production: Non-Durable Goods Materials | Output | 5 | Jan 15, 21 | Dec 20 |
| IPMANSICS | Industrial Production: Manufacturing (SIC) | Output | 5 | Jan 15, 21 | Dec 20 |
| IPB51222S | Industrial Production: Non-Durable Consumer Energy Products: Residential Utilities | Output | 5 | Jan 15, 21 | Dec 20 |
| IPFUELS | Industrial Production: Non-Durable Consumer Energy Products: Fuels | Output | 5 | Jan 15, 21 | Dec 20 |
| CUMFNS | Capacity Utilization: Manufacturing (SIC) | Output | 2 | Jan 15, 21 | Dec 20 |
| HWI | Help-Wanted Index for United States | Labor | 2 | NA | Nov 20 |

| | | | | | |
|---|---|---|---|---|---|
| HWIURATIO | Ratio of Help Wanted/No. Unemployed | Labor | 2 | NA | Nov 20 |
| CLF16OV | Civilian Labor Force Level | Labor | 5 | Feb 5, 21 | Jan 21 |
| CE16OV | Employment Level | Labor | 5 | Feb 5, 21 | Jan 21 |
| UNRATE | Unemployment Rate | Labor | 2 | Feb 5, 21 | Jan 21 |
| UEMPMEAN | Average Weeks Unemployed | Labor | 2 | Feb 5, 21 | Jan 21 |
| UEMPLT5 | Number Unemployed for Less Than 5 Weeks | Labor | 5 | Feb 5, 21 | Jan 21 |
| UEMP5TO14 | Number Unemployed for 5-14 Weeks | Labor | 5 | Feb 5, 21 | Jan 21 |
| UEMP15OV | Number Unemployed for 15 Weeks & Over | Labor | 5 | Feb 5, 21 | Jan 21 |
| UEMP15T26 | Number Unemployed for 15-26 Weeks | Labor | 5 | Feb 5, 21 | Jan 21 |
| UEMP27OV | Number Unemployed for 27 Weeks & Over | Labor | 5 | Feb 5, 21 | Jan 21 |
| CLAIMS | Initial Claims | Labor | 5 | Feb 5, 21 | Jan 21 |
| PAYEMS | All Employees, Total Nonfarm | Labor | 5 | Feb 4, 21 | Jan 21 |
| USGOOD | All Employees, Goods-Producing | Labor | 5 | Feb 5, 21 | Jan 21 |
| CES1021000001 | All Employees, Mining | Labor | 5 | Feb 5, 21 | Jan 21 |
| USCONS | All Employees, Construction | Labor | 5 | Feb 5, 21 | Jan 21 |
| MANEMP | All Employees, Manufacturing | Labor | 5 | Feb 5, 21 | Jan 21 |
| DMANEMP | All Employees, Durable Goods | Labor | 5 | Feb 5, 21 | Jan 21 |
| NDMANEMP | All Employees, Nondurable Goods | Labor | 5 | Feb 5, 21 | Jan 21 |
| SRVPRD | All Employees, Service-Providing | Labor | 5 | Feb 5, 21 | Jan 21 |
| USTPU | All Employees, Trade, Transportation, and Utilities | Labor | 5 | Feb 5, 21 | Jan 21 |
| USWTRADE | All Employees, Wholesale Trade | Labor | 5 | Feb 5, 21 | Jan 21 |
| USTRADE | All Employees, Retail Trade | Labor | 5 | Feb 5, 21 | Jan 21 |
| USFIRE | All Employees, Financial Activities | Labor | 5 | Feb 5, 21 | Jan 21 |
| USGOVT | All Employees, Government | Labor | 5 | Feb 5, 21 | Jan 21 |
| CES0600000007 | Average Weekly Hours of Production and Nonsupervisory Employees, Goods-Producing | Labor | 1 | Feb 5, 21 | Jan 21 |
| AWOTMAN | Average Weekly Overtime Hours of Production and Nonsupervisory Manufacturing | Labor | 2 | Feb 5, 21 | Jan 21 |
| AWHMAN | Average Weekly Hours of Production and Nonsupervisory Employees, Manufacturing | Labor | 1 | Feb 5, 21 | Jan 21 |
| HOUST | Housing Starts: Total: New Privately Owned Housing Units Started | Housing | 4 | Jan 21, 21 | Dec 20 |
| HOUSTNE | Housing Starts in Northeast Census Region | Housing | 4 | Jan 21, 21 | Dec 20 |
| HOUSTMW | Housing Starts in Midwest Census Region | Housing | 4 | Jan 21, 21 | Dec 20 |
| HOUSTS | Housing Starts in South Census Region | Housing | 4 | Jan 21, 21 | Dec 20 |
| HOUSTW | Housing Starts in West Census Region | Housing | 4 | Jan 21, 21 | Dec 20 |
| PERMIT | New Private Housing Permits | Housing | 4 | Jan 28, 21 | Dec 20 |
| PERMITNE | New Private Housing Units Authorized by Building Permits in the Northeast Census Region | Housing | 4 | Jan 28, 21 | Dec 20 |

| | | | | | |
|---|---|---|---|---|---|
| PERMITMW | New Private Housing Units Authorized by Building Permits in the Midwest Census Region | Housing | 4 | Jan 28, 21 | Dec 20 |
| PERMITS | New Private Housing Permits, South | Housing | 4 | Jan 28, 21 | Dec 20 |
| PERMITW | New Private Housing Units Authorized by Building Permits in the West Census Region | Housing | 4 | Jan 28, 21 | Dec 20 |
| ACOGNO | Manufacturers' New Orders: Consumer Goods | Cons. | 5 | Feb 4, 21 | Dec 20 |
| AMDMNO | New Orders for Durable Goods | Cons. | 5 | Feb 4, 21 | Dec 20 |
| ANDENO | Manufacturers' New Orders: Nondefense Capital Goods | Cons. | 5 | Feb 4, 21 | Dec 20 |
| AMDMUO | Manufacturers' Unfilled Orders: Durable Goods | Cons. | 5 | Feb 4, 21 | Dec 20 |
| BUSINV | Total Business Inventories | Cons. | 5 | Jan 15, 21 | Nov 20 |
| ISRATIO | Total Business: Inventories to Sales Ratio | Cons. | 2 | Jan 15, 21 | Dec 20 |
| M1SL | M1 Money Stock | Money | 6 | Feb 4, 21 | Dec 20 |
| M2SL | M2 Money Stock | Money | 6 | Feb 4, 21 | Dec 20 |
| M2REAL | Real M2 Money Stock | Money | 5 | Jan 28, 21 | Dec 20 |
| BOGMBASE | Monetary Base; Total | Money | 6 | Jan 28, 21 | Dec 20 |
| TOTRESNS | Total Reserves of Depository Institutions | Money | 6 | Jan 28, 21 | Dec 20 |
| NONBORRES | Reserves of Depository Institutions, Nonborrowed | Money | 7 | Jan 28, 21 | Dec 20 |
| BUSLOANS | Commercial and Industrial Loans, All Commercial Banks | Money | 6 | Feb 5, 21 | Dec 20 |
| REALLN | Real Estate Loans, All Commercial Banks | Money | 6 | Feb 5, 21 | Dec 20 |
| NONREVSL | Total Nonrevolving Credit Owned and Securitized, Outstanding | Money | 6 | Feb 5, 21 | Dec 20 |
| CONSPI | Nonrevolving consumer credit to Personal Income | Money | 2 | Feb 5, 21 | Dec 20 |
| S&P 500 | S&P 500 | Finan. | 5 | Daily | Feb 21 |
| S&P indust | S&P's Common Stock Price Index: Industrials | Finan. | 5 | NA | Dec 20 |
| S&P div yield | S&P's Composite Common Stock: | Finan. | 2 | NA | Dec 20 |
| S&P PE ratio | Dividend Yield S&P's Composite Common Stock: Price-Earnings Ratio | Finan. | 5 | NA | Oct 20 |
| FEDFUNDS | Effective Federal Funds Rate | Finan. | 2 | Feb 5, 21 | Jan 21 |
| CP3M | 3-Month Commercial Paper Rate | Rates | 2 | Feb 5, 21 | Jan 21 |
| TB3MS | 3-Month Treasury Bill: Secondary Market Rate | Rates | 2 | Feb 5, 21 | Jan 21 |
| TB6MS | 6-Month Treasury Bill: Secondary Market Rate | Rates | 2 | Feb 5, 21 | Jan 21 |
| GS1 | 1-Year Treasury Constant Maturity Rate | Rates | 2 | Feb 5, 21 | Jan 21 |
| GS5 | 5-Year Treasury Constant Maturity Rate | Rates | 2 | Feb 5, 21 | Jan 21 |
| GS10 | 10-Year Treasury Constant Maturity Rate | Rates | 2 | Feb 5, 21 | Jan 21 |
| AAA | Moody's Seasoned Aaa Corporate Bond Yield | Rates | 2 | Daily | Feb 21 |
| BAA | Moody's Seasoned Baa Corporate Bond Yield | Rates | 2 | Daily | Feb 21 |

| | | | | | |
|---|---|---|---|---|---|
| COMPAPFF | 3-Month Commercial Paper Minus FEDFUNDS | Rates | 1 | Feb 5, 21 | Jan 21 |
| TB3SMFFM | 3-Month Treasury Bill Minus FEDFUNDS | Rates | 1 | Feb 5, 21 | Jan 21 |
| TB6SMFFM | 6-Month Treasury Bill Minus FEDFUNDS | Rates | 1 | Feb 5, 21 | Jan 21 |
| T1YFFM | 1-Year Treasury Constant Maturity Minus FEDFUNDS | Rates | 1 | Feb 5, 21 | Jan 21 |
| T5YFFM | 5-Year Treasury Constant Maturity Minus FEDFUNDS | Rates | 1 | Feb 5, 21 | Jan 21 |
| T10YFFM | 10-Year Treasury Constant Maturity Minus FEDFUNDS | Rates | 1 | Feb 5, 21 | Jan 21 |
| AAAFFM | Moody's Seasoned Aaa Corporate Bond Minus FEDFUNDS | Rates | 1 | Feb 5, 21 | Jan 21 |
| BAAFFM | Moody's Seasoned Baa Corporate Bond Minus FEDFUNDS | Rates | 1 | Feb 5, 21 | Jan 21 |
| TWEXAFEGSMTH | Trade Weighted U.S. Dollar Index: Advanced Foreign Economies, Goods and Services | Finan. | 5 | Feb 1, 21 | Jan 21 |
| EXSZUS | Switzerland / U.S. Foreign Exchange Rate | Finan. | 5 | Daily | Feb 21 |
| EXJPUS | Japan / U.S. Foreign Exchange Rate | Finan. | 5 | Daily | Feb 21 |
| EXUSUK | U.S. / U.K. Foreign Exchange Rate | Finan. | 5 | Daily | Feb 21 |
| EXCAUS | Canada / U.S. Foreign Exchange Rate | Finan. | 5 | Daily | Feb 21 |
| WPSFD49207 | Producer Price Index by Commodity: Final Demand: Finished Goods | Prices | 6 | Jan 15, 21 | Dec 20 |
| WPSFD49502 | Producer Price Index by Commodity: Final Demand: Personal Consumption Goods (Finished Consumer Goods) | Prices | 6 | Jan 15, 21 | Dec 20 |
| WPSID61 | Producer Price Index by Commodity: Intermediate Demand by Commodity Type: Processed Goods for Intermediate Demand | Prices | 6 | Jan 15, 21 | Dec 20 |
| WPSID62 | Producer Price Index by Commodity: Intermediate Demand by Commodity Type: Unprocessed Goods for Intermediate Demand | Prices | 6 | Jan 15, 21 | Dec 20 |
| OILPRICE | Spot Oil Price: West Texas Intermediate | Prices | 6 | Feb 3, 21 | Jan 21 |
| PPICMM | Producer Price Index by Commodity: Metals and Metal Products: Primary Nonferrous Metals | Prices | 6 | Jan 15, 21 | Dec 20 |
| CPIAUCSL | Consumer Price Index for All Urban Consumers: All Items in U.S. City Average | Prices | 6 | Jan 13, 21 | Dec 20 |
| CPIAPPSL | Consumer Price Index for All Urban Consumers: Apparel in U.S. City Average | Prices | 6 | Jan 13, 21 | Dec 20 |
| CPITRNSL | Consumer Price Index for All Urban Consumers: Transportation in U.S. City Average | Prices | 6 | Jan 13, 21 | Dec 20 |
| CPIMEDSL | Consumer Price Index for All Urban Consumers: Medical Care in U.S. City Average | Prices | 6 | Jan 13, 21 | Dec 20 |
| CUSR0000SAC | Consumer Price Index for All Urban Consumers: Commodities in U.S. City Average | Prices | 6 | Jan 13, 21 | Dec 20 |
| CUSR0000SAD | Consumer Price Index for All Urban Consumers: Durables in U.S. City Average | Prices | 6 | Jan 13, 21 | Dec 20 |

| | | | | | |
|---|---|---|---|---|---|
| CUSR0000SAS | Consumer Price Index for All Urban Consumers: Services in U.S. City Average | Prices | 6 | Jan 13, 21 | Dec 20 |
| CPIULFSL | Consumer Price Index for All Urban Consumers: All Items Less Food in U.S. City Average | Prices | 6 | Jan 13, 21 | Dec 20 |
| CUSR0000SA0L2 | Consumer Price Index for All Urban Consumers: All Items Less Shelter in U.S. City Average | Prices | 6 | Jan 13, 21 | Dec 20 |
| CUSR0000SA0L5 | Consumer Price Index for All Urban Consumers: All Items Less Medical Care in U.S. City Average | Prices | 6 | Jan 13, 21 | Dec 20 |
| PCEPI | Personal Consumption Expenditures: Chain-type Price Index | Prices | 6 | Jan 29, 21 | Dec 20 |
| DDURRG3M086SBEA | Personal consumption expenditures: Durable goods (chain-type price index) | Prices | 6 | Jan 29, 21 | Dec 20 |
| DNDGRG3M086SBEA | Personal consumption expenditures: Nondurable goods (chain-type price index) | Prices | 6 | Jan 29, 21 | Dec 20 |
| DSERRG3M086SBEA | Personal consumption expenditures: Services (chain-type price index) | Prices | 6 | Jan 29, 21 | Dec 20 |
| CES0600000008 | Average Hourly Earnings of Production and Nonsupervisory Employees, Goods-Producing | Labor | 6 | Feb 5, 21 | Jan 21 |
| CES2000000008 | Average Hourly Earnings of Production and Nonsupervisory Employees, Construction | Labor | 6 | Feb 5, 21 | Jan 21 |
| CES3000000008 | Average Hourly Earnings of Production and Nonsupervisory Employees, Manufacturing | Labor | 6 | Feb 5, 21 | Jan 21 |
| UMCSENT | University of Michigan: Consumer Sentiment | Cons- | 2 | Jan 29, 21 | Dec 20 |
| MZMSL | MZM Money Stock | Money | 6 | Feb 7, 21 | Dec 20 |
| DTCOLNVHFNM | Consumer Motor Vehicle Loans Owned by Finance Companies, Outstanding | Money | 6 | Jan 19, 21 | Nov 20 |
| DTCTHFNM | Total Consumer Loans and Leases Owned and Securitized by Finance Companies, Outstanding | Money | 6 | Jan 19, 21 | Nov 20 |
| INVEST | Securities in Bank Credit at All Commercial Banks | Money | 6 | Weekly | Jan 21 |
| VXOCLS | CBOE S&P 100 Volatility Index: VXO | Finan. | 1 | Daily | Feb 21 |
| T5YIFR | 5-Year, 5-Year Forward Inflation Expectation Rate | Expec. | 1 | Daily | Feb 21 |
| MICH | University of Michigan: Inflation Expectation | Expec. | 1 | Jan 29, 21 | Dec 20 |

# Chapter 3

# A Mixed Frequency Model for the Euro Area Labor Market*

## 3.1 Introduction

Understanding labor market dynamics is of high importance for interpreting the macroeconomic developments in an economy. While there is a substantial literature to understand the dynamics of labor markets in the US from a structural point of view (see, among many, Gertler, Sala, and Trigari (2008), Mumtaz and Zanetti (2012), and Christiano, Eichenbaum, and Trabandt (2016)) and also for forecasting purposes (e.g. Montgomery, Zarnowitz, Tsay, and Tiao (1998), Askitas and Zimmermann (2009), and D'Amuri and Marcucci (2017)), not many studies are available to understand euro area labor market developments. The need to cover the euro area labor market is relevant because its structure is quite different from the US, in terms of regulations, composition of the labor force, as well as the dynamics of the ins and outs of unemployment (also known as the job market flows). With this paper, we aim at filling this gap. We introduce a model for the aggregate euro area labor market with the twofold purpose of interpreting the main movements in the labor market variables through the lenses of structural shocks, and at the same time, being able to produce reliable forecasts and economically interpretable nowcasts.

Changes and shocks in the labor market have repercussions in macroeconomic fluctuations, and an extensive literature is analyzing the role of labor market shocks to the economy. In the context of new Keynesian models, these labor market shocks are modeled either as exogenous shifts in the dis-utility

*This chapter is based on a research paper that is joint work with Agostino Consolo and Claudia Foroni.

of supplying labor or as movements in wage mark-ups (see Galí (2011), Galí, Gertler, and López-Salido (2007), Galí, Smets, and Wouters (2012), and Phaneuf, Sims, and Victor (2018)). At the same time, these models describe the frictions in the labor market and their consequences for macroeconomic dynamics.

However, in this paper, we focus on the labor market from an empirical perspective, seeking to describe the role of different macroeconomic and labor market shocks. To reach our goal, we develop a structural vector autoregression (SVAR) model, which includes mixed frequency data, identifying shocks with sign restrictions. We are, in fact, interested in obtaining a "real-time" evaluation of the dynamics in the euro area labor market. Therefore, we face the fact that some variables are available at monthly frequency (such as the unemployment rate and survey measures), while other labor market indicators (such as employment and labor market flows) are available only at quarterly frequency and with different publication delays. To address data availability issues, we choose to set up a mixed frequency model, a natural framework capable to accounting for data with different frequencies and publication lags. While the literature on mixed frequency techniques is vast by now, in this paper we follow the approach of Schorfheide and Song (2015) and use a mixed frequency Bayesian VAR (MF-BVAR). The choice of this method is driven by the purpose of our study: first, we want to have a set of variables depicting the labor market and macroeconomic dynamics; second, we want to be able to provide a reliable forecast of the main variables; and third, we want to have a structural interpretation in light of economic shocks, which are likely to explain the history of the time series, as well as the projected nowcasts. A Bayesian VAR set up is, therefore, very convenient for us, given that it allows for identifying shocks via sign restrictions in a straightforward manner. Specifically, we augment the methodology of Schorfheide and Song (2015), by including a step that draws impact matrices that fulfill the imposed restrictions. To do so, we follow the methodology of Rubio-Ramirez, Waggoner, and Zha (2010). While there are few examples of structural mixed frequency VARs (see Foroni and Marcellino (2014) and Ghysels (2016)), to the best of our knowledge, however, no previous papers use sign restrictions in mixed frequency VARs and, therefore, we aim at closing a methodological gap. Moreover, our sign-restricted SVAR also provides a powerful policy tool for practitioners, given that it allows the interpretation of the drivers of nowcasts in terms of the structural shocks.

We find satisfactory results in terms of forecasting, especially when looking at quarterly variables, such as employment growth and the job finding rate.

These findings are aligned with most of the results available in the mixed frequency literature, which suggest that the content available in higher frequency data helps improve the forecasting accuracy of lower frequency variables. Additionally, we also find that our model produces suitable industrial production growth forecasts. The unemployment rate is more difficult to predict, given that the information contained in its own lags is often already sufficient to provide a good forecast. Further, we look into the shocks that drove the labor market and macroeconomic dynamics from 2002 to early 2020. We find noteworthy insights. First, demand shocks were the main drivers during the past Great Recession. Second, shocks originating in the labor market play an important role in explaining the period of low inflation and low wage growth from 2013 onward. We further dig into the corona virus (COVID-19) period, in order to find an early assessment of the shocks explaining this crisis. We find that, in contrast to the Great Recession, aggregate supply and labor supply are important drivers of key labor market variables. Furthermore, in the early estimates for the nowcast of the first quarter of 2021, we find signs of a recovery in the labor market mainly driven by aggregate supply, aggregate demand, and wage-bargaining shocks.

As a further contribution of our paper, we consider the importance of the labor market flows. First, these variables are used to refine the shock identification. Second, we assess whether they play a role in the forecasting of labor market variables, as some papers in the literature show (see Barnichon and Nekarda (2012) and Barnichon and Garda (2016)). In contrast to the results in this literature, we find no evidence that the inclusion of job market flows in the model produces more accurate forecasts. The nature of this result lies in the significant publication delay of job market flows. Unlike the US, the availability of job market flows in the euro area has a delay of two quarters.

The remainder of the chapter is organized as follows: Section 3.2 describes in detail the notation, the MF-BVAR of Schorfheide and Song (2015), and the inclusion of sign restrictions in their algorithm. Section 3.3 provides a description of our baseline model and an economic interpretation of the main results. In section 3.4, we conduct a pseudo real-time forecasting analysis. We conclude in section 3.5.

## 3.2 Methodology

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

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

### 3.2.1 The mixed frequency Bayesian VAR of Schorfheide and Song (2015)

We consider a set of $N$ variables divided in two different blocks, $x_t = [x'_{m,t}, x'_{q,t}]'$, for $t = 1, \ldots, T$ months. The first block contains $N_m$ monthly variables, which are originally available at this frequency; whereas the second block $x_{q,t}$ includes $N_q$ variables that are the monthly counterpart of variables available at the quarterly frequency. Therefore, the variables in block $x_{q,t}$ are latent. Moreover, we define the vector $y_{q,t}$ as the observable quarterly variables, which have observations every third month and missing values otherwise. We assume that the vector $x_t$ evolves as the following VAR :

$$x_t = c + A_1 x_{t-1} + \cdots + A_p x_{t-p} + u_t, \quad u_t \overset{iid}{\sim} N(0, \Sigma), \tag{3.1}$$

where $c$ is a vector of intercepts, $A_i$ are matrices of reduced-form parameters, for $i = 1, \ldots, p$, and $u_t$ is a vector of reduced-form errors.

We re-write the VAR in equation (3.1) in terms of the two blocks as follows:

$$\begin{bmatrix} x_{m,t} \\ x_{q,t} \end{bmatrix} = \begin{bmatrix} c_m \\ c_q \end{bmatrix} + \begin{bmatrix} A_{mm} & A_{mq} \\ A_{qm} & A_{qq} \end{bmatrix} \begin{bmatrix} z_{m,t-1} \\ z_{q,t-1} \end{bmatrix} + \begin{bmatrix} u_{m,t} \\ u_{q,t} \end{bmatrix}, \tag{3.2}$$

where $z_{m,t-1} = [x'_{m,t-1}, x'_{m,t-2}, \cdots, x'_{m,t-p}]'$ is an $N_m p \times 1$ vector with the lags of the monthly variables and the $N_q p \times 1$ vector, $z_{q,t-1} = [x'_{q,t-1}, x'_{q,t-2}, \cdots, x'_{q,t-p}]'$, has the lags of the latent variables. The matrix of parameters has four submatrices: $A_{mm}$, an $N_m \times N_m p$ matrix of parameters governing the relationship among monthly variables; $A_{mq}$, an $N_m \times N_q p$ matrix containing the impact of the latent variables into the monthly block; $A_{qm}$, an $N_q \times N_m p$ matrix representing the impact of monthly variables into the equations of the latent variables; and $A_{qq}$, an $N_q \times N_q p$ matrix ruling the interactions among the latent variables. The blocks of constants, $c_q$ and $c_m$, have the dimensions $N_q \times 1$ and $N_m \times 1$, respectively. The same dimensions apply for the blocks of error terms $u_{q,t}$ and $u_{m,t}$. In a similar way, we partition the covariance matrix into four blocks:

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

To obtain estimates of both the parameters and the latent variables, we write the state-space representation of the model. To do so, we denote $T$ as the last month for which we have at least one observation in the monthly block; $T_{bq}$ is the time period at which we have a quarterly balanced set; and $T_b$ is the data point for which we have a balanced panel in the monthly block. Note that, not all monthly variables might be available between $T_b$ and $T$. In a similar fashion, the quarterly set can also have ragged-edges. Summarizing, we can have three types of missing observations: (i) mixed frequencies from $t = 1, \ldots, T_b$; (ii) ragged edges in the quarterly set; and (iii) ragged edges in the monthly variables.[1] As an illustration of the different pattern of missing observations, in table 3.1, we consider an example of a data set with three monthly and three quarterly variables. The character "x" represents an available data point; whereas "NaN" denotes a missing observation.

Until time $t = T_b$, the state vector only corresponds to the latent quarterly block. However, due to missing observations in the monthly variables between $T_b$ and $T$, a subset of the monthly variables becomes a state. For this reason, we split our problem into two state-space representations. The first state-space model approaches mixed frequencies, ragged-edges in the quarterly variables, and the fact that we are interested in obtaining an estimate of $x_{q,t}$, the monthly counterpart of the quarterly variables. The second state-space model deals with the publication delays in the monthly block.

[1]In this chapter, we do not assess the problem of missing observations due to different starting dates. For methods dealing with such problems see chapter 2.

Table 3.1: Type of missing observations

| | $x_{m1,t}$ | $x_{m2,t}$ | $x_{m2,t}$ | $y_{q1,t}$ | $y_{q2,t}$ | $y_{q3,t}$ | |
|---|---|---|---|---|---|---|---|
| Jun 19 | x | x | x | x | x | x | $t = T_{bq}$ |
| Jul 19 | x | x | x | NaN | NaN | NaN | |
| Aug 19 | x | x | x | NaN | NaN | NaN | |
| Sep 19 | x | x | x | x | x | NaN | |
| Oct 19 | x | x | x | NaN | NaN | NaN | |
| Nov 19 | x | x | x | NaN | NaN | NaN | |
| Dec 19 | x | x | x | x | NaN | NaN | $t = T_b$ |
| Jan 20 | x | x | NaN | NaN | NaN | NaN | |
| Feb 20 | x | NaN | NaN | NaN | NaN | NaN | $t = T$ |

Note: The table shows an example of the different types of missing observations. "x" represents one available data point and "NaN" represents a missing value.

**A state-space for mixed-frequency variables**

We define the state and measurement equations for $t = 1, \cdots, T_{bq}$. To do so, we partition the block-VAR of equation (3.2) into the observable part $x_{m,t}$ and the latent part $x_{q,t}$. We define the state vector, $S_t$, as follows:

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

$S_t$ stacks present and past values of the latent variables and it has a dimension of $N_s \times 1$, with $N_s = N_q(p+1)$. We assume $S_t$ evolves as the following state equation:

$$S_t = \Gamma_c + \Gamma_z z_{m,t-1} + \Gamma_s S_{t-1} + \Gamma_u u_{q,t}, \tag{3.3}$$

where

$$\Gamma_c = \begin{bmatrix} c_q \\ 0_{(N_q \times p)\times 1} \end{bmatrix}, \quad \Gamma_z = \begin{bmatrix} A_{qm} \\ 0_{(N_q \times p)\times(N_m \times p)} \end{bmatrix}$$
$$\Gamma_s = \begin{bmatrix} A_{qq} & 0_{N_q} \\ I_{(N_q \times p)} & 0_{(N_q \times p)\times N_q} \end{bmatrix}, \quad \text{and} \quad \Gamma_u = \begin{bmatrix} I_{N_q} \\ 0_{(N_q \times p)\times N_q} \end{bmatrix}.$$

The dimensions of state matrices $\Gamma_c$, $\Gamma_z$, $\Gamma_s$, and $\Gamma_u$ are $N_s \times 1$, $N_s \times N_m p$,

$N_s \times N_s$, and $N_s \times N_q$, respectively.

To link the observable variables in $y_{q,t}$ with the latent states $x_{q,t}$, we introduce variable $\tilde{y}_{q,t}$, which is the monthly average of the latent states.[2] Thus,

$$\tilde{y}_{q,t} = \Lambda_s S_t, \tag{3.4}$$

where $\Lambda_s = \begin{bmatrix} \frac{1}{3} I_{N_q} & \frac{1}{3} I_{N_q} & \frac{1}{3} I_{N_q} & 0_{N_q \times (N_s - N_q)} \end{bmatrix}$, assuming the number of lags in the VAR is at least three. Therefore, the following relationship holds

$$y_{q,t} = M_{q,t} \tilde{y}_{q,t}, \tag{3.5}$$

where $M_{q,t}$ is an $N_q \times N_q$ selection matrix linking the average of the latent states with the observable quarterly variables every third month. This means that, in addition to the monthly block, we observe the quarterly average of the states every third month. Therefore, the measurement equation is:

$$y_t = \Lambda_c + \Lambda_z z_{m,t-1} + \Lambda_{ys} S_t + \Lambda_u u_{m,t}, \tag{3.6}$$

where $y_t = [x_t', y_{q,t}']'$ is a vector of observable variables, and

$$\Lambda_c = \begin{bmatrix} c_m \\ 0_{N_s \times 1} \end{bmatrix}, \quad \Lambda_z = \begin{bmatrix} A_{mm} \\ 0_{N_q \times N_m p} \end{bmatrix},$$
$$\Lambda_{ys} = \begin{bmatrix} 0_{N_m \times N_q} \quad A_{mq} \\ M_{q,t} \Lambda_s \end{bmatrix}, \quad \text{and} \quad \Lambda_u = \begin{bmatrix} I_{N_m} \\ 0_{N_q \times N_m} \end{bmatrix}.$$

To address potential ragged edges in the quarterly variables, which may occur for $t = T_{bq} + 1, \ldots, T_b$, we follow the approach in Durbin and Koopman (2012).

### A state-space for monthly ragged-edges

The second state-space representation considers the case of ragged-edges in the monthly block. Although we treat ragged-edges in the quarterly set, this approach does not apply for the monthly variables. This is because, so far, the monthly variables are observable. However, when the monthly block contains ragged-edges, a subset of the monthly variables becomes a state. We define the new state vector as $\tilde{z}_t = [x_t', \ldots, x_{t-p+1}']$, which has a dimension of $N_{\tilde{z}} \times 1$, with $N_{\tilde{z}} = Np + N$. This state vector is only defined for $t = T_b + 1, \cdots, T$, where

[2] We do not distinguish between stock and flow variables, given that assuming the average or the sum only affects the scale of the measurement equation. Note, however, that the assumption of the average (or sum) must be consistent when constructing the latent states and their potential transformations.

only monthly variables are available. We assume the state vector $\tilde{z}_t$ evolves as the VAR:

$$\tilde{z}_t = \tilde{c} + \tilde{\Phi}\tilde{z}_{t-1} + \tilde{u}_t, \quad \tilde{u}_t \overset{iid}{\sim} N(0, \tilde{\Sigma}), \tag{3.7}$$

with covariance matrix

$$\Sigma_{\tilde{z}} = \begin{bmatrix} \Sigma & 0_{Np\times N} \\ 0_{N\times Np} & 0_{N\times N} \end{bmatrix}.$$

$\tilde{c}$, $\tilde{\Phi}$, and $\tilde{u}_t$ are defined as follows:

$$\tilde{c} = \begin{bmatrix} c \\ 0_{Np\times 1} \end{bmatrix}, \quad \tilde{\Phi} = \begin{bmatrix} A_+ & 0_{N\times N} \\ I_{Np} & 0_{Np\times N} \end{bmatrix}, \quad \tilde{u}_t = \begin{bmatrix} u_t \\ 0_{Np\times 1} \end{bmatrix},$$

and have dimensions $N_{\tilde{z}} \times 1$, $N_{\tilde{z}} \times N_{\tilde{z}}$, and $N_{\tilde{z}} \times 1$, respectively. The matrix $A_+ = [A_1, \ldots, A_p]$ stacks the matrices of reduced-form parameters from the VAR in equation (3.1).

The measurement equation exclusively depends on monthly variables that are observable from $t = T_b + 1, \ldots, T$. Thus, we define $N_{\tilde{m}}$ as the number of monthly variables available after $T_b$. The measurement equation is defined as:

$$\tilde{y}_t = M_{\tilde{z}}\tilde{z}_t, \tag{3.8}$$

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

### 3.2.2 Bayesian estimation

Schorfheide and Song (2015) develop a two-block Gibbs sampler, in order to obtain draws from the conditional posterior distributions of the parameters and states of the model. Specifically, they sample the state vectors via the Carter-Kohn algorithm (see Carter and Kohn (1994)), which is the Bayesian counterpart of the Kalman filter and smoother. Given the states, the second block consists on sampling the parameters of the VAR in equation (3.1), i.e., $\Phi = [c, A_1, \ldots, A_p]$ and the reduced-form covariance matrix $\Sigma$.

To sample the parameters of the VAR, we consider a Normal - Inverse Wishart prior as follows:

$$\text{vec}(\Phi)|\Sigma \sim \mathcal{N}\left(\text{vec}(\underline{\Phi}), \Sigma \otimes \underline{V}\right) \quad \text{and} \quad \Sigma \sim iW\left(S, d\right), \tag{3.9}$$

where $\underline{\Phi} = [\underline{c}, \underline{A}_1, \ldots, \underline{A}_p]$ has the prior mean of the reduced-form parameters and $\underline{V}$ is a diagonal matrix with the prior variance of the reduced-form parameters. $\underline{V}_j$ denotes a block of $\underline{V}$ corresponding to equation $j$. Therefore, $\underline{v}_{j,k}$ denotes the $k$-th element in the diagonal of $\underline{V}_j$. Given our assumption of a Gaussian likelihood, the prior (3.9) is conjugate. Following the Minnesota prior version of Sims and Zha (1998) and Del Negro and Schorfheide (2011), the scale covariance matrix is $S = diag(s_1, \cdots, s_N)$, whose diagonal elements are the standard deviation of each variable during a training sample. We set the degrees of freedom to $d = N+2$, the minimum number such that the mean of an inverse Wishart distribution exists, see Kadiyala and Karlsson (1997).

The moments of the normal prior distribution take the following form:

$$\underline{A}_{i,jk} = \begin{cases} \delta_i & \text{if } \; j = k \quad \text{and} \; i = 1 \\ \quad 0 & \text{otherwise} \end{cases}$$
$$\underline{v}_{j,k} = \begin{cases} \left(\frac{\lambda_1 s_j}{i}\right)^2 & \text{if } \quad j = k \\ \left(\frac{s_j \lambda_1}{s_k \; i^{\lambda_2}}\right)^2 & \text{if } \quad j \neq k \end{cases} \tag{3.10}$$

where $\underline{A}_{i,jk}$ is the $(j,k)$-th element of matrix $\underline{A}_i$, for $i = 1, \ldots, p$. We set a diffuse prior for the intercept term. When a variable is not stationary, e.g., the unemployment rate, we shrink the autoregressive parameters toward a random walk and therefore $\delta_i = 1$. In contrast, when a time series is stationary, e.g., the employment growth rate, we shrink it toward a white noise, thus $\delta_i = 0$. Therefore, the diagonal elements of parameter matrix $A_1$ equal one when the variables are I(1) and 0, otherwise. Moreover, the off-diagonal elements of $A_1$ and the elements of matrices $A_i$, for $i > 1$ are zero. For the prior covariance matrix $\underline{V}$, we assume it is diagonal, where we impose that the more distant lags and the coefficients from variable $k$ have a smaller weight in the equation of $x_{j,t}$, for $j, k = 1, \cdots, N$. The overall shrinkage of the parameters is ruled by $\lambda_1$ and the hyperparameter $\lambda_2$ rules the shrinkage of higher-order lags. In general, the larger the hyperparameters, the stronger the shrinkage.

Following Schorfheide and Song (2015), we implement the prior through dummy observations (see Sims and Zha (1998)).[3] This approach augments the data with the following artificial observations:

[3]For detailed explanation of how it is implemented, see also Del Negro and Schorfheide (2011).

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

where $J = \text{diag}(1, \cdots, p)$. We denote the augmented data by $X^* = [X', x_d']'$, $Z^* = [Z', z_d']'$, where $X$ is the $T \times N$ matrix of data and $Z$ is a $T \times (Np+1)$ matrix with the lagged values of the data and a constant. Therefore, we consider the following augmented VAR:

$$X^* = Z^*\Phi^* + U^*, \tag{3.11}$$

where $U^* = [U', u_d']'$, and the time dimension is $T^* = T + T_d$. The augmented model combines the prior and the likelihood of the data. Thus, the posterior distribution takes the following form:

$$\begin{aligned} \text{vec}(\Phi|X, \Sigma \sim \mathcal{N}\left(\hat{\Phi}, \Sigma \otimes \left(X^{*\prime}X^*\right)^{-1}\right) \\ \Sigma|X \sim iW(\hat{\Sigma}, T^* + 1 - Np), \end{aligned} \tag{3.12}$$

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

The vector of hyperparameters, $\Lambda = [\lambda_1, \lambda_2]$, governs the prior, therefore an important issue to consider is its estimation. Due to the nature of latent states and observable time series in the VAR, the marginal data density (MDD) does not have a closed-form solution. Thus, the methodologies that obtain the optimal hyperparameters through the optimization of the MDD are not feasible, e.g., Giannone et al. (2015), Chan, Jacobi, and Zhu (2020). Schorfheide and Song (2015) approximate the MDD through the harmonic mean estimator of Geweke (1999). Once they obtain the approximation, the optimal parameters can be estimated over a grid. In this paper, we follow their approach for obtaining optimal values for the overall degree of shrinkage $\lambda_1$. We set the decay parameter $\lambda_2 = 2$, a standard value selected in the literature. We show the considered grid and the selected hyperparameter for the model in appendix 3.A.1.

### 3.2.3 Shock identification with sign restrictions

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

We link the reduced-form VAR from equation (3.1) with the structural macroeconomic shocks, $\varepsilon_t$, as follows:

$$u_t = B\varepsilon_t, \ \varepsilon_t \overset{iid}{\sim} N(0, I_N), \tag{3.13}$$

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

$$B^* = PQ,$$

where $Q$ is a rotation matrix, $P = \text{chol}(\Sigma)$, and chol denotes the lower-triangular Cholesky decomposition. To generate draws of the rotation matrix, Rubio-Ramirez et al. (2010) propose an algorithm based on a QR decomposition, which translates to an independent Haar-uniform prior of the rotation matrix.[4] In our framework, once we obtain a draw of the states and the parameters of the VAR, we draw $B^*$ for up to 100,000 candidate matrices until we find a draw of $B^*$ that fulfills the sign restrictions. In this paper, we consider a partially-identified model (see section 3.3), therefore, we corroborate that the non-identified shocks have a different set of signs than the restricted elements of the shocks of interest.

## 3.3 A model for the euro area labor market

Our VAR model includes eight variables: industrial production growth rate ($\Delta ip_t$), an index to identify the relative strength of the manufacturing relative

[4]We are aware that, by following this methodology, we rely on an informative prior, which itself does not depend on the data. However, we follow the technique by Rubio-Ramirez et al. (2010) since this is the most common approach in the literature.

to the service sector (which for simplicity we call MS index ($ms_t$)),[5] inflation ($\Delta p_t$), wage growth ($\Delta w_t$, measured by compensation per employee), unemployment rate ($u_t$), employment growth ($\Delta e_t$), and the job flows, specifically the job finding rate ($f_t$) and job separation rate ($s_t$). A detailed description of the variables and their transformations is found in Appendix 3.A. We estimate the model using a sample spanning from January 1998 to February 2020. The vintage of the data corresponds to February 28, 2020. On this day, the data set has the ragged-edge pattern as in table 3.2. The character "x" denotes an available observation, whereas "NaN" depicts a missing value. Note that the estimation of the MF-BVAR nests the computation of the nowcasts corresponding to the current and past months of the unemployment rate and the industrial production growth rate, and the nowcast of the current month of inflation; as well as the nowcasts of the current quarter of employment growth, and the nowcasts of the current and past two quarters of wage growth and the job flows. To estimate the model, we consider twelve lags of the endogenous variables.[6]

Table 3.2: Ragged-edges by February 28, 2020

| | Monthly variables | | | | Quarterly variables | | | |
|---|---|---|---|---|---|---|---|---|
| | $u_t$ | $\Delta ip_t$ | $\Delta p_t$ | $ms_t$ | $\Delta w_t$ | $\Delta e_t$ | $f_t$ | $s_t$ |
| Sep/Q3 20 | x | x | x | x | x | x | x | x |
| Oct 20 | x | x | x | x | NaN | NaN | NaN | NaN |
| Nov 20 | x | x | x | x | NaN | NaN | NaN | NaN |
| Dec/Q4 20 | x | x | x | x | NaN | x | NaN | NaN |
| Jan 20 | NaN | NaN | x | x | NaN | NaN | NaN | NaN |
| Feb 20 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |

Note: The table reports a snapshot of the ragged-edges and the mixed frequency nature of our data set. "x" indicates an available data point and "NaN" represents a missing data point.

With this set of variables, we aim at identifying six shocks. Specifically, two demand shocks, domestic and foreign; a technology shock; and three shocks originating in the labor market, a labor supply shock, a wage bargain-

[5]The MS index is defined as the difference between the growth rates of the Purchasing Managers' Index (PMI) in manufacturing and services: $MS = \Delta \ln PMI_t^M - \Delta \ln PMI_t^S$. We consider surveys instead of the gross-value-added in both sectors, given that the former represent expectations and therefore react more promptly to the impact of shocks than the latter.

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

ing shock, and a mismatch shock. The identification is obtained by means of sign restrictions. We consider the identification scheme of table 3.3, where all the restrictions are imposed on impact.

Table 3.3: Identification scheme via sign restrictions

| | Demand | | Supply | Labor Market | | |
|---|---|---|---|---|---|---|
| | Domestic | Foreign | Technology | Labor Supply | Mismatch | Wage Bargaining |
| $u_t$ | - | - | - | - | - | - |
| $\Delta ip_t$ | + | + | + | - | + | + |
| $\Delta p_t$ | + | + | - | + | /// | - |
| $\Delta w_t$ | /// | /// | + | + | + | - |
| $\Delta e_t$ | /// | /// | /// | /// | /// | /// |
| $ms_t$ | - | + | /// | /// | /// | /// |
| $f_t$ | + | + | + | /// | + | /// |
| $s_t$ | - | - | - | /// | + | /// |

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

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

Following Mumtaz and Zanetti (2015), we further use the information of labor market flows for the identification of neutral technology shocks. A neutral technology shock represents an increase in productivity, which reduces the marginal costs for firms and, therefore, pushes inflation down. The production expansion creates incentives for increasing hiring and translates into a rise in the job finding rate. Moreover, the higher productivity makes firms more willing to keep their employees, therefore decreasing the job separation rate. Consequently, the unemployment rate also decreases. However, a positive technology shock also creates a positive shift in the labor demand curve, which increases output and wage growth.

Both labor supply and wage bargaining shocks generate an inverse co-movement between output and real wages (see Foroni, Furlanetto, and Lepetit (2018a)). In the first case, an exogenous increase in labor supply leads to an increase in the number of job seekers, making it easier for firms to fill vacancies and to reduce hiring costs. Thereby, leading to a decrease in unemployment, wage growth, and inflation, as well as an increase in output. In the second case, a reduction in the bargaining power of workers has a direct negative effect on wage growth, thus contributing to lower marginal costs and lower inflation. Since firms now capture a larger share of the surplus associated with employment relationships, they post more vacancies, contributing to a decrease of unemployment.

A negative wage bargaining (or wage mark-up) shock leads firms to capture a larger share of the bargaining surplus. A reduction in the bargaining power of workers leads to a decline in wages. Therefore, firms increase hiring and vacancy posting increases, leading to a decrease in unemployment. Matching efficiency shocks can be interpreted as reallocation shocks. In line with search and matching models with endogenous job destruction (see Pissarides (2000)), an exogenous increase in mismatch efficiency shifts the job creation curve outward, increasing both the labor market tightness and wages. The increase in efficiency makes it easier for workers to find a job and therefore the job finding rate increases. The lower mismatch reduces the costs of firing people, thus, firms get an incentive to search a better candidate matching the job, creating a rise in the job separation rate. Additionally, this shock shifts the Beveridge curve inward, which translates into lower unemployment (see Consolo and Dias da Silva (2019), for further details).

### 3.3.1 Drivers of the euro area labor market

Figures 3.9 to 3.14 from appendix 3.B report the cumulative impulse responses of the variables in the MF-BVAR to aggregate supply, aggregate domestic demand, aggregate foreign demand, labor supply, mismatch, and wage bargaining shocks, respectively.[7] The shaded areas show the 68% point-wise credibility bands, whereas the blue line depicts the point-wise median. We choose the median as the central tendency of the impulse responses, since it is the optimal solution of the sum of the absolute loss of the impulse re-

[7]We do not report results for the MS index, since this variable is not typically monitored and it was exclusively included for identification purposes. However, results are available upon request.

sponses (see Baumeister and Hamilton (2015, 2018)).[8] We find that aggregate supply and aggregate foreign demand shocks have the most persistent effects on real variables. This is because the unemployment rate and industrial production increase for about a year and for the first six months after the shocks, respectively. Moreover, we find that prices increase and remain significant for about a year after an aggregate foreign demand shock. Although we remain agnostic about the prior sign of wages when a labor supply shock hits the economy, we find that this shock seems to have an impact on wages, given that compensation per employee rises for about six months after the shock. From the side of the job flows, we find that the job finding rate rises after aggregate supply, aggregate demand (both foreign and domestic), and mismatch shocks. However, the job separation rate only mildly decreases after an aggregate supply shock.

Through the lenses of our model, we aim at explaining the dynamics in the euro area labor market, by interpreting which shocks explain their developments. In Figures 3.1 to 3.7, we report the historical decomposition of the variables based on our benchmark model, in deviations from their mean. For the variables previously considered in first differences, we construct the year-over-year rate, given that this is the most monitored transformation for policy purposes. All figures report the median of the posterior distribution of the historical decomposition.

We summarize the main economic findings. First, labor market developments depend not only on the macroeconomic shocks, i.e., aggregate demand and supply shocks, but they depend strongly also on shocks originated internally in the labor market. During the Great Recession, the model points at demand shocks (domestic and foreign) as the main factors explaining the dynamics of most of the variables, influencing both real and nominal variables. However, looking at the period starting in 2013, the role of shocks originated in the labor market (labor supply, wage bargaining power, and mismatch) become more important in explaining low wage growth (and, consequently, low inflation). In particular, the wage bargaining shock plays an important role as a driver of the wage inflation, since it reflects the overall effects stemming from reforms in labor market institutions implemented in the euro area following the 2010 Sovereign Debt Crisis. This is consistent with the interpretation of the wage bargaining shock in our model, where it captures both a change in the pure bargaining power of workers and a change in the workers' outside

[8] We are aware of the critique that there are many possible loss functions to consider (Kilian and Lütkepohl (2017), chapter 13). Nevertheless, we choose the median as a central tendency given that this is standard and the most frequent approach in the literature.

option. The latter indeed decreased both for the effect of the crisis and also for the increased flexibility of labor market institutions across some euro area countries (see Koenig, Manning, and Petrongolo (2016)).

Furthermore, we also find that the mismatch shock complements the wage bargaining shock in explaining key labor market developments during the euro area Sovereign Debt Crisis, in line with a standard search and matching model à la Pissarides (2000). According to Consolo and Dias da Silva (2019), the degree of labor market mismatch has increased following the euro area Sovereign Debt Crisis, which is also visible in the outward shift of the euro area Beveridge curve as of 2011. In our model, this is reflected in the historical decomposition of the job finding rate in figure 3.4, which suggests a negative contribution from job matching efficiency starting from 2011. Consistent with the search and matching framework, higher mismatch in the labor market has led to lower wage growth over the same period, as visible in figure 3.3. As in Elsby, Hobijn, and Şahin (2013), the dynamics of the unemployment rate during the Sovereign Debt Crisis are also driven by the mismatch shock, which features an important cyclical component.

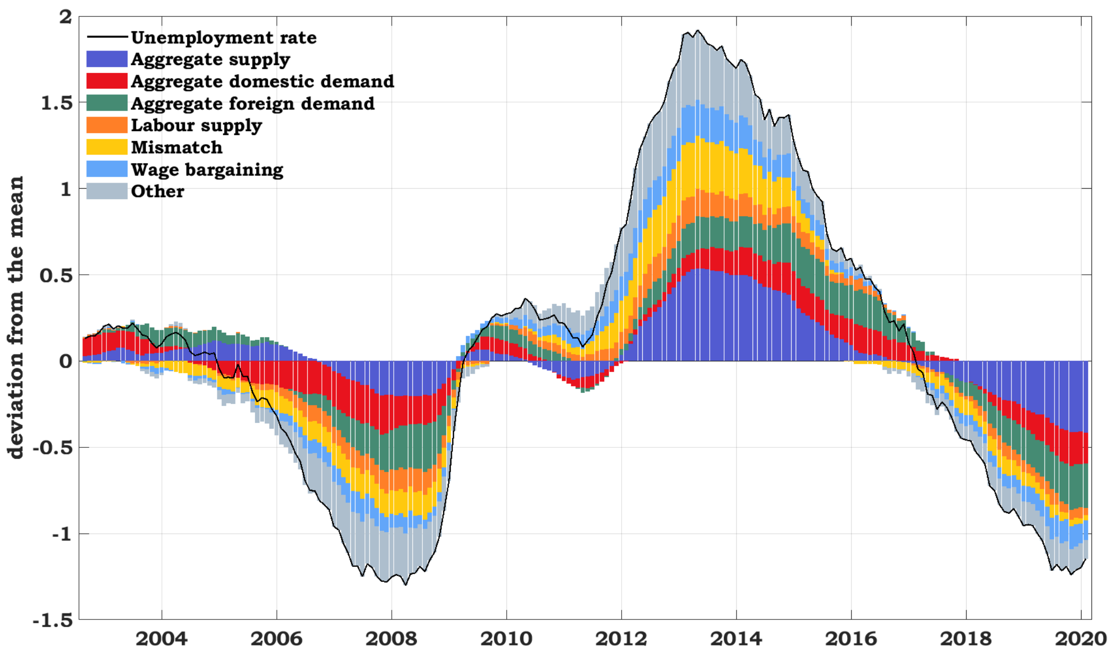


Figure 3.1: Historical decomposition of the unemployment rate

Note: The graph shows the median posterior distribution of the historical decomposition.

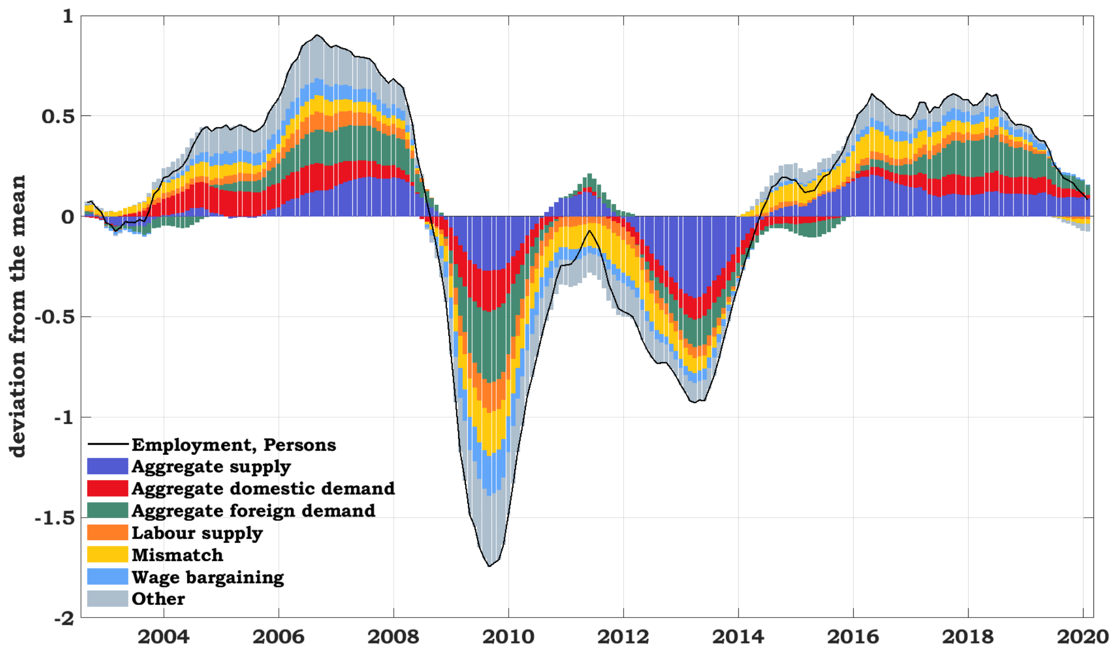


Figure 3.2: Historical decomposition of the employment growth rate

Note: The graph shows the median posterior distribution of the historical decomposition.

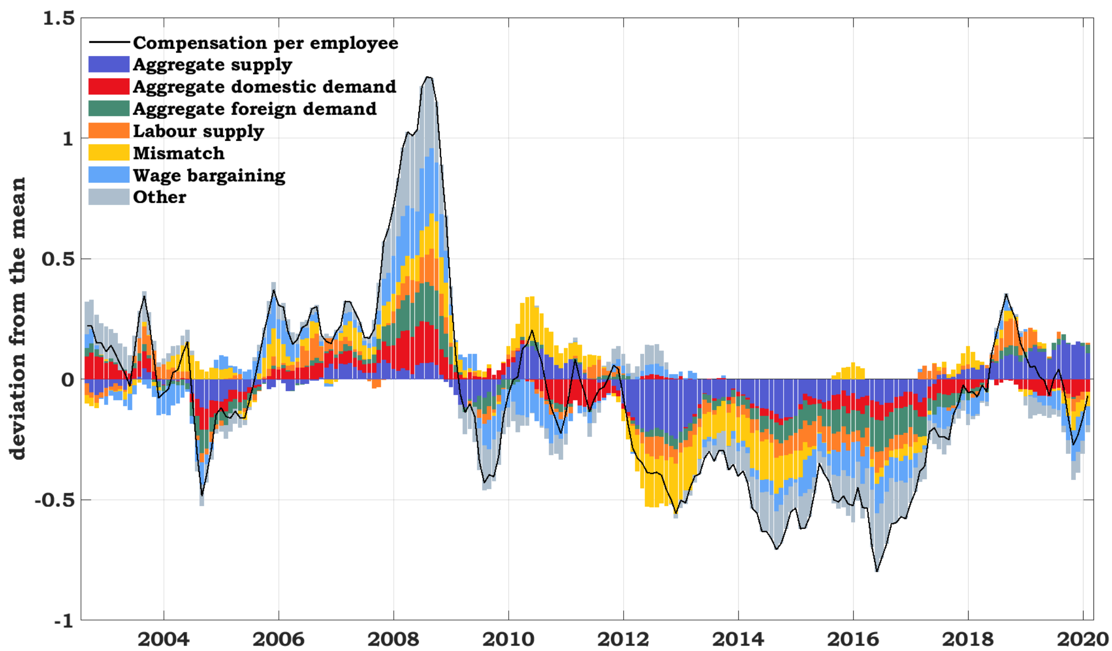


Figure 3.3: Historical decomposition of the wage growth rate, measured by compensation per employee

Note: The graph shows the median posterior distribution of the historical decomposition.

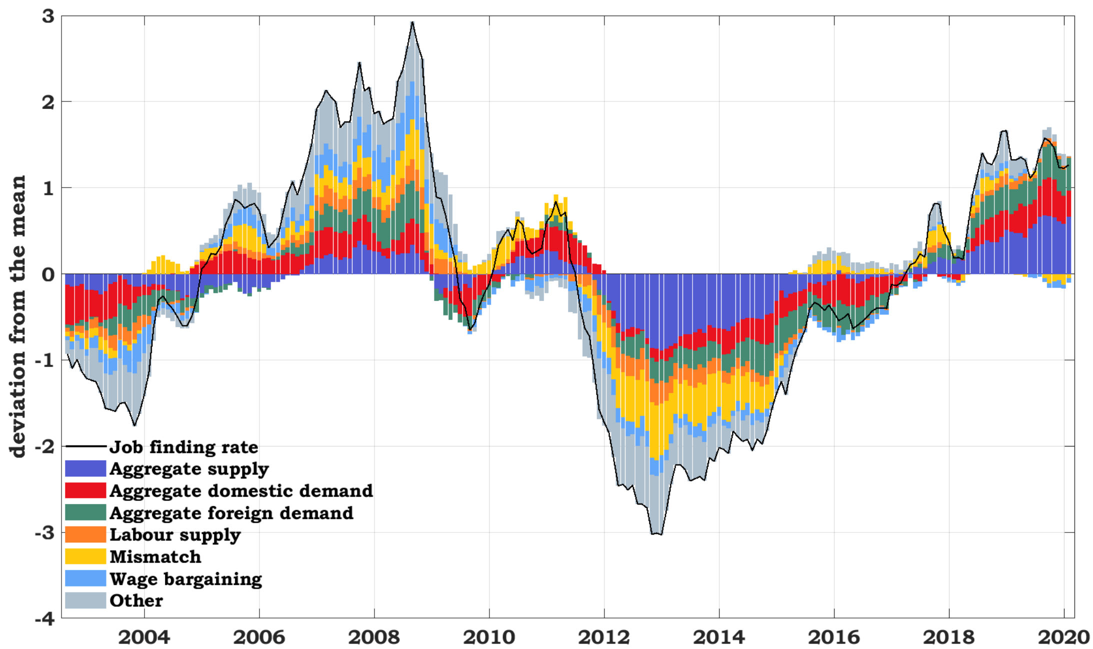


Figure 3.4: Historical decomposition of the job finding rate

Note: The graph shows the median posterior distribution of the historical decomposition.

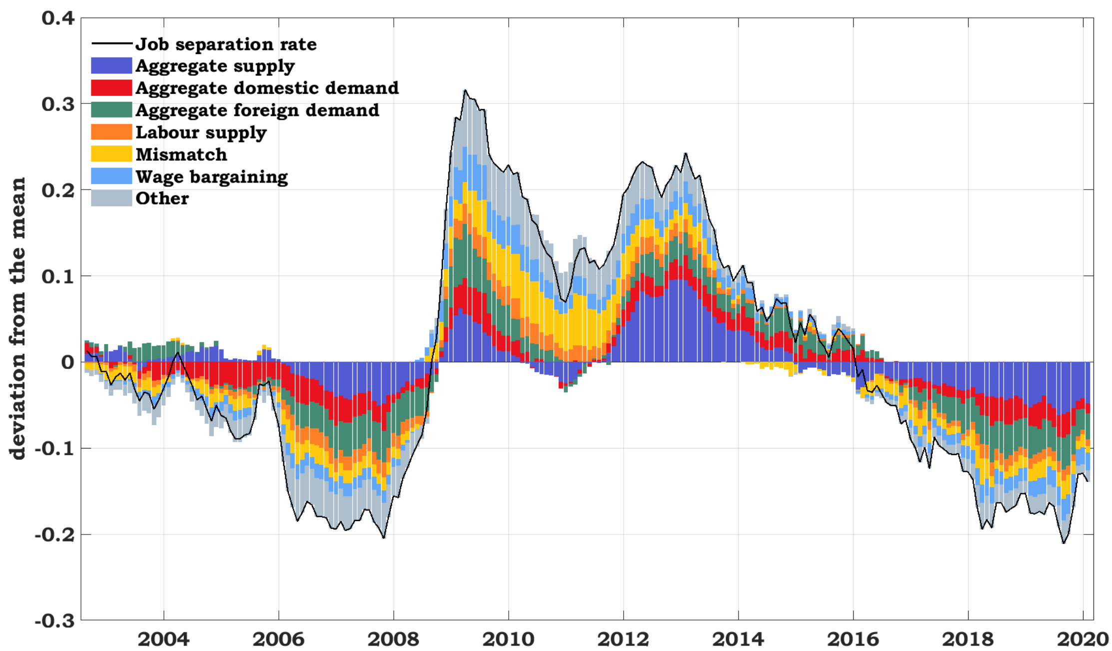


Figure 3.5: Historical decomposition of the job separation rate

Note: The graph shows the median posterior distribution of the historical decomposition.

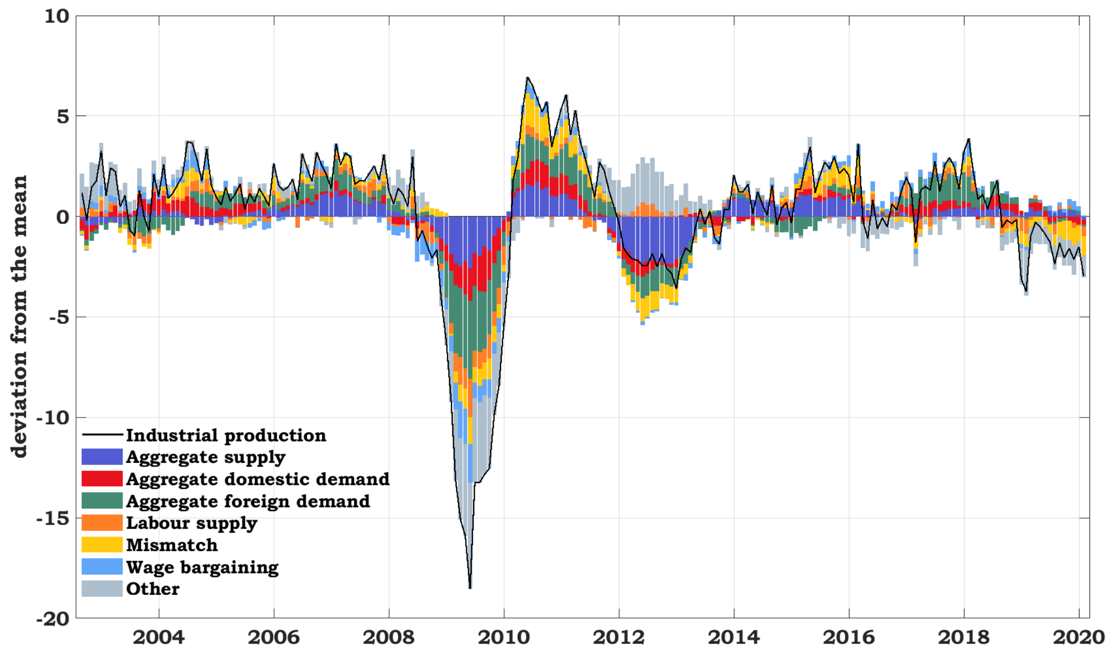


Figure 3.6: Historical decomposition of the industrial production growth rate

Note: The graph shows the median posterior distribution of the historical decomposition.

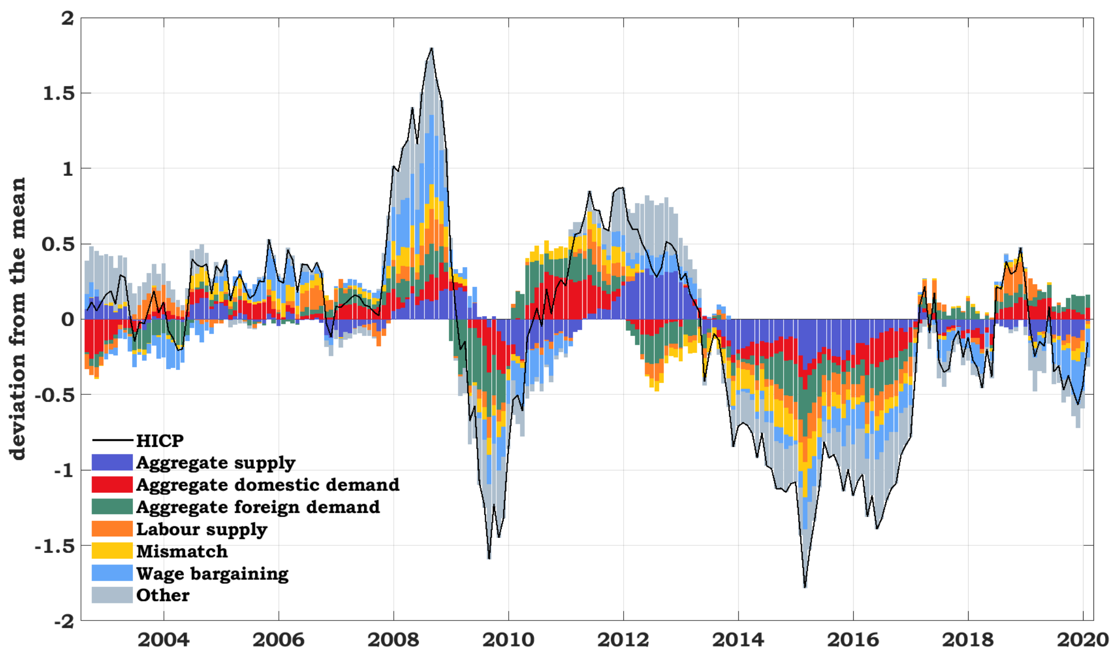


Figure 3.7: Historical decomposition of inflation

Note: The graph shows the median posterior distribution of the historical decomposition.

As we detail in the next section, one advantage of our model is that it can provide an economic interpretation also to nowcasts. In the figures, for example, the last observation is often not observable, but it is the outcome of the model estimation. Therefore, our contribution of augmenting the model of Schorfheide and Song (2015) to an SVAR provides a key tool for policy work.

### 3.3.2 An early assessment of the COVID-19 period

The pandemic caused by the novel corona virus (COVID-19) triggered an unprecedented decline in the euro area economic activity, as well as even-lower levels of inflation. Additionally, the labor market experienced frictions that were represented by a historical decline in employment and total hours worked. However, the aggregate euro area unemployment rate slowly increased, reflecting the high take-up rate of job retention schemes and transitions into inactivity (see Anderton, Botelho, Consolo, Dias da Silva, Foroni, Mohr, and Vivian (2021), for an overview).

In this subsection, we re-estimate the MF-BVAR model considering a sample containing the COVID-19 crisis. Specifically, we now take a sample spanning from January 1998 to March 2021. The vintage of the data corresponds to March 8, 2021. In this case, the ragged-edge structure of the data is summarized by table 3.4. As previously stated, the estimation of our benchmark model provides us with a nowcast for the missing months and quarters.

Table 3.4: Ragged-edges by March 8, 2021

| | Monthly variables | | | | Quarterly variables | | | |
|---|---|---|---|---|---|---|---|---|
| | $u_t$ | $\Delta ip_t$ | $\Delta p_t$ | $ms_t$ | $\Delta w_t$ | $\Delta e_t$ | $f_t$ | $s_t$ |
| Sep/Q3 20 | x | x | x | x | x | x | x | x |
| Nov 20 | x | x | x | x | NaN | NaN | NaN | NaN |
| Dec/Q4 20 | x | x | x | x | NaN | x | NaN | NaN |
| Jan 21 | x | NaN | x | x | NaN | NaN | NaN | NaN |
| Feb 21 | NaN | NaN | x | x | NaN | NaN | NaN | NaN |
| Mar 21 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |

Note: see table 3.2.

We show the cumulative impulse responses of the model in figures 3.15 to 3.20, from appendix 3.C. In contrast to the results in the previous section, we observe a stronger impact of aggregate supply and aggregate demand shocks to unemployment, prices, and the job flows. This means that positive supply and demand shocks yield to a persistent decrease in the unemployment rate and the job separation rate, as well as an increase in the job finding rate, lasting about three years after the shocks. Moreover, positive supply shocks reduce prices for about two years, whereas positive demand shocks raise prices for about three years. Contrary to the results based on a sample before COVID-19, we find a more sensitive response of prices to domestic demand shocks. All in all, these results are in line with the interpretation that the shock stemming from the COVID-19 pandemic is a mixture of supply and demand components.

From the side of labor market shocks, we find that a positive labor supply shock, which rises the participants in the labor market, yields an increase in wages and employment for about two years and a quarter of a year after the shock, respectively. Furthermore, a mismatch shock that raises the efficiency in the labor market, increases industrial production for the next three years after the shock. Finally, a negative wage bargaining shock reduces the power of workers to negotiate wages, therefore leading to a decrease in the compensation per employee for almost two quarters after the shock.

In Figure 3.8, we report the historical decomposition of the variables for the months affected by the COVID-19 pandemic. The MF-BVAR model interprets the decline in the employment rate observed during the crisis as being induced primarily by a combination of supply-side and demand shocks. In particular, the negative impact of the labor supply shock captures workers who lost their jobs during the pandemic crisis and did not immediately search for new jobs. This reflects the impact of lockdown and containment measures introduced by national governments during the pandemic, which forced many shops and firms to temporarily close or reduce their operations. Demand shocks reflect constraints on the demand for services as a consequence of the lockdown measures, as well as other factors, such as an increase in uncertainty during the pandemic, which restrained consumption. Unlike in the COVID-19 pandemic, the dominant shock during the trough of the financial crisis in 2009 was related to demand, which accounted for a larger share of the decline in employment than the two supply-side shocks. A similar picture, although with a stronger role for demand shocks and a smaller role for labor supply shock, is found in the historical decomposition of industrial production. The small response of euro area unemployment to the decline in activity (which stayed well below the euro area average, as shown by the negative numbers in the figure) can be attributed to the job retention schemes that aimed to protect employment and limit unemployment, as well as to a large number of workers transitioning into inactivity, rather than into unemployment. Thus, the shock composition of the unemployment rate is therefore quite different than the one of employment. Shocks originated in the labor market play a big role also in explaining nominal variables (in particular, wages and, consequently, inflation), through the role of negative wage bargaining and labor supply shocks. This reflects the fact that even the measures to contain employment losses imply a reduction in wages per person.

One of the main policy issues in the euro area is the low-inflation environment that the zone experienced since the 2010s. The COVID-19 shock exacerbated this trend, where inflation even reached deflation episodes in the summer 2020.[9] The low inflation in this period was generally governed by aggregate domestic demand and a decrease in the labor force. The effects of domestic demand can be associated with the temporary decrease in the VAT in Germany, from 19% to 16% from July to December 2020.

Note that the nowcasts in the historical decomposition are scaled to deviations of the mean. To provide an overview of the raw predictions, I present the nowcasts in table 3.5. The reported nowcasts correspond to the mean posterior distribution, whereas the numbers in brackets represent the 16$^{\text{th}}$ and 84$^{\text{th}}$ percentiles.

Table 3.5: Nowcasts of key macroeconomic and labor market variables

| panel (a): quarterly variables | | | | |
|---|---|---|---|---|
| | Compensation | Employment | Job finding rate | Job separation rate |
| Q4/20 | 1.60 [-0.20, 3.39] | -1.93 | 19.92 [17.48, 22.37] | 1.45 [1.33, 1.56] |
| Q1/21 | 3.01 [0.42, 5.61] | -1.33 [-1.99, -0.66] | 21.02 [18.35, 23.65] | 1.57 [1.43, 1.71] |
| **panel (b): monthly variables** | | | | |
| | Unemployment | Industrial production | Inflation | |
| Jan 21 | 8.10 | -1.55 [-3.38, 0.33] | 0.90 | |
| Feb 21 | 8.15 [8.07, 8.23] | -0.92 [-3.84, 1.97] | 1.30 [1.10 1.50] | |
| Mar 21 | 8.11 [7.99, 8.24] | 9.94 [6.42, 13.45] | 1.80 [1.47 2.14] | |

Note: The nowcasts correspond to the mean posterior distribution of the forecasts, the numbers in brackets show the 68% percentiles.

In the early estimates for the nowcast of the first quarter, we find signs of a recovery in the labor market mainly driven by aggregate supply, aggregate demand, and wage bargaining shocks. The impact of the latter does not necessarily mean that the workers gained bargaining power during this period.

[9]For a deeper assessment of the low inflation environment in the euro area and its implications for monetary policy, see chapter 1.


Figure 3.8: Historical decomposition of key labor market and macroeconomic variables during the COVID-19 sample

Note: This figure shows the main drivers of the variables in the MF-BVAR in terms of economic shocks. The last observations of the panels depict the nowcasts and its drivers.

Rather, this shock captures the “gain” obtained by the workers due to the short-term working schemes, which allowed them to have the same wage rate at the expenses of less hours worked.

## 3.4 Forecasting performance

We use the model described in Section 3.3 to estimate forecasts of the main euro area economic variables, with a particular focus on the labor market variables. Specifically, we evaluate forecasts up to one-year ahead for compensation per employee growth, employment growth rate, as well as the in- and out-flows of unemployment. Moreover, we include the results for industrial production growth and inflation.[10]

Our sample spans from January 1998 to February 2021 and we carry out a pseudo real-time forecasting exercise for the period from January 2006 to the end of the sample. The data set we consider is mixed frequency and with ragged edges, given that the series have different publication delays. For this exercise, we assume that we update our data set on the tenth day of the month, such that we have the latest released figure of the unemployment rate. Table 3.6 shows an example of the ragged-edge pattern within the months of the quarter, where “x” means that the information is available, “x*” denotes a flash estimate provided by Eurostat, and “NaN” indicates a missing observation. We split the flow of data into three blocks: beginning, middle and end. This is because, for the case of the quarterly variables, we divide the forecast evaluation into these groups, based on the information set available in each month of the quarter when the forecast is computed. The first group corresponds to the first month of the quarter (January, April, July, and October; “beginning”); the second to the months of February, May, July, and November (“middle”); and the third, to March, June, September, and December (“end”). Forecasting horizons change according to the group. As a clarifying example, if we compute the forecasts in January, the forecast of the first quarter corresponds to a two-months ahead horizon, while if we are in February, the forecast of the first quarter corresponds to a one-month ahead forecast, and when we are in March, the nowcast corresponds to the forecast of the first quarter.

[10] We omit results from the MS variable, since it is not a variable that it is typically monitored. Although we initially introduce this variable for identification purposes, we keep it in the model since this specification gives more accurate forecasts in contrast to a model that excludes the variable.

Table 3.6: Data flow within quarters

| | | Monthly variables | | | | Quarterly variables | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | $u_t$ | $\Delta ip_t$ | $\Delta p_t$ | $ms_t$ | $\Delta w_t$ | $\Delta e_t$ | $f_t$ | $s_t$ |
| Beginning | Sep/Q3 | x | x | x | x | x* | x* | x | x |
| | Oct | x | x | x | x | NaN | NaN | NaN | NaN |
| | Nov | x | NaN | x | x | NaN | NaN | NaN | NaN |
| | Dec/Q4 | NaN | NaN | x* | x | NaN | NaN | NaN | NaN |
| | Jan | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| Middle | Sep/Q3 | x | x | x | x | x | x | x | x |
| | Oct | x | x | x | x | NaN | NaN | NaN | NaN |
| | Nov | x | x | x | x | NaN | NaN | NaN | NaN |
| | Dec/Q4 | x | NaN | x | x | x* | x* | NaN | NaN |
| | Jan | NaN | NaN | x* | x | NaN | NaN | NaN | NaN |
| | Feb | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| End | Nov | x | x | x | x | NaN | NaN | NaN | NaN |
| | Dec/Q4 | x | x | x | x | x | x | x* | x* |
| | Jan | x | NaN | x | x | NaN | NaN | NaN | NaN |
| | Feb | NaN | NaN | x* | x | NaN | NaN | NaN | NaN |
| | Mar | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |

Note: The table reports a snapshot of the ragged-edges and the mixed frequency nature of our data set. "x" indicates an available data point, "x*" denotes a flash estimate, and "NaN" represents a missing observation.

We construct the forecasts based on an expansive window approach. For each date in the evaluation sample, we estimate the model based on 20000 draws, using the initial 10000 as burn-in sample. We compute each $h$-step ahead prediction through an iterative forecasting equation, based on the reduced-form parameters of the MF-BVAR from equation (3.1).

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

$$RMSFE(h) = \sqrt{\frac{\sum_{t=\tau_0}^{\tau_1-h}\left(\hat{y}_{i,t+h|t} - y^o_{t+h}\right)^2}{\tau_1 - h - \tau_0 + 1}}, \tag{3.14}$$

where $y^o_{t+h}$ denotes the realized value of variable $i$ and $\hat{y}_{i,t+h|t}$ is the $h$-step ahead forecast of variable $i$. $\tau_0$ and $\tau_1$ are the indices of the full sample corresponding to the period before the start of the evaluation sample and the end of the evaluation sample, respectively. The computation of equation (3.14) changes depending on the frequency of the variable. For monthly variables, the time index $t$ and the horizon $h$ denote months, where the forecasts are computed up to twelve-months ahead and the indices $\tau_0$ and $\tau_1$ correspond to the months of December 2005 and September 2019, respectively. For quarterly variables, the indices and the horizons are in terms of quarters. This means that, in this case, $\tau_0$ and $\tau_1$ denote quarters Q4 2005 and Q3 2019, respectively. Moreover, the forecasts are computed for up to four quarters ahead.

As a benchmark, we compute forecasts based on univariate AR models, where for each variable and each month or quarter of the evaluation sample, we choose the optimal number of lags through the Bayesian Information Criterion (BIC). We estimate the AR model based on normal - inverse Gamma priors, where, as in the case of the MF-BVAR, we estimate 20000 draws and keep the last 10000 for inference. For both the MF-BVAR and the AR, we consider the point forecasts based on the mean posterior distribution of the forecasts.

Results are reported in Table 3.7, where we show the RMSFE of our model relative to the RMSFE of the AR process. Therefore, whenever the number reported is smaller than one, it indicates a superior performance of the model relative to the AR. The table reports the forecasting performance both of quarterly (panel (a)) and monthly variables (panel (b)).

What we can see is that we obtain significant gains when predicting the quarterly labor market variables (table 3.7, panel (a)). This is consistent with most of the evidence concerning mixed frequency models, in which the higher frequency information typically helps improve the forecasting performance of low frequency variables. The results are particularly satisfactory for the employment growth and the job flows. The results on the good performance in forecasting the flows is novel in the literature and it is useful since it provides further insights to the labor markets, going beyond the classical variables of employment and unemployment. Further, the results confirm that the information flow during the quarter matters, since the performance tends to improve as more information is acquired over the quarter. Nevertheless, the forecast performance tends to improve also when the quarterly information on the previous period becomes available.

In Table 3.7, panel (b), we report the results for the monthly variables. Although less commonly applied, it is also possible to include quarterly information to predict monthly variables, if the content contained in the lower frequency information carries important information (see Foroni et al. (2018b)). In this case, results are more mixed. While in the case of industrial produc-

Table 3.7: Forecasting performance: RMSFE relative to an AR benchmark - Full sample

Panel (a): quarterly variables

| | Employment growth | | | Wage growth | | | Job finding rate | | | Job separation rate | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Beginning | Middle | End | Beginning | Middle | End | Beginning | Middle | End | Beginning | Middle | End |
| Q(-1) | 1.63 | | | 1.10 | | | 1.27 | **0.96** | | 1.61 | 3.07 | |
| Q(0) | 1.26 | **0.94** | **0.90** | 1.12 | **0.96** | 1.01 | **0.92** | **0.92** | 1.01 | 1.20 | 1.52 | 1.21 |
| Q(+1) | 1.06 | **0.95** | **0.95** | 1.07 | 1.09 | 1.12 | **0.80** | **0.81** | **0.87** | **0.97** | 1.03 | 1.00 |
| Q(+2) | **0.95** | **0.92** | **0.96** | 1.03 | 1.05 | 1.04 | **0.77** | **0.75** | **0.85** | **0.89** | **0.87** | **0.89** |
| Q(+3) | **0.93** | **0.93** | **0.90** | 1.02 | 1.03 | 1.08 | **0.81** | **0.79** | **0.89** | **0.85** | **0.80** | **0.85** |
| Q(+4) | **0.90** | **0.92** | **0.91** | **0.99** | 1.00 | 1.02 | **0.84** | **0.83** | **0.93** | **0.82** | **0.76** | **0.82** |

Panel (b): monthly variables

| | Unemployment rate | | | | Industrial production growth | | | | Inflation | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | All | Beginning | Middle | End | All | Beginning | Middle | End | All | Beginning | Middle | End |
| M(-2) | | | | | **0.89** | **0.82** | **0.91** | **0.98** | | | | |
| M(-1) | 1.14 | 1.23 | 1.02 | 1.22 | **0.96** | **0.87** | **0.98** | 1.00 | | | | |
| M(0) | 1.19 | 1.22 | 1.12 | 1.21 | **0.96** | 1.01 | **0.92** | **0.96** | 1.03 | 1.09 | 1.03 | **0.97** |
| M(+1) | 1.14 | 1.19 | 1.14 | 1.10 | **0.95** | **0.90** | 1.01 | **0.98** | 1.02 | 1.09 | **0.97** | 1.00 |
| M(+6) | 1.14 | 1.19 | 1.13 | 1.09 | 1.02 | 1.03 | **0.99** | 1.04 | 1.07 | 1.08 | 1.08 | 1.06 |

The table reports the RMSFE of the MF-BVAR relative to an AR benchmark with lag length selected according to the BIC criterion for each variable. Numbers less than one indicate a superior performance of the MF-BVAR. Panel (a) reports the forecasting performance for quarterly variables, panel (b) for monthly variables. The forecast horizon is expressed in months or quarters respectively, and with results organized depending on which month of the quarter the forecast is produced, since they are based on different information sets.

tion the results are particularly encouraging, this is not the case for the other two monthly variables we have in the model, inflation and the unemployment rate. This is most likely based on the fact that the unemployment rate and inflation are relatively timely and quite persistent. Therefore, the information contained in the last month available is dominating over the information included in other series that are released with a bigger delay.

To further investigate this good performance, we also consider a sub-sample, the period from January 2008 to December 2012, corresponding to the Great Recession for the euro area.[11] The results are fully consistent with those on the full sample, and reported in Table 3.8.

Further, we investigate a simpler MF-BVAR specification by excluding the job market flows from the variables. The results show that the use of flows does not help in improving the forecasting performance of labor market variables. This actually goes against the findings of Barnichon and Nekarda (2012) and Barnichon and Garda (2016) for the unemployment rate. However, in our set up, we aim at forecasting the monthly unemployment rate and not the quarterly one, as in the literature. Thus, in our case, the job flows have the disadvantage of being significantly delayed in their release over the monthly information included in the unemployment itself. Nevertheless, these are important in the analysis of the labor market and, in the euro area, the lag in the availability of this type of information needs to be considered. However, given that the performance is not significantly deteriorated by them (and in some cases even improved), we include the job market flows in our main model, since we use them for explaining the economic intuition behind the analysis. Results without flows are reported in Table 3.9 and can be directly compared with the results in Table 3.7, given that the AR benchmark is the same.

Finally, we check whether the performance of our MF-BVAR is superior in terms of density forecasting. To do so, for each forecasting horizon, we evaluate density forecasts by computing the log-predictive likelihood (LPL, see Geweke and Amisano (2010)), for both the MF-BVAR and the AR. This criterion is defined as follows:

$$LPL(i,h) = \log p(y_{i,t+h} = y^o_{i,t+h}|Y), \tag{3.15}$$

where $p(y_{i,t+h} = y^o_{i,t+h}|Y)$ is the predictive density evaluated at the realized value of variable $i$ at time $t+h$ and $Y$ denotes the data available until $T$. To compare

[11] We did not consider the COVID sub-sample, because it would span less than one year of our sample and would not allow us to properly check the forecasting performance, especially at longer horizons.

Table 3.8: Forecasting performance: RMSFE relative to an AR benchmark - Great Recession sample

panel (a): quarterly variables

| | Employment growth | | | Wage growth | | | Job finding rate | | | Job separation rate | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Beginning | Middle | End | Beginning | Middle | End | Beginning | Middle | End | Beginning | Middle | End |
| Q(-1) | 1.70 | | | 1.08 | | | 1.45 | 1.01 | | 1.88 | 3.78 | |
| Q(0) | 1.27 | **0.92** | **0.89** | 1.23 | **0.94** | 1.00 | **0.99** | 1.00 | 1.04 | 1.30 | 1.70 | 1.32 |
| Q(+1) | 1.03 | **0.97** | **0.96** | 1.19 | 1.16 | 1.22 | **0.85** | **0.88** | **0.86** | 1.01 | 1.09 | 1.05 |
| Q(+2) | **0.94** | **0.92** | **0.97** | 1.15 | 1.12 | 1.18 | **0.81** | **0.82** | **0.86** | **0.90** | **0.89** | **0.90** |
| Q(+3) | **0.89** | **0.89** | **0.92** | **0.91** | 1.23 | 1.29 | **0.83** | **0.84** | **0.92** | **0.84** | **0.79** | **0.85** |
| Q(+4) | **0.82** | **0.87** | **0.88** | **0.94** | 1.04 | 1.04 | **0.85** | **0.88** | **0.97** | **0.80** | **0.73** | **0.81** |

panel (b): monthly variables

| | Unemployment rate | | | | Industrial production growth | | | | Inflation | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | All | Beginning | Middle | End | All | Beginning | Middle | End | All | Beginning | Middle | End |
| M(-2) | | | | | **0.79** | **0.62** | **0.84** | **0.97** | | | | |
| M(-1) | 1.33 | 1.66 | 1.12 | 1.34 | **0.93** | **0.87** | 1.00 | **0.93** | | | | |
| M(0) | 1.32 | 1.36 | 1.20 | 1.40 | **0.93** | 1.00 | **0.88** | **0.95** | 1.06 | 1.30 | 1.09 | **0.93** |
| M(+1) | 1.23 | 1.24 | 1.22 | 1.22 | **0.90** | **0.80** | **0.99** | **0.95** | 1.04 | 1.18 | **0.93** | 1.00 |
| M(+6) | 1.15 | 1.19 | 1.16 | 1.11 | **0.99** | **0.98** | **0.94** | 1.06 | 1.14 | 1.16 | 1.20 | 1.10 |
| M(+12) | 1.08 | 1.11 | 1.10 | 1.03 | **0.98** | **0.99** | **0.79** | 1.15 | 1.18 | 1.23 | 1.22 | 1.12 |

Note: The table reports the RMSFE of the MF-BVAR model relative to an AR benchmark with lag length selected according to the BIC criterion for each variable. Numbers less than one indicate a superior performance of the SVAR. Panel (a) reports the forecasting performance for quarterly variables, panel (b) for monthly variables. The forecast horizon is expressed in months or quarters respectively, with results organized depending on which month of the quarter the forecast is produced, since they are based on different information sets. The sample considered in the forecast evaluation span January 2008 - December 2012.

Table 3.9: Forecasting performance: RMSFE relative to an AR benchmark - Benchmark model without flows

panel (a): quarterly variables

| | Employment growth | | | Wage growth | | |
|---|---|---|---|---|---|---|
| | Beginning | Middle | End | Beginning | Middle | End |
| Q(-1) | 1.34 | | | 1.03 | | |
| Q(0) | 1.09 | **0.93** | **0.86** | 1.08 | **0.96** | **0.98** |
| Q(+1) | **0.96** | **0.90** | **0.80** | 1.06 | 1.07 | 1.06 |
| Q(+2) | **0.88** | **0.84** | **0.82** | 1.03 | 1.06 | 1.03 |
| Q(+3) | **0.90** | **0.91** | **0.81** | 1.02 | 1.03 | 1.06 |
| Q(+4) | **0.87** | **0.89** | **0.89** | **0.99** | 1.00 | 1.02 |

panel (b): monthly variables

| | Unemployment rate | | | | Industrial production growth | | | | Inflation | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | All | Beginning | Middle | End | All | Beginning | Middle | End | All | Beginning | Middle | End |
| M(-2) | | | | | **0.92** | **0.84** | **0.94** | 1.01 | | | | |
| M(-1) | 1.15 | 1.23 | 1.07 | 1.19 | **0.97** | **0.90** | 1.01 | **0.98** | | | | |
| M(0) | 1.18 | 1.21 | 1.20 | 1.15 | **0.96** | 1.01 | **0.91** | **0.96** | 1.01 | 1.05 | 1.01 | **0.99** |
| M(+1) | 1.13 | 1.18 | 1.19 | 1.03 | **0.94** | **0.89** | 1.00 | **0.98** | 1.02 | 1.07 | **0.99** | **0.98** |
| M(+6) | 1.09 | 1.16 | 1.13 | **0.98** | 1.03 | 1.04 | 1.01 | 1.05 | 1.04 | 1.03 | 1.05 | 1.04 |
| M(+12) | 1.02 | 1.08 | 1.05 | **0.94** | 1.00 | **0.99** | 1.01 | 1.02 | 1.07 | 1.07 | 1.05 | 1.08 |

Note: The table reports the RMSFE of the MF-BVAR model without job market flows relative to an AR benchmark with lag length selected according to the BIC criterion for each variable. Numbers less than one indicate a superior performance of the MF-BVAR. Panel (a) reports the forecasting performance for quarterly variables, panel (b) for monthly variables. The forecast horizon is expressed in months or quarters respectively, with results organized depending on which month of the quarter the forecast is produced, since they are based on different information sets.

between the two models, we follow Geweke and Amisano (2010) and compute the average of the differential between log-predictive likelihoods (ALPL) as follows:

$$ALPL(i,h) = \frac{1}{\tau_1 - h - \tau_0 + 1} \sum_{t=\tau_0}^{\tau_1 - h} LPL_{MF-VAR}(i,h) - LPL_{AR}(i,h). \tag{3.16}$$

As clarified by Korobilis and Pettenuzzo (2019), positive values of the differential means that, on average, the MF-BVAR model produces more accurate density forecasts than the AR. Similar as in the computation of the RMSFE, the time index and the forecast horizon change depending on the frequency of the variable.

Tables 3.10 to 3.12 show the results for density forecasts mirroring the previous tables for the RMSFE. Numbers in bold show the instances when the MF-BVAR produces more accurate density forecasts than the AR, in terms of the ALPL. Looking at the tables, our results are more mixed than for the point-forecast evaluation. The findings in terms of the RMSFE for the job finding rate and the industrial production growth are confirmed. However, we do not find a better performance of density forecasts from our model, for employment growth and the longer horizons of the job separation rate. In contrast, we find that our model improves the density forecasting of wage growth for longer horizons and the nowcasts of the current quarter for the job separation rate. Furthermore, we find that these gains are not so strongly present when assessing the Great Recession period (table 3.11).

Similar to the results for the point-forecasts, we find no additional gain stemming from the inclusion of job flows in the model (table 3.12).

Table 3.10: Average log-predictive likelihood - AR vs benchmark model - Full sample

Panel (a): quarterly variables

| | Employment growth | | | Wage growth | | | Jof finding rate | | | Job separation rate | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Beginning | Middle | End | Beginning | Middle | End | Beginning | Middle | End | Beginning | Middle | End |
| Q(-1) | -0.08 | | | -0.15 | | | -0.01 | **0.07** | | **0.03** | -0.01 | |
| Q(0) | -0.12 | -0.34 | **0.27** | -0.13 | 0.00 | -0.09 | **0.23** | **0.31** | **0.04** | **0.21** | **0.34** | **0.13** |
| Q(+1) | -0.04 | -0.38 | **0.09** | -0.22 | -0.16 | -0.16 | **0.42** | **0.56** | **0.12** | -0.34 | -0.66 | -0.05 |
| Q(+2) | **0.11** | -0.33 | **0.06** | -0.20 | -0.33 | -0.25 | **0.53** | **0.67** | **0.32** | -0.88 | -1.20 | -0.36 |
| Q(+3) | -1.21 | -4.84 | **0.31** | **2.52** | -2.05 | -0.23 | **0.43** | **0.52** | **0.27** | -1.20 | -1.72 | -1.46 |
| Q(+4) | -1.30 | **0.66** | **0.79** | **6.32** | **1.55** | **3.56** | **0.39** | **0.43** | **0.03** | -1.00 | -0.97 | -2.91 |

Panel (b): monthly variables

| | Unemployment rate | | | | Industrial production growth | | | | Inflation | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | All | Beginning | Middle | End | All | Beginning | Middle | End | All | Beginning | Middle | End |
| M(-2) | | | | | **0.09** | **0.17** | **0.06** | **0.03** | | | | |
| M(-1) | -0.11 | -0.20 | **0.01** | -0.15 | **0.04** | **0.06** | **0.02** | **0.03** | | | | |
| M(0) | -1.04 | -1.41 | -0.67 | -1.15 | **0.10** | **0.04** | **0.07** | **0.21** | -0.03 | -0.05 | -0.10 | **0.07** |
| M(+1) | -1.10 | -1.28 | -0.87 | -1.34 | **0.06** | **0.10** | **0.03** | **0.07** | -0.01 | -0.06 | **0.03** | -0.01 |
| M(+6) | -1.97 | -1.77 | -4.18 | -0.72 | **0.00** | **0.00** | **0.04** | -0.02 | -0.06 | -0.07 | -0.06 | -0.07 |
| M(+12) | -3.30 | **0.10** | -4.56 | -7.49 | -0.16 | -0.34 | -0.14 | -0.13 | -0.09 | -0.14 | -0.07 | -0.07 |

Note: The table reports the average of the differential between the log-predictive likelihood of the MF-BVAR and an AR model, where the number of lags is selected via the BIC criterion for each variable and each forecasting period. Panel (a) shows the results for quarterly variables and panel (b) for the monthly variables. The forecast horizon is expressed in months or quarters respectively, with results organized depending on which month of the quarter the forecast is produced, since they are based on different information sets.

Table 3.11: Forecasting performance: Average log-predictive likelihood - Benchmark model vs AR model - Great Recession sample

Panel (a): quarterly variables

| | Employment growth | | | Wage growth | | | Jof finding rate | | | Job separation rate | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Beginning | Middle | End | Beginning | Middle | End | Beginning | Middle | End | Beginning | Middle | End |
| Q(-1) | -0.24 | | | 0.00 | | | -0.19 | 0.00 | | -0.24 | -0.39 | |
| Q(0) | -0.34 | -1.40 | **0.17** | -0.15 | **0.14** | -0.02 | -0.07 | **0.31** | -0.22 | -0.18 | -0.04 | -0.20 |
| Q(+1) | -0.01 | -1.93 | -0.30 | -0.41 | -0.18 | -0.28 | **0.07** | **0.20** | -0.08 | -2.21 | -3.60 | -0.82 |
| Q(+2) | **0.58** | -1.42 | -0.31 | -0.61 | -0.39 | -0.51 | **0.57** | **0.64** | **0.19** | -5.20 | -6.81 | -2.49 |
| Q(+3) | **0.27** | -2.22 | **0.97** | -0.61 | -0.61 | -0.87 | **0.94** | **0.68** | -0.03 | -8.92 | -11.42 | -8.90 |
| Q(+4) | -1.77 | **0.46** | -0.28 | -1.33 | -0.97 | -0.96 | **1.77** | **0.67** | -0.61 | -13.51 | -9.82 | -23.72 |

Panel (b): monthly variables

| | Unemployment rate | | | | Industrial production growth | | | | Inflation | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | All | Beginning | Middle | End | All | Beginning | Middle | End | All | Beginning | Middle | End |
| M(-2) | | | | | **0.23** | **0.51** | **0.14** | **0.07** | | | | |
| M(-1) | -0.27 | -0.51 | -0.07 | -0.30 | **0.10** | **0.10** | **0.02** | **0.19** | | | | |
| M(0) | -2.11 | -2.50 | -1.61 | -2.97 | **0.02** | -0.08 | **0.06** | **0.07** | -0.10 | -0.10 | -0.34 | **0.08** |
| M(+1) | -2.47 | -2.49 | -2.60 | -3.55 | **0.17** | **0.36** | **0.05** | **0.19** | -0.02 | -0.20 | **0.13** | 0.00 |
| M(+6) | -5.55 | -6.11 | -17.35 | -2.29 | **0.07** | **0.19** | **0.20** | -0.08 | -0.15 | -0.21 | -0.30 | -0.21 |
| M(+12) | -10.50 | **3.04** | -36.04 | -61.52 | **0.01** | **0.05** | **0.44** | -0.40 | -0.19 | -0.71 | -0.51 | -0.46 |

Note: The table reports the average of the differential between the log-predictive likelihood of the MF-BVAR and an AR model, where the number of lags is selected via the BIC criterion for each variable and each forecasting period. Panel (a) shows the results for quarterly variables and panel (b) for the monthly variables. The forecast horizon is expressed in months or quarters respectively, with results organized depending on which month of the quarter the forecast is produced, since they are based on different information sets. The sample considered in the forecast evaluation span January 2008 - December 2012.

Table 3.12: Forecasting performance: Average log-predictive likelihood - Benchmark model without flows

panel (a): quarterly variables

| | Employment growth | | | Wage growth | | |
|---|---|---|---|---|---|---|
| | Beginning | Middle | End | Beginning | Middle | End |
| Q(-1) | -0.02 | | | -0.13 | | |
| Q(0) | -0.08 | -0.31 | **0.31** | -0.11 | **0.00** | -0.09 |
| Q(+1) | 0.00 | -0.31 | **0.32** | -0.21 | -0.14 | -0.14 |
| Q(+2) | **0.30** | -0.20 | **0.33** | -0.20 | -0.32 | -0.23 |
| Q(+3) | -0.71 | -6.13 | **0.23** | **2.14** | -1.66 | -0.22 |
| Q(+4) | -1.10 | -0.16 | -1.06 | **6.21** | 1.21 | **3.15** |

panel (b): monthly variables

| | Unemployment rate | | | | Industrial production growth | | | | Inflation | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | All | Beginning | Middle | End | All | Beginning | Middle | End | All | Beginning | Middle | End |
| M(-2) | | | | | **0.07** | **0.17** | **0.04** | **0.00** | | | | |
| M(-1) | -0.13 | -0.21 | -0.07 | -0.14 | **0.03** | **0.05** | **0.00** | **0.05** | | | | |
| M(0) | -1.11 | -1.35 | -1.21 | -0.91 | **0.10** | **0.03** | **0.08** | **0.20** | -0.01 | -0.01 | -0.06 | **0.04** |
| M(+1) | -1.25 | -1.20 | -1.78 | -0.95 | **0.07** | **0.11** | **0.03** | **0.07** | -0.01 | -0.04 | **0.01** | **0.01** |
| M(+6) | -2.57 | -2.80 | -4.42 | -1.45 | -0.01 | -0.01 | **0.03** | -0.04 | -0.04 | -0.04 | -0.04 | -0.05 |
| M(+12) | -3.12 | -2.36 | -7.39 | -2.10 | **0.73** | **0.56** | -0.13 | **0.17** | -0.06 | -0.11 | -0.04 | -0.11 |

Note: The table reports the average of the differential between the log-predictive likelihood of the MF-BVAR without job market flows and an AR model, where the number of lags is selected via the BIC criterion for each variable and each forecasting period. Panel (a) shows the results for quarterly variables and panel (b) for the monthly variables. The forecast horizon is expressed in months or quarters respectively, with results organized depending on which month of the quarter the forecast is produced, since they are based on different information sets.

## 3.5 Conclusions

In this chapter, we consider the mixed frequency VAR model of Schorfheide and Song (2015), which we modify to a structural model identified by sign restrictions, with the purpose to understand the dynamics of the euro area labor market. We divide our analysis into a structural identification of shocks and a forecasting exercise.

We obtain satisfactory results in terms of the point-forecast performance, especially for quarterly variables as the employment growth rate and the job market flows. Moreover, we find that our model is suitable for obtaining accurate density forecasts of industrial production growth and the job finding rate. Therefore, we show that, for a subset of the variables, the information content in high frequency data helps improve the forecasts of lower frequency variables and vice versa. For the monthly unemployment rate, we cannot beat an AR benchmark. This is due to the persistent nature of the variable, where the last lags are the most important information for obtaining a good forecast.

In terms of economic interpretation, we find that demand shocks were the main drivers of the variables in our model, during the past Great Recession. Moreover, shocks originating in the labor market played an important role in explaining the period of low inflation and low wage growth from 2013 onward. In an early assessment of the COVID-19 crisis, we find that aggregate supply and labor supply shocks govern the dynamics in the developments of the labor market. Furthermore, we find signs of a recovery in employment and wage inflation, mainly explained by wage bargaining shocks, which capture the ”gain” from the workers as a consequence of the several short-term schemes of work. Specifically, workers worked less hours but retained the same wage rate.

Overall, our model provides an important tool for policy work, given that it permits the interpretation of the full history of the time series, as well as the latest nowcasts in terms of macroeconomic shocks via a structural VAR model.

## 3.A Data description

| Name | Description | Transformation | Frequency | Source |
|---|---|---|---|---|
| UR | Unemployment rate (as a % of labor force) | Levels | M | ECB-SDW |
| IP | Industrial production for the euro area | $\Delta$ln(IP) | M | ECB-SDW |
| HICP | HICP - Overall index | $\Delta$ln(HICP) | M | ECB-SDW |
| PMIM | Purchasing Managers' Index: Manufacturing | $\Delta$ln(PMIm) | M | ECB-SDW |
| PMIS | Purchasing Managers' Index: Services | $\Delta$ln(PMIs) | M | ECB-SDW |
| YIELD | Euro area 1-year Government Benchmark bond yield | Levels | M | ECB-SDW |
| SLOPE* | Slope of the yield curve, difference between Euro area ten-year and two-year yields, $r_{t,10Y} - r_{t,2Y}$ | Levels | M | ECB-SDW |
| W | Compensation per employee | $\Delta$ln(w) | Q | ECB-SDW |
| E | Employment (in thousands of persons) | $\Delta$ln(e) | Q | ECB-SDW |
| $F^+$ | Job finding rate | Levels | Q | ECB-SDW |
| $S^+$ | Job separation rate | Levels | Q | ECB-SDW |

*Own calculations; $^+$ computed by the Supply Side, Labour and Surveillance division at the ECB.

### 3.A.1 Results from the MDD optimization

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

$$\Lambda_1 = [0.01\ 0.72\ 1.44\ 2.15\ 2.86\ 3.58\ 4.29\ 5.00\ 5.72\ 6.43\ 7.14\ 7.86\ 8.57\ 9.28\ 10]$$

Table 3.13 shows the constellation of hyperparameters that yield the maximum MDD for each of the models considered.

Table 3.13: Optimal hyperparameters

| Hyperparameters | Benchmark | No flows |
|---|---|---|
| $\lambda_1$ | 5.00 | 5.00 |

# 3.B Impulse responses of main macroeconomic and labor market shocks

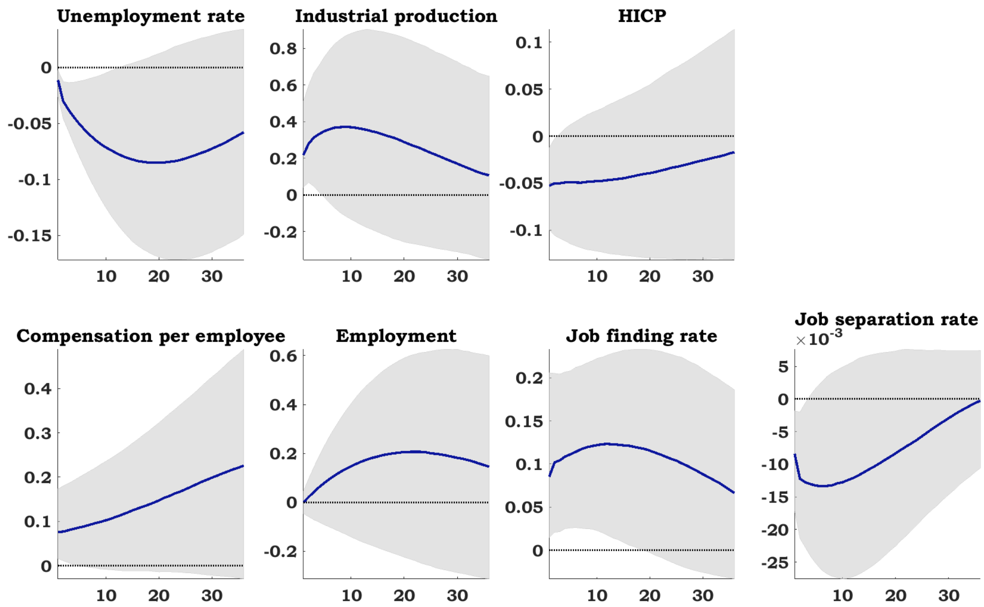


Figure 3.9: Cumulative impulse responses of an aggregate supply shock

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

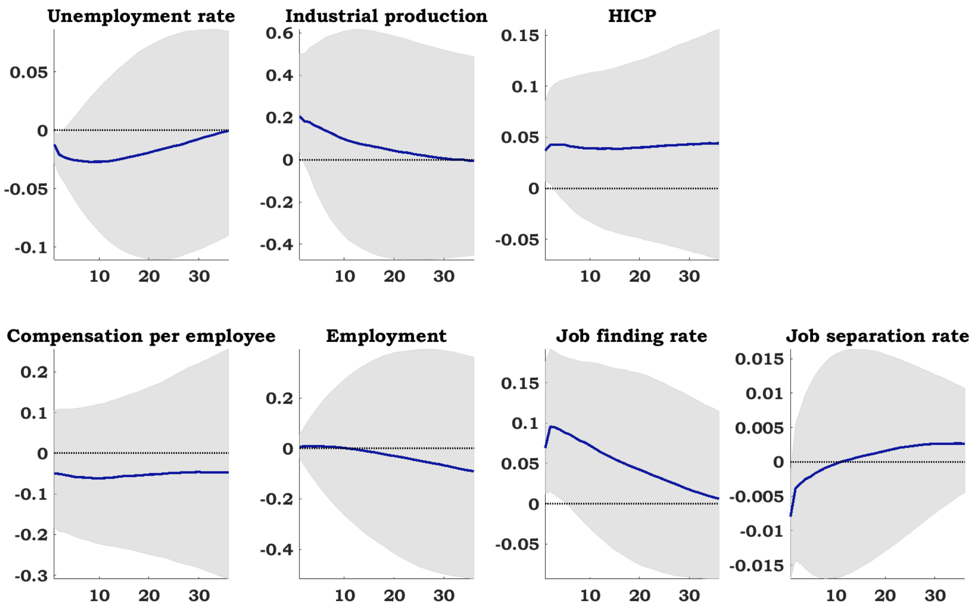


Figure 3.10: Cumulative impulse responses of an aggregate domestic demand shock

Note: See figure 3.9

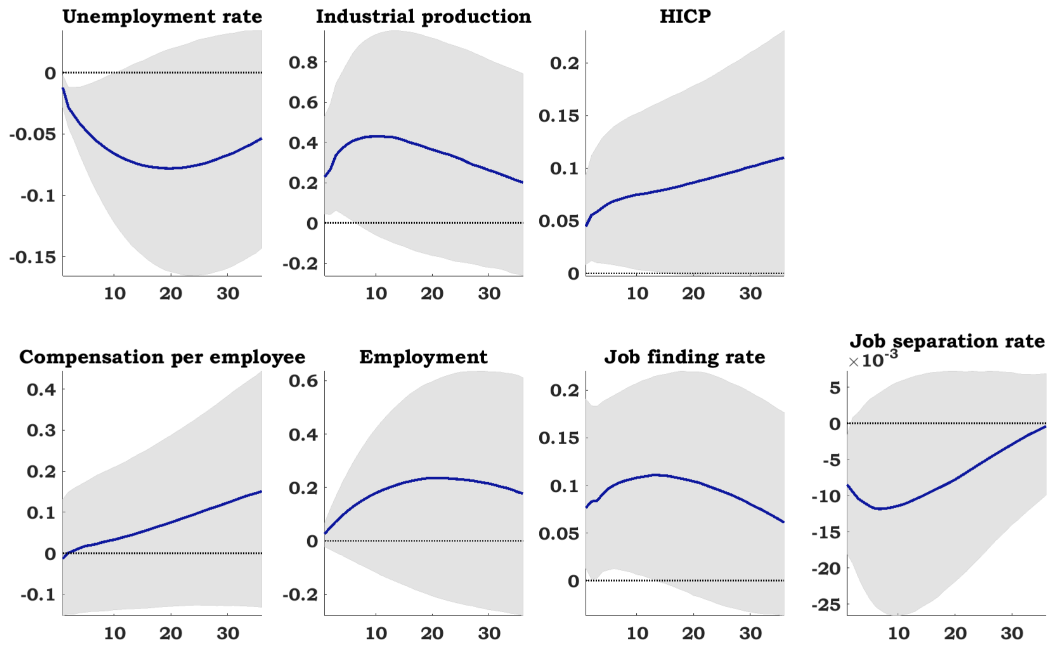


Figure 3.11: Cumulative impulse responses of an aggregate foreign demand shock

Note: See figure 3.9

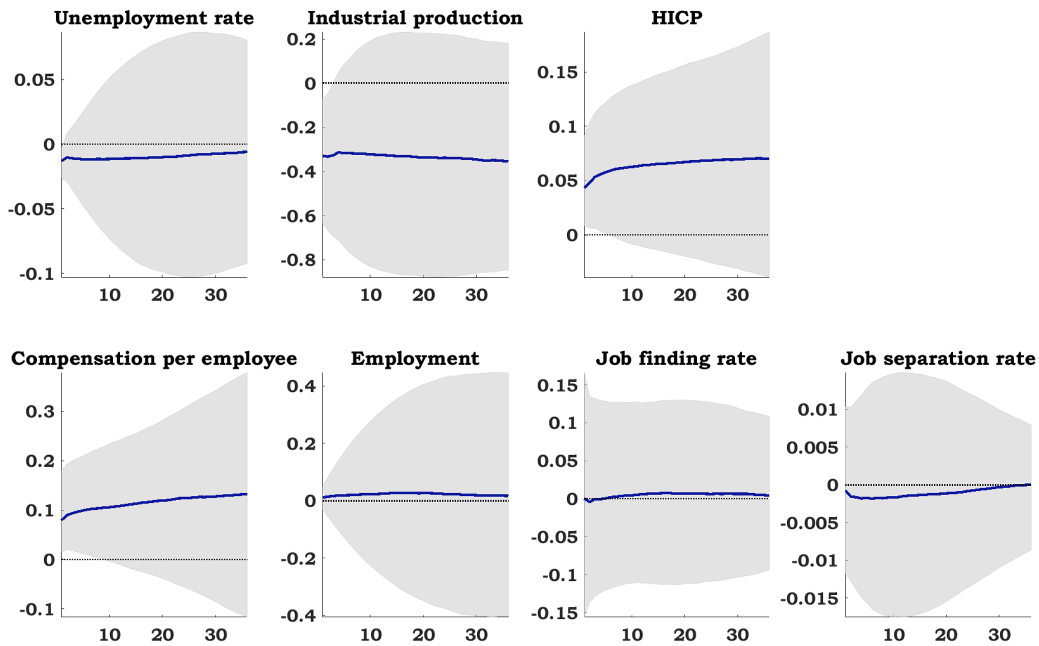


Figure 3.12: Cumulative impulse responses of a labor supply shock

Note: See figure 3.9

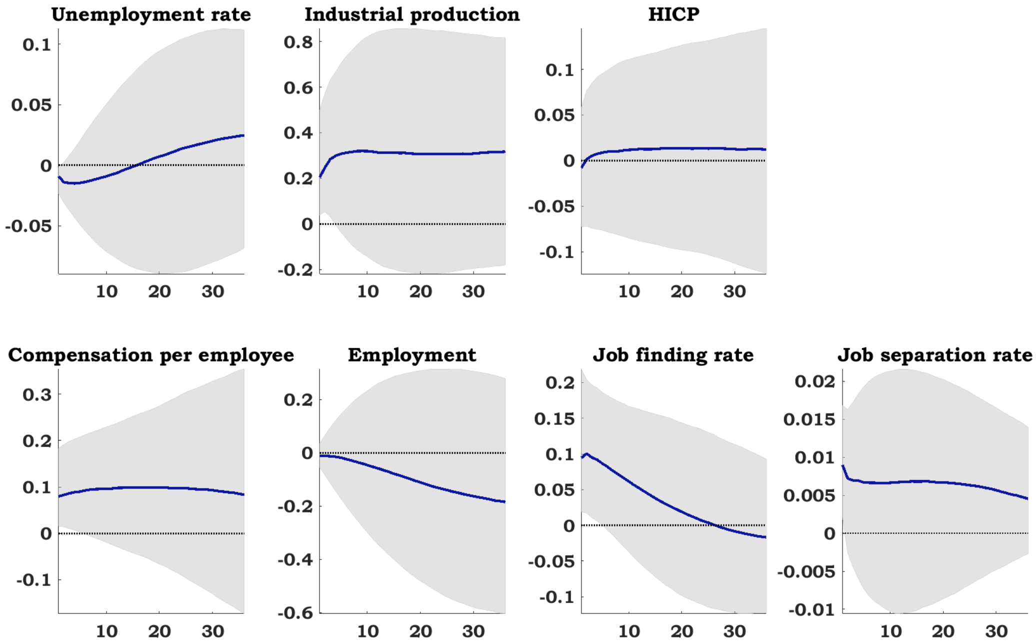


Figure 3.13: Cumulative impulse responses of a mismatch shock

Note: See figure 3.9

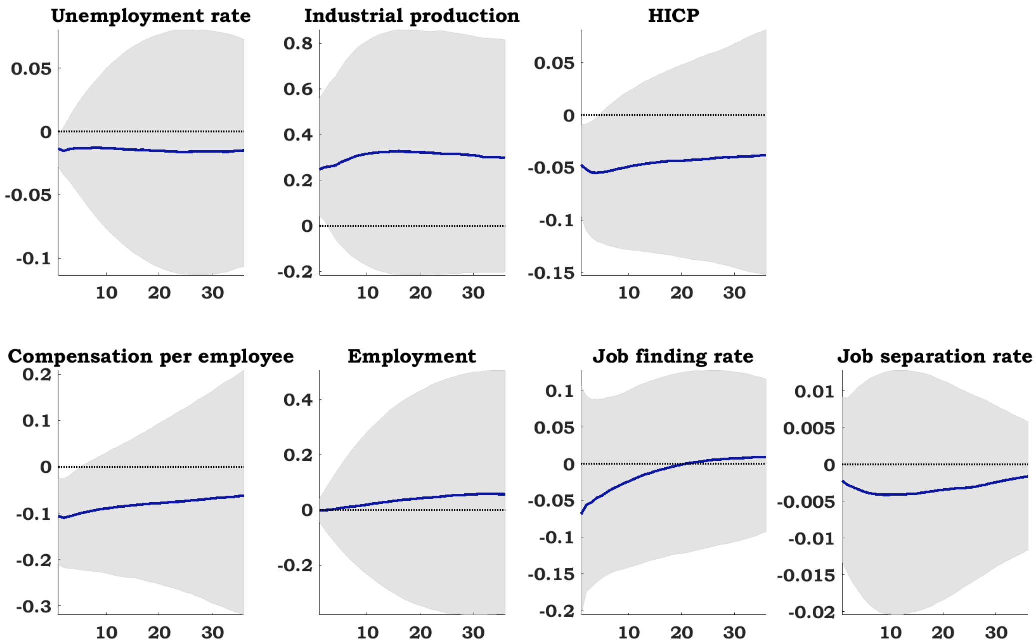


Figure 3.14: Cumulative impulse responses of a wage bargaining shock

Note: See figure 3.9

## 3.C Impulse responses of main macroeconomic and labor market shocks - COVID-19 sample

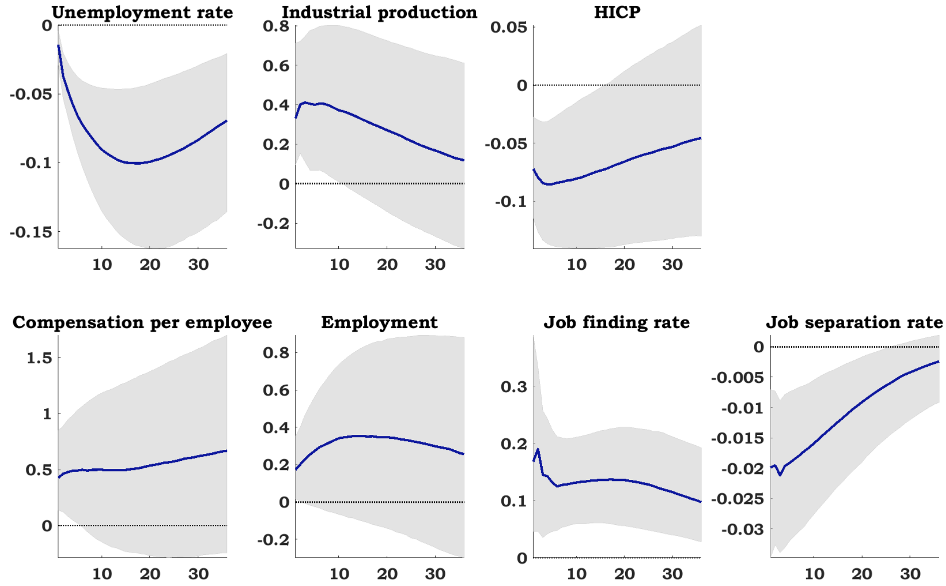


Figure 3.15: Cumulative impulse responses of an aggregate supply shock

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

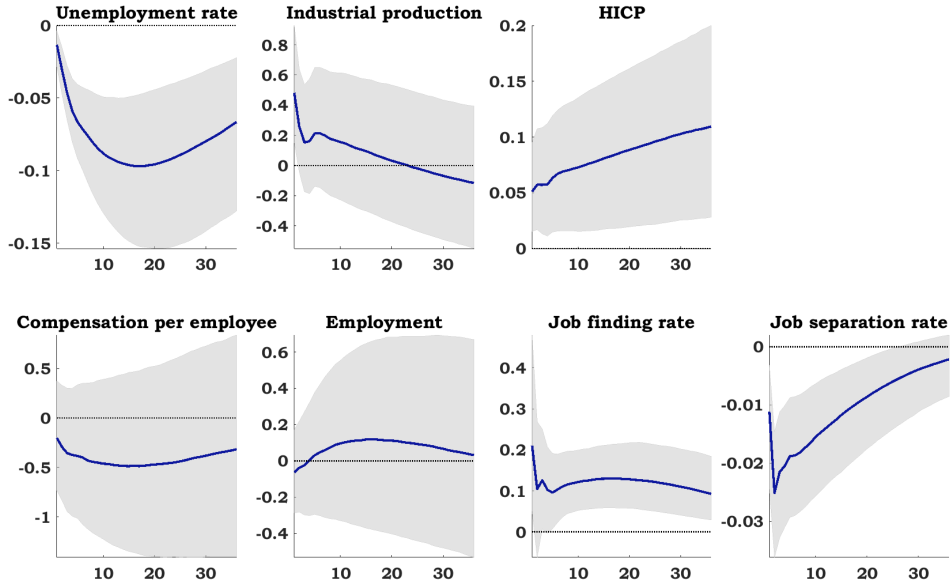


Figure 3.16: Cumulative impulse responses of an aggregate domestic demand shock

Note: See figure 3.15

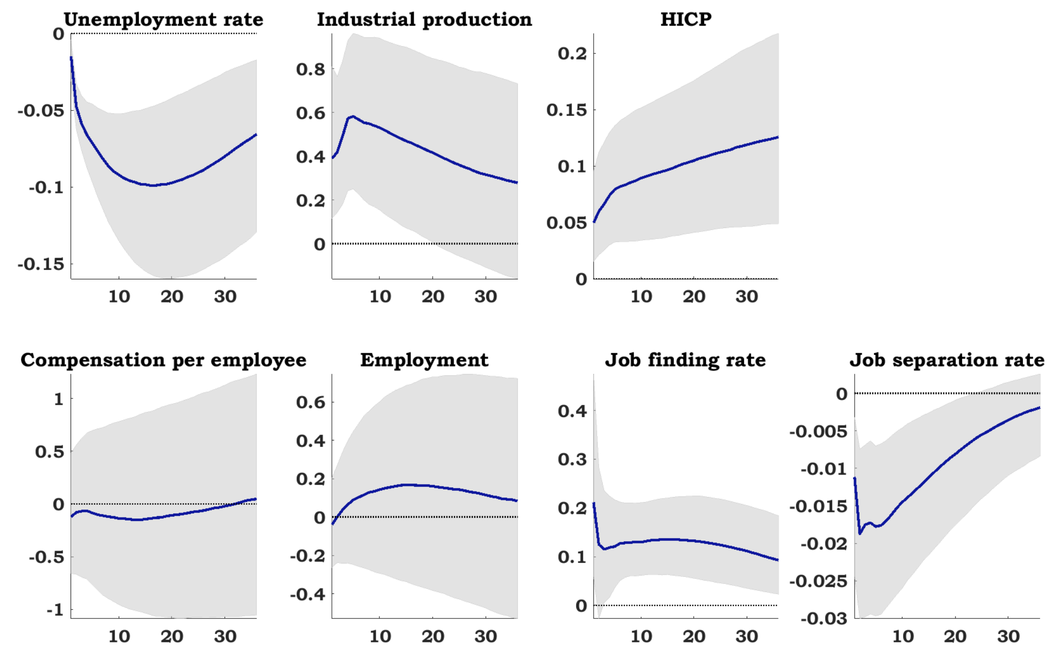


Figure 3.17: Cumulative impulse responses of an aggregate foreign demand shock

Note: See figure 3.15

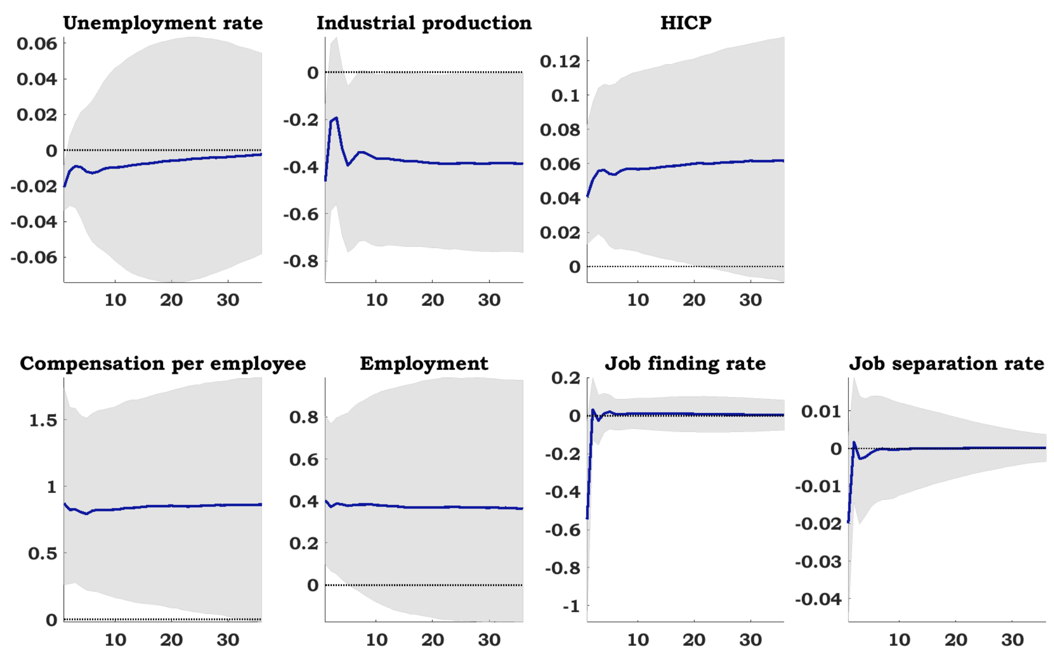


Figure 3.18: Cumulative impulse responses of a labor supply shock

Note: See figure 3.15

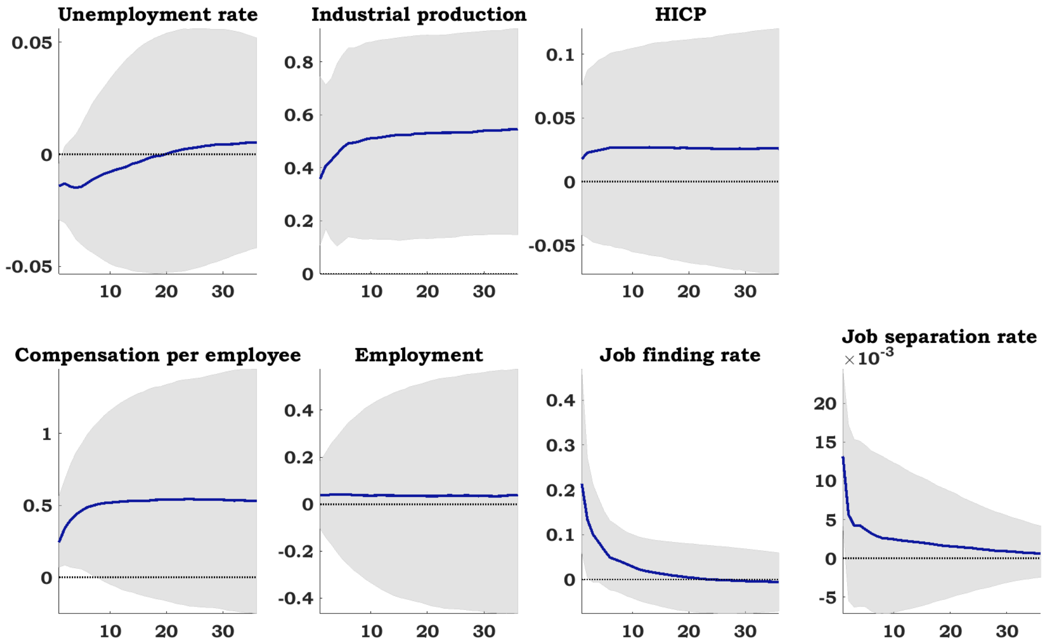


Figure 3.19: Cumulative impulse responses of a mismatch shock

Note: See figure 3.15

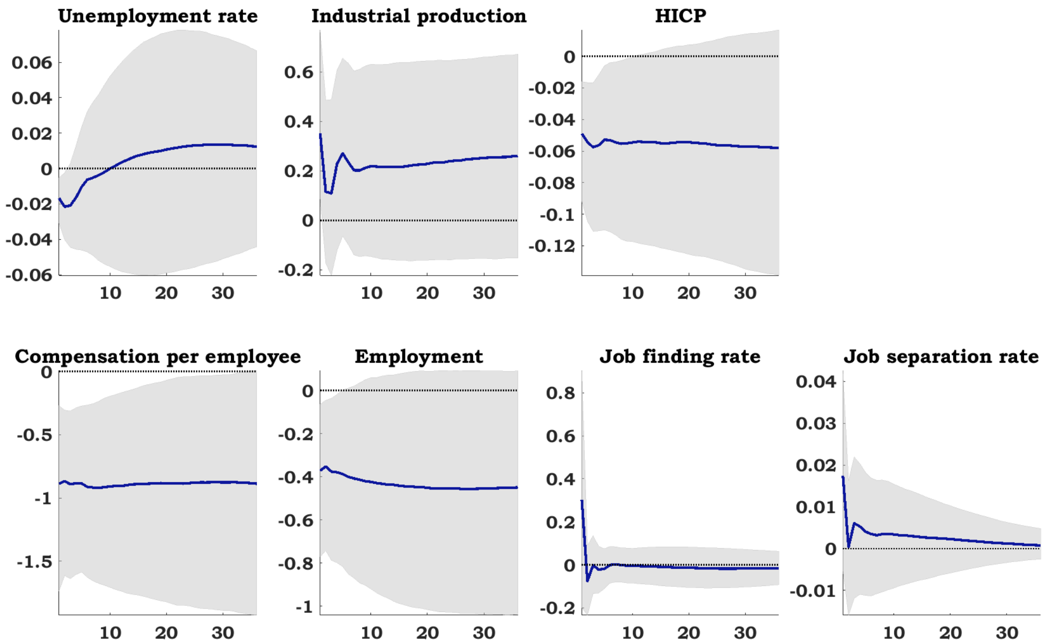


Figure 3.20: Cumulative impulse responses of a wage bargaining shock

Note: See figure 3.15

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# Erklärung gem. § 4 Abs. 2

Hiermit erkläre ich, dass ich mich noch keinem Promotionsverfahren unterzogen oder um Zulassung zu einem solchen beworben habe, und die Dissertation in der gleichen oder einer anderen Fassung bzw. Überarbeitung einer anderen Fakultät, einem Prüfungsausschuss oder einem Fachvertreter an einer anderen Hochschule nicht bereits zur Überprüfung vorgelegen hat.

Catalina Martínez Hernández
Berlin, June 24, 2021

# Liste verwendeter Hilfsmittel

Erklärung gem. § 10 Abs. 3

- MATLAB R2019a
  - Econometric toolbox
  - Optimization toolbox
  - Parallel Computing toolbox
  - Statistics toolbox
- LaTeX
- Microsoft Excel
- Siehe auch Literatur- und Quellenangaben

Die Schätzungen der Methoden in dieser Dissertation wurden im Cluster Curta (ehemaliger Soroban) an der Freien Universität Berlin ausgefürt.